Nonbank Lending and the Transmission of Monetary Policy: Evidence from U.S. Small Business Loans

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[PRELIMINARY DRAFT]

Abstract

Nonbank lending has reshaped the original credit markets since the Global Financial Crisis. This paper finds that nonbanks expand significantly when monetary policy tightening. Using Uniform Commercial Code filings, I find that a one percent increase in the Federal Funds rates is associated with a 1.4 percent rise in nonbank market share. Nonbanks gain significantly more market share in counties where banks hold greater market power in local deposit markets. These findings are robust to controls for the bank capital channel and time-varying firm heterogeneity. The real impacts suggest that the interest-rate-driven rise in nonbank lending does not promote local economic development, as bankruptcy rates and unemployment rates both increases significantly in more concentrated counties following interest rate hikes. This paper highlights the importance of nonbanks in the transmission of monetary policy to small business lending.

Keywords: nonbank financial intermediary, transmission of monetary policy, small business lending

JEL Codes: G21, G23, G38

1 Introduction

The Federal Reserve started using interest rates as the major monetary policy tool again in March 2022. Previous literature has extensively analyzed credit channels of monetary policy through bank loan supply (Bernanke and Blinder, 1988; Kashyap and Stein, 1993; Jiménez, Ongena, Peydró, and Saurina, 2012; Drechsler, Savov, and Schnabl, 2017, etc.). They find that when the central bank raises the short-term interest rates, banks will reduce loan supply. However, the rapid growth of nonbank lending has fundamentally transformed the credit markets. Nonbanks are lenders who do not take deposits. According to Preqin (2022), asset under management of direct lending[1] has surged sixfold from \$100 billion in 2014 to \$592 billion in 2022. More recently, “The way companies borrow money is changing forever” and “Private markets remain attractive, even in a higher-rate world”[2] make major business headlines, raising a fundamental question: how will nonbanks respond when the central bank adjusts the interest rates? Will nonbanks contract new lending as banks or extend their lending to absorb banks’ market share?

Understanding the questions is important. The central bank lifts interest rates to cool over-investment and overspending, relying on major credit suppliers to transmit policy effects to firms and households. Given that nonbanks now play a significant role alongside banks as lenders, the efficiency of the transmission of monetary policy depends on their lending responses. If nonbanks reduce loan supply as much as banks, the transmission remains effective. Otherwise, if nonbanks contract less new lending, firms and households may substitute toward nonbank credits, weakening policy effectiveness. Therefore, a higher share of nonbank loans relative to bank loans implies less efficient monetary policy transmission.

To approximate the answer, I analyze small business loan data for three reasons. First, nonbank lending is closely related to small business lending, with nonbank lenders providing half of all U.S. small business loans in 2022[3]. Second, small businesses contract significantly

[1] Direct lending is a type of nonbank credit directly negotiated between a nonbank lender and a borrower.
[2] Ungarino (2024); The Economist (2023)
[3] Bipartisan Policy Center

more than larger companies after monetary policy tightening (Gertler and Gilchrist, 1993, 1994). Last but not least, small businesses are important economic drivers, contributing nearly half of U.S. employment, stimulating innovation and entrepreneurship, and attracting immigrants (Mills, 2018).

I examine the Uniform Commercial Code (UCC) filings of 1996-2021 to provide systematic evidence on how much market share nonbanks gain during tight money periods. I utilize two sets of UCC samples. One is the national UCC data[4] containing county-level UCC loan volumes for 50 states and the District of Columbia from 2007 to 2021. The data set consists of non-real-estate, secured loans, which account for up to 73% of all U.S. small business loans, more than either the Community Reinvestment Act (CRA) data or the Small Business Administration data (Gopal and Schnabl, 2022). The other is the state-level UCC data covering loan-level Florida UCC filings. The state-level UCC data traces back to 1996, which contains a much larger variation over time series to study. More importantly, state-level UCC data provides detailed information on the underlying loans, lenders, and borrowers. Typical nonbank lenders in the sample include finance companies, FinTechs, manufacturing companies and captive finance companies, etc.

I first document that an increase in the short-term interest rate is associated with a national rise in nonbank lending at the quarter level. When the Federal Funds rates move higher, loan volume of bank new lending shrinks, while nonbank new lending expands. Specifically, a one percentage point (pp) positive change in the Federal Funds rates is associated with a 1.4 pp greater gain in nonbank market share. It suggests a significant impact of nonbanks on the national credit supply when monetary policy gets tight.

I also show that the growth of nonbank lending is not driven by nonbanks' anticipation of changes in monetary policy. Prior literature suggests that the Federal Funds rates incorporate market expectations about the changes in the interest rates. This raises a concern that the observed expansion in nonbank market share may reflect not a structural shift, but

[4] The national UCC is aggregated to county-level from loan-level data provided by a commercial vendor, Mailinglist.

a correlation between nonbanks' interest rate expectations and their lending activity. To address the concern, I estimate impulse responses of nonbank market share to monetary policy shocks. I use two types of shocks, each representing a major identification strategy. One is the narrative-based Romer and Romer (2004) (RR) shock using data from the Greenbook forecasts. The other is the high-frequency measure based on futures market reactions around the Federal Open Market Committee (FOMC) announcements as suggested in Gürkaynak, Sack, and Swanson (2005) (GSS). Both are designed to identify unanticipated monetary surprises. I find that a one standard deviation increase in either the RR or GSS shocks is associated with a 0.35 pp greater expansion in nonbank market share. This magnitude is comparable to the nonbank expansion linked to a one standard deviation increase in the Federal Funds rates.

The time-series evidence raises a question of whether the increase in nonbank market share is caused by the supply side or the demand side. Do nonbanks expand to fill the void as banks reduce loan supply during tight money periods? Or, do small businesses prefer nonbank lenders because of faster processes and easier approval? I address the identification challenge by the deposit channel Drechsler et al. (2017). When the Federal Funds rates increase, banks exploit market power to widen deposit spreads for profits. In response, depositors move their deposits to invest in assets with higher yields[5]. The deposit outflows are substantial for two main reasons. First, the volume is large because yield-sensitive depositors hold only the minimum liquidity necessary in deposit accounts. Second, since banks offer below-market rates on deposits, these outflows cannot be fully offset by switching to other funding sources, such as wholesale funding (Kashyap, Rajan, and Stein, 2002). As a result, banks have to cut back on new lending, creating space for nonbanks to step in.

I examine the mechanism at the county level by exploiting geographical variation in deposit market power. Under the deposit channel, deposit outflows should be greater, and the decline in bank loan supply should be larger in counties where banks have more market

[5]For instance, deposits may shift to money market funds (Xiao, 2020) or online banks (Erel, Liebersohn, Yannelis, and Earnest, 2023).

power in local deposit markets. Therefore, the growth of nonbank market share should be higher in more concentrated counties. I measure deposit competition by the standard Herfindahl-Hirschman Index (HHI). My analysis reveals that deposit outflows are 43 basis points (bp) larger in high-concentration (HHI above 75th percentile, 0.393) counties than in low-concentration (HHI below the 25th percentile, 0.179) counties after a 100 bp increase in Federal Funds rates. Nonbank market share grows 34 bp more in high-concentration counties in the subsequent quarter to an increase in the Federal Funds rates, as a result of a significant reduction in bank new lending and a smaller contraction in nonbank new lending. Bank new lending reduces by 2.15 pp more in high-concentration counties, while nonbank new lending only declines by half as much. These results suggest a more significant nonbank expansion in more concentrated counties when interest rates increase.

I also verify that the growth of nonbank market share is not driven by alternative channels of the transmission of monetary policy. Wang, Whited, Wu, and Xiao (2022) compare the explanatory power of the bank reserve channels, the bank capital channels, and the deposit channel. They summarize that the bank capital channel and deposit channel account for most of the variation in banks' responses to changes in monetary policy. To distinguish between the two channels, I exploit national UCC data to show that banks are reducing small business lending primarily due to deposit outflows rather than declines in equity. This suggests that the rise in nonbank market share is driven by the deposit channel, not the bank capital channel.

A potential endogeneity concern is that the HHI index may be correlated with local lending opportunities. For example, more concentrated counties may be less economically developed, with small businesses that are less likely to qualify for bank loans. I address this concern using two strategies. First, I use the national UCC data to compare the growth in nonbank market share between high- and low-concentration counties, controlling for county-level lending opportunities. If the effects are driven by lending opportunities, then controlling for business characteristics should reduce the coefficient estimates or weaken their statistical significance. However, the results show that the effects of the deposit channel remain significant, with the estimated coefficients largely unchanged.

Second, I exploit loan-level variation and control for firm-specific lending opportunities, measured by firm age, size, and industry. I estimate firm age by linking the state-level UCC data to Florida corporate records. I also proxy for firm size using the number of officers listed in the corporate records. To classify industries, I use ChatGPT to infer each firm's industry based on its name. I include firm age, size and industry and county-level macroeconomic variables, along with their interactions with changes in the Federal Funds rates, as controls at the loan level. The results find that nonbank loans are more likely to be originated in counties where banks have greater market power. One may question that my identification is noisy, and the results can be due to selection bias. To address this, I conduct the Oster (2019) test to examine coefficient stability. The Oster test suggests that the unobservables must be twice as important as the current controls to eliminate the treatment effects. In other words, it is unlikely that adding unobservable confounders will weaken the treatment effects.

Next, I analyze county-level heterogeneity in the nonbank expansion during periods of monetary tightening. I find that a one pp higher firm exit rate is associated with a 28 bp greater growth of nonbank market share. However, the nonbank loans are not extended to firms that are the most financially demanding, as counties where firms depend more heavily on external financing show significantly smaller gain in nonbank market share.

Finally, I examine the real effects of increased nonbank lending using national UCC data. In the first three quarters following a interest rate rate hike, firm exit rates are slightly lower in counties with more concentrated nonbank lending. However, this pattern reverses in the second year, when exit rates become significantly higher. On average, the exit rate in high-concentration counties is 5 bp higher than in low-concentration counties during the second year. This suggests that while the expansion of nonbank lending may temporarily delay small business failures, it does not fully offset the negative effects of tighter credit conditions. Consistent with this, unemployment rates are significantly higher in high-concentration counties over the eight quarters following a rate hike, with an average increase of 11 bp. These findings indicate that nonbank lending does not cushion the adverse local economic effects of monetary tightening.

This paper contributes to studying the shadow banking channels of the transmission of monetary policy. On the supply side, Nelson, Pinter, and Theodoridis (2018) find that shadow banks expand balance sheets while commercial bank assets contract after the tightening of monetary policy. Xiao (2020) suggests tight monetary policy leads to deposit inflows to money market funds. Agarwal, Hu, Roman, and Zheng (2023) document nonbank expansion in mortgage markets during tight money periods. On the demand side, Ottonello and Winberry (2020) study public firms' sensitivity to monetary policy changes and find financially constrained public firms less responsive to monetary policy shocks. Albuquerque and Mao (2023) suggest tight monetary policy even creates better credit market conditions for zombie firms. However, Caglio, Darst, and Kalemli-Özcan (2021) find the opposite for private firms, with short-balance-sheet private firms facing greater difficulty obtaining bank loans under tighter monetary policy. Elliott, Meisenzahl, Peydró, and Turner (2022) discover a shift toward nonbank lending in syndicated lending, mortgage lending, and consumer lending given positive monetary policy shocks. I find a shift toward nonbanks in small business lending and direct lending in periods of high interest rates.

This paper also closely relates to the literature on nonbank lending. Previous research explains the post-crisis expansion of nonbanks by faster application processes, openness to financially constrained firms, and reduced regulatory burden (Buchak, Matvos, Piskorski, and Seru, 2018; Fuster, Plosser, Schnabl, and Vickery, 2019; Chernenko, Erel, and Prilmeier, 2022; Block, Jang, Kaplan, and Schulze, 2024, etc.). However, questions remain about whether the shift toward nonbank lending is permanent or transitory. More recently, Acharya, Cetorelli, and Tuckman (2024) propose a transformation view where markets swing between banks and nonbanks over time. My findings suggest that tight monetary policy results in a short-term expansion of nonbanks.

This paper also connects to prior studies on small business lending. Banks, especially larger institutions, have substantially reduced small business loan supply following the Global Financial Crisis due to regulatory burden (Cortés, Demyanyk, Li, Loutskina, and Strahan, 2020), leading to economic contraction in affected counties (Chen, Hanson, and Stein, 2017). Given that banks have substantially reduced small business lending, while nonbanks have substituted as major credit suppliers to small businesses (Gopal and Schnabl, 2022), my paper finds that the substitution of banks by nonbanks does not fully offset the negative effects of monetary policy tightening on small business financing.

2 Data and Identification

The main data set is about the Uniform Commercial Code (UCC) filings, which are secured, non-real-estate loans covering up to 73% of U.S. small business loans. I supplement the data sets with (1) Wharton Research Data Services (WRDS) company subsidiary data, (2) Florida corporate records, (3) Standard and Poor's Capital IQ Database, (4) Dun and Bradstreet database, (5) National Information Center (NIC) data, (6) Summary of Deposits data sets from Federal Deposit Insurance Corporation (FDIC), (7) bank data from U.S. Call Reports, (8) county-level demographics and business dynamics data from U.S. Census and the Bureau of Labor Statistics, (9) time-series macroeconomic variables from Federal Reserve Economic Database (FRED), and (10) Compustat Database.

2.1 The UCC Data

The Uniform Commercial Code is one of the uniform acts regulating sales and commercial transactions across 50 states and the District of Columbia in the U.S. Although the UCC laws are flexible for modification, most states enact them with minimal changes. Article 9 of UCC governs secured transactions so that it guarantees three rights of creditors. First, creditors can get an official report on security interests created. Second, when a debtor pledges the same collateral to multiple creditors, the filings clarify creditors' order of priority when the debtor bankrupts. Third, the filings will be officially published and creditors can check whether the security interests have been created by others online. The filing fee is quite affordable, ranging from \$15 to \$25 in most states. Therefore, creditors are strongly motivated to file a UCC statement for the protection of their security interests.

The UCC filings cover secured, non-real-estate loans and leases as governed by the UCC articles. Loans secured by real property are not included because they are registered with the county or lower-level administration that maintains the deed of the property. However, UCC filings are generally registered with the Secretary of State. Although UCC loans are non-real-estate loans, the UCC data accounts for up to 73% of all U.S. small business loans (Gopal and Schnabl, 2022). They also suggest that the coverage of UCC data is more comprehensive than either the Community Reinvestment Act (CRA) data or the Small Business Administration (SBA) data when studying small business lending. More importantly, the UCC data includes the name and address information of lenders and borrowers, while the CRA data contains limited information on nonbank lenders. One note is that leases are kept in my sample because small businesses often use them as a substitute for loans[6]. In addition, financial leases are almost identical to loans, except that lessees do not own the collateral but borrowers keep the ownership.

The UCC data does not report the dollar amount of loans, but this does not make the disadvantage of the data. As mentioned in Petersen and Rajan (1994) and Deyoung, Gron, Torna, and Winton (2015), loan officers tend to adjust loan quantity to small businesses rather than loan prices under economic uncertainty. Thus, using the number of loan origination captures how lenders adjust their loan supply to small businesses after the tightening of monetary policy.

A variety of papers utilize the UCC data to study small business lending, secured lending,

[6] Financially constrained firms utilize more leases (Eisfeldt and Rampini, 2009; Rampini and Viswanathan, 2013)

and relationship lending. Edgerton (2012) finds that firms will have limited credit access if they are in a relationship with distressed lenders using California UCC data. Murfin and Pratt (2019) studies captive financing using UCC data directly from all available states. Gopal and Schnabl (2022) is the first paper to utilize the national UCC data set provided by the commercial lender, Mailinglist, and suggest a "permanent" shift toward nonbank lending in small business loans since the Global Financial Crisis. Gopal (2021) studies lenders' collateral specialization with the state-level UCC data from Texas.

I utilize two sources of UCC data. One is a county-level dataset covering all 50 states and the District of Columbia from the first quarter of 2007 to the last quarter of 2021, henceforth, the national UCC data. It is composed of total loan volumes by lender type and counties aggregated from the loan-level dataset provided by a commercial vendor.[7] The other is loan-level data on Florida UCC loans spanning from the first quarter of 1996 to the last quarter of 2021, henceforth the state-level UCC data[8]. Section 3.6 provides further details comparing the two UCC samples. Section 2.6 shows that the level of economic development in counties sampled in the state-level UCC data is comparable with that in counties sampled in the national UCC data.

I keep all original filings where debtors are located in the filing state, because the filed debtor address must be the head office or the location of incorporation of the firm. The state-level UCC data contains filing dates and names and locations of lenders and borrowers. It requires extensive cleaning. I eliminate non-name descriptions, correct common typos, and extend frequent acronyms. I regard each original filing as a loan approval and the filing date as the date of origination.

There is a small fraction of public firms and large private firms. To focus on small businesses, I link the state-level UCC data with the WRDS company subsidiary data to remove public firms and their subsidiaries. I also link state-level ucc data with the Standard

[7] The vendor is Mailinglist.com. I do not have the access to the loan-level data, but only have the aggregated county-level data.

[8] Available at https://floridaucc.com/

and Poor's Capital IQ Database by name to remove large private firms. I also drop firms in public administration by linking with Dun and Bradstreet database. Although Dun and Bradstreet data is not time-series, I argue that the time-series variation in the industry of public administration firms is limited.

I link the state-level UCC data with Florida corporate records[9] to exclude non-profit firms, uniquely identify borrowers by the corporation number, and estimate firm age. Firms are matched by location and then linked with the closest match by name. Figure A2 suggests the missing rate of the linkage between Florida UCC filings and Florida corporate records over quarters. Because the missing rate drops significantly after 2002, I run the loan-level analysis using firm age with data after 2002 to avoid potential survivorship bias.

I classify Florida debtors into NAICS 2-digit industry by ChatGPT model 4.1 nano. Similar to Natural Language Processing (NLP) techniques, GPT models can identify keywords, such as "auto", "recycling", or "md pa", in the debtor names. Moreover, ChatGPT models are better at understanding complex words, such as "taxxpert", or typoes than NLP algorithms. Table A1 shows the snapshot of the GPT-identified industry in the sample.

Next, I move to identify the lenders. Because government-sponsored loans might not contract during tight money periods, I remove government-sponsored loans by name parsing. Government-sponsored loans are loans where all lenders are government agencies, such as the Small Business Administration, Fannie Mae, Freddie Mac, USDA, Department of Treasury, and other federal or state government agencies. Similarly, I also drop syndicated loans, where all lenders are syndicated agents, such as administrative agents or trustees, to focus on direct lending.

I identify bank lenders by linking the state-level UCC data with National Information Center (NIC) data. Nonbank subsidiaries of banks or bank holding companies are also identified as bank lenders because affiliated companies to big banks also reduce small business lending (Chen et al., 2017). In addition, if a lender cannot be found in the NIC data but has

[9] Available at https://dos.fl.gov/sunbiz/other-services/data-downloads/.

"bank", "credit union", or "national association" in its name, I also identify the lender as a bank lender. The steps on data cleaning of the state-level UCC data and of the national UCC data are both the same as suggested in Gopal and Schnabl (2022).

2.2 Bank Data

The deposit holding data comes from FDIC's Summary of Deposits. I estimate the local deposit market competition by the standard Herfindahl Index (HHI) as suggested in Drechsler et al. (2017). The county-level deposit HHI is computed annually by summing squared bank deposit shares.

County-level bank equity is measured by linking the U.S. Call reports with FDIC's Summary of Deposits (SOD). I follow the procedure described in Drechsler et al. (2017) to construct bank variables and estimate the county-level bank equity by a weighted average of BHC-level bank equity to assets ratio using number of branches as the weights.

2.3 County Demographics and Business Dynamics

County-level demographics and controls of lending opportunities come from the U.S. Census and the Bureau of Labor Statistics (BLS). The unemployment rate comes from the BLS Local Area Unemployment Statistics. Population and number of business establishments is from the U.S. Census County Business Pattern Program and Population Estimates Program, respectively. County-level percentages of firms by size, age, and industry are derived from U.S. Census Business Dynamics Statistics. Annual data sets are converted to quarterly data using linear interpolation.

Using the percentage of firms by industry, I also find the lease-adjusted external financing dependence index of each county. Assuming that public firms and private firms have comparable dependence on external financing if they are in the same industry, I first estimate the industry-level external financing dependence index according to the methodology of Rajan and Zingales (1996) (RZ) using the Compustat Database. The RZ index is calculated by the difference between capital expenditures and cash flow from operation over capital expenditures, where cash flow from operation is cash flow from operation (#110) plus decrease in inventory, increase in account payables, and decrease in account receivables. Because over 99% of the cash flow from operation is missing, I sum up income before extraordinary items (#123), depreciation and amortization (#125), deferred taxes (#126), equity in net loss (#106), sales of property, plant and equipment and investments (#213), and other funds from operation (#217) to fill the missing. In addition, I find the lease-adjusted RZ index (LARZ) by replacing capital expenditures with total rental payments plus capital expenditures. Then, the industry-level LARZ is the median of the firm-level values as in RZ. I find the county-level LARZ index as the weighted average of industry-level LARZ, where weights are number of firms in the county.

2.4 Federal Reserve Economic Database

The Federal Reserve Economic Database (FRED) provides the Federal Funds effective rates and time-series macroeconomic controls, including the Consumer Price Index (CPI), real GDP growth, unemployment rate, CBOE market volatility (VIX) index, and TED spread. I estimate changes in the Federal Funds effective rates as the proxy for changes in monetary policy in the main specification. However,

2.5 Monetary Policy Shocks

There are two different methodologies for measuring monetary policy shocks. One is the narrative approach led by Romer and Romer (2004), which is called “narrative” because they use numerical forecasts extracted from the Federal Reserve’s Greenbook. They estimate monetary policy shocks as the residuals from regressing the Federal Funds target rate on the Federal Funds effective rate and the macroeconomic forecasts. The other is the high-frequency identification, which proxies for monetary policy shocks using the changes in Federal Funds futures rates within a narrow window around the Federal Open Market

Committee (FOMC) announcements so that the changes in prices only reflect unpredicted information on monetary policy.

I utilize one measure from each method to study how nonbank market share responds to monetary policy shocks. For the narrative approach, I extend the Romer and Romer shocks to December 2018[10] according to the algorithm from Wieland and Yang (2020). For high-frequency identification, I collect the Gürkaynak et al. (2005) (GSS) shocks extended by Acosta, Brennan, and Jacobson (2024)[11].

2.6 Summary Statistics

Table 1 reports the descriptive statistics on the underlying data sets used for analysis later. It also presents the statistics by dividing the data into high- and low-HHI counties based on the median. Panel A and Panel B present an overview on national UCC data and state-level UCC data at the county level, respectively. The average unemployment rate and number of business establishments per capita in Panel A are similar to those in Panel B, suggesting comparable levels of economic development between counties covered by the state-level UCC data and those in the national UCC data. Panel C describes firm age and number of officers in the state-level UCC data at the loan level.

3 Results

3.1 Aggregate Effects

I first examine if there is a national growth of nonbank lending following an increase in the Federal Funds rates. Specifically, I run the following regression.

$$y_{t+1} = \alpha + COVID_t + \beta DFF_t + \gamma \mathbf{X}_t + \varepsilon_t \tag{1}$$

[10]This is constrained by data availability of the Greenbook Forecasts.

[11]The monetary policy shocks are available from Miguel Acosta's website: https://www.acostamiguel.com/research.html

where y_{t+1} is the changes in nonbank market share, growth of bank new lending or growth of nonbank new lending from quarter t to t+1. DFF is the changes in the Federal Funds effective rate from quarter t-1 to t. $\mathbf{X}_t$ are macroeconomic controls, including log consumption price index, real GDP growth, the unemployment rate, the market volatility index (VIX), and the TED spread, which captures systematic risks in the banking sector. I also include a COVID dummy variable, which equals one between 2020Q1 and 2021Q2 and zero otherwise. Standard errors are Newey-West computed with four lags.

Table 3 presents the results. Column (1) suggests that a one percent increase in the Federal Funds rates is associated with a 1.4 pp increase in the U.S. nonbank market share in the next quarter. Correspondingly, columns (2) and (3) show that banks reduce loan supply, while nonbanks increase loan supply in the same quarter when nonbank market share grows significantly.

3.2 Monetary Policy Shocks

Previous literature argues that the changes in the Federal Funds rates contain both unexpected and expected information on the monetary policy shocks, so macroeconomic or financial data can respond positively to the changes in the Federal Funds rates due to the positive correlation between the expectation and the responses[12]. To examine whether the nonbank expansion is caused by nonbanks' anticipation or by a structural shift toward nonbank lending, I model local projection impulse responses of nonbank market share to monetary policy shocks.

I estimate a standard Jordà (2005) local projection model and plot impulse responses to figure out whether nonbank market share increases significantly within a year after positive monetary policy shocks. I examine the effects using two monetary policy shocks, each of which represents one of the leading approaches. One is the Romer and Romer (2004) (RR) shocks, which represent the narrative identification. The other is the Gürkaynak et al.

[12]See Sims (1992), Kuttner (2001), Ramey (2016), etc.

(2005) (GSS) shocks, which represent the high-frequency identification and also exclude irreversibility caused by forward guidance when studying responses to monetary policy. Detailed introduction on the two measures are given in Section 2.5.

Figure 1 displays the impulse responses. The outcome variable is changes in nonbank market share. Panel (a) shows that one standard deviation increase in Romer and Romer shocks (0.25) will lead to a 0.35 pp increase in thge growth of nonbank market share in the second subsequent quarter. Comparably, panel (b) finds that one standard deviation increase in the GSS shocks (0.04) leads to 0.36 pp in the second subsequent quarter. The magnitude is close to what Table 3 suggests. Given one standard deviation increase in the Federal Funds rates (0.4), nonbank market share will grow by 0.56 pp. I find the expectation on monetary policy imposes minor effects on the nonbank expansion, consistent with the explanation provided by Drechsler et al. (2017).

3.3 Baseline analysis

The time-series evidence raises a question of whether the rise in nonbank market share is driven by supply-side or demand-side effects. Is the expansion of nonbanks a response to reduced loan supply from banks during periods of monetary tightening? Or does it reflect a shift in borrower preferences, with small businesses turning to nonbank lenders for quicker processing and more accessible credit?

In this section, I analyze what explains the rise in nonbank lending driven by the higher interest rates. I address the identification challenge through the deposit channel (Drechsler et al., 2017). When the Federal Funds rates increase, banks exploit their market power to widen deposit spreads for profits. Consequently, depositors withdraw their savings to invest in high-yield assets, such as money market funds. The deposit outflows are substantial for two reasons. First, the volume is large because rational depositors maintain only enough funds for the liquidity demand. Second, banks pay below-market rates on deposits, so outflows cannot be perfectly substituted by alternative sources, such as wholesale funding (Kashyap et al., 2002). As a result, banks must reduce new lending, leaving a void for nonbanks.

I evaluate how nonbank market share, nonbank new lending, bank new lending, and deposit growth respond differently in high HHI counties relative to low HHI counties given a rise in the Federal Funds rates. The baseline specification is defined below.

$$\begin{aligned} y_{i,t+1} = {} & \alpha + \alpha_t + \alpha_i + \gamma DepositHHI_{i,y-1} + \beta DFF_t \times DepositHHI_{i,y-1} \\ & + \delta Macros_{i,t} + \theta DFF_t \times Macros_{i,t} + \varepsilon_{i,t} \end{aligned} \tag{2}$$

where $y_{i,t+1}$ can be changes in nonbank market share, log bank loan origination plus one, log nonbank loan origination plus one from quarter t to t+1, or the percentage growth of deposits. It is calculated over quarter t-1 to t+1, as DFF is the changes in the Federal Funds effective rate from quarter t-1 to t, and the deposits can start leaving banks immediately as the interest rates increase. DepositHHI measures the deposit competition in the county for the most recent year. Macroeconomic controls include the unemployment rate, business establishments per capita, log population, and the respective interaction with DFF to capture the heterogeneity of local lending opportunities[13]. County fixed effects are controlled to capture time-invariant county characteristics. Quarter fixed effects are controlled to capture time-series macroeconomic trends. Standard errors are clustered by quarter[14] because changes in the Federal Funds rates have no variation at the county level.

Table 4 reports the estimates. Given a one percent increase in the Federal Funds rates, deposit growth is 43 bp lower in high-concentration counties (HHI above 75th percentile, 0.393) relative to low-concentration counties (HHI below 25th percentile, 0.179), as shown in column (5). Correspondingly, banks reduce new lending by 2% more, while nonbank new lending declines by 1% more in high-concentration counties, as shown in columns (2) and (3) respectively. The relatively smaller contraction in nonbank new lending leads to a 34 bp

[13]The coefficient of DFF×DepositHHI remains significant with different sets of county-level macroeconomic controls.

[14]The results are also robust to adding the interaction between changes in the Federal Funds rates and state dummy variable or finding double-cluster standard errors by state and quarter as shown in Table A2

more increase in nonbank market share in high-concentration counties, as shown in column (1).

One may notice that the deposit outflow is significant only after controlling log population. It is not controlled in the models explaining other outcome variables for log population is highly correlated with DepositHHI as shown in Table 2. The coefficient of deposit outflows is only significant after controlling county size, which can be log population, log number of business establishments, or any alternative measure. It indicates that the levels of deposit growth in smaller counties is too small comparing to larger counties.[15].

3.4 Other Channels of Monetary Policy Pass-through

In the previous section, I have shown that the effects of the deposit channel are significant when explaining the local nonbank expansion. However, banks can reduce loan supply for different reasons when monetary policy tightening. Previous literature suggests that bank loan contraction results from decreasing lending capital, which can be caused by rising reserve requirements or lower bank equity in addition to deposit outflows after the tightening of monetary policy. Later, other research discusses whether reserve requirements can be so influential to result in the reduction in bank loan supply (Romer and Romer, 1990; Bernanke and Gertler, 1995; Woodford, 2010; Drechsler et al., 2017). More recently, Wang et al. (2022) compare different bank channels of the transmission of monetary policy and suggest that both bank equity channel[16] and deposit channel are equally important when explaining banks' responses to monetary policy.

The bank capital channel suggests that tighter monetary policy will reduce bank equity through balance sheet mismatch and therefore constrain banks' lending capital. To examine whether deposit HHI picks up some explanatory power of the bank equity channel, I directly add county-level bank equity and its interaction with changes in the Federal Funds rates to

[15] The effects of the deposit channel are still significant when explaining changes in nonbank market share after controlling log population and its interaction with changes in the Federal Funds rates or other comparable controls.

[16] In this section, bank equity channel and the bank capital channel are used interchangeably.

the main specification as shown in column (1)-(3) of Table 4. If changes in bank equity lead to nonbank expansion, the main estimates will lose significance.

Table 5 presents the results. The coefficients of DFF×DepositHHI are very close to the coefficients in Table 4. The coefficients when explaining changes in nonbank market share and growth of bank new lending are still significant at the same level. Therefore, the bank capital channel does not attenuate the estimates on the deposit channel.

Then, how does county-level bank capitalization affect the transmission of monetary policy in small business lending? From column (2), the coefficient of DFF×BankEquity is positive when explaining bank new lending, though insignificant. It is intuitive since counties where banks are better capitalized should be able to lend more. What is surprising is that nonbank new lending also grows faster in those counties where bank equity is generally higher, while changes in nonbank market share are more slowly. It indicates a nonlinear relationship between county-level bank equity and nonbank loan supply.

3.5 County-level Business Dynamics

One may question whether the rise in nonbank lending results from special demand on nonbank loans or from bank loan contraction. I control local business dynamics to capture heterogeneity of local lending opportunities. Formally, I estimate the following regression.

$$\begin{aligned}\Delta Nonbank\ Market\ Share_{i,t+1} = {} & \alpha + \alpha_t + \alpha_i \\ & + \gamma DepositHHI_{i,y-1} + \beta DFF_t \times DepositHHI_{i,y-1} \\ & + \delta_1 BusinessDynamics_{i,t} + \theta_1 DFF_t \times BusinessDynamics_{i,t} \\ & + \delta_2 Macros_{i,t} + \theta_2 DFF_t \times Macros_{i,t} + \varepsilon_{i,t}\end{aligned} \tag{3}$$

I control county-level business dynamics, including the percentage of small firms, the percentage of young firms, the percentage of new firms, firm exit rate, and the lease-adjusted external financing index (LARZ). Small firms are firms with fewer than 20 employees. Young firms are firms aged under five. New firms are firms just established. Firm exit rate is the percentage of firms bankrupted. LARZ is the lease-adjusted Rajan and Zingales (1996) index as defined in section 2.3. Macroeconomic controls are the unemployment rate and business establishments per capita. County fixed effects and quarter fixed effects are controlled. Standard errors are clustered by quarter.

Table 6 presents the results. Because the percentage of new firms and percentage of young firms are highly correlated as shown in Table 2, I first run each firm characteristics control independently in columns (1) to (5). Column (6) includes all controls except for the percentage of new firms and its respective interaction with the change in Federal Funds rates and column (7) includes all controls except for the percentage of young firms and its respective interaction with the change in Federal Funds rates.

The results suggest that controls of business activities do not affect the effects of the deposit channel on the gain in nonbank market share. Furthermore, adding some of the controls even makes the coefficient of DFF×DepositHHI slightly more significant as shown in columns (2), (5), (6), and (7). On average, nonbank market share will grow 33-39 bp faster in high-concentration counties (HHI above 75th percentile, 0.393) than in low-concentration counties (HHI below 25th percentile, 0.179). The magnitudes of the coefficients are very close to the estimates in Table 4. Hence, county-level heterogeneity in business activities exerts limited impact on the treatment effects.

The magnitude of coefficient of DFF×Firm Exit is almost 10 times larger than the coefficient of DFF×Small Firms(%) in column (6) and almost 4 times larger than the coefficient of DFF×New Firms(%) in column (7). It finds that rising interest rate pushes nonbank expansion significantly in counties where bankruptcy rates are larger. However, are nonbanks helping those financially constrained firms? A surprising finding is that the growth of nonbank share decreases in counties where firms are generally dependent on external financing, as shown in columns (5), (6), and (7). Nonbanks may pick borrowers to lend, as they specialize in selecting borrowers Gopal (2021). In parallel with real impacts evaluated in Section 3.8, bankruptcy rates of small businesses are higher in counties where the growth of nonbank market share is more significant following a positive change in the Federal Funds rates. Therefore, nonbanks might choose to lend to borrowers less dependent on external financing, which tend to be those more likely to repay the proceeds when monetary policy becomes tighter. As a consequence, there are limited positive real impacts of the nonbank expansion during tight money periods.

3.6 Loan-level Evidence

From the previous section, changes in treatment effects are very limited after controlling county-level proxies for lending opportunities. However, Jiménez et al. (2012) suggest that the most robust way to capture lending opportunities is to compare the approval of loan applications from the same firm in the same month.

For granular evidence, I turn to the state-level UCC data. First, I show that the deposit channel also explains the variation in nonbank expansion across counties using the state-level UCC data. I estimate the same model as in Table 4. Table 7 reports the results. The coefficient of DFF×DepositHHI is slightly larger than the coefficient in Table 4 when explaining the changes in nonbank market share. After interest rates increase by 1 pp, nonbank market share will increase by 1 pp more in high-concentration counties (HHI above 75th percentile, 0.497) than in low-concentration counties (HHI below 25th percentile, 0.183). Although the increase in nonbank market share is larger in state-level ucc data than the national UCC data, it is intuitive for two reasons. First, the coefficient of DFF×DepositHHI is also larger when explaining the deposit outflow using state-level UCC data relative to the national UCC data. Second, the national UCC data is also collected from state governments of the 50 states and the District of Columbia, but the data vendor links the original UCC filings with the National Establishment Time-series (NETS) Database for borrower characteristics, such as industry, age, etc. Therefore, some firms, especially tiny firms, can be removed from the national UCC data by the vendor if the firms cannot be found in the NETS database.

Therefore, the state-level UCC data have a slightly better coverage of small businesses than the national UCC data. Because nonbanks are more likely to lend to those smaller firms, it is intuitive that the effects of the deposit channel are even larger with tiny firms in the state-level data.

Next, I move to examine whether nonbank loans are more likely to be originated in high-HHI counties or not. Because almost 99% of the firms only file in one county in the same quarter, I cannot compare whether nonbanks originate more loans to the same firm in high HHI counties than in low HHI counties. Therefore, I directly control time-varying firm heterogeneity and the interaction with changes in the Federal Funds rates at the loan level. To capture different levels of lending opportunities, I control firm age, size and industry. Formally, I estimate the linear probability model below.

$$
\begin{aligned}
Nonbank_{i,t+1,c,d,l} = {} & \alpha + Industry_d \times Quarter + \alpha_i + \theta_1 Macros_{i,t} + \theta_2 DFF_t \times Macros_{i,t} \\
& + \beta_1 DepositHHI_{i,y-1} + \beta_2 DFF_t \times DepositHHI_{i,y-1} \\
& + \theta_1 ln(FirmAge_{y-1,d}) + \theta_2 DFF \times ln(FirmAge_{y-1,d}) \\
& + \theta_1 Number\ of\ Officers_d + \theta_2 DFF \times Number\ of\ Officers_d \\
& + \theta_1 I.(Number\ of\ Officers_d \geq 6) \\
& + \theta_2 DFF \times I.(Number\ of\ Officers_d \geq 6) + \varepsilon_{i,t}
\end{aligned} \tag{4}
$$

The dependent variable, $Nonbank_{i,t+1,c,d,l}$, is the dummy variable equaling one if creditor c is nonbank of loan l lending to debtors d at county i in quarter t+1. Deposit HHI is the value of last year in county i.

Firm age and size are measured after linking Florida UCC filings with Florida corporate records. Firm age is the number of years between the year of the UCC filing and the year of incorporation plus one. Firm size is the number of officers reported in Florida Corporate Records. Although the number of officers might not be the exact number of employees of the firms, it should be highly positively correlated with the size of the business. One note is that firm size is not time-varying. According to Ayyagari, Demirguc-Kunt, and Maksimovic (2021), size at birth explains the largest variation in firm size and growth in the future. Therefore, I argue that controlling the initial number of employees can effectively capture variation in firm size across small businesses. Because at most 6 officers will be recorded, I compose the dummy variable $I.(Number\ of\ Officers_d \geq 6)$, which equals to one when the firm files with 6 officers and zero otherwise.

Firm industry is identified based on firm names with the help of ChatGPT. Industry and quarter double fixed effects are controlled to capture industry-specific time-varying lending opportunities.[17] County fixed effects are also controlled to capture county-specific variation. Double-cluster standard errors by county and quarter are reported in parentheses. Because the missing rate is particularly high before 2002 when linking Florida UCC data with Florida corporate records data set, the underlying loans cover 2002Q1-2021Q4 to avoid potential survivorship bias.

As shown in Table 8, I first run the regression without adding any firm variables in column (1). By comparing column (1) to columns (2)-(4), adding firm variables and the respective interaction only decreases the coefficient of DFF×Deposit HHI by a limited amount.

One may question the accuracy rate of firm industry identified by ChatGPT. To prove coefficient stability of Table 8, I run the Oster test as introduced in Oster (2019) for the model in column (4) without including county fixed effects. As the Oster test quantifies the impact of unobservables on the causal effects, there is no need to add fixed effects that capture latent factors. More importantly, as firm industry is regarded as a noisy measure, running the Oster test will naturally capture how much the industry is misidentified. The principle of the Oster test is that coefficients and R-squared generally move together and this is associated with less selection bias. As suggested in Oster (2019), I set the maximum R-squared equal to 1.3 times adjusted R-squared of column (4) in Table 8 and find the δ

[17]Few companies change industry over their history because their names are changed.

to make treatment effects zero. As shown in Table 8, δ is -2.03, which suggests that the unobservables have to be at least twice as important as the current controls to make the coefficient 0.046 zero. Given that the coefficient is very small and close to zero and $|\delta| > 1$, it suggests the coefficient of DFF$\times$Deposit HHI is robust to unobservables.

Since a loan can involve multiple lenders or be originated jointly by a bank and a nonbank, I re-estimate the model above using only loans with one borrower and one single lender or with multiple lenders that are either all banks or all nonbanks. As found in column (1) of Table 9, the coefficient of DFF$\times$Deposit HHI is close to the coefficients in Table 8 using data of loans having only one lender and one borrower. The coefficient becomes larger using data of loans with at least one lender, either all banks or all nonbanks, as shown in column (2) of Table 9. As the underlying loans of column (1) are also included in the underlying loans of column (2), nonbanks are more likely to cooperate as a group to lend during periods of high interest rates.

3.7 County Characteristics of Nonbank Expansion

So far, I have established a short-term rise in nonbank lending led by the deposit channel after the tightening of monetary policy. Next, I ask which counties receive more nonbank loan supply during tight money periods using the national UCC data. Specifically, I estimate the following regression.

$$\begin{aligned}\Delta Nonbank\ Market\ Share_{i,t+1} &= \alpha + \alpha_t + \alpha_i + \gamma DepositHHI_{i,y-1} + \beta_1 DFF_t \times DepositHHI_{i,y-1} \\ &+ \beta_2 DFF_t \times DepositHHI_{i,y-1} \times BusinessDynamics_{i,t} \\ &+ \delta_1 BusinessDynamics_{i,t} + \delta_2 Macros_{i,t} + \theta_2 DFF_t \times Macros_{i,t} + \varepsilon_{i,t}\end{aligned} \tag{5}$$

The outcome variable is the changes in nonbank market share of county i from quarter t to t+1. Quarter fixed effects and county fixed effects are controlled. Standard errors are clustered by quarter. The three-term interactions capture which business characteristics of counties attract more nonbank supply through the deposit channel.

Table 10 presents the results. As shown in column (1), nonbank loan supply is even greater in counties where the firm exit rate is higher after controlling deposit HHI. In comparison, column (5) suggests that nonbank credit access is significantly more constrained in counties where firms demand more external financing. These findings are parallel with the findings in Section 3.5.

3.8 Real Effects

Then, I move to study the real effects of the nonbank expansion through the deposit channel. I analyze how future firm exit rate, percentage of new firms, and unemployment rates change in high HHI counties relative to low HHI counties. In particular, I estimate the regression model below.

$$\begin{aligned} y_{i,t+h} =& \alpha + \alpha_t + \alpha_i + \gamma DepositHHI_{i,y-1} + \beta DFF_t \times DepositHHI_{i,y-1} \\ &+ \delta Macros_{i,t} + \theta DFF_t \times Macros_{i,t} + \varepsilon_{i,t} \end{aligned} \tag{6}$$

where $y_{i,t+h}$ is the firm exit rate, the percentage of new firms, and the unemployment rate of county i in quarter t+h, h=1, 2, ...8. The macroeconomic controls are the unemployment rate and number of business establishments per capita. Standard errors are clustered by quarter.

Given a positive change in the Federal Funds rates, firm exit rates are weakly lower in the first following year and significantly higher in the second year in counties where the interest rate-driven gain in market share is stronger, as shown in Panel A of Table 11. On average, high-concentration counties (HHI above 75th percentile, 0.393) have a 5 bp higher firm exit rate than low-concentration counties (HHI below 25th percentile, 0.179) in the second following year. Panel B shows that the percentage of new firms in high-concentration counties is slightly lower. Panel C finds that the unemployment rate is significantly higher in counties where nonbanks will gain more market share. On average, the unemployment rate is 11 bp higher in high-concentration counties than in low-concentration counties, given a 100 bp increase in the Federal Funds rates. In summary, the interest rate-driven nonbank expansion does not exert strong positive effects on the local economy.

4 Conclusion

This paper raises a systematic evidence that a tighter monetary policy will lead to a significant increase in nonbank market share. Given an increase in the Federal Funds rates, nonbank market share rises in the next quarter as a result of a smaller decline in nonbank new lending relative to bank new lending. The rise in nonbank lending is robust to using different measures of changes in monetary policy, either the changes in the Federal Funds rates, Romer and Romer (2004) shocks or Gürkaynak et al. (2005) shocks. The level of nonbank expansion is also comparable across various measures of monetary policy.

I explain the increase in nonbank market share by the deposit channel of the transmission of monetary policy. Given a positive change in the Federal Funds rates, I find that banks reduce loan supply due to substantial deposit outflows in counties where the local deposit markets are more concentrated. Meanwhile, nonbank market share increases significantly more in more concentrated counties. The findings hold beyond controlling the bank capital channel or county-level lending opportunities. To validate the supply-side effects further, I control time-varying firm heterogeneity at the loan level and find minimal reduction in the effects. To ease concerns about the unobservables, I run the Oster test and find that the treatment effects are robust to selection bias.

I find that the gain in nonbank market share is more significant in counties where firm exit rates are higher or where firms are less dependent on external financing. It indicates that nonbanks are not helping the most financially constrained firms, but those less distressed in concentrated counties. To evaluate the subsequent economic impacts of the nonbank expansion in more concentrated counties, I analyze how firm exit rate, percentage of new firms, and the unemployment rate will change in the subsequent 8 quarters following an increase in the Federal Funds rates. Firm exit rate and the unemployment rate increase persistently in concentrated counties.

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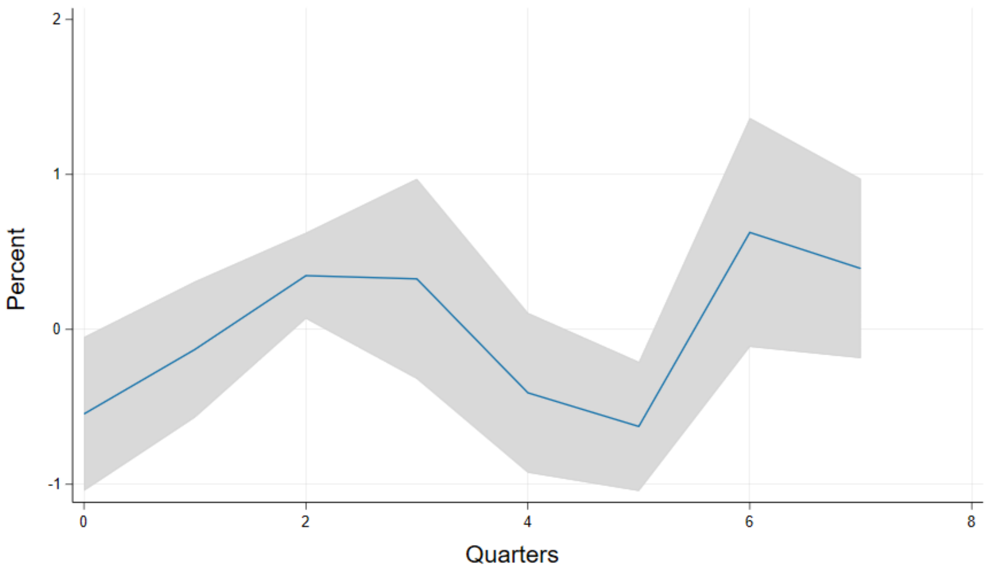
Figures

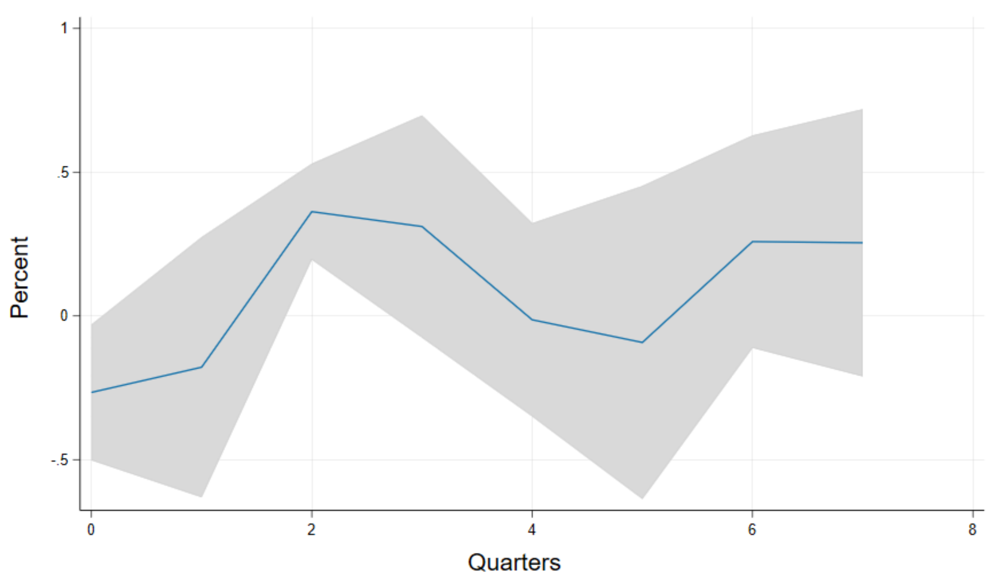
Figure 1: Monetary Policy Shocks and Nonbank Expansion

This figure shows the impulse response of changes in nonbank market share to one standard deviation of Romer and Romer (2004) shocks (0.25) as shown in panel (a) or one standard deviation of Gürkaynak et al. (2005) shocks (0.04) as shown in panel (b). I estimate Jordà (2005) local projection as $\Delta NonbankMarketShare_{t+h} = \alpha + \beta mps_t + \gamma z_t + \varepsilon_t, h = 0, 1, 2, ...8$. The control variable z_t includes 4 lags of the dependent variable, 4 lags of the monetary policy shocks, and 4 lags of the log consumption product index, real GDP growth, VIX index, unemployment rate, and TED spread rate. Standard errors are computed with Newey-West standard errors with four lags. The grey area represents the 90% confidence interval.

(a) RR shocks



(b) GSS shocks



Tables

Table 1: Summary Statistics

This table reports summary statistics and a breakdown by high and low HHI using the median. Panel (a) describes the county-level national UCC data. The underlying data spans from 2007Q1 to 2021Q4. Panel (b) shows the descriptive statistics of the county-level data by aggregating the state-level UCC data. The underlying data covers 1996Q1-2021Q4. Panel (c) describes the distribution of firm age in the loan-level state-level UCC data of 1996Q1-2021Q4. Units of the variables are reported in parentheses.

	All		High HHI		Low HHI	
	Mean	SD	Mean	SD	Mean	SD
Panel A: National UCC Data						
Number of Loans	71.32	199.15	28.60	86.40	114.06	261.19
ΔNonbank Market Share (%)	0.18	21.28	0.18	25.25	0.17	16.44
Deposits (000)	3.31	24.62	1.75	18.23	4.86	29.59
DepositHHI	0.32	0.20	0.46	0.20	0.18	0.05
Unemployment	6.20	3.03	6.31	3.24	6.10	2.80
Establishments per capita.	23.18	8.85	22.58	10.16	23.78	7.26
Population (000)	105.36	330.39	33.88	127.38	176.89	438.09
Bank Equity	0.04	0.05	0.03	0.05	0.05	0.05
New Firms (%)	5.87	2.06	5.71	2.30	6.03	1.78
Young Firms (%)	25.04	6.18	24.38	6.25	25.70	6.03
Small Firms (%)	74.14	6.25	74.57	7.01	73.71	5.35
Firm Exit Rate (%)	6.32	2.23	6.36	2.72	6.27	1.58
Number of Firms	1944.76	6296.21	603.51	2483.11	3291.35	8344.63
LARZ	0.58	0.08	0.59	0.09	0.57	0.07
Observations (County × Quarter)	178708		89379		89329	
Panel B: County-level State-level UCC Data						
Number of Loans	78.56	235.53	34.82	167.32	192.92	330.53
ΔNonbank Market Share (%)	0.12	27.15	0.13	31.16	0.07	12.24
Deposits (000)	2.89	14.14	1.65	13.80	6.15	14.48
DepositHHI	0.37	0.25	0.46	0.24	0.14	0.03
Unemployment (%)	5.63	2.57	5.64	2.65	5.59	2.35
Establishments per capita.	21.08	6.40	20.36	6.40	22.95	6.02
Observations (County × Quarter)	30108		21778		8330	
Panel C: Loan-level State-level UCC data						
Firm Age	8.47	8.66	8.35	8.68	8.60	8.64
Number of Officers	1.78	1.03	1.84	1.06	1.72	0.99
Observations (Filings)	993621		499047		494574	

Table 2: Correlation Table

This table provides the correlation matrix of selected variables. The underlying data set is the national UCC data linked with county-level demographics spanning over 2007Q1-2021Q4.

	New Firms	Young Firms	Small Firms	Firm Exit Rate	Ln(Number of Firms)	LARZ	Establishments per capita.	Unemployment	DepositHHI	Bank Equity	Ln(Population)
New Firms	1										
Young Firms	0.766	1									
Small Firms	0.264	0.365	1								
Firm Exit Rate	0.264	0.350	0.116	1							
Ln(Number of Firms)	0.278	0.350	-0.0246	0.0736	1						
LARZ	-0.120	-0.140	0.172	-0.0251	-0.225	1					
Establishments per capita.	0.0369	0.0839	0.317	-0.0359	0.108	-0.134	1				
Unemployment	-0.0757	-0.0114	-0.0689	0.198	0.0169	0.00749	-0.287	1			
DepositHHI	-0.0627	-0.0684	0.103	0.0155	-0.663	0.0907	-0.0547	0.0240	1		
Bank Equity	0.137	0.264	0.0751	0.169	0.323	-0.0541	0.0457	0.167	-0.221	1	
Ln(Population)	0.279	0.340	-0.0953	0.0959	0.972	-0.202	-0.112	0.0955	-0.635	0.311	1

Table 3: Nonbank Expansion and Federal Funds Rates

This table provides the responses of loan origination volumes in the next quarter following a positive change in the Federal Funds rates. The underlying dataset consists of the quarterly total number of loan origination, aggregated from the national UCC data covering 2007Q1 to 2021Q4. The dependent variable is the growth of nonbank market share in column (1), the growth of bank new lending in column (2), and the growth of nonbank new lending in column (3). The growth rates of bank and nonbank loan origination are both winsorized at 1%. DFF is the changes in Federal Funds rates. Standard errors are reported in parentheses and computed with Newey-West standard errors with four lags. * $p < .10$, ** $p < .05$, *** $p < .01$

	ΔNonbank Market Share (1)	ΔBank New Lending (2)	ΔNonbank New Lending (3)
DFF	1.417***	-2.286	3.458
	(0.50)	(2.74)	(3.95)
log CPI	-6.073**	-45.996	-71.083
	(2.61)	(42.89)	(50.15)
Real GDP growth	-0.043	0.750	0.588
	(0.05)	(0.64)	(0.76)
VIX	0.003	-0.410**	-0.403
	(0.02)	(0.20)	(0.25)
Unemployment	-0.165**	0.940	0.284
	(0.07)	(0.90)	(0.97)
TED spread	0.275	-0.995	0.153
	(0.27)	(2.75)	(2.97)
COVID	YES	YES	YES
Adj.R-squared	0.08	0.05	0.07
Obs.	61	61	61

Table 4: Nonbank Expansion and the Deposit Channel

This table examines that the deposit channel explains the nonbank expansion following a positive change in the Federal Funds rates. The underlying data is the national UCC data, spanning from 2007Q1 to 2021Q4. ΔNonbank Market Share is in the unit of percentage points. ΔBank New Lending, ΔNonbank New Lending, and ΔDeposits are 100 times changes in log bank loan origination plus one, 100 times changes in log nonbank loan origination plus one, and 100 times changes in log deposits, respectively. ΔBank New Lending and ΔNonbank New Lending are winsorized at 1%. DFF is the change in the Federal Funds rates in the previous quarter. Standard errors clustered by quarter are reported in parentheses. P-value of the F-test is reported because the adjusted R-squared can be negative. Note that when the p-value is less than 0.05, it suggests the regression model is meaningful to explain the outcome variable, even though the explained variation is limited. * $p < .10$, ** $p < .05$, *** $p < .01$

	ΔNonbank Market Share	ΔBank New Lending	ΔNonbank New Lending	ΔDeposits
DFF×DepositHHI	2.353**	-10.232***	-5.619	-1.426**
	(0.91)	(2.83)	(4.32)	(0.65)
DepositHHI	-0.755	0.182	-1.044	-0.601
	(1.19)	(3.26)	(2.71)	(1.67)
Unemployment	-0.109	0.491**	0.195	-0.249***
	(0.07)	(0.21)	(0.22)	(0.09)
Establishments per capita.	0.031	-0.265*	-0.155	0.114
	(0.07)	(0.15)	(0.17)	(0.07)
DFF x Unemployment	-0.260***	0.678***	-0.189	0.138*
	(0.08)	(0.20)	(0.20)	(0.07)
DFF x Establishments per capita.	-0.011	-0.001	-0.029	-0.004
	(0.02)	(0.06)	(0.06)	(0.02)
Ln(Population)				4.075
				(4.07)
DFF x Ln(Population)				-0.133
				(0.31)
County f.e.	Yes	Yes	Yes	Yes
Quarter f.e.	Yes	Yes	Yes	Yes
Adj.R-squared	-0.01	0.02	0.02	0.30
Obs.	175497	175497	175497	178678
P-value of F test	0.00	0.00	0.50	0.00

Table 5: The Alternative Channel

This table compares the effects of the bank capital channel to the effects of the deposit channel. The underlying data is the national UCC data set spanning from 2007Q1 to 2021Q4. The dependent variables are defined in the same way as shown in Table 4. ΔBank New Lending and ΔNonbank New Lending are winsorized at 1%. DFF is the change in the Federal Funds rates in the previous quarter. Bank equity is the weighted average of bank equity to assets, with the number of branches of the bank in the county as the weights. The control variables are unemployment rate, business establishments per capita, and the respective interaction terms with DFF. Standard errors clustered by quarter are reported in parentheses. P-value of the F-test is reported because the adjusted R-squared can be negative. Note that when the p-value is less than 0.05, it suggests the regression model is meaningful to explain the outcome variable, even though the explained variation is limited. * $p < .10$, ** $p < .05$, *** $p < .01$

	ΔNonbank Market Share (1)	ΔBank New Lending (2)	ΔNonbank New Lending (3)
DFF x DepositHHI	2.276**	-10.212***	-5.324
	(0.88)	(2.70)	(4.08)
DFF x Bank Equity	-1.397	0.347	5.379
	(4.05)	(15.34)	(16.00)
DepositHHI	-0.745	0.142	-0.985
	(1.19)	(3.25)	(2.71)
Bank Equity	0.606	-1.944	2.110
	(1.82)	(7.48)	(6.40)
Macroeconomic Controls	Yes	Yes	Yes
County f.e.	Yes	Yes	Yes
Quarter f.e.	Yes	Yes	Yes
Adj.R-squared	-0.01	0.02	0.02
Obs.	175497	175497	175497
P-value of F test	0.00	0.00	0.71

Table 6: County-level Lending Opportunities

This table examines how county-level lending opportunities will affect the nonbank growth in more concentrated counties. The underlying data set is the national UCC data spanning from 2007Q1 to 2021Q4. Small firms, young firms, and new firms are the percentage of firms with fewer than 20 employees, the percentage of firms aged under 5, and the percentage of newly established firms, respectively. LARZ is the lease-adjusted external dependence index. DFF is the change in the Federal Funds rates in the previous quarter. The control variables are unemployment rate, business establishments per capita, and the respective interaction with DFF. Standard errors clustered by quarter are reported in parentheses. P-value of the F-test is reported because the adjusted R-squared can be negative. Note that when the p-value is less than 0.05, it suggests the regression model is meaningful to explain the outcome variable, even though the explained variation is limited. * $p < .10$, ** $p < .05$, *** $p < .01$

	ΔNonbank Market Share						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
DFF x DepositHHI	2.354**	2.538**	2.286***	2.352***	2.512***	2.488***	2.624***
	(0.92)	(0.98)	(0.85)	(0.88)	(0.88)	(0.83)	(0.90)
DepositHHI	-0.758	-0.731	-0.743	-0.755	-0.760	-0.775	-0.760
	(1.19)	(1.20)	(1.17)	(1.19)	(1.19)	(1.18)	(1.20)
Firm Exit Rate	0.030					0.042	0.036
	(0.04)					(0.04)	(0.04)
DFF x Firm Exit Rate	0.081					0.128*	0.096
	(0.07)					(0.07)	(0.07)
Small Firms		-0.001				0.024	0.013
		(0.04)				(0.05)	(0.05)
DFF x Small Firms		-0.037				-0.013	-0.028
		(0.02)				(0.02)	(0.02)
Young Firms			-0.025			-0.031	
			(0.03)			(0.03)	
DFF x Young Firms			-0.030			-0.048	
			(0.05)			(0.06)	
New Firms				-0.002			-0.006
				(0.05)			(0.05)
DFF x New Firms				-0.004			-0.029
				(0.10)			(0.10)
LARZ					-2.426	-2.601	-2.418
					(2.63)	(2.68)	(2.65)
DFF x LARZ					-4.171**	-4.258***	-3.694**
					(1.67)	(1.37)	(1.73)
Macroeconomic Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County f.e.	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter f.e.	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj.R-squared	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01
Obs.	175081	175081	175081	175081	175081	175081	175081
P-value of F-test	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Table 7: Nonbank Growth Through the Deposit Channel In State-level UCC Data

This table examines whether the gain in nonbank market share is significant in more concentrated counties using the state-level UCC data spanning from 1996Q1 to 2021Q4. Variable definitions are the same as shown in Table 4, except that the outcome variable of column (4) is the deposit growth over quarter t to t+1. The growth rates of bank new lending, nonbank new lending, and deposits are winsorized at 1%. Standard errors clustered by quarter are reported in parentheses. P-value of the F-test is also reported, because the adjusted R-squared can be negative. Note that when the p-value is less than 0.05, it suggests the regression model is meaningful to explain the outcome variable, even though the explained variation is limited. * $p < .10$, ** $p < .05$, *** $p < .01$

	ΔNonbank Market Share	ΔBank New Lending	ΔNonbank New Lending	ΔDeposits
	(1)	(2)	(3)	(4)
DFF x DepositHHI	3.222**	-7.248***	1.807	-1.682***
	(1.36)	(2.51)	(2.46)	(0.55)
DepositHHI	-0.025	-1.597	-0.909	4.067**
	(1.64)	(2.96)	(3.17)	(1.64)
Unemployment	-0.151	0.096	-0.281	-0.025
	(0.11)	(0.27)	(0.24)	(0.08)
Establishments. per capita.	-0.039	-0.040	-0.115	0.104**
	(0.18)	(0.31)	(0.27)	(0.05)
DFF x Unemployment	0.150	0.166	0.559**	-0.052
	(0.17)	(0.36)	(0.23)	(0.06)
DFF x Establishments. per capita.	0.044	0.083	0.224***	0.043
	(0.03)	(0.08)	(0.08)	(0.03)
ln(Population)				0.707
				(1.40)
DFF x ln(Population)				-0.198
				(0.13)
County f.e.	Yes	Yes	Yes	Yes
Quarter f.e.	Yes	Yes	Yes	Yes
Adj.R-squared	-0.00	0.00	0.00	0.45
Obs.	28941	28941	28941	30023
P-value of F test	0.00	0.12	0.00	0.01

Table 8: Loan-level Evidence

This table reports the results from linear probability models to determine whether nonbank loans are more likely to be originated in more concentrated counties following an increase in the Federal Funds rates. The underlying data set is loan-level state-level data between 1996Q1 and 2021Q4. The control variables are unemployment rate, business establishments per capita, and respective interaction terms with DFF. Standard errors are double clustered by county and quarter in parentheses. δ value of the Oster test is reported in the last row for the model in column (4) after excluding county fixed effects. * $p < .10$, ** $p < .05$, *** $p < .01$

	I.Nonbank (1)	I.Nonbank (2)	I.Nonbank (3)	I.Nonbank (4)	I.Nonbank (5)
DFFx DepositHHI	0.055**	0.045*	0.046*	0.046*	0.054**
	(0.0256)	(0.0245)	(0.0244)	(0.0244)	(0.0254)
DepositHHI	-0.049*	-0.049*	-0.050*	-0.051*	-0.050*
	(0.0283)	(0.0276)	(0.0275)	(0.0275)	(0.0282)
DFF x ln(Firm Age)			0.005**	0.004*	0.011***
			(0.0022)	(0.0022)	(0.0022)
ln(Firm Age)			-0.017***	-0.015***	-0.009***
			(0.0010)	(0.0010)	(0.0011)
Number of Officers				-0.014***	-0.012***
				(0.0011)	(0.0011)
DFF x Number of Officers				0.001	0.001
				(0.0023)	(0.0024)
I.(Number of Officers≥6)				0.035***	0.005
				(0.0090)	(0.0089)
DFF x I.(Number of Officers≥6)				0.019	0.028
				(0.0189)	(0.0216)
Macroeconomic Controls	Yes	Yes	Yes	Yes	Yes
Quarter f.e.	Yes	No	No	No	Yes
Industry-Quarter f.e.	No	Yes	Yes	Yes	No
County f.e.	Yes	Yes	Yes	Yes	Yes
Adj.R-squared	0.02	0.07	0.07	0.07	0.02
Obs.	787840	787840	787840	787840	787840
δ of Oster Test given $\beta = 0$				-2.03	

Table 9: Single Type Loans vs. Mixed Type Loans

This table estimates the linear probability models to compare the nonbank expansion across counties and types of loans. Column (1) analyzes filings with one unique lender and one unique borrower. Column (2) estimates the likelihood when more than one lenders, either all banks or all nonbanks, originate the loans. The underlying data set is loan-level state-level data between 1996Q1 and 2021Q4. Standard errors are double clustered by county and quarter in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$

	I.Nonbank	
	Single Lender	All (Non)Bank
	(1)	(2)
DFF x DepositHHI	0.045*	0.052**
	(0.0261)	(0.0260)
DepositHHI	0.020	-0.048*
	(0.0277)	(0.0285)
Number of Officers	-0.014***	-0.014***
	(0.0010)	(0.0011)
DFF x Number of Officers	0.003	0.000
	(0.0022)	(0.0024)
I.(Number of Officers≥6)	0.035***	0.035***
	(0.0088)	(0.0094)
DFF x I.(Number of Officers≥6)	0.005	0.018
	(0.0204)	(0.0194)
DFF x ln(Firm Age)	0.004*	0.005**
	(0.0023)	(0.0023)
ln(Firm Age)	-0.014***	-0.016***
	(0.0010)	(0.0010)
Unemployment	0.006***	0.004***
	(0.0011)	(0.0011)
Establishments. per capita.	-0.002*	-0.002*
	(0.0012)	(0.0011)
DFF x Unemployment	0.006**	0.006**
	(0.0029)	(0.0028)
DFF x Establishments. per capita.	-0.000	-0.000
	(0.0004)	(0.0004)
Industry-Quarter f.e.	Yes	Yes
County f.e.	Yes	Yes
Adj.R-squared	0.07	0.07
Obs.	610636	751240

Table 10: Which Counties Have Stronger Nonbank Expansion?

This table examines how differences in business activity across counties are related to the growth of nonbank lending, given rising interest rates. The underlying data set is the national UCC data spanning from 2007Q1 to 2021Q4. Variable definitions and macroeconomic controls are the same as Table 6. Standard errors clustered by quarter are reported in parentheses. P-value of the F-test is reported because the adjusted R-squared can be negative. Note that when the p-value is less than 0.05, it suggests the regression model is meaningful to explain the outcome variable, even though the explained variation is limited. * $p < .10$, ** $p < .05$, *** $p < .01$

	ΔNonbank Market Share				
	(1)	(2)	(3)	(4)	(5)
DFF x DepositHHI x Firm Exit Rate	0.277**				
	(0.13)				
DFF x DepositHHI x Small Firms		-0.095			
		(0.06)			
DFF x DepositHHI x Young Firms			-0.070		
			(0.11)		
DFF x DepositHHI x New Firms				0.076	
				(0.09)	
DFF x DepositHHI x LARZ					-8.027**
					(3.79)
DFF x DepositHHI	0.445	9.815*	4.243	1.893	7.150***
	(1.39)	(5.16)	(3.68)	(1.24)	(2.54)
DepositHHI	-0.773	-0.726	-0.744	-0.749	-0.780
	(1.20)	(1.20)	(1.17)	(1.19)	(1.19)
Firm Exit Rate	0.036				
	(0.04)				
Small Firms		-0.002			
		(0.04)			
Young Firms			-0.026		
			(0.03)		
New Firms				0.001	
				(0.05)	
LARZ					-2.398
					(2.65)
Macroeconomic Controls	Yes	Yes	Yes	Yes	Yes
County f.e.	Yes	Yes	Yes	Yes	Yes
Quarter f.e.	Yes	Yes	Yes	Yes	Yes
Adj.R-squared	-0.01	-0.01	-0.01	-0.01	-0.01
Obs.	175081	175081	175081	175081	175081
P-value of F-test	0.00	0.00	0.00	0.00	0.00

Table 11: The Real Effects

This table estimates the sensitivity of firm exit rate, percentage of new firms, and unemployment rates to the nonbank expansion driven by the deposit channel in the following 8 quarters after a positive change in the Federal Funds rates. The underlying data set is the national UCC data spanning from 2007Q1 to 2021Q4. Variable definitions and macroeconomic controls are the same as Table 6. Standard errors clustered by quarter are reported in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$

	Panel A. Firm Exit Rate							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
DFF x DepositHHI	-0.001	-0.072	-0.027	0.037	0.119*	0.119*	0.182**	0.199**
	(0.06)	(0.07)	(0.07)	(0.08)	(0.06)	(0.07)	(0.07)	(0.10)
DepositHHI	-0.161*	-0.113	-0.078	-0.047	0.009	0.059	0.095	0.148
	(0.09)	(0.09)	(0.09)	(0.10)	(0.11)	(0.12)	(0.12)	(0.11)
Macroeconomic Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County f.e.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter f.e.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj.R-squared	0.31	0.32	0.32	0.33	0.33	0.33	0.32	0.32
Obs.	172128	168867	165712	162580	159405	156230	153143	150046

	Panel B. New Firms							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
DFF x DepositHHI	-0.180*	-0.124	-0.084	-0.033	-0.056	-0.023	-0.036	-0.116
	(0.09)	(0.11)	(0.14)	(0.17)	(0.14)	(0.11)	(0.10)	(0.07)
DepositHHI	0.053	-0.039	-0.127	-0.172**	-0.202**	-0.269***	-0.377***	-0.463***
	(0.09)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)
Macroeconomic Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County f.e.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter f.e.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj.R-squared	0.57	0.56	0.55	0.55	0.55	0.55	0.55	0.56
Obs.	172128	168867	165712	162580	159405	156230	153143	150046

	Panel C. Unemployment							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
DFF x DepositHHI	0.640	0.835***	1.037***	0.746***	0.700***	0.797***	0.678**	0.273
	(0.48)	(0.22)	(0.20)	(0.18)	(0.21)	(0.22)	(0.26)	(0.33)
DepositHHI	-0.243***	-0.420***	-0.305***	-0.186***	-0.393***	-0.524***	-0.383***	-0.198**
	(0.08)	(0.09)	(0.09)	(0.06)	(0.09)	(0.10)	(0.10)	(0.08)
Macroeconomic Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County f.e.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter f.e.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj.R-squared	0.90	0.85	0.87	0.89	0.84	0.82	0.83	0.86
Obs.	172536	169267	166104	162964	159781	156598	153503	150398

Appendix A.

Figure A2: Missing Rate (%) Linking Florida UCC with Florida Corporate Records

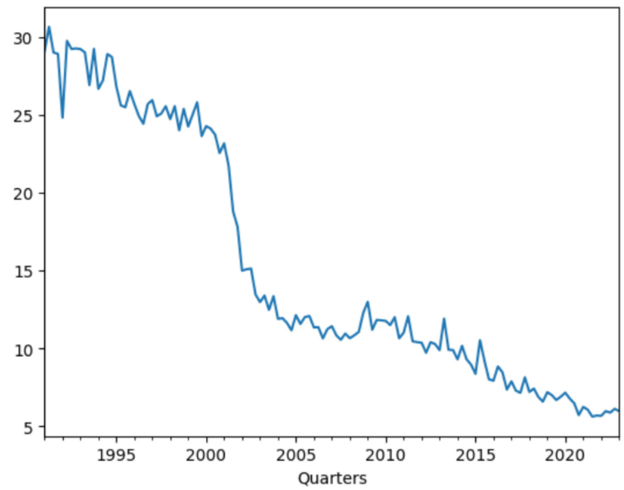


Table A1: How Representative Is Industry of GPT

This table reports the distribution of borrowers' industry identified by ChatGPT. The underlying data set is the state-level UCC data sets of 1996-2021.

NAICS 2 Industry	(%)
Professional scientific and technology services	17.87
Retail trade	15.54
Healthcare and social assistance	11.93
Real estate rental and leasing	10.17
Construction	6.75
Arts entertainment and recreation	6.60
Other services except for public administration	6.32
Manufacturing	5.79
Transportation and warehousing	5.03
Wholesale trade	4.31
Accommodation and food services	3.45
Management of companies and enterprises	2.28
Agricultural forestry fishing and hunting	1.38
Information	0.82
Educational services	0.73
Administration support and waste management	0.69
Mining	0.10

Table A2: Alternative Clustering and Interaction with States

This table add the interaction between changes in Federal Funds rates and a state dummy variable to Table 4. Clustering of standard errors is also changed to double-clustering by state and quarter as reported in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$

	ΔNonbank Market Share	ΔBank New Lending	ΔNonbank New Lending	ΔDeposits
	(1)	(2)	(3)	(4)
DFF x DepositHHI	2.360***	-10.268***	-5.632**	-1.427**
	(0.90)	(2.11)	(2.23)	(0.71)
DepositHHI	-0.753	0.173	-1.048	-0.600
	(1.31)	(3.25)	(2.90)	(1.48)
Unemployment	-0.109**	0.492***	0.195	-0.249***
	(0.05)	(0.16)	(0.18)	(0.03)
Establishments per capita.	0.032	-0.267*	-0.156	0.114***
	(0.07)	(0.15)	(0.15)	(0.03)
DFF x Unemployment	-0.266***	0.712***	-0.177	0.135***
	(0.06)	(0.22)	(0.20)	(0.04)
DFF x Establishments per capita.	-0.011	0.000	-0.029	-0.004
	(0.02)	(0.05)	(0.05)	(0.01)
Ln(Population)				4.087***
				(1.28)
DFF x Ln(Population)				-0.134
				(0.13)
DFF x State	Yes	Yes	Yes	Yes
County f.e.	Yes	Yes	Yes	Yes
Quarter f.e.	Yes	Yes	Yes	Yes
Adj.R-squared	-0.01	0.02	0.02	0.30
Obs.	175497	175497	175497	178678
P-value of F test	0.00	0.00	0.14	0.00