WORKING PAPER · NO. 2025-44

Credit Card Entrepreneurs

Ufuk Akcigit, Raman S. Chhina, Seyit Cilasun, Javier Miranda, and Nicolas Serrano-Velarde

MARCH 2025

THE UNIVERSITY OF CHICAGO
BECKER FRIEDMAN INSTITUTE FOR ECONOMICS

5757 S. University Ave.
Chicago, IL 60637
Main: 773.702.5599
bfi.uchicago.edu

Credit Card Entrepreneurs

Ufuk Akcigit Raman S. Chhina Seyit Cilasun

Javier Miranda Nicolas Serrano-Velarde*

March 15, 2025

Abstract

Beginning in January 2021, over less than two years, credit card usage by small U.S. businesses nearly doubled, interest payments rose by 60%, and delinquencies reached 2.8%. In this paper, we utilize near real-time QuickBooks data from over 1.6 million small businesses and a targeted survey to highlight the critical role that credit card financing plays in small business activity. We find, first, monthly credit card payments were up to three times higher than loan payments during this time. Second, we use targeted surveys of these small businesses to establish credit cards as a key financing source in response to firm-level shocks, such as uncertain cash flows and overdue invoices. Third, we highlight the critical role of credit cards as a key financial transmission mechanism. Following the Federal Reserve's rate hikes in early 2022, banks cut credit card supply, leading to a 15.75% drop in balances and a 10% decline in revenue growth, as well as a 1.5% decrease in employment growth among U.S. small businesses. These higher rates also rendered interest payments unsustainable for many, contributing to half of the observed increase in delinquencies. Lastly, a simple heterogeneous firm model with a cash-in-hand constraint illustrates the significant macroeconomic impact of credit card financing on small business activity.

Keywords: Small Businesses, Entrepreneurship, Credit Cards, Credit, Job Creation, Turnover.
JEL codes: J23, J63, 047.

*Akcigit: University of Chicago. Chhina: University of Chicago. Cilasun: TED University. Miranda: Halle Institute for Economic Research, and Friedrich-Schiller University Jena. Serrano-Velarde: Bocconi University. The author's wish to thank Intuit's staff broadly for invaluable assistance. Raman Singh Chhina would like to thank Stanford University for providing access to RateWatch data while he was a visiting researcher.

Disclaimer: Ufuk Akcigit is an independent contractor for Intuit Inc. The opinions in this paper are those of the authors and do not necessarily reflect the views of Intuit. All results have been reviewed to ensure no confidential information is disclosed on individual QuickBooks subscribers or their employees. All information shared follows Intuit's Data Stewardship principles and is in accordance with Intuit's Privacy Statement. The authors did not have direct access to subscriber data and worked closely with Intuit staff to produce the results in the paper.

1 Introduction

> "We use a credit card every single day. That can include buying burritos for my team in the morning, to buying a piece of equipment, to buying materials. It's a heck of a lot easier to go swipe a credit card than to get a loan."
>
> — Judd Robertson, Business owner, Mighty Pine Heating and Air, *Intuit QuickBooks Small Business Index Annual Report*, 2025

> "One of my strategies has always been to not get a credit card with a high credit limit. It's very easy to end up hitting that limit and then you're stuck with extra charges in interest month to month."
>
> – Tanya Zurock, Business owner, Wild Prairie Soap Company, *Intuit QuickBooks Small Business Index Annual Report*, 2025

Credit cards are one of the most debated sources of small business financing in the US economy. They have been instrumental in the early stages of some notable entrepreneurial successes, such as Airbnb's "Visa financing round" and Reed Hastings, founder of Netflix, who used credit cards to cover initial expenses and test mailings for his DVD rental service.[1] However, their high interest rates can just as easily lead to the downfall of many small businesses, turning a potential lifeline into a financial burden. Between January 2021 and January 2023, a period marked by rising monetary rates, transactions on small business credit cards nearly doubled, making credit card payments three times as high as loan payments, and interest burdens on credit cards soared by 60%. Despite the critical role of credit card financing in sustaining small businesses, its importance and impact on their economic health remain largely unexplored due to a previous lack of comprehensive data. Our study addresses this important gap by utilizing high-quality and near-real-time data from nearly 1.6 million small businesses using the Intuit QuickBooks online platform, complemented by large-scale surveys of these businesses, offering new insights into the consequences of credit card financing on small businesses in the US.[2]

Small and young businesses are essential for job creation, innovation, and economic growth (Birch, 1987; Neumark, Wall, and Zhang, 2011; Haltiwanger, Jarmin, and Miranda, 2013; Akcigit and Kerr, 2018; Sedláček and Sterk, 2017). According to the most recent US Bureau of Labor Statistics and US Census Bureau numbers, businesses with less than 10 workers account for about 80% of all employers in the US and employ more than 13 million workers. Small businesses in the U.S. have also undergone significant structural transformations over the past few decades. There

[1] "We did raise a round of financing. We call it the Visa round. (...) We would go through Visa after Visa, then to MasterCard, and finally to Amex, maxing out credit cards. That's how we funded ourselves." – Joe Gebbia, founder Airbnb, *How I Built This*, October 17, 2016

[2] All information shared follows Intuit's Data Stewardship principles and is in accordance with Intuit's Privacy Statement. The authors did not have direct access to subscriber data and worked closely with Intuit staff to produce the results in the paper. Near real-time refers to actual pulls of information, not a live data feed.

have been growing concerns about declining rates of entrepreneurship and associated young firm activity, a pervasive trend observed across industries, regions, and firm size categories (Decker et al., 2016; Decker and Haltiwanger, 2023; Akcigit and Ates, 2023; Biondi et al., 2023). Similarly, financing options for entrepreneurs and small businesses have changed markedly in the last decade. While large banks have increasingly retreated from offering term loans, this reduction has been partially offset by fintech lenders and, notably, by credit card financing (Bord, Ivashina, and Taliaferro, 2021; Benetton, Buchak, and Garcia, 2022; Gopal and Schnabl, 2022). However, comprehensive data on the combined financial and operational activities of small U.S. businesses necessary to assess the economic impact of these changes remains limited.

Our analysis overcomes these limitations of traditional small business data by leveraging novel information from Intuit QuickBooks, a platform offering accounting, payroll, payment processing, and time-tracking solutions for small businesses. These data offers unique insights into small business activity and financing in the US. First, as a leading provider of these services in the US, Intuit QuickBooks served 7.1 million small business customers globally as of July 2022, including 5.9 million QuickBooks Online subscribers. Second, the data is highly granular, with businesses setting up automatic feeds to provide real-time monthly information. Third, and most importantly, the data enables us to combine insights on small business real activity—such as quarterly revenue and employment growth —with detailed financial information from bank feeds and supply chain data from invoices. This allows us to track financial decisions across all intermediaries and across the most important financing instruments, including cash, credit cards, and loans. Finally, our collaboration with Intuit QuickBooks enables us to field surveys to their customer base that add valuable information on entrepreneurs' socio-demographics, expectations, shocks, and financing preferences.[3]

The first step of our analysis is to shed light on aggregate trends in small firm growth and financing over the past five years. To achieve this, we compute monthly and quarterly statistics from the near real-time data from the Intuit QuickBooks platform. We re-weight and benchmark the data with official statistics to make it nationally representative instead of representing changes in the Intuit QuickBooks customer base (Akcigit et al., 2023). Regarding real activity, both the employment data and the revenue data from the Intuit QuickBooks Small Business Index indicate a sustained decline in small business growth following a robust recovery from the pandemic. On the financing side, the data reveals a novel insight: contrary to traditional views of corporate finance and banking, U.S. small firms rely heavily on credit card financing. During the sample period, monthly credit card repayments were up to three times higher than loan repayments. Similarly, credit card interest burden rose by 60% during the post-COVID monetary policy tightening that began in March 2022, leading to elevated levels of credit card delinquencies.

We then introduce a custom-designed survey targeting small U.S. businesses that subscribe to

[3]In all cases the data are treated in accordance with Intuit's Privacy Safeguards. The authors did not have direct access to confidential subscriber data.

the platform. The survey aims to study the cross-sectional determinants of credit card financing among entrepreneurs by linking detailed transaction-level data with complementary survey information. Fielded to over 5,602 businesses in the US across six quarters, the survey focuses on three key areas. First, it collects data on entrepreneur and business demographics, such as business age and employment, which are not systematically captured by the platform. Second, it explores the preferences and usage of various financing methods, including perceptions of the benefits and costs of credit card financing. Finally, it gathers information on shocks faced by entrepreneurs, such as financial constraints and uncertainties about future cash flows.[4]

Using this unique combination of datasets, we present three key insights into entrepreneurs' use of credit card financing. First, more than 55% of businesses report using business credit cards for financing in the past 12 months, far exceeding reliance on alternatives such as credit lines, loans, or internal funding. Entrepreneurs particularly value credit card financing for its accessibility and flexibility in managing cash flow shocks. Second, transaction data on loans and credit card payments highlights that younger firms, smaller firms, and those with lower cash reserves consistently allocate a larger share of their payments to credit card financing. Finally, we assess the role of credit cards within a firm's pecking order, particularly as a buffer against economic shocks. From the survey we identify unexpected firm-specific shocks in terms of financial conditions, uncertainty in cash flow forecasts, and overdue payments by customers. We show that, in response to these shocks, firms primarily adjust their financing structure by reducing their repayments on credit cards. Instead, their reliance on loans and internal cash remains unaffected.

Next we turn to the question of whether the widespread use of credit cards among small businesses have any real effects on small firm outcomes. To address this question, we leverage the full transaction-level data in three steps. First, we identify a supply shock to credit card debt by exploiting the varying exposure of credit card intermediaries to the monetary policy tightening in early 2022. Next, we examine how differences in firms' exposure to this credit supply shock affected their real outcomes, such as revenue and employment growth. Finally, we show how the unexpected increase in the cost of credit card balances led to debt overhang, pushing firms into delinquency on their credit card obligations.

In the first step of this analysis, we document how the sharp monetary policy tightening—increasing Federal Reserve rates from near zero to five percentage points within a year—led to a differential contraction in the supply of credit card financing. Credit card intermediaries with greater exposure to interest rate risk on their liabilities responded by raising APRs on credit cards more significantly. To address concerns about the endogeneity of lending terms, we extend our analysis to transaction-level data, leveraging information on firms borrowing simultaneously from multiple banks (Khwaja and Mian, 2008). This approach exploits within-firm-quarter variation in lending across banks with differing exposures to monetary policy shocks, allowing us to flexibly control for firm-specific demand shocks. Our estimates reveal a significant 15.75% reduction

[4]Survey responses were fully anonymized in compliance with Intuits data stewardship policies.

in credit card balances among small businesses borrowing from intermediaries that were more adversely affected by the interest rate shock.

We next turn to the question of whether the changes to the supply of credit card financing impacted real outcomes and growth dynamics of small firms. To do so, we estimate how the exposure to adversely exposed credit card intermediaries affected quarterly growth rates of firm revenues and employment. A one standard deviation lower income gap of credit card providers combined with a 5% increase in monetary policy rates implies 10.5% lower quarterly revenue growth for small firms, and a reduction of 1.5% in terms of quarterly employment growth from our most conservative estimates. These effects are not trivial if we consider that in 2022, the United States small business population (with between 1 and 9 employees) employed almost 14 million workers, and experienced annual net growth of 5.9%, adding over 815,000 jobs.[5] Importantly, the specifications isolate the supply shock due to credit card financing as we are able to simultaneously control for quarterly loan and cash reliance by firms. In addition, the estimates are robust to granular controls for demand shocks across geography, industry, and time.

The results highlight the critical role of credit card financing in supporting U.S. business activities. However, this access comes with a trade-off: while credit cards offer flexibility and accessibility, they also expose entrepreneurs to the risk of escalating debt and mounting interest payments. We quantify the risks of credit card debt overhang for US small businesses in the context of the cost shock associated to the monetary policy transmission. Our estimates indicate that a 1 percentage point increase in monetary policy rate amplifies the effect of a 10% higher initial interest rate on the probability of delinquency by an additional 0.05 percentage points. Over the entire period of monetary tightening, this cumulative effect translates to a 0.25 percentage point increase in the probability of delinquency. This impact is notable, as average delinquency rates rose from 2.2% and peaked at 2.8% during the same period.

Lastly, we integrate the estimates from our empirical analysis to build and calibrate a heterogeneous firm model of aggregate small business activity. We then use the calibrated model to evaluate the impact of credit card financing on the transmission of interest rate shocks and long-term loan supply shocks to small business output. In the model, entrepreneurs face idiosyncratic and aggregate MIT shocks and can hold three types of assets: liquid savings, credit card debt, and long-term loans. Fixed costs associated with long-term borrowing generate a natural pecking order between credit cards and long-term debt, while a cash-in-hand constraint creates scope for credit card financing to influence output. The calibrated model highlights that credit cards can have a dual effect in the context of interest rate or loan shocks. In the short run, credit cards expand borrowing capacity and serve as a financial buffer during downturns—allowing small businesses to secure funding when revenues decline and access to long-term loans becomes more constrained. However, this flexibility comes at a cost. The high interest rates on credit card debt increase debt service burdens, which can dynamically erode firms' cash flows

[5] Estimates from the U.S. Census Bureau, Longitudinal Business Dynamics statistics.

and slow the recovery.

Literature This dataset uniquely positions us to study the role of credit card financing with crucial business dynamism indicators such as employment and sales growth. Small businesses, particularly young ones, disproportionally contribute jobs to the economy and are an important indicator of business dynamism (Haltiwanger, Jarmin, and Miranda, 2013; Akcigit and Ates, 2023; Akcigit et al., 2023; Sedlácek and Sterk, 2019). Small businesses are also the most prone to facing financial frictions and their growth crucially depends on the availability of sources of financing. Although there is a large literature on financial frictions and their impact on firm performance (Gertler and Gilchrist, 1994; Sharpe, 1994; Chari, Christiano, and Kehoe, 2007; Moscarini and Postel-Vinay, 2012; Fort et al., 2013; Crouzet and Mehrotra, 2020), most of the studies lack direct financial information or focuses on larger firms and long-term loans. Our contribution in this literature is twofold. First, we study the impact of financial frictions on the outcomes of young and small firms using firm level financial information. This is made possible by our unique data which allows us to jointly study financial and real outcomes for small firms which is not possible in studies which rely solely on credit bureau data. Second, while it is well established that the credit availability is crucial for firm growth, there are significant variations in the impacts of different kinds of credit. We contribute by showing that small firms rely heavily on credit cards as a source of financing and that this method of financing differs substantially from long term loans in terms of its usage and impacts on real outcomes in response to idiosyncratic firm level shocks and aggregate shocks.

Our paper also contributes to the recent literature highlighting how small business lending underwent major changes in the last decades (Chen, Hanson, and Stein, 2017; Bord, Ivashina, and Taliaferro, 2021; Benetton, Buchak, and Garcia, 2022; Gopal and Schnabl, 2022). Large banks have retreated from lending term loans. Some amount of this reduction has been filled by Fintech lenders (Gopal and Schnabl, 2022) and by regional banks (Bord, Ivashina, and Taliaferro, 2021). A considerable amount of the lending by large intermediaries was shifted to credit card financing. Benetton, Buchak, and Garcia (2022) for example, report that almost 90% of the US firms have at least one credit card. And the amount of small business credit card lending accounts by large banks has almost doubled since 2010 while term loan lending has stalled. Benetton and Buchak (2024) demonstrate that the high interest rates on business credit cards are primarily driven by markups rather than lender costs, and argue that incorporating undrawn credit limits into risk-weighted capital regulations could be counterproductive to bank stability.

Finally, this paper contributes to the literature on the determinants and implications of credit card financing. A substantial body of research in both microeconomics and macroeconomics has examined the factors influencing household decisions related to credit card use and consumption choices (Ru and Schoar, 2016; Lee and Maxted, 2023; Bornstein and Indarte, 2023). Additionally, recent studies have explored the transmission of monetary policy into consumer

credit card lending (Agarwal et al., 2018; Chava et al., 2023; Indarte, 2023). However, despite some notable exceptions, analyses linking credit card financing to entrepreneurship and small business financing decisions remain relatively scarce. An early contribution by (Blanchflower, Evans, and Robinson, 2004) underscored the importance of credit card financing for small businesses, using data from the 1998 Survey of Small Business Finances. More recently, (Chatterji and Seamans, 2012) and Fonseca and Wang (2022) establish the connection between credit card financing and entrepreneurship, while Berger et al. (2024) study the role of relationship lending for business credit cards during COVID-19. Our contribution to this literature is twofold. First, we establish the existence of a transmission mechanism of monetary policy into business credit cards. Second, we are, to the best of our knowledge, the first to trace these changes in the supply of credit card financing to real outcomes of small businesses.

2 Data Construction

We leverage novel data from Intuit QuickBooks customers, which provides accounting, payroll, payments, and time-tracking software for small businesses in the US, UK, and Canada.[6] These data offer unique insights into small business activity and financing in the US. First, as a leading provider of these services in the US, Intuit QuickBooks served 7.1 million online small business customers globally as of July 2022, including 5.9 million QuickBooks Online subscribers. Second, the data is highly granular, with businesses setting up automatic feeds to provide real-time monthly information. Third, and most importantly, the data enables us to combine insights on small business activity—such as revenue and employment—with detailed financial information from bank feeds and supply chain data from invoices. This allows us to track financial decisions across all intermediaries and financing instruments, including cash, credit cards, and loans. Finally, our collaboration with Intuit QuickBooks enables us to field surveys to their customer base that add valuable information on entrepreneurs' socio-demographics, expectations, shocks, and financing preferences. We complement these data with information on financial intermediaries from the Consolidated Financial Statements for Bank Holding Companies, along with credit card interest rate data from RateWatch.

2.1 Intuit QuickBooks

Revenue and Employment Data The revenue sample consists of 1.6 million businesses in the US and comprises both employer firms as well as non-employers and self employed individuals with positive revenue.[7] The QuickBooks platform helps subscribers automatically track various types of transactions in and out of their savings and checking accounts including bank deposits,

[6] We follow Intuit's strict privacy safeguards. Also note that near real-time refers to actual pulls of information, not a live data feed.

[7] 1.6 million businesses represents a cleaned dataset of U.S. based credit card bank feed data from QuickBooks Online accounts, limited to customers with consistent and automated bank feeds.

credit card transactions, payments received, bills paid, and expenses in real time. For each transaction, QuickBooks provides an initial categorization by matching transactions to sales receipts and invoices on the platform, but users are required to review and confirm that income transactions are correctly classified as revenue. Users typically do this with a 3 to 6 month lag — often when they need to meet their income tax reporting obligations. For real-time classification, we use a machine learning algorithm trained on previous user classifications to get an up-to-date labeling of deposit transactions as revenue for the firm. To construct our revenue based index of small business activity, we restrict the sample to employer firms that subscribe to the platform's payroll functionalities (described below). However, for the analysis in Section 5, we utilize the full dataset.

The payroll sample consists of 450,000 businesses in the US and is dominated by small business with between 1 and 19 employees.[8] In this paper we work with monthly data which is aggregated from weekly or by-weekly paychecks issued in a given pay period. Details regarding the characteristics of this sample are available in Akcigit et al. (2023).

Firm Financial Data For the firm financial outcomes we are able to leverage the entirety of the QuickBooks database. We limit our analysis to the firms in the sample that have their savings/current bank accounts and borrowing accounts such as credit cards automatically linked with the software. This ensures a high quality and timely gathering of the firm's financial accounts.[9] We also observe payments towards loans from the user checking and savings account and any principal deposits related to loans or government assistance programs during the Covid-19 pandemic. The variables are identified by a keyword matching algorithm that classifies the transactions in the firm's checking/savings account statements.

To analyze the borrowing dynamics of small businesses on their credit card products, we collaborated with Intuit to construct several variables from raw transaction feeds. While Intuit's customer data do not include detailed credit card account statements, such as those available from credit bureaus like Experian or TransUnion, we were able to accurately reconstruct key credit card financial metrics using direct transaction data. For instance, we identified the total interest paid by business owners on their credit cards by isolating transactions labeled as interest payments or fees in the feed. From this information, we inferred the statement cycle dates for each credit card. These dates enabled us to aggregate total outflows during the statement cycle to calculate "total usage" and total inflows to determine "total payments." The difference between these two metrics was then classified as the "monthly balance." Using the inventory method, we

[8] 450,000 businesses represent a cleaned dataset of U.S. attached payroll accounts from QuickBooks Online accounts within the bank feed sample described above.

[9] Transactions are recorded almost in real time. These accounts update their transactions on Quickbooks automatically, via a bank feed connection. The frequency of bank feed updates varies by institution, but in general occurs at least once per day, with many feeds updating multiple times a day. During each update, bank feeds send transaction-level data for the day, as well as the latest balance on the account. Period start and end dates are not included in the feed updates.

aggregated monthly balances by adding total fee and interest charges to the balance, providing a comprehensive view of credit card borrowing behavior over time.[10]

In addition, it was possible to link the information for each credit card with its issuing financial intermediary. The automated feeds uniquely identify each intermediary but do not enable direct mapping to external sources. Therefore, we proceed in two steps: first, a fuzzy matching algorithm is applied to align the bank names from the Call Report data with the user-entered bank names. A single reliably matched Call Report record, makes it then possible to use the unique internal keys generated by the automated bank feeds to close the links on all records using such keys. Appendix B details the match rates in the sample along with corresponding distributions. The Call Report data provides detailed data on the bank's assets and their composition, their liabilities and obligations, and their capital accounts including the bank's equity positions. Information is available at a quarterly frequency.

Survey Data Survey data provides additional information on convenience samples. The Intuit QuickBooks Small Business Insights Survey is conducted online at regular intervals, typically every three months, in the US, Canada, and the UK. It is commissioned by Intuit QuickBooks and targets small business owners and decision-makers. The survey gathers responses from two primary sources: Dynata audience panels and Intuit QuickBooks customer base. In this paper, we report on survey data from the Intuit QuickBooks customer base.

The number of participants from the Intuit QuickBooks customer base varies across survey waves. In the July 2024 wave, 2,315 participants were involved (1,505 from the US, 405 from Canada, and 405 from the UK). These respondents are QuickBooks Online subscribers who have been active in their accounts within the last 30 days. All participants complete the survey via an online form and are incentivized to participate.

Respondents from the Intuit QuickBooks customer base consented to link their survey responses with data from their QuickBooks accounts, providing us with a unique dataset that combines survey feedback with Intuit transaction data. This allows us to gain valuable insights into incentives, goals, and perceptions, and to assess their impact on firm-level indicators. Additionally, since we have previous surveys dating back to the first quarter of 2023, we are able to establish a panel setup, enabling us to analyze the dynamic relationships between survey variables and data from QuickBooks accounts over time.

[10] In Appendix D, we present a benchmarking exercise using a subsample of 179,000 firms for which credit bureau data from Vantage is available. Our constructed measures of credit card reliance and term loan reliance align closely with the corresponding records in the credit bureau files. The balances are also consistent with those reported by (Benetton and Buchak, 2024).

2.2 RateWatch Data

RateWatch collects data from a representative sample of bank branches in the US on a weekly frequency. The dataset gathers information on deposit rates, fees and interest rates on different credit products such as credit cards, mortgages and auto loans. We use the data on APR rates from the credit card products which are consistently reported throughout our analysis period i.e. April 2021 to April 2023. To make the analysis consistent with the firm level regressions, we aggregate the data up at the Bank Holding Company (BHC) by mapping each branch to its parent bank and the bank holding company. The APR is then computed as the simple mean over the banks and branches. For each BHC we keep it in the analysis if its data is reported for more than 19 months in our 25 month analysis period. The missing values are imputed as the mean of the previous and next months. Lastly, as the Call Report data is at a quarterly frequency we aggregate RateWatch data on a quarterly frequency by using the mean of all the reported values in the measurement period.

2.3 Bank Level Data

To construct estimates for bank performance at the holding company level we use the data from The Consolidated Financial Statements or FR Y-9C filings for Bank Holding Companies. These reports have to be filed with the Federal Reserve by all US bank holding companies with total consolidated assets of $500 million or more. We follow Gomez et al. (2021) and Paul (2023) directly to construct three bank level variables 1) income gap, 2) log of total assets 3) equity to assets ratio. Appendix B details the construction of the income gap variable and the summary statistics for the banks in our sample.

3 Stylized Facts

The first step of our analysis is to shed light on recent trends in small firm growth and financing over the past five years. To achieve this, we analyze near real-time data from the Intuit QuickBooks platform, using it to compute aggregate monthly and quarterly statistics. Regarding real activity, both the employment data and the revenue data from the Intuit QuickBooks Small Business Index indicate a sustained decline in small business growth following a robust recovery from the pandemic. On the financing side, the transaction data reveals a surprising trend: contrary to traditional views of corporate finance and banking, U.S. small firms rely heavily on credit card financing. This reliance is evident not only in the payment flows directed toward credit card balances but also in the persistently high levels of interest costs and late payments over the past two years.

3.1 Small Business Activity after COVID-19

Official statistics tracking small business activity at a high frequency have limitations.[11] Here we make use of the Intuit QuickBooks Small Business Index monthly series covering the period between 2015 and 2024 to document small business activity during this time. The QB SBI combines near real time information from over 450,000 QuickBooks online payroll subscribers in the US with the Bureau of Labor Statistics' Business Employment Dynamics (BED), and the Job Openings and Labor Turnover Survey (JOLTS) data which is available with significant lag. The methodology involves a model to discipline the Intuit data business entry, exit, expansion and contractions to match the available BED and JOLTS data, the model is then used to predict out of sample to produce disciplined near real time estimates of small business activity. For a detailed description of the model and its performance see Akcigit et al. (2023).

We follow a similar methodology to get the nationally representative average revenue statistics for the same set of firms described above i.e. firms with 1-9 employees. However, we follow a different methodology to re-align the series due to lack of regular official revenue statistics for benchmarking. We first construct firm level total revenue receipts, per month, as described in Sec 2.1. Then, to deal with platform growth, we restrict the sample of firms to three month continuers, remove any outliers i.e. firms with revenues more than the 98th percentile and negative values, and seasonally adjust the data to remove any seasonal patterns. To construct a nationally representative series from these firm level estimates, we first aggregate the revenue growth numbers to fifty regions and twelve sectors in the United States. We then calculate region sectors weights as a ratio of the Quarterly Census of Employment and Wages to QuickBooks share of establishments and use them to re-weight the numbers to get our final series. The resulting series uses information from 10.1 million firm-month observations for 230,000 distinct firms over the sample period. The revenue data from the Intuit QuickBooks Small Business Index in the US is expressed in average real monthly revenue per small business, adjusted to 2017 dollars to account for inflation.[12]

Small business activity for firms with between 1 to 9 employees experienced significant declines during the COVID-19 shut-downs both in terms or employment and real revenue as shown by the employment data (Figure 1a) and revenue data (Figure 1b) from the Intuit QuickBooks Small Business Index.[13] This decline was followed by a rapid recovery during 2021 and into early 2022. During this time small businesses were able to take advantage of low interest COVID-19 relief loans in excess of $900 billion mainly through the Paycheck Protection Program (PPP) and the Economic Injury Disaster Loan (EIDL) (Sedlacek and Sterk, 2020). The Federal Reserve lowered the federal funds rate to near zero in March 2020. The swift recovery and rising inflation

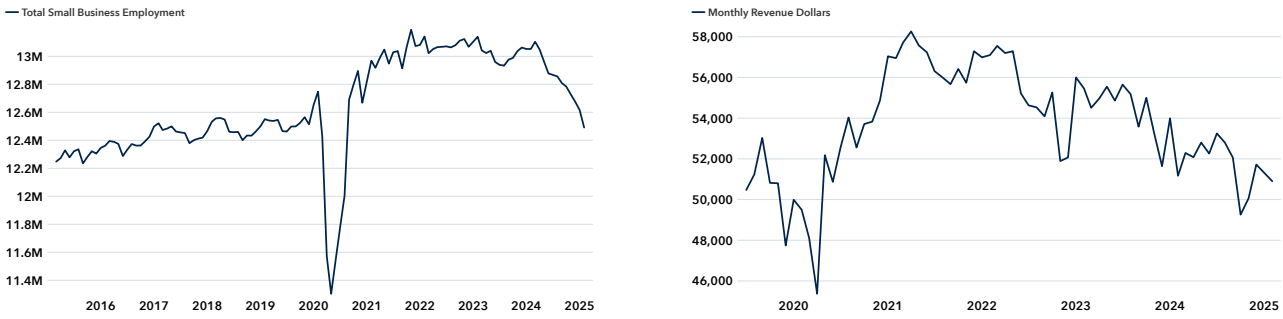
[11] The US Bureau of the Census BTOS is a very large sentiment survey collected every two weeks but does not track business activity per se. The Bureau of Labor Statistics JOLTS offers data for small business at a monthly frequency but the sample for small business is small and their entry/exit model is known to introduce biases.

[12] Details are provided in Akcigit et al. (2024).

[13] For a detailed description of the methodology behind these indexes see Akcigit et al. (2023, 2024).

led the Federal Reserve to reverse course in March of 2022 with a series of federal fund rate hikes. Early 2022 marks an inflection point for the small business recovery followed by sustained declines through 2024. Small business employment peaked at 13.1 million jobs in November of 2021 according to the Intuit Quickbooks Small Business Index. In March 2022 that number was slightly lower at 13 million jobs. In May 2023, after 11 rate hikes, that total reached its low point at 12.7 million jobs, a 3% decline. During that time, average small business revenue expressed in real (2017) dollars fell by 4.6% from 54.2 to 51.7 thousand dollars.

Figure 1: Intuit QuickBooks Small Business Index



(a) Employment Index

(b) Revenue Index

Source: Intuit QuickBooks Small Business Index (Akcigit et al., 2023). The figures plot the monthly employment and real revenues respectively on the y-axis and month the x-axis.

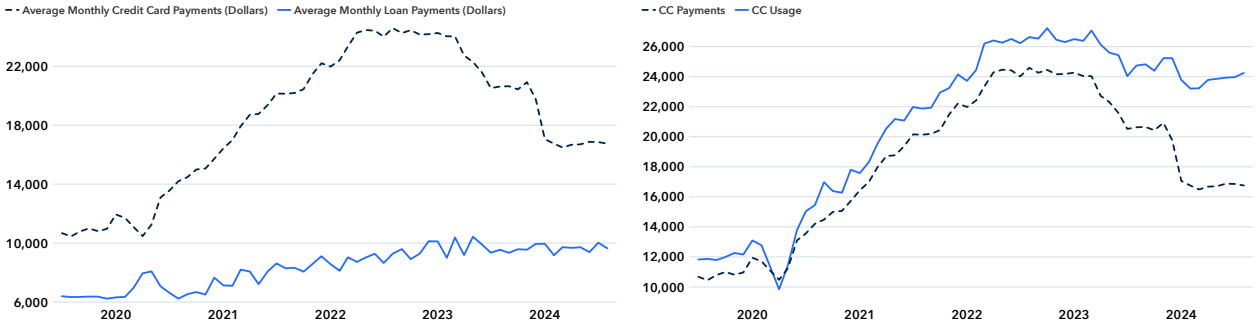
3.2 Importance of Credit Card Financing for Small Firms

Figs. 2a and 2b highlight the scale of credit card usage among small businesses in the U.S., particularly during periods of business cycle fluctuations. These figures rely on high-quality, directly observed, and automatically recorded measures of financing activity on the platform, specifically credit card and loan payments as well as credit card usage. To compute the aggregate series we follow a similar approach to the revenue series. However, here we restrict the sample to the firms that we consistently observe over our analysis period, remove any outliers i.e. firms with revenues more than the 98th percentile and negative values, and seasonally adjust the data to remove any seasonal patterns. The data is then re-weighted as before to be nationally representative.

Measuring reliance on credit cards and loans through allocated payments offers several key advantages. First, loan payments are observed in the data as the total amount covering both principal and interest. Similarly, using total payments for credit cards ensures a consistent basis for comparing the importance of these financing instruments in supporting business activities. Second, similar to trade credit financing (Giannetti, Burkart, and Ellingsen, 2011; Giannetti, Serrano-Velarde, and Tarantino, 2021), payments and usage of credit cards capture their importance as a source of short-term financing for businesses, even when balances are fully repaid.

Fig. 2a plots the aggregate payments into credit cards and loans for a balanced panel of firms in

Figure 2: Credit Card Usage Among US Small Business



(a) Payments Into Credit Cards and Loans

(b) Credit Card Usage and Payments

Notes: Panel (A) plots the average credit card payments and average loan payments for the firms in the sample. Panel (B) plots the credit card usage along with credit card payments for the same set of firms.

the QuickBooks data. We aggregate the total payments in each category at the sector and region level, seasonally adjust and then re-weight each region-sector cell to make the data nationally representative. We find that credit card payments are large, in absolute terms and also in relation to respective aggregate loan payments.[14] Monthly payments into credit cards were 24,000 dollars a month during July 2022 and about three times the corresponding number for loan payments.

Fig. 2b illustrates the growing reliance on credit card financing through trends in usage and repayments. First, the figure reveals that over time, credit card usage consistently exceeds payments, leading to increasing balances that extend beyond the short-term interest-free financing period. Second, a significant divergence between usage and payments emerges with the onset of monetary policy tightening. Specifically, following the start of monetary policy tightening in 2022, credit card usage remains stable at elevated levels, while businesses substantially reduce their payments into credit cards.

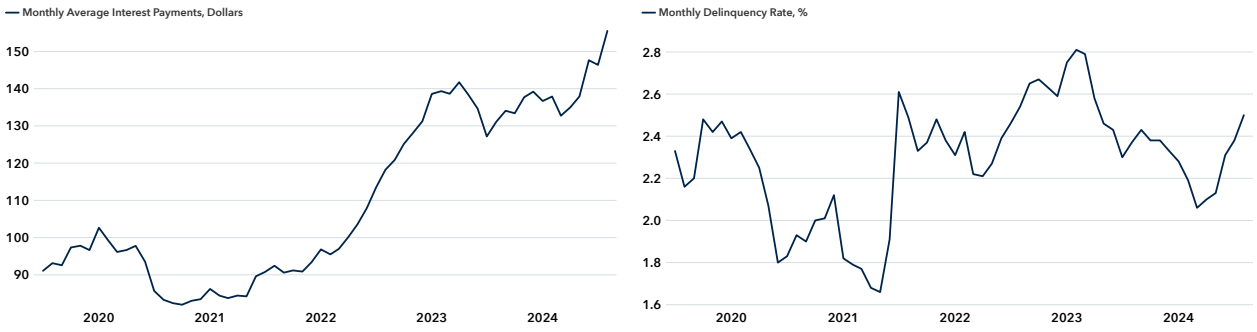
3.3 Interest Burden of Credit Card Financing

Unlike traditional credit panel data, our dataset offers the distinct advantage of allowing us to directly observe the actual interest paid by each firm on every credit card. We can therefore trace the dynamics in credit card usage and payments directly into aggregate interest payments and delinquencies on credit cards. Fig. 3a plots monthly interest payments in the balanced re-weighted panels. Consistent with the aggregate dynamics of credit card usage and payments, the figure shows a sharp rise in interest payments as the monetary policy tightening begins. Interest Payments on credit cards go up by 60% in this short period of time. While the ability to draw on credit card debt can expand the debt capacity of small firms, particularly during

[14]Credit lines are included within the loan categorization. For a subsample of companies using the platform's loan management application, we can further differentiate between loan financing sources. Specifically, we quantify the importance of credit lines within the overall loan category, observing that their share remained relatively stable over time, consistently accounting for 25% of total loan balances.

turbulent economic periods, it also carries the risk of escalating into unsustainable financial costs for these businesses. Fig. 3b confirms the increasing burden by plotting monthly delinquency rates, calculated as the ratio of firms paying late fees on their credit cards to the total number of firms using credit cards. Consistent with the increasing usage of credit cards firms also sustained significantly more late payments during the monetary policy shock, with the share of firms incurring late fees peaking at 2.8% in early 2023. This evidence aligns with the trend of credit card financing becoming not only more important for small firms but also significantly more expensive.[15]

Figure 3: Credit Cards: Interests and Delinquencies



(a) Interest Payments on Credit Cards

(b) Delinquencies on Credit Cards

Notes: Panel (A) plots the average interest payments on credit cards for the firms in the sample. Panel (B) plots the monthly delinquency rates for the same set of firms.

4 Credit Card Financing by Small US Businesses

The evidence in the previous section underscores the increasing importance of credit card financing for small U.S. businesses. In this section, we integrate transaction data from the Intuit platform with firm surveys we conducted in 2023 and 2024. A key advantage of the Intuit QuickBooks platform data is the ability to observe small business cash flows at the level of individual transactions. The linked survey, in turn, provides crucial insights into the demographics of businesses and entrepreneurs, their preferences, and the shocks affecting their business environments. As a result, we are uniquely positioned to examine how small firms allocate their cash flows between borrowing and servicing different types of financing instruments — credit cards, cash, and loans — based on their liquidity buffers, microeconomic shocks, and preferences.

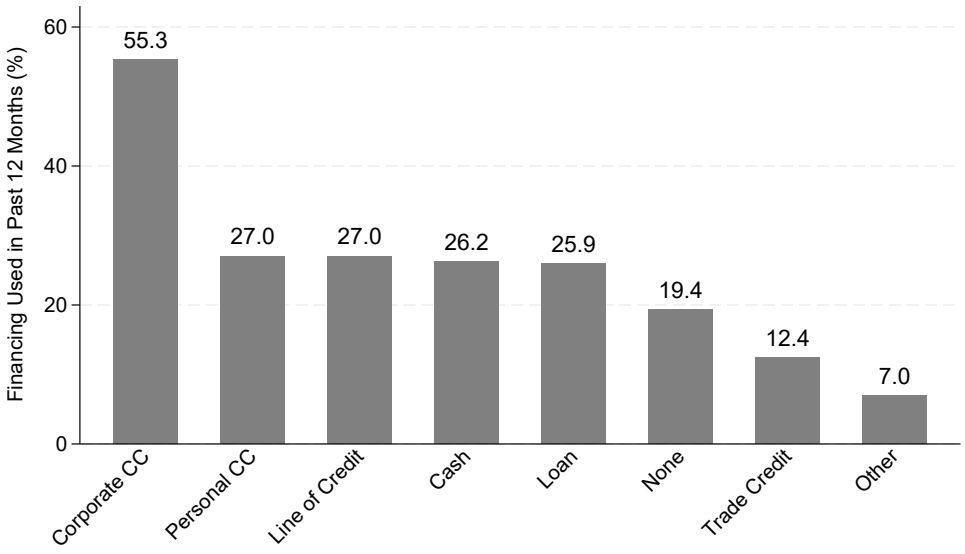
4.1 Stylized Facts on Credit Card Financing of Small Businesses

The first point we address in this section is the relative importance of credit card usage compared to other financing instruments. To explore this, in collaboration with Intuit QuickBooks we

[15]The delinquency rates are also comparable, albeit slightly higher, to the ones reported in (Benetton and Buchak, 2024) for the sample period 2014 to 2019.

surveyed over 4,500 businesses across three waves, asking them to provide a detailed breakdown of the financing instruments they used in the previous 12 months. The options included external and internal sources, as well as hybrid sources like personal credit cards and home equity lines of credit. Figure 4 presents the main responses from entrepreneurs.

Figure 4: Business Financing Used Over Past 12 Months



Notes: The figure shows the response to the following question, "Which of the following financing options has the business used over the past 12 months?" Sample of US respondents from the Intuit QuickBooks Small Business Insights Survey, fielded to 5602 Intuit QuickBooks business customers at a quarterly frequency between the first quarter of 2023 and the second quarter of 2024.

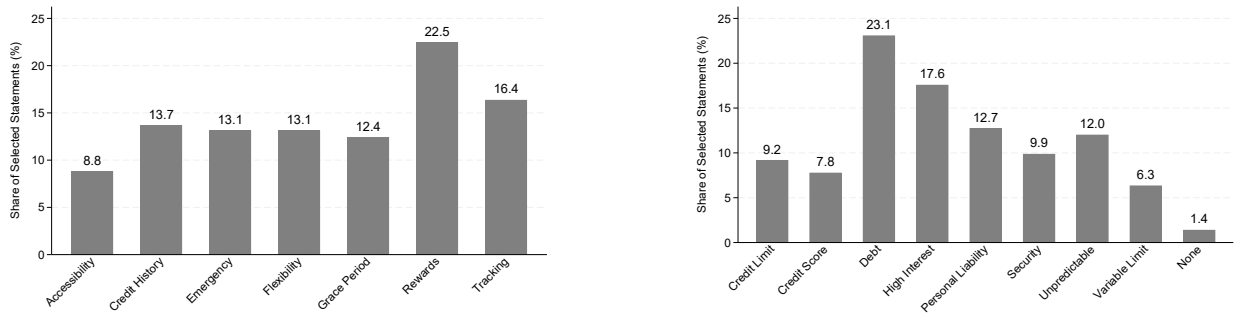
Business credit cards are the most commonly used financing instrument, with 55% of businesses reporting their use over the past year. Personal credit cards and lines of credit follow in use but with only half the frequency of business credit cards. Additionally, a notable 26% of respondents rely on personal cash and loans to fund their business operations. The predominant use of credit cards reported by our survey respondents aligns with previous findings on small business finance. (Blanchflower, Evans, and Robinson, 2004; Mach and Wolken, 2009; Robinson, 2010; Robinson and Smith, 2023; Benetton and Buchak, 2024).

To better understand the reasons for the pervasive use of credit card financing we asked survey respondents to list the benefits and costs associated to them. Figures (5a) and (5b) plot the share of responses relative to the main advantages and disadvantages associated to using credit cards for business financing.

Figure 5a shows a clear distinction between financial and transactional motives for the use of business credit cards. In more than 61% of responses, firms underlined the financial benefits of relying on business credit cards. These financial advantages relate to the fact that credit cards

are considered easy to obtain (*Accessibility*, 8.8%), provide funding when facing unexpected expenses (*Emergency*, 13.1%), and provide the ability to flexibly decide about repayments (*Flexibility*, 13.1%). In addition, 12.4% of respondents indicate that credit cards provide a cheap instrument to satisfy short-term financing needs (*Grace Period*). Finally, transactional motives are captured in 22.5% of answers, where respondents highlight lucrative rewards as the main advantage of credit card usage (*Rewards*).

Figure 5: Benefits and Costs Associated to Business Credit Cards



(a) Benefits

(b) Costs

Notes: The figure presents the responses to the following questions: "Which of the following, if any, do you see as the main advantages of using credit cards for business financing?" in panel (A), and "Which of the following, if any, do you see as the main disadvantages of using credit cards for business financing?" in panel (B). Sample of US respondents from the Intuit QuickBooks Small Business Insights Survey, fielded to 5602 Intuit QuickBooks business customers at a quarterly frequency between the first quarter of 2023 and the second quarter of 2024.

Figure 5b plots the disadvantages associated to credit card financing for business activities. The most critical disadvantages relate to the possibility that debt or interest payments spiral out of control, i.e., a snowballing effect of credit card financing. In 23.1% of responses the ease of using credit cards is associated to risks of debt accumulation (*Debt*). Similarly, in 17.6% of responses, firms identify the substantial interest charges on accumulated balances as a limitation of this financing method (*High Interest*). Respondents also point out uncertainty about interest rates (*Unpredictable*, 12%) and credit limits (*Variable Limit*, 6.3%) as additional drawbacks. Importantly, 9.3% of respondents indicate that credit limits may not be sufficient to cover substantial business outlays (*Credit Limit*).

The picture that emerges hints at a source of financing that small US businesses value for its accessibility and flexibility in buffering against cash flow shocks. At the same time, this comes at the cost of credit card debt potentially spiralling out of control.

In Figure 6 we combine the survey information with the anonymized transaction data provided by Quickbooks customers to better understand the determinants of financial choices made by small U.S. businesses. As before, to ensure comparability between credit card and loan financing, we focus on monthly cash flow payments allocated to both types of financing. More specifically,

we quantify the relative share of firm payments allocated to servicing credit card debt and loans. We compute *Share CC Payments* and *Share Loan Payments* as the total monthly payments directed toward credit card and loan servicing, relative to the firm's three-month lagged checking and savings balances. These shares reflect the intensity of reliance on each of the two external financing sources and allow us to study their dependence on firm characteristics. We explore heterogeneity in financial choices across traditional proxies for financial constraints: cash stocks, firm age, and firm size.

Figure 6 reveals two striking patterns. First, firms allocate a consistently larger share of payments to credit card debt compared to loans. Second, the share of payments to credit cards systematically decreases with higher levels of cash stocks, firm age, and size. In Panel A, we examine the shares of credit card and loan payments across quartiles of cash deposits in checking and savings accounts. A clear declining pattern emerges: cash-poor firms (in the lowest quartile) allocate over 10% of their cash to credit card payments, compared to less than 2% for loan payments. As we move up the cash stock distribution, credit card payment shares decline to 5%, while loan payment shares increase to around 4%. Panel B combines payment shares with survey data on firm age. Credit card reliance is highest for young firms, especially those under 10 years old, and declines as firms mature. Finally, Panel C incorporates survey data on the number of employees, confirming a striking negative relationship between firm size and credit card reliance. This relationship is particularly strong for self-employed individuals, who allocate 16% of their payments to servicing credit card debt and less than 1.5% to loans. Consequently, the cross-sectional patterns suggest that credit card financing is more prevalent among firms more likely to face financial constraints, and which may not be able to secure loan financing.

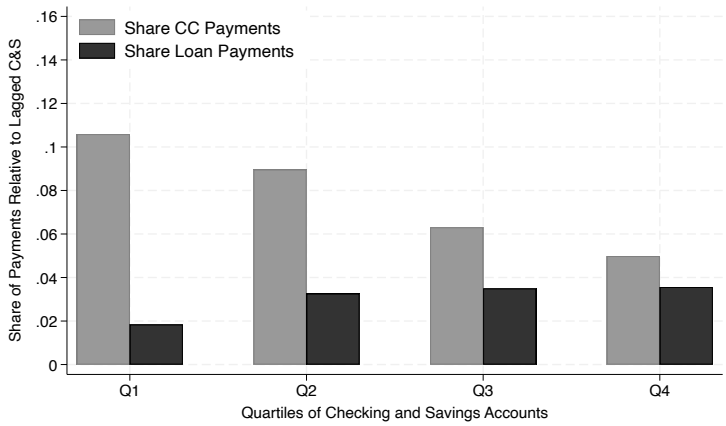
4.2 Cash Flow Shocks and Credit Card Usage

The previous evidence underscores the significant role of credit cards in financing small business activities in the U.S. The reliance on and preference for credit cards highlight their unique ability to flexibly accommodate shocks faced by entrepreneurs. We now present more systematic evidence linking the shocks experienced by small business owners to their reliance on credit cards. First, we leverage the survey data to separate credit card reliance from credit card preferences. Second, we estimate a pecking order regression to examine the role of credit cards—compared to loans and internal cash—in buffering economic shocks encountered by entrepreneurs.

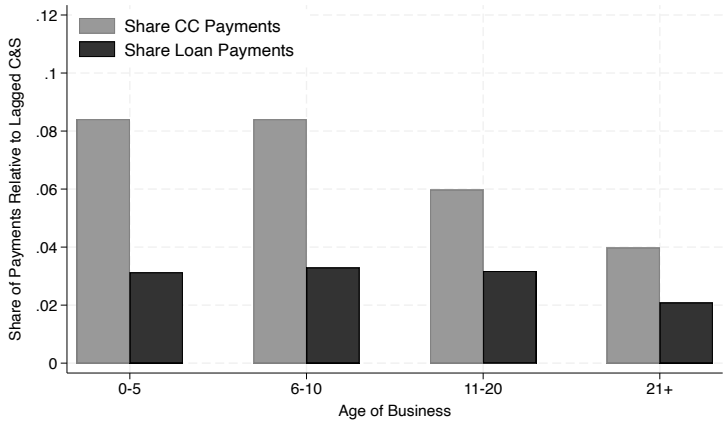
4.2.1 Reliance vs Preference

Credit cards offer small businesses a convenient financing option that is easily accessible while also providing attractive rewards and points for users. This latter feature suggests that entrepreneurs may choose to use credit cards not only as a means of borrowing but also because of the benefits associated with rewards and transaction ease. To disentangle these motivations, we directly ask survey respondents about their preferences for using credit cards and analyze how

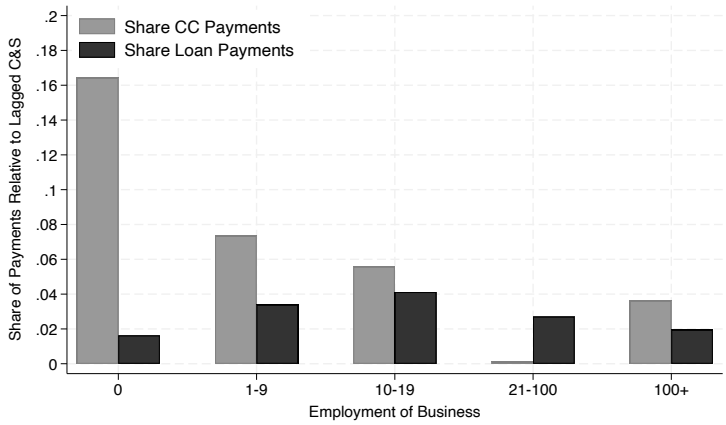
Figure 6: Credit Card and Loan Payments Relative to Cash Stocks



(a) Credit Card use vs Liquidity



(b) Credit Card use vs Age



(c) Credit Card use vs Employment

Notes: The figure plots the monthly share of credit card and loan payments made by respondents' businesses. These shares are defined as the total monthly payments directed towards loan or credit card servicing relative to the firm's three-month lagged checking and savings balances. In panel (A), the shares are plotted as a function of quartiles of balances in checking and savings accounts, ranging from the lowest 25% (Q1) to the highest 25% (Q4). In panels (B) and (C), the shares are plotted as a function of the age and size of the business, respectively. The sample includes 5,602 US respondents from the Intuit QuickBooks Small Business Insights Survey, fielded quarterly between the first quarter of 2023 and the second quarter of 2024.

their usage responds to the firm's financial condition.

Figures 7a and 7b utilize survey information on credit card usage, preferences, and economic shocks among small businesses. The light gray bars represent the share of respondents who reported becoming significantly or somewhat more reliant on credit cards over the past 12 months. The dark bars reflect respondents' stated preferences for financing instruments, specifically indicating the share who identified credit cards as their most preferred option when given equal access to various financial tools.

Panel A, on the left, shows responses based on whether entrepreneurs experienced a general worsening of the cost and availability of financing (*Financial Worsening*). The figure reveals an inverse relationship between preferences and actual usage. Among firms that did not report a worsening of financial conditions, only 20% increased their reliance on credit cards in the past year. In contrast, nearly 50% of firms facing tighter access to external finance reported increased credit card reliance. Notably, this higher usage does not reflect a greater preference for credit cards: the share of unconstrained firms that preferred credit cards was 35%, compared to only 20% among constrained firms. Panel B, on the right, presents responses based on whether entrepreneurs reported more than 20% of their invoices as overdue (*Customers High Overdue*). Again, we observe an inverse relationship: reliance on credit cards is 10 percentage points higher among entrepreneurs experiencing late customer payments, while their preference for credit cards is 7 percentage points lower. Consequently, a significant component of credit card reliance is driven not by an intrinsic preference for the financing instrument but by external constraints within the business environment.[16]

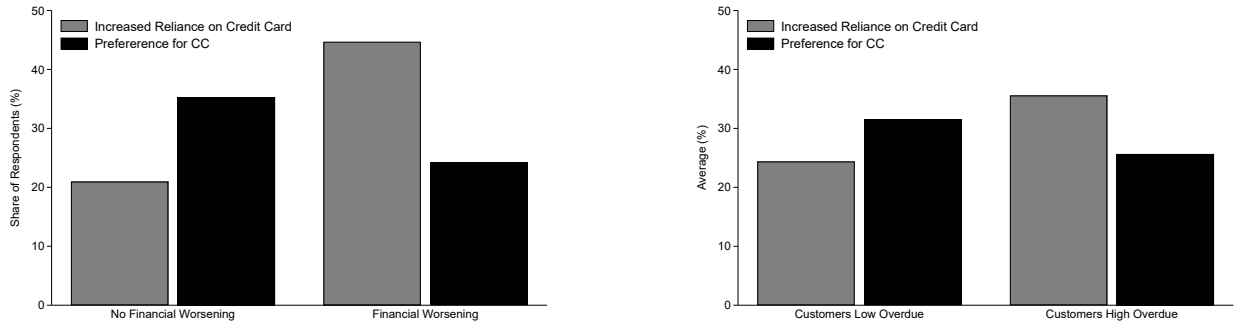
4.2.2 Pecking Order

We next set up a specification to systematically assess the role of credit cards within a firm's pecking order, particularly as a buffer against economic shocks. The pecking order theory in corporate finance suggests that companies prioritize financing sources based on their sensitivity to information asymmetry, preferring internal funds over external sources, and issuing debt over equity (Myers, 1984).

As in Figure 6, we calculate, for each firm, the share of cash flow payments allocated to loan payments, credit card payments, and cash withdrawals, relative to lagged cash holdings. We then assess the response of these payment flows to three distinct types of shocks faced by entrepreneurs, as identified in the survey of QuickBooks customers. The first measure captures entrepreneurs reporting a worsening in financial conditions over the past three months. The second shock relates to uncertainty in entrepreneurs' short-term (three-month) cash flow forecasts. Lastly, based on transaction data, we compute the share of invoices that have been overdue in

[16]This finding is consistent with previous studies (Brown, Gustafson, and Ivanov, 2021; Benetton and Buchak, 2024), which demonstrate that for credit lines and business credit cards, usage is positively correlated with ex-post shocks. Specifically, a negative shock to a firm's business being cushioned by short-term borrowing.

Figure 7: Small Business Preference vs Usage of Financing Tools



(a) Financial Worsening

(b) Percent of Invoices Due

Notes: The figure presents the responses to the following survey questions. Light grey bars indicate the share of businesses that selected "more reliant" in response to the question, "Over the last year, did the business become more or less reliant on credit cards?" Dark grey bars indicate the share of businesses that selected "credit card" as the most preferred option in response to the question, "If your business had equal access to the following financing options, which would you choose first and which would you choose last?" Panel (A) differentiates responses based on whether respondents selected "yes" or "no" to the question, "Looking back over the past 12 months, has the cost and availability of financing got worse?" Panel (B) differentiates responses based on high/low customers overdue, defined as whether more than 20% of invoices were reported as overdue in response to the question, "As an estimate, what percentage of your sales invoices are currently overdue by 30 days or more?" The sample includes 5,602 US respondents from the Intuit QuickBooks Small Business Insights Survey, fielded quarterly between the first quarter of 2023 and the second quarter of 2024.

the past three months. The specification below then estimates how firm i in month t adjusts its reliance on each financial instrument s in response to these shocks:

$$\begin{aligned}\frac{\text{Payments}_{ist}}{\text{Cash Holding}_{it-3}} = \eta_i + \delta_t + \alpha_{CC}\mathbb{1}(\text{CC}_{st}) + \alpha_{Cash}\mathbb{1}(\text{Cash}_{st}) + \alpha_{Shock}\text{Shock}_{it} \\ + \beta_{CC}\mathbb{1}(\text{CC}_{st}) \times \text{Shock}_{it} + \beta_{Cash}\mathbb{1}(\text{Cash}_{st}) \times \text{Shock}_{it} \\ + \phi_1 \text{Log CC Use}_{it} + \phi_2 \text{Log Revenues}_{i,t-3} + \phi_3 \text{Log Cash Holdings}_{i,t-3} + \epsilon_{ist}\end{aligned} \tag{1}$$

where the dependent variable $\frac{\text{Payments}_{ist}}{\text{Cash Holding}_{it-3}}$ is the share of cash flow payments in month t allocated to loan payments, credit card payments, and cash withdrawals, relative to lagged cash holdings in $t-3$. In other words each observation of firm i at time t is split according to the three securities s. The binary variables CC_{st} and $Cash_{st}$ identify separately flows to payments of credit cards and use of internal cash, with loan payments being the omitted baseline category. $Shock_{it}$ is defined in three ways: $FinWorse_{it}$, $Uncertainty_{it}$, $Sharelate_{it}$. $FinWorse_{it}$ is a binary variable equal to one if firm i reported worsening financial conditions in the past three months. $Uncertainty_{it}$, is a binary variable equal to one if firm i reported to be somewhat or very unconfident about their sales revenue forecast over the next quarter. $Sharelate_{it}$ is the ratio between the total amount

of late invoices relative to the total amount of invoices. Importantly, *Log CC Use* holds constant the usage of credit cards by firm i at time t and therefore the specification isolates the choice of paying into the card. The specification also includes additional controls for the lagged level of log cash holdings, quarterly revenues, as well as η_i firm fixed effects and δ_t time- fixed effects at the quarterly level. Standard errors are clustered at the firm level.

Table 1 reports the estimates for the change in a firms payment allocation for credit cards, loans, and cash withdrawals. The number of observations across the three columns varies either because survey questions were introduced at different points in time, or because they rely on customers using the invoicing functionalities on the platform.

Column 1 presents estimates for the differential impact of the financial shock on payments allocated to credit cards, loans, and cash withdrawals. The level differences on the credit card and withdrawal dummies are consistent with the descriptive evidence in Figure 6 and with the traditional pecking order theories. Firms rely primarily on internal cash to finance their operations. Amongst the external sources of financing the share of payments devoted to credit cards is 3.5% points higher relative to loans. The interaction between each instrument and the shock reveals that the main margin of adjustment for firms, in reaction to a financial shock, is to reduce their payments into credit cards by 3.2% points. Holding constant the usage of the credit card this indicates that entrepreneurs are relying more on credit card financing by paying down less of their usage. Column 2 confirms the finding using uncertainty about cash flows as a shock to their financial payment structure. The estimates again suggest that, in response to this uncertainty, firms do not alter their use of internal cash as the coefficient is not only statistically insignificant but also economically small. Instead they again adjust payments into credit cards downwards. Finally, in column 3, we estimate the adjustment in the financing of the firm using the share of unpaid and late invoices. Similar to columns 1 and 2, we find no adjustment of payments in terms of internal cash or loans. The main margin is again a lowering of the payment into the credit cards, a one standard deviation increase of such late invoices lowering payments into credit cards by 1.1% points (.34*-.033). Thus, exploiting three distinct sources of cash flow and financing uncertainty at the firm level we find evidence consistent with the special role of credit cards in smoothing out these shocks.

5 Impact of Credit Card Debt Supply on Small Businesses Outcomes

The previous section documented the prevalence and use of credit cards among small businesses. In this section, we use the richness of transaction level data to study how the supply of credit financing impacts real outcomes of these businesses with an emphasis on their revenues, employment, and debt burden. We proceed in two steps, first we identify a differential credit card supply shock to small firms based on their banking partners during the 2022 monetary policy tightening. We then use differences in the exposure to this credit card debt shock across firms to

TABLE 1: RESULTS

	Dependent variable: Share of Payment Flows		
	(1) Financial Constraints	(2) Uncertainty	(3) Late Payments
Shock_{it}	0.033	0.004	0.014
	(0.034)	(0.016)	(0.035)
$\mathbb{1}(\text{CC}_{st})$	0.035**	0.045***	0.045***
	(0.016)	(0.005)	(0.012)
$\mathbb{1}(\text{Cash}_{st})$	1.039***	0.988***	1.026***
	(0.035)	(0.011)	(0.025)
$\mathbb{1}(\text{CC}_{st}) \times \text{Shock}_{it}$	-0.032*	-0.033***	-0.033*
	(0.019)	(0.009)	(0.017)
$\mathbb{1}(\text{Cash}_{st}) \times \text{Shock}_{it}$	0.020	-0.007	-0.029
	(0.045)	(0.030)	(0.043)
$\text{Log Cash Holdings}_{i,t-3}$	-0.090***	-0.109***	-0.112***
	(0.024)	(0.013)	(0.020)
$\text{Log Revenues}_{i,t-3}$	0.060***	0.040***	0.072***
	(0.020)	(0.007)	(0.017)
Log CC Use_{it}	0.016***	0.010***	0.008**
	(0.005)	(0.002)	(0.004)
Year*Quarter FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Observations	2,244	11,748	5,551
R-squared	0.736	0.699	0.718

Notes: The dependent variable, *Share of Payment Flows*, is the ratio of total cash flows in month t allocated to security s (loan payments, credit card payments, or cash withdrawals) relative to lagged cash holdings in $t-3$. CC_{st} and $Cash_{st}$ are binary variables identifying credit card usage and internal cash, respectively, with loan payments as the omitted baseline. *Log CC Use* measures total credit card usage by firm i at time t. The variable $Shock_{it}$ is defined differently across columns: in column (1) as $FinWorse_{it}$, a binary indicator for worsening financial conditions in the past three months; in column (2) as $Uncertainty_{it}$, a binary indicator for being somewhat or very unconfident about next-quarter sales forecasts; and in column (3) as $Sharelate_{it}$, the ratio of late invoices to total invoices. *Log Lagged Revenues* represents total revenues in the previous quarter, while *Log Lagged Quarterly C&S* denotes the log of checking and savings account balances in the previous quarter. The specification includes firm and quarterly time-fixed effects. The survey sample comprises 5,602 U.S. businesses across six quarters (TBC), with varying sample sizes due to wave-specific questions and response rates. Survey data cover $FinWorse_{it}$ and $Uncertainty_{it}$, while other variables are derived from platform data. Standard errors are clustered at the firm level. $*p < 0.1$, $**p < 0.05$, $***p < 0.01$.

study its impact on real outcomes.

5.1 Credit Card Debt Supply Shock

The monetary policy rate hikes at the beginning of 2022 were among the sharpest in recent history. The rates increased nine times over a period of twelve months, rising from nearly zero to five percentage points. The magnitude and speed of rate hikes came as a surprise to the banking system and led to the failures of intermediaries such as Silicon Valley Bank, First Republic Bank, and Signature Bank. Importantly, for our analysis, there was significant heterogeneity in the exposure of banks to this interest rate shock. The heterogeneity is in large parts driven by the mis-match in interest rate exposures of a banks' assets and liabilities (Mishkin and Eakins, 2006; Gomez et al., 2021). Gomez et al. (2021) show, using data across a long time horizon, that this exposure impacts the supply of long term debt and its price for large firms; here we show that it matters equally for credit card financing of small firms.

5.1.1 Bank Heterogeneity: Income Gap

The main measure we use to study heterogeneity in the exposure of different banks to the monetary policy shock is the bank's income gap (Mishkin and Eakins, 2006; Gomez et al., 2021) defined as follows:

$$\text{Income Gap}_{bt} = \frac{\text{RSA}_{bt} - \text{RSL}_{bt}}{\text{Total Assets}_{bt}}$$

where the gap is the difference between the dollar value of assets (RSA_{bt}) that reprice or mature within a year and the dollar value of liabilities (RSL_{bt}) that reprice or mature within a year; both normalised by the bank's total assets. Appendix B.1 details the construction of the income gap variable at the Bank Holding Company level (BHC). We report the summary statistics on the income gap and other BHC level control variables such as net assets and equity ratio in Table B.3. Our sample includes 192 banks with a mean income gap of 0.16 and a standard deviation of 0.21.

Intuitively, a tightening of monetary policy acts as a positive income shock for banks with a positive income gap, thus alleviating potential constraints on lending. By contrast, banks which see a *relative* decline in their income due to the duration mismatch on their assets and liabilities might directly reduce new credit supply to its customers and/or pass on the rates more aggressively to borrowers to make up for the short-fall in income. These changes in lending standards cause the supply of credit card debt and the price of credit card debt to vary across firms depending on their banking partners. The next two subsections provide evidence on the transmission of monetary policy into lending along with the methodological specifications.

5.1.2 Income Gap and Credit Card Interest Rate

To motivate our method for assessing banks' exposure to these policy changes, we begin by comparing how banks with varying income gaps set interest rates on credit card products since 2021 and during the period of monetary tightening. In the beginning of March 2022, the Federal Funds Rate was zero but over the course of the next year it was increased nine times to reach five percent per annum. We test whether this rate hike was passed on heterogeneously by different banks depending on their income gap. Specifically we run the specification in Eq. 2.

$$\text{APR}_{bt} = \omega_b + \delta_t + \sum_{k=-4}^{4} \beta_k \text{gap}_{b,k} + \sum_{x \in \text{Bank Controls}} \mu_x x_{b,t} + \epsilon_{bt} \tag{2}$$

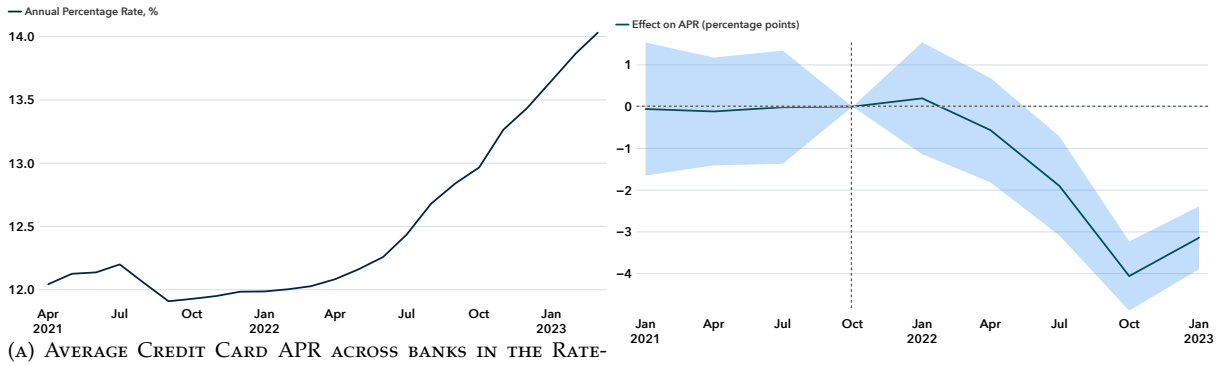
where the dependent variable APR_{bt} is the interest rate that bank b charged at time $t \in \{-4, ..., 0, 1, ..., 4\}$ i.e. four quarters before and after the March 2022 rate hikes measured using the RateWatch data, and $\text{gap}_{b,k}$ is the income gap of the bank as described in the previous section. A negative estimate of β would imply that banks with larger income gap tend to increase the interest rates *less* on credit card products as compared to banks with a lower or negative income gap. The specification also includes a vector $x_{b,t}$ of bank controls including log assets and equity ratio, as well as ω_b bank fixed effects and δ_t time-fixed effects at the quarterly level. Standard errors are clustered at the bank level. For the analysis in this section, we use RateWatch data on "Platinum Cards", as it is consistently reported over time for most intermediaries. We calculate the mean quarterly rates at the Bank Holding Company level by aggregating up over all the subsidiaries of the BHC. It's worth noting that estimates of the transmission channel in this sample might be relatively conservative, as platinum credit cards are typically linked to higher credit ratings. Additionally, some adjustments in bank lending policies may involve changes to credit limits, which are not captured directly in interest rate data (Agarwal et al. (2018); Rodano, Serrano-Velarde, and Tarantino (2018)).

Figure 8a first shows that the onset of monetary policy tightening coincided with a substantial rise in the average APR charged on credit cards, increasing by 2 percentage points, from 12% to 14%, between early 2022 and early 2023. We then test how the policy rates differentially affected credit card conditions by banks according to their income gap. More specifically, we estimate the dynamic specification in Eq. 2.

Figure 8b plots the coefficients estimated for β_k, measuring the differential change in APR across banks with different exposure to the interest rate change. They show, first of all, the absence of differential pre-trend in banks' lending policies before the tightening of monetary policy. Second, they suggest that, consistent with Gomez et al. (2021), differences in income gaps across banks transmit into the setting of interest rates on credit cards. More specifically, the figure suggests that banks with a high income gap kept their rates significantly lower with respect to banks

with a low income gap. In terms of magnitude, a one standard deviation in the gap measure of translates into a .84 (-4*.21) percentage point lower APR charged after the policy change.

FIGURE 8: APR AND INCOME GAP



(A) AVERAGE CREDIT CARD APR ACROSS BANKS IN THE RATEWATCH DATA

(B) INCOME GAP AND INTEREST RATES

Notes: Panel (A) plots the Average APR for Platinum Credit Cards in the RateWatch data. Panel (B) plots the estimates of the coefficient β_k from the specification in Eq. 2 i.e. $\text{APR}_{bt} = \omega_b + \delta_t + \sum_{k=-4}^{4} \beta_k \text{gap}_{b,k} + \sum_{x \in \text{Bank Controls}} \mu_x x_{b,t} + \epsilon_{bt}$. Here β_k measures the effect of income gap on the APR charged by the Bank.

5.1.3 Income Gap and Credit Card Debt Supply for Small Businesses

Our estimates of Eq. 2 provide useful initial evidence for assessing how banks' income gaps influence their credit card lending policies. However, these estimates might be biased if credit demand and supply shocks are correlated. To address endogeneity concerns in lending terms, we shift our analysis to transaction-level data. Specifically, the QuickBooks customer data enables us to apply the framework outlined in Khwaja and Mian (2008) to analyze the bank lending channel by leveraging information on firms borrowing simultaneously from multiple banks. We begin with the following specification to estimate credit card-level outcomes for small firms:

$$\begin{aligned} \log CC_{i \to b,t} = \delta_{i,t} + \omega_b + \alpha(\text{gap}_{i \to b,t-1} \times \Delta\text{Fed Funds}_t) + \sum_{x \in \text{control}} \mu_x (x_{i \to b,t-1} \times \Delta\text{Fed Funds}_t) \\ + \phi \text{gap}_{i \to b,t-1} + \sum_{x \in \text{control}} \psi_x x_{i \to b,t-1} + \phi_1 \log \text{ Loan Payments}_{i \to b,t-1} \\ + \phi_1 \log \text{ Cash Holdings}_{i \to b,t-1} + \epsilon_{i,b,t} \end{aligned} \tag{3}$$

where $\log CC_{i \to b,t}$ is the financing outcome for firm i borrowing from bank b in quarter t, $\text{gap}_{i \to b,t-1}$ denotes the lagged income gap of bank b in quarter $t-1$, and $x_{i \to b,t-1}$ denotes additional controls for lagged characteristics of bank b in quarter $t-1$. The specification includes fixed effects for the firm-quarter, $\delta_{i,t}$, and bank, μ_b. The standard errors are clustered at the firm-quarter and bank levels. We study four different credit card outcomes for the firms in our sample: credit card balances, usage, payments, interest payments, with detailed definitions in

Appendix B. In addition to the income gap, we also control for other bank characteristics that may affect credit card debt supply, such as bank assets and equity ratios. Importantly, our data also allows us to control for log loan payments and log cash holdings of firm i at bank b, isolating the effect on credit cards from other possible sources of transmission.

In this context, α, the interaction term between $\text{gap}_{i \to b, t-1}$ and $\Delta\text{Fed Funds}_t$, captures how variations in banks' exposure to interest rate risk impact their lending behavior in response to a tightening of monetary policy. By including firm-time fixed effects, denoted as $\delta_{i,t}$, we can distinguish between demand and supply shocks by focusing on borrowers that engage with multiple banks in a given quarter. Essentially, this methodology leverages within-firm-quarter variations in lending across banks with differing exposures to monetary policy shocks, thereby allowing to flexibly control for demand shocks experienced by firms.

Results Table 2 reports the estimates for the change in bank credit card lending after the monetary policy hikes. Column 1 presents estimates for the differential impact of the policy tightening on credit card balances. The interaction between the lagged income gap of intermediaries and changes in monetary policy rates is positive and statistically significant. It suggests that banks with a higher income gap are less likely to restrict their credit card supply compared to those with a lower income gap. These banks hold relatively more interest-sensitive assets, causing their income and lending capacity to rise following a policy rate increase. Economically, the magnitude of the differential lending adjustment is substantial. A one percentage point increase in the FED's policy rate leads banks with an income gap one standard deviation below the mean to reduce their credit card financing by 3.15% (0.21*0.15) relative to banks at the mean. Over the course of a monetary tightening in which policy rates increased by five percentage points, the lending shock to small businesses interacting with low income gap banks would amount to a 15.75% reduction in credit card balances as compared to the high income gap banks.

Column 2 confirms that small business usage of credit cards diverged across banks with high versus low income gaps. Once again, the interaction term yields a positive and statistically significant coefficient. Interestingly, the magnitude of the increase in credit card usage is more pronounced than the change in credit balances. This is because, as shown in column 3, payments into these credit card accounts also increased significantly over the period but less so as compared to their usage — driving up the borrowing.

TABLE 2

	Dependent variable:				
	log CC balance	log CC usage	log CC payments	log CC interest	Interest > 0
	(1)	(2)	(3)	(4)	(5)
$\text{gap}_{t-1} \times \Delta\text{FFR}_t$	0.150^{**}	0.415^{***}	0.390^{***}	0.799^{**}	0.141^{**}
	(0.060)	(0.070)	(0.112)	(0.331)	(0.065)
gap_{t-1}	-0.763^{***}	-1.444^{***}	-1.303^{***}	0.155	0.162^{*}
	(0.090)	(0.194)	(0.298)	(0.419)	(0.083)
$\text{loan payments}_{t-1}$	0.024^{***}	0.027^{***}	0.010	0.004	0.001
	(0.006)	(0.005)	(0.006)	(0.006)	(0.001)
$\text{log cash balance}_{t-1}$	0.933^{***}	0.953^{***}	0.938^{***}	0.550^{***}	0.078^{***}
	(0.050)	(0.052)	(0.066)	(0.034)	(0.005)
Firm-Quarter FE	Y	Y	Y	Y	Y
Bank FE	Y	Y	Y	Y	Y
Bank Level Controls	Y	Y	Y	Y	Y
Observations	1,934,518	1,934,518	1,932,546	1,934,518	1,934,518
R^2	0.713	0.706	0.707	0.800	0.782

Notes: This table presents estimates of α and ϕ from the regression:$\log CC_{i\to b,t} = \delta_{i,t} + \omega_b + \alpha(\text{gap}_{i\to b,t-1} \times \Delta\text{Fed Funds}_t) + \sum_{x\in\text{control}} \mu_x(x_{i\to b,t-1} \times \Delta\text{Fed Funds}_t) + \phi\text{gap}_{i\to b,t-1} + \sum_{x\in\text{control}} \psi_x x_{i\to b,t-1} + \phi_1\log\text{ loan payments}_{t-1} + \phi_2\log\text{ cash balance}_{t-1} + \epsilon_{i,b,t}$. Firm is denoted by i, and the bank is denoted by b; δ_{it} . Firm is denoted by i, and the bank is denoted by b; δ_{it} denotes firm-quarter fixed effects and ω_b denotes bank fixed effects. It differs from the main specification in Sec 5 as it doesn't includes any bank controls except for the income gap. Each column represents results for a credit card level dependent variable i.e. Credit Card Balances, Usage, Payments, Interest Charged Amount and a Dummy for Interest Charged of firm i's credit card from bank b. Appendix B provides a detailed description of the variables. The main independent variable is $(\text{gap}_{i\to b,t-1} \times \Delta\text{Fed Funds}_t)$ which is an interaction of the bank b's income gap last quarter with the change in Federal Funds rate. ΔFFR is measured in percentage points i.e. it takes a value 1 if Fed Funds Rate goes from 4% to 5%. The standard errors are clustered at the firm-quarter level. The regression also controls for two other bank variables $x \in \{\log \text{assets}, \text{equity ratio}\}$ to isolate the effect of income gap. $*p < 0.1, **p < 0.05, **p < 0.01$.

Columns 4 and 5 provide estimates of how monetary policy shocks are transmitted through borrowing i.e. interest payments on credit cards. Specifically, column 4 provides estimates on the amount of credit card interest payments of firm i to bank j in period t. Column 5 provides estimates from a linear probability model where the dependent variable is a dummy for whether an interest was charged on firm i from bank b in period t. In column 4, the coefficient on the interaction term is positive and large, indicating that total interest payments differed substantially between credit cards issued by banks with varying income gaps. Over the course of the monetary tightening, small businesses accumulated 84% (.21*0.799*5) more interest payments with credit cards from banks with a high income gap. Similarly, column 5 shows that small businesses

started paying interest in credit card account with high income gap banks. Following a one percentage point increase in FED rates, small businesses had a 3 percentage point (0.21 * 0.141) higher probability of paying interest on credit card accounts at banks with income gaps one standard deviation above the mean.

5.1.4 Income Gap and Credit Card Debt Supply: Dynamic Effects

We next extend the analysis to examine the dynamic effects associated with the bank lending channel. To do so, we estimate the impact of the income gap on our dependent variables for each quarter, both before and after the first rate hike in March 2022.

$$\begin{aligned}\log CC_{i\to b,t} = \delta_{i,t} + \omega_b + \sum_{k=-4}^{4} \alpha_k \text{gap}_{i\to b,k} + \sum_{k=-4}^{4} \sum_{x\in\text{control}} \mu_{x,k} x_{i\to b,k} + \phi \text{gap}_{i\to b,t-1} \\ + \phi_1 \log \text{ Loan Payments}_{i\to b,t-1} + \phi_2 \log \text{ Cash Holdings}_{i\to b,t-1} + \epsilon_{i,b,t}\end{aligned} \tag{4}$$

Importantly, this specification allows us to assess the potential presence of differential pre-trends in banks' credit card policies before the policy shock. Given that the Fed Funds Rate was nearly zero for the four quarters preceding March 2022, the banks' income gap should have had no significant effect on any of the outcome variables during this period. However, as rates began to rise, if the income gap accurately reflects exposure to interest rate risk, we would expect to observe differential changes in credit card policies following March 2022.

Results Figures 9a, 9b, 10a, and 10b display the estimates from the dynamic specification in Eq. 4. These plots illustrate the differential impact of banks' income gaps on small businesses' credit card usage, payments, balances, and interest charges over time.

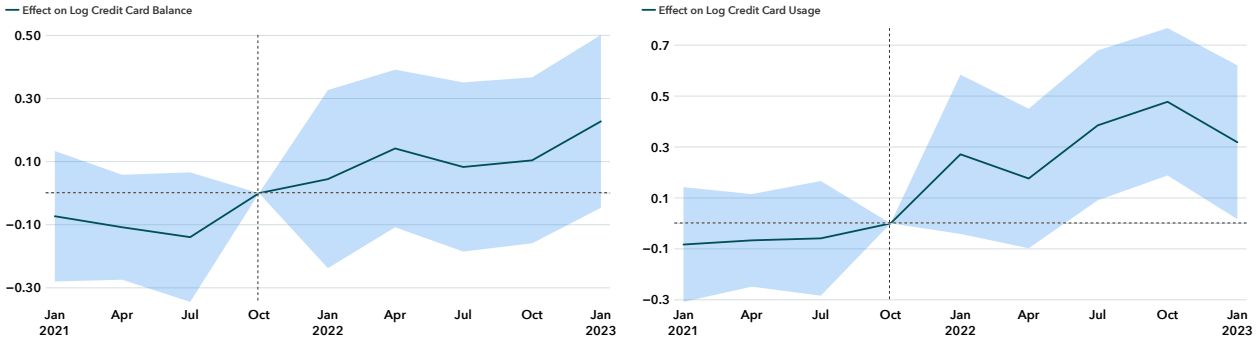
Two key insights emerge from these estimates. First, they confirm that prior to the FED's policy change—marked by the dotted vertical line—credit card supply across banks with different income gaps followed similar trends. In the four quarters preceding the monetary policy shift, when the Fed Funds Rate was effectively zero and banks faced no differential interest rate risk, we cannot reject the null hypothesis that $\alpha_k = 0$ for $k = -1$ to -4 at the 5% confidence level. However, after March 2022, when the Fed began raising rates, financial intermediaries started adjusting their credit card lending practices based on their interest rate exposure, as captured by their income gap. In every case, we observe a gradual adjustment in these policies that aligns with the successive policy rate hikes.

5.1.5 Robustness Checks

We next assess the robustness of our estimates for the transmission mechanism of monetary policy into credit card lending. We begin by estimating Equation 3, but including only fixed effects and no additional controls. The estimates for this specification are presented in Table C.1

in Appendix C. Next, we alternatively fix the income gap level to its March 2022 value, coinciding with the moment of the policy tightening. Results are shown in Table C.2 in Section C. Finally, in Table C.3, we extend the main specification by adding bank characteristics that can interact with the transmission of monetary policy. In all cases estimates remain qualitatively unchanged. Our estimates therefore provide consistent evidence for the credit card lending channel of monetary policy at the firm-bank level.

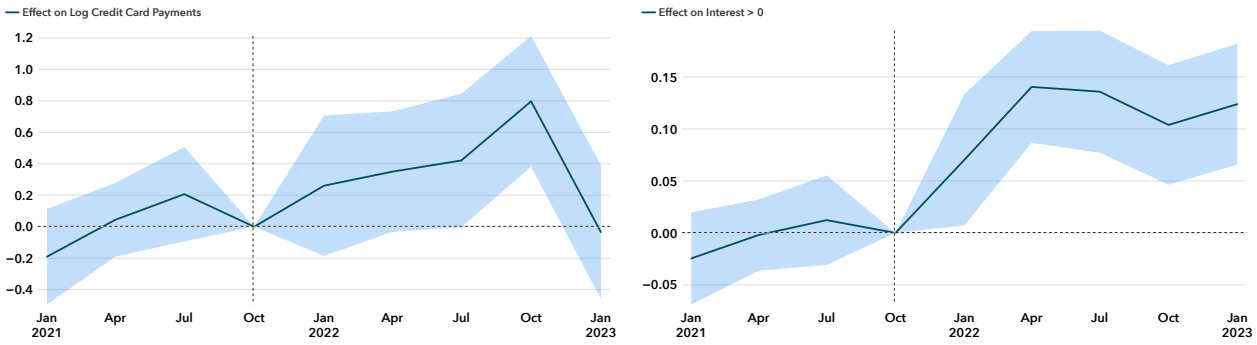
FIGURE 9: DYNAMICS



(A) CC BALANCES (B) CC USAGE

Notes: The figure presents estimates of α_k for $k = -4$ to 4 i.e. four quarters pre and post the rate hikes beginning in March 2022, from the regression: $L_{i\to b,t} = \delta_{i,t} + \mu_b + \sum_{k=-4}^{4} \alpha_k \text{gap}_{i\to b,k} + \sum_{k=-4}^{4} \sum_{x\in\text{control}} \gamma_{x,k} x_{i\to b,k} + \phi \text{gap}_{i\to b,t-1} + \phi_1 \log \text{ Loan Payments}_{i\to b,t-1} + \phi_2 \log \text{ Cash Holdings}_{i\to b,t-1} + \epsilon_{i,b,t}$. The regression includes fixed effects at the firm-quarter and the bank level. The dependent variable in panels (A) and (B) is the credit card balance and credit card usage of firm j from bank i in period t.

FIGURE 10: DYNAMICS



(A) CC PAYMENTS (B) INTEREST > 0

Notes: The figure presents estimates of α_k for $k = -4$ to 4 i.e. four quarters pre and post the rate hikes beginning in March 2022, from the regression: $L_{i\to b,t} = \delta_{j,t} + \mu_b + \sum_{k=-4}^{4} \alpha_k \text{gap}_{i\to b,k} + \sum_{k=-4}^{4} \sum_{x\in\text{control}} \gamma_{x,k} x_{i\to b,k} + \phi \text{gap}_{i\to b,t-1} + \phi_1 \log \text{ Loan Payments}_{i\to b,t-1} + \phi_2 \log \text{ Cash Holdings}_{i\to b,t-1} + \epsilon_{i,b,,t}$. The regression includes fixed effects at the firm-quarter and the bank level. The dependent variable in panels (A) and (B) is the credit card payments and a dummy for whether an interest was charged on firm j from bank b in period t.

A key question is whether supply shocks at the firm-bank relationship level also affect firm-level borrowing. Firms might mitigate bank-specific credit card supply shocks by borrowing

from other banks or turning to alternative financing sources. To address this concern, Table C.4 presents firm-level estimates, controlling for the same variables related to credit card usage and including granular sector-time and region-time fixed effects. The results indicate that firms are unable to fully offset the credit card supply shocks from their banking partners. This highlights the importance of tracking these shocks to assess their impact on the real outcomes of small businesses.

5.2 Real Effects of Credit Card Debt on Small Business Revenue and Employment

Using the relationship between bank income gap and credit card debt supply, we next turn to the question of whether the changes to the supply of credit card financing impacted real outcomes and growth dynamics of small firms. To do so, we leverage the quarterly level information about revenues and employment and estimate the following specification at level of firm i in quarter t:

$$\begin{aligned}\Delta Y_{it} = \eta_i + \delta_t + \alpha(\overline{\text{gap}}_{i,t-1} \times \Delta\text{Fed Funds}_t) + \phi\overline{\text{gap}_{i,t-1}} + \phi_1 \log \text{Loan Payments}_{i,t-1} \\ + \phi_2 \log \text{Cash Balance}_{i,t-1} + \sum_{x \in \text{Bank Controls}} \mu_x \overline{x_{i,t-1}} + \varphi_{SIC,t} + \psi_{Zip,t} + \epsilon_{it}\end{aligned} \tag{5}$$

where the dependent variable, ΔY_{it}, is the change in log revenues and log employment for firm i between quarter t and $t-1$. The exposure to the monetary policy shock, $\overline{\text{gap}}_{i,t-1}$, is now defined as the weighted average of the income gap of banks that extend credit cards to firm i, where weights are based on credit card usage by the firm i of bank j. Again $\overline{x_{i,t-1}}$ denote additional controls for lagged banks characteristics that are weighted across intermediaries that finance firm i in quarter $t-1$. To disentangle the credit card channel of monetary policy from other sources of firm financing we simultaneously control for loan payments and cash balances. *Loan Payments*$_{i,t-1}$ measures the total loan payments made by firm i in quarter $t-1$. *Cash Balance*$_{i,t-1}$ measures the total cash balance of firm i in quarter $t-1$. Finally, the specification includes fixed effects at the level of the firm (ω_i), time (δ_t), ZIP code by time ($\psi_{Zip,t}$), and industry by time ($\varphi_{SIC,t}$). Standard errors are double clustered at the firm and state level.

The specification is similar in spirit to those in the previous section albeit with two significant differences. First, we can't use the same identification strategy to isolate the effects of monetary policy. In the previous section we relied on the variation in the gap across banking partners while controlling for interacted firm and time fixed effects ($\delta_{j,t}$). We can't follow the same strategy to estimate firm outcomes. We can however include detailed interactions of local area and time fixed effects, ($\psi_{Zip,t}$), under the assumption that firms in a local area experience similar demand shocks. The identification now comes from the variation in exposure of banking partners to the monetary shock within the local areas. Similarly we can include interactions in industry and time fixed effects, ($\varphi_{SIC,t}$), to control for industry specific demand shocks across time. Second, for employment outcomes, we observe information only for firms that also make use of the payroll

software, thereby reducing the sample size.

Results For our first set of results we focus on the sample of firms that have more than one banking partner for consistency with the previous section. Tables 3 and 4 provide two insights. First, firms that experienced a larger decrease in access to credit cards were unable to sustain employment and revenue growth in the short run. Second, consistent with the role of credit cards in financing day-to-day operations at the firm, the most economically significant impact materializes in terms of constraints on small firms growing their revenues. The effects on employment are however not trivial suggesting credit cards also help managing payroll.

Table 3 provides estimates for the impact of supply shocks by credit card providers on quarterly growth rates of revenue. The average quarterly sales growth of small US businesses during this period was on average 1.4%. Column (1) suggests that a 1 standard deviation lower income gap of credit card providers combined with a 1 percentage point increase in monetary policy rates lead to 2.1% (.21*.1) lower quarterly revenue growth for firms. The estimates are robust to the inclusion in columns (2) to (5) of controls for the usage of loan financing and cash balances. This supports the idea that credit cards are crucial source of financing for daily business operations within the financing hierarchy. Column (4) includes additional characteristics of credit card providers, while column (5) further controls for geography and industry-level shocks common to small businesses over time.

Table 4 provides the estimates for the impact of credit card constraints on employment growth. The estimates in column (1) suggest that a standard deviation lower income gap by credit card providers results in a 0.3% (.21*.013) decrease in quarterly employment growth of firms. The monetary tightening by five percentage points therefore translates into a 1.5% lower employment growth. These effects are not trivial if we consider that between March 2021 and March 2022 – the year before the FFR started rising, the United States small business population (with between 1 and 9 employees) employed almost 14 million workers, and experienced annual net growth of 5.9%, adding over 815,000 jobs.[17] A 1.5% decline represents a 25% decline in growth rates directly from the monetary policy response from our most conservative estimate but could have been more than twice as much. Column (2) controls for reliance on loan financing by small firms, column (3) controls for cash balances, and column (4) also includes a lagged control for firm revenues. As before, columns (5) and (6) add characteristics of intermediaries and flexible controls for demand shock across the industry and geography dimension. The point estimates are similar in magnitude even though the inclusion of additional fixed effects shrinks the sample and estimates are not statistically significant.

[17] Estimates from the U.S. Census Bureau, Longitudinal Business Dynamics statistics, 2022.

TABLE 3

	Dependent variable:				
	Δ log Revenue$_t$				
	(1)	(2)	(3)	(4)	(5)
$\overline{\text{gap}}_{t-1} \times \Delta$ FFR$_t$	0.102***	0.102***	0.102***	0.107***	0.063***
	(0.012)	(0.012)	(0.012)	(0.012)	(0.021)
$\overline{\text{gap}}_{t-1}$	−0.073***	−0.073***	−0.073***	−0.137**	−0.058
	(0.018)	(0.018)	(0.018)	(0.056)	(0.094)
log loan payments$_{t-1}$		−0.071	−0.070	−0.071*	−0.070
		(0.045)	(0.045)	(0.038)	(0.059)
log cash balance$_{t-1}$			−0.027***	−0.027***	−0.025***
			(0.001)	(0.001)	(0.002)
$\overline{\text{log assets}}_{t-1}$				−0.001	−0.001
				(0.001)	(0.002)
$\overline{\text{equity ratio}}_{t-1}$				0.514**	0.122
				(0.255)	(0.431)
Firm FE	Y	Y	Y	Y	Y
Quarter FE	Y	Y	Y	Y	N
Region Quarter FE	N	N	N	N	Y
Sector Quarter FE	N	N	N	N	Y
Observations	1,004,682	1,004,682	1,003,148	1,003,148	582,068
R^2	0.128	0.128	0.129	0.129	0.397

Notes: This table presents estimates from the regression: $\Delta\log \text{Revenue}_{it} = \eta_i + \delta_t + \alpha(\overline{\text{gap}}_{i,t-1} \times \Delta\text{Fed Funds}_t) + \phi\overline{\text{gap}_{i,t-1}} + \phi_1 \text{Loan}_{i,t-1} + \phi_2 \text{Cash Balance}_{i,t-1} + \sum_{x\in\text{Bank Controls}} \mu_x \overline{x_{i,t-1}} + \varphi_{SIC,t} + \psi_{Zip,t} + \epsilon_{it}$. Firm is denoted by i and η_i and δ_t represent firm and quarter fixed effects. The dependent variable measures the change in log revenues of the firm as compared to the last quarter. The main independent variables $+\phi\overline{\text{gap}_{i,t-1}}$ and $\alpha(\overline{\text{gap}}_{i,t-1} \times \Delta\text{Fed Funds}_t)$ are the usage-weighted average income gap of the firm's credit card banking partners and it's interaction with the change in federal funds rate. To ensure that the effects are not driven by long term loan supply for the firm we control lagged loan payments and also control for two additional bank level variables: $\overline{\text{log assets}}_{t-1}$, $\overline{\text{equity ratio}}_{t-1}$ which are again, usage-weighted, average log assets and equity ratio of the firm's banking partners. Column (1) presents the baseline results with no additional controls. Column (2)-(3) successively add control for loan payments and other bank level variables. Column (4) adds region-quarter and sector quarter fixed effects. A sector is defined at the two digit NAICS level and the region is defined at the five digit zip code level. $*p < 0.1$, $**p < 0.05$, $**p < 0.01$.

TABLE 4

	Dependent variable:					
	Δ log Employment$_t$					
	(1)	(2)	(3)	(4)	(5)	(6)
$\overline{\text{gap}}_{t-1} \times \Delta$ FFR$_t$	0.013*	0.013*	0.013*	0.015**	0.017**	0.023
	(0.007)	(0.007)	(0.007)	(0.008)	(0.008)	(0.018)
$\overline{\text{gap}}_{t-1}$	−0.007	−0.007	−0.006	−0.012	0.034	0.087
	(0.010)	(0.010)	(0.010)	(0.012)	(0.034)	(0.085)
log loan payments$_{t-1}$		−0.0004	0.002	−0.018	−0.023	−0.012
		(0.014)	(0.013)	(0.026)	(0.027)	(0.084)
log cash balance$_{t-1}$			−0.005***	−0.005***	−0.005***	−0.004**
			(0.001)	(0.001)	(0.001)	(0.002)
log revenue$_{t-1}$				−0.044***	−0.044***	−0.043***
				(0.002)	(0.002)	(0.003)
$\overline{\text{log assets}}_{t-1}$					−0.002***	−0.004***
					(0.001)	(0.001)
$\overline{\text{equity ratio}}_{t-1}$					0.154	0.423
					(0.159)	(0.391)
Firm FE	Y	Y	Y	Y	Y	Y
Quarter FE	Y	Y	Y	Y	Y	N
Region Quarter FE	N	N	N	N	N	Y
Sector Quarter FE	N	N	N	N	N	Y
Observations	203,926	203,926	200,945	172,618	172,618	108,338
R^2	0.157	0.157	0.156	0.178	0.179	0.762

Notes: This table presents estimates from the regression: $\Delta\text{log Employment}_{it} = \eta_i + \delta_t + \alpha(\overline{\text{gap}}_{i,t-1} \times \Delta\text{Fed Funds}_t) + \phi\overline{\text{gap}}_{i,t-1} + \phi_1\text{Loan}_{i,t-1} + \phi_2\text{Revenue}_{i,t-1} + \phi_3\text{Cash Balance}_{i,t-1} + \sum_{x\in\text{Bank Controls}} \mu_x\overline{x_{i,t-1}} + \varphi_{SIC,t} + \psi_{Zip,t} + \epsilon_{it}$. Firm is denoted by i and η_i and δ_t represent firm and quarter fixed effects. The dependent variable measures the change in log employment of the firm as compared to the last quarter. The regression sample is a set of firm for which we consistently observe employment information over our sample period. The main independent variables $+\phi\overline{\text{gap}}_{i,t-1}$ and $\alpha(\overline{\text{gap}}_{i,t-1} \times \Delta\text{Fed Funds}_t)$ are the usage-weighted average income gap of the firm's credit card banking partners and it's interaction with the change in federal funds rate. To ensure that the effects are not driven by long term loan supply for the firm we control lagged loan payments and also control for two additional bank level variables: $\overline{\text{log assets}}_{t-1}$, $\overline{\text{equity ratio}}_{t-1}$ which are again, usage-weighted, average log assets and equity ratio of the firm's banking partners. Additionally to isolate the effect of credit supply from other shocks to the firm the regression also controls for the lagged log Revenue at the firm level. Column (1) presents the baseline results with no additional controls. Column (2)-(3) successively add control for loan payments and other bank level variables. Column (4) adds region-quarter and sector quarter fixed effects. A sector is defined at the two digit NAICS level and the regions are defined at the five digit zip code level. $*p < 0.1$, $**p < 0.05$, $***p < 0.01$.

5.2.1 Robustness Checks

The estimates for employment growth rates are smaller than for revenue growth, but they need to be qualified in two important ways. First, the revenue sample includes businesses without employees that are on average smaller and likely more volatile. Table C.5 in Appendix C shows that the magnitude of the revenue effects is reduced by 1/2 when we limit the revenue sample to firms with employment. We further assess the sensitivity of the employment estimates to the addition to the sample of employers with a single banking relationship, which includes smaller firms in Appendix C, Table C.6. The full employment sample consists of about 355,000 unique firms. The estimates are strongly significant and 2.5 times larger suggesting significantly higher employment effects when considering the full population of small businesses. Results are significant even after including fixed effects for the geography by quarter and industry by quarter interactions. Second, information on employment and revenue is conditional on platform participation and as such we are not able to quantify the impact on the exit margin. Thus our estimates likely under-estimate the total impact of credit card supply shocks.

Appendix C Table C.7 provides equivalent revenue estimates for the full set of firms. The revenue sample consists 1.9 million firms. Our estimates for α, the coefficient which measures the effect of average income gap (interacted with Fed Funds Rate) on firms real outcomes, remains robust.

5.3 Credit Card Overhang

The previous results highlight the critical role of credit card financing in supporting U.S. business activities. In particular, the ability to draw on existing credit card limits enables small businesses to navigate firm-level and aggregate shocks. However, this access comes at a cost. As illustrated in Figures (5a) and (5b), entrepreneurs face a trade-off between the flexibility and accessibility of credit card financing and the heightened risk of escalating debt and interest payments.

We proceed to quantify the risks associated with credit card financing in the context of monetary policy transmission. Specifically, we assess how the monetary policy tightening led to escalating costs of credit card debt and increased repayment delinquencies among businesses. To this end, we estimate the following specification for firm i in quarter t:

$$\begin{aligned}\text{Delinquency}_{it} = \eta_i + \delta_t &+ \alpha_1 \text{Log CCard Interest}_{t-1} + \alpha_2 \text{Log CCard Interest}_{t-1} \times \Delta\text{FFR}_t \\ &+ \beta_1 \text{Log Loan Paymnts}_{t-1} + \beta_2 \text{Log Loan Paymnts}_{t-1} \times \Delta\text{FFR}_t \\ &+ \phi_1 \text{Log Cash Balance}_{t-1} + \phi_2 \text{Log Cash Balance}_{t-1} \times \Delta\text{FFR}_t \\ &+ \sum_{x \in \text{Firm Controls}} \mu_x x_{i,t-1} + \sum_{x \in \text{Firm Controls}} \tilde{\mu}_x x_{i,t-1} \times \Delta\text{FFR}_t + \epsilon_{it}\end{aligned}$$

The dependent variable, Delinquency_{it}, is a binary indicator equal to one if firm i incurred a late

fee on any of its credit card payments during quarter t. The variable Log CC Interest$_{t-1}$ represents the logarithm of the interest charged on firm i's credit cards in the previous quarter ($t-1$), while Log CC Interest$_{t-1} \times \Delta$FFR$_t$ captures the interaction between these interest payments and the change in the Federal Funds Rate (FFR) during quarter t. To flexibly account for variations in credit card usage and repayment practices, we include controls for CC Payments, CC Usage, and their interactions with changes in the Federal Funds Rate. Consistent with the approach in previous sections, we also consider the role played by access to alternative sources of financing for small firms and their interactions with monetary policy. Specifically, we include variables for loan payments (Log Loan Payments$_{t-1}$ and Log Loan Payments$_{t-1} \times \Delta$FFR$_t$) and internal cash stocks (Log Cash Balances$_{t-1}$ and Log Cash Balances$_{t-1} \times \Delta$FFR$_t$). To control for changes in firm demand, we include granular quarterly controls for revenues (Log Revenue$_{t-1}$). The model also incorporates fixed effects at multiple levels: firm (η_i), quarter (δ_t), quarter-SIC, and quarter-ZIP code fixed effects. The specification is estimated at the firm level to account for borrowers' joint optimization across multiple credit cards. Robust standard errors are clustered at the firm level and at the region-level to ensure accurate inference.

In our specification, the coefficient α_1 captures the relationship between credit card delinquencies and interest payments during periods of stable monetary policy. In contrast, α_2 reflects how this sensitivity changes when monetary policy rates increase. This coefficient therefore measures the extent to which firms can absorb or smooth the cost shock induced by such policy changes. If credit card financing represents a relatively minor source of funding, firms are likely to adjust their credit card usage or shift to alternative financing options, such as loans or internal cash reserves. Under this scenario, α_2 would be close to zero and economically insignificant. Conversely, if firms are unable to adjust their financing structure and the costs associated with credit card debt escalate, α_2 would be economically significant, particularly in comparison to α_1. To further investigate the link between financial constraints and the sensitivity of delinquencies to escalating interest payments, we also conduct a subsample analysis. Specifically, we split our estimation based on the levels of internal cash reserves and credit card interest payments in January 2022. Firms with positive interest payments just before the monetary tightening, as well as those with lower internal liquid cash during that period, are expected to exhibit greater sensitivity to the cost shock induced by the policy change.

Results Table 5 presents the estimated coefficients for the specification in the above Section. The columns progressively incorporate additional controls and interactions: measures of credit card usage and payment behavior (column 2), loan financing and cash holdings (column 3), and time interactions with industry and geographic factors (column 4). Across all specifications, the interaction term between lagged credit card interest rates and changes in the federal funds rate is positive and statistically significant. This result highlights the significant economic impact of monetary policy shocks in pushing firms toward unsustainable credit card terms. In column 4, the estimates indicate that a 1 percentage point increase in the monetary policy rate amplifies the

effect of a 10% higher prior interest payment on the probability of delinquency by an additional 0.048 percentage points. Over the entire period of monetary tightening, this cumulative effect translates to a 0.24 percentage point increase in the probability of delinquency.[18] This impact is notable, as average delinquency rates rose from 2.2% and peaked at 2.8% during the same period. Furthermore, the interaction term captures an effect that is substantial relative to the baseline level effect of interest payments during periods of stable monetary policy.

Table 5: Credit Card Delinquency and Rate Hikes

	Dependent variable:			
	Delinquency			
	(1)	(2)	(3)	(4)
log CC Interest$_{t-1}$ $\times\Delta$FFR$_t$	0.0048**	0.0049**	0.0045**	0.0045***
	(0.0022)	(0.0022)	(0.0022)	(0.0003)
log CC Interest$_{t-1}$	0.0049***	0.0045***	0.0044***	0.0045***
	(0.0016)	(0.0016)	(0.0015)	(0.0002)
CC Controls	N	Y	Y	Y
Loan and Cash Controls	N	N	Y	Y
Firm FE	Y	Y	Y	Y
Quarter FE	Y	Y	Y	N
Sector Quarter + Region Quarter FE	N	N	N	Y
Observations	988,862	976,819	966,391	961,678
R^2	0.43	0.43	0.43	0.44

The dependent variable is Delinquency$_t$ i.e. a dummy variable which is equal to one if the firm had a late charge posted on at least one of its credit cards in the current quarter. The independent variable log CC Interest$_{t-1}$ measures the log of the total interest charges paid by the firm in the preceding quarter and ΔFFR$_t$ measures the change in the Federal Funds Rate. First column of the table presents the baseline results with no additional controls and sector quarter and region quarter fixed effects. Column (2) controls for credit card level variables log CC Usage$_{t-1}$, log CC Usage$_{t-1}$ $\times\Delta$FFR$_t$, log CC Payments$_{t-1}$, log CC Payments$_{t-1}$ $\times\Delta$FFR$_t$. In column (3) we control other firm level controls: log Revenue$_{t-1}$, log Loan Payments$_{t-1}$, log Loan Payments$_{t-1}$ $\times\Delta$FFR$_t$, log Cash Balances$_{t-1}$ and log Cash Balances$_{t-1}$ $\times\Delta$FFR$_t$. Column (4) adds sector quarter and region quarter fixed effects in addition to the above controls. A sector is defined at the two digit NAICS level and the regions are defined as US States. $*p < 0.1$, $**p < 0.05$, $***p < 0.01$.

Table 6 presents the estimates from the full specification across various subsamples of firms. In columns (1) and (2), firms are categorized based on the median level of liquid cash stocks in January 2022. The sensitivity of delinquencies to interest payments is significantly higher for firms with low liquid cash stocks in column (2) compared to those with high liquid cash stocks in column (1). Additionally, firms with below-median liquid cash stocks exhibit a significantly greater sensitivity to the cost shocks associated with monetary tightening. Specifically, for these firms, a 5 percentage point increase in policy rates leads to a predicted increase in delinquencies of 0.23 percentage points. By contrast, for firms with above-median liquid cash stocks, the same

[18] A 1-unit increase in the log level variable raises the probability of delinquency by 0.0048 (or 0.48 percentage points). This implies that a 10% increase in prior interest payments increases delinquency probability by 0.048 percentage points. Over a 5-percentage-point monetary policy increase, the cumulative effect is 0.24 percentage points.

monetary tightening results in only a 0.15 percentage point increase in delinquencies. A similar pattern is observed in columns (3) and (4), where firms are split between those with no credit card interest payment in January 2022 and those with positive credit card interest payments, respectively. In column (4), firms with positive exposure to credit card debt at the start of the tightening were disproportionately more vulnerable to subsequent cost increases. The monetary policy tightening made higher initial interest payments unsustainable, leading to a 0.29 percentage point increase in delinquencies as opposed to only 0.11 percentage points for firms with no interest payments in January 2022. Taken together, these estimates suggest that the costs of credit card debt escalated following the tightening of monetary policy, particularly for financially vulnerable firms.

Table 6: Credit Card Delinquency and Rate Hikes

	Dependent variable: Delinquency			
	Cash Split		Interest Split	
	High Cash_{2022}	Low Cash_{2022}	$\text{Interest}_{2022} = 0$	$\text{Interest}_{2022} > 0$
	(1)	(2)	(3)	(4)
log CC Interest_{t-1} $\times \Delta\text{FFR}_t$	0.0031^{***}	0.0046^{***}	0.0023^{***}	0.0047^{***}
	(0.0004)	(0.0004)	(0.0007)	(0.0005)
log CC Interest_{t-1}	0.0047^{***}	0.0057^{***}	0.0038^{***}	0.0056^{***}
	(0.0004)	(0.0004)	(0.0012)	(0.0004)
Controls (CC, Loans, Cash)	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y
Quarter FE	Y	Y	Y	Y
Sector-Quarter	Y	Y	Y	Y
Region-Quarter FE	Y	Y	Y	Y
Observations	297,846	297,897	291,178	304,565
R^2	0.35	0.41	0.28	0.4

The dependent variable is Delinquency_t i.e. a dummy variable which is equal to one if the firm had a late charge posted on at least one of its credit cards in the current quarter. The independent variable log CC Interest_{t-1} measures the log of the total interest charges paid by the firm in the preceding quarter and ΔFFR_t measures the change in the Federal Funds Rate. The regression controls for log Revenue_{t-1}, log CC Usage_{t-1}, log CC Usage_{t-1} $\times\Delta\text{FFR}_t$, log CC Payments_{t-1}, log CC Payments_{t-1} $\times\Delta\text{FFR}_t$, log Loan Payments_{t-1}, log Loan Payments_{t-1} $\times\Delta\text{FFR}_t$, log Cash Balances_{t-1} and log Cash Balances_{t-1} $\times\Delta\text{FFR}_t$. The specifications also add sector quarter and region quarter fixed effects. A sector is defined at the two-digit NAICS level and the regions are defined as US States. High Cash_{2022} columns represents the results from running the regression on the sample which had above median cash balances in their checking/savings account prior to the rate hikes. Low Cash_{2022} similarly represents the results from the sample of the firms which had below median balances. $\text{Interest}_{2022} = 0$ is the sample of which firms which did not pay any interest on credit cards in January 2022 i.e. non-borrower firms. $\text{Interest}_{2022} > 0$ represents the sample of firms which had some amount of borrowing on their credit cards. $*p < 0.1$, $**p < 0.05$, $***p < 0.01$.

6 Implications for Small Business Aggregate Outcomes

In this section, we integrate the firm-level estimates from Sections 5.1 and 5.2 into a heterogeneous firm model that captures the key trade-offs of credit card financing versus long term loans in presence of idiosyncratic and aggregate shocks. We calibrate additional parameters of the model to match the amount of credit card debt, long term balances and revenues in our sample. We then use the calibrated model to illustrate the impact of credit card financing on the transmission of an interest rate hike and long term loan supply shocks to small business output.

The central friction in the economy is a cash-in-hand constraint, whereby entrepreneurs must finance labor and capital purchases before the realization of production output. In standard model of financial frictions, the firms are constrained on the amount of intra-period loans they can acquire to deal with the mis-match based only on their net assets (Jermann and Quadrini, 2012). We rather allow the entrepreneur to finance the purchases either by its liquid savings or importantly via credit card debt. In order to capture the fact that all input purchases may not be possible to be paid via credit cards such as wages and bank to bank transfers we assume that credit cards are an imperfect substitute for cash balances. The next section lays out the full model.

6.1 Environment

The time is continuous. There are a continuum $i \in [0, 1]$ of infinitely lived entrepreneurs in the economy who maximize their lifetime utility

$$\mathbb{E}_0 \int_0^\infty e^{-\rho t} u(c_{i,t}) dt$$

subject to the budget constraint. Here $c_{i,t}$ denotes consumption and $u(c_{i,t})$ denotes the flow utility. The expectation is with respect to the idiosyncratic productivity shocks z_{it} which the entrepreneur faces over time.

Entrepreneurs hold three types of assets—liquid savings ($a_{it} \geq 0$), credit card debt ($a_{it} < 0$) and long term loans ($m_{it} \geq 0$). The interest rate on liquid savings is r_t^a and the interest rate on credit cards is r_t^{CC} such that $r_t^{CC} > r_t^a$. We denote long term debt by m_{it} and it is paid down at a constant rate ζ and carries an interest rate r_t^m. As a result the budget constraint of the entrepreneur i can be represented as follows

$$\begin{aligned} \dot{a}_{i,t} &= r_t^a a_{i,t}^+ + (r_t^{CC}) a_{i,t}^- - c_{i,t} - (r_t^m + \zeta) m_{i,t} + \Pi(z_{i,t}, a_{i,t}) \\ \dot{m}_{i,t} &= -\zeta_t m_{i,t} \\ a_{i,t} &\geq \underline{a} \\ m_{i,t} &\geq \underline{m} \end{aligned} \tag{6}$$

where $\Pi(z_{it}, a_{it})$ are the profits that the entrepreneur earns from its production decisions.

The entrepreneur can freely adjust its credit card debt and liquid savings but to adjust their long term debt they need to pay a fixed cost and after paying that cost they can change it to any level desired. The fixed cost can take two values Ψ_t and $\tilde{\Psi}_t$ (with $\tilde{\Psi}_t << \Psi_t$) depending on whether the entrepreneur wants to pre-pay its long term loan balance or increase it's outstanding balance by getting a new loan. Specifically, given their state (a, m), they can choose (a', m') given by the following equations

$$a' - m' = \begin{cases} a - m + \tilde{\Psi}, & \text{if } m' \in [0, m), \ \& \ b' \leq b \\ a - m + \Psi, & \text{if } m' \in [m, \underline{m}), \ \& \ b' \geq b \end{cases}$$

Production:— Each entrepreneur owns a constant returns to scale (CRS) technology which uses capital k_{it} and labor l_{it} to produce the homogeneous good y_{it}:

$$y_{i,t} = \xi_t (z_{i,t} k_{i,t})^{\alpha} l_{i,t}^{1-\alpha}$$

The capital share $\alpha \in (0, 1)$ is the same across entrepreneurs. Capital depreciates at the rate δ. Idiosyncratic productivity z_t follows a Poisson jump process. Given the idiosyncratic productivity, the entrepreneur hires labor in the labor market at a wage rate w_t. It also rents capital from (un-modeled) households and the rental rate of the capital equals to its user cost i.e. $r_t + \delta$.

Friction:— The key friction in the economy is modeled as a "cash in hand" constraint i.e. the entrepreneur needs to purchase labor and capital before production and can do so by using either liquid savings balances[19] or credit card debt. Cash-in-hand of both types is subject to span of control issues which we denote by the exponents ϵ_a and ϵ_b[20]. Specifically, we denote savings balances by $a_t^+ := \max\{a_t, 0\}$ and credit card debt by $a_t^- := \min\{a_t, 0\}$. This implies that after choosing the level of current period savings balances, a_t^+ or credit card debt a_t^-, the entrepreneur solves the following maximization problem:

$$\Pi(z_{i,t}, a_{i,t}) = \max_{k,l} \left\{ \xi_t (z_{i,t} k_{i,t})^{\alpha} l_{i,t}^{1-\alpha} - w_t l_{i,t} - (r_t + \delta) k_{i,t} + \kappa z_{i,t} \right\}$$

subject to

$$w_t l_{i,t} + (r + \delta) k_{i,t} \leq \theta((|a_{i,t}^-|)^{\epsilon_a} + (a_{i,t}^+)^{\epsilon_b})$$

Here $\theta > 1$ parsimoniously captures the fact that the entrepreneur may acquire intra-period loans (Jermann and Quadrini, 2012) in proportion to its already raised cash.[21] The entrepreneur also

[19] Long-term loans are also paid into liquid savings account

[20] In the estimation and calibration we find that $\epsilon_a < \epsilon_b$ i.e. credit cards are imperfect substitutes for liquid balances. This follows from the fact that credit cards cannot be used by the entrepreneurs to make many kinds of payments such as paying wages or making direct bank to bank transfers.

[21] Discrete time analogous timing is as follows: The entrepreneur starts the period by paying off its existing credit

makes exogenous operating profits given κz_{it}[22]. This production specification implies that output is linear in capital and hence given a_t^+, a_t^-, the output is given by

$$y_{i,t} = \bar{y}(z_{i,t})\theta((a_{i,t}^+)^{\epsilon_b} + (|a_{i,t}^-|)^{\epsilon_a}) \tag{7}$$

where $\bar{y}(z_{it}) = \frac{\xi^{\frac{1}{\alpha}}\left(\frac{(1-\alpha)}{w}\right)^{\frac{1-\alpha}{\alpha}} z_{it}}{\left[w\xi^{\frac{1}{\alpha}}\left(\frac{(1-\alpha)}{w}\right)^{\frac{1}{\alpha}} z_{it} - (r+\delta)\right]}$

6.2 Value Functions

The entrepreneur makes the optimal forward-looking choices of production, consumption and she adjusts long term loans and liquid/credit card balances by solving the Hamilton-Jacobi-Bellman as described below. The entrepreneur's value function $V(a, m, z)$ depends on the value of adjusting it's portfolio which we describe here first.

Value of long term loan adjustment:—We define the adjustment value function as:

$$V^{adj} = \max\{V^{\text{new loan}}(a, m, z), V^{pre}(a, m, z)\}$$

i.e. the entrepreneur considers both the decisions of increasing the loan or pre-paying and chooses the option which gives the maximum value. The values of getting a new loan is given by:

$$V^{\text{new loan}}(a, m, z) = \max_{a', m'} V^n(a, m, z)$$
$$\text{subject to}$$
$$a' - m' = a - m - \Psi, \text{ given } a' > a, m' > m$$

and the value of pre-paying the loan is given by

$$V^{\text{pre pay}}(a, m, z) = \max_{a', m'} V^n(a, m, z)$$
$$\text{subject to}$$
$$a' - m' = a - m - \tilde{\Psi}, \text{ given } a' < a, m' < m$$

Given the expression for V^{adj} we now describe the entrepreneur's final value function.

Entrepreneur Value Function:— The entrepreneur's overall value function is given by Eq. 8. We assume that the entrepreneur gets the option to adjust the portfolio at an exogenous rate λ^a, and

card liabilities $a_{t-1}^-(1 + r_t^a + \omega^{CC})$. Then decides on the new level of debt a_t^-, given that debt purchases the maximum amount of inputs it can by securing $\theta - 1$ additional intra-period loan. In the second half of the period, the entrepreneur produces and consumes.

[22]This ensures that consumption is positive even with zero assets or credit card debt.

can only make the decision to adjust $\mathbf{1}_{\{V^{adj}>V+\Psi^U\}}$ when it receives the opportunity

$$\begin{aligned}\rho V(a,m,z) = \max_c \Big\{ u(c) + \frac{\partial V}{\partial a}\dot{a} + \frac{\partial V}{\partial m}\dot{m} + \sum_{z' \neq z} \lambda^{z \to z'} [V^n(;z') - V^n(;z)] \\ + \lambda^a \mathbf{1}_{\{V^{adj}>V+\Psi^U\}} [V^{adj} - V - \Psi^U] \Big\}\end{aligned} \tag{8}$$

This value function has a standard interpretation. The first term on the right hand side denotes the flow utility from consumption and the remaining three terms in the first line denote the change in value because of the change in entrepreneur's liquid savings/credit card debt (a_t), long term debt (m_t) and the idiosyncratic productivity z_t when they do not adjust their long term balances. The second line denotes the change in value if the entrepreneur changes their long term debt by paying the fixed costs.

This framework provides a tractable mechanism to explain the key empirical patterns in the data and their implications for small businesses. Most importantly, the model assumptions effectively capture the idea that "it's a heck of a lot easier to swipe a credit card than to secure a loan." They also allow us to generate the observed pecking order in financing decisions, particularly when firms face idiosyncratic shocks. At the same time, to maintain tractability, we abstract from certain channels and patterns. For instance, we do not explicitly model entrepreneurial default. This is because, in our data, delinquency does not necessarily imply exclusion from financial markets but rather the accumulation of late fees. Additionally, our main goal in this structural exercise is to quantify the smoothing benefits and dynamic debt service costs of credit cards. Our model also abstracts from explaining the joint patterns of firms and households simultaneously holding credit card debt and liquid savings (Telyukova, 2013; Lee and Maxted, 2023). Addressing this would likely require incorporating elements, such as behavioral biases, that are beyond the scope of this paper.

6.3 Calibration

To calibrate the model we rely on our estimates from Sections 5.1, 5.2 and aggregate statistics from Table B.5. One of the key parameters of the model is the elasticity of the firm level output with respect to an exogenous shock to credit card debt, ϵ_a. We recover this elasticity by combing the estimates from the impact of monetary policy shock on credit card financing and the subsequent transmission of the credit card supply shock into firm level revenue growth. This procedure gives us the value of $\epsilon_a = 0.66$. We set the interest rate on credit cards and long term loans to match with the average interest rate from RateWatch data and calibrate the remaining key parameters to hit three key aggregate moments, 1) average quarterly revenues, 2) average liquid balances (which includes long term loans) and 3) average credit card debt as observed in Table B.5. We provide the full description of the steady state outcomes of the model and the calibrated parameters in Appendix A.

6.4 A Simple Accounting Exercise: the Credit Card Multiplier

Entrepreneurs in the model optimally choose the level of credit card debt, liquid savings and cash balances given the fixed costs of accessing new loans and idiosyncratic productivity shocks. The model provides a direct relationship between the observed distribution of credit card debt and the aggregate small business output in the economy. We use this relationship to define Θ^{CC}, the contribution of credit card financing in producing aggregate small business output as

$$\mathbb{E}[Y_t] = \underbrace{\bar{Y}\theta\mathbb{E}[(a_t^-)^{\epsilon_a}]}_{\Theta^{CC}} + \underbrace{\bar{Y}\theta\mathbb{E}[(a_t^+)^{\epsilon_b}]}_{\Theta^{L}} \tag{9}$$

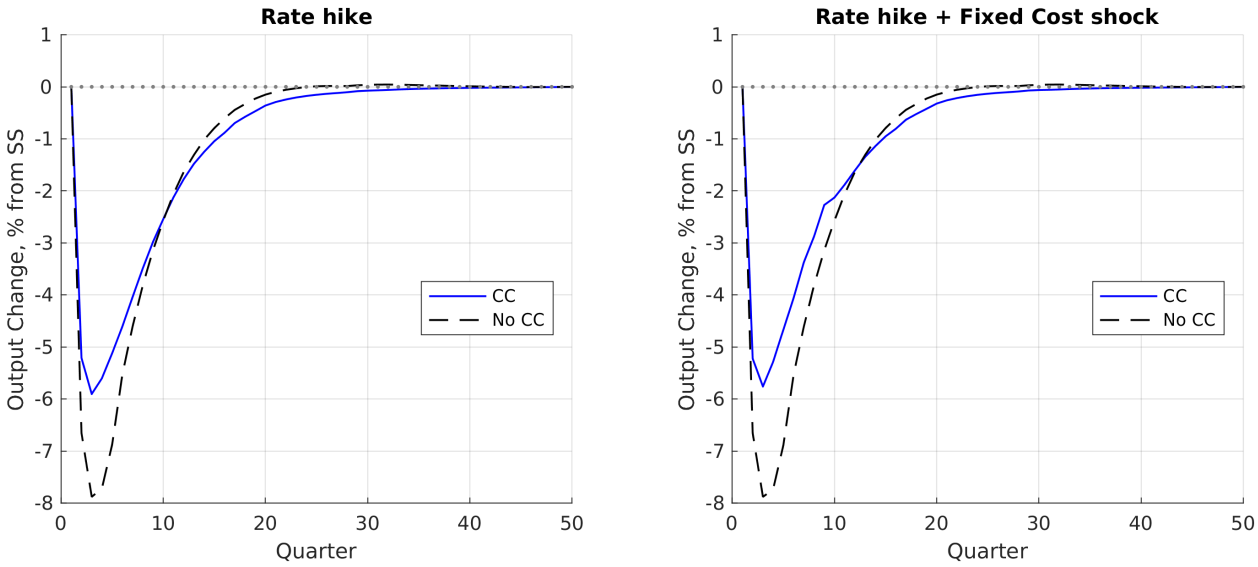
where $\mathbb{E}[(a_t^-)^{\epsilon_a}] = \int (a_t^-)^{\epsilon_a} g_t(a)da$, $\mathbb{E}[(a_t^+)^{\epsilon_b}] = \int (a_t^+)^{\epsilon_b} g_t(a)da$ and $\bar{Y} = \int \bar{y}(z_t)g^z(z)dz$ where a^- is the observed credit card debt and $g(a)$ is its distribution. The first term in the numerator of Eq. 9 quantifies the amount of purchases an entrepreneur can make using credit cards for production, while the second term quantifies the contribution to output from liquid savings and long-term loans converted into liquid savings. Using the steady-state distribution of credit card debt in our model, along with the calibrated parameters θ and ϵ_b and our estimate of ϵ_a, we find that credit cards account for 7.13% of small business production in the steady state. This decomposition underscores the significant role that credit cards play in sustaining small business output.[23] This reliance on credit cards can have important implications for the transmission of aggregate shocks to small business output, which we explore next.

6.5 Role of credit cards in the transmission of aggregate shocks

Credit cards can play a dual role in transmitting interest rate and long-term debt supply shocks within the small business economy. First, when an interest rate hike is fully passed through to both credit cards and long-term loans, the increased cost of borrowing leads entrepreneurs to reduce their overall use of debt for production and consumption. This immediate deleveraging effect on output is determined by the total amount of debt an entrepreneur holds—the combined balance of long-term loans and credit card debt. Second, the composition of that total debt further shapes both the static and dynamic responses to interest rate shocks. In a static framework, access to credit card financing allows entrepreneurs to substitute long-term loans with credit card borrowing, thereby mitigating the immediate dip in output and consumption. This smoothing effect arises because the fixed adjustment costs associated with long-term loans often create a region of inaction, preventing optimal rebalancing of debt. However, this flexibility comes at a cost. Relying more on credit card debt, which generally carries higher interest rates per dollar than long-term loans, can lead to larger debt service burdens and contribute to a slower recovery over time.

[23] This does not imply that eliminating credit cards would lower small business output by 7.13%, as entrepreneurs would dynamically adjust by increasing their long-term loans and savings. In fact, in a simple counterfactual scenario where credit cards are completely removed, output actually increases because entrepreneurs save more and consume less.

Figure 11: IRF to Interest Rate and Long Term Loan Credit Supply Shocks



Note: First panel of the figure plots the IRF of output as a percentage change from the steady state value after an equal real rate hike shock to both credit cards and long term loans. It keeps the deposit rates fixed. The second panel plots the IRF in response to shocks from the first panel plus an increase in the fixed cost of getting new loans i.e. long term credit supply reduction.

In our calibrated model, the steady state with credit cards shows that entrepreneurs hold lower liquid savings and total debt compared to a scenario without credit cards.[24] This difference arises because, without credit cards, entrepreneurs face a tighter borrowing constraint on total debt, prompting them to increase precautionary savings (partially financed by long-term loans). As a result, the overall debt level is higher without credit cards, leading to a more pronounced deleveraging process that reduces both savings and long-term loans, ultimately causing a larger drop in output (as illustrated by the dashed black line in Fig. 11). In contrast, in the presence of credit cards, entrepreneurs can partially substitute long-term debt with credit card borrowing after a shock, reducing their total debt to a lower level. However, the higher interest rates on credit card debt increase their debt service costs, which slows down the recovery to steady state production levels.

To conclude, the model reveals an aggregate tradeoff between the static and dynamic effects of credit card financing. In the short run, credit cards expand borrowing capacity and serve as a financial buffer during downturns. Similar to lines of credit, small businesses can draw on their credit cards to secure funding when revenues decline and access to long-term loans becomes more constrained. However, this flexibility comes at a cost. The high interest rates on credit card debt lead to increased debt service burdens, which can erode firms' cash flows and constrain

[24] Table A.3 in Appendix A compares the steady state of the economy with and without credit cards. Despite the significant reliance on credit cards, eliminating credit card debt completely raises average firm revenues by $6,000. This occurs for two reasons. First, entrepreneurs anticipating the unavailability of credit card borrowing for production boost their liquid savings from $118,000 to $138,000. Second, they increase their long-term debt balances from $450,000 to $477,000.

their ability to produce.

7 Conclusion

Small firms and entrepreneurs are vital drivers of dynamism in the US economy. Over recent decades, they have experienced profound shifts in their competitive and financing landscapes. However, these transformations and their implications for small business dynamism remain underexplored, primarily due to the scarcity of up-to-date data on their financial and economic performance. This study fills a critical gap by leveraging high-quality, near-real-time data from nearly 1.6 million small businesses on the Intuit QuickBooks Online platform, complemented by extensive surveys. These resources provide fresh insights into the impact of credit card financing on small businesses in the US.

This dataset uniquely positions us to study the role of credit card financing with crucial business dynamism indicators such as employment and sales growth. First, we demonstrate the aggregate importance of credit card financing: during the sample period, monthly credit card repayments were up to three times higher than loan repayments. Second, we use the survey to establish the importance of credit cards in the pecking order of financing sources in response to firm-level shocks, such as uncertainty about cash flows and overdue invoices. Third, we assess the impact of the monetary policy tightening that began in the first quarter of 2022 on credit card financing, leveraging it as a shock to credit availability. Our analysis shows that rate hikes led banks to reduce credit card supply, causing a 15.75% decline in balances. This credit contraction adversely affected small business performance, reducing quarterly revenue growth by 10% and employment growth by 1.5%. We also demonstrate that the monetary policy shock heightened the financial vulnerability of small businesses by making existing interest payments unsustainable, contributing approximately 50% of the observed increase in credit card delinquencies.

References

Agarwal, Sumit, Souphala Chomsisengphet, Neale Mahoney, and Johannes Stroebel. 2018. "Do banks pass through credit expansions to consumers who want to borrow?" *The Quarterly Journal of Economics*, 133(1): 129–190.

Akcigit, Ufuk, and R. William Kerr. 2018. "Growth through Heterogeneous Innovations." *Journal of Political Economy*, 126(4): 1374–1443.

Akcigit, Ufuk, and Sina T Ates. 2023. "What happened to US business dynamism?" *Journal of Political Economy*, 131(8): 2059–2124.

Akcigit, Ufuk, Raman Chhina, Seyit Cilasun, Javier Miranda, Eren Ocakverdi, and Nicolas Serrano-Velarde. 2024. "Intuit QuickBooks Small Business Index: Methodology Addendum." Accessed: 2025-02-10.

Akcigit, Ufuk, Raman Singh Chhina, Seyit M Cilasun, Javier Miranda, Eren Ocakverdi, and Nicolas Serrano-Velarde. 2023. "Intuit QuickBooks Small Business Index: A new employment series for the US, Canada, and the UK." National Bureau of Economic Research.

Benetton, Matteo, and Greg Buchak. 2024. "Revolving Credit to SMEs: The Role of Business Credit Cards." *Available at SSRN 4997456*.

Benetton, Matteo, Gregory Buchak, and Claudia Robles Garcia. 2022. "Wide Or Narrow?: Competition and Scope in Financial Intermediation."

Berger, Allen N, Christa HS Bouwman, Lars Norden, Raluca A Roman, Gregory F Udell, and Teng Wang. 2024. "Piercing through opacity: Relationships and credit card lending to consumers and small businesses during normal times and the COVID-19 crisis." *Journal of Political Economy*, 132(2): 484–551.

Biondi, Filippo, Sergio Inferrera, Matthias Mertens, and Javier Miranda. 2023. "Declining Business Dynamism in Europe: The Role of Shocks, Market Power, and Technology." Halle Institute for Economic Research (IWH) Discussion Paper 19/2023, Halle (Saale). Available at EconStor.

Birch, David GW. 1987. *Job Creation in America: How Our Smallest Companies Put the Most People to Work.* Free Press, New York.

Blanchflower, David G., David S. Evans, and David T. Robinson. 2004. "Liquidity Constraints and the Role of Credit Cards in Small Business Financing." *Journal of Economic Perspectives*, 18(2): 83–107.

Bord, Vitaly M, Victoria Ivashina, and Ryan D Taliaferro. 2021. "Large banks and small firm lending." *Journal of Financial Intermediation*, 48: 100924.

Bornstein, Gideon, and Sasha Indarte. 2023. "The impact of social insurance on household debt." *Available at SSRN 4205719*.

Brown, James R, Matthew T Gustafson, and Ivan T Ivanov. 2021. "Weathering cash flow shocks." *The Journal of Finance*, 76(4): 1731–1772.

Chari, V. V., Lawrence J. Christiano, and Patrick J. Kehoe. 2007. "The Gertler-Gilchrist Evidence on Small and Large Firm Sales." Manuscript.

Chatterji, Aaron K, and Robert C Seamans. 2012. "Entrepreneurial finance, credit cards, and race." *Journal of Financial Economics*, 106(1): 182–195.

Chava, Sudheer, Rohan Ganduri, Nikhil Paradkar, and Linghang Zeng. 2023. "Shocked by bank funding shocks: Evidence from consumer credit cards." *The Review of Financial Studies*, 36(10): 3906–3952.

Chen, Brian S, Samuel G Hanson, and Jeremy C Stein. 2017. "The decline of big-bank lending

to small business: Dynamic impacts on local credit and labor markets." National Bureau of Economic Research.

Crouzet, Nicolas, and Neil R Mehrotra. 2020. "Small and large firms over the business cycle." *American Economic Review*, 110(11): 3549–3601.

Decker, Ryan A, John Haltiwanger, Ron S Jarmin, and Javier Miranda. 2016. "Declining business dynamism: What we know and the way forward." *American Economic Review*, 106(5): 203–207.

Decker, Ryan, and John Haltiwanger. 2023. "Surging Business Formation in the Pandemic: Causes and Consequences?" *Brookings Papers on Economic Activity*, 3–24.

Fonseca, Julia, and Jialan Wang. 2022. "How much do small businesses rely on personal credit." *Work in Progress*.

Fort, Teresa C, John Haltiwanger, Ron S Jarmin, and Javier Miranda. 2013. "How firms respond to business cycles: The role of firm age and firm size." *IMF Economic Review*, 61(3): 520–559.

Gertler, Mark, and Simon Gilchrist. 1994. "Monetary policy, business cycles, and the behavior of small manufacturing firms." *The Quarterly Journal of Economics*, 109(2): 309–340.

Giannetti, Mariassunta, Mike Burkart, and Tore Ellingsen. 2011. "What you sell is what you lend? Explaining trade credit contracts." *The Review of Financial Studies*, 24(4): 1261–1298.

Giannetti, Mariassunta, Nicolas Serrano-Velarde, and Emanuele Tarantino. 2021. "Cheap trade credit and competition in downstream markets." *Journal of Political Economy*, 129(6): 1744–1796.

Gomez, Matthieu, Augustin Landier, David Sraer, and David Thesmar. 2021. "Banks' exposure to interest rate risk and the transmission of monetary policy." *Journal of Monetary Economics*, 117: 543–570.

Gopal, Manasa, and Philipp Schnabl. 2022. "The rise of finance companies and fintech lenders in small business lending." *The Review of Financial Studies*, 35(11): 4859–4901.

Haltiwanger, John, Ron S. Jarmin, and Javier Miranda. 2013. "Who Creates Jobs? Small Versus Large Versus Young." *Review of Economics and Statistics*, 95(2): 347–361.

Indarte, Sasha. 2023. "Financial crises and the transmission of monetary policy to consumer credit markets." *The Review of Financial Studies*, 36(10): 4045–4081.

Jermann, Urban, and Vincenzo Quadrini. 2012. "Macroeconomic effects of financial shocks." *American Economic Review*, 102(1): 238–271.

Khwaja, Asim Ijaz, and Atif Mian. 2008. "Tracing the impact of bank liquidity shocks: Evidence from an emerging market." *American Economic Review*, 98(4): 1413–1442.

Laibson, David, Peter Maxted, and Benjamin Moll. 2021. "Present bias amplifies the household balance-sheet channels of macroeconomic policy." National Bureau of Economic Research.

Lee, Sean Chanwook, and Peter Maxted. 2023. "Credit card borrowing in heterogeneous-agent models: Reconciling theory and data." *Available at SSRN 4389878*.

Mach, Traci L., and John D. Wolken. 2009. "The Use of Credit by Small Businesses: Evidence from the Surveys of Small Business Finances." *Economic Inquiry*, 47(1): 112–126.

Mishkin, Frederic S, and Stanley G Eakins. 2006. *Financial markets and institutions.* Pearson Education India.

Moscarini, Giuseppe, and Fabien Postel-Vinay. 2012. "The contribution of large and small employers to job creation in times of high and low unemployment." *American Economic Review*, 102(6): 2509–2539.

Myers, Stewart C. 1984. "Capital structure puzzle."

Neumark, David, Brandon Wall, and Junfu Zhang. 2011. "Do Small Businesses Create More Jobs? New Evidence for the United States from the National Establishment Time Series." *Review of Economics and Statistics*, 93(1): 16–29.

Paul, Pascal. 2023. "Banks, maturity transformation, and monetary policy." *Journal of Financial Intermediation*, 53: 101011.

Robinson, David T. 2010. "The Financing Choices of Small Firms: Evidence from the Survey of Small Business Finances." *Review of Financial Studies*, 23(8): 3048–3077.

Robinson, David T., and Antony Smith. 2023. "Credit Cards as a Financing Tool for Small Businesses: Trends and Implications." *Journal of Entrepreneurial Finance*, 15(3): 211–235.

Rodano, Giacomo, Nicolas Serrano-Velarde, and Emanuele Tarantino. 2018. "Lending standards over the credit cycle." *The Review of Financial Studies*, 31(8): 2943–2982.

Ru, Hong, and Antoinette Schoar. 2016. "Do credit card companies screen for behavioral biases?" National Bureau of Economic Research.

Sedláček, Petr, and Vincent Sterk. 2017. "The growth potential of startups over the business cycle." *American Economic Review*, 107(10): 3182–3210.

Sedlácek, Petr, and Vincent Sterk. 2019. "Reviving american entrepreneurship? tax reform and business dynamism." *Journal of Monetary Economics*, 105: 94–108.

Sedlacek, Petr, and Vincent Sterk. 2020. "Startups and employment following the COVID-19 pandemic: A calculator."

Sharpe, Steven A. 1994. "Financial Market Imperfections, Firm Leverage, and the Cyclicality of Employment." *American Economic Review*, 84(4): 1060–1074.

Telyukova, Irina A. 2013. "Household need for liquidity and the credit card debt puzzle." *Review of Economic Studies*, 80(3): 1148–1177.

A Model Appendix

A.1 Aggregate Quantities

Let $g_t(a, m, z)$ denote the distribution of entrepreneur's states at any given time t and $g^z(z)$ denotes the stationary marginal distribution of idiosyncratic productivity which is exogenously pinned down by the diffusion process. An advantage of the production function specification in Sec. is that we can directly get the total output in the economy is a function of aggregate liquid balances and credit card debt directly by integrating Eq. 7[25].

$$\mathbb{E}[Y_t] = \bar{Y}\theta \left(\mathbb{E}[a_t^-] + \mathbb{E}[a_t^+]\right)$$

where $\mathbb{E}[a_t^-] = \int (a_t^-)^{\epsilon_a} g_t(a)da$, $\mathbb{E}[a_t^+] = \int (a_t^+)^{\epsilon_b} g_t(a)da$ and $\bar{Y} = \int \bar{y}(z_t)g^z(z)dz$ are the aggregate liquid balances. This provides a decomposition of the output into its direct contributions from liquid balances and credit card debt. Credit card debt, however, also indirectly impacts output by lowering the entrepreneurs future savings as it has to pay off the high interest rate credit card debt.

A.2 Parameters, Estimation and Calibration

The model generates several aggregate and individual level moments which we use as targets to internally calibrate and estimate the parameters of the model before doing counterfactual analysis. We calibrate the model at a quarterly frequency. The model has 13 parameters

$$\{\rho, r^a, r^{CC}, r^m, \zeta, \Psi, \tilde{\Psi}, \lambda^a, \alpha, \delta, \theta, \epsilon_a, \epsilon_b\}$$

We take the three interest rate parameters r^a, r^{CC}, r^m directly from the RateWatch data. We use standard values from literature for six long term loan and production parameters $\zeta, \Psi, \tilde{\Psi}, \lambda^a, \alpha, \delta,$. To estimate the elasticity of firm level output to credit card debt supply ϵ_a we use our estimates from Sec 5. Finally, we calibrate the remaining three parameters ρ, θ and ϵ_b to hit three key aggregate moments with the details provided below.

Estimating ϵ_a:— The impact of credit card financing on contemporaneous output is governed by the parameter ϵ_a. Taking logs and first differencing the Equation 7 gives the following causal relationship between individual level credit card balances and output

$$\log y_{i,t} - \log y_{i,t-1} = \epsilon_a(\log a_{i,t} - \log a_{i,t-1}) + \epsilon_{i,t}$$

where $\epsilon_{it} := \log \pi(z_{i,t}) - \log \pi(z_{i,t-1})$. We recover ϵ_a using our estimates in Section 5.1.3. Specif-

[25]While empirically we do observe entrepreneurs and households holding both liquid balances and credit card debt at the same time, standard heterogeneous agent models with idiosyncratic risk are not able to match this feature (Telyukova, 2013; Lee and Maxted, 2023). In this paper, we are rather interested in the choice between long term loans and credit cards, and its impact on production, hence we follow the standard heterogeneous agent literature

ically, our income gap specification isolates the effect of credit card debt on firm level output and ϵ_a is given by the ratio of the estimates in the reduced form and the first stage equation i.e. $\frac{0.1}{0.15} \approx 0.66$.

Externally Calibrated parameters:—We take the average interest rates on the credit cards in our time period from RateWatch data and set the base line at 12% per annum. We also exogenously set the borrowing limit on credit cards to be \$50,000. The frictions in adjusting long term debt are governed by the fixed cost parameters Ψ and $\tilde{\Psi}$. We set them to \$5,000 and \$200 respectively. The long term loans are paid at the rate of 4.5% which gives them an half life of 15 years.

Table A.1: Parameters and Calibration

Parameter	Description	Value	Source/Target
Interest Rates			
r^a	Deposit Rate	1%	Fed Funds Rate
r^{CC}	Credit Card Rate	13%	RateWatch Data
r^m	Long Term Rate	7.5%	RateWatch Data
ρ	Discount Rate	4.5%	Average Credit Card Debt
Production			
θ	Cash in hand multiplier	1.7	Average Revenue
ϵ_a	Output elasticity to CC debt	0.66	Estimated in Sec 5.1.3
ϵ_b	Output Elasticity to Cash	0.82	Average Savings Balance
Long term Loans			
λ^a	Adjustment arrival rate	One/month	
Ψ	Loan increase fixed cost	\$5,000	Laibson, Maxted, and Moll (2021)
$\tilde{\Psi}$	Pre-pay fixed cost	\$200	Laibson, Maxted, and Moll (2021)
ζ	Repayment rate	4.5%	Half life of 15 years

Internally Calibrated parameters:—We internally calibrate three parameters to match the three key aggregate moments of our data. We target average revenue of the entrepreneurs to be roughly \$100,000 per quarter, average liquid savings to be \$120,000 and credit card debt to be \$11,000. The two parameters in the cash in hand constraint θ and ϵ_b pin down the average revenues and savings balances (including long-term loans) in the economy. We also calibrate the discount rate to match the average level of credit card debt. The model performs well in hitting these targets with corresponding moments in the data and the model shown in Table A.2. We find the calibrated elasticity of output to cash holdings equal to 0.82 which is higher than the corresponding elasticity for credit card debt.

Table A.2: Model and Data Aggregate Moments

	Model	Data
Production		
Revenues	\$100,000	\$108,431
Assets and Liabilities		
Credit Card Debt	\$14,000	\$11,062
Liquid Balances	\$118,000	\$121,647

A.3 Counterfactual Steady State

In our main counterfactual exercise, we use the calibrated model to study the response of aggregate output to an interest rate shock with credit card debt completely shut down. We assume that the long term debt is completely elastically supplied at rate r^m. As a result when we shut down the supply of credit card debt by setting the borrowing limit $\underline{a}$ to zero, we find that the entrepreneurs increase both their liquid savings and the long term balances.

Table A.3: Aggregate outcomes in the Steady State

	With Credit Cards	No Credit Cards
Production		
Revenues	\$100,000	\$106,000
Assets and Liabilities		
Credit Card Debt	\$14,000	\$0
Liquid Balances	\$118,000	\$138,000
Long Term Balances	\$450,000	\$477,000

As Table A.3 shows, the liquid balances go up from \$118,000 to \$138,000 and long term balances rise from \$450,000 to \$477,000. As the amount of production in our model is completely pinned down by the total liquid balances that the entrepreneur holds (cash balances + credit card debt), the total output increases in counterfactual scenario. This happens because the the rise in liquid balances offsets the entire loss due to the removal of credit cards. In Fig. 11 we provide the impulse responses of output in response to interest rate shocks in our baseline and counterfactual economies.

B Data Appendix

B.1 Bank Data and Descriptive Statistics

Bank Data We construct bank level variables using the data from FR Y9-C reports provided by the FFIEC National Information Center Database[26]. This data is at the Bank Holding Company level and we map the subsidiary banks to the BHCs by using the mapping between the RSSD IDs of the parents and the offsprings[27]. All of the variables are then constructed at the quarterly level for each BHC.

Mapping BHCs to banks of the users in QuickBooks is not straightforward. In majority of the cases, QuickBooks users input the name of the bank themselves, manually, in their accounts while in other cases the names are generated automatically. We first do a Fuzzy match of the bank names in QuickBooks account with the bank names in the Call Report data. Next, we de-dupe the matches manually and roll them up to the Bank Holding Company Level. This procedure is followed for both Checking/Savings accounts and Credit Card accounts. For loan disbursals and payments, we first identify deposits and debits in the checking accounts which are associated with a loan using a machine learning algorithm. Then we get the name of the issuing bank from the payee details and again do a fuzzy match with the bank names in the call report data.

Matched Credit Card and Cash Data To map BHC data to QuickBooks' credit card and savings data, we utilized the `fuzzyjoin` R package to match BHC bank names to connected QuickBooks account bank names. Only matches with at least 90% confidence were retained. Account names in QuickBooks vary, so we used the bank feed's unique ID (referred to as *Institution ID*) to fill in missing matches.

Example of CC and Cash Account Match (Before Filling Nulls):

QBO Account Name	Institution ID	BHC Matched Name
Chase	1	Chase
JP Morgan Chase	1	NULL

Example of CC and Cash Account Match (After Filling Nulls):

QBO Account Name	Institution ID	BHC Matched Name
Chase	1	Chase
JP Morgan Chase	1	Chase

[26] `https://www.ffiec.gov/npw/FinancialReport/FinancialDataDownload`
[27] `https://www.ffiec.gov/npw/FinancialReport/DataDownload`

Matched Loan Payments Data Loan accounts are not connected to QuickBooks as frequently as credit cards and checking/savings accounts. Loan payments are attributed by classifying checking/savings account transactions to loan account banks. To map BHC data to QuickBooks' loan payments data, we used the `fuzzyjoin` R package to match BHC bank names to payee names from transactions classified as loan payments. Only matches with at least 90% confidence were retained.

Example of Loan Payments Match:

QBO Account Name	Transaction Payee Name	BHC Matched Name
Chase	Suntrust	Suntrust
JP Morgan Chase	BoA	Bank of America

Variable Definitions

- **Assets**: The total value of Bank's assets. It is given by the variable BHCK2170.
- **Equity Ratio**: It is defined as $1 - \frac{\text{Total Liabilities}}{\text{Total Assets}}$. Total Liabilities is given by the variable BHCK2948.
- **Income Gap**: The difference between the dollar value of assets that reprice or mature within a year and the dollar value of liabilities that reprice or mature within a year divided by the bank's total assets.

Table B.1: Rate Sensitive Assets (All Domestic)

Variable	Definition
BHCK31970	Assets that reprice or mature within one year

Table B.2: Rate Sensitive Liabilities (All Domestic)

Variable	Definition
BHCK3296	Interest bearing deposits that reprice or mature within one year
BHCK3298	Long term debt that reprices within one year
BHCK3408	variable rate preferred stock
BHCK3409	long term debt that matures within one year

Summary Statistics - Bank Level Table. B.3 shows the summary statistics for the banks in our credit regressions sample which are matched with atleast one firm.

Table B.3: Quarter Summary Stats at the Bank Level

Variable	N	Mean	Std. Dev.	Min	Pctl. 25	Pctl. 50	Pctl. 75	Max
Income Gap	192	0.16	0.21	-0.52	0.06	0.15	0.30	0.81
log Bank Assets	192	15.63	1.77	13.51	14.21	15.16	16.51	21.89
Equity ratio	192	0.11	0.03	0.04	0.09	0.11	0.12	0.35

B.2 Platform Data

Platform Data For the firm financial outcomes we are able to leverage the entirety of the QuickBooks database. We limit our analysis to the firms in the sample that have their savings/current bank accounts and borrowing accounts such as credit cards automatically linked with the software. This ensures a high quality and timely gathering of the firm's financial accounts.

Variable Definitions

- **Cash Stocks**: Cash balances in checking and savings accounts.
- **Cash Withdrawals**: Total monthly outflows from checking and savings accounts net of loan and credit card payments.
- **Credit Card Balance**: We use a monthly average balance definition in our analysis. It is calculated as the average of users daily balances. For a revolver i.e. a person who uses the credit card but pays back in full every month has a constant Monthly Average Balance. However, as they start to revolve credit card debt they average daily balances don't fall back to zero. With interest accruing over time the daily balances increase over time and so do the Monthly Average balance. Hence, this definition captures the borrowing on credit cards well. Note that the statement balance also captures the same dynamics as the end of period statement balances capture both usage and revolving balance similar to our measure here. To capture the exact amount of borrowing we rely on identifying transactions on the card which put the interest charges and late fees on the user accounts.
- **Credit Card Payments**: It captures the total payments made by the business owner into a credit/towards the credit card balance in every month.
- **Credit Card Usage**: It is the total amount of purchases made on a credit card within a given calendar month.
- **Delinquency**: The ratio of firms paying late fees on their credit cards to the total number of firms using credit cards.
- **Delinquency Rates**: The ratio of firms paying late fees on their credit cards to the total number of firms using credit cards.

- **Employment**: monthly total unique employees paid through payroll.
- **Interest and Late Fee**: These are captured form the credit card transaction data as charges which are labeled as interest charges or late fee. For interest charges we use a machine learning model which is trained on manually classified transactions labeled as interest payments. For late fee we do a keyword matching with strings such as “late fee", “late chg", “late charge" etc.
- **Share CC Payments**: total monthly payments directed toward credit card relative to the firm’s three-month lagged checking and savings balances. In the linked survey sample it is calculated as the total monthly CC payments across the four main banks of the firm. Checking and savings balances are computed as the sum of savings/checking deposits, excluding loan disbursals in this month.
- **Sharelate**: ratio of the firm’s total amount of late invoices to the total amount of all of its invoices. Late payments are calculated as the difference between the total amount due across invoice horizons (same day as the invoice creation date, 1–30 days after, 31–90 days after, and more than 90 days after) and the total amount fully paid by the respective due dates. This difference is then divided by the total invoice amount across all horizons.
- **Share Loan Payments**: total monthly payments by firm directed towards loan servicing relative to the firm’s three-month lagged checking and savings balances. Loan payments are calculated as the firms’ sum of savings/checking transactions labeled as loan payments in this month.
- **Share Cash Payments**: total monthly savings/checking withdrawals relative to the firm’s three-month lagged checking and savings balances.
- **Revenue**: For every deposit in the associated checking/savings account of the firm, QuickBooks provides an initial categorization by matching transactions to sales receipts and invoices on the platform, but users are required to review and confirm that income transactions are correctly classified as revenue. We aggregate all of these transactions at the firm-month level to get the total revenue for the firm. For the real time revenue index, we use a simple model to map net deposits into implied revenue for the transactions which haven’t yet been manually classified by the users.

Table B.4: Summary Statistics at the Firm Level Q4.2021 (Quarterly - More than Two Credit Cards)

Variable	N	Mean	Std. Dev.	Min	Pctl. 25	Pctl. 50	Pctl. 75	Max
Average CC Balance	71,516	19,648	31,927	0	4,626	10,633	22,473	958,633
Total CC Usage	71,516	49,257	83,856	0	8,561	22,262	53,002	995,402
Total CC Payments	71,516	48,284	84,702	0	7,217	20,789	51,803	996,296
Total CC Interest	71,516	226	527	0	0	0	186	14,650
Total Non-zero CC Interest	32,483	498	690	0	58	234	656	14,650
Max Delinquency	71,516	0.157	0.364	0	0	0	0	1
Last Employment Value	13,665	20.48	29.78	1	6	12	24	962
Quarterly Employment Growth	13,665	0.011	0.259	-0.99	-0.074	0	0.098	0.992
Total Revenue	61,757	200,056	218,568	0	42,654	114,603	280,954	999,952
Quarterly Revenue Growth	61,757	0.027	0.433	-1.00	-0.25	0.025	0.315	1.00
Total Loan Payments	88,806	8,696	36,088	0	0	599	5,322	992,620
Total Non-zero Loan Payments	47,698	16,190	47,995	0	1,840	4,682	12,533	992,620
Average Cash Balances	78,204	198,261	232,354	0	28,882	100,665	284,414	999,945

Table B.5: Summary Statistics at the Firm Level Q4.2021 (Quarterly - All Firms)

Variable	N	Mean	Std. Dev.	Min	Pctl. 25	Pctl. 50	Pctl. 75	Max
Average CC Balance	585,596	11,062	23,752	0	1,644	4,512	11,656	978,171
Total CC Usage	585,596	30,512	62,864	50	3,992	11,405	30,180	997,807
Total CC Payments	585,596	28,849	61,947	0	2,722	9,845	28,225	999,250
Total CC Interest	585,596	108	321	0	0	0	21	9,000
Total Non-zero CC Interest	170,147	371	507	0	51	174	482	9,000
Max Delinquency	585,596	0.069	0.253	0	0	0	0	1
Last Value Employment	120,981	9.50	15.99	1	2	5	10	962
Quarterly Growth Employment	120,981	0.009	0.271	-0.990	0	0	0.05	0.992
Total Revenue	569,538	108,431	161,762	0	14,805	44,295	125,756	999,968
Quarterly Growth Revenue	569,538	0.025	0.449	-1.00	-0.261	0.016	0.323	1.00
Total Loan Payments	756,898	5,669	29,998	0	0	0	2,243	995,051
Total Non-zero Loan Payments	295,004	14,544	46,688	0	1,541	3,731	10,527	995,051
Average Cash Balances	726,162	121,647	182,203	0	11,414	44,227	146,244	999,980

Summary Statistics - Firm Level Platform Data

Survey Data The Intuit QuickBooks Small Business Insights Survey is conducted online at regular intervals, typically every three months, in the US, Canada, and the UK. It is commissioned by Intuit QuickBooks and targets small business owners and decision-makers. The survey gathers responses from two primary sources: Dynata audience panels and Intuit QuickBooks customer base. In this paper, we employed survey data from Intuit QuickBooks customer base.

The number of participants from the Intuit QuickBooks customer base varies across survey waves. In the July 2024 wave, 2,315 participants were involved (1,505 from the US, 405 from Canada, and 405 from the UK). These respondents are QuickBooks Online subscribers who have been active in their accounts within the last 30 days. Efforts are made to ensure the survey samples are

as representative as possible, such as rebalancing the Intuit QuickBooks sample to reflect the distribution of small businesses by industry and region. All participants complete the survey via an online form and are incentivized to participate.

Respondents from the Intuit QuickBooks customer base consented to link their survey responses with data from their QuickBooks accounts, providing us with a unique dataset that combines survey feedback with Intuit transaction data. This allows us to gain valuable insights into incentives, goals, and perceptions, and to assess their impact on firm-level indicators. In the analysis we use survey information from US respondents that have linked bank account on the platform - as proxied by the availability of non-zero checking and savings information.

Variable Definitions

- **Benefits Associated to Business Credit Cards**: It is obtained from the question "Which of the following, if any, do you see as the main advantages of using credit cards for business financing?". The response options provided are:
  - Accessibility: Credit cards are easy to obtain
  - Build credit history: Helps to build business's credit profile, making it easier to secure other forms of financing in the future
  - Emergency funding: Credit cards can serve as a backup source of funding in emergencies or when facing unexpected expenses
  - Flexiblity: ability to carry a balance and decide whether to make minimum payments or pay off the full balance
  - Interest-free grace period: Providing short-term financing without incurring interest charges if balance is paid in full each month
  - Rewards and benefits: Such as cashback, travel miles, or discounts
  - Tracking: Credit card statements provide a detailed record of expenses, simplifying bookkeeping
- **Costs Associated to Business Credit Cards**: It is obtained from the question "Which of the following, if any, do you see as the main disadvantages of using credit cards for business financing". The response options provided are:
  - Credit score impact: Late payments can make it more challenging to access other types of financing in the future - Which of the following, if any, do you see as the main disadvantages of using credit cards for business financing?
  - Debt accumulation: The ease of using credit cards can lead to debt accumulation
  - High-interest rates: Carrying a balance can lead to substantial interest charges

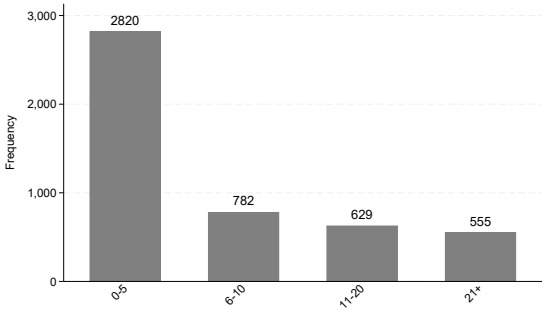
  - Limited credit limit: Credit card limits may not be sufficient to cover substantial business expenses
  - Risk of personal liability: Many cards require a personal guarantee, putting personal assets at risk
  - Security risks: It may expose your business to cybersecurity risks
  - Unpredictable interest rates: Credit card interest rates can fluctuate
  - Variable credit limit: Credit card issuers can change your credit limit at any time

- **Financial Worsening**: If a respondent selected "yes" in response to the survey question, "Looking back over the past 12 months, has the cost and availability of financing got worse?".
- **FinWorse**: Based on the survey question "Looking back over the past 3 months, has the cost and availability of financing got worse?", FinWorse is a binary variable equal to one if firm i reported worsening financial conditions in the past three months.
- **Percent of Invoices Due**: The percentage of invoices as overdue, based on the survey question "As an estimate, what percentage of your sales invoices are currently overdue by 30 days or more?"
- **Preference**: If a respondent selected "credit card" as the most preferred option in response to the survey question, "If your business had equal access to the following financing options, which would you choose first and which would you choose last?".
- **Reliance**: If a respondent selected "more reliant" in response to the survey question, "Over the last year, did the business become more or less reliant on credit cards?".
- **Uncertainty**: Based on the survey question "How sure are you about your SALES REVENUES forecast?", Uncertainty is a binary variable equal to one if firm i reported to be somewhat or very unconfident about their sales revenue forecast over the next quarter.

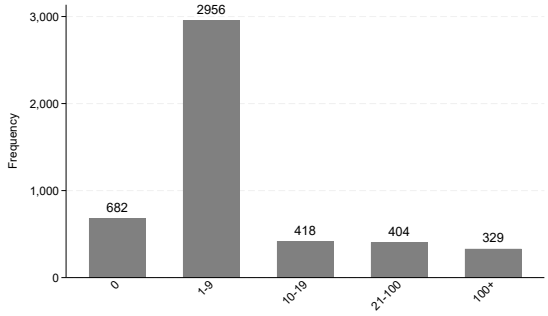
Summary Statistics - Firm Level Survey Data

	N	Mean	Std. Dev.	Min	Pctl. 25	Pctl. 50	Pctl. 75	Max
Log Quarterly Revenues	4,296	10.88	1.88	-3.51	9.93	11.02	12.07	16.48
Share of Monthly Loan Payments	4,627	0.02	0.04	0.00	0.00	0.00	0.01	0.17
Share of Monthly CC Payments	4,789	0.05	0.11	0.00	0.00	0.00	0.00	0.43
Share of Monthly Cash Payments	4,627	1.40	1.38	0.00	0.60	0.99	1.55	5.83
Increased Reliance on CC	1,048	0.29	0.46	0.00	0.00	0.00	1.00	1.00
High Uncertainty of Revenue Forecast	4,635	0.13	0.33	0.00	0.00	0.00	0.00	1.00
Business CC as First Preference	2,114	0.30	0.46	0.00	0.00	0.00	1.00	1.00
Worsening of Financial Conditions	868	0.59	0.49	0.00	0.00	1.00	1.00	1.00
Share of Late Invoices	1,976	0.53	0.35	0.00	0.22	0.54	0.87	1.00

FIGURE B.12: DISTRIBUTION OF RESPONDENTS



(A) AGE



(B) EMPLOYMENT

C Robustness Checks

C.1 Baseline Specification (No Control Variables)

Table C.1: Baseline Specification (No Control Variables)

	Dependent variable:				
	log CC Balance	log CC Usage	log CC Payments	log CC Interest	Charged Interest
	(1)	(2)	(3)	(4)	(5)
$\text{gap}_{t-1} \times \Delta\text{FFR}_t$	0.277***	0.161***	0.249***	−0.020	0.198***
	(0.031)	(0.042)	(0.051)	(0.067)	(0.022)
gap_{t-1}	−0.599***	−1.435***	−0.879***	−1.746***	0.402***
	(0.092)	(0.205)	(0.177)	(0.137)	(0.118)
Observations	2,316,890	2,316,890	2,316,890	2,316,890	2,316,890
R^2	0.705	0.700	0.723	0.862	0.775
Firm-Quarter FE	Y	Y	Y	Y	Y
Bank FE	Y	Y	Y	Y	Y

Notes: This table presents estimates of α and ϕ from the regression: $\log CC_{i\to b,t} = \delta_{i,t} + \omega_b + \alpha(\text{gap}_{i\to b,t-1} \times \Delta\text{Fed Funds}_t) + \phi\text{gap}_{i\to b,t-1} + \epsilon_{i,b,t}$. Firm is denoted by i, and the bank is denoted by b; δ_{it} denotes firm-quarter fixed effects and ω_b denotes bank fixed effects. It differs from the main specification in Sec 5 as it doesn't include any bank controls except for the income gap. Each column represents results for a credit card level dependent variable, i.e., Credit Card Balances, Usage, Payments, Interest Charged Amount, and a Dummy for Interest Charged of firm i's credit card from bank b. Appendix B provides a detailed description of the variables. The main independent variable is $(\text{gap}_{i\to b,t-1} \times \Delta\text{Fed Funds}_t)$, which is an interaction of the bank b's income gap last quarter with the change in the Federal Funds rate. ΔFFR is measured in percentage points, i.e., it takes a value of 1 if the Fed Funds Rate goes from 4% to 5%. The standard errors are clustered at the firm-quarter level. The regression also controls for two other bank variables $x \in \{\text{log assets}, \text{equity ratio}\}$ to isolate the effect of the income gap. $*p < 0.1$, $**p < 0.05$, $***p < 0.01$.

C.2 Baseline Specification (No Control Variables) with Fixed Income Gap

Table C.2: Baseline Specification (No Control Variables) with Fixed Income Gap

	Dependent variable:				
	log CC Balance	log CC Usage	log CC Payments	log CC Interest	Charged Interest
	(1)	(2)	(3)	(4)	(5)
$\text{gap}_{t=\text{Jan 2022}} \times \Delta\text{FFR}_t$	0.343***	0.234***	0.427***	0.682***	0.119***
	(0.040)	(0.053)	(0.034)	(0.097)	(0.010)
Firm-Quarter FE	Y	Y	Y	Y	Y
Observations	3,054,112	3,054,112	3,054,112	3,054,112	3,054,112
R^2	0.708	0.703	0.688	0.793	0.775

Notes: This table presents estimates of α and ϕ from the regression: $\log CC_{i\to b,t} = \delta_{i,t} + \omega_b + \alpha(\text{gap}_{i\to b,2022} \times \Delta\text{Fed Funds}_t) + \phi\text{gap}_{i\to b,2022} + \epsilon_{i,b,t}$. Firm is denoted by i, and the bank is denoted by b; δ_{it} denotes firm-quarter fixed effects and ω_b denotes bank fixed effects. It differs from the main specification in Sec 5 as it keeps the income gap fixed at the January 2022 levels i.e. before the monetary policy rate hikes began. Each column represents results for a credit card level dependent variable i.e. Credit Card Balances, Usage, Payments, Interest Charged Amount and a Dummy for Interest Charged of firm i's credit card from bank b. Appendix B provides a detailed description of the variables. The main independent variable is $(\text{gap}_{i\to b,2022} \times \Delta\text{Fed Funds}_t)$ which is an interaction of the bank b's income gap in January 2022 with the change in Federal Funds rate. ΔFFR is measured in percentage points i.e. it takes a value 1 if Fed Funds Rate goes from 4% to 5%. The standard errors are clustered at the firm-quarter level. The regression also controls for two other bank variables $x \in \{\log \text{assets}, \text{equity ratio}\}$ to isolate the effect of income gap. $*p < 0.1$, $**p < 0.05$, $**p < 0.01$.

C.3 Baseline Specification Only Bank Controls

Table C.3: Baseline Specification Only Bank Controls

	Dependent variable:				
	log CC Balance	log CC Usage	log CC Payments	log CC Interest	Interest > 0
	(1)	(2)	(3)	(4)	(5)
$\text{gap}_{t-1} \times \Delta\text{FFR}_t$	0.145^{***}	0.378^{***}	0.374^{***}	0.699^{**}	0.129^{**}
	(0.049)	(0.061)	(0.122)	(0.290)	(0.057)
gap_{t-1}	-0.746^{***}	-1.346^{***}	-1.463^{***}	0.157	0.154^{*}
	(0.112)	(0.193)	(0.268)	(0.417)	(0.081)
Firm-Quarter FE	Y	Y	Y	Y	Y
Bank FE	Y	Y	Y	Y	Y
Bank Level Controls	Y	Y	Y	Y	Y
Observations	2,331,308	2,331,308	2,328,140	2,331,308	2,331,308
R^2	0.704	0.699	0.701	0.792	0.774

Notes: This table presents estimates of α and ϕ from the regression: $\log CC_{i\to b,t} = \delta_{i,t} + \omega_b + \alpha(\text{gap}_{i\to b,t-1} \times \Delta\text{Fed Funds}_t) + \sum_{x\in\text{control}} \mu_x(x_{i\to b,t-1} \times \Delta\text{Fed Funds}_t) + \phi\text{gap}_{i\to b,t-1} + \sum_{x\in\text{control}} \psi_x x_{i\to b,t-1} + \epsilon_{i,b,t}$. Firm is denoted by i, and the bank is denoted by b; δ_{it} denotes firm-quarter fixed effects and ω_b denotes bank fixed effects. Each column represents results for a credit card level dependent variable i.e. Credit Card Balances, Usage, Payments, Interest Charged Amount and a Dummy for Interest Charged of firm i's credit card from bank b. Appendix B provides a detailed description of the variables. The main independent variable is $(\text{gap}_{i\to b,t-1} \times \Delta\text{Fed Funds}_t)$ which is an interaction of the bank b's income gap last quarter with the change in Federal Funds rate. ΔFFR is measured in percentage points i.e. it takes a value 1 if Fed Funds Rate goes from 4% to 5%. The standard errors are clustered at the firm-quarter level. The regression also controls for two other bank variables $x \in \{\text{log assets}, \text{equity ratio}\}$ to isolate the effect of income gap. $*p < 0.1$, $**p < 0.05$, $***p < 0.01$.

C.4 Credit Card Outcomes at the Firm Level

Table C.4: Credit Card Outcomes at the Firm Level

	Dependent variable:				
	log CC Balance	log CC Usage	log CC Payments	log CC Interest	Interest > 0
	(1)	(2)	(3)	(4)	(5)
$\text{gap}_{t-1} \times \Delta\text{FFR}_t$	0.339^{***}	0.228^{***}	0.112	0.156^{**}	0.015^{**}
	(0.090)	(0.087)	(0.093)	(0.076)	(0.007)
gap_{t-1}	-4.255^{***}	-4.504^{***}	-1.320^{***}	-0.977^{***}	-0.156^{***}
	(0.436)	(0.437)	(0.437)	(0.327)	(0.030)
Firm Controls (CC, Loans, Cash)	Y	Y	Y	Y	Y
Bank Controls	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y
Region-Quarter FE	Y	Y	Y	Y	Y
Sector Quarter FE	Y	Y	Y	Y	Y
Observations	573,761	573,761	573,727	573,761	573,761
R^2	0.846	0.860	0.847	0.852	0.776

Notes: This table presents estimates from the regression: $\Delta\log \text{CC}_{it} = \eta_i + \delta_t + \alpha(\overline{\text{gap}}_{i,t-1} \times \Delta\text{Fed Funds}_t) + \phi\overline{\text{gap}_{i,t-1}} + \chi_1\text{Loan}_{i,t-1} + \chi_2\text{Revenue}_{i,t-1} \sum_{x\in\text{Bank Controls}} \mu_x\overline{x_{i,t-1}} + \varphi_{SIC,t} + \psi_{Zip,t} + \epsilon_{it}$. Firm is denoted by i and η_i and δ_t represent firm and quarter fixed effects. The dependent variable measures the change in log CC outcomes of the firm. The regression sample is a set of firm for which we consistently observe employment information over our sample period. The main independent variables $+\phi\overline{\text{gap}_{i,t-1}}$ and $\alpha(\overline{\text{gap}}_{i,t-1} \times \Delta\text{Fed Funds}_t)$ are the usage-weighted average income gap of the firm's credit card banking partners and it's interaction with the change in federal funds rate. To ensure that the effects are not driven by long term loan supply for the firm we control lagged loan payments and also control for two additional bank level variables: $\overline{\text{log assets}}_{t-1}$, $\overline{\text{equity ratio}}_{t-1}$ which are again, usage-weighted, average log assets and equity ratio of the firm's banking partners. Additionally to isolate the effect of credit supply from other shocks to the firm the regression also controls for the lagged log Revenue at the firm level. $*p < 0.1$, $**p < 0.05$, $**p < 0.01$.

C.5 Revenue Growth for Firms in the Employment Sample

Table C.5: Revenue Growth for Firms in the Employment Sample

	Dependent variable:				
	Δ log Revenue$_t$				
	(1)	(2)	(3)	(4)	(5)
$\overline{\text{gap}}_{t-1} \times \Delta$ FFR$_t$	0.055**	0.055**	0.057**	0.062***	−0.002
	(0.023)	(0.023)	(0.023)	(0.024)	(0.053)
$\overline{\text{gap}}_{t-1}$	−0.026	−0.026	−0.024	−0.141	−0.119
	(0.034)	(0.034)	(0.034)	(0.120)	(0.279)
log loan payments$_{t-1}$		−0.072	−0.070	−0.089	−0.084
		(0.055)	(0.054)	(0.062)	(0.106)
log cash balance$_{t-1}$			−0.025***	−0.025***	−0.026***
			(0.003)	(0.003)	(0.006)
$\overline{\text{log assets}}_{t-1}$				0.0001	0.001
				(0.002)	(0.005)
$\overline{\text{equity ratio}}_{t-1}$				0.517	0.607
				(0.532)	(1.284)
Firm FE	Y	Y	Y	Y	Y
Quarter FE	Y	Y	Y	Y	N
Region Quarter FE	N	N	N	N	Y
Sector Quarter FE	N	N	N	N	Y
Observations	171,825	171,825	171,609	171,609	107,721
R^2	0.135	0.135	0.136	0.136	0.731

Notes: This table presents estimates from the revenue regression but estimated on the sample of approximately 38,000 distinct firms using the payroll functionality and with more than two credit cards. The specification is: $\Delta\text{log Revenue}_{it} = \eta_i + \delta_t + \alpha(\overline{\text{gap}}_{i,t-1} \times \Delta\text{Fed Funds}_t) + \phi\overline{\text{gap}}_{i,t-1} + \phi_1\text{Loan}_{i,t-1} + \phi_2\text{Cash Balance}_{i,t-1} + \sum_{x\in\text{Bank Controls}} \mu_x\overline{x_{i,t-1}} + \varphi_{SIC,t} + \psi_{Zip,t} + \epsilon_{it}$. Firm is denoted by i and η_i and δ_t represent firm and quarter fixed effects. The dependent variable measures the change in log revenues of the firm as compared to the last quarter. The main independent variables $+\phi\overline{\text{gap}}_{i,t-1}$ and $\alpha(\overline{\text{gap}}_{i,t-1} \times \Delta\text{Fed Funds}_t)$ are the usage-weighted average income gap of the firm's credit card banking partners and it's interaction with the change in federal funds rate. To ensure that the effects are not driven by long term loan supply for the firm we control lagged loan payments and also control for two additional bank level variables: $\overline{\text{log assets}}_{t-1}$, $\overline{\text{equity ratio}}_{t-1}$ which are again, usage-weighted, average log assets and equity ratio of the firm's banking partners. Column (1) presents the baseline results with no additional controls. Column (2)-(3) successively add control for loan payments and other bank level variables. Column (4) adds region-quarter and sector quarter fixed effects. A sector is defined at the two digit NAICS level and the region is defined at the five digit zip code level. $*p < 0.1$, $**p < 0.05$, $**p < 0.01$.

C.6 Employment Growth for All Firms (Including Single Credit Card Accounts)

Table C.6: Employment Growth for All Firms (Including Single Credit Card Accounts)

	Dependent variable:					
	Δ log Employment$_t$					
	(1)	(2)	(3)	(4)	(5)	(6)
$\overline{\text{gap}}_{t-1} \times \Delta$ FFR$_t$	0.032***	0.032***	0.033***	0.032***	0.038***	0.034***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.006)
$\overline{\text{gap}}_{t-1}$	−0.011*	−0.011*	−0.014**	−0.023***	0.051***	0.041**
	(0.006)	(0.006)	(0.006)	(0.007)	(0.013)	(0.017)
log loan payments$_{t-1}$		−0.0001	0.001	0.001	0.0004	0.002
		(0.008)	(0.008)	(0.009)	(0.009)	(0.011)
log cash balance$_{t-1}$			−0.006***	−0.005***	−0.005***	−0.006***
			(0.0003)	(0.0003)	(0.0004)	(0.0005)
log revenue$_{t-1}$				−0.037***	−0.037***	−0.037***
				(0.001)	(0.001)	(0.001)
$\overline{\text{log assets}}_{t-1}$					−0.003***	−0.002***
					(0.0003)	(0.0004)
$\overline{\text{equity ratio}}_{t-1}$					0.151***	0.190***
					(0.039)	(0.054)
Firm FE	Y	Y	Y	Y	Y	Y
Quarter FE	Y	Y	Y	Y	Y	N
Region Quarter FE	Y	Y	Y	Y	Y	Y
Sector Quarter FE	Y	Y	Y	Y	Y	Y
Observations	1,235,433	1,235,433	1,217,820	1,057,983	1,057,983	677,206
R^2	0.124	0.124	0.123	0.144	0.144	0.187

Notes: This table presents estimates from the employment regression but estimated on the sample of approximately 355,829 distinct firms using the payroll functionality including those with a single credit card account. This table presents estimates from the regression: $\Delta\text{log Employment}_{it} = \eta_i + \delta_t + \alpha(\overline{\text{gap}}_{i,t-1} \times \Delta\text{Fed Funds}_t) + \phi\overline{\text{gap}}_{i,t-1} + \phi_1\text{Loan}_{i,t-1} + \phi_2\text{Revenue}_{i,t-1} + \phi_3\text{Cash Balance}_{i,t-1} + \sum_{x\in\text{Bank Controls}} \mu_x\overline{x_{i,t-1}} + \varphi_{SIC,t} + \psi_{Zip,t} + \epsilon_{it}$. Firm is denoted by i and η_i and δ_t represent firm and quarter fixed effects. The dependent variable measures the change in log employment of the firm as compared to the last quarter. The regression sample is a set of firm for which we consistently observe employment information over our sample period. The main independent variables $+\phi\overline{\text{gap}}_{i,t-1}$ and $\alpha(\overline{\text{gap}}_{i,t-1} \times \Delta\text{Fed Funds}_t)$ are the usage-weighted average income gap of the firm's credit card banking partners and it's interaction with the change in federal funds rate. To ensure that the effects are not driven by long term loan supply for the firm we control lagged loan payments and also control for two additional bank level variables: $\overline{\text{log assets}}_{t-1}$, $\overline{\text{equity ratio}}_{t-1}$ which are again, usage-weighted, average log assets and equity ratio of the firm's banking partners. Additionally to isolate the effect of credit supply from other shocks to the firm the regression also controls for the lagged log Revenue at the firm level. Column (1) presents the baseline results with no additional controls. Column (2)-(3) successively add control for loan payments and other bank level variables. Column (4) adds region-quarter and sector quarter fixed effects. A sector is defined at the two digit NAICS level and the regions are defined at the five digit zip code level. $*p < 0.1$, $**p < 0.05$, $***p < 0.01$.

C.7 Revenue Growth for All Firms (Including Single Credit Card Accounts)

Table C.7: Revenue Growth for All Firms (Including Single Credit Card Accounts)

	Dependent variable:				
	Δ log Revenue$_t$				
	(1)	(2)	(3)	(4)	(5)
$\overline{\text{gap}}_{t-1} \times \Delta$ FFR$_t$	0.091***	0.091***	0.092***	0.102***	0.073***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.010)
$\overline{\text{gap}}_{t-1}$	−0.066***	−0.066***	−0.077***	0.004	−0.043
	(0.009)	(0.009)	(0.009)	(0.020)	(0.028)
log loan payments$_{t-1}$		−0.026	−0.028	−0.027	−0.060**
		(0.019)	(0.019)	(0.020)	(0.027)
log cash balance$_{t-1}$			−0.028***	−0.028***	−0.029***
			(0.001)	(0.001)	(0.001)
$\overline{\text{log assets}}_{t-1}$				−0.004***	−0.002**
				(0.0005)	(0.001)
$\overline{\text{equity ratio}}_{t-1}$				0.347***	0.280***
				(0.064)	(0.091)
Firm FE	Y	Y	Y	Y	Y
Quarter FE	Y	Y	Y	Y	N
Region Quarter FE	N	N	N	N	Y
Sector Quarter FE	N	N	N	N	Y
Observations	6,283,093	6,283,093	6,276,276	6,276,276	3,816,229
R^2	0.097	0.097	0.097	0.097	0.190

Notes: This table presents estimates from the revenue regression but estimated on the sample of approximately 1,024,029 distinct firms including those with a single credit card account. The specification is: $\Delta\text{log Revenue}_{it} = \eta_i + \delta_t + \alpha(\overline{\text{gap}}_{i,t-1} \times \Delta\text{Fed Funds}_t) + \phi\overline{\text{gap}}_{i,t-1} + \phi_1\text{Loan}_{i,t-1} + \phi_2\text{Cash Balance}_{i,t-1} + \sum_{x\in\text{Bank Controls}} \mu_x\overline{x_{i,t-1}} + \varphi_{SIC,t} + \psi_{Zip,t} + \epsilon_{it}$. Firm is denoted by i and η_i and δ_t represent firm and quarter fixed effects. The dependent variable measures the change in log revenues of the firm as compared to the last quarter. The main independent variables $+\phi\overline{\text{gap}}_{i,t-1}$ and $\alpha(\overline{\text{gap}}_{i,t-1} \times \Delta\text{Fed Funds}_t)$ are the usage-weighted average income gap of the firm's credit card banking partners and it's interaction with the change in federal funds rate. To ensure that the effects are not driven by long term loan supply for the firm we control lagged loan payments and also control for two additional bank level variables: $\overline{\text{log assets}}_{i,t-1}$, $\overline{\text{equity ratio}}_{i,t-1}$ which are again, usage-weighted, average log assets and equity ratio of the firm's banking partners. Column (1) presents the baseline results with no additional controls. Column (2)-(3) successively add control for loan payments and other bank level variables. Column (4) adds region-quarter and sector quarter fixed effects. A sector is defined at the two digit NAICS level and the region is defined at the five digit zip code level. $*p < 0.1$, $**p < 0.05$, $***p < 0.01$.

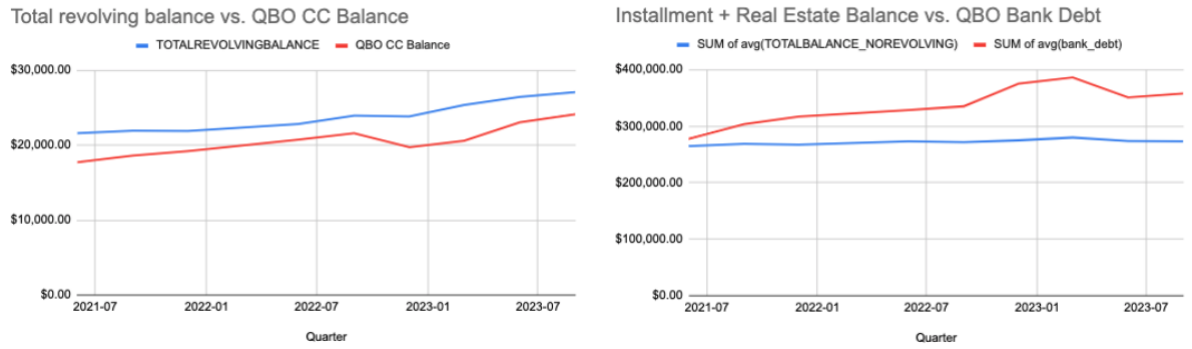
D Bench-marking against Credit Bureau Data

To assess the completeness of our data we benchmark a sample of 179,000 firms against their records from Vantage credit bureau files. Figs. D.13a and D.13b plot the average credit card debt and the installment debt from the two sources. Overall our data captures a large proportion of credit card debt of the small business owners and also tracks it well over time. On average credit bureau balances are about nine percent higher than QuickBooks balances. This is likely due to under-reporting of some credit card account on the platform. However, this ensures that our credit card balance construction method tracks the end of statement balances well.

The average loan balances in our data are higher than those reported in credit bureau data. This is likely due to the broader scope of our dataset, which captures additional sources of credit such as notes payable, financial leases, and trade credit, whereas credit bureau data typically focus on installment credit and liens associated with small businesses.

Additionally, for a subsample of companies using the platform's loan management application, we can further differentiate between loan financing sources. Specifically, we quantify the importance of credit lines within the overall loan category, observing that their share remained relatively stable over time, consistently accounting for 25% of total loan balances.

Figure D.13: Comparison of QuickBooks Data with Credit Bureau Data



(a) Average CC balance Comparison with FICO Data

(b) Average Bank Debt Comparison with FICO