Credit Card Banking

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Abstract

Credit card interest rates average 23%, far exceeding rates on other major loan or bond types. To understand the drivers of these high rates and the economics of credit card banking, we analyze regulatory account-level data on 330 million monthly accounts, representing 90% of the US credit card market. While high default rates partially explain high card interest rates, netting these out still leaves an average interest spread of 10%. Non-interest expenses, including rewards, are more than offset by corresponding non-interest income. Operating costs are large, suggesting a significant role for market power, and explain a sizable part of rate spreads. Yet even after subtracting them, banks' return on credit card lending is over four times their average return on assets. Using the cross section of accounts by default risk, we estimate a price of default risk. We find it is similar to that in high-yield bonds, and implies the average card borrower pays a 4.2% risk premium. Yet, there remains a substantial zero-beta rate of 3% that is unexplained by risk and is specific to credit card lending.

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1 Introduction

Credit cards are one of the most commonly used financial products in the United States. Nationwide, there are around 580 million credit card accounts, with approximately 74% of US adults having a credit card account in their name. Credit cards are now the primary method of payment for consumers, with credit card purchase volume totaling $6 trillion in 2023, or 70% of total retail spending.

Credit cards are also the main way that consumers can obtain unsecured borrowing, making it their primary source of marginal buying power. Indeed, 60% of all credit card accounts are borrowers, i.e., they carry a balance from one month to the next. Thus, for most consumers the price of substituting consumption over time is determined by the interest rate on their credit card rather than the rate on a savings account or treasury bill, as often assumed in macroeconomic models. This makes a big difference because credit card interest rates are *very* high: the average annual percentage rate (APR) on general purpose credit cards in 2023 was 23%, an 18% spread over the average Fed funds rate.

This interest spread is far higher than that on other loans or bonds. For comparison, the interest spread of Commercial and Industrial (C&I) loans (loans to firms) over the Fed funds rate averaged 2.25%, the spread of mortgages over treasuries was 3%, and the spread over treasuries of high-yield US corporate bonds–the riskiest corporate bonds–was 4.21%.

Therefore, in this paper we ask two questions. First, why are credit card rates so high? We analyze credit card lending as an asset class and compare its pricing to that of other types of lending. At the same time, credit card banking is also an intensely retail business, which may be important to understanding credit card rates. Hence, our second aim is understanding the economics of the business of credit card banking. Therefore, we investigate the sources of revenue and costs involved in it, and whether market power plays an important role in it. This helps provide a fuller answer to our first question.

Despite the high interest rates, consumers borrow a substantial amount on credit cards.

At the end of 2023, outstanding credit card balances were $1.1 trillion, with 85% of this due to borrowers, and the rest due to "transactors", accounts that repay their balance by the end of the statement month. Though credit card balances are economically sizable, they accounted for a modest 4.5% of banks' balance sheets during 2010 to 2023. Yet, their high rates meant that they generated a much larger fraction of banks' interest income, 16.6% on average.

Credit card lending is banks' riskiest form of lending, due to being both unsecured and personal lending. From 2010 to 2023, credit card charge-offs averaged 3.96% of balances. In comparison, charge-off rates on business loans and residential mortgages averaged only 0.46% and 0.43%, respectively. Consequently, an average of 53% of banks' annual default losses were due to credit card lending. Surprisingly, default losses on credit cards are a similar order of magnitude as those on corporate bonds, though corporate bonds are roughly ten times larger than credit card balances. Specifically, annual default losses on credit cards were 64% of those on corporate bonds on average over 2010 to 2023, assuming a bond recovery rate of 50% (standard).[1]

We analyze four potential explanations for why credit card rates are so high. The first is that they are compensation for average default losses. The second is that they are needed to pay for the high cost of card "rewards," which banks pay their customers in either cash or airline miles. The third is that credit card rates price in a large default-risk premium, because default risk is undiversifiable and default losses are high in bad economic states. The fourth is that they are due to credit card banks having market power.[2] Market power and risk pricing can also interact, with banks pricing credit card rates using a higher price of default risk than is found in other markets.

Our analysis utilizes a comprehensive supervisory dataset on credit card accounts from

[1]Corporate bond default amounts are from S&P Global Annual U.S. Corporate Default And Rating Transition Study (2023).

[2]The literature has argued that the credit card market lacks competition (Ausubel, 1991; Herkenhoff and Raveendranathan, 2021), has high search or switching costs (Calem and Mester, 1995; Drozd and Nosal, 2008), and that consumers differ in how hard they search for the best rate(Stango and Zinman, 2016).

the Federal Reserve's Y-14M reports. This dataset contains monthly data on approximately 330 million individual credit card accounts from the 20 largest banks, covering over 90% of credit card lending in the U.S. It contains detailed, account-level information, including the account-holder's FICO score, the account's APR, credit limit, monthly balance, purchase volume, fees charged, rewards received, and the account-holder's income and geographic location. The data allows us to calculate the various revenue and expense components of credit card banking at the individual account level.

We track accounts over time in cohorts based on month of origination. This is important for calculating the lifetime returns banks make on accounts because a card's APR spread (the spread of its APR over the Fed Funds rate) is effectively fixed at origination.[3] Thus, in setting an account's APR spread, the bank must consider not only default risk in the near future, but over the account's whole life. By tracking accounts over time, we capture these future defaults in our measures of the returns banks make lendings to these account.

To obtain a sufficiently long time series to capture accounts' lifetime returns, we focus on the cohorts originated between January 2015 and December 2017, and track them until the end of our sample in December 2023. This gives us at least six years of data for each cohort. We further sort each cohort into portfolios by a card's FICO score at origination. FICO is the industry-standard credit score. It's value ranges from 300 to 850, with a higher score indicating lower default risk.

We sort accounts by their FICO at origination in order to obtain a large spread in their default risk. This also creates a large spread in their average APR, as FICO is the main factor banks use to set an account's APR. By tracking the revenues, costs, and defaults of these portfolios over time, we are able to analyze the risks and returns to credit card lending.

For each month we further sort the accounts in the FICO portfolios into portfolios of

[3]This is the case since the Dodd-Frank Act, which prohibits a bank from increasing an account's APR spread on existing borrowing. We show that in practice it is rare for an account's APR spread to change during its life.

borrowers and transactors. This is important because borrowers and transactors generate different risks and revenues. In the months that an account is borrowing, it exposes the bank to default risk and is charged interest, unless it is in a zero-interest promotional period.[4] In the months that an account is a transactor, it poses no default risk and is not charged interest. We find that borrowers make up roughly 60% of all accounts, and that the borrower share of accounts is strongly decreasing in FICO: it is only 20% for FICO scores above 800, but is over 50% for all FICO scores below 720, and rises to almost 80% for FICO scores near 600.

We begin by looking at the interest rates borrowers pay. Two main findings stand out. First, the average APR spread (the spread of the effective interest rate paid over the Fed Funds rate) is high for all FICO scores, so that even accounts with the highest possible FICO (850) pay an average APR spread of 7.2%. Second, the APR spread is strongly increasing in credit risk, rising to an average spread of 21% for FICO 600 accounts.

To see if the APR spreads are just compensation for expected default losses, we compare them to the portfolios' average net charge-off rates (charge-offs net of recoveries). Since we track portfolios over a long time, we compute these rates as the cumulative dollar amount for the given quantity (e.g., default loss) over the sample period divided by the cumulative monthly balance over the same period. We report the rates annualized.

We find that charge-off rates decrease almost linearly with FICO, from 11.7% per year at 600 FICO to 1.3% for 850 FICO. While the charge-off rates are high, especially for the lower FICO scores, they are all far less than their corresponding APR spreads. Thus, the APR spread is mostly *not* due to expected default losses. Moreover, this difference between the APR spread and charge-off rate–the default-adjusted APR spread–is increasing in default risk: from 6% at 850 FICO to 11.7% at 600 FICO.

We then analyze the non-interest income and expense components of credit card banking

[4]Zero-interest promotional periods, typically offered to customers as an incentive to open a new account, usually take place within the account's first twelve months.

to see how they affect profitability. Among these, the most distinct to credit cards are interchange income and rewards expenses. Interchange fees (also called "swipe" fees) are a percentage of a product's purchase price (normally around 2%) that is charged to the seller and split between the credit card network (Visa, Mastercard, American Express), the merchant's bank, and the customer's bank. Most of the fee is earned by the banks, in particular the customer's bank. Rewards are a percentage of the same purchase price that is paid to the cardholder by their bank for using the card. They are paid as cash, airline miles, or points that can be redeemed for cash or travel.

The value of interchange and rewards has become very large. In 2023, the rewards expenses of the six largest card issuers totaled an enormous $67.9 billion. Thus, it is plausible that banks charge high APR spreads to recoup these tremendous expenses. However, we find this is not the case. Rewards expenses are covered by banks' interchange income, as the two are closely intertwined. This is highlighted by the fact that banks' filings report the net of these two quantities as a single category. We find that banks' interchange income is 1.9% of purchase volume on average, while rewards costs are 1.4%.

Net interchange differs greatly between borrowers and transactors. Because transactors repay their balance each month, they have higher purchase volumes, and thus generate substantially higher net interchange income. The also have lower balances. We find that net interchange income is about 5% of balances for transactors, and 0.5% for borrowers. Net interchange income accounts for a large fraction of banks' return on transactors, but is a minor piece for borrowers.

It has been argued that banks use borrowers' interest income to subsidize high reward payments to transactors. However, we do not find this to be the case, since we find that banks make positive net interchange for both transactors and borrowers at all FICO scores.

We also examine non-interchange fee income, which includes late fees, annual fees, and balance transfer fees. On average, accounts incur fees of around 2.6% of their balances. Fee income is highest at the extreme ends of the FICO: many high-FICO accounts pay large

annual fees for premium credit cards, while many low-FICO customers pay substantial fees to transfer balances to new accounts.

Next, we analyze credit cards' operating expenses. Finance research often models banks as portfolios of financial assets and liabilities, and thus overlooks the influence that operating (i.e., non-financial) expenses have on their decisions. One of the main reasons commercial banks have high operating expenses is that they are in large part a retail business.[5] We find that, due to their intensely retail orientation, credit card operations have particularly large operating expenses: 4-5% of balances annually. These costs explain about half of default-adjusted APR spreads.

A key reason that banks incur high operating costs is to obtain market power (i.e., a "franchise") (Drechsler, Savov and Schnabl, 2021). This appears to be particularly true for credit card operations. As evidence of this, we find that one of the largest components of credit card banks' operating expenses is marketing. Credit card banks spend an average of 1-2% of assets each year on marketing, about 10 times the share spent by other banks. This is why the largest credit card banks, Capital One and American Express, are among the biggest marketers in the world, with marketing budgets equal to those of consumer products giants Nike and Coca-Cola.[6]

Combining all income and expenses, including operating expenses, we obtain the return on assets (ROA) for the credit card portfolios. We find that ROA is high: 6.95% for the aggregate portfolio of borrowers, 3.2% for transactors, and 6.5% overall. Moreover, ROA is strongly increasing in borrowers' default risk, increasing from 5% for the high-FICO portfolios to nearly 11% for the low-FICO ones. Thus, ROA exhibits a strongly increasing relation with default risk, similar to the one we found for default-adjusted APR. This suggests that credit card rates price in a default risk premium.

[5]Banks' retail dimension strongly influences their financial characteristics, such as the source and cost of their financing (e.g., deposits), and the assets they invest in (Drechsler, Savov and Schnabl, 2017, 2021).

[6]In 2023 their marketing expenditures were: Nike $4.1B, Coca-Cola $5.0B, Capital One $4.0B, American Express $5.2B.

Two conditions are present that support this hypothesis. The first is that charge-offs are highly correlated across the FICO portfolios, rising together in cycles that are highest during recessions. Therefore, charge-off risk has a common component that cannot be diversified within the credit card market. Second, credit card charge-off rates are highly correlated with default rates on other bank loans, and with default rates in the corporate bond market. Thus, default risk is also undiversifiable across other loan markets. Since default risk has this systematic component, it is plausible that it would be priced.

We test this idea by estimating a single-factor model of default risk in the cross-section of FICO-sorted credit card portfolios.[7] We proxy for the systematic component of default risk with the monthly change in the charge-off rate of the aggregate credit card portfolio. We estimate the beta (exposure) of each FICO portfolio to systematic default risk by regressing the monthly change in its charge-off rate on the proxy. Following the standard asset pricing approach (Fama and MacBeth, 1973), we then estimate the compensation for default-risk beta by regressing the portfolios' ROAs on their betas.

We find that the estimated charge-off betas are strongly and linearly decreasing in accounts' FICO scores. Thus, FICO score is a good proxy for an account's beta to systematic charge-off *risk*. Regressing the portfolios' ROAs on their betas, we estimate the risk premium for charge-off beta to be a highly significant 4.8% per year. We also find that the model's fitted ROAs are close to the actual ROAs across the whole FICO range. Thus, sensitivity to aggregate default risk can fully explain the strong, increasing relation between ROA and FICO score.

The regression's intercept is the ROA of a hypothetical zero-beta borrower, i.e., a borrower with no systematic default risk. The intercept estimate is 2.8%. A test of the model is to compare this estimate to the ROA for transactors, since they have a zero beta by

[7]Credit cards are advantageous for analyzing the default risk premium because (a) of all the asset categories they have the highest sensitivity to the default cycle, (b) a large cross-section of sensitivities is available, and (c) since there are millions of accounts, we can minimize the impact of idiosyncratic noise to obtain precise measures of systematic exposures.

construction, and were not included in the regression. The transactor portfolio has an ROA of 3.2%, very close to the zero-beta estimate.

We then analyze how our estimated default risk premium from credit cards compares to that in other markets. We focus on corporate bonds because they are very large and their default rate is relatively sensitive to the default cycle. Mapping bonds' credit ratings to equivalent FICO scores, we find that their historical risk premiums are very similar to the ROAs of the corresponding FICO portfolios. Hence, it appears that credit card rates and corporate bond yields price in a similar compensation for default risk.

Lastly, we compare credit cards' zero-beta rate to the ROA of the banking sector as a whole, which has a significantly lower average default than even the safest FICO portfolio. The banking sector's pre-tax ROA is around 1.5%. This means that credit cards have a 1.3% higher default-risk-adjusted ROA than the overall banking sector.[8]

Related Literature

The first paper that emphasizes high returns of credit card banking is Ausubel (1991) where the author records that the average ROA of seven banks that are almost exclusively focusing on credit card lending was around 5% from 1983 to 1988. Sinkey and Nash (1993) also measure the riskiness and profitability of credit card banks between from 1984 to 1991 and obtain similar findings. After these two papers, the literature has moved away from studying credit card banking from the perspective of banks to emphasizing more on consumers' borrowing relationship with card issuers. However, the series of annual Congress Reports since 1997 confirms the extraordinary performance of credit card banking in the past two decades. Most recently, Adams, Board and Katcher (2022) examine major banks' credit card loan portfolio and also find high profitability. Similar to us, they find credit card

[8]This value is actually a lower bound because the banking sector has some small default risk, with a charge-off rate around 0.25% of total assets (0.5% of loans and leases). Using the relationship between average charge-offs and default-risk betas estimated from the FICO portfolios implies that bank assets have a beta in the range 0.05-0.1, and hence a default-risk premium between 0.25% and 0.5%.

profitability is mainly driven by borrowers who revolve their balance and pay credit card interest. Our paper takes one step further and investigate why credit card banks charge such a high interest rate.

One explanation that literature offers on high credit card interest rate is credit card issuers' market power. Ausubel (1991) uses secondary resale prices of credit card receivables to show market prices in the rent credit card issuers extract from users. Herkenhoff and Raveendranathan (2021) document that credit card industry engaged in various non-competitive behavior during the 1970s and 1980s and ensuing reforms only resulted in limited oligopolistic competition. Related to the market power story, Bester (1985), Ausubel (1999) and Agarwal, Chomsisengphet and Liu (2010) argue that credit card issuers set interest high enough to mitigate adverse selection. In particular, credit card banks command market power over consumers who do not intend to borrow but ended up borrowing, and thus sets interest rate high enough to successfully deter consumers who are riskier and intend to borrow at the first place. We contribute to this line of literature by documenting and quantifying the importance of credit card banks' market power to their overall profitability.

Our analysis on the systematic risk premium in credit card pricing is also related to the recent work by Fleckenstein and Longstaff (2022). The authors use market prices of credit card asset-backed securities to estimate market risk premium of unsecured consumer lending, and find a modest market risk premium between $1-2\%$. We instead focus on the primary market of credit card issuance and connect credit card banks' risk premium to their profitability.

Finally, our paper is related to the literature on the effects of regulations on consumer credit market. Agarwal et al. (2015) and Han, Keys and Li (2018) find the CARD Act reduces borrowing costs and credit supply especially for non-prime borrowers. We supplement their finding by showing the CARD Act has little impact on credit card banks' overall profitability.

2 Data

2.1 Y-14 Reports

We use a granular and comprehensive supervisory data set on credit card loans from the Federal Reserve's Y-14M reports. They are collected for capital assessments and stress testing and contain account-level information at monthly frequency. All banks in the US with $100 billion or more in total consolidated assets are required to report the information. We focus on the reports' sub-schedule covering credit card loans. This data covers 20 banks, representing over 90% of credit card lending in the US.

We use account-level variables, including the average percentage rate (APR), FICO score, balance, credit limit, purchase volume, and fees. Banks often provide special benefits to cardholders—such as lower introductory rates, reduced fees, or cash and rewards sign-up bonuses—and we can observe whether each account is in such a promotional state. We augment those variables with portfolio-level variables, which are available only at portfolio level, defined by bank, credit card type, lending type.[9] These variables include interest expenses, rewards, interchange income, operating expenses, and fraud expenses to analyze bank-level profitability from the credit card business.

We examine all general purpose reward credit card loans made to consumers. General-purpose cards are accepted by various merchants, unlike private-label cards restricted to specific retailers, and they represent 76% of US credit card lending.[10] We focus on accounts originated between January 2015 and December 2017, tracking them through December 2023. Although the Y-14 data start in 2012, we observe significant gaps in key variables before 2015. By restricting the sample to accounts originated up to 2017, we ensure sufficient

[9]There are four credit card types: General Purpose, Private Label, Business Card, Corporate Card. There are four lending types as well: Consumer Bank Card, Consumer Charge Card, Non Consumer Card, Non Consumer Charge Card.

[10]Within general purpose cards, there is a relatively small subset of cards called classic cards (34.2% of all general purpose cards) that do not offer rewards. We exclude them in our analysis as their business model is very different from reward cards. Among private-label cards, 92% of them are classic cards with no rewards.

follow-up time to assess risk and returns throughout the entire life cycle of credit card accounts. In robustness analysis, we confirm that this choice of endpoint does not bias our findings.

For consistency, we restrict our sample to accounts that (1) start observations within one month of origination, (2) have no missing data throughout, and (3) exit due to charge-off, closure, or continue until December 2023. Instead of using stratified samples like 0.5 percent in other studies, we use the entire dataset. This leaves us with 31 million observations per month, from January 2015 to December 2023, and the summary statistics from portfolio-level data are reported in Table 1.

2.2 Additional Data Sources

Call Reports We complement the Y-14 data with call reports, which contain data on the income statements and balance sheets of all US banks at a quarterly frequency. This data set is useful for comparing the profitability of credit card banks with the rest. We identify credit card banks as those with a personal loan-to-asset ratio exceeding 50% and a personal credit card loan share of personal loans exceeding 90%. This definition follows congress reports,[11] and we confirm that our results are not sensitive to the particular thresholds.

Corporate Bond Data For the comparison of credit cards with corporate bonds, we use the Mergent Fixed Income Securities Database (FISD). We obtain information on a corporate bond's issuance date, issue size, coupon rate, maturity date and credit rating.[12] This dataset also provides us with the historical performance of the issue. In particular, we observe whether the bond matured and entire principal was repaid, the bond defaulted or was called by the issuer.

[11] We follow the series of "Report to the Congress on the Profitability of Credit Card Operations of Depository Institutions": https://www.federalreserve.gov/publications/credit-card-profitability.htm.

[12] We employ the Standard and Poor's ratings as the primary source of credit ratings.

3 Borrowers and FICO Score

Throughout our analysis, we make distinctions along two key dimensions: (1) borrowers versus transactors, and (2) FICO score bins. In this section, we first define the borrowers and transactors and then examine how each group is distributed across FICO score.

3.1 Defining Borrowers vs. Transactors and FICO Score Bins

Borrowers vs. Transactors Credit cards serve two primary functions: transacting, which entails using a credit card for purchases and paying the balance in full before the statement due date, and borrowing, which involves carrying forward a positive unpaid balance. Banks' revenue sources differ between these groups, with interest income derived from borrowing accounts ("borrowers") and transaction fees from transacting accounts ("transactors"), making it important to classify accounts accordingly. In our data, borrowers are defined as accounts that incur finance charges, pay an amount less than the previous balance, experience charge-offs, or undergo a balance transfer, while all other accounts are classified as transactors. Table 3 reports account-level variables comparing borrowers and transactors. As expected, the average daily balance (ADB) is much higher for borrowers, while the interchange fee income and reward expenses are higher for transactors. By definition, transactors are not charged with interests and do not have defaults and recoveries, therefore we did not report those numbers for transactors.

FICO Score Bins We sort accounts into FICO score bins at origination to estimate the associated risk and return on credit card lending for the following reasons. First, FICO score at origination is a useful proxy of ex-ante credit risk(Appendix C Table 5). Second, we confirm that banks set a card's APR spread over Fed funds rate based on FICO at origination and rarely change it, i.e. APR spread is fixed for an account's life(Appendix C Table 6).

Using FICO score bins, we can also link them to corporate bonds with similar default probabilities and compare credit card risk pricing to that in the bond market. We classify accounts into 50 bins by FICO scores (at origination) ranging from 600 to 850.

3.2 Distribution

Since the FICO score is a key dimension in our analysis, we begin by examining the distribution of accounts across FICO scores. This is important because the drivers of profitability likely differ by FICO score.

Figure 1 plots the share of accounts distributed across FICO score at origination. While close to 82% of accounts are relatively uniformly distributed between 670 and 820 based on the number of accounts (either existing or new accounts), with the mode at 695.[13] Once weight the accounts by their ADB,[14] more mass is concentrated between 660 and 750.

Since the source of profit from borrowers is driven by interest income while that from transactors is driven by purchase volume, we also examine the share of borrower within each FICO bin, reported in Figure 2a. Not surprisingly, the share of borrowers is higher for low-FICO accounts. However, it is striking that borrower share is high overall; even at 720, more than half of the accounts are borrowers and almost 20% of accounts with the

[13]These two lines are almost identical because the attrition rates at each origination FICO bin are very similar. The attrition rates are the share of accounts closed at each origination FICO bin, including accounts defaulted, closed by customer request, and closed due to fraud, lost or stolen cards, deceased, or other reasons.

[14]For each account, we use the average daily balances reported by banks as the base measures of balances, and when ADB is missing, we use cycle ending balance (CEB) to fill in the missing values. The reason why ADB might be missing for some accounts because they never borrowed during the entire sample period. ADB is computed if you ever borrowed and will continue to be computed by banks even if you stop borrowing later. We confirmed that ADB is available for majority of the accounts in our sample. We checked that CEB and ADB are very similar across all origination FICOs. For borrowers, we directly use the average daily balance reported by banks as balances, except for the period when a borrower is going to transit to a transactor in the next period. For such period, since the ADB reported by banks mix both the balances from being a borrower and a transactor, we compute the implied ADB for borrowing using the amount of finance charges and APR in that period. For transactors, the balances are obtained from subtracting total balances of all accounts by total balances of borrowers. Transactors' balance comes from previous month's purchase volume since credit cards offer 21-day grace period where no interest will be charged if you pay within this grace period.

FICO score higher than 800, who are considered “superprime" are borrowers. In terms of ADB, more than half of the ADB across *all* FICO score is coming from the borrowers. This suggests that balances carried by borrowers constitute the majority of assets for a bank's credit card business.

Consistent with the borrower shares, we find that the borrowers are important in credit card business in terms of ADB in dollar amounts. Figure 2b suggests that the borrowers account for more than 85% of credit card banks' balance sheets. The peak average ADB is $2,200 for origination FICO between 660 and 720.

4 Credit Card Profit Decomposition

In this section, we examine the first two hypotheses to explain the high effective APR spread by analyzing the main income and expense sources for credit card banks.

4.1 Interest Component and Credit Loss

Considering the importance of borrowers suggested from the previous section, it is natural to hypothesize that the high interest rate spread is driven by expected credit losses.

The interest rate charged on credit card borrowing is known as Annual Percentage Rate (APR) which the is the annualized rate quoted in percentage. Because credit card banks often offer promotional rates, significantly lower than non-promotional rates (e.g., 0%), for a limited time period (e.g., the first 12 months since account opening), we compute effective interest rates. As credit card interests are computed using daily compounding, that is:

$$\text{Interests} = \text{APR} \times \text{Number of days borrowed}/365,$$

we compute effective interest charges in the same way. Because the vast majority of credit card APRs are variable rates, meaning they consist of a constant margin added to the prime

rate,[15] we focus on effective APR spread, defined as effective APR minus prime rate, which is proxied by the Fed funds rate.

Figure 3 plots the effective APR spread across FICO. As one can expect from the distribution of borrowers across FICO bin in the previous section, the effective APR spread increases as FICO decreases. The median effective APR spread increases from 8% for FICOs above 800 to 18% for FICOs below 660 almost linearly. In terms of the overall level, the credit card effective APR spread is much higher than those charged on other types of loans or bonds. For instance, between 1997 and 2024, the mean corporate bond spread is 1.5% for investment-grade bonds, 5.3% for high-yield bonds, and 11.1% for those rated CCC or lower. We analyze cross-asset comparison in more detail in section 5.

Even though credit cards have very high effective APR spreads, credit cards also have very high charge-off rates. Credit card loans are a form of unsecured consumer credit and thus constitute the most risky type of lending for banks. Figure 4 plots the time series of annualized value-weighted charge-off rates for all accounts in Y14-M sample.[16] The average aggregate charge-off rate is 5.1% with a standard deviation of 1.4%. During 2018-2019, credit card charge-off rates remain at very high levels (around 6.5%), declined during 2020-2021, and has increased sharply since 2022 as the Fed started the monetary tightening.

The high average charge-off rates lead us to examine the next question: do high interest spreads enough to compensate for high average charge-off rates? We answer this question by computing the default-adjusted credit spread across origination FICO bins. The default-adjusted credit spread is defined as the interest income rate minus interest expense rate minus charge-off rate.[17]

[15] Ausubel (1991) document that credit card APR was sticky and did not move with Fed funds rates. However, since 1995, credit card APR moves closely with Fed funds rate. In fact, 95% of credit card mail offerings in 2021 have variable rates.

[16] We did not restrict to accounts that are originated between January 2015 and December 2017 but instead look over all accounts in the dataset to give a more precise picture of the aggregate charge-off rates on credit cards. Using our main sample of accounts originated between 2015 and 2017 gives a similar time series of charge-off rates.

[17] As stated in the Data section, we track accounts over lifetime from origination to closure or sample ends, therefore all amounts are computed by summing the relevant components over lifetime for each account.

In Figure 5, we plot the three components of default-adjusted credit spread as annualized shares of ADB.[18] Each component is computed over "lifetime" of each credit card account and then aggregated at the FICO bin level. The annualized interest income rates (in blue) range from 9.1% at FICO 850 to 23% at FICO 600. The annualized net charge-off rates range (in green) from 1.3% at FICO 850 to 9.3% at FICO 600. Both interest income rates and net charge-off rates decrease almost linearly with origination FICOs. The interest expense rates (in red) are flat across all origination FICO bins because we apply the same Fed funds rates to all accounts. As a result, the default-adjusted credit spread (the black line) increases from 6% at FICO 850 to 11.7% at FICO 600. The increase is mostly linear from FICO 850 to FICO 660. The jump at FICO score of 660 is at least in part likely related to the discontinuity in credit card terms for non-prime borrowers.[19] More importantly, it is worth highlighting that the level of default adjusted credit spread is substantial across all origination FICOs, suggesting that the high effective APR is explained only partly by the credit losses. In the next section, we examine whether non-interest components explain the remaining spread.

4.2 Noninterest Components

The noninterest components of credit card business' profits consist of interchange income, rewards expense, fees, and operating expenses.

Interchange and Rewards

Among the noninterest components, interchange and rewards are the two most distinctive features of credit cards. Interchange fees are paid by merchants when customers use credit cards for purchases. Although credit card holders do not pay the interchange fee directly,

[18] Since only borrowers have interest income and net charge-off rates, this figure covers borrowers only.

[19] According to CFPB, there are five credit score levels: (1) deep subprime (FICO below 580); (2) subprime (FICO of 580-619); (3) near-prime (FICO of 620-659); (4) prime (FICO of 660-719); (5) super-prime (FICO of 720 or above). For more details, please see the CFPB website.

they indirectly pay this cost as merchants can raise their prices accordingly. Interchange fees go to the issuing bank and credit card networks.[20] Credit card banks can use interchange income to fund their rewards programs, as both are typically set as a fraction of purchase volume.[21] There are many forms of rewards, the most commonly known ones are cash back rewards, miles, hotel points, and statement credits. The reward rate varies significantly across card, ranging from 1% to 10% of purchase volume.

We estimate the interchange rates and reward rates from the Y14-M portfolio-level data because interchange fees are not available at the account-level (since they are paid by merchants). The Y14M portfolio-level data reports interchange fees and rewards expenses accurately for each bank in each month.[22] Appendix A.1 gives detailed description on how we compute both rates. Given that both interchange and reward rates are driven by purchase volume, we begin by investigating the average purchase volume of borrowers compared to transactors within each FICO score bin. Figure 6 shows that transactors have much higher purchase volumes than borrowers, suggesting that both interchange income and reward expenses would be primarily driven by transactors.

To understand how interchange and rewards contribute to the overall profit of credit card portfolios, we compute lifetime interchange and reward rates. Following the same

[20]There are four credit card networks, VISA, Mastercard, Amex, and Discover. Credit card network is the intermediary between a merchant's bank and a customer's bank, and it transmits a transaction's information through banks. Issuing bank is the issuer of a customer's credit card. The interchange fee is a fraction of a purchase and the majority of the interchange fees goes to issuing banks and the rest goes to card networks. Interchange fees are different for different card networks, Amex and Discover tend to charge higher interchange rates than VISA and Mastercard. Interchange fees also vary from card to card — credit cards with higher rewards usually have higher interchange fees as well. Within the same card network and card type, interchange fees can be different due to different types of purchases (e.g. interchange rates for purchasing at supermarkets is lower than interchange rates for buying at a cloth store). Here is the interchange rates in 2024 listed by VISA: https://usa.visa.com/content/dam/VCOM/download/merchants/visa-usa-interchange-reimbursement-fees.pdf.

[21]Some credit card issuers also offer a one-time sign-up bonus rewards or referral rewards to customers.

[22]Since portfolio-level data does not distinguish between reward cards and classic cards or purchase types or card networks, we only take interchange and reward rates at the bank-month level. To estimate interchange fees and rewards expenses as percentages of purchase volume using portfolio-level data, which only includes total credit card balances, we get purchase volumes from account-level data for each bank monthly. The rates were then adjusted by removing outliers and calculating 12-month moving averages of interchange and rewards rates, resulting in average rates of about 1.9% for interchange and 1.4% for rewards.

approach as in the previous section, we compute the sum of interchange fees (or rewards) for each FICO bin divided by total lifetime ADBs of all accounts in the corresponding bin.[23] Unlike interest income and charge-offs, interchange fees and reward expenses apply to both transactors and borrowers. Therefore, we separate these two groups as shown in Figure 7.

For transactors, Figure 7a shows that the interchange fees as a share of ADB is on average 29% while the reward expenses as a share of ADB is on average 24.6% across all origination FICOs. The net interchange income (green line) which is interchange rates minus rewards rates is around 5% of ADB for almost all origination FICO bins.[24] For borrowers, Figure 7b shows that although the interchange fees and rewards expenses as a share of ADB are much smaller than transactors', the net interchange income rate is still positive at around 0.4%-0.5% of ADB. This suggests that banks are *not* using borrowers to subsidize transactors. However, in a broader sense, reward programs do hurt borrowers because merchants raise prices for all customers to compensate for the interchange fees charged on them. Borrowers purchase much less than transactors but borrowers are sharing the cost of interchange fees through the uniform prices.[25]

Fees

Credit card lending generates various non-interchange fee income, such as annual fees, late fees, balance transfer fees, over-limit fees, cash advance fees, convenience fees, and insufficient funds fees. During our sample period, credit card users incur non-interest fees averaging 2.6% of their balances, accounting for approximately 10% of total credit card lending revenue.

The largest categories are late fees, annual fees, and balance transfer fees. Appendix B

[23] We compute the annualized interchange rates (rewards rates) by dividing sum of lifetime interchange fees (rewards) by sum of lifetime ADBs for accounts within each origination FICO bin and then multiplying by 12.

[24] The spikes at low FICOs (below 630) and the dips at high FICOs (above 810) are due to (1) potentially very low interchange fees but high rewards for high quality card users and the opposite for low quality users, and (2) there are much fewer observations at both extremes of the FICO spectrum.

[25] Borrowers can suffer less if they can get a lower price for paying without a credit card.

Figure 2 shows non-interest fees as a share of ADB by month from account origination, grouped by original FICO scores. As shown in the figure, fee income is seasonal, peaking at an annualized rate of 15% of ADB every 12 months due to annual fees. Annual fees are highest for accounts in the highest and lowest initial FICO bins. Additionally, accounts with lower initial FICOs face high balance transfer fees early on. Users in the lowest initial FICO bin (605) pay non-interest fees equivalent to 65% (annualized) of their ADB within the first month of card opening.

Appendix B Figure 3 presents lifetime fee income as a percentage of lifetime ADB across the original FICO distribution for both borrowers and transactors. For borrowers, fee income remains fairly stable between FICO scores of 660 and 800, averaging around 2%, with the lowest 1.9% at an original FICO of 740. At higher FICO levels, fee income rises to 2.8% due to increased annual fees. Subprime borrowers incur fees exceeding 3% with accounts below 640 reaching 4%, driven by higher balance transfer income and late penalties.

Transactors exhibit higher fee income as a share of ADB due to their typically lower balances. They follow a similar pattern to borrowers, with prime accounts averaging about 4.8% of ADB in fee income, while subprime accounts see fee income as high as 10%. It is worth noting that transactors with low original FICO scores do not incur balance transfer or late fees, by our definition of a transactor. Their high fee income as a percentage of ADB is primarily due to the limited number of transactors in this FICO range and their relatively low ADB.

We calculate the credit card portfolio's net non-interest income by adding fee income to interchange income and then subtracting rewards expenses and non-default charge-offs. Non-default charge-offs include losses due to fraud, death, and other non-credit-related reasons. These charges are minimal and represent only 0. 016% of the balances.

Borrowers' net non-interest income is substantial, averaging 2.7%, and remains relatively steady for accounts with an original FICO above 660. In the subprime range, net non-interest income increases as FICO decreases, reaching 6% at an original FICO of 600, largely

due to higher balance transfer fees and net interchange income. Transactors have higher net non-interest income, ranging from 6% to 10% for FICO scores above 660. This income remains stable between FICO scores of 660 and 800, at 10%, but drops to 6% at 850 due to higher reward expenses. Although net non-interest income is also elevated for low-FICO transactors, they represent a small share of subprime balances, with transactors accounting for less than 5% of balances in the subprime segment.

To sum up, for borrowers, we have shown that credit card lenders earn a substantial default-adjusted credit spread of 8.9% and net non-interest income of 2.7%. We combine both interest and non-interest income to calculate the gross lending margin of credit card lending. Appendix B Figure 4 shows significant variation across origination FICO scores and a strong increase with accounts' ex ante credit risk. The gross lending margin rises from 9.5% at an 850 FICO to 13% at 660 FICO, reaching 18% at a 600 FICO. It is important to note that the gross lending margin represents the amount lenders earn from borrowers after accounting for interest, non-interest expenses, and credit losses. Borrowers who carry balances over time face notably higher all-in costs. Even the safest borrowers, with an origination FICO of 850, incur a 10% default adjusted spread above the short-term rate, while higher-risk borrowers can pay up to 20%.

4.3 Operating Expenses

Banks are not merely portfolios of financial assets and liabilities; they are, to a large extent, retail businesses. Credit card lenders exemplify this retail-facing aspect of banking, engaging in extensive consumer interactions. From customer acquisition and applicant screening to card administration and customer service, these activities generate significant operating expenses.

For example, Appendix B Figure 5 displays the components of Capital One's operating expense at the bank level and financial results of its credit card segment.[26] Salaries and

[26]Capital One's annual report reports non-interest expense. However, it excludes rewards expenses from

marketing represent the largest portions of its operating expenses, with other major costs including occupancy, communications, and data processing. In 2023, Capital One held an average of $141 billion credit card loans, representing 45% of its loan portfolio and 30% of its total assets. The bank's overall operating expense totaled $20 billion. Yet it attributed $12.5 billion to credit card operations, which is 8.9% of its credit card assets and 60% of bank's total operating expenses.

Y-14 data tracks banks' monthly spending on various operational costs related to credit card services. This includes marketing, servicing, cardholder billing, payment processing, card issuance, authorizations, and general card administration for general-purpose credit cards. Operating expenses are significant, averaging 4-5% of balances from 2014 to 2023. This figure is significantly higher than the combined costs of collections, fraud, and interchange processing, which total less than 0.5%. Notably, operating expenses account for approximately half of the default-adjusted APR.

Drechsler, Savov and Schnabl (2021) show that banks pay significant fixed operating costs to gain market power over retail deposits, enabling them to borrow at rates that are both below and less sensitive to market fluctuations. We find this is particularly true for credit card lenders by focusing on their marketing expense.

Marketing is one of the largest components of operating expenses for credit card lenders, making these banks some of the biggest marketers. In 2023, for instance, Capital One spent $4 billion on marketing, while American Express spent $5.5 billion. For comparison, major retailers such as Nike and Coca-Cola spent $4 billion and $5 billion, respectively. Appendix B Figure 6 using Call Report data, contrasts the marketing expenses of credit card banks with those of non-credit card banks. It shows that banks with significant credit card lending spend, on average, 1-2% of assets on marketing annually, whereas this figure is below 0.1% for other banks. It's worth noting that our definition of credit card banks may

non-interest expenses, as it records net interchange fees under non-interest income. For consistency with our terminology, we refer to Capital One's reported non-interest expenses as operating expenses.

include institutions with a still a significant portion of non-credit card assets, meaning the marketing expense as a share of assets would be even higher if we focus on their credit card portfolios.

We further present suggestive evidence that higher credit card operating costs allow banks to charge higher interest rate on accounts with similar ex-ante credit risk. Appendix B Figure 7 illustrates this relationship by plotting average interest income as a percentage of balance against operating expenses, while controlling for account's FICO at origination. We demonstrate this formally by regressing the average APR margin of a group of accounts—aggregated by issuing bank, origination date, FICO score at origination, and date—on the operating expense rate, which varies at the issuing bank*date level, while controlling for FICO score at origination. Our regression results indicate that, among accounts with similar ex-ante credit risk, a 1% increase in the operating expense rate is associated with a 13 basis point increase in the APR spread. (Appendix C Table 7).

4.4 Putting all Together: Return on Assets

We have outlined all the key components of the profit of a credit card lender. On the interest side, lenders earn income from borrowers who do not pay their balance in full within the billing cycle's grace period. For these borrowers, lenders charge interest based on their average daily balance and APR. Revolving balances also pose a credit risk, as these borrowers may default on their outstanding debt. Credit card lender fund borrowing at market short rate. On the non-interest side, card users generate interchange income for the bank from their purchase volume and pay various fees, including annual, late, and balance transfer fees. A substantial portion of interchange income funds rewards for card users, while another significant non-interest expense for lenders is the card's operating cost.

Combining these profit components gives us the Return on Assets (ROA) for credit card lending. We define ROA as the sum of interest and non-interest income, minus expenses

and charge-offs. Figure 8 displays the ROA for borrowers across different FICO scores at origination, as a percentage of lifetime ADB. The ROA is notably high and increases significantly with ex-ante credit risk, rising from 5% for borrowers with an initial FICO of 800 to 8% at 660 and reaching 11% at 625. The magnitude of increase in ROA with default risk is similar to the one we found for default-adjusted APR.

For transactors, ROA remains relatively flat, stabilizing around 3.6% between FICO scores of 680 and 820 (Appendix B Figure 8). The lower ROA observed at higher FICO scores is driven by higher rewards costs, while the higher ROA among riskier subprime borrowers is largely due to shorter and fewer transacting periods, leading to lower ADB. Notably, the transactor's margin is slightly lower than that of even the safest borrowers and remains independent of ex-ante credit risk. This is expected, as transactors, by definition, carry no credit risk, and lenders set transactor pricing based on an assumption of zero credit risk. Both the independence of transactor ROA from FICO scores and the observed increase in borrower ROA with rising credit risk suggest that credit card pricing may be substantially driven by risk.

The high ROA of credit card lending is reflected in the aggregate ROA of banks specializing in this sector. According to the FDIC Quarterly Report for 2024Q2, the average ROA for credit card banks is 3.18% (ROE of 31.03%), compared to an average ROA of 1.2% (ROE of 12.26%) for commercial banks. Figure 9 dpresents a time series of ROA for credit card and non-credit card banks. We compute ROA in the same way as account-level credit card net margin, except that we substitute provision for credit losses in place of actual charge-offs to align with reported financial ratios. Over the past 25 years, credit card banks have maintained an ROA around 3%, roughly three times higher than that of non-specialized banks. This rate is lower than the net margin on credit card accounts due to the presence of other, lower-return business segments within credit card banks. During crises, credit card banks' ROA declines sharply, reaching around zero due to high provisions for credit losses, as seen in 2008 and during COVID-19. Despite these provisions, credit card banks' returns

generally remain as high as those of other banks, indicating that the substantial spreads earned in credit card lending can effectively absorb losses during economic downturns.

5 Credit Card Risk Premium

Another reason why credit card rates and its ROA may be elevated is due to the high risk premium associated with credit card charge-offs. As we showed in previous section, the Return on Assets (ROA) for credit card portfolios is closely linked to the default risk of their borrowers. Specifically, accounts with lower FICO scores (higher risk) are associated with a substantially higher ROA, suggesting that the elevated returns on credit card lending are, in part, a reflection of a risk premium. In addition, if these charge-offs tend to be particularly burdensome during economic downturns, aligning with periods of heightened financial stress, banks may require higher compensation for bearing this risk. This raises the question of whether the risk premium on credit card lending is consistent with those observed in other asset markets, where returns are similarly elevated to compensate for increased risk exposure during adverse economic conditions.

Figure 9 illustrates the time series of charge-off rates across various types of loans and corporate bonds. Panel (a) shows that credit card charge-offs strongly correlate with other loan types, especially during recessions. Notably, credit card lending exhibits the highest and most sensitive charge-off rates, reinforcing the notion that it should carry a more significant credit risk premium relative to other lending types. Panel (b) demonstrates the relationship between speculative-grade corporate bond defaults and credit card charge-offs. Both exhibit substantial co-movement and comparable default rates.[27] Overall, this comparison suggests that corporate bonds may serve as a useful benchmark for assessing the risk premium in credit card lending.

[27]However, corporate bonds maintain a higher recovery rate of around 40%, compared to the much lower 15% for credit card charge-offs.

There is a substantial heterogeneity in average charge-offs and their time variation across credit card accounts with different original FICO. The life cycle of charge-offs, depicted in Panel (a) of Figure 10, shows a distinct pattern tied to borrowers' initial FICO scores. Accounts originating with higher FICO scores have relatively low charge-off rates of around 2.5%, whereas accounts with FICO scores of 660 and 600 experience much higher rates, around 10% and 15%, respectively. This trend is especially pronounced as promotional APR periods expire, causing charge-offs to spike as financial stress on borrowers increases. Panel (b) of Figure 10 shows a time series evolution of credit card charge-offs across FICO scores. It confirms that credit card charge-offs vary considerably across FICO scores, with lower-FICO portfolios showing both higher charge-off levels and greater volatility, especially during economic downturns.

Motivated by the aggregate and cross-sectional evidence, we quantify the risk exposure for each origination FICO score bin using two-stage approach of Fama and MacBeth (1973). Specifically, we first estimate a one-factor model of FICO-specific charge-offs as a function of the aggregate charge-off rate on credit card lending. For each FICO portfolio i, we calculate its sensitivity, β_i, to the aggregate default rate using the following specification:

$$\Delta\text{Charge-off Rate}_{i,t} = \alpha_i + \beta_i \Delta\text{Charge-off Rate}_t + \epsilon_{i,t} \tag{1}$$

Figure 11 presents these beta estimates plotted against the corresponding charge-off rate for each FICO portfolio. The results reveal a strong single-factor structure in the charge-off risks for FICO portfolios, with charge-off beta linearly increasing with the average charge-off rate. Low FICO portfolios (600-650) with high charge-off rates around 8-10% exhibit strong exposure to aggregate risk, with betas ranging from 1.2 to 1.6. In contrast, high FICO portfolios (800-850), with lower charge-off rates between 1-3%, show minimal sensitivity to aggregate default rate fluctuations, with betas close to zero.

Second, we use the FICO-specific risk exposures from the first stage to estimate the

price of risk and the corresponding risk premium. To this end, we regress the ROA of FICO portfolio i on its risk exposure, β_i, using the following specification:

$$ROA_i = \lambda + \gamma\beta_i + \nu_i \tag{2}$$

Figure 12 presents the credit card ROA, the estimated risk premium, $\gamma\beta_i$, and the fitted ROA from Equation 2, $\lambda + \gamma\beta_i$, across the FICO distribution. The results suggest that the one-factor model provides an excellent fit to the ROA data. We find that the price of risk, γ, is approximately 0.048, while the estimated risk premium ranges from 1-2% for the highest FICO group (800-850) to 6-8% for the lowest FICO group (600-650). Notably, the zero-beta rate ($\lambda = 0.028$) is very close to the ROA on transactor accounts, which carry no risk as these accounts involve no borrowing.

Finally, we compare our estimates of credit card risk premia to those observed in the corporate bond market. Corporate bond credit spreads, defined as the difference between yields on defaultable corporate debt and Treasury rates, are typically wider than would be implied by expected default losses alone. This phenomenon, known as the credit spread puzzle, has been attributed to a credit risk premium that compensates for increased credit risk, especially during economic downturns (e.g., Collin-Dufresn, Goldstein and Martin, 2001; Amato and Remolona, 2003). To calculate the corporate bond credit risk premium, we use Mergent FISD historical data on corporate bond issuances from 1990 to 2023. For each bond, we track its history, including issuance details (date, amount and coupon), as well as whether and when the bond matured, defaulted or was called by the issuer. This allows us to construct cash flows to investors based on a buy-and-hold strategy, assuming the investor can borrow at the Treasury rate of similar maturity to the corporate bond. In the event of a bond default, we assume an average recovery rate of 40%, consistent with Standard & Poor's (S&P) estimates. Similar to our approach for credit cards, we form portfolios of bond investments categorized by initial credit rating and compute the

internal rate of return (IRR) for each buy-and-hold strategy, with the IRR representing the default-adjusted spread. To facilitate the comparison between bonds and credit cards, we map corporate bond ratings to FICO scores based on the 5-year expected default rates provided by S&P and our own calculations for credit cards. Figure 13 presents both the credit card risk premium estimated from the one-factor model (black line) and the default-adjusted spread for corporate bonds (blue line). Interestingly, the credit card risk premium closely aligns with the default-adjusted spread for similarly rated high-yield corporate bonds. However, the risk-adjusted ROA for credit cards is higher than that for corporate bonds of comparable risk.

6 Robustness

In this section, we examine whether other factors, such as bank capital requirements, explain the high ROA documented in the previous section.

6.1 Capital Requirements

Bank regulations, such as Basel III, require banks to hold a specified fraction of risk-weighted assets (RWA) as capital, providing a buffer against potential losses. RWA assigns varying risk weights to assets based on their riskiness, ensuring banks allocate more capital to riskier exposures; for example, cash or government bonds have a 0% risk weight, while riskier loans have higher weights (e.g., 100%). Consequently, if credit card loans require substantial capital holdings, banks may seek higher returns, increasing both the intercept and the slope of the ROA as a function of FICO score shown in Figure 8.

To examine this hypothesis, we compute the risk weights assigned to credit card loans and their implied cost of regulatory capital. Credit card exposures are classified into credit risks coming from retail exposures.[28] Within the retail exposure category, transactor and

[28]The retail exposure class includes the following types of exposures: (1) exposures to an individual person

borrower accounts require different amount of RWA.[29] Banks can calculate RWA using either the standardized approach, defined by the Basel Committee, or the advanced approach, which relies on internally developed models. Under the Collins Amendment of the Dodd-Frank Act, banks using the advanced approach must also apply the standardized approach and use the lower of the two total risk-based capital ratios to assess compliance with minimum capital requirements.

To implement these institutional details, we classify banks in Y14-M sample as standardized approach banks if they do not report the internally calculated variables such as probability of default. Banks that report those variables are classified as advanced approach banks. We then calculate the risk weights for each origination FICO bin for transactors, borrowers, and all users separately.[30] Under the standardized approach, the risk weight applied to borrowers is 75%, and to transactors is 45%. Under the advanced approach, the risk weights are calculated based on the following formulas provided by the BIS[31]: for borrowers, $max\left\{0.75, 12.5 \cdot \left[LGD \cdot N\left(\frac{G(PD)}{\sqrt{(1-.04)}} + \sqrt{\frac{.04}{(1-.04)}} \cdot G(0.999)\right) - PD \cdot LGD\right]\right\}$; for transactors, $max\left\{0.45, 12.5 \cdot \left[LGD \cdot N\left(\frac{G(PD)}{\sqrt{(1-.04)}} + \sqrt{\frac{.04}{(1-.04)}} \cdot G(0.999)\right) - PD \cdot LGD\right]\right\}$.[32]

or persons; and (2) exposures to SMEs (as defined in CRE20.47) that meet the "regulatory retail" criteria set out in CRE20.65(1) to CRE20.65(3). Exposures to SMEs that do not meet these criteria will be treated as corporate SMEs exposures under CRE20.47. For more information, visit the BIS website.

[29]The retail exposure class consists of the following three sets of exposures: (1) "Regulatory retail" exposures that do not arise from exposures to "transactors" (i.e. "borrowers"). (2) "Regulatory retail" exposures to "transactors". (3) "Other retail" exposures. "Transactors" are obligors in relation to facilities such as credit cards and charge cards where the balance has been repaid in full at each scheduled repayment date for the previous 12 months. Obligors in relation to overdraft facilities would also be considered as transactors if there has been no drawdown over the previous 12 months. For more information, visit the BIS website.

[30]For borrowers, the advanced approach generally give higher risk weights than standardized approach. In contrast, the 45% risk weight from standardized approach tend to bind for transactors since their PDs are low. For all users, we take a weighted average of the risk weights for borrowers and transactors within each origination FICO bin (i.e. share of borrowers $\times$ risk weights for borrowers + share of transactors $\times$ risk weights for transactors).

[31]For more information, visit the BIS website.

[32]$N(x)$ denotes the cumulative distribution function for a standard normal random variable (i.e., the probability that a normal random variable with mean zero and variance of one is less than or equal to x). $G(z)$ denotes the inverse cumulative distribution function for a standard normal random variable (i.e., the value of x such that N(x) = z). $R = 0.04$ denotes the asset correlation which is the degree of the obligor's exposure to the systematic risk factor. The asset correlations, in short, show how the asset value (e.g. sum of all asset values of a firm) of one borrower depends on the asset value of another borrower. Probability of

Figure 14 plots the risk weights of borrowers, transactors, and all users by FICO bin, and it shows that they are decreasing in origination FICO. In addition, we find that borrowers' risk weights are more than twice as high as those of transactors.

Next, we compare the ROA of credit card borrowers in Figure 8 to the implied cost of regulatory equity. To compute this, for each FICO bin, we multiply the average ROA per risk weight by the risk weight of the respective FICO bin i:

$$\text{Implied Cost of Regulatory Equity}_i = \frac{\text{Average ROA}}{\text{Average RW}} \times \text{RW}_i$$

We use an average ROA of 1.5% and an average risk weight of 70%, which are the average values for US commercial banks. Figure 14b shows that the implied cost of equity is lower than the ROA for credit card borrowers, suggesting that the capital requirement for credit card accounts does *not* bind and therefore does *not* explain the high ROA.

7 Conclusion

In this paper, we study the economics of credit card banking and analyze the factors contributing to high credit card loan rates. Although credit cards experience high default rates, these alone do not account for the elevated rates, as banks sustain a 10% average net spread after defaults. Non-interest expenses, such as rewards, are substantial but largely offset by corresponding non-interest income. Operating costs are also high, suggesting a strong role for market power in this sector. Even after accounting for these factors, credit card lending achieves a return on assets four times the banking average. Using account-level data, we estimate the risk premium component of this return based on the probability of default and find that risk explains much of the variation in net lending margins, with the average borrower commanding a 4.2% risk premium, similar to high-yield bonds. However, a notable

0.999 denotes the confidence level to derive conservative value. For more information, please see this BIS document.

non-risk component of roughly 3% remains, specific to credit card lending.

References

Adams, Robert, Vitaly Board, and Bradley Katcher. 2022. "Credit Card Profitability." *FEDS Notes*, Washington: Board of Governors of the Federal Reserve System: https://doi.org/10.17016/2380–7172.3100.

Agarwal, Sumit, Souphala Chomsisengphet, and Chunlin Liu. 2010. "The Importance of Adverse Selection in the Credit Card Market: Evidence from Randomized Trials of Credit Card Solicitations." *Journal of Money, Credit and Banking*, 42(4): 743–754.

Agarwal, Sumit, Souphala Chomsisengphet, Neale Mahoney, and Johannes Stroebel. 2015. "Regulating Consumer Financial Products: Evidence from Credit Cards." *The Quarterly Journal of Economics*, 130(1): 111–164.

Amato, Jeffery D, and Eli M Remolona. 2003. "The credit spread puzzle." *BIS Quarterly Review, December*.

Ausubel, Lawrence. 1991. "The Failure of Competition in the Credit Card Market." *The American Economic Review*, 81(1): 50–81.

Ausubel, Lawrence. 1999. "Adverse Selection in the Credit Card Market." *Working Paper*.

Bester, Helmut. 1985. "Screening vs. Rationing in Credit Markets with Imperfect Information." *The American Economic Review*, 75: 56–78.

Calem, Paul, and Loretta Mester. 1995. "Consumer Behavior and the Stickiness of Credit-Card Interest Rates." *The American Economic Review*, 85(5): 1327–1336.

Collin-Dufresn, Pierre, Robert S Goldstein, and J Spencer Martin. 2001. "The determinants of credit spread changes." *The Journal of Finance*, 56(6): 2177–2207.

Drechsler, Itamar, Alexi Savov, and Philipp Schnabl. 2017. "The Deposits Channel of Monetary Policy." *The Quarterly Journal of Economics*, 132(4): 1819–1876.

Drechsler, Itamar, Alexi Savov, and Philipp Schnabl. 2021. "Banking on Deposits: Maturity Transformation without Interest Rate Risk." *The Journal of Finance*, 76(3): 1091–1143.

Drozd, Lukasz, and Jaromir Nosal. 2008. "Competing for Customers: A Search Model of the Market for Unsecured Credit." *Working Paper*.

Fama, Eugene F, and James D MacBeth. 1973. "Risk, return, and equilibrium: Empirical tests." *Journal of political economy*, 81(3): 607–636.

Fleckenstein, Matthias, and Francis A. Longstaff. 2022. "The Market Risk Premium for Unsecured Consumer Credit Risk." *The Review of Financial Studies*, 35(10): 4756–4801.

Han, Song, Ben Keys, and Geng Li. 2018. "Unsecured Credit Supply, Credit Cycles, and Regulation." *The Review of Financial Studies*, 31(3): 1184–1217.

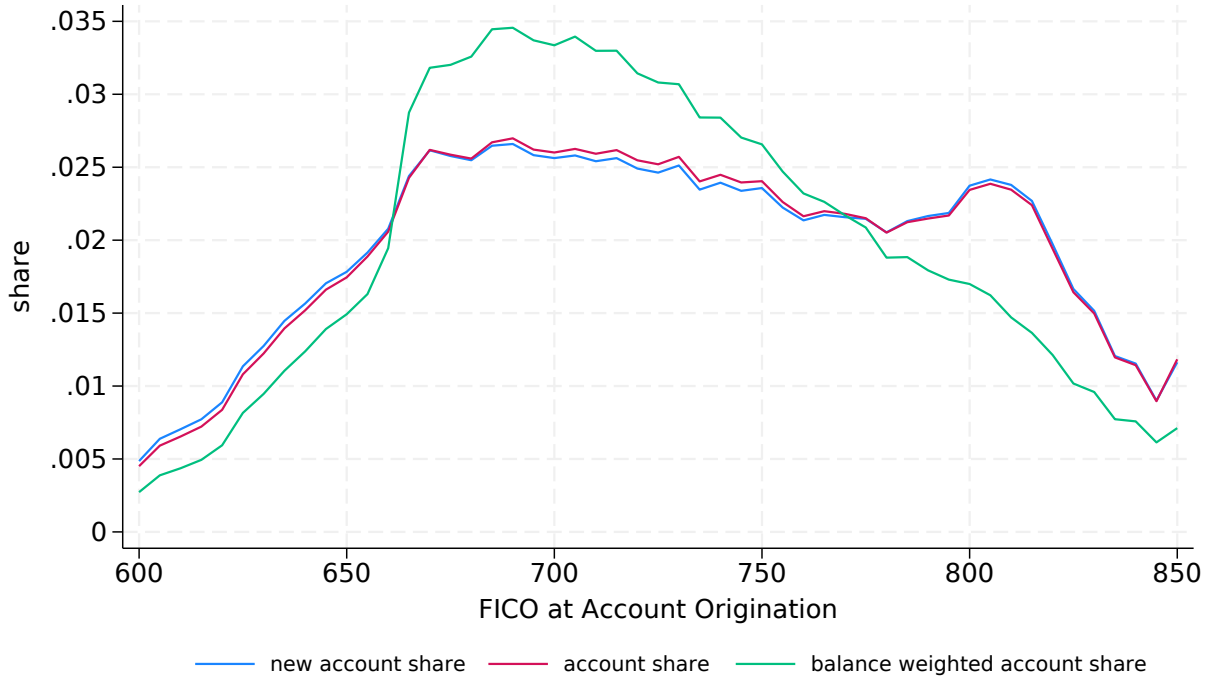
Herkenhoff, Kyle, and Gajendran Raveendranathan. 2021. "Who Bears the Welfare Costs of Monopoly? The Case of the Credit Card Industry." *NBER Working Paper*, http://www.nber.org/papers/w26604.

Sinkey, Joseph, and Robert Nash. 1993. "Assesing the Riskiness and Profitability of Credit-card Banks." *Journal of Financial Services Research*, 7: 127–150.

Stango, Victor, and Jonathan Zinman. 2016. "Borrowing High versus Borrowing Higher: Price Disperson and Shopping Behavior in the U.S. Credit Card Market." *The Review of Financial Studies*, 29(4): 979–1006.

Figures

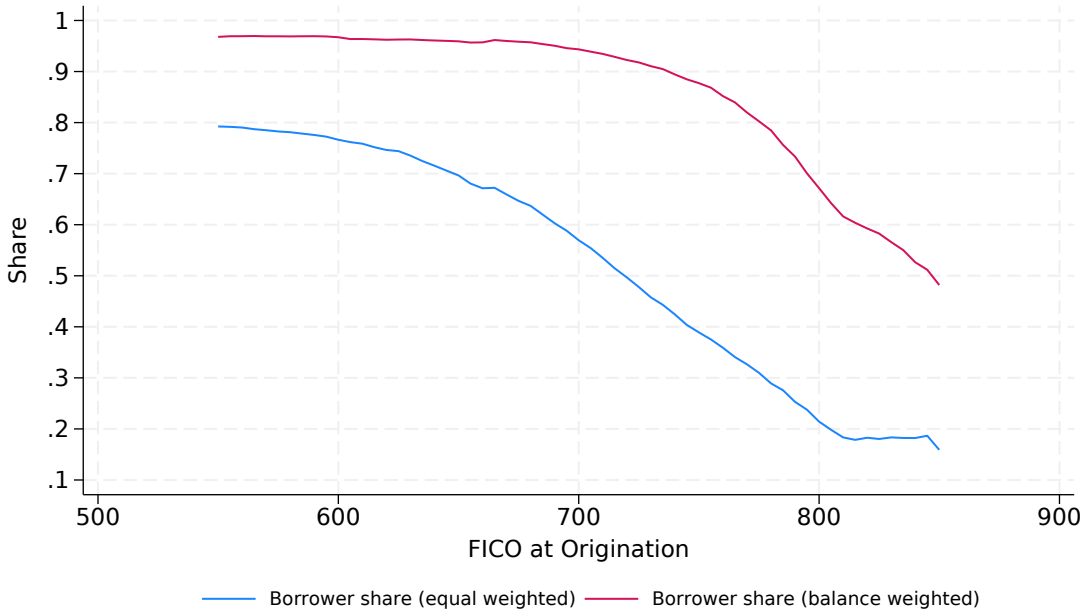
Figure 1: Distribution of Accounts by Origination FICO



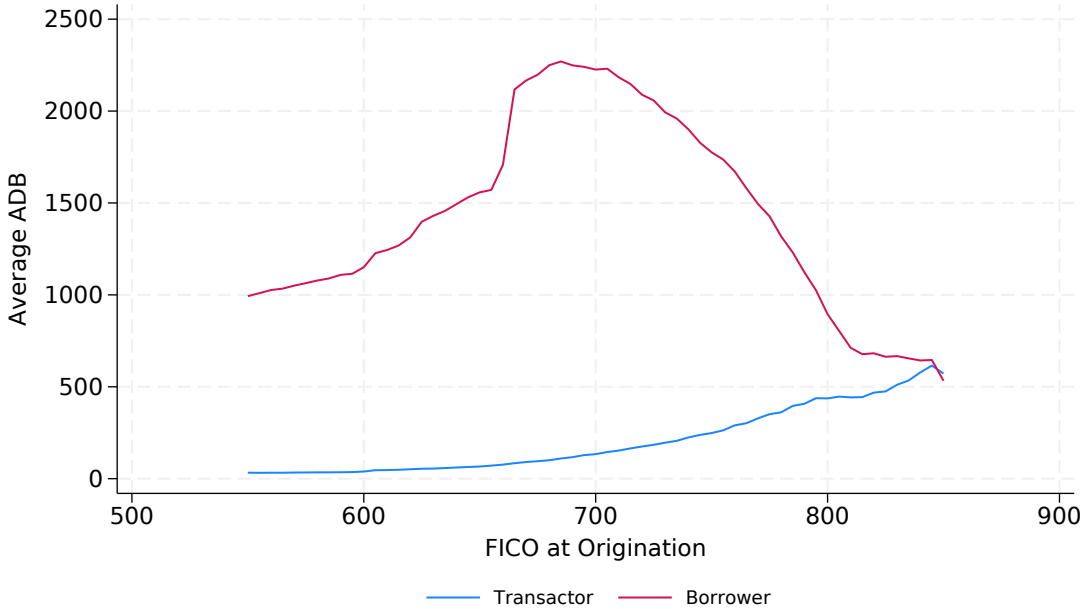
Note: This figure plots the equal-weighted share of all accounts (red line), equal-weighted share of new accounts (blue line), and value-weighted share of all accounts (green line). Equal-weighted shares are computed by dividing the number of accounts (or new accounts) within each origination FICO bin by the total number of accounts (or new accounts) across all origination FICO bins. Value-weighted shares are computed by dividing the sum of average daily balance (ADB) of accounts within each origination FICO bin by the sum of ADB across all origination FICO bins. New accounts are accounts that are newly generated in each month and we identify such accounts by checking whether an account's date of origination is the same as the current date for each date in the sample (as mentioned in the data section, all dates are at monthly frequency ranging from January 2015 to December 2023).

Figure 2: Borrower Share and ADB by Origination FICO

(a) Borrower Share

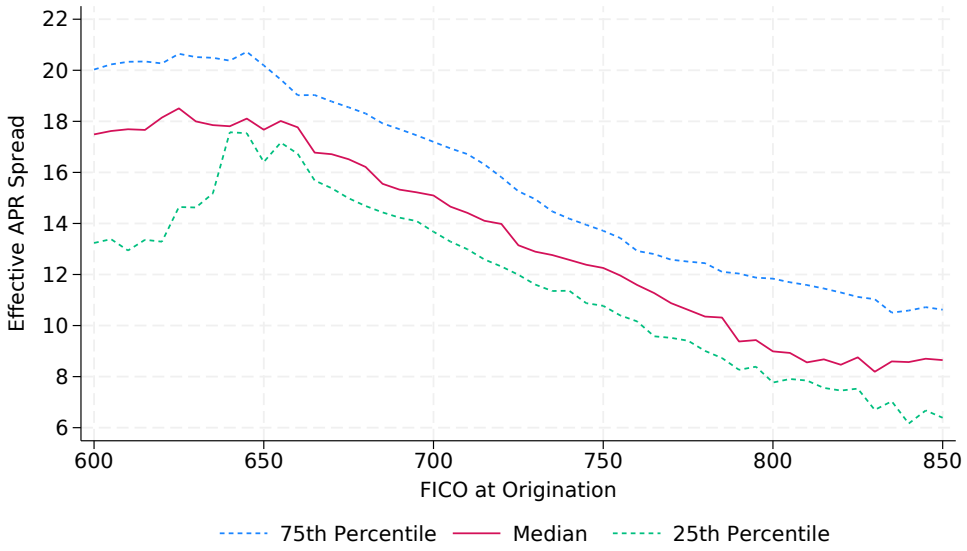


(b) Borrower vs. Transactor ADB



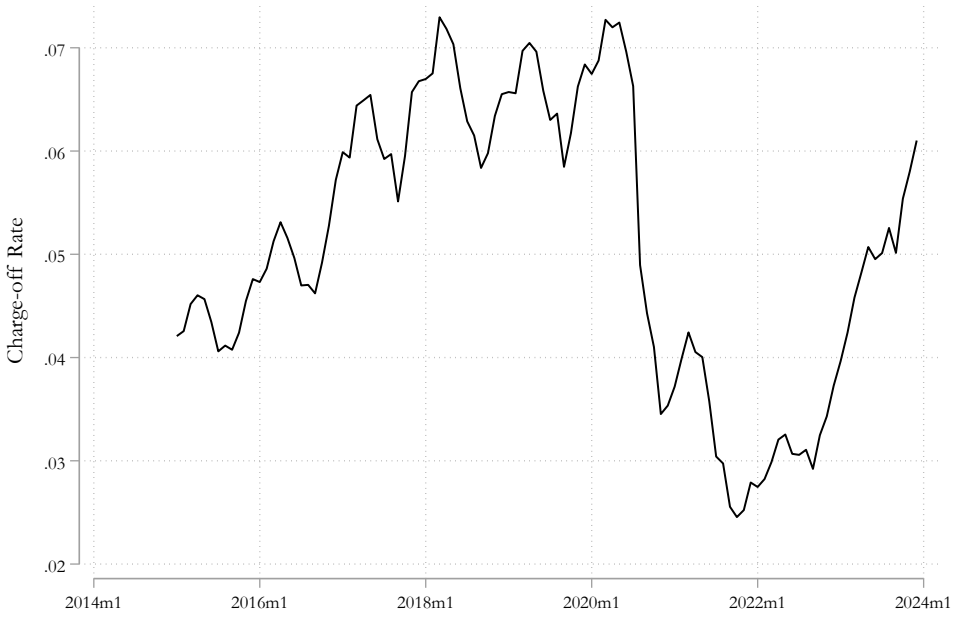
Note: Panel 2a plots the equal-weighted (blue line) and value-weighted (red line) share of borrowers for each origination FICO bin. As explained in Figure 1, equal weighted share is the number of borrowing accounts divided by total number of accounts for each origination FICO bin, and value-weighted share is the sum of ADB for borrowing accounts divided by sum of ADB for all accounts within each origination FICO bin. Panel 2b plots the average ADB of borrowers and transactors by origination FICO.

Figure 3: Effective APR Spread by Origination FICO



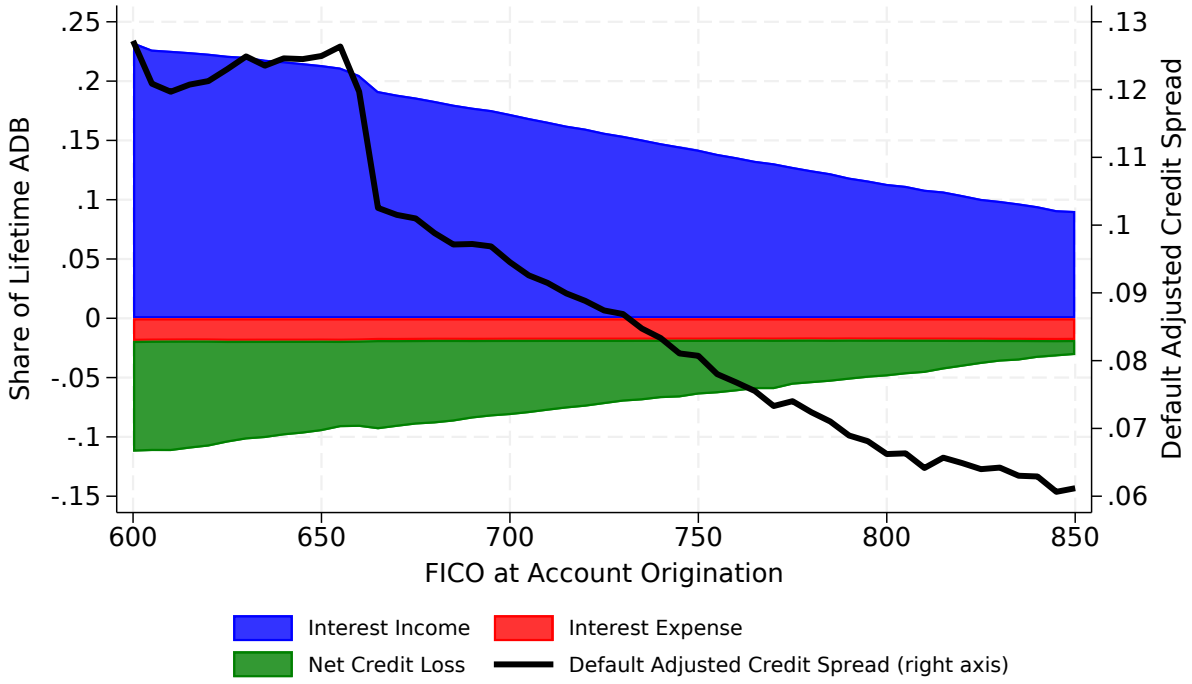
Note: This figure plots the 25th percentile, median, and 75th percentile of effective APR spreads across origination FICO bins.

Figure 4: Times-series of Average Charge-off Rate



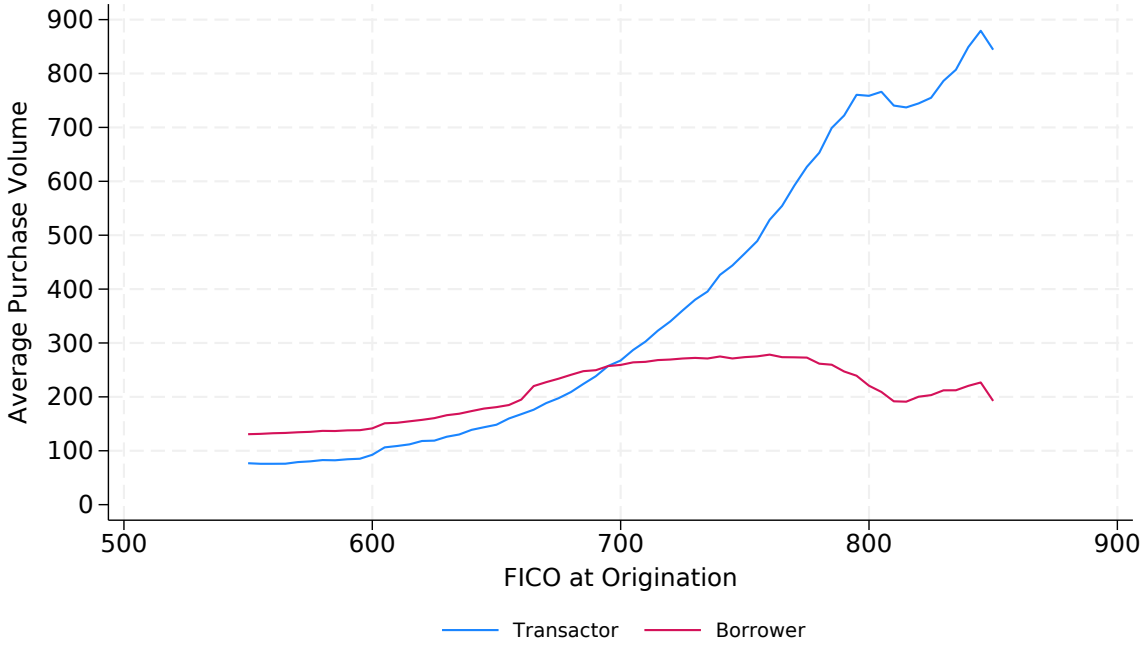
Note: This figure plots the average charge-off rates (i.e. (total amounts of charge-offs divided by total amounts of ADB) $\times$ 12) over time from 2015 to 2023.

Figure 5: Interest Income and Charge-offs by Origination FICO



Note: This figure plots the annualized interest income, interest expense, charge-off rates, and default-adjusted credit spreads by origination FICO bins. We compute the annualized interest income rate (the blue part) by first summing interest charges over lifetime for each account, then summing the lifetime interest incomes of all accounts within each origination FICO bin, divided by the sum of lifetime ADB (total interest charges over lifetime for each account) of all accounts within each origination FICO bin, and finally multiply this ratio by 12. Net charge-off rates (the green part, and we also call it net credit loss) are computed similarly by dividing sum of lifetime charge-offs net of recoveries by sum of lifetime ADBs for all accounts within each origination FICO bin and then multiplying by 12. The recovery rate for credit cards is very low. The share of recovered amounts out of total charge-offs are around 10%. Interest expense rate (the red part) is computed by first getting amounts of interest expenses from the Fed funds rate times ADB, then dividing sum of lifetime interest expenses by sum of lifetime ADBs for all accounts within each origination FICO bin, and multiplying by 12. Interest income rates are placed above 0 while interest expense rates and charge-off rates are plotted in the negative region of this figure.

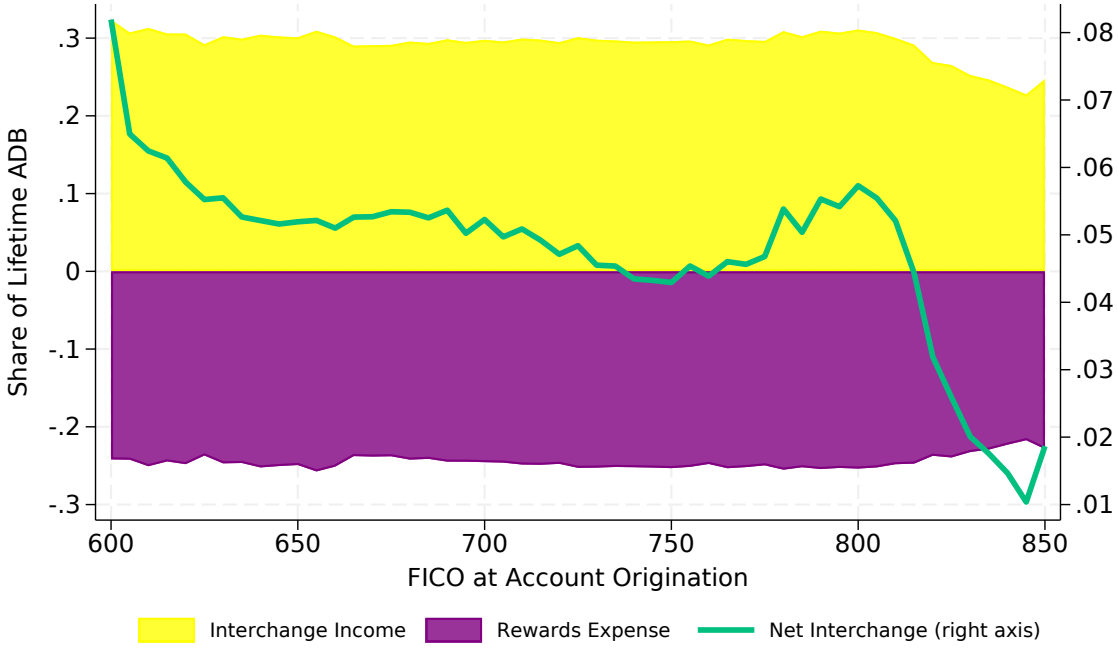
Figure 6: Purchase Volumes by Borrowers and Transactors



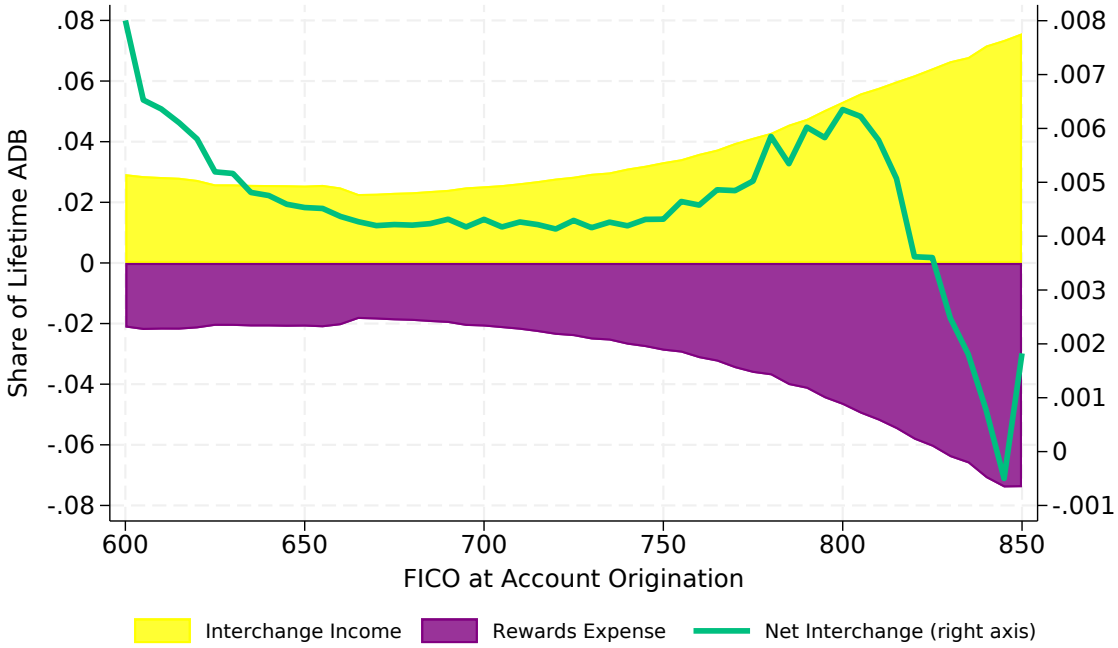
Note: This figure plots the average dollar amounts of purchase volumes for borrowers and transactors within each origination FICO bin.

Figure 7: Interchange and Rewards by Origination FICO

(a) Transactors

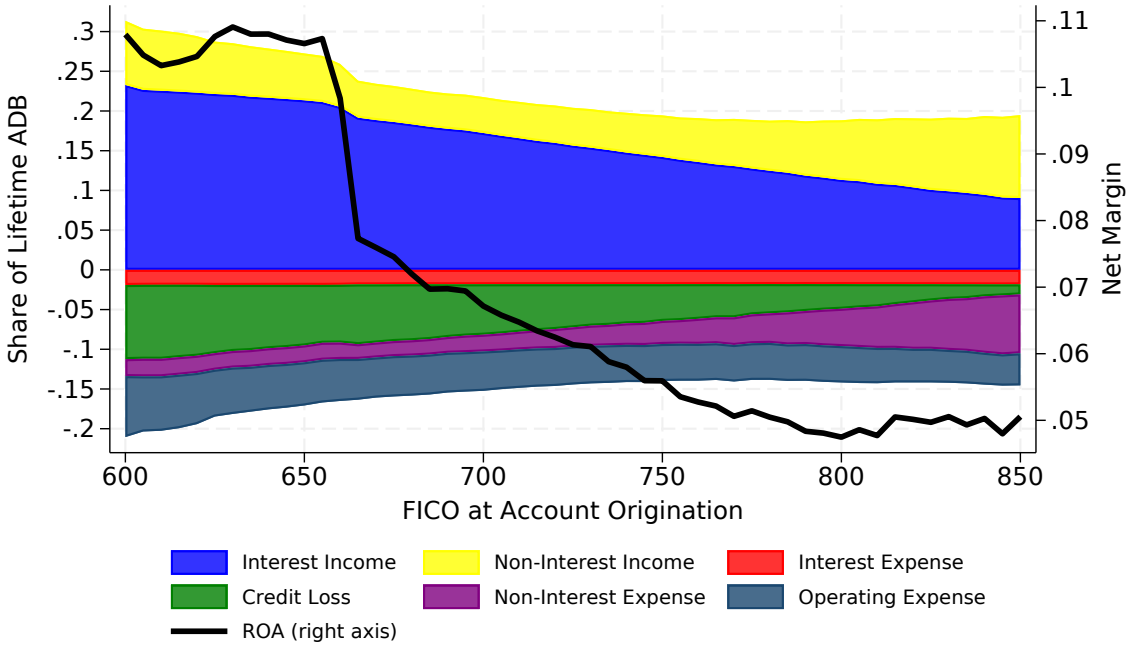


(b) Borrowers



Note: Panel 7a plots the annualized interchange income, reward expenses, and net interchange income as a share of ADB across origination FICO bins for transacting accounts. Panel 7b plots the same things but for borrowing accounts.

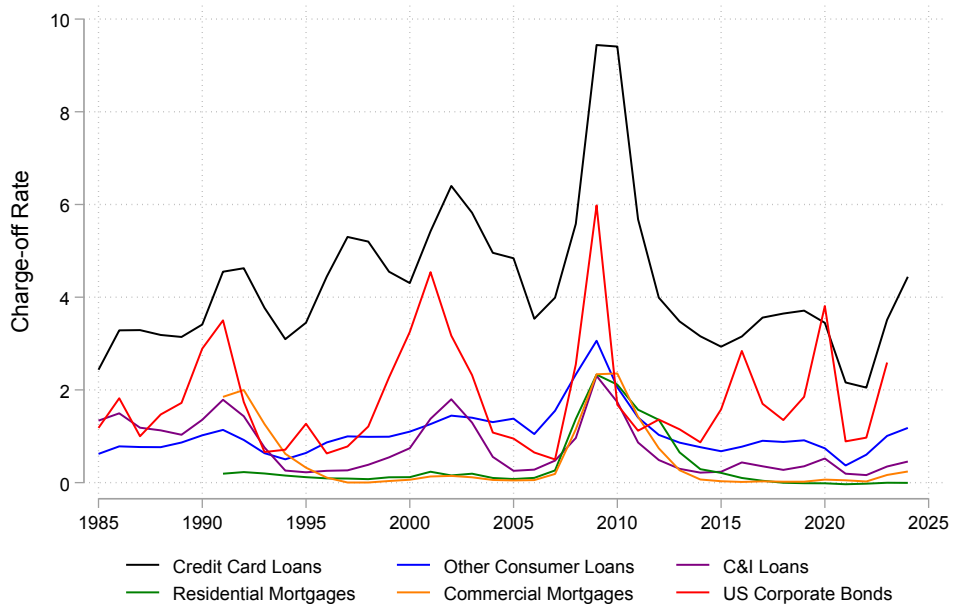
Figure 8: Return on Assets: Borrowers



Note: This figure plots borrowers' interest income, non-interest income (fee income + interchange income), interest expense, net charge-offs, non-interest expense (rewards expense + other non-default charge-offs), operating expense as a percentage of lifetime ADB. ROA (net margin) is calculated by summing interest and non-interest income, then subtracting interest, non-interest expenses, net credit losses and operating expenses. All values are annualized.

Figure 9: Default rates across various types of loans and corporate bonds

(a) Bank loans



(b) Credit cards and corporate bonds

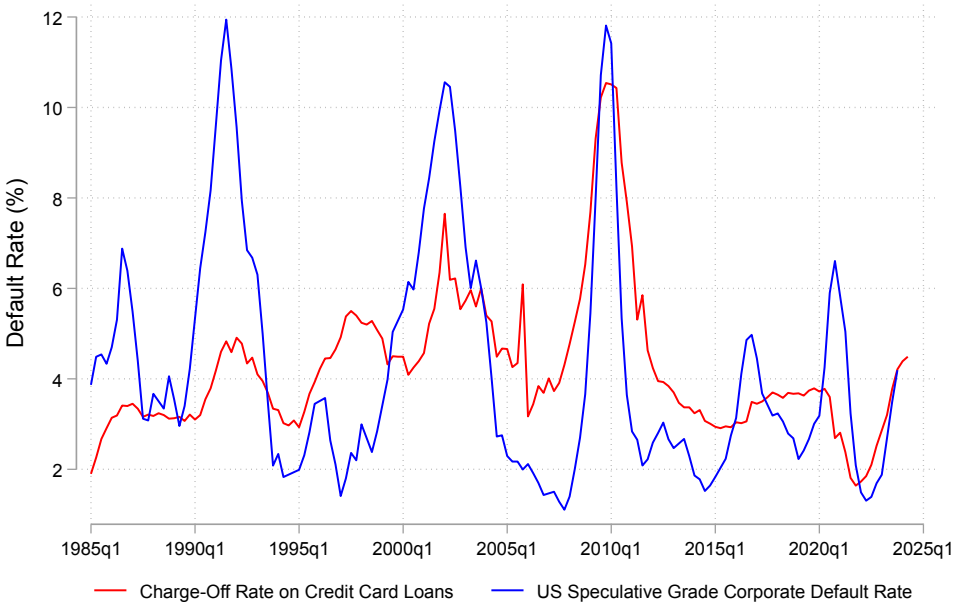
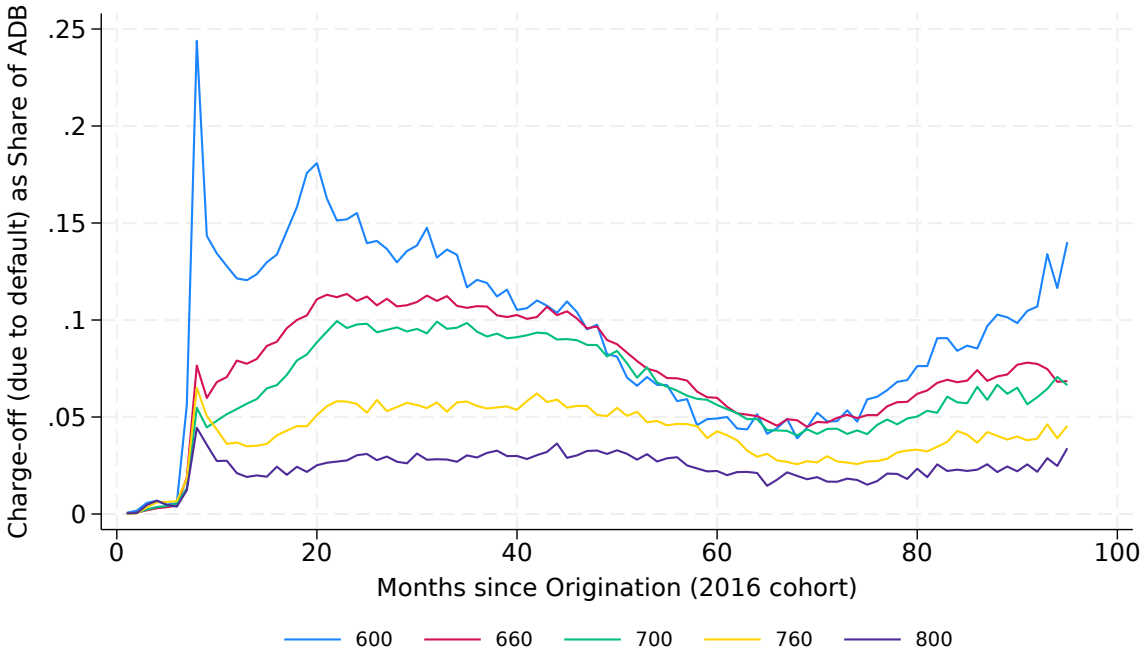


Figure 10: Credit card charge-offs across the original FICO distribution

(a) Life cycle



(b) Time series

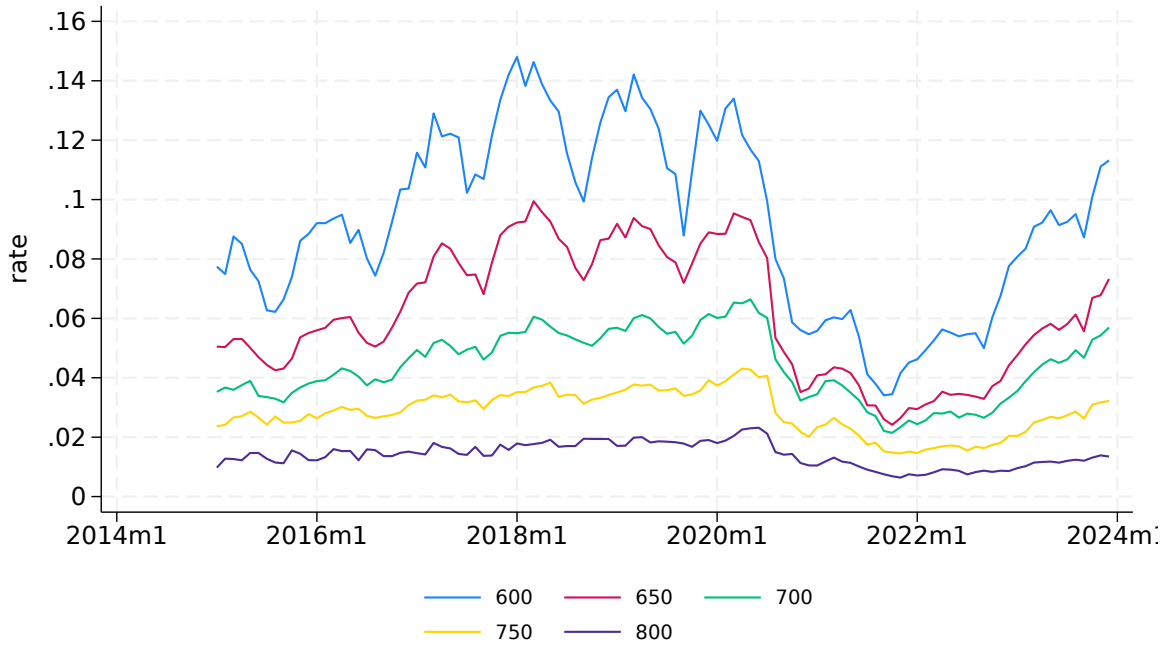


Figure 11: Risk exposure by FICO bin

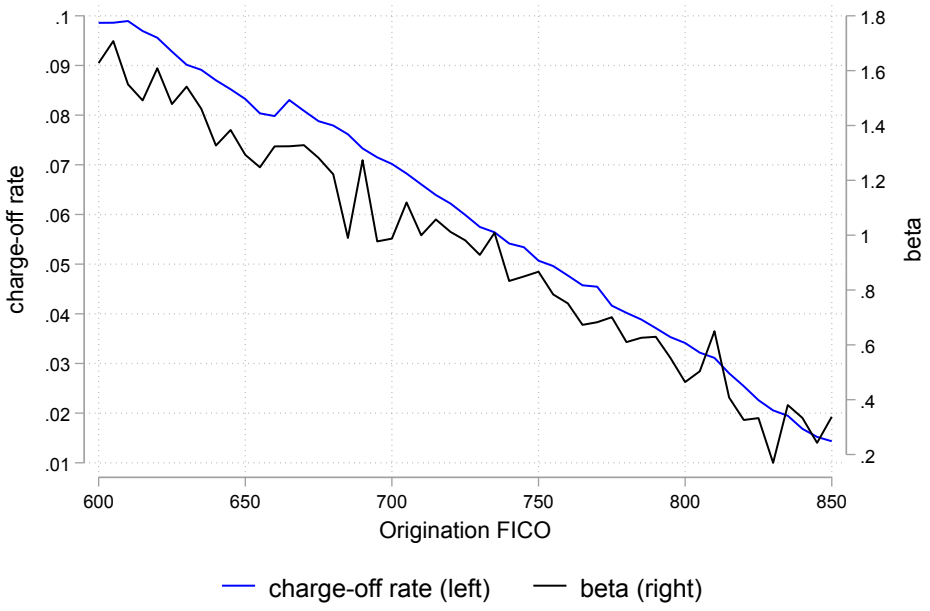


Figure 12: Credit card risk premium by FICO bin

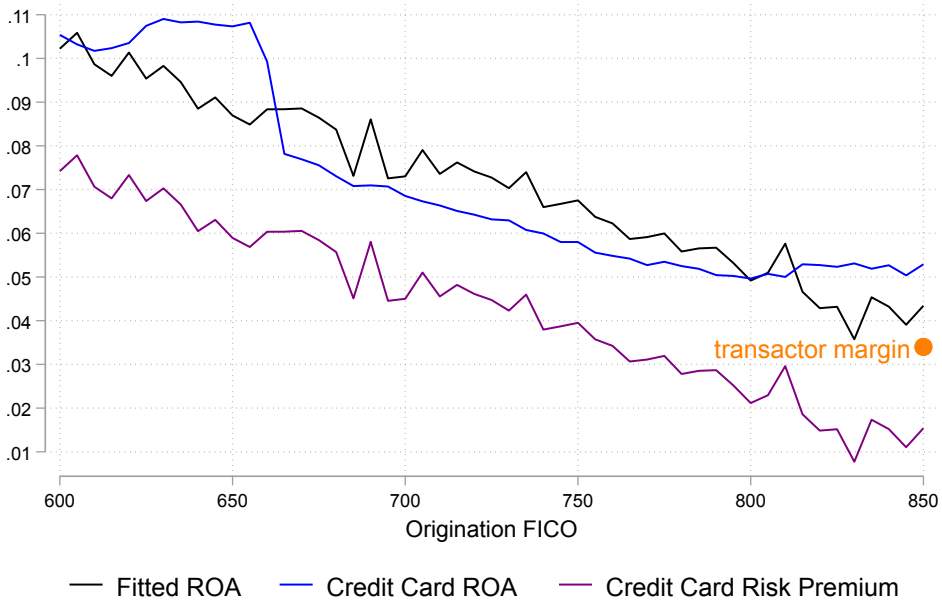


Figure 13: Credit card and corporate bond risk premia

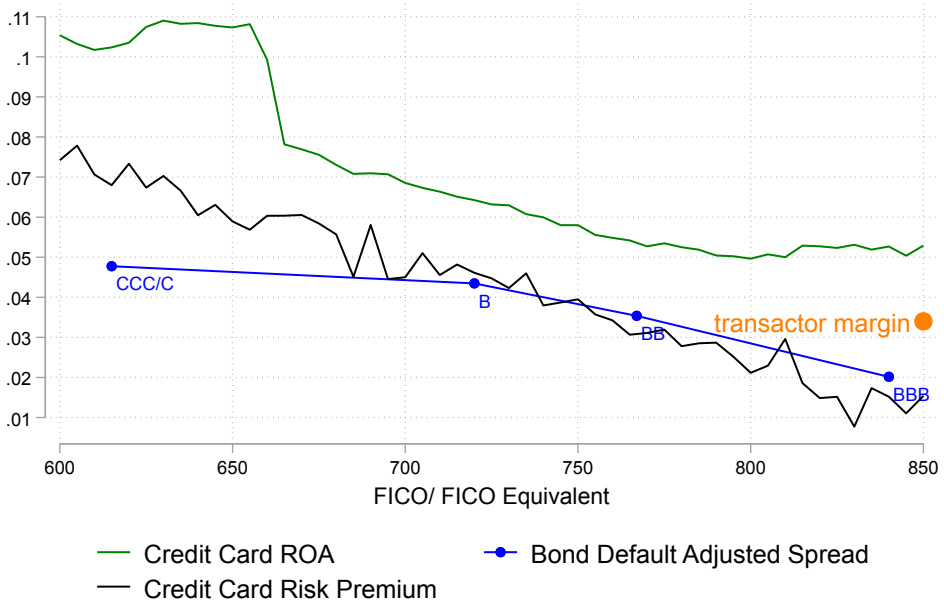
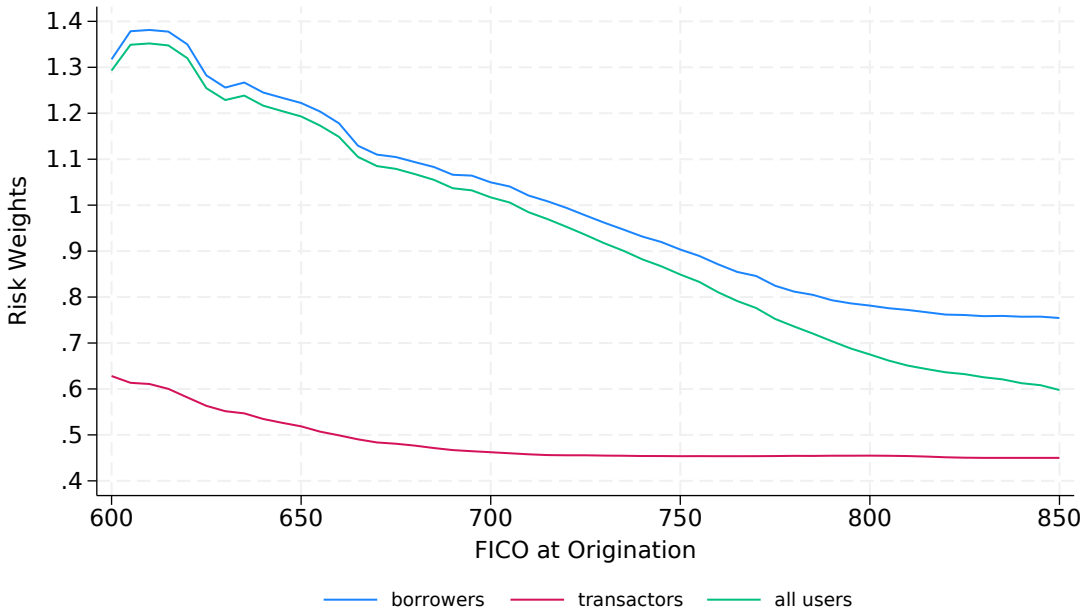
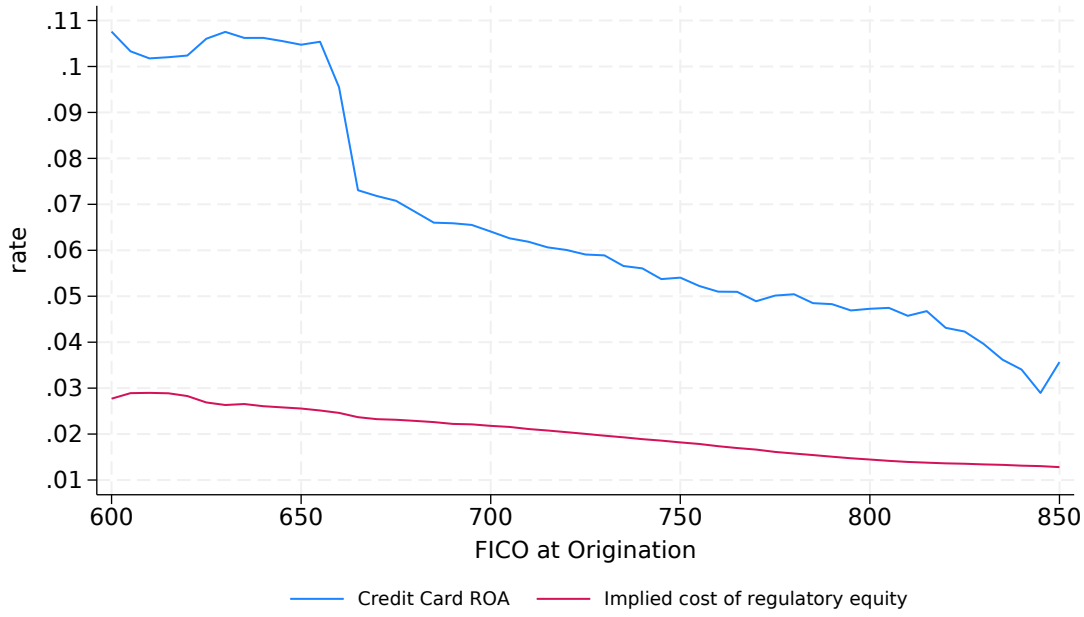


Figure 14: ROA after considering Capital Requirements

(a) Risk Weights by FICO



(b) ROA



Note: Panel 14a plots the risk weights (i.e. risk-weighted assets over total assets) for borrowers (blue line), transactors (red line), and all users (green line) across origination FICO bins. Panel 14b plots the ROA on credit card borrowers (blue line) against the implied cost of regulatory equity (red line).

Tables

Table 1
Summary Statistics

This table reports the summary statistics at the Bank × Monthly date level from portfolio-level data. Month-end balance are in millions of dollars and all other numbers are annualized shares of month-end balances.

	mean	sd	p25	p50	p75
Month-end Balance	2410000	3950000	55051.04	323000	2350000
Interest Component					
Interest Income Rate	0.142	0.125	0.102	0.114	0.127
Interest Expense Rate	0.024	0.022	0.016	0.019	0.022
Default Loss Component					
Charge-off Rate	0.05	0.023	0.04	0.045	0.053
Recovery Rate	0.005	0.004	0.003	0.006	0.008
Loss Provision Rate	0.052	0.045	0.034	0.04	0.051
Non-interest Income					
Fee Income Rate	0.017	0.015	0.012	0.015	0.017
Interchange Income Rate	0.071	0.056	0.048	0.061	0.071
Other Non-interest Income	0.004	0.008	0	0.001	0.004
Non-interest Expense					
Interchange Expense Rate	0.002	0.004	0	0	0.002
Reward Expense Rate	0.048	0.037	0.029	0.036	0.055
Collection Expense Rate	0.002	0.004	0	0	0.004
Fraud Expense Rate	0.003	0.003	0	0	0.003
Other Non-interest Expense	0.049	0.078	0.017	0.037	0.055

Table 2
Summary Statistics For Account-level Data

Table I reports the summary statistics at the origination FICO bin × Origination Month × Bank × Monthly date level from account-level data. All numbers are in dollars except borrower share (in decimals), promotional share (in decimals), and APR Margin (in percentage). All the mean values are value-weighted.

	All Users									
	mean	sd	p25	p50	p75					
Borrower Share	0.465	0.251	0.251	0.454	0.634					
Promotional Share	0.129	0.195	0.002	0.029	0.078					
	Borrowers					**Transactors**				
	mean	sd	p25	p50	p75	mean	sd	p25	p50	p75
ADB	3429.589	1952.881	2199.694	3328.784	4331.051	436.396	527.288	60.4	232.525	442.447
Purchase Volume	500.856	524.743	198.776	355.866	613.422	781.959	783.453	260.952	451.454	728.805
Interchange	9.049	9.848	3.715	6.6	11.318	14.294	15.221	4.918	8.322	13.324
Rewards	7.742	8.275	2.405	4.625	8.841	12.425	13.382	2.957	5.849	10.841
Fees	6.71	16.721	3.49	5.256	7.636	1.818	7.828	0	0	0.196
Non-default Charge-offs	0.038	6.099	0	0	0	0.012	0.75	0	0	0
APR Margin	16.728	6.305	12.853	16.872	20.869					
Interests	47.064	29.548	25.672	43.034	59.611					
Default Charge-offs	18.176	244.909	0	0	15.977					
Recoveries	1.622	30.699	0	0	0					

Table 3
Profit Components by Origination FICO

Table 3 reports the profit components for each origination FICO bin from account-level data for borrowers, transactors, and all users separately. All numbers are expressed as a share of average daily balance except the number of banks.

Origination FICO	No. of Banks	Interest Income Rate	Interest Expense Rate	Net Charge-off Rate	Interchange Rate	Reward Rate	Fee Rate	Non-default Charge-off Rate	Operating Expense Rate	ROA
Borrowers										
600	19	.2291914	.0189699	.0931989	.0289095	.0217632	.0496952	.000046	.0743589	.1041207
620	19	.2232692	.0188725	.0892169	.0272127	.021452	.0436161	.0001088	.0648202	.104305
640	20	.2173356	.0189673	.0805634	.025739	.0209351	.0367737	.0001185	.0559934	.1083018
660	20	.2031825	.0187049	.0743414	.0244155	.0200226	.0287067	.0001237	.0520182	.0949951
680	20	.1844981	.0182668	.0709337	.0232624	.0190499	.0217457	.0001061	.0495249	.0740236
700	20	.1736642	.0181901	.0640813	.0249904	.0207475	.0199487	.0001159	.0481928	.0693893
720	20	.1613007	.0181373	.0571773	.0273652	.0231394	.0192208	.0001274	.0463884	.0647633
740	20	.1495313	.0181035	.0503853	.0305704	.0263428	.0189408	.0001302	.045186	.0605108
760	20	.1376507	.0180552	.04433	.0350833	.0304977	.0191373	.0001394	.0444656	.0557597
780	20	.1266652	.0180245	.0381905	.0421504	.0369121	.0200563	.0001582	.0441397	.0526776
800	20	.1151866	.018018	.0316783	.0515027	.0454053	.0215686	.0002042	.0438197	.050254
820	20	.1054672	.0181134	.0244836	.0605633	.0559088	.0243673	.0002525	.0409477	.0518863
840	20	.095934	.018283	.0164592	.0694288	.0680827	.0268479	.0001917	.0382171	.0521851
850	20	.0904607	.0182692	.012662	.0757904	.0739664	.0285998	.0001266	.0381691	.0528985
Transactors										
600	19	-.009493	.0154611	0	.3137588	.2421308	.1283408	.000287	.0671711	.1130204
620	19	-.0095097	.0160497	0	.302408	.2438892	.1028727	.0003638	.0571813	.0811581
640	20	-.0099322	.0166881	0	.3020972	.2493459	.0855097	.0006608	.0484567	.0643463
660	20	-.010012	.0171519	0	.2996255	.2476462	.0662349	.0006541	.0453031	.0460367
680	20	-.0105388	.0173273	0	.2929843	.2399985	.0515746	.0005821	.04438	.0321977
700	20	-.0072275	.0176847	0	.2967169	.2453286	.0488809	.0004195	.0430064	.0324025
720	20	-.0048751	.0179441	0	.2983334	.2494966	.0514729	.0004295	.0415586	.0360859
740	20	-.003245	.0182014	0	.2964808	.2521418	.0529446	.000366	.0400496	.0360024
760	20	-.0021944	.0182677	0	.2960155	.2514288	.0523576	.0003526	.0405895	.0361248
780	20	-.0016124	.0182472	0	.3013441	.2521263	.0483654	.0003222	.0423154	.0356557
800	20	-.0011969	.0181671	0	.3088273	.253231	.0432632	.0002425	.0441441	.0356792
820	20	-.0007936	.0184425	0	.2830187	.243431	.0448224	.0002853	.0385734	.0266351
840	20	-.0004869	.0188267	0	.2421123	.2260641	.0469742	.0001995	.0339516	.0095997
850	20	-.0004301	.0188763	0	.2472274	.2285671	.0468292	.000184	.0336792	.0123897
All Users										
600	19	.2208643	.0188474	.0899475	.0466547	.0356035	.052439	.0000544	.0741082	.1062446
620	19	.2146318	.0187678	.0859064	.045172	.0361138	.0458149	.0001183	.0645368	.1049054
640	20	.208526	.0188789	.0774405	.0440993	.036279	.0386629	.0001395	.0557013	.1078385
660	20	.1944612	.0186414	.0713003	.0430043	.035607	.0302419	.0001454	.0517435	.0940998
680	20	.1761716	.0182267	.0679053	.0416418	.0343597	.0230192	.0001264	.0493052	.0732596
700	20	.1636672	.0181622	.0605399	.0479546	.0401089	.0215476	.0001327	.0479062	.0683731
720	20	.1490252	.018123	.0529536	.0570372	.0485268	.0216032	.0001498	.0460316	.0636666
740	20	.1341063	.0181134	.0452982	.0694625	.0602707	.022374	.000154	.0446674	.0589757
760	20	.1181006	.0180849	.0381327	.086719	.0755869	.0237814	.0001692	.0439237	.0539956
780	20	.1000108	.0180708	.030255	.1155209	.1000213	.0259386	.0001923	.0437607	.0502936
800	20	.0788885	.0180645	.0217984	.1561018	.1330929	.0283348	.0002162	.0439209	.0472245
820	20	.0630215	.0182449	.0147037	.1788935	.1598242	.032538	.0002656	.0399993	.0422107
840	20	.0517457	.0185322	.0089162	.1832477	.1769646	.0360715	.0001953	.0362623	.0306158
850	20	.0433732	.0185837	.0061022	.2002764	.1912663	.0380439	.0001564	.035843	.0301506

Appendix

A Variable Definition

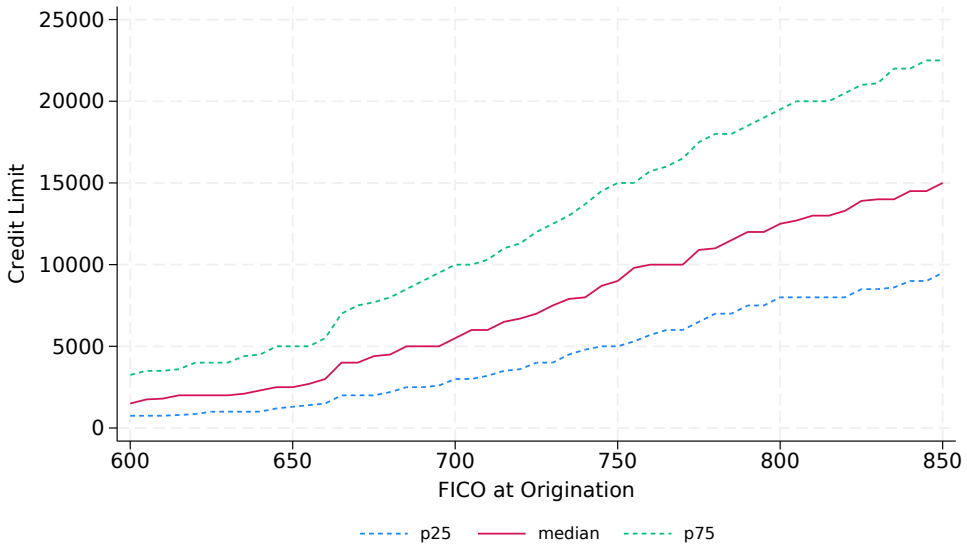
A.1 Interchange Rate and Rewards Rate

Interchange fees and rewards expenses are both dollar amounts in portfolio-level data, and portfolio-level data only has total balances of credit cards but not purchase volumes. To estimate their rates as a percentage of purchase volume, we did the following steps. First, we compute the total amount of purchase volumes of rewards cards and total amount of purchase volumes for both rewards and classic cards for each bank in each month from the account-level data. Next, we merge the two purchase volumes to portfolio-level data. To compute the rewards rate, we divide the amounts of reward expenses by the amounts of purchase volumes of rewards cards. We examine each bank's reward rates one by one by plotting their time-series graphs and find that there are still some outliers for certain banks and certain months. We remove the effect of outliers by (1) dropping banks whose median rewards rates are higher than 5% (2) dropping bank-month observations whose rewards rates are higher than 5% or are negative (3) dropping six small card issuers who have unreasonable levels of reward rates (overall very high and jump up and down from one month to next month), and those banks also have very short sample periods (e.g. only two years of data). The 5% cutoff point is already very conservative since it is a very high number for an average rewards rate across millions of different accounts. To compute the interchange rate, we divide the amounts of interchange fees by the amounts of purchase volume of all cards. Afterwards, we smooth both reward rates and interchange rates by taking their 12-month moving averages. The average interchange (reward) rate as a share of purchase volume in our data is around 1.9% (1.4%). Then we merge the interchange rates and reward rates obtained from the portfolio-level data to the account-level data at the bank-month level.

For accounts that have missing values of interchange or reward rates (e.g. accounts from the 6 banks we dropped when computing reward rates in portfolio-level data), we fill in the missing values by taking the median rates across all banks within each month. Finally, we obtain the dollar amount of interchange fees and rewards for each account in each month by multiplying their associated interchange rates and reward rates with purchase volumes. The total amount of interchange income and rewards expenses for all credit card issuers in 2023 were US$75 billion and US$65 billion, respectively.

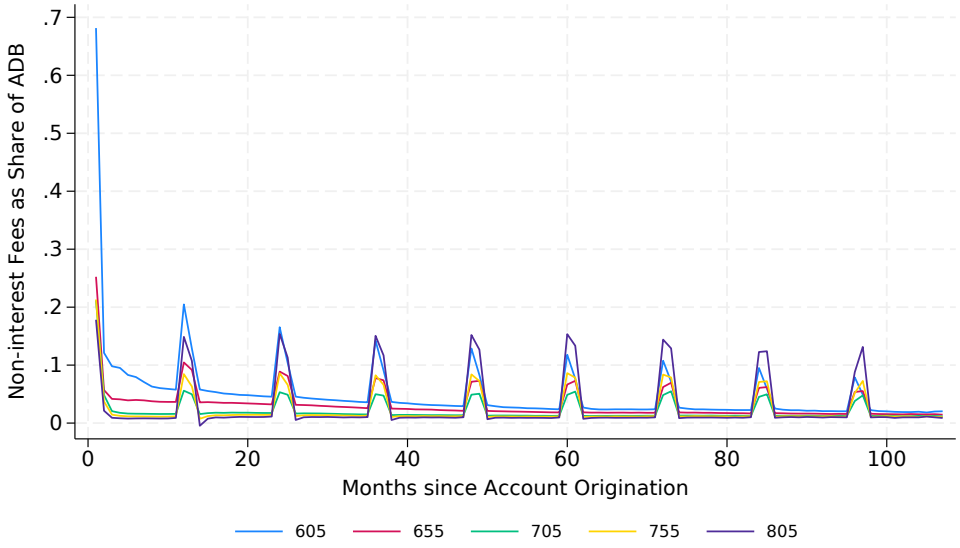
B Figures

Figure 1: Distribution of Credit Limit



Note: This figure plots the 25th percentile, median, and 75th percentile of credit limit across accounts within each origination FICO bin.

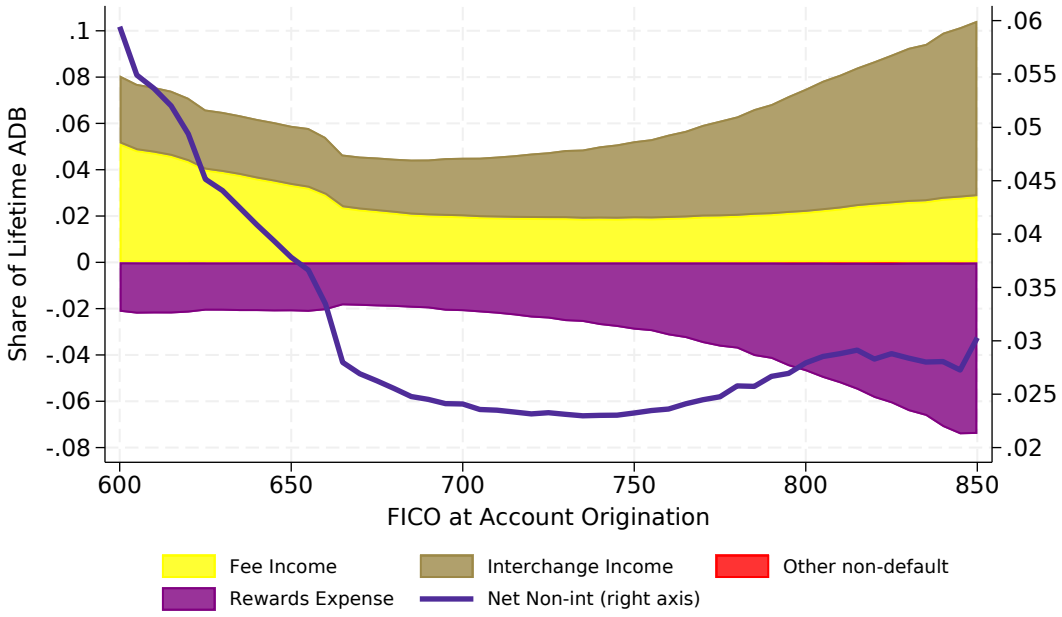
Figure 2: Fee Income



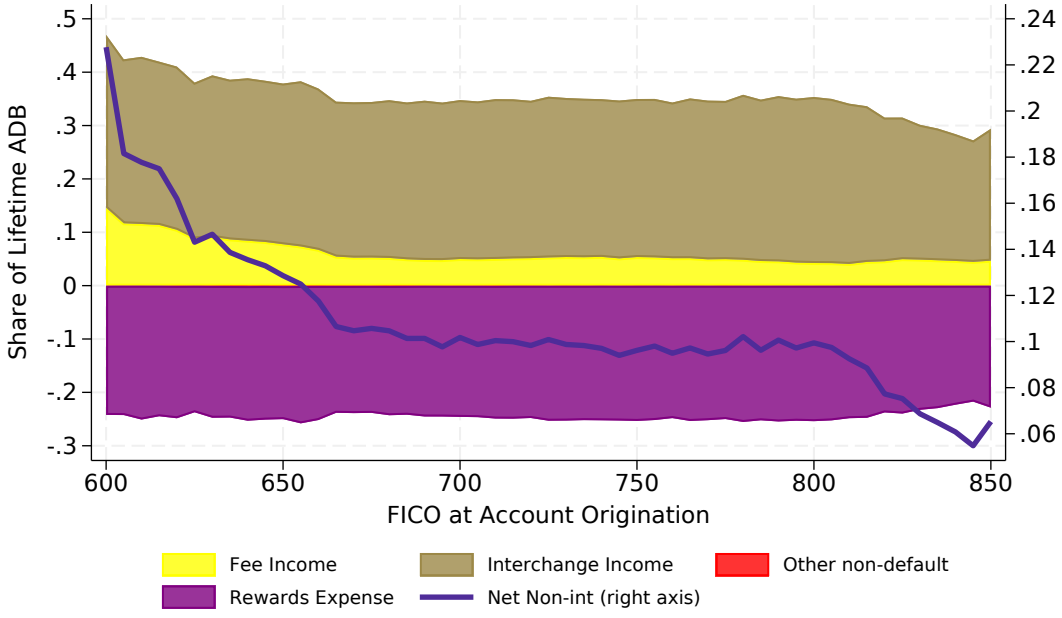
Note: This figure presents the annualized non-interest fee as a percentage of Average Daily Balance (ADB) across account age. Each line corresponds to a group of accounts categorized by origination FICO score bins: 605, 655, 705, 755, and 805.

Figure 3: Non Interest Income

(a) Borrower



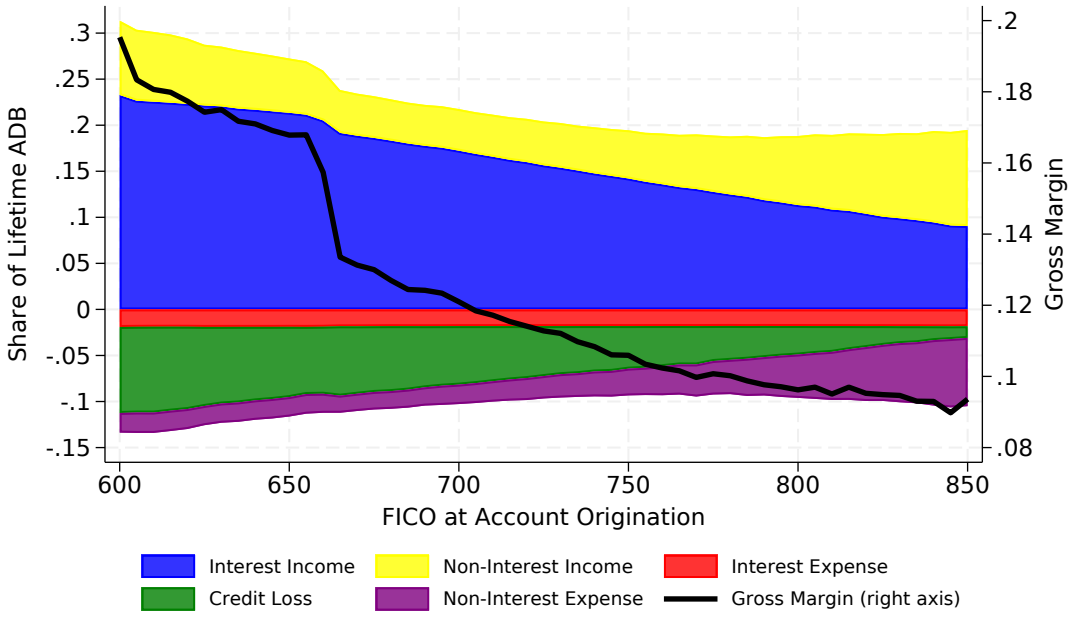
(b) Transactor



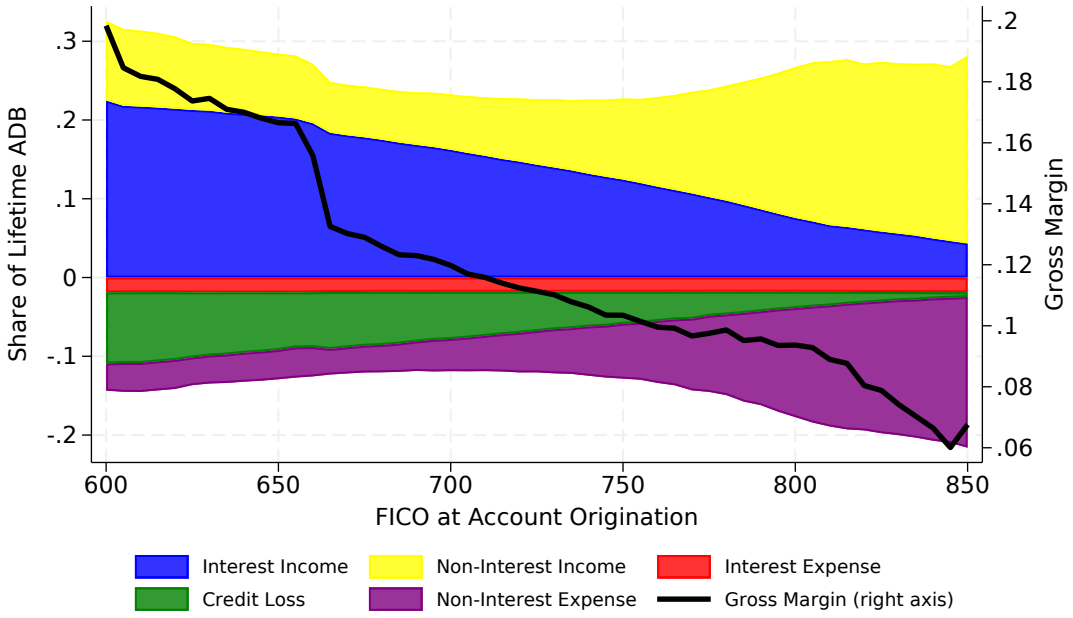
Note: Panel (a) shows interchange income, fee income, rewards expense and charge-offs not due to default as a percentage of ADB for borrowers. Panel (b) presents the same metrics for transactors. Net non-interest income is calculated by summing interchange and fee income, then subtracting rewards expense and charge-off not due to default. All values are annualized.

Figure 4: Gross Margin

(a) Borrower



(b) All Users



Note: Panel (a) plots borrowers' interest income, non-interest income (fee income + interchange income), interest expense, net charge-offs, and non-interest expense (rewards expense + other non-default charge-offs) as a percentage of lifetime ADB. Panel (b) presents the same metrics for transactors. Gross margin is calculated by summing interest and non-interest income, then subtracting interest and non-interest expenses and net credit losses. All values are annualized.

Figure 5: Operating Expense Example: Capital One

(a) Bank Level Non-Interest Expense

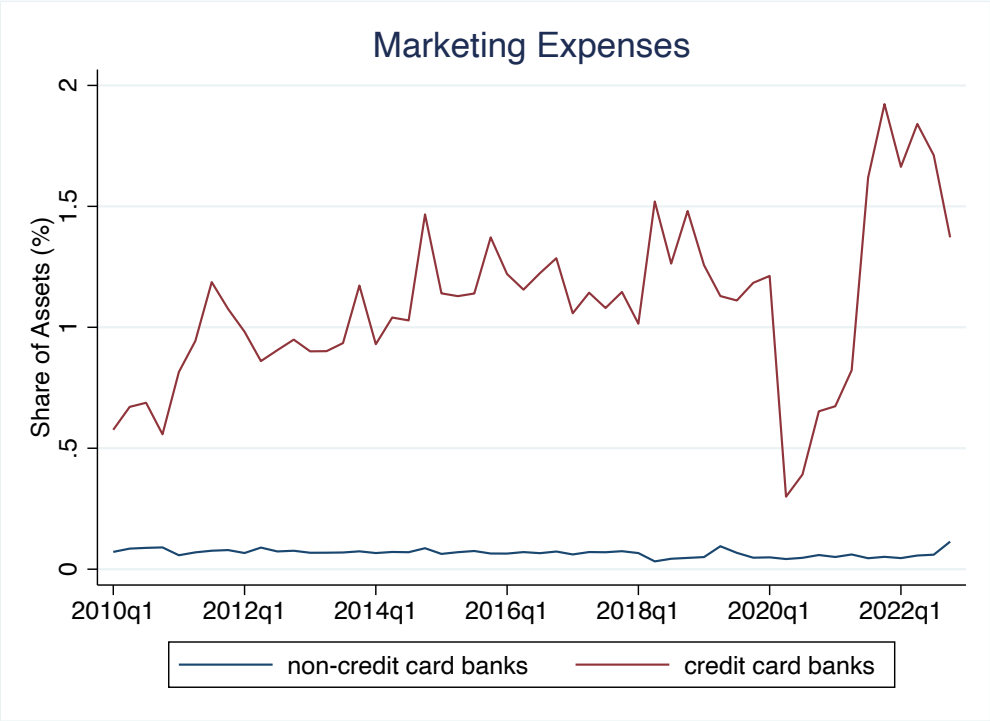
(Dollars in millions)	Year 2023
Operating Expense:	
Salaries and associate benefits[1]	$ 9,302
Occupancy and equipment	2,160
Professional services	1,268
Communications and data processing	1,383
Amortization of intangibles	82
Other non-interest expense:	
Bankcard, regulatory and other fee assessments	548
Collections	353
Other	1,211
Total other non-interest expense	2,112
Total operating expense	$ 16,307
Marketing	4,009
Total non-interest expense	$ 20,316

(b) Credit Card Business Results

(Dollars in millions, except as noted)	2023
Selected income statement data:	
Net interest income	$ 19,729
Non-interest income	5,940
Total net revenue[1]	25,669
Provision (benefit) for credit losses	8,651
Non-interest expense	12,490
Income from continuing operations before income taxes	4,528
Income tax provision	1,071
Income from continuing operations, net of tax	$ 3,457
Selected performance metrics:	
Average loans held for investment	$ 141,572
Average yield on loans[2]	18.54%
Total net revenue margin[3]	18.12
Net charge-offs	$ 6,472
Net charge-off rate	4.57%
Purchase volume	$ 620,290

Note: Panel (a) is a screenshot from Capital One's 2023 Annual Report Table 4. It displays the components of bank's non-interest expense for 2023. Panel (b) is a screenshot of Table 8 from Capital One's 2023 annual report. It summarizes the financial results of Capital One's credit card business and displays selected key metrics for the periods indicated.

Figure 6: Credit Card Banks: Marketing Expenses



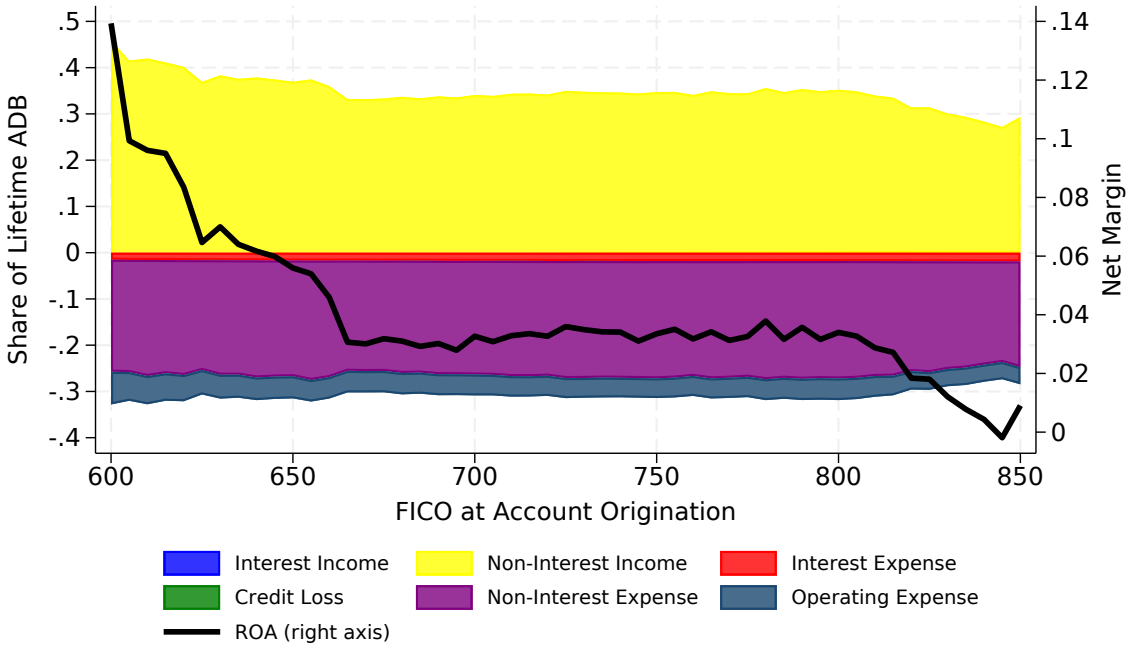
Note: This figure shows marketing expenses as a percentage of total bank assets for credit card banks versus non-credit card banks. Marketing expenses data are from Call Reports. Credit card banks are defined as those with personal loans exceeding 50% of total assets, with over 90% of these personal loans in credit cards, and with assets above $200 million. All numbers are annualized.

Figure 7: Interest Spread v.s. Operating Expense



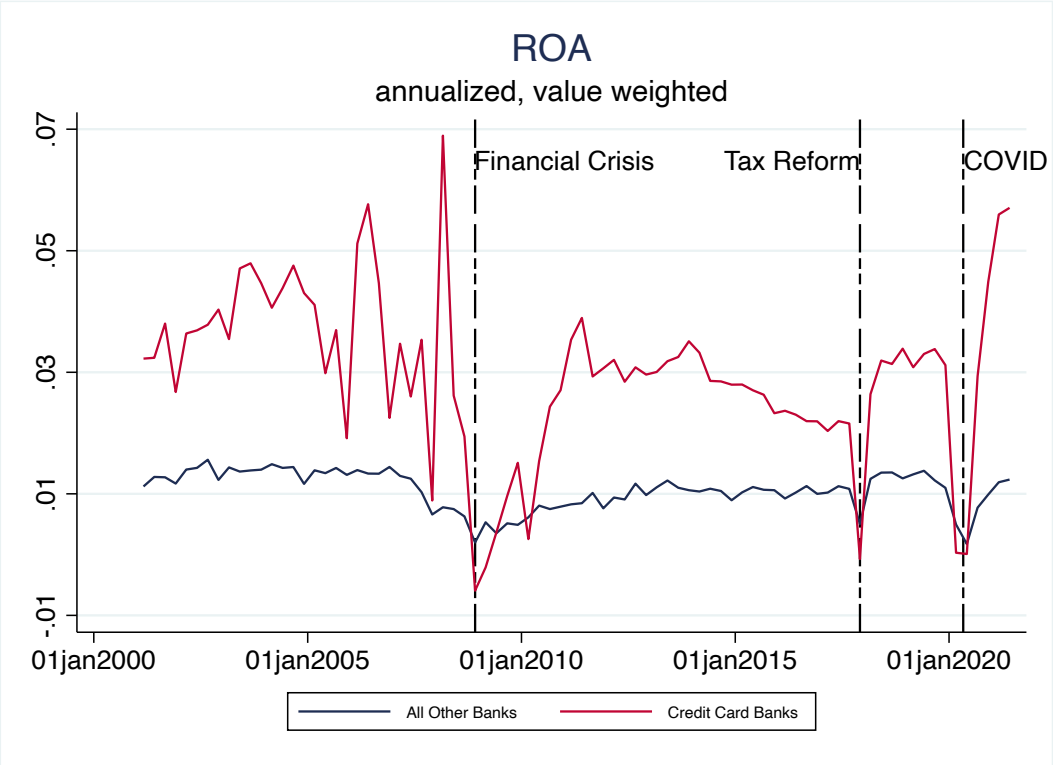
Note:

Figure 8: Return on Assets: Transactors



Note: This figure plots transactors' non-interest income (fee income + interchange income), interest expense, non-interest expense (rewards expense + other non-default charge-offs), operating expense as a percentage of lifetime ADB. By our definition of transactors, they do not incur interest income or default. ROA (net margin) is calculated by subtracting interest, non-interest expenses, net losses and operating expenses from non-interest income. All values are annualized.

Figure 9: Credit Card Banks: Return on Assets



Note: This figure compares the return on assets (ROA) for credit card banks and non-credit card banks. We calculate bank-level ROA using the same definition as for credit card net margin, with one adjustment: we substitute provision for credit losses in place of credit card net charge-offs.

C Tables

Table 4
Distribution of Accounts by Origination FICO

Table I reports the number of accounts and banks, the account share, and the ADB share across origination FICO bins.

Origination FICO	Number of Accounts	Number of Banks	Account Share	ADB Share
550-570	23203656	20	.0071984	.0041232
570-590	35761952	19	.0110943	.0066948
590-610	57239504	19	.0177573	.011624
610-630	1.047e+08	19	.0324749	.0242654
630-650	1.829e+08	20	.0567527	.0478462
650-670	2.556e+08	20	.0792965	.0798768
670-690	3.288e+08	20	.1019894	.1294574
690-710	3.319e+08	20	.1029776	.1333515
710-730	3.231e+08	20	.1002193	.1254782
730-750	3.084e+08	20	.0956611	.1117987
750-770	2.831e+08	20	.0878272	.094491
770-790	2.662e+08	20	.0825882	.0779648
790-810	2.828e+08	20	.0877271	.0665424
810-830	2.548e+08	20	.0790458	.0492759
830-850	1.850e+08	20	.0573902	.0372096

Table 5
Regressions of Charge-off Rate on Origination FICO Bin

This table reports regressions of charge-off rate with different controls and fixed effects (FE). The observations are at the origination FICO bin × Origination Month × Bank level from account-level data. Charge-off rate is the value-weighted average lifetime charge-off rate within each origination FICO-origination month-bank group. We dropped observations with average charge-off rate being negative or greater than one. All "FICO" in the table indicates the FICO bin at origination.

	Charge-off Rate						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Controls		FICO	$FICO^2$				
Origination Date FE	Y	Y	Y	Y	Y		
Origination FICO FE				Y	Y		
Bank FE					Y	Y	
Origination Date*FICO FE						Y	Y
Origination FICO*Bank FE							Y
Observations	32,173	32,173	32,173	32,173	32,173	32,173	32,132
R-squared	0.007	0.085	0.277	0.311	0.489	0.508	0.728
R-squared adjusted	0.00577	0.0835	0.276	0.309	0.487	0.473	0.699
Standard errors in brackets; *** p<0.01, ** p<0.05, * p<0.1							

Table 6
Regressions of APR Spread on Origination FICO Bin

This table reports regressions of APR spread with different controls and fixed effects (FE). The observations are at the origination FICO bin × Origination Month × Bank level from account-level data. APR spread refers to average APR minus Fed funds rate at accounts age of 24 months within each origination FICO-origination month-bank group. All "FICO" in the table indicates the FICO bin at origination.

	APR Spread						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Controls		FICO	$FICO^2$				
Origination Date FE	Y	Y	Y	Y	Y		
Origination FICO FE				Y	Y		
Bank FE					Y	Y	
Origination Date*FICO FE						Y	Y
Origination FICO*Bank FE							Y
Observations	30,366	30,366	30,366	30,366	30,366	30,366	30,332
R-squared	0.021	0.474	0.505	0.547	0.709	0.722	0.871
R-squared adjusted	0.0200	0.473	0.505	0.546	0.708	0.701	0.856
Standard errors in brackets; *** p<0.01, ** p<0.05, * p<0.1							

Table 7
Regressions of APR Spread on Operating Expenses

This table reports regressions of APR spread on annualized operating expense rate with different fixed effects (FE). The observations are at the origination FICO bin × Origination Month × Bank × Monthly level from account-level data. APR spread (in percentage) refers to average APR minus Fed funds rate at accounts age of 24 months within each origination FICO-origination month-bank group.

	APR Spread		
	(1)	(2)	(3)
Operating Expense Rate	16.598***	13.527***	13.358***
	[2.039]	[1.834]	[1.832]
Constant	16.136***	16.261***	16.268***
	[0.093]	[0.085]	[0.085]
Date FE	Y	Y	Y
Origination FICO FE		Y	Y
Origination Date FE			Y
Observations	2,197,605	2,197,605	2,197,605
R-squared	0.027	0.503	0.511
R-squared adjusted	0.0267	0.503	0.511
Standard errors in brackets; *** p<0.01, ** p<0.05, * p<0.1			