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 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.[1] Credit cards are now the primary method of payment for consumers, with purchase volume totaling $6 trillion in 2023, or 70% of retail spending.[2]

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 spread of rates on Commercial and Industrial (C&I) loans (loans to firms) over the Fed funds rate averaged 2.25%, the spread of mortgage rates over treasuries was 3%, and the spread over treasuries of high-yield US corporate bonds–the riskiest corporate bonds–was 4.21%.

This leads us to ask two questions in this paper. 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. Moreover, credit card banking is an intensely retail business, which may be important for understanding credit card rates. Thus, our second aim is to understand the economics of the business of credit card banking. Therefore, we investigate the streams

[1] See Consumer Financial Protection Bureau – Consumer Credit Card Market Report (October 2023).

[2] We compute the total purchase volume based on Nilson Report – Top US General Purpose Credit Card Issuers at Midyear (September 2023). The total retail sales and food services spending in the US were obtained from United States Census Bureau – Advance Monthly Sales for Retail and Food Services.

of revenues and costs involved in it, and whether market power plays an important role in credit card banking. 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 these 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, due to their high rates, they generated a much larger fraction of banks' interest income: 16.6% on average.

Credit card lending is banks' riskiest form of lending, because it is both personal lending and unsecured. 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. As a result, 53% of banks' annual default losses were due on average to credit card lending. Moreover, default losses on credit cards are, surprisingly, a similar order of magnitude as those on corporate bonds, even though corporate bonds outstanding 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 standard bond recovery rate of 50%.[3]

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.

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

The fourth is that they are due to credit card banks having market power.[4] In addition, market power and risk pricing can interact, with banks pricing credit card rates using a higher price of default risk than is seen in other markets.

Our analysis utilizes a comprehensive supervisory dataset on credit card accounts from 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 US. 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 components of revenues and expenses 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.[5] 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 by lending to accounts.

In order to have 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 sort the accounts in each cohort into portfolios by their FICO scores at origination. FICO is the industry standard credit score. Its value ranges from 300 to 850, with a higher score indicating lower default risk.

[4]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 are heterogeneous in how intensely they search for the best rate (Stango and Zinman, 2016).

[5]This is the case since the passage of the CARD 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.

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.

In each month, we further sort the accounts in the FICO portfolios into portfolios of borrowers and transactors. This is important because borrowers and transactors generate different risks and revenues. In the months an account is borrowing, it exposes the bank to default risk and is charged interest, unless it is in a zero-interest promotional period.[6] 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: for FICO scores above 800 it is only 20%, but is over 50% for all FICO scores below 720, and rises to almost 80% for FICO scores near 600.

We begin by analyzing the interest rates that the 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 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 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 average rates by dividing the cumulative dollar amount for the given quantity (APR spread or default loss) over the sample period 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. Although the charge-off rates are high, especially for

[6] 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.

the lower FICO scores, they are much lower than their corresponding APR spreads. Thus, the APR spreads are mostly *not* due to expected default losses. Moreover, the 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 to see how they affect profitability. Among these, the ones that are unique 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, and in particular the customer's bank. Rewards are a percentage of the purchase price that is paid to the cardholder by their bank in return for using the card. Rewards 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 substantially higher purchase volumes, and thus generate correspondingly higher net interchange income. They 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 assets for transactors, but is a minor component of borrowers'.

It has been argued that banks use the interest income from borrowers to subsidize large

reward payments to transactors. We do not find this to be the case since we find that banks make positive net interchange on 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 overlooks the influence that non-financial (operating) 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.[7] 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 fraction 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.[8]

Combining all income and expenses, including operating expenses, we obtain the return on assets (ROA) of the credit card portfolios. We find that ROA is high: 6.95% for the

[7]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).

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

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 is strongly increasing in default risk, similar to what we found for default-adjusted APR. This suggests that credit card rates price in a default risk premium.

Two conditions that we document support this hypothesis. The first is that charge-offs are highly correlated across FICO portfolios, rising together in cycles that are highest during recessions. Hence, 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 undiversifiable (i.e., systematic) component, it is plausible that it would be priced.

We test this by estimating a single-factor model of default risk using the cross-section of credit card portfolios.[9] As a proxy for the systematic component of default risk, we use the change in the monthly charge-off rate of the aggregate credit card portfolio. We estimate the beta (exposure) of each credit card portfolio to systematic default risk by regressing the change in its monthly charge-off rate on the proxy. Following the standard asset pricing approach (Fama and MacBeth, 1973), we then estimate the compensation for default-risk exposure 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, an account's FICO score is a good proxy for its beta to systematic charge-off *risk*. Regressing the portfolios' ROAs on their betas, we estimate the risk premium on 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,

[9]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) there is a large cross-section of sensitivities, and (c) there are millions of accounts, making it possible to obtain precise measures of portfolios' systematic exposures.

exposure to aggregate default risk can fully explain the strong, increasing relation between ROA and FICO score.

The regression intercept is the ROA of a hypothetical zero-beta borrower, that is, a borrower with no systematic default risk. The estimated intercept 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 construction and were not included in the regression. The ROA of the transactor portfolio is 3.2%, very close to the zero-beta estimate.

We then analyze how our estimated credit card default risk premium 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 on the corresponding FICO portfolios. Hence, credit card rates and corporate bond yields appear to price in 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 about 1.5%. This means that credit cards have a 1.3% higher default-risk-adjusted ROA than the overall banking sector.[10]

Related Literature

Our paper contributes to three strands of literature. First, it relates to the literature on bank profitability in credit card markets that comprises both academic studies and industry reports. Most of the academic literature focused on the effects of the CARD Act on the cost of borrowing and bank profit components (Agarwal et al., 2015; Han, Keys and Li, 2018; Nelson, 2024). Among the most closely related studies, Agarwal et al. (2015) demonstrate

[10]This value is actually a lower bound on this difference because the banking sector does have a 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%.

that regulatory limits on credit card fees reduced overall lending income, leading to a decline in bank profitability. They also document the key components of banks' realized average revenues, costs, and profits across the distribution of account-level FICO scores for the pre-CARD Act period (2008–2010), which coincided with the Global Financial Crisis. We complement this literature in three key ways. First, rather than providing a point-in-time snapshot, as is common in prior studies and industry reports (e.g., Consumer Financial Protection Bureau, 2023), we analyze the lifetime profitability of credit card accounts based on their origination FICO scores. This approach is particularly relevant as banks set credit card APRs based on credit scores at origination, and the CARD Act restricts banks from increasing APR spreads after account origination. Second, we differentiate between two types of accounts—borrowers and transactors—since these groups differ significantly in both the revenue they generate for banks and the associated risks. Third, we estimate risk premia across the FICO distribution and calculate the risk-adjusted return on credit card lending. Our findings, based on the post-CARD Act period, show that credit card returns are positive across the entire FICO distribution, with returns highest for the lowest FICO accounts and declining with higher FICO scores. Importantly, we find that borrowers represent a much more profitable segment of the market compared to transactors, but their returns carry substantial risk premia, which account for approximately 25–40% of the credit spread.

Second, we contribute to the broader literature on the estimation of risk-adjusted returns in private markets (e.g., Carhart, 1997; Kaplan and Schoar, 2005; Korteweg and Nagel, 2016; Gupta and Van Nieuwerburgh, 2021). While much of this research has focused on private equity markets, more recent studies examine returns in private credit markets, including corporate loans (Flanagan, forthcoming), collateralized loan obligations (Cordell, Roberts and Schwert, 2023), and private debt funds (Erel, Flanagan and Weisbach, 2024). We extend this body of work by decomposing bank returns and estimating the risk premia in credit card markets. To achieve this, we leverage novel supervisory data tracking individual accounts over their lifetimes from inception. The granularity of these data enables us to

decompose credit card cash flows into various revenue and cost components across accounts with differing ex-ante risk levels. Our findings reveal substantial risk premia ranging from 1-2% for accounts with the highest FICO scores to 6-8% for those with the lowest scores, comparable to credit spreads in the speculative-grade bond market. This account-level analysis complements the results of Fleckenstein and Longstaff (2022), who study risk premia in the unsecured consumer credit market using the prices of credit card asset-backed securities (ABS). They report that credit risk premia for these securities range from 0.5% for the safest tranche to 2% for the riskiest. Their estimates are significantly smaller than ours because credit card ABS are specifically designed to be safer and more collateralized than the underlying credit card accounts on which our risk premium estimates are based.

Finally, we relate to the literature on competitiveness and market power in the credit card market. Prior research has highlighted that this market is characterized by limited competition (Ausubel, 1991; Herkenhoff and Raveendranathan, 2021), high search and switching costs (Calem and Mester, 1995; Berlin and Mester, 2004; Drozd and Nosal, 2008; Galenianos and Gavazza, 2018; Nelson, 2024), and significant heterogeneity in consumers' search intensity for the best rates (Stango and Zinman, 2016). We extend this body of work by showing that banks achieve market power in this market partly by incurring high operating costs, with marketing expenses—primarily focused on customer acquisition—being among the largest components. Our findings show that these costs account for a substantial portion of the high borrowing rates and explain approximately half of the default-adjusted APR spreads. More broadly, these results link our work to studies documenting banks' market power in deposit markets (e.g., Neumark and Sharpe, 1992; Drechsler, Savov and Schnabl, 2021), where banks bear significant fixed costs to maintain deposit franchise, and in other loan markets (e.g., Scharfstein and Sunderam, 2016).

2 Data

2.1 Y-14 Reports

We use a comprehensive, granular supervisory data set on credit card loans from the Federal Reserve's Y-14M reports. The data are collected for capital assessments and stress testing and contain monthly account-level information. 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 more than 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 sign-up bonuses, and we observe these as well. We augment the account-level variables with variables reported as aggregates for portfolios of accounts. Portfolios are defined by the issuing bank, type of credit card, and type of lending.[11] The portfolio-level variables include interest expenses, rewards, interchange income, operating expenses, and fraud expenses. We use this information to calculate the profitability of the credit card business.

The bulk of our analysis focuses on consumer general-purpose reward credit cards. General-purpose cards can be used at all merchants that accept credit cards and account for 90% of all US credit-card lending. In contrast, private label cards can only be used at the retailer associated with the card.[12]

We focus on accounts that originated between January 2015 and December 2017, and

[11] There are four credit card types: general purpose, private label, business card, and corporate card. There are also four lending types: consumer bank card, consumer charge card, non-consumer card, and non-consumer charge card.

[12] Within general-purpose credit cards, there is a subset known as classic cards, which do not offer rewards. In 2023, rewards cards accounted for 82% of general-purpose credit card balances and 92% of purchase volume. Since their business model is different from rewards cards, and since spending and borrowing have increasingly moved to rewards cards , we remove them from the analysis. Among private-label cards, 92% are classic cards, and hence pay no rewards.

track them until December 2023, the end of our sample. Although the Y-14 data start in 2012, there are significant gaps in key variables before 2015. By restricting the sample to accounts by 2017, we ensure that the sample is long enough to assess the risk and returns on these accounts over their life cycle. In robustness analysis, we confirm that our findings are not sensitive to the choice of endpoints.

For consistency, we restrict our sample to accounts that meet the following criteria: (1) observations begin within one month of the account's origination, (2) there are no missing data, and (3) if the account exits the dataset, the reason is specified as either charge-off or closure; otherwise, the account remains active until the end of our sample. In contrast to the usual practice of sampling the data, e.g., studying subsamples of 1% of observations, we analyze the entire dataset. This gives us an average of 31 million observations per month for the period January 2015 to December 2023.

2.2 Other Data Sources

Call Reports We complement the Y-14 data with bank call reports, which contain quarterly data on the income statements and balance sheets of all US banks. We use the call reports to compare the profitability of credit card banks to other banks. We identify credit card banks as those in which (1) personal loans' share of assets exceeds 50%, and (2) at least 90% of personal lending is credit card lending. This definition follows from that used by the Federal Reserve's report to Congress on credit card banking.[13]

Corporate Bond Data We obtain data on corporate bond issues from the Mergent Fixed Income Securities Database (FISD). We use the data to compare the risks and returns of investing in corporate bonds with credit card lending. The dataset contains information

[13]The series of such reports are known as the "Report to the Congress on the Profitability of Credit Card Operations of Depository Institutions": https://www.federalreserve.gov/publications/credit-card-profitability.htm.

on a bond's issuance date, issue size, coupon rate, maturity date, and credit rating.[14] It also provides information that allows us to calculate the return to investing in the issue. In particular, we observe if the bond defaulted (and when), reached maturity and repaid its entire principal, or was called by the issuer.

3 Overview

Table 1 panel A reports summary statistics for components of income and expenses that are important in credit card banking. The underlying data is aggregated at the bank-month level.

The upper left quadrant of panel A reports statistics of the interest income and expense rates. As the table shows, credit card banking is characterized by a very high interest income rate. The average interest spread (interest income rate minus fed funds rate) is 14.2%.

The upper right quadrant reports the average charge-off rate. The average charge-off rate for a bank is 5% during our sample period. There is only modest variation across the banks, as the 25th percentile of charge-off rates is 4% and the 75th percentile is 5.3%. Recovery rates are low, averaging only 0.5%, i.e., about 1/10 of charge-off rates.

The lower two quadrants report interchange income and rewards expenses. We report these as as a share of assets to make them comparable to net interest income. The average interchange income rate is 7.1% of assets, while rewards are 4.8% of assets. Thus, both quantities are a substantial fraction of assets, but interchange income is greater than rewards expenses.

On average, there is another 2.1% worth of assets of non-interest income per year. Of this, 1.7% is due to the various fees banks charge.

The table also shows credit card banks' operational costs, which are their main non-interest expense. These are large, averaging 4.9% of assets annually. They also differ widely

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

in the cross-section. A few operational categories are broken out separately. These are much smaller. In particular, fraud expenses, at 0.3% of assets annually, are not large.

3.1 Borrowers and Transactors

A key distinction in credit card banking is whether an account is a transactor or a borrower (known as a "revolver" in industry terminology), in a given month. Transactors are accounts that repay their balance in full by the end of the statement month, whereas borrowers do not and hence borrow the unpaid amount from the bank. The distinction is important because a transactor poses no default risk to the bank and pays no interest. In contrast, a borrower exposes the bank to default risk and is charged interest. The exception is if the borrower in a zero-interest promotional period. Such promotions are offered to prospective customers as an incentive to open a new account or transfer existing borrowing from another bank ("balance transfer"), with the promotional period normally occurring in the account's first twelve months.

Therefore, in each month, we classify every account as either a transactor or borrower. We classify an account as a borrower if the account either repays less than its previous balance, incurs finance (i.e., interest) charges in the following month, experiences a charge-off, or transferred a balance from another account. All other accounts are classified as transactors.

Table 1 panel B reports summary statistics computed separately for borrowers and transactors. There are several key differences between borrowers and transactors. Borrowers' average daily balance (ADB) is much larger on average than transactors. This is because their ADB includes both their current month's purchase volume and their past borrowing. Since transactors do not borrow, their ADB is due only to the current month's purchase volume. In contrast, transactors' purchase volume is larger than borrowers', in part because they are not encumbered by debt. Since interchange income and rewards payments are

proportional to purchase volume, they are for transactors.

3.2 Distribution of Credit Scores

To study the role of credit risk in credit card banking, we sort accounts by their FICO score at the time of account origination into 50 evently spaced bins spanning 600 to 850. FICO score is the industry standard credit score. It is intended to predict an account's credit risk relative to other accounts (though not its absolute level of risk, which depends on aggregate factors). We use 600 as the lower cutoff because accounts with lower scores than this are rarely originated. Table C1 confirms that FICO score is a strong predictor of charge-off rates in the cross-section.

Because of its informativeness about credit risk, banks use FICO score to set accounts' borrowing terms. In particular, an account's origination FICO Score is highly predictive its APR spread, which is set at origination and usually remains fixed for the account's life. This is due, at least in part, to the CARD Act, which prohibits banks from increasing an account's APR spread on outstanding borrowing. Table C2 shows that fixed effects for origination FICO-origination date and origination FICO-bank explain over 85% of the variation in the cross-section of APR spread. Thus, origination FICO is very informative about the cross-section of APR spreads. The results below further confirm this relationship.

We begin the analysis by examining the distribution of FICO scores across accounts. Figure 1 plots the distribution of FICO scores across accounts. It plots the FICO share of newly originated accounts (blue), all accounts (red), and the ADB-weighted share of all accounts (green). The distributions of new and existing accounts are close to uniform for FICO scores between 670 and 820, with a mode at 695.[15] In contrast, the ADB-weighted

[15]The new and existing account distributions are nearly identical. This is because attrition rates are very similar for each origination FICO bin. Attrition rates are the share of accounts closed, which can occur due to to default, the customer voluntarily closing the account, the card getting lost or stolen, the customer dying, or other reasons.

share is highest for FICO scores between 660 and 750.[16]

Within each FICO bin we further sort the accounts into portfolios of borrowers and transactors. This is important because borrowers and transactors have significantly different streams of income and expenses. Figure 2a plots the share of borrowers across the FICO bins, on an equal weighted basis (blue) and weighted by balances (red). The share of borrowers is monotonically decreasing in FICO score. At 600 FICO, close to 80% of accounts are borrowers. This drops to 50% by 720 FICO, and decreases to a little under 20% for FICO scores over 800 ("superprime"). Because borrowers have substantially higher balances than transactors, their balance-weighted share is substantially higher at all FICO scores. It is close to 100% for the lowest FICOs and remains around 90% for FICO scores up to 750. It then falls, but still remains above 50% for FICO score above 800. Thus, lending to borrowers accounts for most of credit card banks' balance sheets, with only a small share coming from the balances of transactors.

4 Decomposition of Income and Expense Streams

We analyze the numerous income and expense streams of accounts in the cross-section of FICO scores. Importantly, we do so separately for borrowers and transactors, since these differ substantially across the two groups. We begin with the APRs charged by banks.

[16]For each account, we use the ADB reported by banks as the base measures of balances. If ADB is missing, we use an account's cycle ending balance (CEB). ADB is missing for some accounts if they have never been a borrower. However, once an account has borrowed, its ADB continues to be reported even if stops borrowing. In addition, we impute ADB for the final month of a borrowing spell. The reason is that in this final month the ADB mixes the balance from being a borrower with the new balance as a transactor. We impute the final borrow amount from the account's last finance charge and its APR. We compute the balances of transactors for a FICO bin by subtracting the total balances of borrowers from the total balances of all accounts. A transactor's balance is due to the previous month's purchase volume, as there is a 21-day grace period during which the balance can be repaid before interest is charged.

4.1 APRs and Credit Losses

Figure 3 plots the effective interest rate (APR) paid by borrowers across FICO scores. The values subtracting Federal Funds rate, which we call effective interest (APR) spread, are also reported in Table 2 for FICO scores in 20-point increments. We compute the effective APR from the reported interest payments and ADB and subtract the Fed funds rate to get the effective APR spread. The effective APR may differ from the reported APR because of promotions, during which a lower interest rate is charged (e.g., 0%). This is most common in the account's first year, but also occurs at other times. Using the effective APR accounts for the impact of promotions on banks interest income and consumers' cost of credit. We observe that a significant number of borrowers with high origination FICO scores take advantage of 0% APR offers to revolve credit. Notably, the 25th percentile of effective APR among borrowing accounts with an initial FICO score of 750 or higher is 0%.

It is important to note that almost all credit card APRs are a constant spread over the prime rate, which is itself a constant 3.0% spread over the Fed Funds rate.[17] Thus, it is natural to analyze APRs as a spread to the Fed Funds rate.

There main takeaway from Figure 3 and column 3 of Table 2 is that average APR spreads are large. The average APR spread across FICO scores is 14.5%, and even the smallest APR spread exceeds 7%. These spreads are much larger than those on other common types of bonds or loans. For instance, over 1997-2014 the average credit spread on investment-grade and high-yield corporate bonds was only 1.5% and 5.3%, respectively, and even the most distressed high-yield bonds, those rated CCC and below, had an average credit spread (11.1%) smaller than that of most credit cards.

Since credit card lending is unsecured lending to consumers, it is exposed to a significant risk of credit losses. Hence, we first analyze whether the APR spreads are explained by

[17] As of 2022, 98 percent of general purpose accounts in the Y-14 were variable rate cards according to Consumer Financial Protection Bureau (2023). In a highly-cited paper, Ausubel (1991) documented that during the 1980s credit card APRs had low sensitivity to the Fed funds rate. This has not been true for a long time, as credit card APRs have moved closely with the Fed funds rate since at least 1995.

similarly large credit losses.

Figure 4 is a stacked plot comparing the interest income (blue) of borrower accounts in the FICO bins against their credit losses (green) and interest expenses (red). These quantities are plotted on the left axis. Income is plotted as a positive quantity, while losses and expenses are negative. We focus on borrowers since transactors do not have interest income or credit losses.

The (net) credit loss rate measures the quantity of charge-offs per dollar of lending per year over our sample. We net charge-offs against any recoveries, which for credit card lending are small. Interest income is just the interest paid by the accounts. Hence, the rate plotted is exactly the average effective APR rate in Figure 3 . We assume the interest rate paid on financing equals the Fed Funds rate.[18] Thus, the difference between the interest income and expense rates equals the effective APR spread reported in Table 2. In analog with bonds, we can also view it as the credit spread on these accounts.

Since our goal is to understand the profitability of accounts over their lifetime, we plot the annual average rates of these quantities from the time of origination until the end of the sample. To calculate the lifetime average rates for each origination FICO bin, we divide the cumulative monthly dollar amount of the quantity of interest (e.g., net charge-offs) for all accounts in the FICO bin over the sample period by their cumulative monthly balances over the same period. This ratio gives the rate of the given quantity per dollar of monthly balance. To annualize it, we multiply it by 12. To combine the cohorts (origination months) of a FICO score bin, we effectively treat them as one large portfolio and sum the numerator (e.g., net charge-offs over the sample) for all the cohorts of the FICO bin and divide by the sum of their balances. We follow this same approach for all the quantities plotted in the

[18]There are two main reasons why we believe this is appropriate. First, the interest expense rates of banks that engage mainly in credit card lending, such as American Express, Discover, or Synchrony bank, is very close to the Fed Funds rate. The reason is that they lack a deposit franchise and hence fund themselves mostly by selling short-term CDs at competitive rates, i.e., close to the Fed Funds rate. Second, for banks that do have a deposit franchise, and hence obtain deposit financing at lower rates, the difference should be viewed as a payoff to their deposit-taking business, which involves is its own substantial costs, not their credit card business. Thus, to be conservative we set the interest expense rates to the Fed Funds rate.

figures below.

Figure 4 confirms that lifetime credit losses are substantial for many FICO scores. Moreover, they are strongly, nearly linearly, decreasing in FICO score. At the lowest origination FICO score (600), lifetime net credit losses are a very high 9.3% of balances per year. By 720 this decreases to a still large 5.7% of balances per year over the lifetime, which is also the loss rate for credit card lending in the aggregate in the sample. Even at 800 origination FICO ("super-prime" according to Experian), the credit loss rate is still 3.2%. By 850 FICO, the highest possible, the credit loss rate drops to 1.3% per year. Note that these FICO scores are the accounts' score at the time of origination, not at the time of default. By the time an account defaults, its FICO score has usually deteriorated substantially. However, we need to map accounts' credit losses to their origination FICO scores in order to compare them with their APR spreads, which are fixed at origination.

In addition to default-related charge-offs, there are also charge-offs due to fraud. The cost of these is 0.3% of ADB per year, so far smaller than credit-related charge-offs.

To test if APR spreads are just compensation for average default losses, we subtract the credit loss rate for each FICO bin from its effective APR spread. We refer to this as the "default-adjusted credit spread" and plot it on the right axis (black line) in Figure 4.

We find that, despite the high credit loss rates, the default-adjusted credit spreads are positive and large. Thus, credit card borrowers pay rates that are a large spread over expected default losses. Indeed, the average defaulted-adjusted credit spread (balance-weighted) is a very large 8.8% APR.

Figure 4 further shows that the default-adjusted credit spread is strongly decreasing in FICO score. It is close to 12% for FICOs below 660. There is a jump down to 10% between 660 and 670 FICO, likely related to this being the cutoff between non-prime and prime borrowers. The default-adjusted credit spread then decreases nearly linearly from around 10% at 670 FICO to 6% at 850 FICO.

Thus, although all borrowers pay a credit spread this is much larger than their expected

credit loss, the gap is much wider still for lower FICO-score borrowers. This suggests that credit card rates may price in a large credit risk premium, and that the risk premium decreases in borrowers' FICO score. We investigate this hypothesis in section 5.

Next, we analyze accounts' non-interest income and expense streams. We incorporate them into the calculation of returns on the FICO bins and ask to what extent they help explain the large default-adjusted credit spreads we find in Figure 4. We also analyze the returns banks earn on transactors, which are exclusively from non-interest sources.

4.2 Non-interest Income and Expenses

The main non-interest components of credit card business' profits are interchange income, rewards expense, fees, and operating expenses.

Interchange and Rewards

When a credit card is used to make a purchase, the merchant pays a "processing fee" or "swipe fee", which is split between the bank that issued the credit card, the credit card network (Visa, Mastercard, American Express, or Discover), and the "payment processor".

In the US in 2023, these three components of credit card processing fees amounted to $162.5 billion (CMSPI, 2024). The bulk went to interchange fees, the component received by the card-issuing bank. In our data, we find that interchange fees average 1.82% of the purchase price. On top of this is the network fee, which is paid to the credit card network, and is between 10-20bps of the purchase price for Visa and Mastercard. (CMSPI, 2024) [19]

A striking feature of credit cards is the prominence of rewards payments. Rewards are paid to the cardholder by their bank in return for using the card. Like interchange, they are

[19]The total interchange and network fee charged on Visa cards is between 1.51% and 2.5% of the transaction value, plus + $0.10 per transaction for transactions that take place in person ("card present).(https://www.clearlypayments.com/interchange-rates-in-usa/). For "card not present" (i.e., online) transactions, rates are higher, between 1.89% and 2.5% of the transaction value, plus $0.10 per transaction. Mastercard's fees are similar.

also a percentage of the purchase price. Rewards are paid as cash, airline miles, or points that can be redeemed for cash or travel.

Rewards and interchange are closely intertwined. Rewards expenses are covered by banks' interchange income, which is why bank filings usually report the net of the interchange income and rewards expenses as a single value. We find that banks' rewards costs are on average 1.57% of purchase volume. Hence, on average banks pass on 86% of their interchange income as rewards to card users.

We compute the interchange and reward rates from the Y14's portfolio-level data rather than the account-level data. The portfolio data reports the dollar amounts of interchange income and rewards for each bank in each month. We calculate bank-level purchase volume by aggregating the purchase volume of the individual accounts during the month. We then compute the interchange and reward rates by dividing the dollar value of interchange/rewards for the bank by the bank's purchase volume.[20] Appendix A.1 provides a detailed description of how we compute both rates.

Since interchange and rewards are proportional to purchase volume, we first examine the cross-section of purchase volumes by FICO score. We separate borrowers and transactors since we are interested in measuring banks' return on assets for each group. Since transactors do not pay interest, the return banks make on them depends much more on net interchange income.

Figure 5 plots the average purchase volume for borrowers and transactors within each origination FICO bin. We average only active accounts, that is, those that have some purchase volume, payment activity, or balance that month. By construction this includes all borrowers, but excludes transactors that show no activity at all. These inactive accounts do not use up any of the bank's balance sheet, because it does not provide them with any

[20]The account-level data does contain a running sum of unspent rewards. In principle, this could be used to estimate account-level reward rates. However, there are significant limitations to the account-level data. The data does not record how much rewards were spent during month, so one cannot separate new rewards from rewards spent. Also, many account-level rewards entries are missing and, when recorded, are noisy. For these reasons, and to ensure that rewards aggregate correctly, we use the portfolio data.

financing.[21] At the same time, there is little to no cost to the consumer of keeping an inactive account open, as long as it does not have an annual fee. We find that 22.6% of all accounts in our sample are inactive in a given month. Of the active accounts, 57.1% are borrowers and 42.9% are transactors on average.

Figure 5 reveals two main patterns. The first is that average purchase volumes are higher for active transactors than for borrowers across all FICO scores. This is not surprising, since by construction transactor accounts have no debt, and hence are likely to have more capacity to spend.

The second pattern is that average purchase volume is increasing in FICO score for both transactors and borrowers. For transactors, purchase volume rises from a little over $600 per month for 600 FICO to about $1200 for 720 FICO, and is around $1600 per month for FICO of 770 and above. For borrowers, purchase volume averages $200 for 600 FICO, rising to $600 for 720 FICO, and reaching around $1300 by 850 FICO. This is not surprising either, because an account holders' FICO scores and incomes are strongly positively related, hence accounts with higher FICO scores tend to have more spending power.

To understand how interchange and rewards contribute to the overall profitability of credit card portfolios, we compute lifetime interchange and reward as a fraction of ADB following the same procedure as above for interest income and credit losses. Figure 6 plots the cross-section of these rates. As above, the rates are annualized. Unlike interest income and charge-offs, interchange fees and reward expenses apply to both transactors and borrowers, and we plot them separately.

Figure 6a plots the results for transactors. Note that interchange and rewards are plotted on the left axis, while the difference between them, net interchange, is plotted on the right. As the figure shows, for transactors, interchange income (yellow) is close to 30% of ADB on

[21] Since they do not use up any balance sheet, it actually doesn't matter for anything else we do whether we exclude them or not. We exclude them here because we are interested in seeing average purchase volume for cards that are actually used. Inactive accounts may impose some administrative costs on the bank. These are included in operating costs, which we amortize over all active accounts.

an annualized basis for FICO scores between 600 and 800. Above 800 the average drops to around 24%. Rewards expenses (purple) are about 24-25% from 600 to 800 FICO and then drop slightly to around 23%.

This means that the interchange income generated by transactors for the bank is akin to it charging a 30% interest rate on the funds it (implicitly) provides them, though the payment is made by merchants, not the cardholders.

This is a very high rate. To understand how it arises, recall that the average interchange rate is about 1.9% of purchase volume. This means it is over 2% of ADB, which is the average balance during the month and hence is less than purchase volume as long as the purchases are not all at the beginning of the month. Annualizing this figure (by multiplying by 12) gives the average annual rate of 29%. Similar calculations explain why the annual interchange expense rate is 24.6% of ADB on average.

While a majority of interchange income is passed through to cardholders as rewards payments, net interchange income is substantial for transactors. Figure 6a shows that between 640 FICO and 810 FICO the average net interchange rate is about 5% of ADB annually. Thus, due to interchange banks earn an annual rate of about 5% per dollar of financing they provide to transactors for purchases.

For borrowers, interchange and rewards rates per dollar of ADB are much lower than for transactors. Figure Figure 6b shows that average annual interchange income per dollar of ADB is flat at around 3% for FICO scores below 740, and then increases monotonically to 7.5% by 850 FICO. This increase is mainly due to a higher ratio of purchase volume to ADB for the high-FICO accounts. There is a similar pattern for rewards expenses: they are about 2% for FICO scores below 700, then rise to 7.4% by 850 FICO.

Net interchange income annually per dollar of ADB (right axis) is also much smaller for borrowers. It is uniformly less than or equal to 0.8% per year, and is between 0.4% and 0.6% for FICO between 620 and 815. For the highest FICO scores net interchange falls below 0.2%. The decrease is due to premium credit cards paying higher rewards rates. Such

premium cards are mainly held by higher income, and thus higher FICO score, cardholders.

Thus, Figure Figure 6 shows the net interchange income earned from transactors is large relative to assets. As we show below, it accounts for the bulk of the return on assets from transactors. In contrast, for borrowers it is a marginal component of return on assets compared to the magnitudes of interest income and credit spreads. Nevertheless, net interchange is positive for borrowers. Thus, rewards do not explain credit cards' high APRs; to the contrary, since net interchange is positive, it adds to the large default-adjusted credit spreads, and deepens the puzzle of why credit card APRs are so high.

Fees

Credit card lending also generates other fee income besides interchange fee, including annual fees, late fees, balance transfer fees, over-limit fees, cash advance fees, convenience fees, and insufficient funds fees. During our sample period, such fees average 2.6% of credit card balances, accounting for approximately 10% of total credit card lending revenue.

The largest categories are late fees, annual fees, and balance transfer fees. Figure B1a in the appendix plots average non-interest fees by FICO bin as a share of ADB during the life cycle of an account, starting from account origination. Fee income is seasonal, peaking every 12 months when annual fees are charged. Annual fees are highest for accounts in the highest and lowest initial FICO bins. At both extremes they are above 1% of ADB in the first few years.

Another significant source of fees is balance transfer fees, which accounts pay in order to transfer their borrowing from another credit card. These fees are highest for the lowest FICO accounts. Specifically, the 600 and 650 FICO accounts pay an annualized 6% and 2% of ADB, respectively, as a transfer fee in the first month following origination.

Table 2 reports income from fees as a percentage of ADB across FICO bins for borrowers (panel A), and transactors (panel B). For borrowers, fee income is highest for subprime FICO scores (660 and below), driven by balance transfer fees and late penalties. Account with 600

FICO score pay nearly 5% in fees on average, and even those with 640 FICOs pay nearly 3.7%. For FICO scores between 680 and 800, fee income is flat at around 2%. Above 800 FICO score fees rise again, to nearly 2.9% for 850 FICO score, driven by the higher annual fees charged by premium cards, which are more common in this FICO range. The overall ADB-weighted average fee income for borrowers is 2.29% of ADB.

Fee income as a share of balances is high for transactors. Subprime accounts again generate the highest fees as a share of ADB, with fee income of 6.6% to 12.8% of ADB. The high rate is due to annual fees and the relatively low ADB of these accounts (not to balance transfer or late fees, since transactors do not incur these fees by construction). For FICO scores of 680 and above, fee income is flat at around 4-5%. The overall ADB-weighted average fee income for transactors is 4.94%.

Adding interchange and fee income and subtracting reward expenses gives net non-interest income. Net non-interest income as a fraction of ADB is substantial for borrowers and very large for transactors: for borrowers the ADB-weighted average is 2.7% of ADB, for transactors it is 9.35% of ADB. Since transactors do not pay interest, this is all of the income earned from them.

Adding the non-interest income to the default-adjusted credit spread, we get the gross lending margin, the return lenders earn from borrowers after accounting for all marginal income and expenses, but not operating expenses. We find that credit card lenders earn a very large 11.5% average gross margin on borrowers. Figure B2a plots the cross-section of gross margin by FICO bin. Like its components, it is decreasing in FICO score, from about 17.5% for a 600 FICO score to 9% at 850 FICO. Thus, shows that the gross lending margin is large for all FICO scores–even the very safest borrowers generate a 9% gross lending margin. At the same time, there is also a large cross-sectional spread, with higher-risk borrowers corresponding to much larger gross margins.

4.3 Operating Expenses

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

To illustrate this, we examine the operating expenses of Capital One Bank. Capital One is arguably the bank most specialized in lending to general purpose credit cards. It was founded as a credit card lender and is today the third largest credit card lender, following JP Morgan and Citibank, which have far larger overall balance sheets. Figure B3 in the appendix present excerpts from Capital One's 2023 annual report that detail the components of its operating expenses for the whole bank, and for just its credit card operations. In addition to its credit card operations, Capital One maintains a substantial deposit franchise, accounted for mainly under its "Consumer Banking" segment, and provides lending and other services to firms under its "Commercial Banking" segment.

Figure B3a shows that salaries and marketing are the largest components of operating expenses. Other major costs are for occupancy, and for communications and data processing. In 2023, Capital One held an average of $141 billion in credit card loans, which represented 45% of its loan portfolio and 30% of its total assets (it also had significant securities holdings). As Figure B3a shows, the bank's overall operating expenses, including marketing, totaled $20.3 billion. It attributed $12.5 billion to its credit card operations, shown in Panel B of Figure B3b as the "non-interest expense" of its credit card segment.[22]

These figures show that the credit card segment incurs a disproportionate fraction of the operating expenses (including marketing) compared to its share of assets. The credit card segment represents 30% of Capital One's assets, but 61.6% of its operating expenses.

[22]The the $20.3 billion is also listed as "non-interest expense" in Figure B3a. Adding up the non-interest expense for each of the three business segments confirms that they sum up to $20.3 billion.

Another interesting comparison is to Capital One's Commercial Banking segment. It had an average of $92.5 billion of loans (65% of the magnitude for credit card loans) and was attributed $2.0 billion of non-interest expense (16% of the magnitude of credit loans). If its operating expenses had scaled proportionately with its loan book, the operating expenses of commercial banking would have been $8.2 billion instead. For comparison, the pre-tax net income of the commercial banking segment was only $0.9B. This comparison illustrates how much greater are the non-financial costs involved in operating and marketing the credit card business, which is highly retail-facing, than the commercial banking business, which is not.

Another way to assess the operating expenses is as a share of assets. For Capital One's Credit Card segment, operating expenses are 8.8%. This means Capital One has to make 8.8% on every dollar of ADB just to repay its operating costs. This is a very large amount. To put this in perspective, operating expenses to assets for the aggregate US commercial bank system in 2023 was 2.2%. This was also very close to the ratios for JP Morgan, Bank of America, and Citigroup. Thus, Capital One's credit card segment was four times as costly to operate as the average bank asset.

The pattern of higher operating expenses from credit card lending, as seen with Capital One, extends more broadly in the banking sector. Using Call Report data from 2010 to 2023 and focusing on banks with active credit card operations, we regressed each bank's quarterly operating expense rate (as a share of total assets)[23] on the proportion of loans made up by credit cards. We find that banks with a loan portfolio composed entirely of credit card loans incur annual operating expenses that are, on average, 14.9% higher than those of banks with no credit card loans.

The Y-14 also contains data on operating expenses reported by the banks. This includes spending on servicing, billing, card issuing, and authorizations. It does *not* include the

[23]We use the non-interest expense variable in Call Report as our measure of operating expense. This variable does not include rewards expense, but contains salaries, occupancy, data processing, marketing, communications and etc.

costs of debt collections, fraud, and interchange processing, which are recorded separately. It does include spending on marketing, which is very substantial, and which we discuss in more detail below.

We find that operating expenses are large. In the Y-14 data they average 4.85% of balances for our sample, as shown in Panel C of Table 2. Thus, operating costs offset a substantial part of the gross margin.

Drechsler, Savov and Schnabl (2021) show that banks pay significant fixed operating costs to gain market power in the retail deposit market. This enables them to borrow at rates that are both below market rates, and are relatively insensitive to market fluctuations. Since credit card banking is highly retail in nature, the same mechanism is likely at work here. That is, credit card banks spend so much on fixed operating expenses because it gives them substantial pricing power, i.e., a credit card franchise. This would help explain their large default-adjusted spreads and gross lending margins.

One way to examine this hypothesis is to look at credit card banks' spending on marketing. The role of marketing is to generate additional demand for a product without changing the product itself. If the firm has pricing power this additional demand generates additional profit by increasing the markup the firm can charge for a given level of supply.

If we observe large spending on marketing, this implies that marketing is effective (or perceived as such) at increasing demand for the product, and hence at increasing the price the firm can charge for a given supply. For credit cards this price is the APR spread, fees, or interchange rate it is able to charge.

We find that marketing is one of the largest components of operating expenses for credit card lenders, and that credit card banks are some of the biggest marketers in the US. For instance, in 2023, Capital One spent $4 billion on marketing, and American Express spent $5.5 billion. According to Statista this made them the sixth and seventh largest advertisers in the US in 2022. For comparison, their marketing expenses were similar to the total marketing expenses of international consumer products giants Nike ($4 billion) and Coca-

Cola ($5 billion). They were also large compared to the largest banks: Bank of America, the second-largest US bank, had 6.7 times the assets of Capital One in 2023, but spent less than half ($1.9 billion) on marketing, while JP Morgan, the largest US bank, with 8 times the assets of Capital One, spent about the same ($4.5 billion).

More generally, using the Call Reports we compare the marketing expenses of banks that have a relatively high share of loans in credit card lending, which we classify as "credit card banks," to all other commercial banks. Figure B4 plots the result. Credit card banks spend between 1-2% of their assets annually on marketing, compared to less than 0.1% for all other banks. Even this estimate for credit card banks is a lower bound, since banks that meet the classification for this still include significant shares of non-credit card assets, as in the case for Capital One. If we were able to isolate the marketing expenses attributable specifically to the credit card business, their share of assets would be even higher.

The fact that marketing's share of assets is more than ten times higher for the credit card business is consistent with it being a highly retail, consumer-oriented business, making marketing an effective channel for generating demand and thus increasing pricing power.

To examine how credit card banks spending on operating expenses relates to their ability to generate additional income, Figure 7 plots banks' interest spread and gross margin against their operating expenses, as a share of ADB. We plot this at the bank-origination FICO bin level—where each dot is scaled by its total ADB- and focus within origination FICO bins of 650, 700 and 750. Notably, especially among the largest credit card operators, banks with higher operating expenses within the same FICO bin tend to charge higher interest spreads and realize greater gross margins.

In Table 3 we analyze this with a cross section regression. We regress borrower interest spread, net charge-off rate, and gross margin of accounts originated within the same FICO bin by the same bank, on the originating bank's average operating expense rate over these accounts' lifetime, controlling for the FICO at origination. Our regression results show that, within portfolios of the same credit risk, a 1% increase in a bank's operating expense

rate is associated with a 62-basis-point increase in the interest spread charged to borrowers. However, we find no relationship between a portfolio's operating expenses and its ex-post default rate after controlling for borrowers' ex-ante credit scores. This suggests that higher operating expenses—potentially reflecting more intensive screening or greater marketing expenses—do not lead to the selection of borrowers with better or worse unobservable credit profiles, given the same credit score.

It is also important to note that the primary business of credit card operators for borrowers is credit revolving rather than transaction-based services. Recall that borrowers generate much lower purchase volumes compared to transactors, which may reduce the need for extensive customer service. To the extent that operating expense rate is similar across both borrowers and transactors, higher operating expenses provide credit card banks with greater pricing power, allowing them to charge borrowers higher interest spreads.

The last column of Table 3 examines how operating expenses relate to the gross margin of credit card operations, considering both transactors and borrowers within the same origination FICO bin. Gross margin is defined as the interest spread plus net interchange and fee income minus net charge-offs and other non-operating expenses such as fraud. The results indicate that a 1% increase in the operating expense rate is associated with a 1.2% rise in gross margin, translating to a 0.2% increase in net margin. Thus, higher operating expenses enhance a credit card bank's pricing power, ultimately leading to greater returns on assets.

Accounting for operating expenses, we have now covered all the of the main components of credit card banks' income and expenses. In the next section we combine these to calculate their return on assets for each FICO bin.

4.4 Putting all Together: Return on Assets

Adding together all of an account's streams of income and expenses per dollar of ADB, over its lifetime, gives us the banks' return on assets (ROA) for the account. The last column of Table 2 reports this for each FICO bin, and separately for borrowers and transactors. Specifically, ROA equals interest spread minus net charge-offs (default-adjusted credit spread), plus net interchange income (interchange minus rewards), plus the fee income rate, minus the operating expense rate. There are also a few very small non-interest categories of expenses that are not listed in the table.

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 flat at 3.6% between FICO scores of 680 and 820 (Figure B6 in the appendix). 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 the assumption of zero credit risk. Both flat transactor ROA across FICO scores and the steep increase in borrower ROA with rising credit risk suggest that credit card pricing may be largely driven by risk.

The high ROA of credit card lending is reflected in the aggregate ROA of banks specializing in this sector.[24] Figure B7 presents 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,

[24] According to the FDIC Quarterly Report for 2024:Q2, 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.

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

As we showed in previous section, the ROA for credit card portfolios is closely linked to the default risk of their borrowers. Specifically, accounts with lower FICO scores (higher default risk) are associated with substantially higher ROA. This suggests that the elevated returns on credit card lending are, in part, a reflection of a default risk premium. In addition, if these charge-offs tend to be particularly high 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 default rates on other loan types, especially during recessions. Notably, credit card charge-off rates are the highest and most sensitive to the default cycles. The commonality in defaults, and the fact that the common component spikes in recessions, suggests that this common default risk is undiversifiable (i.e., systematic) across other loan markets and may be priced.

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.[25] This comparison suggests that corporate bonds may serve as a useful benchmark for assessing the risk premium in credit card lending.

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 charge-offs are highly correlated cross the FICO portfolios, rising and falling in tandem with the aggregate charge-off rate. This indicates the presence of a common, undiversifiable component of charge-off risk within the credit card market. Moreover, the sensitivity of a portfolios' charge-off rate to the aggregate charge-off rate is strongly decreasing in its FICO score. Hence, the lower the portfolio's FICO score the greater its aggregate charge-off risk. To sum up, credit cards provide a unique advantage for studying the default risk premium due to: i) their high sensitivity to the default cycle compared to other asset classes, ii) the wide range of sensitivities observed across different credit card portfolios, and iii) the availability of millions of accounts, enabling highly precise measurement of portfolios' systematic risk exposures.

Motivated by this aggregate and cross-sectional evidence, we quantify the risk exposure for each FICO score bin portfolio using the two-stage approach of Fama and MacBeth (1973). Specifically, we first estimate a single-factor model of default risk using the cross-

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

section of credit card portfolios. We use the monthly change in the aggregate credit card portfolio's charge-off rate as a proxy for the systematic component of default risk. For each FICO portfolio i, we estimate its beta (exposure) to systematic default risk by regressing the change in its monthly charge-off rate on the change in the charge-off rate of the aggregate credit card portfolio 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 strongly and linearly increasing with the average charge-off rate and decreasing with accounts' FICO scores. Thus, an account's FICO score is a good proxy for its beta to systematic charge-off risk. 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 compensation for default-risk exposure (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:

$$ROA_i = \lambda + \gamma\hat{\beta}_i + \nu_i \tag{2}$$

Figure 12 and Table 4 present 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 indicate that the one-factor model fits the ROA data exceptionally well, with the model's fitted ROAs closely aligning with the actual ROAs across the entire FICO range. Hence, the

exposure to aggregate default risk can fully explain the strong, increasing relation between the FICO score and its ROA. We find that the price of default risk, γ, is a highly significant 5% per year, while the estimated risk premium ranges from 1-2% for the highest FICO group (800-850) to 6-8.5% for the lowest FICO group (600-650). Thus, the risk premium accounts for roughly 20% of the credit spread for the least risky borrowers and 38% for the riskiest ones, a contribution similar to that of direct default costs.

Our estimates imply that the regression intercept, λ, which can be interpreted as the ROA of a hypothetical borrower with no systematic default risk exposure (zero-beta borrower), is equal to 2.7%. Notably, the zero-beta rate is very close to the 3.2% ROA of the transactor portfolio, which have a zero beta by construction and carry no risk as these accounts involve no borrowing. Note that transactors were not included in the regression, and generate income through interchange and fees rather than interest charges. The consistency of their ROA with the predicted zero-beta rate provides additional support to the view that the rest of the FICO portfolios' ROAs are compensation for their default risk betas.

Next, we compare the zero-beta rate of credit cards to the ROA for the banking sector as a whole, which experiences significantly lower average default rates than even the safest FICO portfolios. The banking sector's pre-tax ROA is approximately 1.5%, indicating that credit cards yield a 1.3% higher default-risk-adjusted ROA than the overall banking sector. Importantly, this value represents a lower bound on the difference, as the banking sector has small default risk, with charge-offs averaging about 0.25% of total assets (or 0.5% of loans and leases). Based on the relationship between average charge-offs and default-risk betas derived from FICO portfolios, we estimate that bank assets have a beta in the range of 0.05 to 0.1, translating to a default-risk premium of approximately 0.25% to 0.5%.

Finally, we examine how our estimates of credit card default risk premium compare to those observed in the other markets. We focus on corporate bonds due to their significant size and high sensitivity of their default rates to the default cycle. 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.

Similarly 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 with comparable risk.

6 Other Factors: Capital Requirements

In this section, we examine whether bank capital requirements could explain the high ROA on credit card portfolios documented in the previous sections. 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 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.[26] Within the retail exposure category, transactor and borrower accounts require different amount of RWA.[27] 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,

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

[27]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.

borrowers, and all users separately.[28] 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[29]: 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, $max\left\{0.45, 12.5 \cdot \left[LGD \cdot N\left(\frac{G(PD)}{\sqrt{(1-.04)}} + \sqrt{\frac{.04}{(1-.04)}} \cdot G(0.999)\right) - PD \cdot LGD\right]\right\}$.[30] Figure 14a 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.

[28] 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 × risk weights for borrowers + share of transactors × risk weights for transactors).

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

[30] $N(x)$ 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 0.999 denotes the confidence level to derive conservative value. For more information, please see this BIS document.

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

References

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.

Berlin, Mitchell, and Loretta J Mester. 2004. "Credit card rates and consumer search." *Review of Financial Economics*, 13(1-2): 179–198.

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

Carhart, Mark M. 1997. "On persistence in mutual fund performance." *The Journal of finance*, 52(1): 57–82.

CMSPI. 2024. "State of the Industry Report." *White Paper*.

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.

Consumer Financial Protection Bureau. 2023. "The Consumer Credit Card Market." *Report*.

Cordell, Larry, Michael R Roberts, and Michael Schwert. 2023. "CLO performance." *The Journal of Finance*, 78(3): 1235–1278.

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*.

Erel, Isil, Thomas Flanagan, and Michael S Weisbach. 2024. "Risk-Adjusting the Returns to Private Debt Funds." National Bureau of Economic Research.

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

Flanagan, Thomas. forthcoming. "The value of bank lending." *Journal of Finance*.

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.

Galenianos, Manolis, and Alessandro Gavazza. 2018. "Regulatory intervention in consumer search markets: The case of credit cards." Working paper.

Gupta, Arpit, and Stijn Van Nieuwerburgh. 2021. "Valuing private equity investments strip by strip." *The Journal of Finance*, 76(6): 3255–3307.

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.

Kaplan, Steven N, and Antoinette Schoar. 2005. "Private equity performance: Returns, persistence, and capital flows." *The journal of finance*, 60(4): 1791–1823.

Korteweg, Arthur, and Stefan Nagel. 2016. "Risk-adjusting the returns to venture capital." *The Journal of Finance*, 71(3): 1437–1470.

Nelson, Scott. 2024. "Private information and price regulation in the us credit card market." *Econometrica*.

Neumark, David, and Steven A Sharpe. 1992. "Market structure and the nature of price rigidity: evidence from the market for consumer deposits." *The Quarterly Journal*

of Economics, 107(2): 657–680.

Scharfstein, David, and Adi Sunderam. 2016. "Market power in mortgage lending and the transmission of monetary policy." *Unpublished working paper. Harvard University*, 2.

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

This figure plots the distribution of observations in our sample based on FICO scores at account origination, with accounts grouped into 5-point FICO bins. The new account share plots the proportion of accounts originated within each FICO bin relative to the total number of accounts originated in the sample. The account share plots the proportion of account-month observations during the sample period associated with each FICO bin relative to the total number of observations. The balance-weighted account share plots the proportion of lifecycle balances (average daily balances) from accounts in each FICO bin relative to the total balance. Details on the sample construction are provided in Section 2.1.

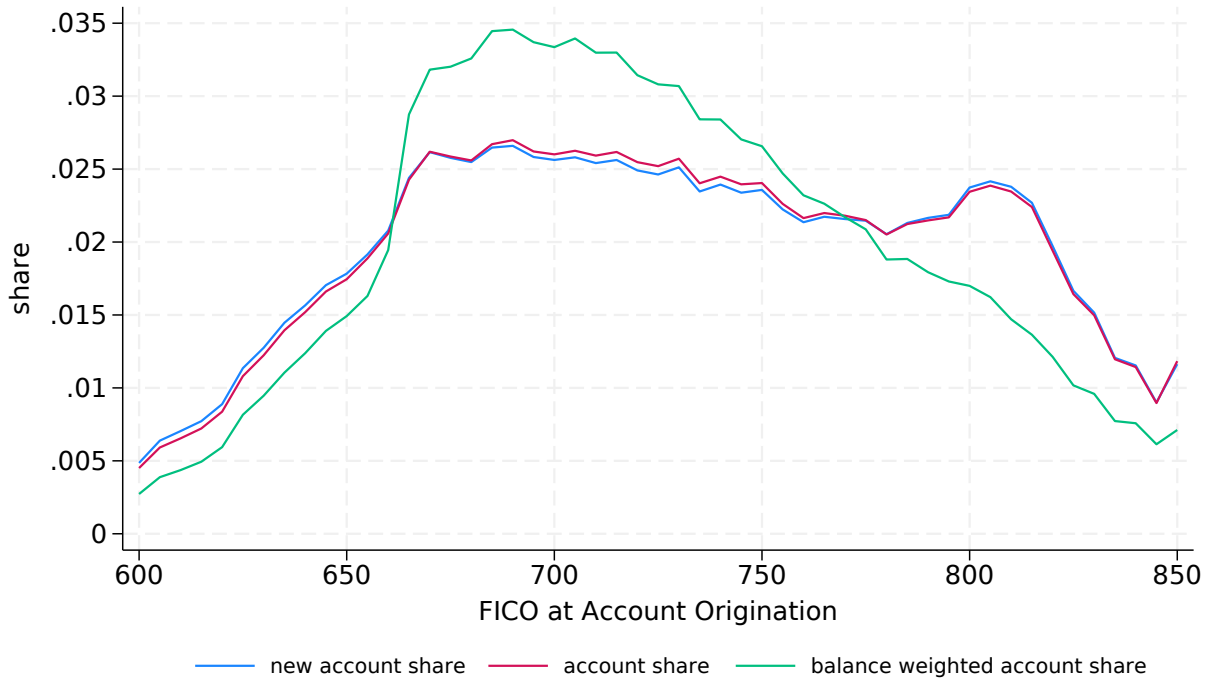
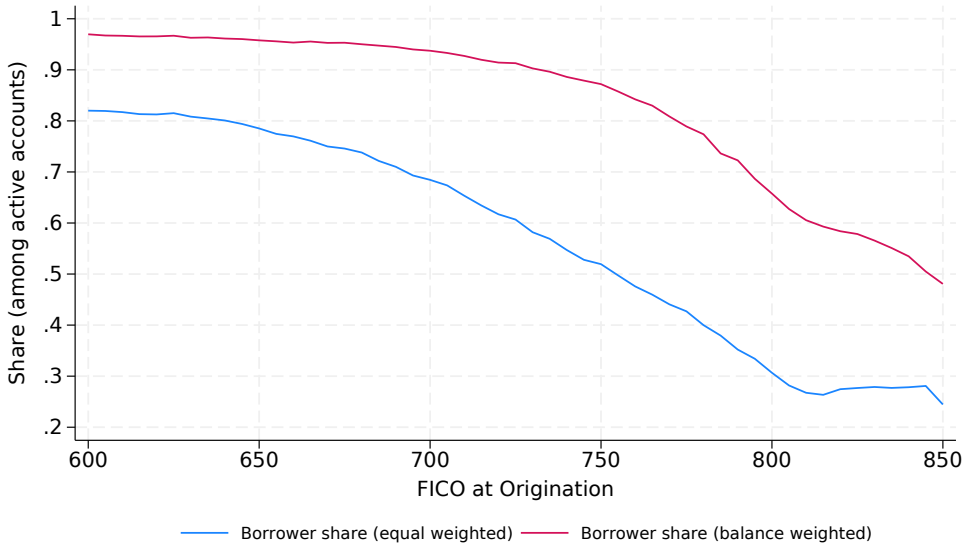


Figure 2: Borrower Share and ADB by Origination FICO

Panel (a) plots the proportion of observations and total balances attributed to borrowers in our sample. A borrower is defined as an account that either revolves a balance (does not repay full balance within the grace period) or is charged off in a given month. The equal-weighted borrower share represents the share of monthly active account-level observations that are classified as a borrower, within each 5-point FICO score bin at origination. The balance-weighted borrower share plots the share of the bank's total credit card balance (ADB) held by borrowing accounts, also within each FICO bin at origination. Panel (b) plots the average ADB for borrowers and active transactors. Active transactors are defined as accounts that do not revolve a balance (i.e., are not borrowers) but exhibit positive cycle ending balance, or purchase or payment activity within a given month.

(a) Borrower Share



(b) Borrower vs. Transactor ADB

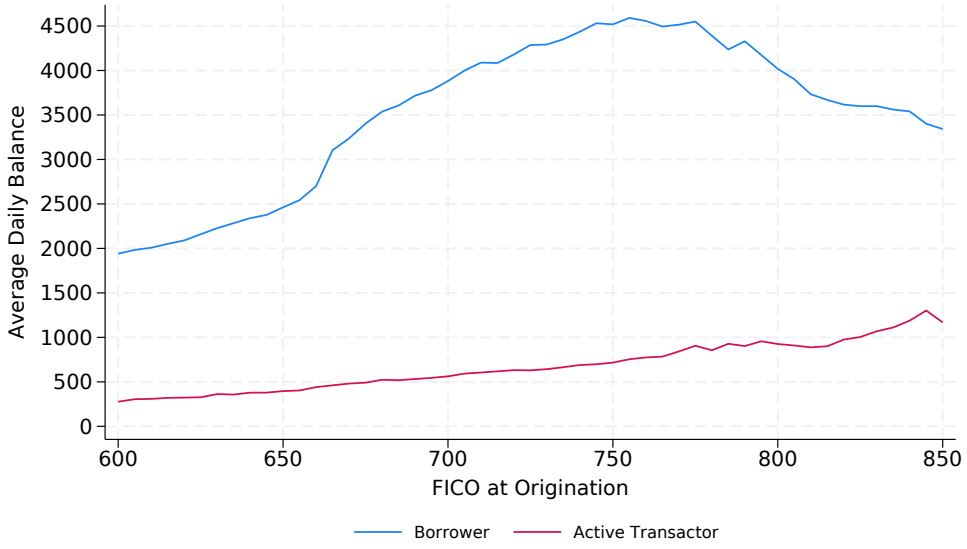


Figure 3: Effective Interest Rate Paid by Borrowers

This figure shows the 25th percentile, average, and 75th percentile of the effective interest rates paid by borrowing accounts within each FICO score bin at origination. The sample is restricted to observations where the account is classified as a borrower. The effective interest rate is calculated by dividing the reported finance charge by the borrower's ADB. All rates are annualized. Average is weighted by ADB of borrowers in a FICO bin.

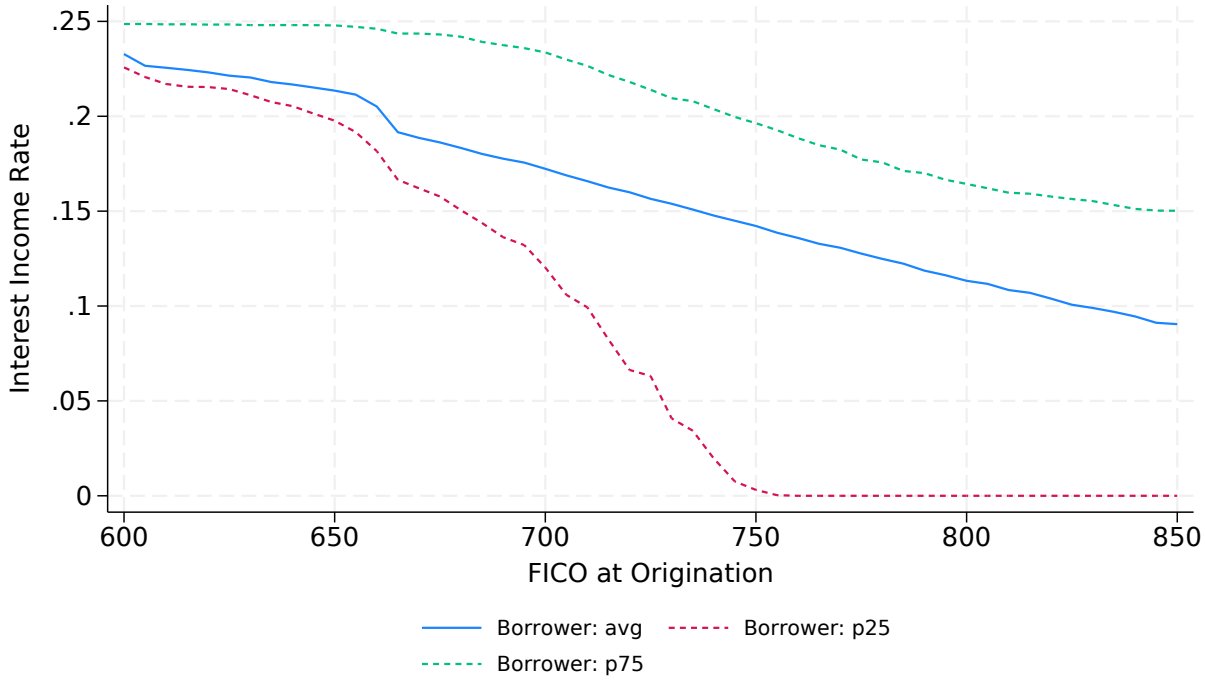


Figure 4: Interest Income and Charge-offs by Origination FICO

This figure plots interest income, interest expense and credit losses for borrowers by origination FICO bins. Within each FICO bin, we calculate portfolio's ADB, interest income, interest expense, and net credit losses by summing these variables up for all accounts in the FICO bin over their lifetime in the sample period. Interest income is the account's finance charge. Interest expense is calculated by multiplying the account's ADB by the federal funds rate for the corresponding month. Net credit loss is calculated by subtracting recoveries from charge-offs, where the reason for the charge-off is listed as default or bankruptcy. We compute the respective rates by dividing lifetime interest income, interest expense, and net credit loss by the lifetime ADB. The default-adjusted credit spread is then defined as the interest income rate minus the interest expense rate and net credit loss rate. All rates are annualized.

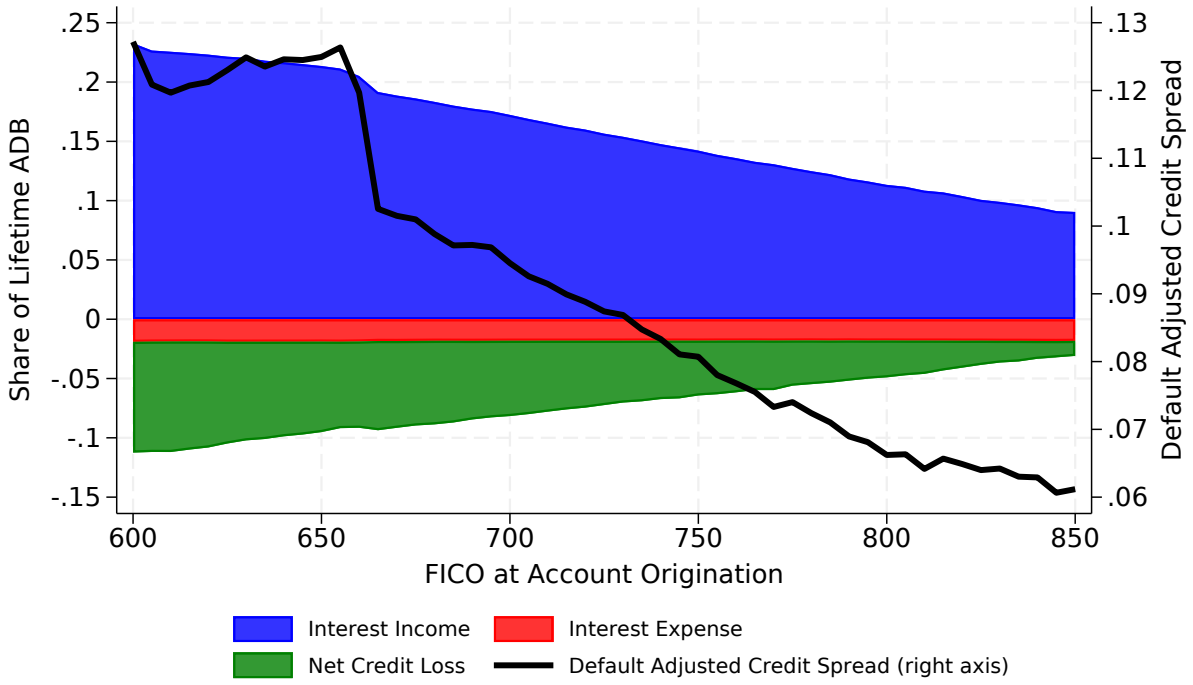


Figure 5: Purchase Volumes by Borrowers and Transactors

This figure plots the average purchase volumes (in dollars) for borrowers and active transactors within each origination FICO bin. Borrowers and active transactors are defined as in Figure 2.

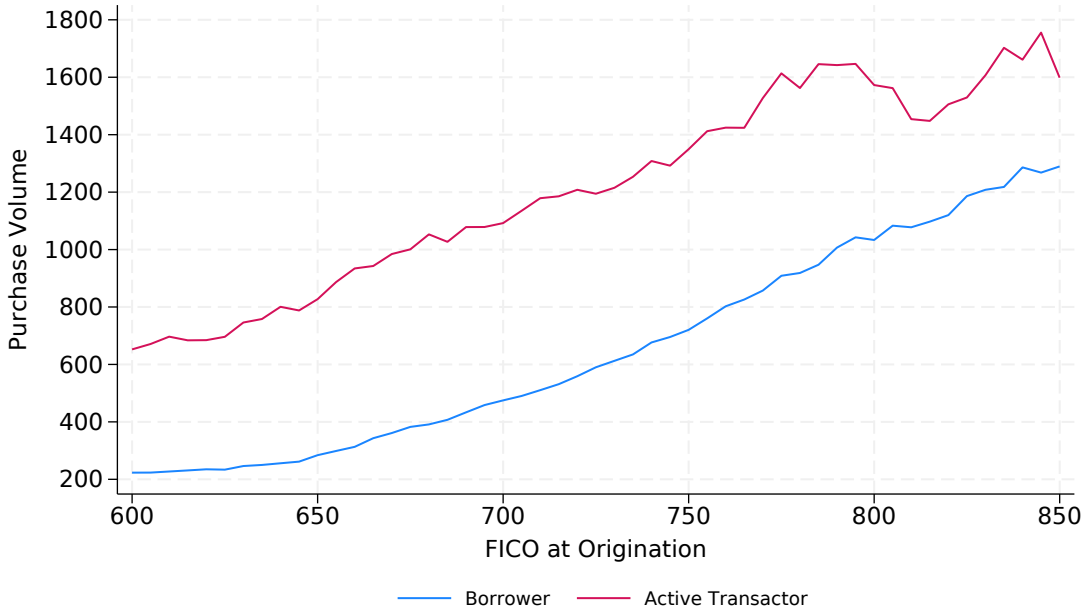
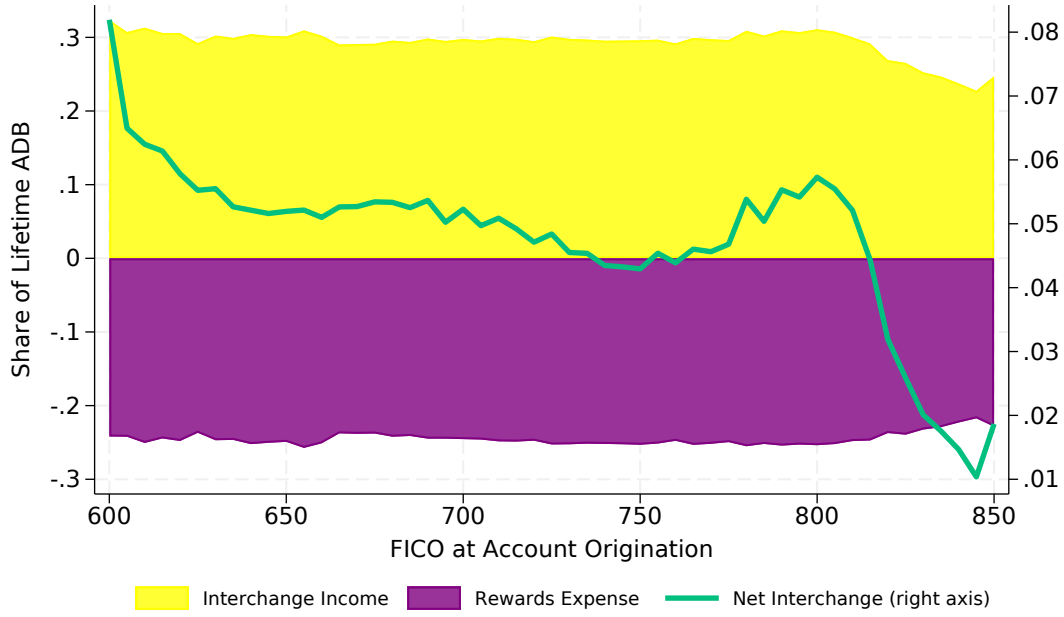


Figure 6: Interchange and Rewards by Origination FICO

This figure plots interchange income, rewards expenses and net interchange income (interchange − rewards) as a share of ADB. Interchange income and rewards are calculated by multiplying the interchange and rewards rates, derived from portfolio-level data, by each account's purchase volume. We compute interchange and rewards rate by dividing the cumulative monthly dollar amount for all accounts in a given FICO bin over their lifetime by their cumulative ADB. Panel (a) is for transactors while panel (b) is for borrowers in our sample. All values are annualized.

(a) Transactors



(b) Borrowers

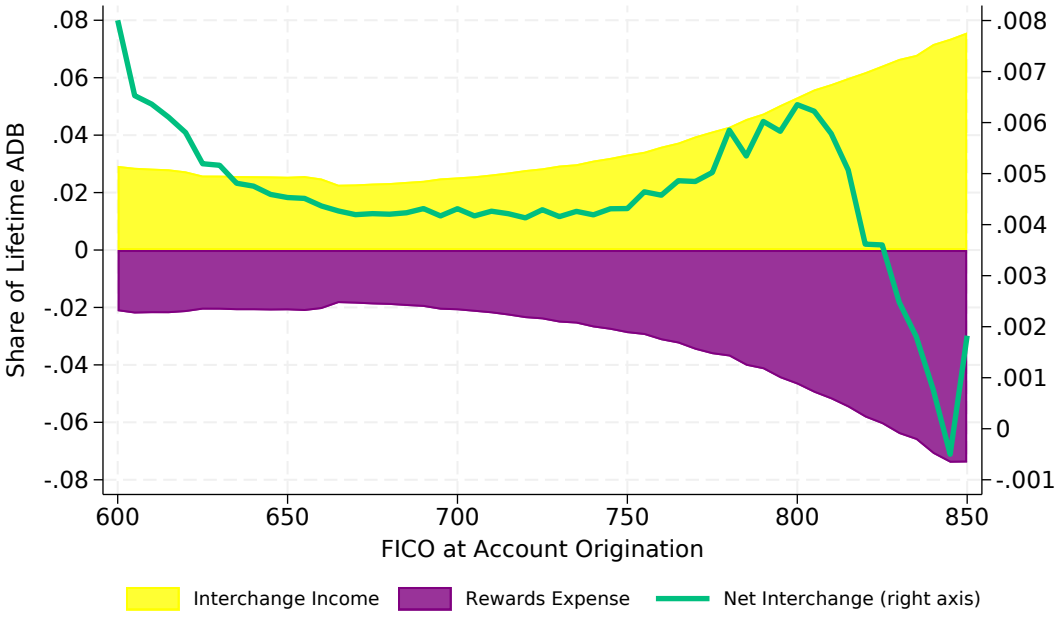
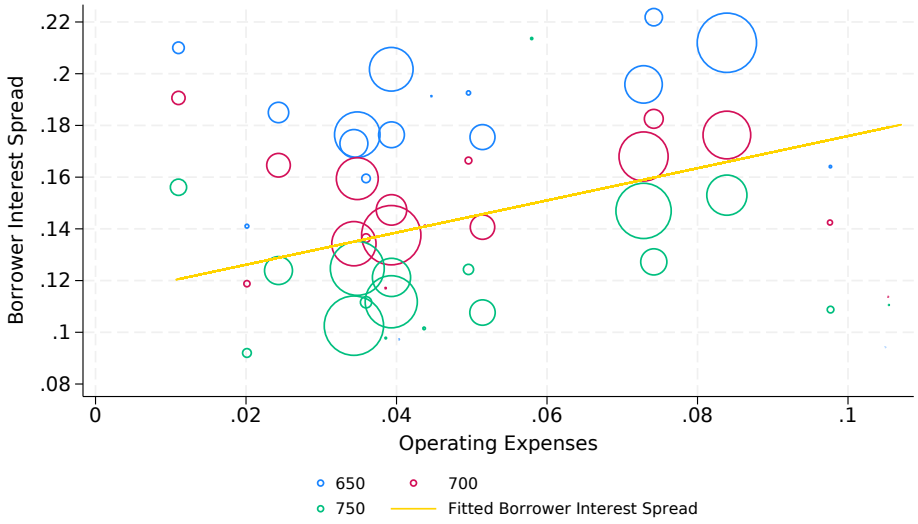


Figure 7: Operating Expense and Profit Component

Panel (a) presents a scatter plot of borrowers' interest spreads against operating expense rates for different banks, restricting to portfolios with origination FICO scores of 650, 700, and 750. Borrower interest spread is calculated as the total finance charges minus interest expenses across all borrower observations within a bank-origination FICO bin, divided by the total borrower ADB in that bin. The operating expense rate is measured at the bank-month level, then merged to the account level and averaged within each bank-origination FICO bin. The size of each bubble represents the relative total borrower ADB within its origination FICO bin. The yellow line is the fitted line from regressing borrower's average interest spread rate on the average operating expense rate with origination FICO fixed effect. The regression is weighted using borrower's ADB as analytic weights. Panel (b) follows the same structure as Panel (a) but replaces the y-axis variable with gross margin for all accounts within a bank-origination FICO bin. Gross margin is defined as the net interest spread plus net interchange and fee income, minus net charge-offs and other non-operating expenses such as fraud. All rates are annualized.

(a) Interest Spread



(b) Gross Margin

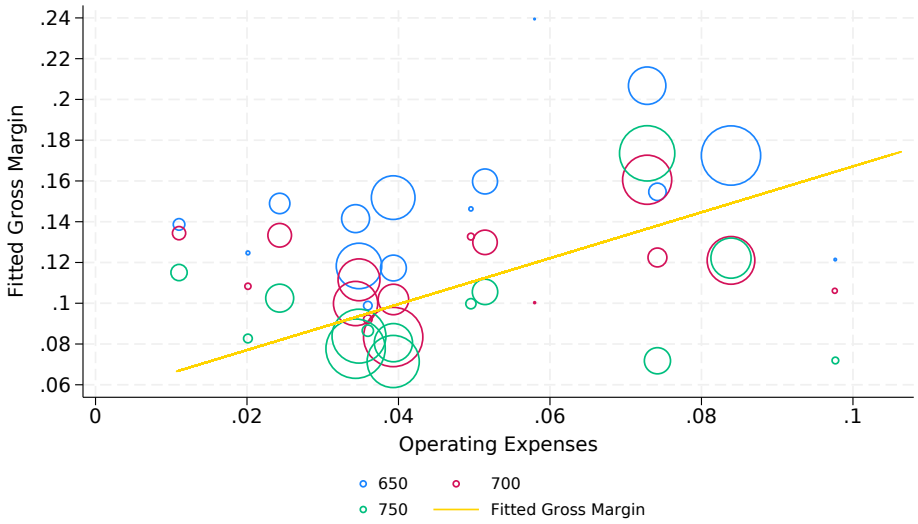


Figure 8: Return on Assets: Borrowers

This figure plots all income and expense components related to credit card banking for borrowers and the final ROA (right axis). Income is plotted as a positive quantity, while losses and expenses are negative. Interest income, interest expense and credit loss are as defined in Figure 4. Non-interest income includes interchange income as computed in **??** plus fee income. Non-interest expense includes rewards income in **??** plus operating expenses, interchange expenses and fraud. All lifetime average rate variables are constructed similarly as before: for each origination FICO bin, we divide the cumulative monthly dollar amount of the quantity of interest for all accounts in the FICO bin over their lifetime by their cumulative ADB. ROA is defined as interest spread minus net charge-offs, plus net interchange income (interchange minus rewards), plus the fee income rate, minus the operating expense rate and other non-operating expenses. All rates are annualized.

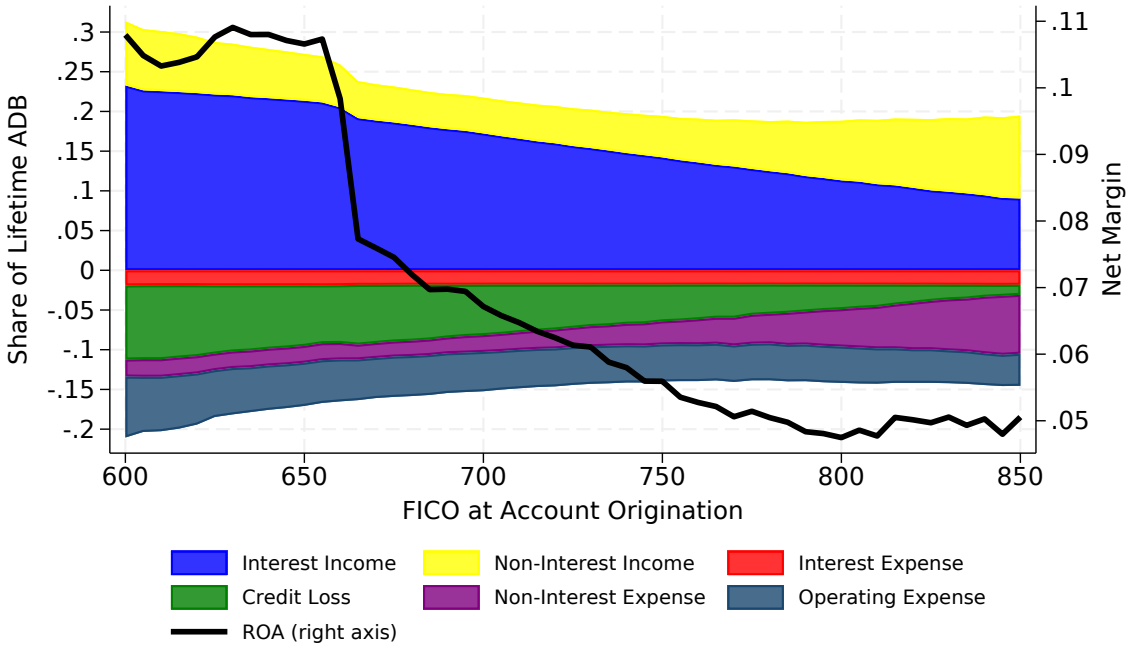
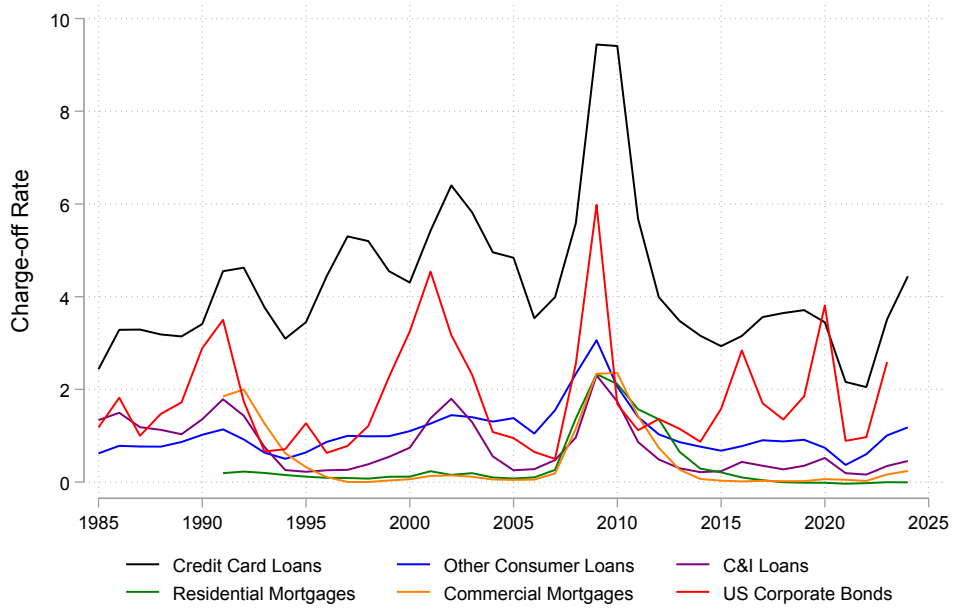


Figure 9: Default rates across various types of loans and corporate bonds

(a) Bank loans



(b) Credit cards and corporate bonds

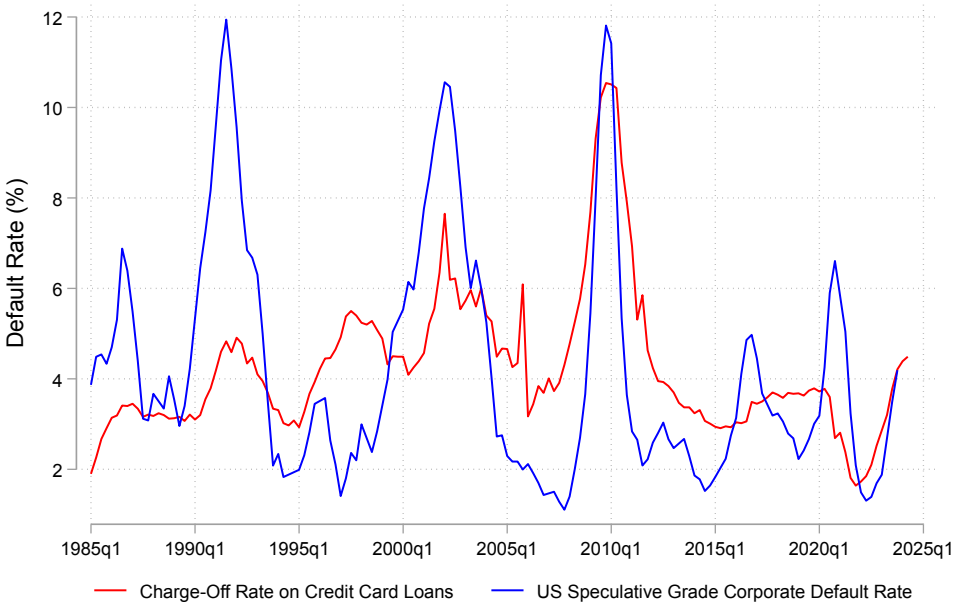
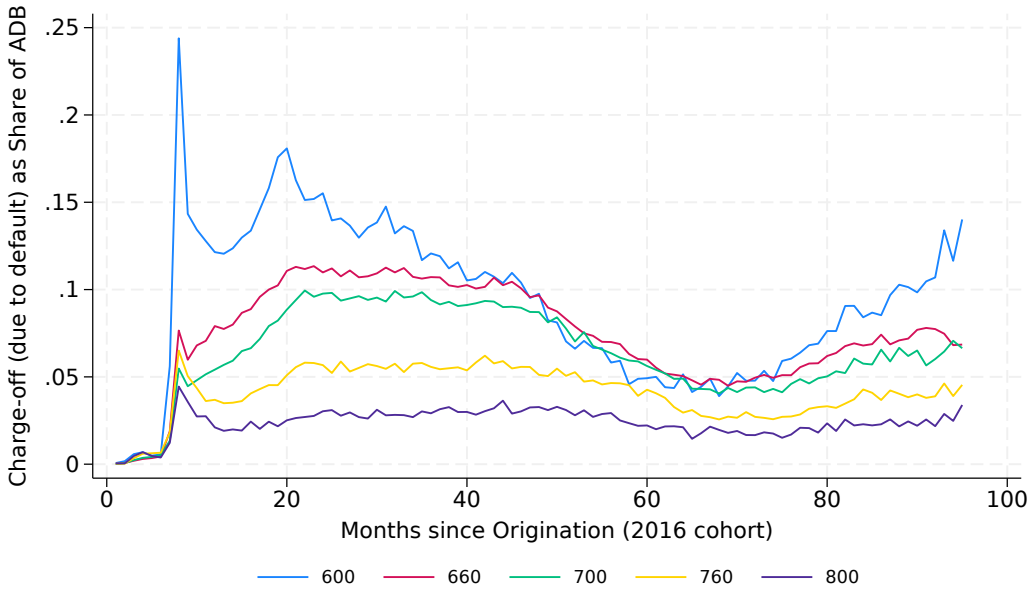


Figure 10: Credit card charge-offs across the original FICO distribution

(a) Life cycle



(b) Time series

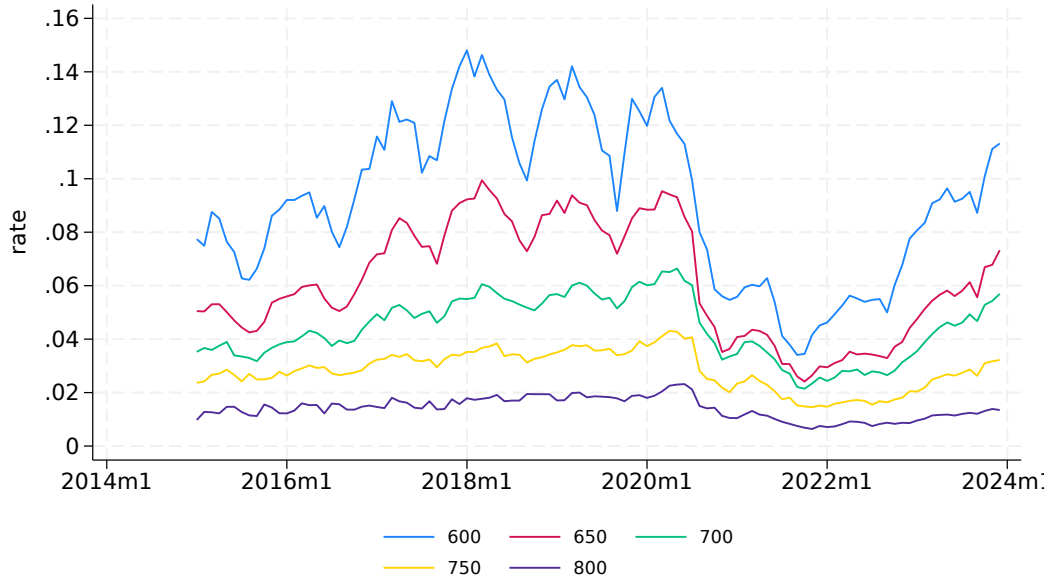


Figure 11: Risk exposure by FICO bin

This figure plots the estimates of the risk exposure for each origination FICO bin (right axis) and their actual charge-off rate (left axis). For each FICO bin, we estimate its beta to systematic default risk by regressing the change in its monthly charge-off rate on the change in the charge-off rate of the aggregate credit card portfolio using the following 1. Charge-off rate is defined the same as in Figure 4.

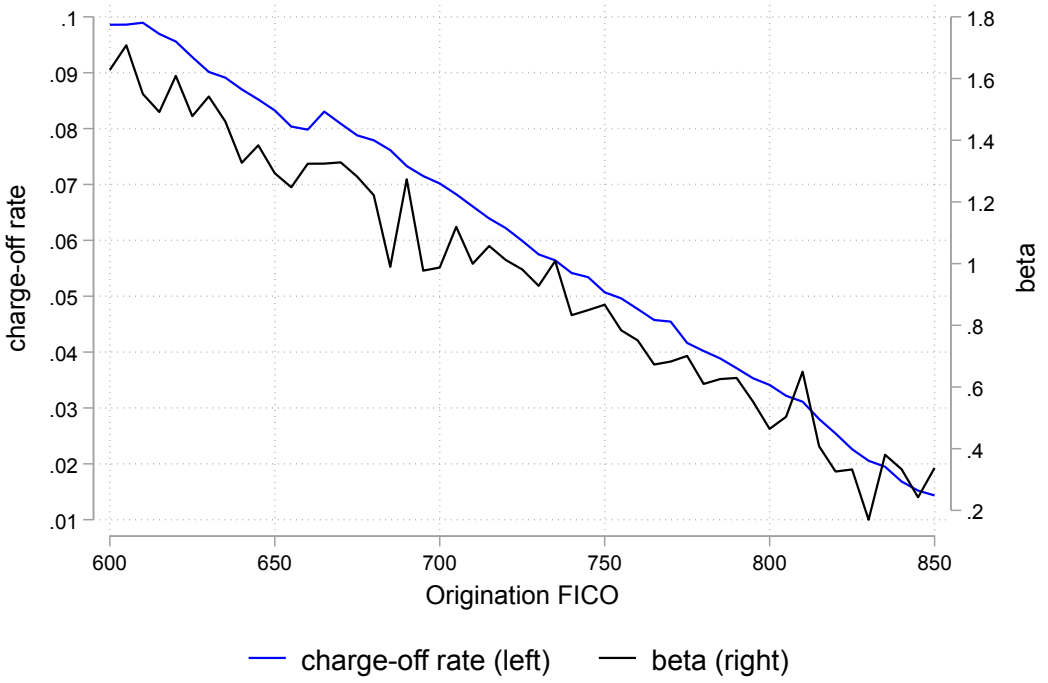


Figure 12: Credit card risk premium by FICO bin

This figure presents actual borrower ROA, estimated risk premium, fitted ROA from risk premium estimation. Borrower's ROA is the same as in Figure 8. We regress the ROA of borrower FICO portfolio i on its risk exposure, β_i, using specification 2. Fitted ROA is defined as the predicted value of ROA using the estimates from Equation 2 ($\hat{\lambda} + \hat{\gamma}\hat{\beta}_i$). Risk premium corresponds to $\hat{\gamma}\hat{\beta}_i$. Transactor margin is the average transactor ROA across all transactors (Figure B6); we compare them with borrower portfolio of 850 FICO since transactors entails zero credit risk.

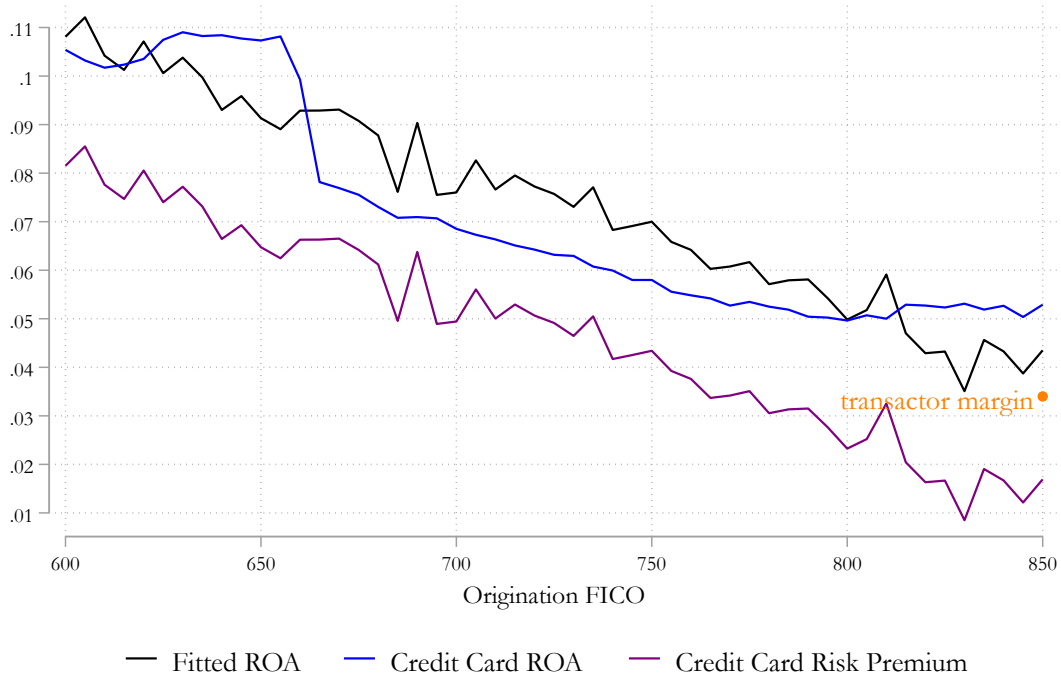


Figure 13: Credit card and corporate bond risk premia

This figure compares credit card borrowers' realized ROA and our estimated risk premium with default adjusted spread of corporate bonds of different initial credit ratings. Credit card ROA and risk premium are the same as in Figure 12. The bond default-adjusted spread is calculated by estimating the internal rate of return (IRR) for a buy-and-hold strategy on bonds with the same initial rating across all corporate issuances from 1990 to 2023. Corporate bond ratings are then mapped to FICO scores based on the five-year probability of default, using data from S&P and our estimates from Y-14.

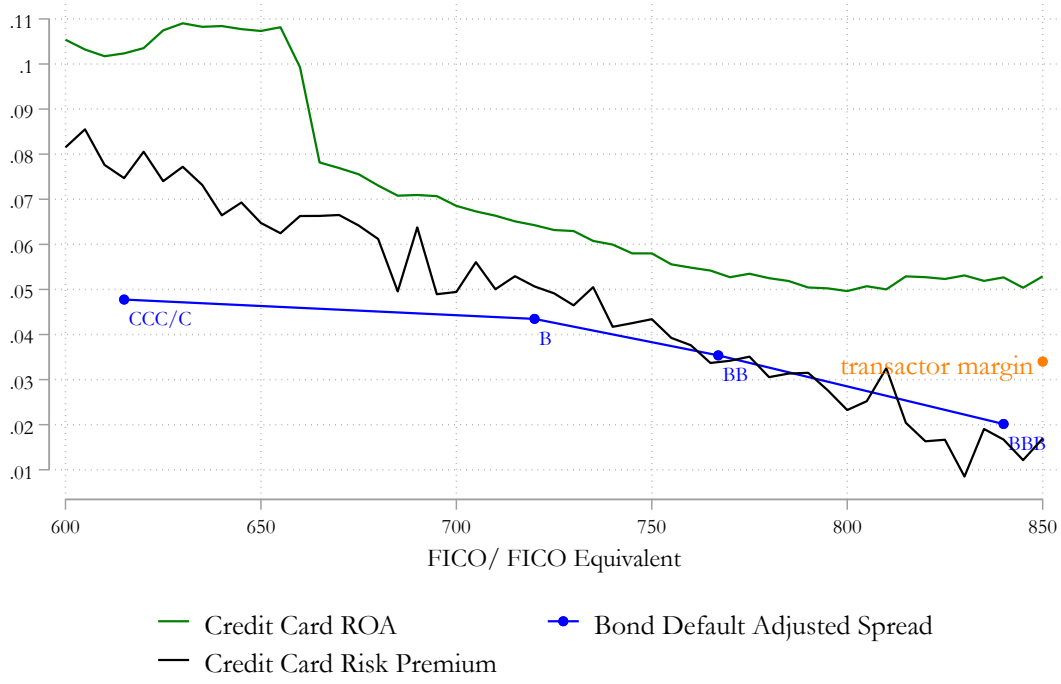
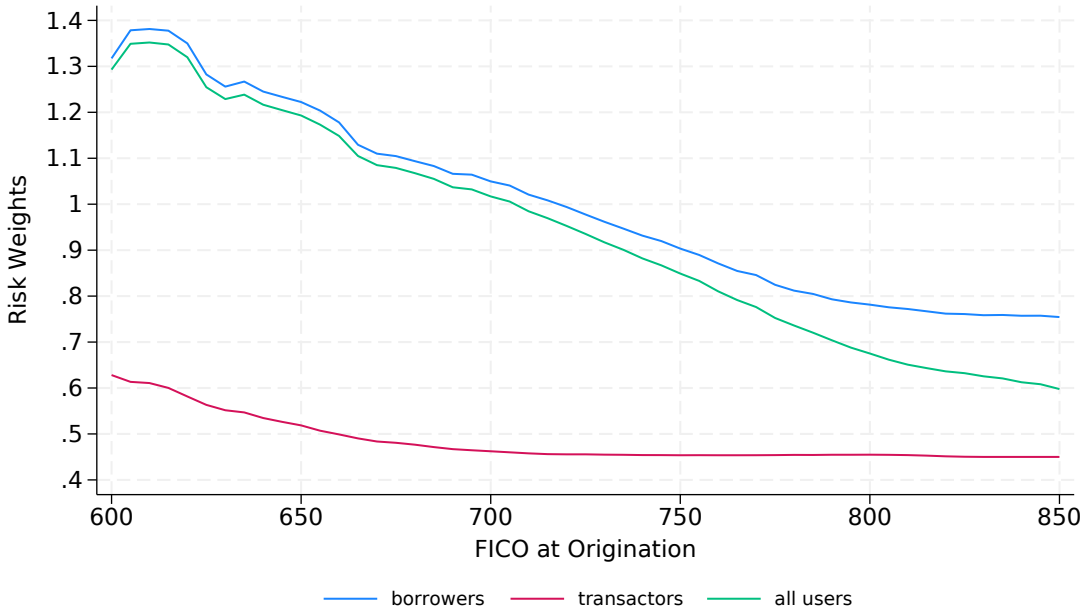


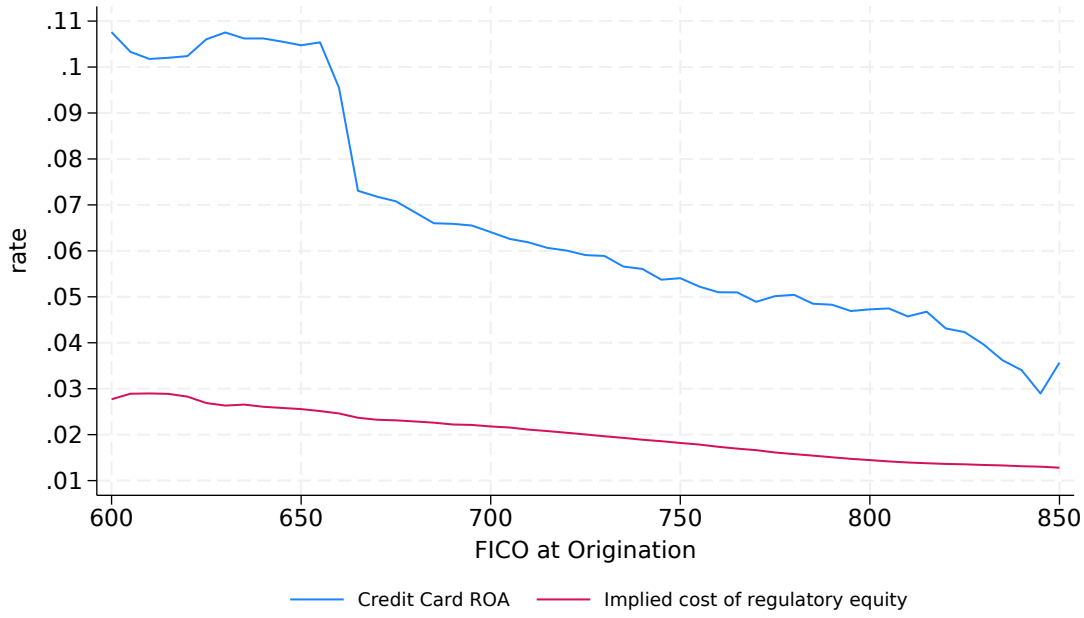
Figure 14: ROA after considering Capital Requirements

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).

(a) Risk Weights by FICO



(b) ROA



Tables

Table 1
Summary Statistics

Panel A presents summary statistics for income and expense components at the bank-month level, based on Y-14 portfolio-level data. The analysis is restricted to general-purpose consumer credit card portfolios. All variables are scaled by each bank's month-end balances and annualized. Panel B provides summary statistics for key balance, fee, and rate variables at the account level, focusing on accounts originated in January 2015 within our cleaned sample. All variables, except rate variables, are reported in dollar amounts. The definitions of borrowers and active transactors are provided in Section 3.

Panel A: Portfolio Level

	mean	s.d.		mean	s.d.
Interest			**Loss**		
Interest Income	0.142	0.125	Charge-off	0.05	0.023
Interest Expense	0.024	0.022	Recovery	0.005	0.004
Non-Interest Income			**Non-Interest Expense**		
Fee Income	0.017	0.015	Reward	0.048	0.03
Interchange	0.071	0.056	Collection	0.02	0.01
Other	0.004	0.008	Fraud	0.003	0.002
			Other Operating	0.049	0.078

Panel B: Account Level

	N (millions)	p25	p50	p75	mean
Borrowers					
ADB	49.63	805.59	2058.78	4382.68	3340.33
Purchase Volume	49.63	0.00	50.72	392.82	507.28
Finance Charge	49.63	4.03	24.49	62.32	45.43
Effective Interest Rate (%)	49.63	12.36	20.10	23.60	16.63
APR (%)	49.63	14.99	20.24	23.49	17.47
Late Fee	5.88	25.00	35.00	37.00	28.39
Annual Fee	0.97	39.00	49.01	95.00	67.10
Balance Transfer Fee	0.31	139.30	46.02	97.25	180.00
Total Non-interest Charge	8.24	25.00	35.00	39.00	37.25
Charge-off (due to default)	0.23	942.96	2392.02	4845.04	3722.04
Charge-off (all reasons)	0.23	941.99	2391.02	4843.18	3721.34
Recovery	0.05	187.72	612.29	1750.00	1424.25
Credit Limit	49.63	2300.00	5000.00	10000.00	7353.82
Active Transactors					
ADB	34.55	4.86	154.73	726.97	750.32
Purchase Volume	34.55	58.00	411.16	1437.76	1312.33
APR (%)	34.55	14.24	16.99	20.99	16.35
Annual Fee	0.84	39.00	75.00	95.00	80.29
Total Non-interest Charge	1.55	2.91	39.00	94.68	49.32
Credit Limit	34.55	4600.00	9000.00	15000.00	10895.47

Table 2
Profit Components by Origination FICO

This table presents the breakdown of profit components by origination FICO bins, grouped in 20-point increments, separately for borrowers, transactors, and all users. ADB share represents the proportion of lifetime ADB contributed by accounts within a given FICO bin relative to the total ADB for each user group. All average rate variables are constructed using the same methodology as in Figure 8: for each origination FICO bin, we compute the cumulative monthly dollar amount of the variable of interest across all accounts in that bin over their lifetime, then divide by their cumulative ADB. Variable definitions are provided in Section 4, and all rates are annualized.

Origination FICO	ADB Share (%)	Interest Spread (%)	Net Charge-off (%)	Interchange (%)	Reward (%)	Fee (%)	Operating Expense (%)	ROA (%)
Panel A: Borrowers								
600	0.79	21.02	9.32	2.89	2.18	4.97	7.25	10.61
620	2.72	20.44	8.92	2.72	2.15	4.36	6.40	10.53
640	5.36	19.84	8.06	2.57	2.09	3.68	5.63	10.80
660	8.93	18.45	7.43	2.44	2.00	2.87	5.28	9.41
680	14.45	16.62	7.09	2.33	1.90	2.17	5.05	7.30
700	14.69	15.55	6.41	2.50	2.07	1.99	4.94	6.81
720	13.55	14.32	5.72	2.74	2.31	1.92	4.80	6.30
740	11.72	13.14	5.04	3.06	2.63	1.89	4.70	5.86
760	9.48	11.96	4.43	3.51	3.05	1.91	4.64	5.37
780	7.20	10.86	3.82	4.22	3.69	2.01	4.61	5.06
800	5.34	9.72	3.17	5.15	4.54	2.16	4.59	4.81
820	3.45	8.74	2.45	6.06	5.59	2.44	4.33	4.94
840	1.91	7.77	1.65	6.94	6.81	2.68	4.06	4.97
850	0.39	7.22	1.27	7.58	7.40	2.86	4.04	5.05
Average (ADB-weighted)		14.51	5.73	3.17	2.72	2.29	4.92	6.80
Panel B: Transactors								
600	0.15	-	-	31.38	24.21	12.83	6.55	11.49
620	0.52	-	-	30.24	24.39	10.29	5.68	8.16
640	1.38	-	-	30.21	24.93	8.55	4.95	6.33
660	2.30	-	-	29.96	24.76	6.62	4.69	4.44
680	4.69	-	-	29.30	24.00	5.16	4.60	3.05
700	5.78	-	-	29.67	24.53	4.89	4.49	3.04
720	7.27	-	-	29.83	24.95	5.15	4.38	3.38
740	8.93	-	-	29.65	25.21	5.29	4.25	3.35
760	11.14	-	-	29.60	25.14	5.24	4.30	3.36
780	12.53	-	-	30.13	25.12	4.84	4.46	3.33
800	17.73	-	-	30.88	25.32	4.33	4.63	3.35
820	14.19	-	-	28.30	24.34	4.16	4.16	2.36
840	10.88	-	-	24.21	22.61	4.70	3.74	0.61
850	2.51	-	-	24.72	22.86	4.68	3.70	0.90
Average (ADB-weighted)		-	-	29.04	24.62	4.94	4.34	2.92
Panel C: All Users								
600	0.71	20.20	8.99	4.67	3.56	5.24	7.23	10.83
620	2.46	19.59	8.59	4.52	3.61	4.5	6.37	10.58
640	4.86	18.96	7.74	4.41	3.63	3.8	5.60	10.75
660	8.11	17.58	7.13	4.30	3.56	3.02	5.26	9.32
680	13.15	15.79	6.79	4.16	3.44	2.30	5.03	7.22
700	13.54	14.55	6.05	4.80	4.01	2.15	4.92	6.70
720	12.74	13.09	5.30	5.70	4.85	2.16	4.77	6.19
740	11.36	11.60	4.53	6.95	6.03	2.24	4.66	5.70
760	9.60	10.00	3.81	8.67	7.56	2.38	4.58	5.19
780	7.92	8.19	3.03	11.55	10.00	2.59	4.58	4.82
800	6.76	6.08	2.18	15.61	13.31	2.83	4.26	3.95
820	5.00	4.48	1.47	17.89	15.98	3.25	3.91	2.77
840	3.07	3.32	0.89	18.32	17.70	3.61	3.86	2.73
850	0.71	2.48	0.61	20.03	19.13	3.80	3.86	2.73
Average (ADB-weighted)		12.37	4.99	7.82	6.77	2.63	4.85	6.39

Table 3
Relationship between Operating Expenses and Profit Components

This table presents regressions of interest spread, net charge-off rate, and gross margin on the operating expense rate. Obversations are aggregated at the bank-origination FICO bin level from account-level data. Interest spread is defined as the sum of finance charge less interest expense across all borrower observations in a bank-origination FICO bin, then divided the total borrower ADB in that bin. Similarly, the net charge-off rate is calculated as total charge-offs minus recoveries divided by the bin's total ADB, and gross margin is computed as total gross profit over total ADB. The operating expense rate is measured at the bank-month level. We merge this to account level and average within each bank-origination FICO bin. Regressions are weighted by bin level total ADB.

	Interest Spread	Net Charge-off	Gross Margin
Operating Expense	0.622***	0.139	1.127**
	[0.119]	[0.149]	[0.528]
Constant	0.114***	0.043***	0.055**
	[0.008]	[0.007]	[0.020]
Origination FICO FE	Y	Y	Y
Observations	919	908	908
R^2	0.895	0.734	0.489
R^2 adjusted	0.888	0.718	0.453

Standard errors in brackets and are clustered at bank level; *** p<0.01, ** p<0.05, * p<0.1

Table 4
Risk Premium Estimates by Origination FICO

This table presents estimates of the risk exposure for each FICO score bin portfolio using the two-stage approach of Fama and MacBeth (1973). We first estimate a single-factor model of default risk using the cross-section of credit card portfolios. We use the monthly change in the aggregate credit card portfolio's charge-off rate as a proxy for the systematic component of default risk. For each FICO portfolio i, we estimate its beta to systematic default risk by regressing the change in its monthly charge-off rate on the change in the charge-off rate of the aggregate credit card portfolio using the following 1. Second, we use the FICO-specific risk exposures, *beta*, from the first stage to estimate the compensation for default-risk exposure and the corresponding risk premium. To this end, we regress the ROA of FICO portfolio i on its risk exposure, β_i, using specification 2. Fitted ROA is defined as the predicted value of ROA using the estimates from Equation 2 ($\hat{\lambda} + \hat{\gamma}\hat{\beta}_i$). Risk premium corresponds to $\hat{\gamma}\hat{\beta}_i$. We define risk-adjusted ROA as the difference between ROA and the risk premium. Adjusted standard errors are in parenthesis.

Parameter Estimates	$\hat{\lambda}$ 0.0266 (0.0042)	$\hat{\gamma}$ 0.0501 (0.0029)			
Origination FICO	$\hat{\beta}$	ROA	Fitted ROA	Risk Premium	Risk-adj. ROA
600	1.628	10.61%	10.81%	8.15%	2.46%
	(0.235)		(0.73%)	(0.48%)	(0.48%)
620	1.609	10.53%	10.71%	8.05%	2.47%
	(0.172)		(0.73%)	(0.47%)	(0.47%)
640	1.327	10.80%	9.30%	6.64%	4.15%
	(0.109)		(0.66%)	(0.39%)	(0.39%)
660	1.324	9.41%	9.29%	6.63%	2.79%
	(0.079)		(0.66%)	(0.39%)	(0.39%)
680	1.222	7.30%	8.78%	6.12%	1.18%
	(0.077)		(0.64%)	(0.36%)	(0.36%)
700	0.987	6.81%	7.60%	4.94%	1.86%
	(0.065)		(0.58%)	(0.29%)	(0.29%)
720	1.012	6.30%	7.73%	5.07%	1.24%
	(0.079)		(0.59%)	(0.30%)	(0.30%)
740	0.833	5.86%	6.83%	4.17%	1.68%
	(0.112)		(0.55%)	(0.24%)	(0.24%)
760	0.751	5.37%	6.42%	3.76%	1.61%
	(0.121)		(0.54%)	(0.22%)	(0.22%)
780	0.610	5.06%	5.71%	3.06%	2.01%
	(0.116)		(0.51%)	(0.18%)	(0.18%)
800	0.464	4.81%	4.98%	2.32%	2.49%
	(0.144)		(0.48%)	(0.14%)	(0.14%)
820	0.326	4.94%	4.29%	1.63%	3.31%
	(0.122)		(0.46%)	(0.10%)	(0.10%)
840	0.333	4.97%	4.33%	1.67%	3.30%
	(0.154)		(0.46%)	(0.10%)	(0.10%)
850	0.338	5.05%	4.35%	1.69%	3.36%
	(0.152)		(0.46%)	(0.10%)	(0.10%)

Appendix

A Variable Definition

A.1 Interchange Rate and Rewards Rate

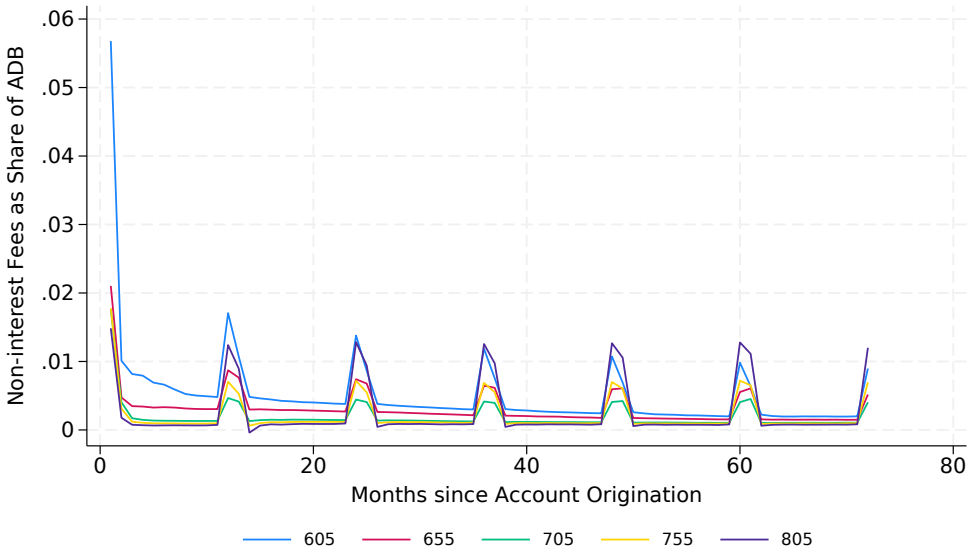
Interchange fees and rewards expenses are both dollar amounts in portfolio-level data, and portfolio-level data only has total balances of credit cards but not purchase volumes. To estimate their rates as a percentage of purchase volume, we did the following steps. First, we compute the total amount 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.

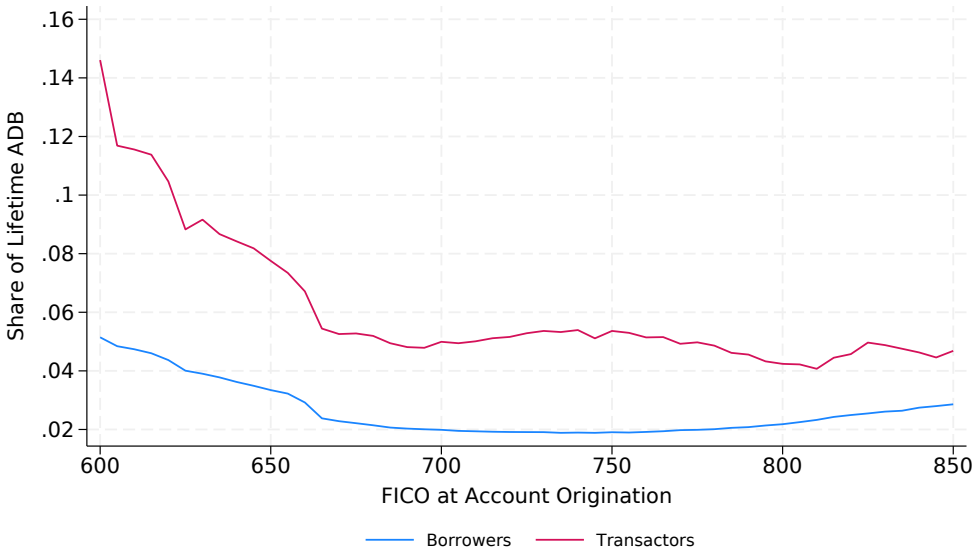
B Figures

Figure B1: Fee Income

(a) Fee Income over Account's Lifetime



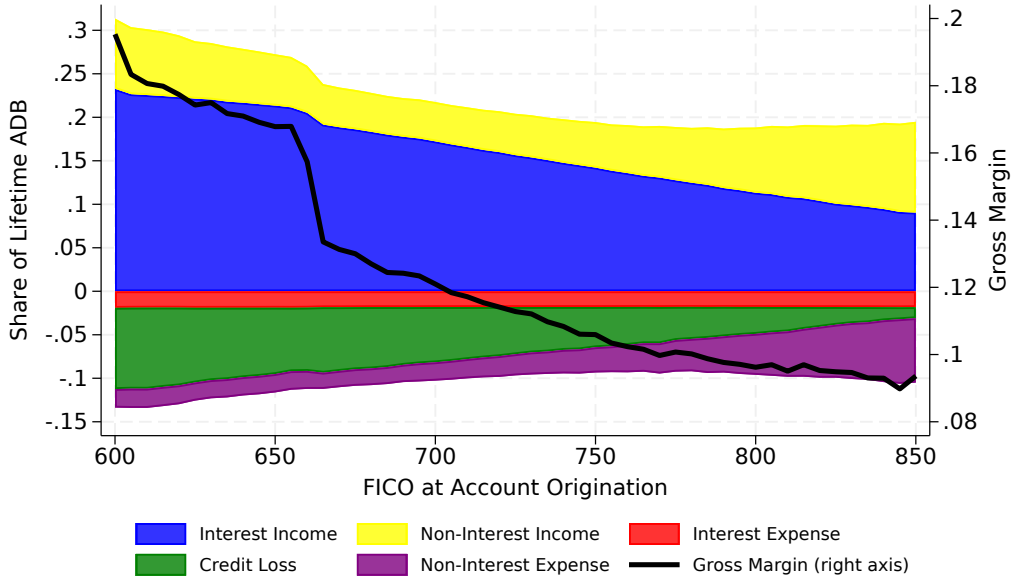
(b) Fee Income by Origination FICO



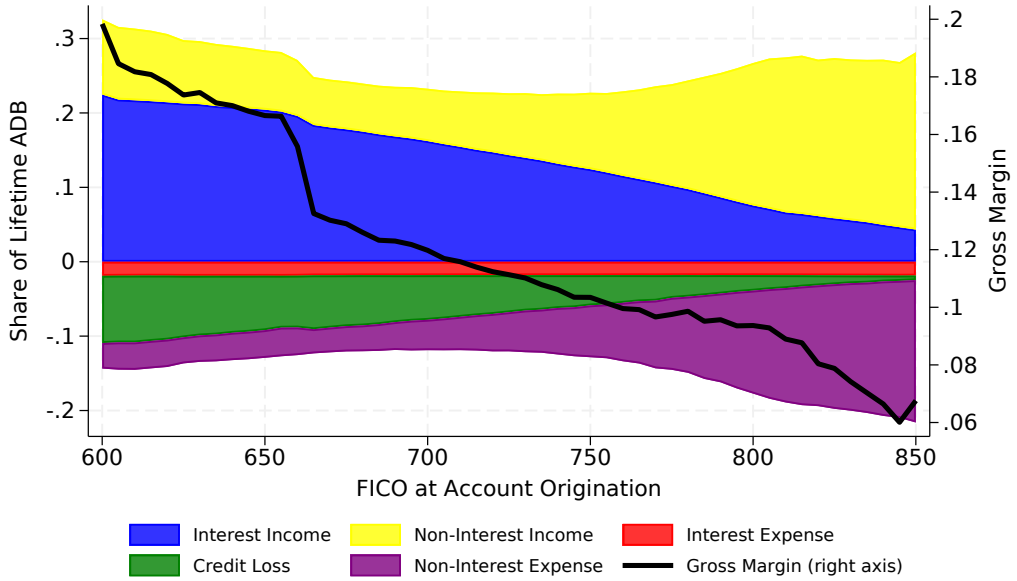
Panel (a) plots the non-interest fee as a percentage of ADB across account age. Each line corresponds to a group of accounts categorized by origination FICO score bins: 605, 655, 705, 755, and 805. Panel (b) plots the non-interest fees as a share of lifetime ADB across origination FICO score bins for borrowers and transactors respectively. All values are annualized.

Figure B2: Gross Margin

(a) Borrower



(b) All Users



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 B3: Operating Expense Example: Capital One

(a) Bank Level Non-Interest Expense

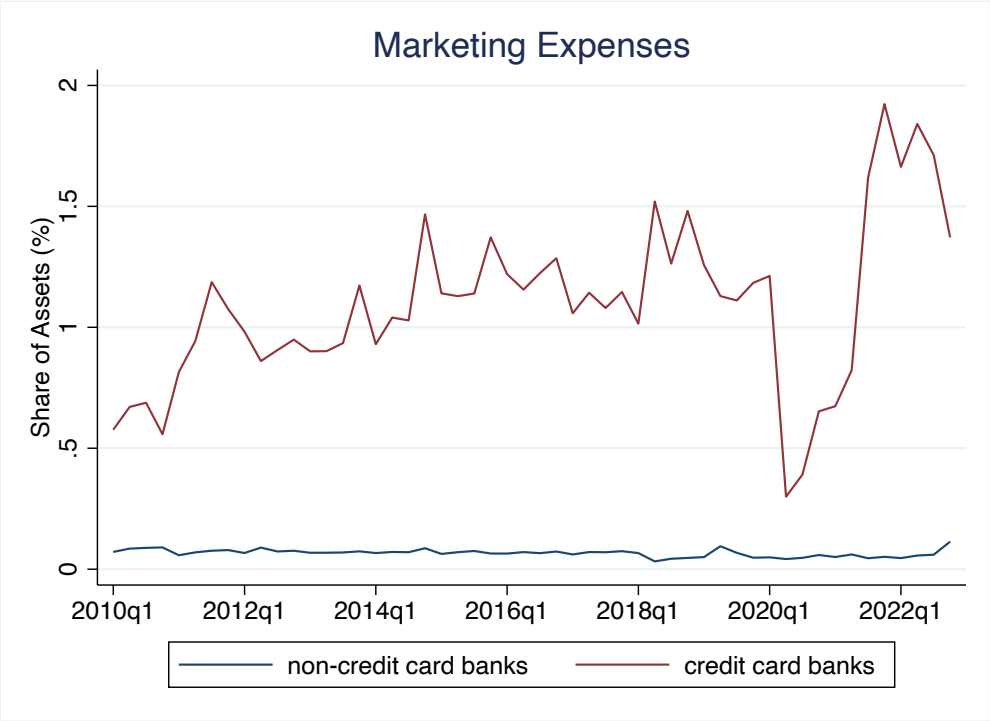
(Dollars in millions)	Year 2023
Operating Expense:	
Salaries and associate benefits[1]	$ 9,302
Occupancy and equipment	2,160
Professional services	1,268
Communications and data processing	1,383
Amortization of intangibles	82
Other non-interest expense:	
Bankcard, regulatory and other fee assessments	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

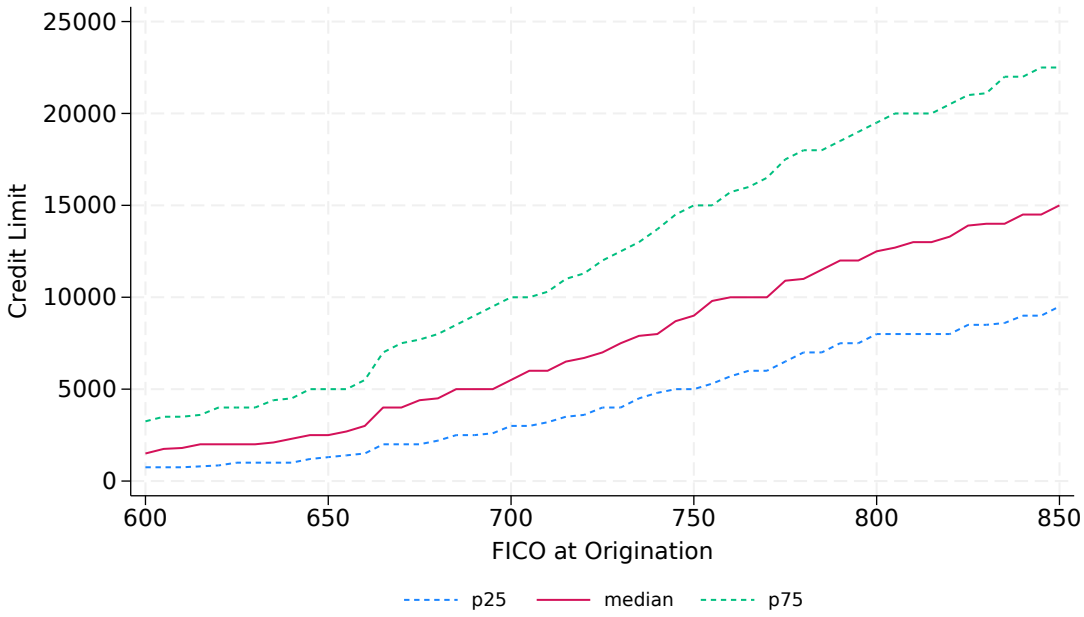
Panel (a) is a screenshot from Capital One's 2023 Annual Report Table 4. It displays the components of bank's non-interest expense for 2023. Panel (b) is a screenshot of Table 8 from Capital One's 2023 annual report. It summarizes the financial results of Capital One's credit card business and displays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

Figure B4: Credit Card Banks: Marketing Expenses



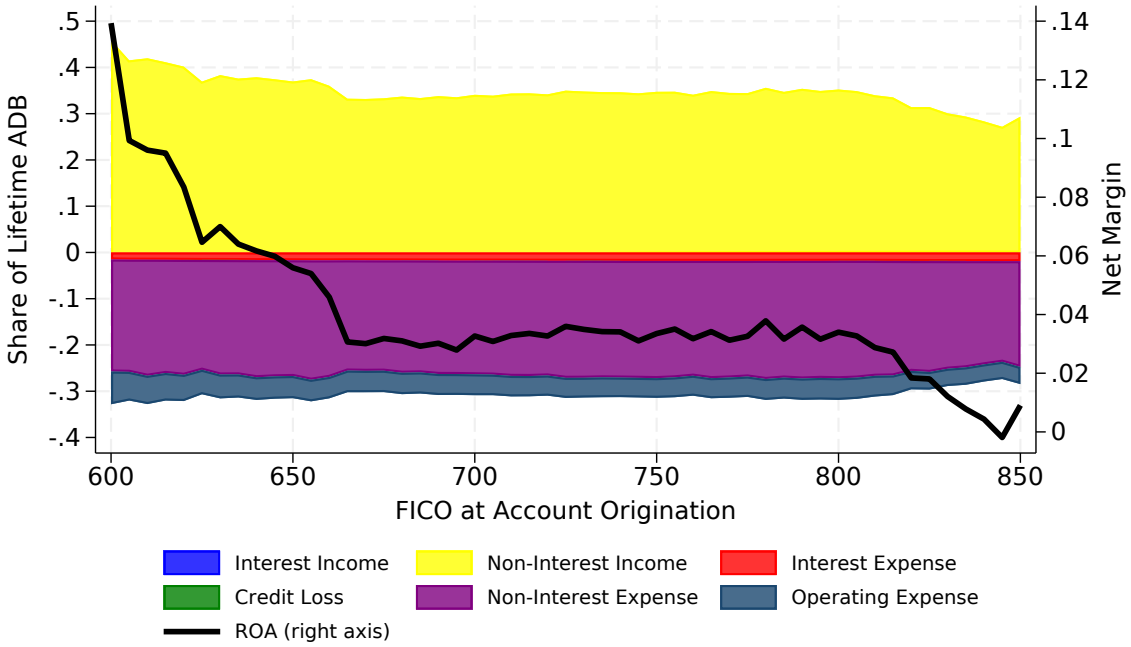
This figure shows marketing expenses as a percentage of total bank assets for credit card banks versus non-credit card banks. Marketing expenses data are from Call Reports. Credit card banks are defined as those with personal loans exceeding 50% of total assets, with over 90% of these personal loans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

Figure B5: Distribution of Credit Limit



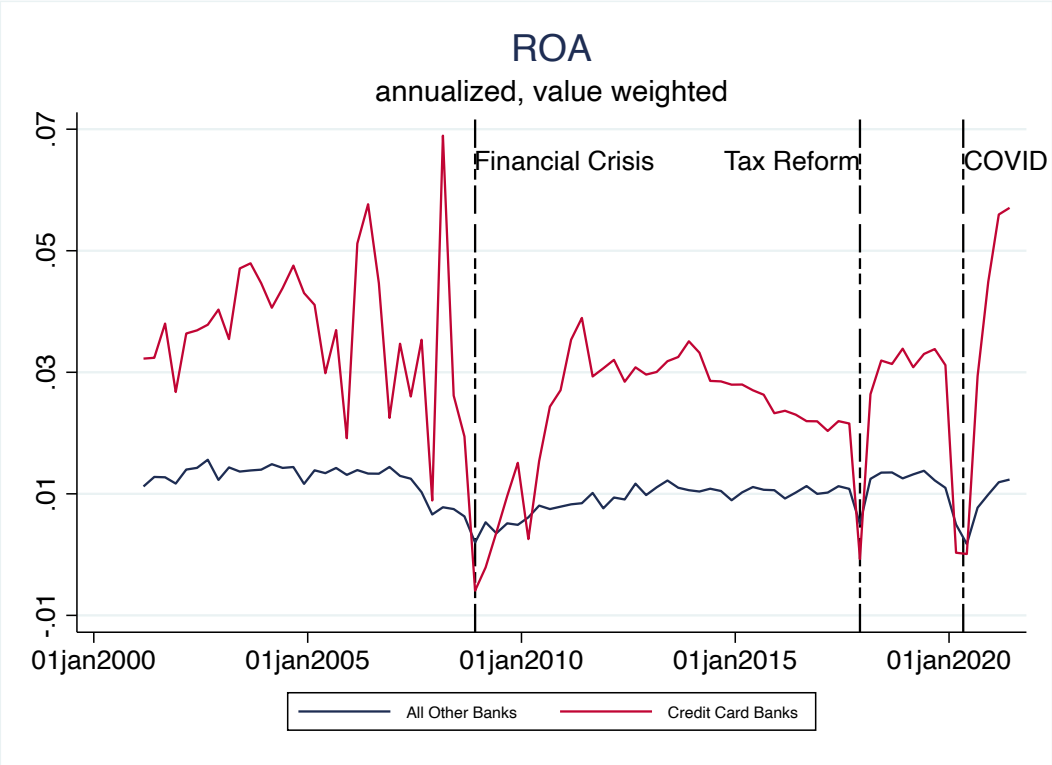
This figure plots the 25th percentile, median, and 75th percentile of credit limit across accounts within each origination FICO bin.

Figure B6: 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 B7: 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 C1
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 × Cohort (year-month at origination) × 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, FICO^2				
Cohort FE	Y	Y	Y	Y	Y		
Origination FICO FE				Y	Y		
Bank FE					Y	Y	
Origination FICO × Cohort 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 C2
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 × Cohort (year-month at origination) × 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, FICO^2				
Cohort FE	Y	Y	Y	Y	Y		
Origination FICO FE				Y	Y		
Bank FE					Y	Y	
Origination FICO × Cohort 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 C3
Distribution of Accounts by Origination FICO

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

Origination FICO	Number of Accounts (million)	Number of Banks	Account Share	ADB Share
550-570	0.2	20	.007	.004
570-590	3.6	19	.011	.007
590-610	57.2	19	.0178	.012
610-630	104.7	19	.0325	.024
630-650	182.9	20	.0568	.048
650-670	255.6	20	.0791	.080
670-690	328.8	20	.102	.129
690-710	331.9	20	.103	.133
710-730	323.1	20	.100	.125
730-750	308.4	20	.096	.112
750-770	283.1	20	.088	.094
770-790	266.2	20	.083	.078
790-810	282.8	20	.088	.066
810-830	254.8	20	.079	.049
830-850	185.0	20	.057	.037