Small Firm Credit Card Financing and Interest Rate Conditions

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Abstract

This paper studies how small firms respond to monetary policy and recessions. I use new micro data on small firm credit card use to document the role of cards for financing and liquidity management. In the cross section, credit card balances and limits both increase with firm size. Card slack, the unused portion of the credit card available for liquidity, is therefore higher for larger firms. Over time, card slack often co-moves with aggregate deposits, but declined in the COVID recession when deposits increased. To explain these facts, I develop a quantitative model of constrained firms with liquidity demand. I show that smaller, more constrained firms optimally use credit cards more for borrowing and less for liquidity than larger firms. Monetary policy tightening affects larger firms relatively more by raising their cost of liquidity.

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1 Introduction

How do small firms respond to monetary policy and recessions? A large literature on models with borrowing constraints often features firms obtaining financing through loans from banks or managing liquidity using cash and deposits. However, recent empirical work shows that small firms rely on business credit cards. Since small firms often face constraints when accessing traditional bank loans, credit cards serve as a more accessible source of financing. Credit cards also provide liquidity, since unused credit lines can be drawn on to cover unexpected expenses. While recent work highlights the financing role of credit cards for small firms, less is known about their liquidity function and how it interacts with borrowing.

This paper examines the dual role of credit cards as both a tool for financing and liquidity for small firms. I use new, proprietary micro data from a major business credit reporting database to document facts characterizing small U.S. firms' use of credit cards in the cross section and over time. I then develop a quantitative model of entrepreneurs with borrowing constraints and liquidity needs to interpret these facts. This model is quantified to match small firm balance sheet outcomes and is used to study the transmission of monetary policy to small firms in a counterfactual exercise.

The main dataset used in this paper comes from a major business credit bureau, covering small U.S. firms and their borrowing from 2014 to 2021. This dataset primarily represents the smallest firms, with most firms in the sample employing fewer than 50 employees. An important advantage of the dataset is the ability to observe both credit card limits and balances. I use this data to measure a firm's immediately accessible liquidity that can be drawn on to meet funding needs or payment deadlines. Throughout the paper, I refer to the firm's unused credit card capacity, difference between the limit and the balance, as card slack.

I show that credit cards play an important role in small firm's financing and liquidity management. Credit card balances account for a larger share of a firm's total outstanding balances for smaller firms. Smaller firms tend to use credit cards more for borrowing and hold higher card balances, while larger firms use cards more for liquidity and hold more card slack and deposits. Firms manage liquidity across these two instruments based on their relative opportunity cost. I formally measure these costs using interest rate spreads relative to the treasury bill (T-bill) rate, where I use the card borrowing rate for card slack and the deposit savings rate for deposits. I show that following a contractionary monetary policy shock, these spreads widen, increasing the cost of liquidity. Since larger firms rely more on liquidity, monetary policy tightening generates stronger output effects for them than for smaller firms.

I use the business credit database to document facts on the cross section of small U.S. firms that characterize their liquidity and financing needs across size and their response to

the start of the COVID recession. I first show that small firms' credit card balances, limits, and slack increase with firm size. Furthermore, credit card limits and slack rise more quickly across size relative to balances. These facts suggest that smaller, constrained firms use cards primarily for borrowing, while larger firms use cards for liquidity.

When examining small firms' card use at the start of the COVID recession, I find that average slack and limit declined while balances rose slightly. This coincides with a decrease in both the federal funds rate and the spread between the deposit rate and treasury bill rate and an increase in the spread between the card rate and the T-bill rate. These time series facts imply a shift in how firms manage liquidity between card slack and deposits. Consistent with this interpretation, FDIC Call Reports data show aggregate slack falling and aggregate deposits rising during this same period.

I then present a quantitative model of the entrepreneurial sector that highlights the tradeoff between keeping a credit card balance for financing versus holding card slack for liquidity services. In this model, entrepreneurs face borrowing constraints on credit cards and traditional loans. Liquidity is modeled as an input into the entrepreneur's production function that can be obtained from either from holding credit card slack or deposits. The model includes productivity and interest rate risks and is quantified to fit balance sheet positions across firms and over time.

The model highlights that credit cards and deposits each serve a dual purpose: they are used not just for borrowing or saving, respectively, but also for liquidity management. The marginal cost of using a credit card includes not just the cost of borrowing but also the liquidity cost of reducing card slack. Similarly, the tradeoff of holding deposits includes both the posted savings rate and the liquidity benefit they provide. As a result, firms are willing to accept a lower financial return on deposits and require a lower financial borrowing rate on credit cards to account for the liquidity value of each instrument. Firms therefore choose between holding liquidity in the form of card slack or deposits based on the relative price of liquidity, which is reflected in the card and deposit interest rate spreads.

This framework interprets the increase in the credit card slack to balance ratio across firm size as arising from low wealth firms being more borrowing-focused and high wealth firms being more liquidity-focused. Meanwhile, the model associates the fall in credit card limits during the start of COVID with reductions in firms' productivity which lowers their available card borrowing limits. Similarly, the rise in slack and fall in deposits here come from the diverging movements in card and deposit rates and spreads. In this period, card rates stay elevated while deposit and T-bill rates falls, leading to card spreads widening more than deposit spreads. As a result, the cost of using deposits for liquidity becomes cheaper relative to card slack.

The model is quantified to match moments of the small firm balance sheet in both the cross section and over time. While some parameters are set based on the literature or to

fit observed interest rate paths in the period of interest, the key part of the quantification strategy involves jointly estimating parameters governing the technology and financing constraints. These parameters are chosen to match cross-sectional balance sheet positions across firm sizes and the time-series movements of aggregate deposits and card slack. To compute the model-implied moments, I simulate entrepreneurs along the empirical path of interest rates from 2014 to 2021. With this strategy, the model captures the data patterns of increasing card balances, limits, and slack across size and the time-series trends of aggregate card slack and deposits over this period.

I then use the model to perform counterfactual exercises, the first of which examines what would happen if credit cards provided no liquidity. Without card liquidity, more firms across all wealth levels hold less card slack and more card balances. Credit cards are now primarily used to finance deposits for liquidity. As Consequently, the average card limit moves more closely over time with the average card balance instead of the average card slack. This change reduces larger firms' output the most since wealthier firms are more liquidity-focused.

My main counterfactual examines how firms respond to a monetary policy shock occurring in June 2017. To estimate the pass-through of monetary policy into the model's interest rates, I compute impulse responses of the T-bill rate and the spreads between the T-bill rate and the card, deposit, and loan rates to an unexpected contractionary monetary policy shock. Using local projections with high-frequency monetary policy shocks from Bauer and Swanson (2023), I find that the T-bill rate responds strongly, while pass-through to the card, deposit, and loan rates is limited. As a result, in this counterfactual, I apply only the impulse response of the T-bill rate to the empirical interest rate path starting in 2017 when simulating model-implied balance sheet outcomes.

Under this counterfactual, monetary policy tightening raises the cost of holding liquidity, which disproportionately affects larger firms, because they rely more on liquidity. Limited pass-through of the contractionary shock to card and deposit rates widens their respective spreads relative to the T-bill rate, with deposit spreads widening more than card spreads. Consequently, firms reduce their card slack and reduce their deposits even more in response to the wider spreads. Since they hold relatively more liquidity than smaller firms, larger firms experience greater deviations in output in response to the temporary increase in liquidity costs.

The rest of the paper is as follows. Section 2 provides institutional context on small firms' financing sources and introduces the business credit dataset. Section 3 introduces stylized facts developed using the data. Section 4 overviews the model and intuition for how it explains the empirical facts. Section 5 discusses the quantification. Section 6 presents the counterfactual exercises of removing liquidity from credit cards and analyzing impulse responses from monetary policy shocks. Finally, Section 7 concludes.

Related Literature. By studying the role of credit cards as both financing and liquidity tools for firms, this paper contributes to several strands of literature addressing these firm needs.

The first area consists of work studying the macroeconomic implications of SME financing. A large literature has answered these questions for firms in general including by Oliner and Rudebusch (1996), Jermann and Quadrini (2012), Chodorow-Reich (2014), Duygan-Bump, Levkov, and Montoriol-Garriga (2015), and Greenwald (2019), Blank and Maghzian (2024) among many others. Many papers model firms with financing constraints to understand how heterogeneous firms respond to monetary policy and recessions (Sharpe (1994), Bernanke, Gertler, and Gilchrist (1999), Ippolito, Ozdagli, and Perez-Orive (2018), Crouzet and Mehrotra (2020)). More specifically, research has examined the macro implications of SME financing (Gertler and Gilchrist (1994), Begenau and Salomao (2018), Caglio and Darst (2021), Dinlersoz, Kalemli-Ozcan, Hyatt, and Penciakova (2018), and Chodorow-Reich, Darmouni, Luck, and Plosser (2022)). Due to limited data availability, most studies of small firms focus on those at the larger end of the size spectrum and on financing tools such as traditional loans and credit lines. Furthermore, publicly available datasets typically report bank loans and public borrowers. Meanwhile, the business credit database includes non-bank loans and private firms, characteristics often attributed to these smallest firms. My paper contribution complements this work by focusing on the smallest firms and their reliance on credit card borrowing.

My work also relates to the literature studying the role of credit cards for small firm financing. Most research on credit cards focuses on consumer use (Ausubel (1991), Gross and Souleles (2002), Stango and Zinman (2016), Bornstein and Indarte (2023)) due to the wider availability of data. A relatively smaller literature exists linking credit card use to business operations. Early work by Blanchflower and Evans (2004) use survey data to document the prevalence of credit cards, both personal and business cards, for small firm financing. More recent studies by Agarwal, Chomsisengphet, Mahoney, and Stroebel (2015), Fonseca and Wang (2022), and Berger, Bouwman, Norden, Roman, Udell, and Wang (2024) also provide evidence of this trend.

The recent availability of micro data on small firm credit cards has led to current work studying the factors behind these borrowing patterns. For instance, Benetton and Buchak (2024), the only other work to my knowledge using this paper's business credit database to study small firm use of credit cards, document cross-sectional facts on firm card use and develops a structural model to understand the drivers of firm demand for card financing. My paper complements their work by presenting facts from the dataset over time from the years 2014 to 2021 to study how card financing is affected by interest rate conditions. I also build on their analysis linking firms' credit card demand to cash flow volatility hedging needs by emphasizing the role of credit cards as liquidity service providers. Meanwhile, Ak-

cigit, Chhina, Cilasun, Miranda, and Serrano-Velarde (2025) use micro-data from accounting software company, Intuit Quickbooks, to study monetary policy transmission to firm use of business credit cards and implications for employment and revenue outcomes. The ability of the Intuit dataset to report on transaction flows allows these authors to highlight the nature of credit cards as a financing tool. Since the business credit dataset reports on credit card limits, which provide a liquidity measure via credit card slack, my paper complements this work by studying how the role of credit cards in meeting financing needs interacts with their liquidity function.

Additionally, my research relates to the broad literature on liquidity management. Related work examines how deposits and loan commitments affect banks' liquidity management (Kashyap, Rajan, and Stein (2002), Gatev and Strahan (2006), Gatev, Schuermann, and Strahan (2009), Ivashina and Scharfstein (2010), Bräuning and Ivashina (2024)). In particular, my paper contributes to the literature on firms' liquidity choices. Many papers study how firms use instruments such as cash and credit lines for liquidity (Holmstrom and Tirole (1998), Lins, Servaes, and Tufano (2010), Acharya, Almeida, and Campello (2013), Begenau and Palazzo (2021)). Since the smallest firms tend to lack access to credit lines, I contribute to this area by introducing credit card slack as a key source of liquidity. The business credit database allows me to study how small firms manage card slack and deposits to meet their liquidity needs.

Finally, my theoretical model contributes to the literature on models of money demand. This literature traditionally models cash as the primary source of liquidity, while recent work incorporates multiple forms of liquidity, such as in Telyukova and Wright (2008), Nosal and Rocheteau (2011), Lucas Jr and Nicolini (2015), Piazzesi and Schneider (2018), Begenau and Landvoigt (2022), and Krishnamurthy and Li (2023). I extend this literature by modeling card slack as an additional liquidity source that also provides financing benefits to better understand its trade-offs with deposits.

2 Background and Data

One challenge the literature has faced when studying small firm financing options, which tend to be costlier and more constrained than those for larger firms, is the lack of available data. With access to data on small firm borrowing in the U.S., I show that small firms rely more on expensive financing options such as credit cards.

2.1 Institutional Background: Small Firm Credit Card Use

Relatively little is known about small firms' financing behaviors due to the lack of data availability. However, small firms play a key role in the economy, with those less than 100 employees making up 34.6% of U.S. private employment and producing 26.4% of total U.S.

private output (Georgi, Morrow, and Highfill, 2021). Most datasets widely used for research (e.g., Compustat) only cover larger firms. However, small firms differ in their financing sources from larger firms. Small firms are shown to have trouble obtaining much needed sources for financing (Evans and Jovanovic (1989); Rauh (2006); Whited and Wu (2006); Adelino, Ma, and Robinson (2017)), and unlike larger firms, they often cannot access cheap financing from the bond market.

Survey evidence and white paper articles show that small firms heavily rely on credit cards and term loans for financing. As reported in Figure 1 by the Federal Reserve Bank 2023 Small Business Credit Survey, the majority (56%) of employer firms with fewer than 500 employees report borrowing through business credit cards with the second most popular choice being term loans (53%) (Banks, 2024). This response is primarily driven by the smallest groupings of firm respondents with less than 20 employees. As the size grouping increases, term loans and in some cases, credit lines, become a key source of financing.

While the use of credit cards for borrowing is prevalent among small firms, the cost to do so is not cheap. Interest rates on business credit cards are relatively expensive, documented to be around 13% on the RateWatch dataset. These trends contrast with larger, public firms that may mainly use business credit cards as a transaction product and have access to bond and equity markets for cheaper sources of financing. Similar financing patterns are shown when nonemployer firms are surveyed, with credit cards are cited as the most commonly used financing product at 45% with loans or line of credit being the second most popular choice at 27% (Banks, 2018).

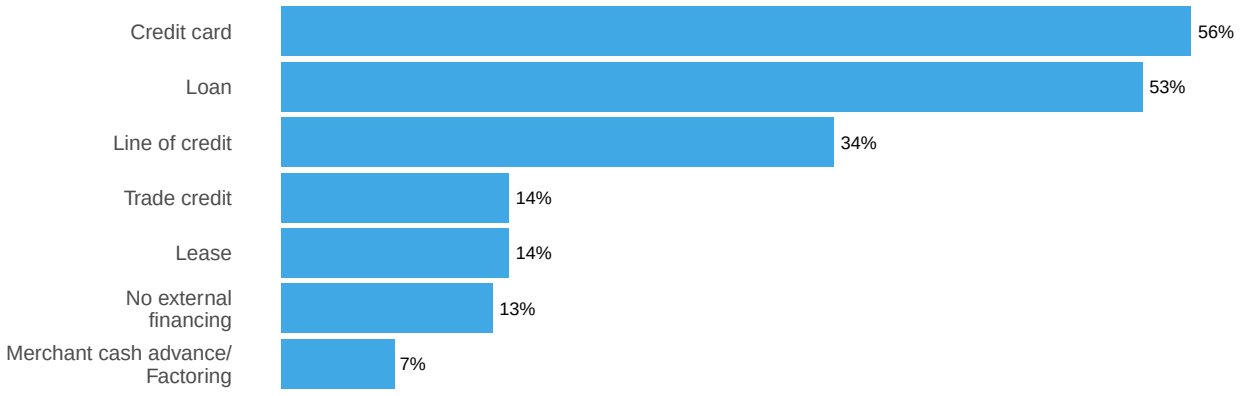


Figure 1: Survey Responses on Small Firm Financing

Notes: This figure reports responses from a survey of 6131 firms with 1-499 employees by the Federal Reserve Bank 2023 Small Business Credit Survey. Firms were asked what products they used on a regular basis for financing and credit and were allowed to select multiple choices.

A key reason small firms use credit cards is for liquidity. Credit cards help small business owners address cash emergencies and extend payment terms. JP Morgan Chase reports on

the role of credit cards as an alternative source of liquidity to cash that helps firms manage irregular cash flows (Wheat and Mac, 2023). They show data evidence of small firms with more cash liquidity having lower credit card balances and document how card balances fall as deposit balances increase during the start of COVID.

2.2 Data

The main dataset of this paper is from a major business credit database and provides information on small firms' borrowing and credit limits in both the cross section and over time. I then compute relative borrowing shares by size from the business credit data to connect it to aggregate data.

Business Credit Database. I use new, proprietary data from a major business credit bureau to study small firms' borrowing in the cross section and during the years surrounding the start of the COVID recession. The dataset is reported at the firm-lender type-borrowing option level at semiannual frequency from the years 2014 to 2021. It contains granular information on the liabilities side of the small firm balance sheet and also includes firm characteristics such as category groupings on employee count.

This proprietary database provides extensive credit reporting on U.S. businesses using contributions by financial lenders. The credit bureau then uses this information to construct business credit score reports that are then sold to lenders and businesses. These lenders consist of banks, non-depository institutions, and credit unions. Because of my interest in focusing on smaller firms which tend to use the products reported in the database the most for financing, I perform my analysis on firms with less than 100 employees. As a result, I work with a subsample of roughly 39.8 million firm-time period observations.

The dataset reports on borrowing options used by small firms that I then use later to construct the firm's balance sheet. In this paper, I combine term loans and lines of credit into an overall loan category for my analysis. While lines of credit are frequently studied as sources of liquidity in the firm liquidity management literature, the smallest firms tend to not have access to these options relative to credit cards. In the business credit database, only around 3% have a line of credit compared to 44% of the firms having credit cards. As a result, I separate out credit cards to study their role as a primary liquidity small firms and combine line of credit and term loan observations to match balance sheet moments.

Table 1 reports relevant summary statistics on the dataset's credit card, loan, and size variables in my subsample. Conditional on having a credit card, the per-firm average limit is \$18,787, the average balance is \$5,132, and the average utilization rate is around 27%. The mean quantity of credit cards per firm is 1.53 implying the average firm has around one credit card. Facts documented on firm credit card use will condition on observations where Experian lists the firm as owning at least one credit card. Meanwhile, conditional on owning

a loan,the average outstanding balance is much larger at $106,418, and the mean number of loans in this subsample is around 1.93. However, more observations in the full analysis sample involve firms with credit cards (44%) than firms with other loans (12.9%). Across employee-size categories, the majority of firms have fewer than 5 employees (61%), with 5–19 employee firms accounting for 32.7% and 20–99 employee firms accounting for 6.3%.

One key assumption I make with the data is that the balances viewed on any given firm's credit cards are revolving. The dataset cannot distinguish whether the snapshot on the credit card balance for any given firm is paid off on time or are paid interest on and carried to the next period. However, policy articles suggest that small firms often carry revolving balances such as in the JP Morgan Chase report on small business credit usage (Wheat and Mac, 2023). Furthermore, Akcigit, Chhina, Cilasun, Miranda, and Serrano-Velarde (2025) also provide evidence that small firms carry around a credit card balance that they pay interest on.

Table 1: Summary Statistics

Variable	**Value**
Credit Card Statistics	
Card limit (mean; $000s)	18.787
Card balance (mean; $000s)	5.132
Utilization (mean; %)	27.318
Quantity (mean; per firm-period)	1.530
Observations (sub-total)	17,750,995
Other Loan Statistics	
Outstanding balance ($000s)	106.418
Quantity (mean; per firm-period)	1.928
Observations (sub-total)	5,141,280
Employee Size Share (%)	
Employees 1–4	61.0
Employees 5–19	32.7
Employees 20–99	6.3
Total Observations	39,836,795

Notes: This table reports relevant summary statistics from the business credit dataset. Credit card statistics include average credit limit, average utilization of the credit card limit, and average quantity of credit cards per firm, all of which are conditional on owning a card. This section also reports the number of observations where a firm owns at least one credit card. For other loans (term loans and line of credit), statistics include average outstanding balance and average quantity of credit cards per firm-period, both of which are conditional on owning a loan. This section also includes number of observations where a firm owns at least one loan. Finally, the table reports on the percentage breakdown of employee size shares and total number of observations.

I confirm that the business credit dataset is representative of the size distribution for U.S.

small firms with under 100 employees by comparing it with Census data. For this analysis, I compare the number of observations at the state-time period level in each employee size group to those reported in the Census County Business Patterns and Nonemployer Datasets.[1] Table 2 reports the average ratios resulting from this analysis. The business credit data sample covers 36-48% firms reported in the Census datasets for employment size categories under 100 employees. Given this alignment, I use the relative size shares from the business credit data to scale the aggregate data on borrowing, deposits, and fixed assets.

Table 2: Coverage Relative to Census Data

Employee Size Category	Coverage Ratio (Credit Data to Census)
Less than 5	0.48
5–9	0.48
10–19	0.39
20–49	0.36
50–99	0.39

Notes: This table reports the ratio of counts of observations in the business credit database to counts in the combined Census County Business Patterns and Nonemployer datasets, aggregated at the size category-state-time period level. On average, the business credit dataset comprises 36–48% of the corresponding Census counts.

Aggregate Data. I bring in aggregate data on deposits and fixed assets to inform the assets side of the small firm balance sheet. For cross-sectional data, I use average aggregate mean and short term debt numbers reported in Caglio and Darst (2021)'s paper on the SME balance sheet. This data allows me to report information on the balance sheet as a share of fixed assets.

For time series data, I use the Federal Flow of Funds and FDIC Call Reports. To better isolate the effects related to interest rate conditions, I detrend all time series with inflation and further detrend the FDIC Call Reports time series on aggregate household and firm card slack and deposits with the average pre-COVID growth of the two series weighted by their values in the initial period of the time series. I report all balance sheet time series values as a share of average fixed assets, constructed using the Federal Flow of Funds series[2].

To construct the aggregate card slack and deposit series, I index the detrended series to start at the initial values of constructed aggregate series for card slack and deposits for small

[1]The Census data reports at the establishment level while the full business credit database reports at the legal business entity level. Due to restricting the database to the smallest firms with under 100 employees that tend to only have a single location and a single centralized legal entity, each observation can be equivalently considered either at the establishment or firm level.

[2]The fixed assets series is constructed by taking nonfinancial assets and subtracting inventories and market value of land for nonfinancial noncorporate businesses.

firms in order to report the values as shares of fixed assets[3]. In performing this analysis, I am assuming that small firms act similarly to other firms and households in their optimization of liquidity needs.

3 Stylized Facts

In this section, I document facts from the business credit dataset suggesting that smaller firms rely on using credit cards to meet financing needs; meanwhile, larger firms use other types of loans for financing needs and use credit cards primarily for liquidity management. I also show that at the onset of COVID, average firm credit card limits and slack declined while average card balances increased. I then use aggregate data from Federal Flow of Funds and FDIC Call Reports to show that aggregate card slack also fell during the start of COVID while aggregate deposits rose, implying a shift in how firms sourced their liquidity.

3.1 Cross-sectional Facts with Business Credit Data

In this subsection, I use the business credit dataset to document facts on small firms in the cross section to demonstrate the importance of credit cards as a financing tool, especially for smaller firms, and a liquidity tool, especially for larger firms.

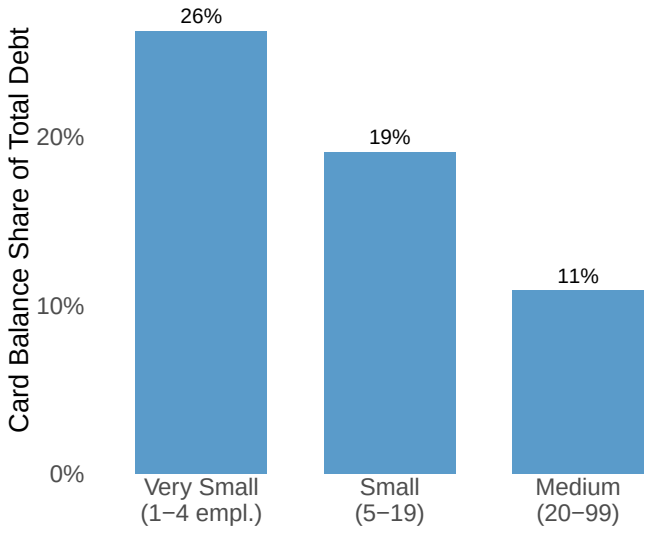
Fact 1: Credit card balances account for a larger share of firms' total outstanding balances for smaller firms.

Figure 2 shows that the share of card borrowing is highest for the smallest size group in the sample and decreases as the size increases. Shares in this figure are computed as aggregate card borrowing as a fraction of aggregate total debt borrowing. The smallest size group, Very Small (1-4 employees), has the highest card balance share relative to their total reported debt at 26%, the middle group, Small (5-19 employees), has a lower share at 19%, and the largest size group, Medium (20-99 employees) has the lowest share at 11%. This trend highlights the importance of credit cards for small firm financing, with the smallest firms relying on cards more for borrowing than larger firms.

Meanwhile, larger firms in the sample rely more on other forms of borrowing. Figure 3 reports average credit card and loan balances for each size group relative to the smallest size category, Very Small. As size increases, the average balance increases faster for loans than for cards. This trend reflects the limited access that the smallest firms have to other types of

[3]To proxy small for firm card balances, I use FDIC's Commercial and Industrial loans under $100,000 series for small businesses and multiply by the average computed card utilization from the business credit dataset in each period. To proxy for small firm deposits, I sum the Federal Flow of Fund's series on checking and savings accounts for nonfinancial noncorporate businesses.

Figure 2: Share of financing with cards decreases with size.



Notes: This figure documents aggregate credit card borrowing as a share of aggregate borrowing for small firms in the business credit data sample by size categories (Very Small: 1-4 employees, Small: 5-19 employees; Medium: 20-99 employees). The smallest size group, Very Small, has the highest share of card balance relative to their total reported debt at 26%, the middle group, Small, has the second share at 19%, and the largest size group, Medium has the lowest share at 11%.

credit such as term loans and lines of credit. As a result, credit cards play a more significant role in smaller firms' financing needs compared to larger firms.

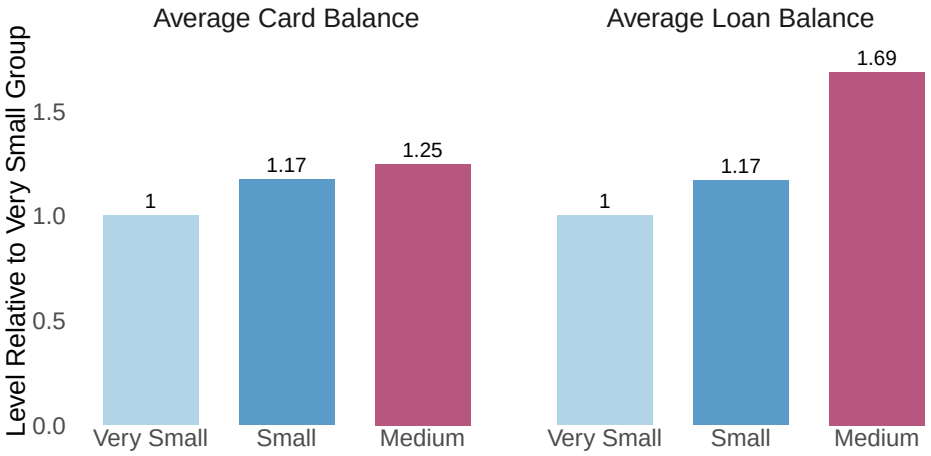
Fact 2: Average credit card limits and slack increase faster across size than average balance.

Small firms also differ by size in the magnitude of their average credit card limit, slack, and balance. Figure 4 reports these averages by size group relative to the smallest size category. The figure shows that larger firms on average have higher credit card limits and more card slack relative than to card balances. This trend implies that while larger firms have the capacity to spend more on their credit card, they do not utilize it as much. As a result, larger firms hold more slack than balance relative to their smaller firm counterparts as shown in Figure 5. These facts suggest that liquidity considerations are more important to larger firms, which maintain more slack relative to balances on their credit cards.

3.2 Time Series Facts with Business Credit Data

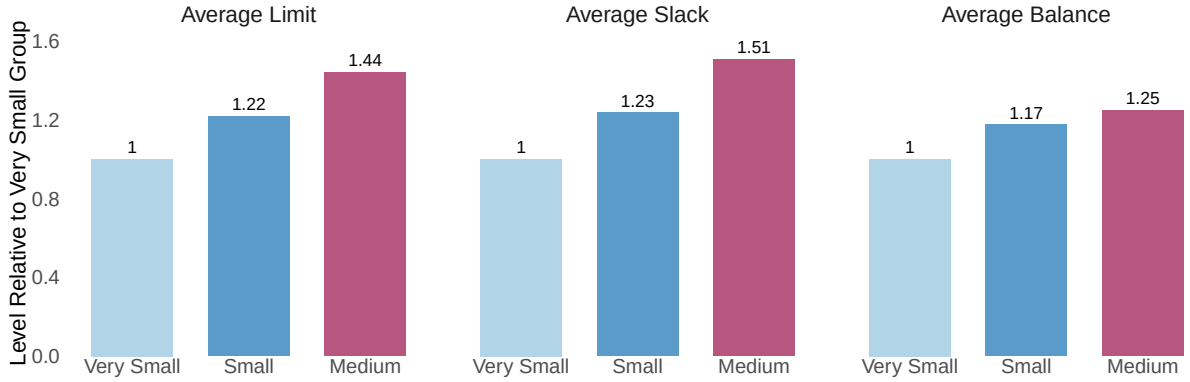
This subsection examines how the average credit card limit changes during the years leading up to and at the onset of the COVID recession. I find that movements in the limit coincide more with changes in card slack than in the balance.

Figure 3: Average Credit Card and Loan Balances by Firm Size.



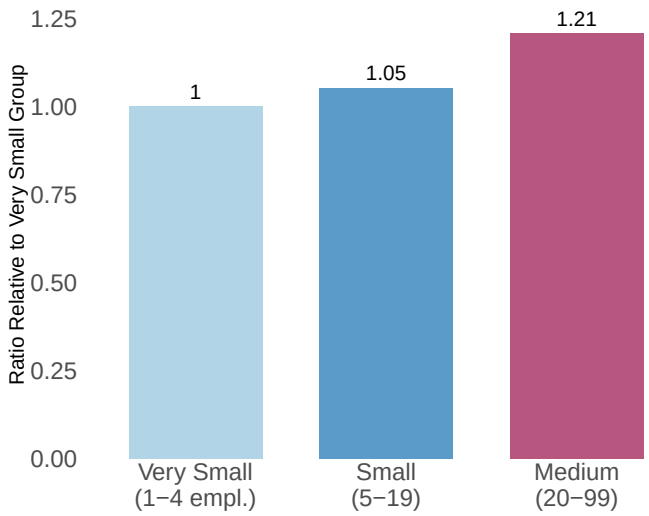
Notes: This figure documents average balances of credit cards (left panel) and other loans (right panel) relative to the level reported for the smallest size group, Very Small. The size groups are Very Small (1-4 employees), Small (5-19 employees), and Medium (20-99 employees). Credit card balances rise more slowly across size group relative to loan balances.

Figure 4: Level of Credit Card Limit, Slack, and Balance Across Size.



Notes: This figure documents average credit card limits, slack, and balance across size relative to the level reported for the smallest size group, Very Small. The size groups are Very Small (1-4 employees), Small (5-19 employees), and Medium (20-99 employees). Credit card limits and slack rise faster across size group relative to their balances.

Figure 5: Credit Card Slack-to-Balance Ratio Across Size.



Notes: This figure documents the ratio of average credit card slack to average credit card balance relative to the ratio reported for the smallest size group, Very Small. The size groups are Very Small (1-4 employees), Small (5-19 employees), and Medium (20-99 employees). Credit card slack relative to balance increases across size suggesting that liquidity via slack is more important for larger firms.

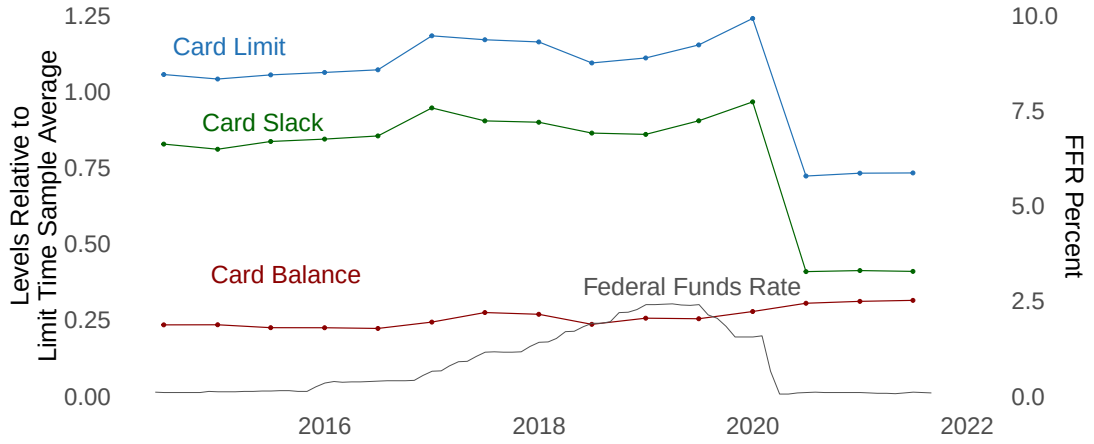
Fact 3: Average credit card limit and slack slightly increase from the years 2014-2019 before fall sharply at the start of COVID.

The business credit dataset shows that average credit card limits and slack not only increase with firm size, but they also move similarly over time during the years 2014-2021. Figure 6 plots average card balance, limit, and slack over time along with the interest rate and spread between the deposit and T-bill rates. This figure normalizes the card limit by its time sample average and shows card slack and balances as components relative to the limit's time sample mean. Over time, card limits and slack move together: both increase as the interest rate rises and then fall sharply at the start of COVID in 2020. In contrast, card balances move less closely with limits and slack, rising only slightly during the start of COVID. These trends suggest that movements in the card limit are correlated with liquidity needs proxied by the card slack measure.

3.3 Time Series Facts with Aggregate Slack and Deposits Data

Having shown evidence suggesting the role of credit card slack as a liquidity service, I further investigate this relationship by comparing movements in card slack with a common liquidity source for small firms: deposits. I complement business credit data with aggregate data series to study how aggregate slack co-moves with aggregate deposits in the years

Figure 6: Average Credit Card Limit, Slack, and Balance Across Time.



Notes: This figure documents the average credit card limit, slack, and balance across time. Levels are reported relative to the time sample average of the card limit such that the slack and balance lines add up to the limit line. Credit card slack co-moves with card limit, in which both increase slightly as the federal funds rate increases and then fall sharply at the start of COVID.

leading up to and at the beginning of the COVID recession.

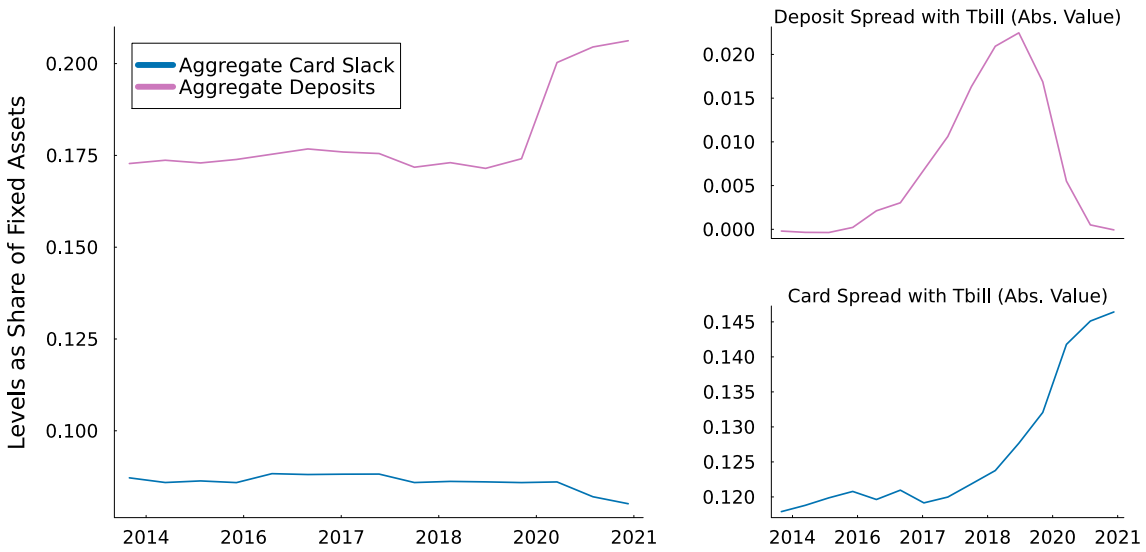
Fact 4: At the start of COVID, aggregate card slack declined while aggregate deposits increased, coinciding with a rise in card spreads and fall in deposit spreads during this period.

Since the business credit data suggest that slack movements may be correlated with liquidity needs during the start of the COVID recession, I additionally show with aggregate data from the Federal Flow of Funds and FDIC Call Reports that comovements in aggregate slack and deposits indicate a shift in how firms obtained liquidity during this period. Figure 7 plots aggregate slack and deposits as a share of fixed assets following the methodology discussed in Section 2 and shows that at the start of COVID, slack declined while deposits rose. At the same time, the deposit spread falls while the card spread remains elevated. These facts suggest that the reallocation of firms' liquidity sources coincided with a divergence in the relative prices of these sources. A version of this plot is shared in Appendix Figure A.2 where both time series are indexed to start at the same initial value to emphasize their co-movement.

4 Model

To understand the mechanisms underlying the documented stylized facts on small firm credit card use, I develop a quantitative model of the entrepreneurial sector to show how

Figure 7: Aggregate Deposits and Slack Across Time.



Notes: This figure plots aggregate deposits and card slack as a share of fixed assets from the years 2014 to 2021. Both series move similarly in the years leading up to COVID and then diverge when COVID starts in 2020. The right panel shows the absolute value of the card and deposit spreads relative to the T-bill. For a version of this plot with the absolute magnitude of these spreads, refer to Appendix Figure A.1

.

small firms manage financing and liquidity needs. In this model, an entrepreneur faces borrowing constraints on credit cards and traditional loans and obtains liquidity from cards and deposits. This liquidity then becomes an input into the firm's production. Finally, the entrepreneur faces productivity and interest rate risk. I then use Euler equations from the deterministic setting to illustrate the key mechanisms of the model. These equations show the implications of having a borrowing option with liquidity services and how relative costs can affect liquidity management.

4.1 Model Set-up

The economy consists of an infinitely-lived entrepreneur managing liquidity and financing. This entrepreneur's assets include capital K_t and a short-term T-bill B_t. The entrepreneur can borrow with credit cards $Card_t$ and traditional loans $Loan_t$ and can obtain liquidity by holding card slack, which is the difference between the credit card limit and the balance $CardSlack_t = CardLimit_t - Card_t$ or by holding deposits D_t. The model also includes several sources of uncertainty: idiosyncratic TFP shocks, firm exit shocks, interest rate shocks, and aggregate TFP shocks.

Preferences. The entrepreneur has CRRA per-period utility in consumption C_t and discount factor β:

$$u(C_t) = \frac{C_t^{1-\gamma_c}}{1-\gamma_c}. \tag{1}$$

Technology and Timing. The entrepreneur produces one type of consumable good using capital and liquidity as inputs with decreasing returns to scale technology.

$$Y_t = A_t K_t^{\theta_K} L_t^{\theta_L} \quad \theta_K, \theta_L < 1. \tag{2}$$

Here, liquidity preferences at time t are a CES aggregate of credit card slack and deposit choices made in the prior period $t-1$:

$$L_t = (\alpha D_{t-1}^{\frac{\sigma-1}{\sigma}} + (1-\alpha)(CardSlack_{t-1})^{\frac{\sigma-1}{\sigma}})^{\frac{\sigma}{\sigma-1}}, \tag{3}$$

where $\sigma > 1$ is the elasticity of substitution parameter and α is the weight the entrepreneur puts on deposits versus credit cards in their liquidity preferences.

Law of motion for capital K_t is dependent on constant depreciation rate δ and investment choice I_t:

$$K_{t+1} = (1-\delta)K_t + I_t. \tag{4}$$

Each period t, the entrepreneur can choose to consume C_t, invest I_t into capital, borrowing on their credit card $Card_t$ and loan $Loan_t$ at their respective rates $r_{card,t}$ and $r_{loan,t}$, and invest in deposits D_t and T-bills B_t at their respective rates $r_{D,t}$ and $r_{B,t}$. Their budget constraint then states that the amount that the sum of output produced Y_t, return on previous period T-bills and deposits, and the amount borrowed on the credit card and loan should equal the amount consume, the amount invested in capital, T-bills, and deposits, and the amount paid back on the credit card and loan debt:

$$\begin{aligned} & Y_t + (1+r_{D,t-1})D_{t-1} + (1+r_{B,t-1})B_{t-1} + Card_t Loan_t \\ = \; & C_t + I_t + D_t + B_t + (1+r_{Loan,t-1})\, Loan_{t-1} + (1+r_{Card,t-1})\, Card_{t-1}. \end{aligned} \tag{5}$$

Finally, the entrepreneur faces constraints on borrowing from cards and loans. They can only borrow up to a proportion of the capital stock they commit to in the next period K_{t+1} when they make their current capital investment choice:

$$Loan_t \leq \phi K_{t+1}; Card_t \leq \varphi K_{t+1} \tag{6}$$

TFP shocks. Log TFP A_t follows an AR(1) process characterized by persistence ρ_A and mean zero error ε^A_{t+1} with variance σ^2_A:

$$\log A_{t+1} = \rho_A \log A_t + \varepsilon^A_{t+1}, \quad \varepsilon^A_{t+1} \sim N(0, \sigma^2_A). \tag{7}$$

Firm exit shock. With probability p_{exit}, the entrepreneur exits and is replaced with a new entrepreneur starting at the minimum wealth state.

Interest rate shocks. The Tbill rate also follows an AR(1) process characterized by persistence ρ_B and mean zero error ε^B_{t+1} with variance σ^2_B:

$$r_{B,t+1} - \bar{r}_B = \rho_B \left(r_{B,t} - \bar{r}_B\right) + \varepsilon^B_{t+1}, \quad \varepsilon^B_{t+1} \sim N(0, \sigma^2_B), \tag{8}$$

where $\bar{r}_B$ is the unconditional mean of the T-bill rate.

All other interest rates co-move with the T-bill up to some factor β_m: $r_{m,t} = \bar{r}_{m,t} + \beta_m \cdot (r_{B,t} - \bar{r}_{B,t})$ for $m \in \{card, D, loan\}$.

Crisis regime shocks. With probability $p_{recession}$, the economy leaves the normal regime and enters the crisis regime. In the crisis state, realized productivity faces a haircut: $(1 - \beta_{crisis})A_t$. Interest rates are also set to their crisis state value: $r_{B,t,crisis}, r_{card,t,crisis}, r_{loan,t,crisis}, r_{D,t,crisis}$.

Bellman Equation. Define the entrepreneur's wealth at time $t+1$, W_{t+1}, as:

$$\begin{aligned} W_{t+1} = {} & Y_{t+1}(K_{t+1}, L_{t+1}) + (1-\delta)K_{t+1} + (1 + r_{D,t})D_t + (1 + r_{B,t})B_t \\ & - (1 + r_{\text{card},t})Card_t - (1 + r_{loan,t})Loan_t. \end{aligned} \tag{9}$$

Then, the Bellman equation for the entrepreneur can be expressed with wealth as a state variable:

$$\begin{aligned} V(W_t, A_t, r_{B,t}) = {} & \max_{C_t, Card_t, Loan_t, D_t, B_t, K_{t+1}} \frac{C_t^{1-\gamma_c}}{1-\gamma_c} \\ & + \beta \mathbb{E}_{A_{t+1}, r_{B,t+1} | A_t, r_{B,t}} \left[(1 - p_{exit})V(W_{t+1}, A_{t+1}, r_{B,t+1}) + p_{exit}V(0, A_{t+1}, r_{B,t+1})\right], \end{aligned} \tag{10}$$

subject to time t budget constraint:

$$C_t + K_{t+1} + D_t + B_t = W_t + Card_t + Loan_t, \tag{11}$$

the credit limit constraint with the limit definition substituted in:

$$Card_t \leq \varphi K_{t+1}, \tag{12}$$

the loan borrowing constraint:

$$Loan_t \leq \phi K_{t+1}, \tag{13}$$

and non-negativity constraints for cards, loans, T-bills, and deposits:

$$Card_t \geq 0; Loan_t \geq 0; B_t \geq 0; D_t \geq 0. \tag{14}$$

4.2 Model Intuition

This subsection uses Euler equations from the model under the deterministic, unconstrained setting to highlight model mechanisms that affect card use for liquidity management. The entire set of Euler equations for both the deterministic, unconstrained setting and the full setting can be found in Appendix Section B.1.

Model Mechanism: Rate of return on card use differ from traditional loan borrowing through its liquidity service.

Define ρ_t as the entrepreneur's internal rate of return such that:

$$1 + \rho_t = \frac{u'(C_t)}{\beta\, u'(C_{t+1})}. \tag{15}$$

Then, the first order condition (FOC) for traditional loans in the model shows that the internal rate of return is set equal to the loan rate:

$$1 + \rho_t = 1 + r_{loan,t}. \tag{16}$$

Meanwhile, the FOC for credit cards includes a marginal product term from getting liquidity from holding card slack. As a result, the first order condition for credit cards sets:

$$1 + \rho_t = \underbrace{(1 + r_{\text{card,t}})}_{\text{card rate}} + \underbrace{\theta_L(1-\alpha)\,\frac{Y_{t+1}}{L_{t+1}}\,L_{t+1}^{\frac{1}{\sigma}}\,(CardSlack_t)^{-\frac{1}{\sigma}}}_{\substack{\text{marginal product of card slack} \\ \text{via liquidity}(MP_{CardSlack,\,t})}}. \tag{17}$$

Here, the borrowing rate on the credit card is less than then internal rate of return due to the liquidity service.

Model Mechanism: Tradeoffs between card and deposits for liquidity depend on relative prices.

Similar to the FOC for cards, the FOC for deposits also includes a liquidity service expressed through a marginal product term:

$$\underbrace{1+\rho_t}_{\substack{\text{discount}\\ \text{rate}}} = \underbrace{(1+r_{D,t})}_{\text{deposit rate}} + \underbrace{\theta_L \alpha \frac{Y_{t+1}}{L_{t+1}} L_{t+1}^{\frac{1}{\sigma}} D_t^{-\frac{1}{\sigma}}}_{\substack{\text{marginal product of deposit use}\\ \text{via liquidity}(MP_{D,t})}}. \tag{18}$$

Denote $\pi_t = \rho_t - r_{B,t}$ as the internal premium over the T-bill rate. To compare use of credit cards versus deposits for liquidity, I take the ratio of the card and deposit marginal product terms to construct a relationship between their relative quantities and prices. Equation 19 shows that the tradeoff between use of cards and deposits for liquidity depends on their prices, or relative internal returns. Here, the relative internal return consists of the internal premium adjusted by the relative spread with the T-bill rate:

$$\frac{MP_{D,t}}{MP_{CardSlack,t}} = \underbrace{\frac{D_t}{CardSlack_t}}_{\text{ratio of quantities}} = \underbrace{\left(\frac{\pi_t - (r_{B,t} - r_{\text{card},t})}{\pi_t - (r_{B,t} - r_{D,t})}\right)^{\sigma}}_{\text{ratio of relative internal return}} \tag{19}$$

Model Mechanism: Comovement of credit cards and deposit premiums affects liquidity overall.

To evaluate the tradeoffs between choosing capital and liquidity, I take the capital FOC:

$$1+\rho_t = (1-\delta) + \underbrace{\frac{\partial L_{t+1}}{\partial K_{t+1}} + A\theta_L K_{t+1}^{\theta_K} L_{t+1}^{\theta_L - 1}(1-\alpha)\varphi L_{t+1}^{\frac{1}{\sigma}}, (\varphi K_{t+1} - Card_t)^{\frac{-1}{\sigma}}}_{\text{marginal product of capital } MP_{K,t+1}} \tag{20}$$

and construct a relationship between quantities capital and liquidity:

$$\frac{L}{K} + \frac{\partial L_{t+1}}{\partial K_{t+1}} = \frac{\theta_L}{\theta_K} \underbrace{\frac{\overbrace{\pi_t + r_{B,t} + \delta}^{\text{relative price of capital}}}{\left[\alpha(\pi_t - (r_{B,t} - r_{D,t}))^{1-\sigma} + (1-\alpha)\left(\pi_t - (r_{B,t} - r_{\text{card},t})\right)^{1-\sigma}\right]^{\frac{1}{1-\sigma}}}}_{\text{relative price of liquidity bundle}} \tag{21}$$

Here, the liquidity price index mirrors the construction of liquidity, consisting of a CES aggregate of deposit and card relative prices. Overall liquidity demand falls when deposit and card spreads widen together. This relationship illustrates how overall liquidity can move and affect both liquidity demand for deposit and card slack.

4.3 Policy Functions

While the previous section discusses the model's mechanisms under an unconstrained, deterministic setting, the full model has constraints and shocks. This section discusses the policy functions help to highlight the intuition of the full model. These policy functions are computed for entrepreneurs taking interest rate shocks into account. Figure 8 plots optimal policy functions for deposit holdings, capital stock, consumption, card balance, loan balance, and T-bill holdings under a low interest rate and median TFP state.

Entrepreneurs with high wealth levels focus more on their liquidity needs, holding card slack and deposits. Due to the liquidity penalty of card use, card borrowing winds down first for larger firms before loan borrowing. Meanwhile, entrepreneurs with low wealth focus more on their borrowing needs, holding more balances on their cards and loans and holding fewer deposits. Figure 9 zooms in on the policy functions at this end of the wealth grid where the entrepreneur's card and loan borrowing constraints bind.

In environments characterized by these interest rate and TFP states, most wealth levels focus on accumulating more capital and liquidity and investment in T-bills is zero. Under a high enough interest rate state, entrepreneurs with high enough wealth levels stop accumulating more capital and liquidity and invest more wealth in T-bills as shown in Appendix Figure A.3.

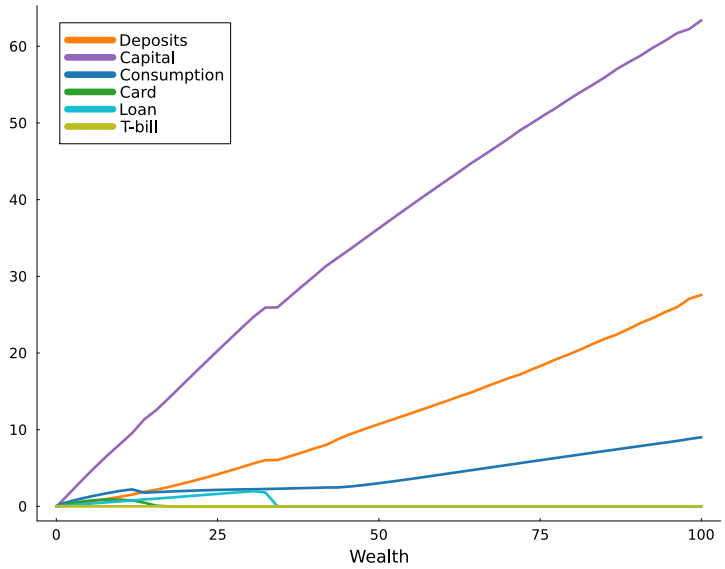
4.4 Simulated Stationary Distribution

Under these optimal policy functions, I simulate 100,000 entrepreneurs over 1000 periods. In addition to facing the shocks discussed in the model setup, the interest rate shocks described in Equation 8 are simulated as a common path of shocks shared by all entrepreneurs. Figure 10 shows the resulting stationary distribution. Most of the mass in this distribution is concentrated at the low end of the wealth grid, where entrepreneurs rely on credit cards for borrowing.

5 Model Quantification

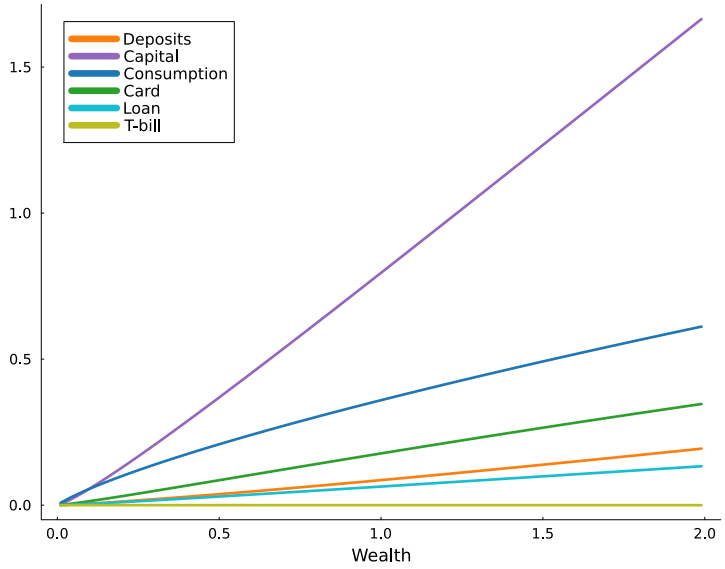
In this section, I discuss how I quantify the model to fit the balance sheet of small firms in the cross section and over time. I first outline the quantification strategy used to set the model's parameters. I then present the model-implied moments alongside their empirical counterparts.

Figure 8: Policy Function as a Function of Wealth



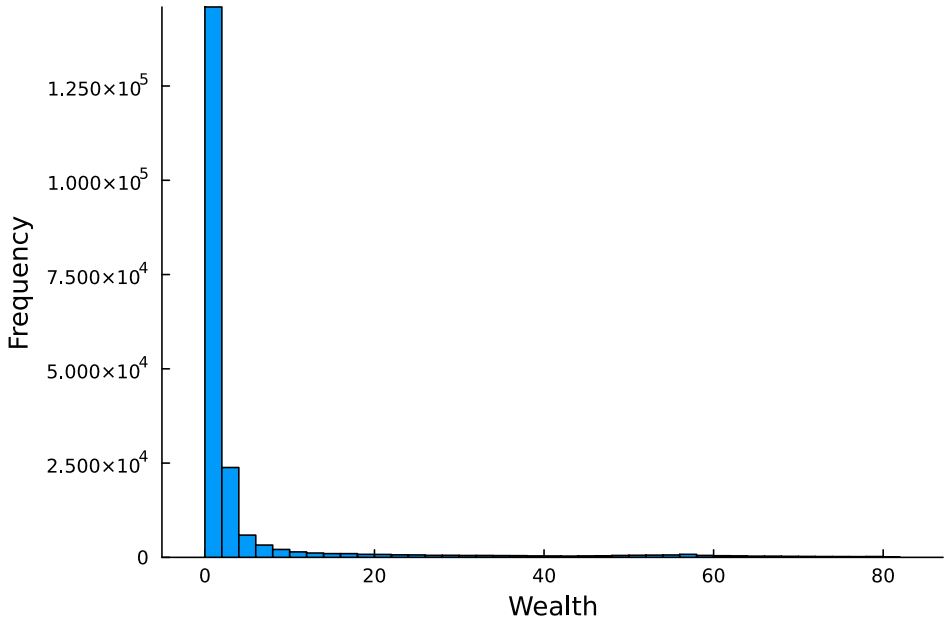
Notes: This figure plots the policy functions of an entrepreneur for the following choices under an environment characterized by a low interest rate and median TFP state: deposit holdings, capital stock, consumption, card balance, loan balance, and T-bill holdings. The policy functions show that entrepreneurs with low wealth are more borrowing focus and hold balances on their cards and loans. Meanwhile, as wealth accumulates, the entrepreneur becomes more liquidity-focused and holds more card slack and deposits. The parameters used to compute these policy functions are listed in Table 3.

Figure 9: Policy Functions Focused on Low End of Wealth Grid



Notes: This figure plots the same policy functions as Figure 8 under an environment characterized by a low interest rate and median TFP state but focused on the far left end of the wealth grid. For entrepreneurs with little wealth, card and loan borrowing constraints both bind. More borrowing is done at these wealth levels and relatively fewer deposits are held. The parameters used to compute these policy functions are listed in Table 3.

Figure 10: Simulated Stationary Distribution



Notes: This figure shows the simulated stationary distribution under the above optimal policy functions. Most of the mass of this distribution is on the far left end of the wealth grid where entrepreneurs' borrowing constraints bind and credit cards are used to meet financing needs. The parameters used in this simulation are listed in Table 3.

5.1 Parameter Estimation Strategy

This section discusses the strategy for setting parameters in the model. Some parameters are set externally, including parameters related to the entrepreneurs' preferences, firm depreciation, and the idiosyncratic shock process. I then use data to discipline parameters related to the common interest rate path. Finally, I perform a joint estimation of parameters governing technology and financing constraints to match sample averages of balance sheet positions by firm group and along the time path of aggregate deposit and card slack holdings. Table 3 summarizes the parameters estimated in this procedure.

Externally Set Parameters. The first section of Table 3 lists parameters set according to the standard literature. These parameters include the entrepreneur's CRRA power parameter γ_c, the capital depreciation parameter, and parameters governing the idiosyncratic TFP shocks.

Aggregate Shock Process. The next section of Table 3 covers parameters associated with the aggregate interest rate path that are estimated using FRED data. Table 4 lists in details lists these parameters associated with the common rath path process in both the non-crisis state and crisis state. Parameters are estimated using FRED data on the 3 month

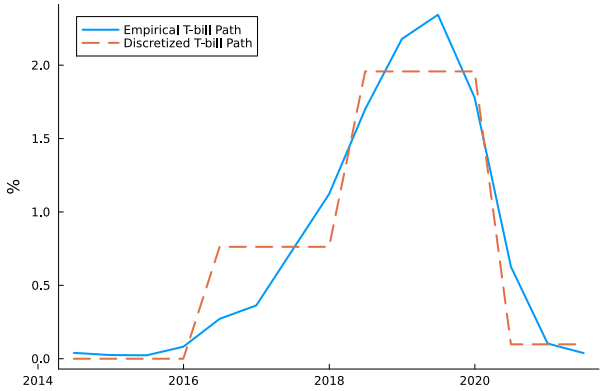
treasury bill, commercial bank rate on credit cards, bank prime loan rate, and national savings rate from the years 2014 to 2021. The parameters governing the degree to which the T-bill rate moves with all other interest rates are estimated with this data using Ordinary Least Squares (OLS):

$$r_B = \hat{\beta}^i r_i \tag{22}$$

Internal Estimation of Parameters. The final set of parameters consist of technology and financial constraint parameters that are jointly estimated to match moments in the cross section of the small firm balance sheet and their dynamics over time.

Empirical Simulation Procedure. To estimate the model moments, I simulate entrepreneurs facing a common empirical interest rate path from the years 2014 to 2021. To mimic the idea of firms experiencing an interest rate environment near the zero lower bound in the early 2010s, I set the initial wealth distribution to the simulated steady state distribution of entrepreneurs introduced in Section 4.4 that has then faced 6 periods of interest rate corresponding to the low interest rate state in June 2014. I afterwards simulate entrepreneurs experiencing a common path of interest rate shocks based on a 3-state Rouwenhorst discretization of the empirical T-bill path over the 2014 to 2021 period. Figure 11 shows the resulting T-bill rate discretization.

Figure 11: Discretization of T-bill Empirical Path (2014-2021).



Notes: This figure compares the empirical path of the 3-month Treasury bill rate from 2014 to 2021 to its discretized approximation using a 3-state Rouwenhorst process.

Card Shock Process. To aid with matching moments related to credit card borrowing, I include idiosyncratic shocks to card repayment in the model. With probability p_{card}, each entrepreneur pays interest $r_{card,t}$ on a fraction, χ, of the card balance; with probability $1 - p_{card}$, the balance is paid off on time, and no interest is paid. Optimal policy functions and simulations are computed with these shocks taken into account.

Table 3: Estimated Parameters

Parameter	Value	Source/Target
Externally Set		
CRRA power γ_c	2.0	• Standard literature
Capital depreciation δ	0.04	
AR(1) persistence log TFP shock ρ_A	0.95	
AR(1) mean log TFP shock μ_A	1.0	
Estimated from Data		
Crisis state parameters	–	• FRED data (see Table 4 for details)
Non-crisis state parameters	–	
Match Sales Moments		
Output elasticity (capital) θ_K	0.45	• Sales standard deviation
AR(1) Std. dev. log TFP $\sigma_{e,A}$	0.14	
Mean TFP level	0.8	• Sales/fixed assets
Recession factor	0.15	
Match Deposit Moments		
Output elasticity (liquidity) θ_L	0.12	• Aggregate deposits/fixed assets ratio
Liquidity deposit weight α	0.54	• Aggregate government securities/fixed assets ratio
Time preference β	0.89	
Match Debt Moments		
Card payment probability p_{card}	0.50	• Card balance across size
Card limit constraint φ	0.32	
Card balance paid χ	0.50	• Card slack/balance ratio across size
CES elasticity σ	1.5	
Exit probability p_{exit}	0.05	• Loan balance across size
Loan constraint ϕ	0.08	

Notes: This table lists values estimated for parameters in the model, reported at a semi-annual frequency. The first section outlines parameters that are externally set based on standard literature. The second section consists of parameters from the common interest rate shock process that are set based on data. More details on these parameters can be found in Table 4. The final sections consist of parameters that are internally estimated jointly to match moments from the small-firm balance sheet. They include parameters governing the firm's technology to match sales moments, parameters related to liquidity and time discounting to match deposit moments, and parameters related to borrowing and shock processes for card repayment and firm exit to match debt moments.

Table 4: Parameters from Interest Rate Process Estimated with Data

Parameter	Value	Source/Target
Non Crisis State		
T-bill rate mean $\bar{r}_B$	0.0012	FRED: 3 Month Treasury Bill
Card rate mean $\bar{r}_{card}$	0.128	FRED: Commercial Bank Rate on Credit Cards
Card co-movement with T-bill $\hat{\beta}^{card}$	1.21	OLS
Deposit rate mean $\bar{r}_{deposit}$	0.0007	FRED: National Savings Rate
Deposit co-movement with T-bill $\hat{\beta}^{deposit}$	0.0418	OLS
Loan rate mean $\bar{r}_{loan}$	0.039	FRED: Bank Prime Loan Rate
Loan co-movement with T-bill $\hat{\beta}^{loan}$	0.942	OLS
Crisis State		
Crisis entry probability	.08	NBER recession frequency (semi-annual)
Crisis exit probability	0.26	NBER recession frequency (semi-annual)
Tbill rate crisis state r_t^{crisis}	0.0009	FRED COVID average
Card rate crisis state r_t^{crisis}	0.146	FRED COVID average
Loan rate crisis state r_t^{crrisis}	0.03	FRED COVID average
Deposit rate crisis state r_t^{crisis}	0.0006	FRED COVID average

Notes: This table lists values estimated for parameters associated with the common rath path process in both the non-crisis state and crisis state. Parameters in the non-crisis are estimated using FRED data on the 3 month treasury bill, commercial bank rate on credit cards, bank prime loan rate, and national savings rate from the years 2014 to 2020. The parameters governing the degree to which the T-bill rate moves with all other interest rates are estimated with this data using Ordinary Least Squares (OLS). The parameters governing the crisis interest rate values involve estimate the average value of these data series during the first year of the COVID recession (2020-2021) as well as NBER recession data to estimate the probability of entering a crisis.

5.2 Model-Implied Moments

With these parameters, the model is quantified to match the firm's balance sheet in the cross section and over time. In the cross section, the model matches sample averages and the relative increase in borrowing and slack across firm size groups. Over time, the model reproduces the movement of small firms' credit card limits, card slack, and deposit holdings in the years leading up to and at the onset of COVID.

Cross-sectional moments. Table 5 lists the data moments used in the joint internal estimation of parameters and the model-implied moments. These include moments from the firm balance sheet, income and cash flow statements, and credit card and loan borrowing across size. Overall, the model matches sample averages reported in the data including aggregate deposits, aggregate government securities, and sales level. The model also captures the relative increase in balances for credit cards and traditional loans across size as well as the card slack to balance ratio across size.

Figures 12, 13 and 14 show the model counterparts to the empirical patterns on financing and liquidity across size. Overall, the model captures the empirical trends that smaller firms rely more on credit cards for borrowing whereas larger firms rely more on traditional loans for borrowing. In addition, the model reproduces the empirical fact that credit card limits

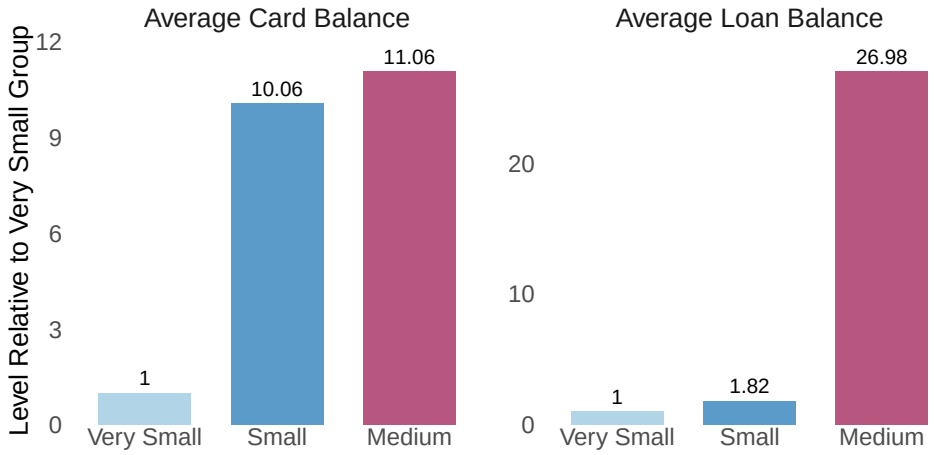
Table 5: Model vs Data Moments

Balance Sheet	**Data**	**Model**
Aggregate Deposits	0.183	0.200
Aggregate Government Securities	0.009	0.007
Income and Cash Flow Sheet		
Sales	0.383	0.399
Sales standard deviation	0.158	0.056
Credit Card Balances by Firm Size		
Very small firms	0.127	0.016
Small firms	0.149	0.161
Medium firms	0.159	0.177
Credit Card Slack / Balance Ratio		
Very small firms	2.599	0.395
Small firms	2.839	0.718
Medium firms	3.270	10.656
Loan Balances		
Very small firms	0.191	0.006
Small firms	0.224	0.079
Medium firms	0.324	0.523

Notes: This table lists the model-implied cross-sectional moments with the data targets, where all moments are reported as a share of physical capital for the model-implied moments and as a share of fixed assets for the data ones. These include moments on the firm balance sheet related to deposits and government securities, moments on the income and cash flow sheet related to sales level and sales standard deviation, and moments on credit card and loan borrowing across size. Overall, the model captures most cross-sectional sample averages as well as the relative increases of moments by size.

and slack rising faster than balances across size, leading to higher slack-to-balance ratios for larger firms. These trends reflect the empirical facts that larger firms rely more on credit cards for liquidity.

Figure 12: Model-Implied Average Card and Loan Balances Across Size.

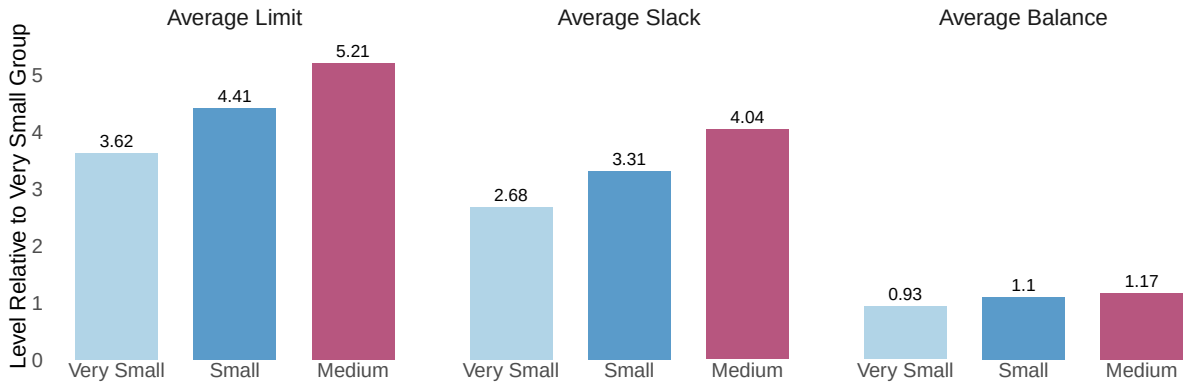


Notes: This figure plots the model generated card and loan balance across size for small firms relative to the level reported for the smallest size group, Very Small. The size groups are Very Small (1-4 employees), Small (5-19 employees), and Medium (20-99 employees). The model captures the empirical fact that loan balances rises faster across size than card balances, implying that larger firms rely more on traditional loans while smaller firms rely more on credit cards for borrowing.

Time-path moments. The model also captures the time variation of trends in card limits, slack, and deposits. Figure 15 plots the model counterpart of card limits, slack, and balance over time and reflects the empirical trend of the card limit and slack moving together as well as the trend of both the limits and slack falling at the onset of COVID. The model therefore suggests that movements in the card limit are tied to firms' liquidity needs.

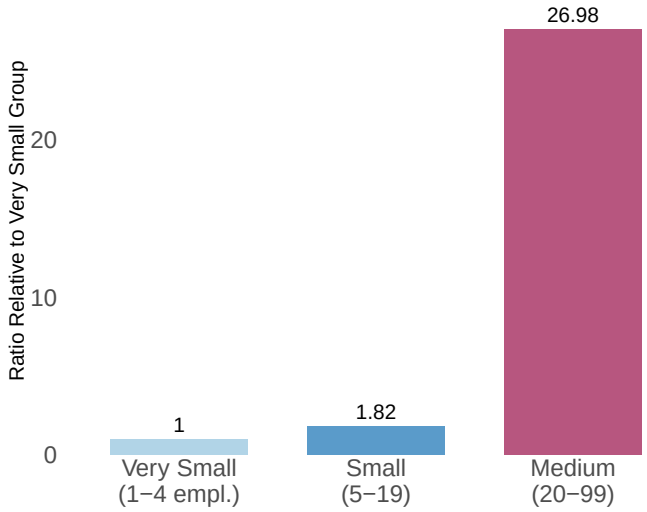
Figure 16 compares the time series plot of the model-generated card slack and deposits over time compared to the data version. Similar to the data counterpart, the model shows the slack and deposits moving in similar directions as their respective spreads with the T-bill rate move similarly. Furthermore, at the onset of COVID in 2020 when the card spread falls and the deposit spread increases, the model reproduces the data trend of aggregate card slack declining and deposits rising. The model therefore interprets the movements in card slack and deposits over time as liquidity management responses to relative changes in the cost of liquidity options.

Figure 13: Model Implied Limits, Slack, and Balance Across Size.



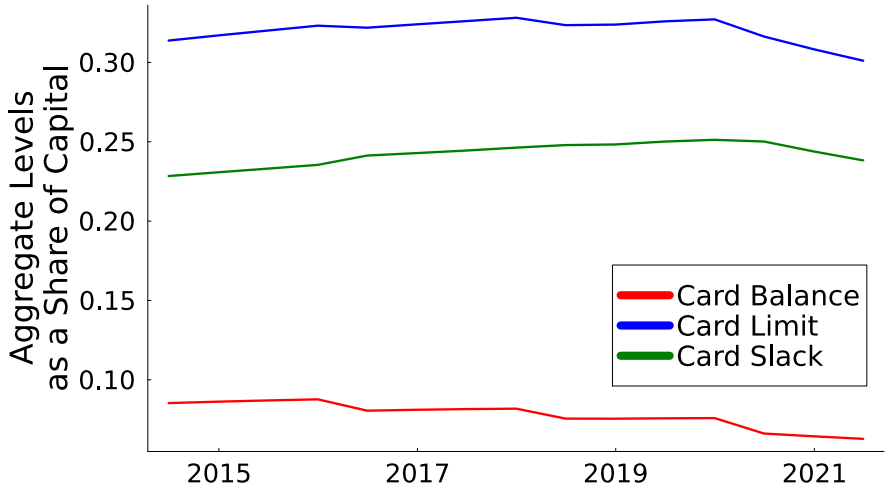
Notes: This figure plots the model implied average card limits, slack, and balance across size relative to the level reported for the smallest size group, Very Small. The size groups are Very Small (1-4 employees), Small (5-19 employees), and Medium (20-99 employees). The model captures the empirical trend that the average card limit and slack rise faster across size relative to card balance.

Figure 14: Model Implied Slack-to-Balance Ratio Across Size.



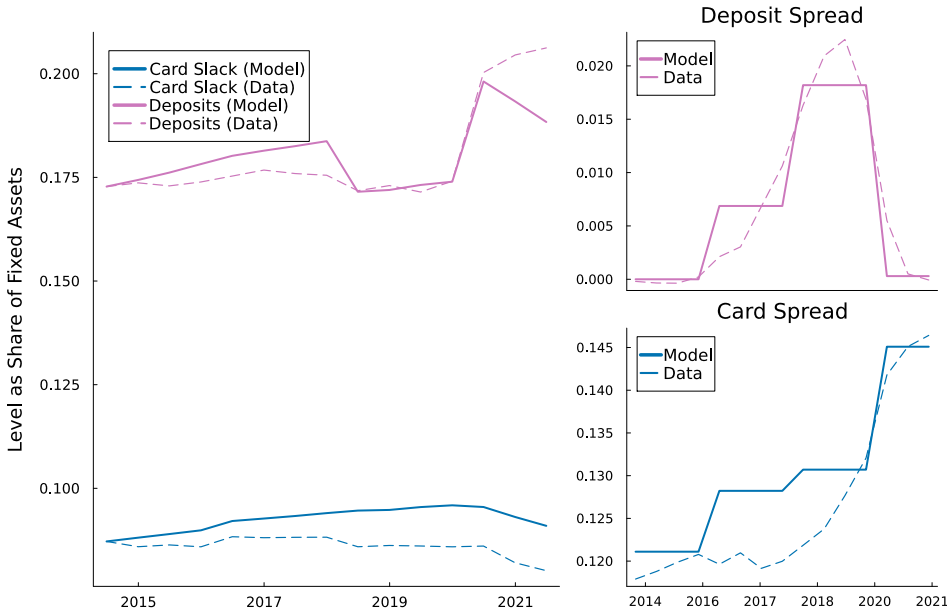
Notes: This figure plots the model implied average slack-to-balance ratio relative to the ratio reported for the smallest size group, Very Small. The size groups are Very Small (1-4 employees), Small (5-19 employees), and Medium (20-99 employees). The model captures the empirical fact that larger firms use cards more for liquidity than for financing compared to the smaller size groups.

Figure 15: Model Implied Card Limits, Slack, and Balance Over Time.



Notes: This figure plots the model-implied average card limit, slack, and balance over time. Each series is reported as a share of physical capital in the model. The model reproduces the empirical pattern in which card limits and slack move together and also reproduces their decline at the onset of COVID.

Figure 16: Model Implied Card Slack versus Deposits.



Notes: This figure plots in the left panel the model implied aggregate card slack and deposits over time. The model series are indexed to start at the initial value of the data counterpart of these time series, which are plotted in dashed for reference. The model overall captures the relative movements of the data counterparts in the years leading up to and at the start of COVID. The right panels of the figure shows the card and deposit spreads with the T-bill rate. As the spreads diverge at the start of COVID, aggregate slack decreases and aggregate deposits increases.

6 Counterfactuals

This section examines two counterfactual scenarios. The first exercise studies what would happen if credit cards did not provide a liquidity service. The second exercise studies impulse responses to a contractionary monetary policy shock. These counterfactuals show that larger firms are more sensitive to these changes due to their greater emphasis on liquidity management.

6.1 Counterfactual: Credit Cards Without Liquidity Service

In this counterfactual, I study the effects of removing liquidity benefits from credit cards. In my model, this exercise is equivalent to setting the liquidity weight on deposits, α, to 1 and removing card slack as a liquidity option:

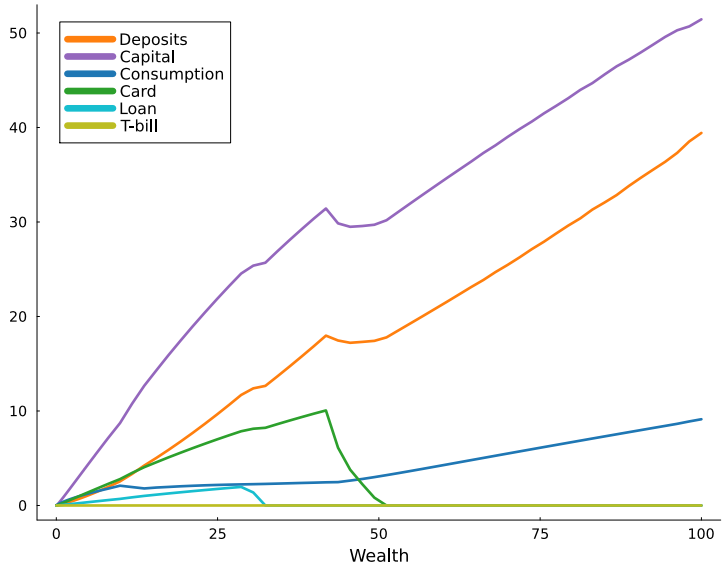
$$L_t = \left(\underbrace{\alpha}_{=1} (D_{t-1})^{\frac{\sigma-1}{\sigma}} + \underbrace{(1-\alpha)}_{=0} (CardSlack_{t-1})^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}}. \tag{23}$$

Removing the card liquidity service affects large firms the most, since these firms place greater importance on maintaining liquidity. Without facing a liquidity penalty from holding card balances, the entrepreneur's optimal policy now features higher levels of card borrowing across all wealth levels, as shown in Figure 17. As a result, under the same empirical exercise simulating TFP and interest rate shocks from the years 2014-2021, average card limits now move more closely with card balances over time as shown in Figure 18. The model counterfactual implies that movements in card limits are driven more by financing needs when credit cards no longer provide liquidity. Table 6 shows that firms reduce their card slack holdings to zero and use card borrowing to finance more deposit holdings for liquidity. Since larger firms are more liquidity-focused, Figure 19 show that they are more affected by not having the additional liquidity option, with their output reducing the most.

6.2 Counterfactual: Impulse Response to Contractionary Monetary Policy Shock

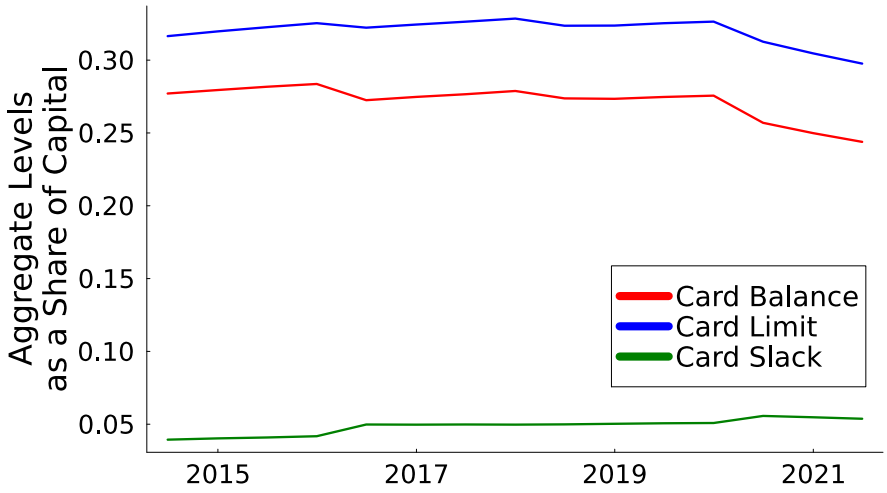
In this counterfactual exercise, find that monetary policy transmission mainly impacts the T-bill rate with limited pass-through to the card, loan, and deposit rates. I perform this counterfactual exercise by estimating the impulse response of the T-bill rate as well as its spreads with the card, deposit, and loan rate on a 10 basis points unexpected policy rate shock. The following local projections are performed with monetary policy shocks from

Figure 17: Optimal Policy Functions When Card Provides No Liquidity Service.



Notes: This figure plots optimal policy functions in which entrepreneurs cannot obtain liquidity from holding card slack. The following policy functions are plotted for an entrepreneur under an environment characterized by a low interest rate and median TFP state: deposit holdings, capital stock, consumption, card balance, loan balance, and T-bill holdings. Compared to Figure 8, entrepreneurs across all wealth levels hold higher card balances.

Figure 18: Optimal Policy Functions When Card Provides No Liquidity Service.



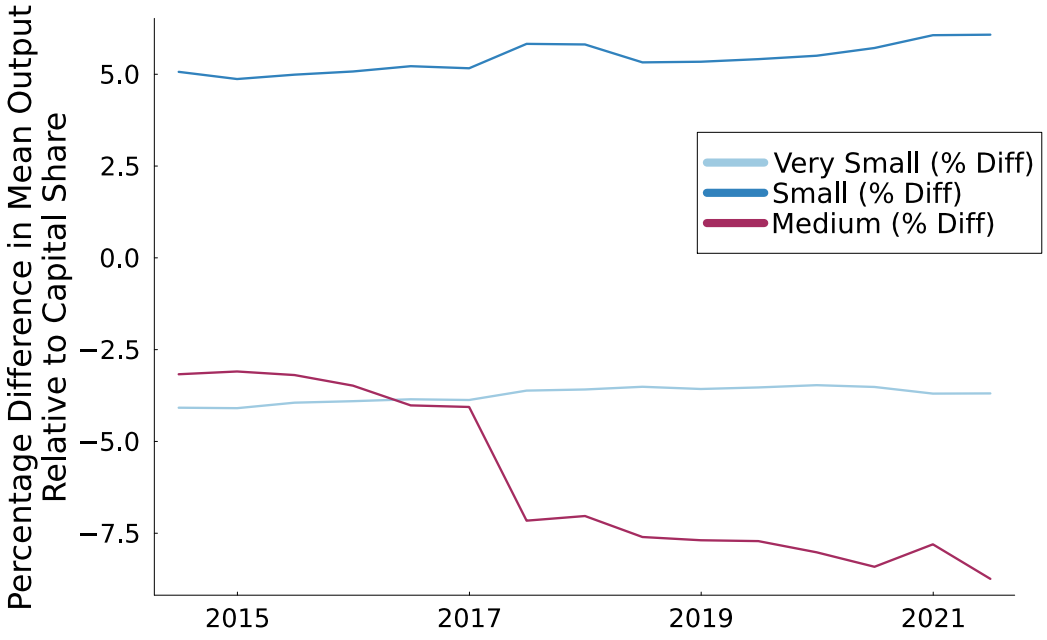
Notes: This figure plots average card limits, slack, and balance as a share of physical capital in the counterfactual in which entrepreneurs cannot obtain liquidity from holding card slack. Compared to Figure 15, card limits move more closely with balances than slack. The model counterfactual implies that without the card liquidity service, movements in limits are driven more by financing needs.

Table 6: Comparison of Cross-sectional Moments With Versus Without Card Liquidity

	Baseline	**No Card Liquidity**	**Difference (%)**
Mean Aggregate Deposits	0.20	0.39	94.30
Average Card Balance			
Very Small	0.02	0.02	44.97
Small	0.16	0.36	124.08
Medium	0.18	2.07	1067.84
Average Card Slack/Balance Ratio			
Very Small	0.40	0.00	−100.00
Small	0.72	0.01	−98.50
Medium	10.66	0.58	−94.54

Notes: This table compares cross-sectional model-implied moments of having card liquidity versus not having card liquidity for small firms when based on the simulation using the empirical path of interest rate shocks from 2014 to 2021. Aggregate deposit holdings, card balances, and card slack-to-balance ratio are reported. When credit cards provide no card liquidity, card slack is reduced to zero while card balances increase to finance more deposits for liquidity.

Figure 19: Output Change From Not Having Card Liquidity Across Size Groups.



Notes: This figure compares output between model scenarios with versus without card liquidity along the empirically simulated path from 2014-2021. Larger firms experience greater drops in output when they do not have credit cards as an additional liquidity source.

Bauer and Swanson (2023):

$$y_{t+h} = \alpha_h + \beta_h \cdot \text{MPS}_t + \varepsilon_{t+h}, \tag{24}$$

where y_{t+h} is either the T-bill rate $r_{B,t+h}$ or the spread with the T-bill rate $r_{i,t+h} - r_{B,t+h}$ for $i \in card, loan, D$. Figure 20 plots impulse responses β_h for each of the spreads with the T-bill rate and the T-bill rate itself. The impulse responses of the spreads exhibit similar dynamics to the T-bill rate response, suggesting that the T-bill rate movements are the primary driver of spread response variation. As a result, apply only the responses to the T-bill rate to the empirical interest rath path starting in 2017.

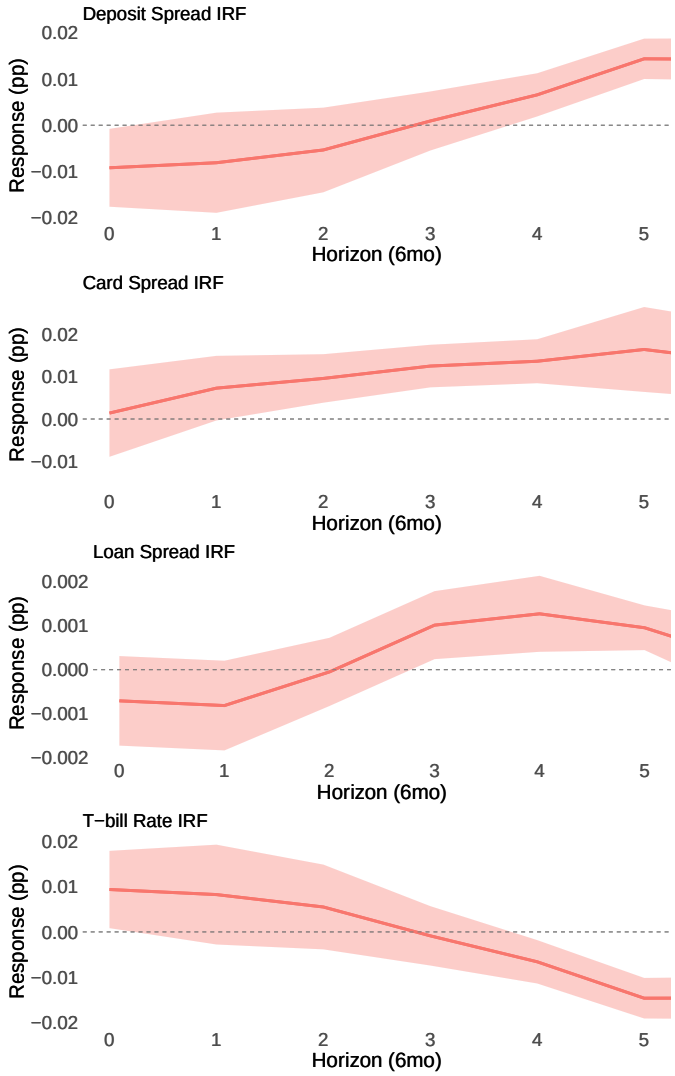
Simulating firms along this counterfactual interest rate path, I find that monetary policy transmission increases the cost of liquidity more for deposits than for credit cards. Figure 21 plots the percentage differences in aggregate deposits and card slack from the baseline scenario without the monetary policy shock, alongside the corresponding changes in the spread paths. While the deposit spread is defined the same as before, I report the effective card spread to better highlight the tradeoffs in holding card slack. The effective card spread is the difference between the T-bill rate and the expected interest rate paid on card balances, where the latter accounts for card repayment shocks. The impulse response of the T-bill rate affects the deposit spread more than the effective card spread. Appendix Figure A.4 illustrates the larger movement in the deposit spread by reporting the percentage changes in the card and deposit spreads. As a result, deposit holdings adjust more strongly than card slack holdings.

The contractionary monetary policy shock also has greater output effects on larger firms, since they rely more on deposits for liquidity. Figure 22 plots percentage differences in output relative to the baseline scenario across firm size groups. The impulse response of the T-bill rate affects the relative cost of holding deposits for liquidity which larger firms use for production. Since larger firms are more sensitive to changes in liquidity costs, they experience greater deviations along the impulse response path.

7 Conclusion

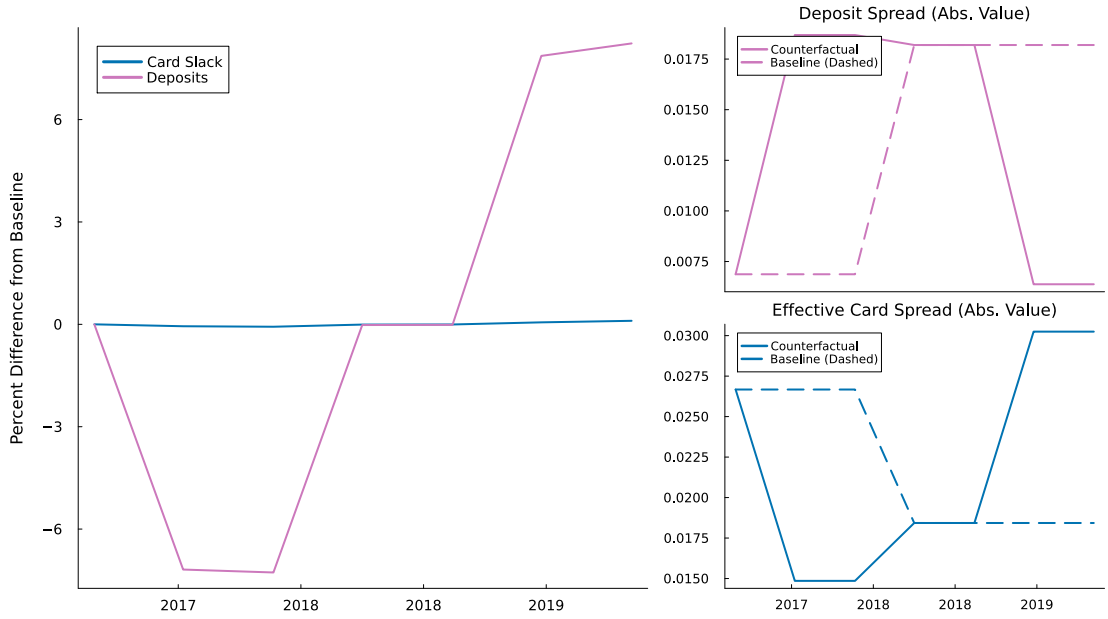
This paper studies the dual role of credit cards as both a financing and liquidity tool. Using new micro data from a major business credit database on small firm credit card use in the U.S, I develop facts that suggest smaller firms rely more on credit cards for financing whereas larger firms rely on credit cards for liquidity management. The data shows that the average credit card limit, slack, and balance all increase with size, with the balance increasing at a slower rate across size than the limit and slack, suggesting liquidity needs matter more for larger firms. Furthermore, I show evidence that small firms' credit card limit use in the

Figure 20: Impulse Response Functions (IRF) to Tightening Monetary Policy Shock.



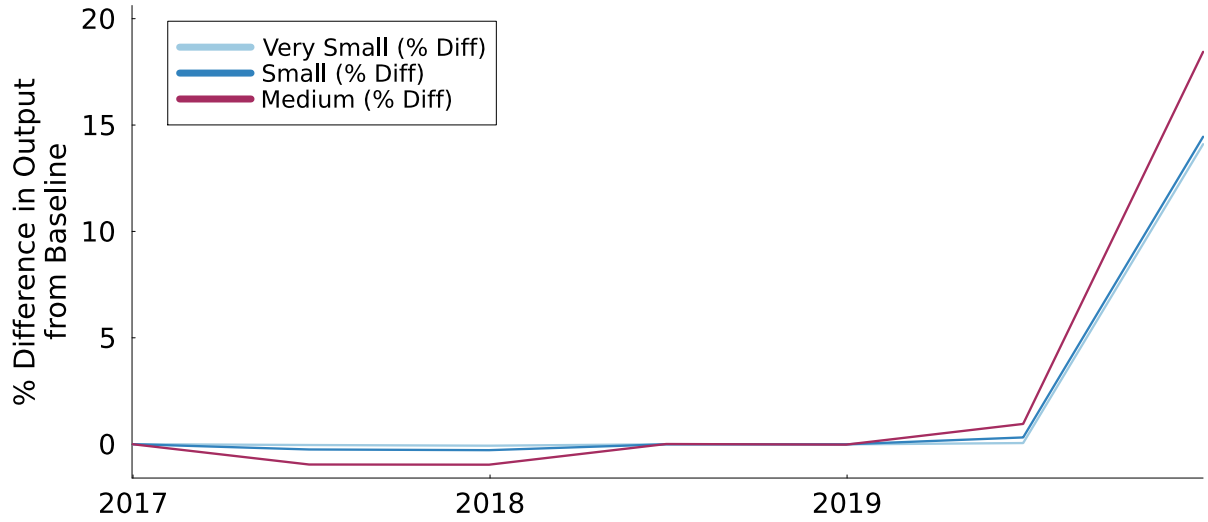
This figure plots impulse responses to a 10 basis point increase in the policy rate. Shaded areas indicate 95% confidence bands constructed using Newey-West HAC standard errors. The top three panels show responses of the deposit, credit card, and loan rate spreads relative to the 3-month T-bill rate. The bottom panel shows the response of the T-bill rate itself. The spread responses closely track the T- bill response, indicating that variation in the rate spreads is primarily driven by changes in the T-bill rate.

Figure 21: Aggregate Deposits and Card Slack Response to Monetary Policy Shock.



Notes: This figure plots the percentage change in aggregate deposits and card slack in response to the contractionary monetary policy shock in the left panel. The right panels show the comparison of the absolute value of the deposit and effective card spreads in the scenarios with and without the impulse response to the T-bill rate. The deposit spread reports the difference between the T-bill rate and the deopsit rate. Meanwhile, the effective card spread is the difference between the T-bill rate and the expected interest rate paid on card balances, where the latter accounts for card repayment shocks. Aggregate deposits experience a greater change in response to the shock since its spread moves more strongly in response to the shock than the card spread. For a version of this plot that shows percentage changes in spreads, refer to Appendix Figure A.4.

Figure 22: Percentage Difference in Average Output by Firm Size in Response to Tightening Monetary Policy Shock.



Notes: This figure plots the response in average output to tightening monetary policy shock across size as a percentage different from the baseline scenario without the policy shock. Larger firms experience more deviations in output along the impulse response path. The policy shock affects the cost of liquidity options, which larger firms rely more on.

years prior to and during onset of the COVID recession coincides with changes in liquidity needs. Average credit card limits move more closely with credit card slack than with card balance over these years, with both the average limit and slack slightly rising from the years 2014-2020 and falling sharply at the start of COVID. Finally, I combine business credit data with aggregate data on card borrowing and deposits to show that the co-movement of aggregate card slack and deposits during these years coincides with the co-movement of their spreads relative to the T-bill rate.

I then develop a quantitative model of constrained firms with liquidity demand to understand these facts. In this model, entrepreneurs face borrowing constraints on credit cards and traditional loan borrowing while using liquidity obtained from cards and deposits as an input into production. This model includes productivity and interest rate risk and is quantified to match balance sheet positions of small U.S. firms in the cross section and over time. The model shows that smaller firms use credit cards more for financing because they have little wealth and are borrowing constrained. Meanwhile, larger firms are relative unconstrained and therefore hold more card slack and deposits to meet liquidity needs. The model also interprets the time series movements of card slack and deposits as being driven by the relative costs of holding the two options for liquidity.

With this model, I study counterfactual exercises to understand what would happen if cards provided no liquidity service. I find that in this scenario, firms would reduce their card slack so that they can use credit cards to finance higher deposit holdings for liquidity.

Larger firms would experience more changes in output since they place greater emphasis on liquidity management compared to smaller firms.

My main counterfactual involves studying the transmission of monetary policy to small firms through a contractionary monetary policy shock. I find that this shock would have limited pass-through to card and deposit rates while affecting the T-bill rate more to increase the relative card and deposit spreads. As a result, larger firms experience greater deviations in outputs in response to the shock, since the policy increases the cost of liquidity, which these firms rely more on.

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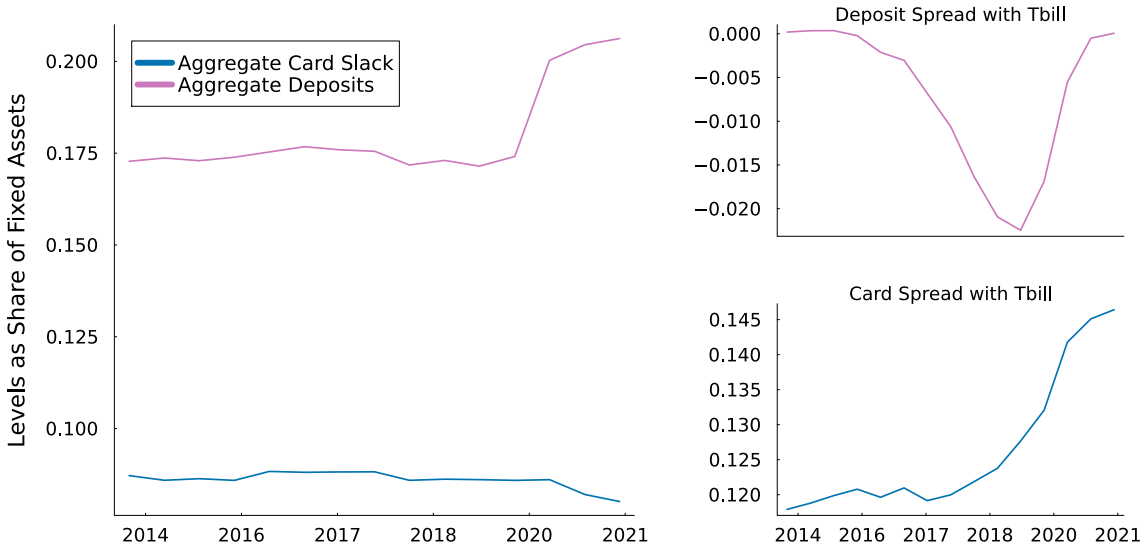
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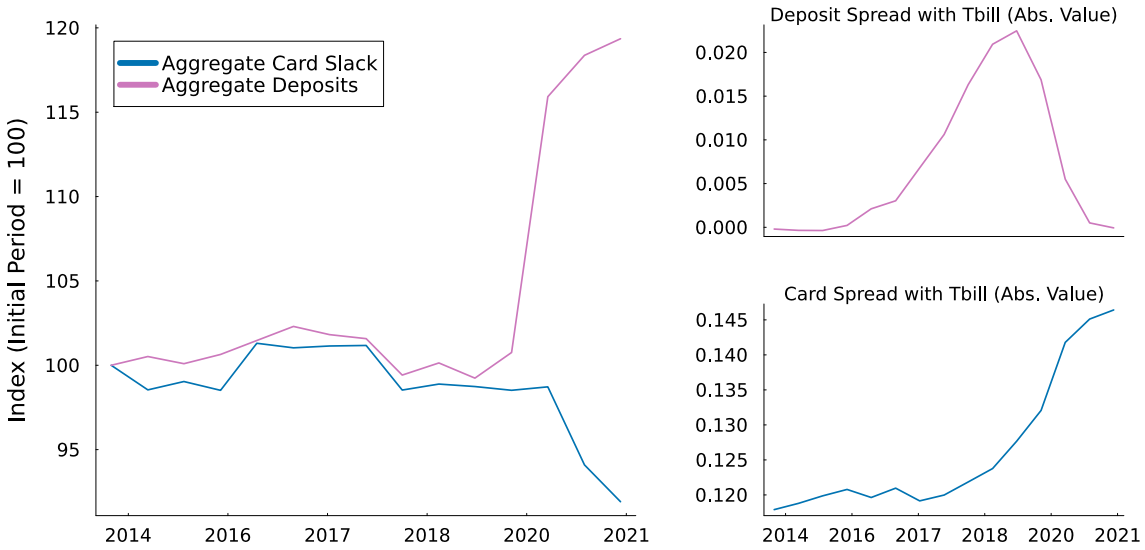
A Additional Figures

Figure A.1: Aggregate Deposits and Slack Across Time with Absolute Values of Spreads.



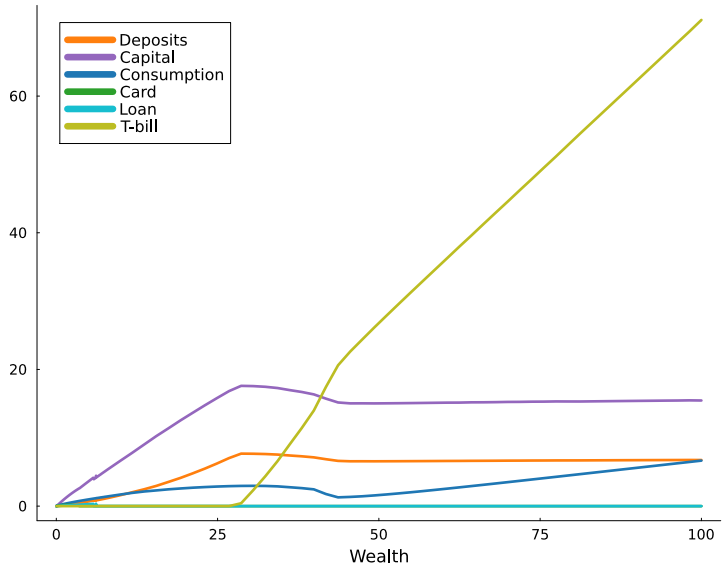
Notes: This figure plots aggregate deposits and slack as a share of fixed assets from the years 2014 to 2021. The right side panel shows the spreads of the deposit and card rate relative to the T-bill rate. Because the deposit rate is usually less than the T-bill rate during this time period, the spread is often negative. A less negative deposit spread is therefore interpreted as a decline in the opportunity cost of using deposits.

Figure A.2: Aggregate Deposits and Slack Across Time.



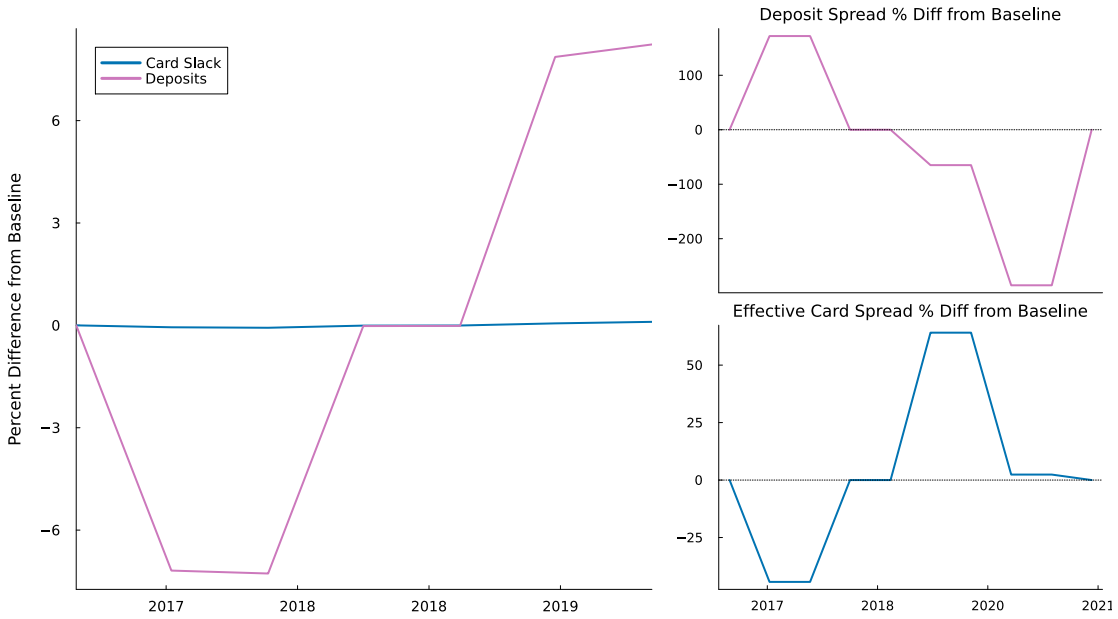
Notes: This figure plots in the left panel, aggregate deposits and slack as a share of fixed assets from the years 2014 to 2021 where both series are indexed at 100 in the initial period of the analysis. The right side panel shows the spreads of the deposit and card rate relative to the T-bill rate. Indexing both series in the left panel to start at the same point emphasizes their positive in the years leading up to COVID and divergence when COVID starts in 2020.

Figure A.3: Policy Function for High Interest Rate and Median TFP State



Notes: This figure plots the policy functions of an entrepreneur in a high interest rate and median TFP state. Policy values are plotted for the following choices: deposit holdings, capital stock, consumption, card balance, loan balance, and T-bill holdings. Due to the high interest rate environment, optimal borrowing amounts are lower across all wealth levels. For large enough wealth levels in this environment, capital stock and deposit holdings reach their steady state levels and entrepreneurs start investing their wealth in T-bills. The parameters of these policy functions are listed in Table 3.

Figure A.4: Aggregate Deposits and Card Slack Response to Monetary Policy Shock with Percentage Changes in Spreads.



Notes: This figure plots the percentage change in aggregate deposits and card slack in response to the contractionary monetary policy shock in the left panel alongside the percentage change in the spreads in the right panels. The deposit spread reports the difference between the T-bill rate and the deopsit rate. Meanwhile, the effective card spread is the difference between the T-bill rate and the expected interest rate paid on card balances, where the latter accounts for card repayment shocks. The percentage change in the effective card spread is much smaller than that for the deposit spreads, which coincides with less movement in aggregate card slack holdings in response to the monetary policy shock relative to aggregate deposit holdings.

B Model Euler Equations

This section shows Euler equations of the model for both the deterministic, unconstrained version and the full version with shocks and constraints.

B.1 Euler Equations for Deterministic, Unconstrained Case

Define discount rate ρ_t of entrepreneur such that:

$$1 + \rho_t = \frac{u'(C_t)}{\beta\, u'(C_{t+1})} \tag{25}$$

Loan FOC.

$$1 + \rho_t = \underbrace{1 + r_{loan,t}}_{\text{loan rate}} \tag{26}$$

Card FOC.

$$1+\rho_t = \underbrace{(1+r_{\text{card,t}})}_{\text{card rate}} + \underbrace{\theta_L(1-\alpha)\,\frac{Y_{t+1}}{L_{t+1}}\,L_{t+1}^{\frac{1}{\sigma}}\,(CardSlack_t)^{-\frac{1}{\sigma}}}_{\substack{\text{marginal product of card slack} \\ \text{via liquidity}(MP_{CardSlack,\,t})}} \tag{27}$$

Deposit FOC.

$$1+\rho_t = \underbrace{(1+r_{D,t})}_{\text{deposit rate}} + \underbrace{\theta_L\alpha\,\frac{Y_{t+1}}{L_{t+1}}\,L_{t+1}^{\frac{1}{\sigma}}\,D_t^{-\frac{1}{\sigma}}}_{\substack{\text{marginal product of deposit use} \\ \text{via liquidity}(MP_{D,t})}} \tag{28}$$

Capital FOC.

$$1+\rho_t = (1-\delta) + \underbrace{A\theta_K K_{t+1}^{\theta_K-1}L_{t+1}^{\theta_L} + A\theta_L K_{t+1}^{\theta_K}L_{t+1}^{\theta_L-1}(1-\alpha)\varphi L_{t+1}^{\frac{1}{\sigma}}(\varphi K_{t+1}-Card_t)^{\frac{-1}{\sigma}}}_{\text{marginal product of capital } MP_{K,t+1}} \tag{29}$$

T-bill FOC.

$$1+\rho_t = 1+r_{B,t} \tag{30}$$

B.2 Euler Equations for Full Case with Constraints and Shocks

The Lagrangian for the full case with constraints and shocks is:

$$\begin{aligned}
\mathcal{L} = {} & \frac{C_t^{1-\gamma_c}}{1-\gamma_c} + \beta V(W_{t+1}) \\
& + \lambda_t[W_t + Card_t + Loan_t - C_t - K_{t+1} - D_t - B_t] \\
& + \mu_t[\varphi K_{t+1} - Card_t] \\
& + \omega_t[\phi K_{t+1} - Loan_t] \\
& + \eta_t[Card_t - 0] \\
& + \nu_t[Loan_t - 0] \\
& + \xi_t[B_t - 0],
\end{aligned} \tag{31}$$

where wealth at time $t+1$, W_{t+1} is defined:

$$W_{t+1} = Y_{t+1} + (1-\delta)K_{t+1} + (1+r_D)D_t + (1+r_B)B_t - (1+p_{card}r_{\text{card}}\chi)Card_t - (1+r_{loan})Loan_t, \tag{32}$$

production function defined as,

$$Y_{t+1} = AK_{t+1}^{\theta_K}L_{t+1}^{\theta_L}, \tag{33}$$

liquidity defined as,

$$L_{t+1} = (\alpha D_t^{\frac{\sigma-1}{\sigma}} + (1-\alpha)(\varphi K_{t+1} - Card_t)^{\frac{\sigma-1}{\sigma}})^{\frac{\sigma}{\sigma-1}}. \tag{34}$$

Denote the stochastic discount factor as M_{t+1} such that $E[M_{t+1}] = \beta(1-p_{exit})E_t\left[\left(\frac{C_{t+1}}{C_t}\right)^{-\gamma_c}\right]$ and the discount rate is $\frac{1}{E[M_{t+1}]}$.

Loan FOC.

$$\underbrace{\frac{1}{\mathbb{E}_t[M_{t+1}]}}_{\text{discount rate}} = \underbrace{1 + r_{\text{loan},t}}_{\text{loan rate}} - \underbrace{\frac{\nu_t - \omega_t}{C_t^{-\gamma_c}\,\mathbb{E}_t[M_{t+1}]}}_{\text{multiplier term}} \tag{35}$$

Card FOC.

$$\begin{aligned}\underbrace{\frac{1}{\mathbb{E}_t[M_{t+1}]}}_{\text{discount rate}} &= \underbrace{(1 + p_{card} r_{\text{card},t}\chi)}_{\text{effective card rate}} + \underbrace{\theta_L(1-\alpha)\,\mathbb{E}_t\left[\frac{Y_{t+1}}{L_{t+1}}\,L_{t+1}^{\frac{1}{\sigma}}\,(\varphi K_{t+1} - \text{Card}_t)^{-\frac{1}{\sigma}}\right]}_{\text{marginal product } (MP_{CardSlack,t})} \\ &+ \underbrace{\frac{\theta_L(1-\alpha)\,\text{Cov}_t(MP_{CardSlack,t},\, M_{t+1}) + Cov_t(M_{t+1}, (i_{card,t+1}\, r_{\text{card,t}}\,\chi))}{\mathbb{E}_t[M_{t+1}]}}_{\text{risk premium}} + \underbrace{\frac{\mu_t - \eta_t}{C_t^{-\gamma_c}\,\mathbb{E}_t[M_{t+1}]}}_{\text{multiplier term}}\end{aligned} \tag{36}$$

Deposit FOC.

$$\begin{aligned}\underbrace{\frac{1}{\mathbb{E}_t[M_{t+1}]}}_{\substack{\text{discount}\\ \text{rate}}} &= \underbrace{(1 + r_{D,t})}_{\text{deposit rate}} + \underbrace{\theta_L\alpha\,\mathbb{E}_t\left[\frac{Y_{t+1}}{L_{t+1}}\,L_{t+1}^{\frac{1}{\sigma}}\,D_t^{-\frac{1}{\sigma}}\right]}_{\text{MP (deposits)}} \\ &+ \underbrace{\theta_L\alpha\,\frac{\text{Cov}_t\left(\frac{Y_{t+1}}{L_{t+1}}\,L_{t+1}^{\frac{1}{\sigma}}\,D_t^{-\frac{1}{\sigma}},\, M_{t+1}\right)}{\mathbb{E}_t[M_{t+1}]}}_{\text{risk premium}} + \underbrace{\frac{\psi_t}{C_t^{-\gamma_c}\,\mathbb{E}_t[M_{t+1}]}}_{\text{multiplier/slack}}.\end{aligned} \tag{37}$$

Capital FOC.

$$\underbrace{\frac{1}{\mathbb{E}_t[M_{t+1}]}}_{\text{discount rate}} = \underbrace{(1-\delta)}_{\text{depreciation}} + \underbrace{\theta_K \, \mathbb{E}_t\left[\frac{Y_{t+1}}{K_{t+1}}\right]}_{\text{MP of capital}} + \underbrace{\theta_K \, \frac{Cov_t\left(\frac{Y_{t+1}}{K_{t+1}},\, M_{t+1}\right)}{\mathbb{E}_t[M_{t+1}]}}_{\text{risk premium (TFP risk)}}$$
$$+ \underbrace{\theta_L(1-\alpha)\varphi \, \mathbb{E}_t\left[\frac{Y_{t+1}}{L_{t+1}} \, L_{t+1}^{\frac{1}{\sigma}} \left(\varphi K_{t+1} - \text{Card}_t\right)^{-\frac{1}{\sigma}}\right]}_{\text{liquidity channel via credit limit}}$$
$$+ \underbrace{\theta_L(1-\alpha)\varphi \, \frac{\text{Cov}_t\left(\frac{Y_{t+1}}{L_{t+1}} \, L_{t+1}^{\frac{1}{\sigma}} \left(\varphi K_{t+1} - \text{Card}_t\right)^{-\frac{1}{\sigma}},\, M_{t+1}\right)}{\mathbb{E}_t[M_{t+1}]}}_{\text{risk premium (TFP-liquidity risk)}} + \underbrace{\frac{\mu_t \varphi + \omega_t \phi}{C_t^{-\gamma_c} \, \mathbb{E}_t[M_{t+1}]}}_{\text{multiplier adjustment}} \tag{38}$$

T-bill FOC.

$$\underbrace{\frac{1}{\mathbb{E}_t[M_{t+1}]}}_{\text{discount rate}} = \underbrace{1 + r_{\text{B},t}}_{\text{T-bill rate}} - \underbrace{\frac{\xi_t}{C_t^{-\gamma_c} \, \mathbb{E}_t[M_{t+1}]}}_{\text{multiplier term}} \tag{39}$$