Specialized banks and the transmission of monetary policy: Evidence from the U.S. syndicated loan market *

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Abstract

Using a sample of U.S. syndicated loans, I examine the impact of banks' sectoral specialization on credit supply in response to monetary policy shocks. First, I show that banks rebalance their portfolios towards their specialized sectors following an expansionary interest rate shock. After a 25 basis point rate reduction, banks increase credit to their sector of specialization by 4% more relative to the other sector. The effect peaks at 10 quarters, with results driven by easing periods. This result holds when controlling for sector-level opportunities and concurrent banks' market structure characteristics. Consistent with the notion that banks specialize in given sectors to leverage their informational advantage, I find, at the bank level, that lenders with more specialized portfolios display improved income performance and reduced loan delinquencies upon expansionary rate shocks. Finally, I document that industries that borrow more from specialized banks register higher debt growth in response to monetary easing shocks. I interpret my results through a model where banks have heterogeneous monitoring technologies across sectors, generating higher lending and responsiveness to rate change in the industry of specialization. My findings emphasize the dual effect of bank sectoral specialization. Specialized banks show heightened responsiveness to monetary policy by increasing credit within their specialized sector and qualitatively align with a redirection of loans toward high-quality projects.

Keywords: Monetary policy; Bank specialization; Bank lending
JEL classification codes: E51; E52; E44; G21

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1. Introduction

Banks serve a crucial role in the economy, primarily through their intermediation functions and by financing valuable projects and businesses (Merton, 1993; Allen and Gale, 2000). Their intermediation capacity and provision of credit are critical for effective monetary policy transmission. Under the bank lending channel, changes in monetary policy significantly influence banks' ability to raise funds, thereby impacting their lending behavior. This channel is further magnified by the heterogeneity in balance-sheet strength (Kashyap and Stein, 1995; Bernanke, 2007; Jiménez et al., 2012).

Since banks are responsible for selecting credit-worthy borrowers and monitoring loans, they are subject to costly information acquisition. Banks specialize in specific industries due to their information advantage built over repeated interactions with borrowers in similar industries (Blickle et al., 2021; Giometti and Pietrosanti, 2022), resulting in heterogeneous bank presence in distinct industries. Therefore, banks' portfolio is far from diversified, with lenders generally allocating 15% or more of their Commercial and Industrial loans (C&I) into their preferred industry (Figure 1a)[1]. Crucially, this pattern is not driven by an industry's prominence in the market (Figure 1b). Banks' industry specialization has, then, been shown to significantly impact credit allocation (Paravisini et al., 2023), security design (Giometti and Pietrosanti, 2022) and reaction to shocks (De Jonghe et al., 2020; Iyer et al., 2022). While much of the literature examined the transmission of industry-specific shocks for specialized banks, limited evidence exists concerning the role of specialized banks in the transmission of monetary policy. Does the banks' exposure to specific sectors influence monetary policy transmission? And if so, how? In other words, do banks exploit their informational advantage in reaction to monetary policy shock, and if so, how does this affect the riskiness of their portfolios and aggregate outcomes?

This paper first shows how banks with different degrees of sector specialization adjust their portfolios in response to a change in monetary policy. Exploiting syndicated loan-level data for the US, I find that, upon a rate reduction, banks with higher levels of industry specialization increase their credit relatively more to their industry of specialization. This suggests that, as rates decline, banks increase lending relatively more to sectors where they have a marginal advantage. Consistently, with this view, the differential effect of specialization is heightened for constrained banks with weak balance sheet ratios, as investing in their portfolio of specialization is their marginal choice when closer to the constraint. Secondly, leveraging bank-level data, I examine the impact of specialization on bank-level income during periods of declining interest rates. Higher portfolio concentration in specialized banks corresponds to improved income performance, lower loan delinquency rates and higher market capitalization[2]. These findings are consistent with specialized banks exploiting their informational advantage to select better

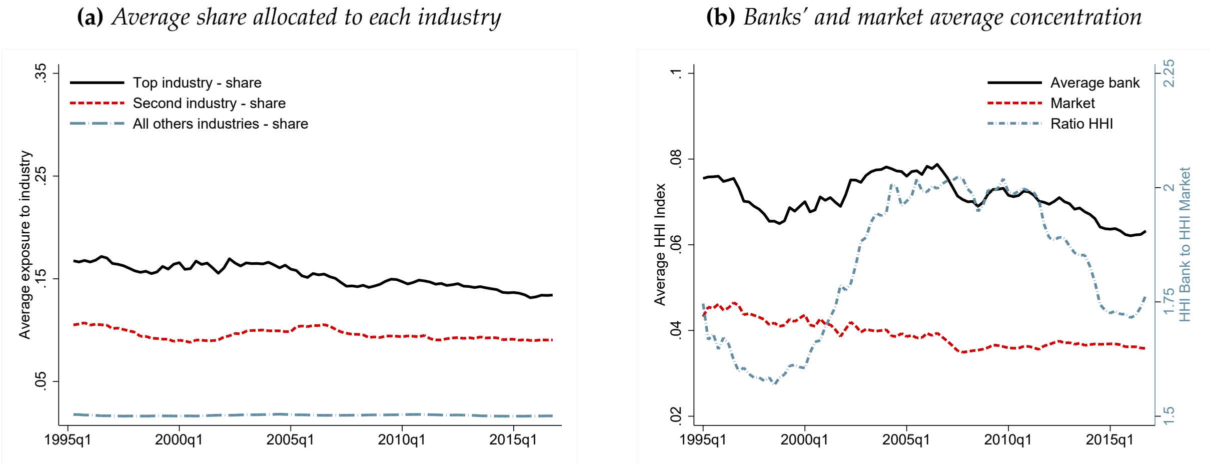
[1]This pattern is also confirmed in Blickle et al. (2021) where they use the FR Y-14 Q archive, which tracks all C&I loans over 1 million USD in size for all stress-tested US bank.

[2]Banks' portfolio concentration measures the overall bank-level degree of specialization, higher levels of industry specialization are associated with higher levels of portfolio concentration.

borrowers without compromising monitoring activity. Finally, I document the aggregate sector impact of banks' specialization by aggregating lending volumes at the sector level. Sectors with higher exposure to specialized lenders experience increased lending volumes following a rate reduction.

These results highlight specialized banks' crucial role in monetary policy transmission. These lenders have increased responsiveness, channeling credit to their specialized sectors. Moreover, qualitative evidence suggests a redirection of loans toward high-quality projects, enhancing overall banking performance.

Figure 1:
Banks portfolio concentration



Note: source Dealscan data. Panel a shows the bank's average (weighted) share of loans allocated to each industry at a given point in time, for banks in the sample. Data is ranked into the average bank's "top" industry, secondary industry, and all other industries. Bank's top industry is defined as the industry into which a bank has invested the largest share of its portfolio outstanding at each point in time in the sample. Panel b depicts the average (weighted) portfolio concentration at the bank level and the corresponding one on the market. The market HHI is constructed as the share of loans to a specific sector over the total volume of the market in a given quarter, while the one for the bank represents the weighted average HHI off all banks' portfolios where the weight is the fraction of a banks volume over the total market as in Giometti and Pietrosanti (2022).

To examine the role that bank specialization plays in the provision of credit supply in the presence of monetary policy changes, I use granular data for bank loans from the US syndicated loan market between 1987 and 2016 at quarterly frequency. Syndicated loan-level data involve multiple lenders jointly providing credit to a borrower. Dealscan collects information at origination that allows me to measure banks' industry exposure. Following the literature (Blickle et al., 2021; Iyer et al., 2022), banks' specialization is defined as the share of a bank's credit allocated to a specific sector relative to a bank's total credit portfolio. This measure captures the extent to which banks concentrate their lending activities in specific sectors and the importance of a sector for a bank. The final data set encompasses 60 industries based on the BEA industry classification, excluding sectors such as FIRE (Finance, Insurance, and Real Estate) and public sector companies. Loan-level data is complemented with comprehensive information on banks and industry characteristics.

I identify monetary policy shocks by utilizing high-frequency surprises in interest rate futures contracts within a 30-minute window around the policy, following the approach outlined by Gürkaynak et al. (2004) and Gertler and Karadi (2015). This method ensures the isolation of exogenous rate variations from other macroeconomic factors and minimizes potential issues of reverse causality.

The main unit of analysis is the outstanding credit volume at the bank-sector-quarter level. My analysis is subject to a common identification challenge in the empirical banking literature: unobserved changes in industry-level lending opportunities and bank-level heterogeneity could bias my results and prevent identifying the bank's loan supply effect stemming from banks' industry specialization. I address this identification challenge by exploiting the disaggregated nature of the data and saturating the bank-sector level regression with granular bank-time, sector-time, and bank-sector fixed effects that isolate credit supply and demand effects at the bank-sector level (Khwaja and Mian, 2008; Jiménez et al., 2012), which could otherwise drive my results. I thus compare the credit growth of the same bank across different sectors. The identifying assumption posits that banks face uniform demand across sectors, regardless of their degree of specialization. To reduce any concern on confounding effect between monetary policy and my measure of specialization I employ slow moving averages for my measure of specialization as Paravisini et al. (2023) and Giometti and Pietrosanti (2022).

The main empirical findings can be summarized as follows. At the bank-sector level, specialized banks consistently increase lending to their specialized sectors in response to monetary policy rate reductions, demonstrating a substantial effect. After a 25 basis point reduction in the monetary policy shock, for a one standard deviation increase in banks' specialization, lenders raise credit volume, on impact, by an additional 50 basis points (bps) towards the sectors of specialization relative to other sectors. In annual terms, this increase represents 2% of the volume between the bank and the sector, illustrating the sizable effect of monetary policy on banks' lending behavior. I conduct several additional robustness tests of my findings. First, I show that alternative measure of specialization that correct for industry prominence in the economy, produce results that quantitatively and qualitatively similar. Second my findings are also confirmed at the loan-level data.

I then employ local projections (Jordà, 2005) to study the long-run implications of this finding, revealing a persistent and economically significant effect of the interplay between banks' sectoral specialization and monetary policy. In particular, a 25 bps cut in rates, for a standard deviation increase in banks' specialization, corresponds to a cumulative growth between the bank and the sector of 4% that peaks at around two years, which represents 20% and 5% of the mean and standard deviation, respectively, of the distribution of bank-sector volume growth for the corresponding horizon in the sample. Moreover, I document that this channel works for both lead arrangers, who oversee and monitor the loan, and participants, reducing any concern about the potential correlation between credit supply shocks and bank-specific loan demand. Importantly, my findings are not driven by other bank's market structure characteristic that may affect the transmission of monetary policy to loan supply and could be correlated with sectoral specialization, such as banks' market shares (Giannetti and Saidi, 2019). Thus, my findings extends beyond the previously studied channels of monetary policy transmission through banks' balance sheets (Jiménez et al., 2012, 2022).

I then show that these results are highly asymmetric. While a reduction in monetary policy incentivizes lenders to redirect funds to sectors with high exposure, a monetary policy tightening does not prompt banks to decrease their lending to sectors with high exposure. This asymmetry aligns with prior evidence indicating that banks tend to shield themselves during tightened lending conditions by maintaining their exposure to their main sectors (Iyer et al., 2022).

Furthermore, despite syndicate loans cover a large fraction of US commercial lending, the sample is populated by large firms, thus I corroborate my analysis using Small Business Lending data from the 7(a) program, available at a yearly frequency, which I used as an external validity check, replicating and confirming my analysis.

The previous evidence confirms that banks exploit their marginal information advantage in response to a monetary policy change. Previous evidence shows that banks become more concentrated when closer to constraints (Blickle et al., 2021), suggesting that when banks have lower balance sheet ratios, investing in their portfolio of specialization becomes the marginal choice as they can generate ex-post higher returns (Blickle et al., 2021). I thus study the implications of banks' specialization around monetary policy change for constrained and unconstrained lenders, as a rate cut allow lenders to escape credit constraints and achieve their desired allocation (Kashyap and Stein, 2000; Jiménez et al., 2012). Bank constraints are measured via equity and liquidity ratios. I find that, for a given level of specialization, banks with weaker balance sheets (low capital and liquidity ratio) respond more to monetary policy rate cuts. Then, I show that my estimates become larger for banks that are more likely to be financially constrained, consistent with financial frictions reinforcing these patterns for specialized lenders[3].

The second set of results explores the implications of banks' specialization at the bank level and its interaction with monetary policy. To quantify the degree of specialization at the bank level, I construct a measure of concentration using the Herfindahl-Hirschman Index (HHI) based on the level of specialization in each industry. According to existing theories and evidence, periods of cheap credit may foster a build-up in risk with potential consequences for the aggregate economy (Granja et al., 2022). Specialized banks can exploit their informational advantage and select high-quality borrowers and seize higher returns (Blickle et al., 2021; Giometti and Pietrosanti, 2022) or instead, as yields are compressed by low rates, they can focus on risky borrowers in their industry of specialization and shirk their costly monitoring duties in the hope of higher returns (Degryse et al., 2021; Eufinger et al., 2022). To answer this question, I look at bank-level income performance and delinquencies for different degrees of portfolio concentration. My findings indicate that banks with higher levels of concentration

[3]Financially constrained banks are banks with below the median liquidity and capital ratio.

experience an increase in return on assets (ROA) and a reduction in the charge-off rate of 3 and 4 bps, respectively, in response to a one standard deviation reduction in the funding rate[4]. These estimates represent 4% (1%) of the standard deviation (mean) and 5% (6%) of the standard deviation (mean) for the observed variation of their respective distributions over the corresponding horizon. These effects are more pronounced and enduring for lead lenders, confirming that specialized banks use their screening capabilities to select better borrowers and increase returns, consistent with the heightened monitoring activity linked to lead arrangers in syndicated lending (Botsch and Vanasco, 2019; Blickle et al., 2020).

Finally I analyze the aggregate implications of the channel previously documented, studying the sector level reactions to monetary policy to different exposures to specialized lenders. I first measure the sector level exposure to specialized banks in the sector and examine its effect for the transmission of monetary policy to aggregate lending and economic activity (employment and value added) growth. Consistent with the previous results, I find that after an easing of monetary policy, sectors exposed to banks that are more specialized in the sector, have a higher increase in aggregate committed lending. In terms of magnitudes, a one standard deviation increase in sector level exposure to specialized banks increases lending growth by 2% per 25 bps decrease in the monetary policy shock, corresponding to an 11% (6%) of the mean (standard deviation) of the empirical distribution. I also document that employment and value added increase, though non significantly.

In the last part of the paper I develop a stylized model that describes how heterogeneous monitoring capacity of banks across sectors can determine at the same time different specialization patterns within banks and the observed effect of monetary policy on loan portfolio re-balances. In a simplified two-period model, banks face heterogeneous decreasing returns to scale across sectors due to different monitoring technologies, generating higher returns in sectors with higher monitoring capabilities. Lenders have preexisting debt commitments that constrain their ability to reduce overall lending after negative shocks. The model rationalizes the findings that, upon a rate cut, banks expand lending in their sector of specialization due to their marginal advantage in monitoring technologies.

My results provide new insights into the propagation of monetary policy to business lending and emphasize the critical role of banks' sectoral specialization in shaping credit allocation. Specialized banks exhibit heightened responsiveness by significantly increasing credit within their specialized sectors. Additionally, the improvement in income performance and the reduction in delinquency, indicates a redirection of loans toward high-quality projects. This dual impact emphasizes the role of specialized banks in monetary policy transmission and their contribution to overall banking performance.

Related literature: My results speak to several strands of literature. First, I add to the large literature that studies the role of banks' heterogeneity in the transmission of monetary policy (Kashyap and Stein, 1995, 2000; Jiménez et al., 2012, 2022; Drechsler et al., 2017; Gomez et al., 2021) in particular, they show that weak balance sheet amplifies the transmission of monetary policy. The existing papers highlighted

[4]Charge-offs are the value of loans and leases removed from the books and charged against loss reserves

the prominent role of balance sheet channels such as size Kashyap and Stein (1995) and balance sheet characteristic Kashyap and Stein (2000); Jiménez et al. (2012), market structure (Drechsler et al., 2017) and the exposure to interest rate risk (Gomez et al., 2021) in the transmission of monetary policy. I add to this literature by providing compelling evidence on how bank industry specialization works beyond them and acts as a key driver of credit supply responses to fed funds changes. When the central bank lowers interest rates, it promotes banks to increase their lending towards the sectors in which they have specialised as they find them more attractive. In addition, my findings suggest that this channel is amplified by banks' financial frictions. To the best of my knowledge, this paper is the first to focus on identifying how banks' sectoral specialization interacts with monetary policy.

My paper is closely related to the contemporaneous work on local mortgage market concentration and monetary policy of Casado and Martinez-Miera (2023). While their work primarily focuses on the impact of monetary easing on mortgage lending and origination in the specialized market, my analysis shifts the attention to commercial lending. Unlike mortgage lending, commercial lending involves higher monitoring and screening costs for banks, limiting the securitization potential of commercial loans and intensifying moral hazard risks within the bank, making it suitable to test implications for banks' risk taking. By examining the dynamics of commercial lending, my paper offers valuable insights into the conditions under which sectoral specialization plays a significant role in the transmission of aggregate funding shocks. I demonstrate that the specialized knowledge acquired by banks in specific sectors enables them to exploit economies of scale and effectively manage risks associated with commercial lending. This highlights the relevance of sectoral specialization in shaping the transmission mechanisms of monetary policy within the broader financial system and its consequence for bank risk taking behaviour.

On this strand of literature, my analysis is mostly close to studies that focus on bank market-structure characteristics and the transmission of shocks (Goetz et al., 2016; Doerr and Schaz, 2021; Paravisini et al., 2023; Iyer et al., 2022). Banks traditionally incur substantial costs for acquiring information through monitoring and screening activities. However, they also benefit from economies of scale in acquiring location-specific or sector-specific knowledge, thereby resulting in portfolios that are far from diversified (Blickle et al., 2021). Notably, banks' specialization in specific sectors allows them to gather information on common aspects shared by firms within those sectors Paravisini et al. (2023); Giometti and Pietrosanti (2022); Iyer et al. (2022); Di and Pattison (2022). These lending-specific advantages give rise to concentrated and more procyclical bank portfolios in which shocks are amplified (Iyer et al., 2022). The main focus of papers in this literature is to show that negative idiosyncratic shocks emanating from industries in which the bank is exposed lead to bank reallocation towards their sector of specialization, which does not compensate for the decrease in the other sector, thus further propagating the shocks. A novel contribution of my paper relative to this literature is documenting that when a favorable monetary policy shocks hit banks, they react by funneling credit toward their sector of specialization leading to an increase in overall borrowing by exposed sectors. My findings differ from De Jonghe et al. (2020) which instead focuses on a specific wholesale market freeze event that hit Belgian banks upon the collapse of Lehman Brothers. My results highlight a noteworthy response of banks to a decrease in lending rates, whereby they increase their lending activities toward their specialized sectors.

This strategic shift, however, raises concerns regarding potential idiosyncratic risks at the bank level Goetz et al. (2016, 2013) and the subsequent impact on lending standards (Mian and Sufi, 2009; Granja et al., 2022). By contributing to this literature, my empirical evidence sheds light on an intriguing aspect: specialized banks not only demonstrate an improvement in their overall performance but also exhibit a reduction in delinquencies. These results challenge the prevailing notion that banks, following an easing of monetary policy, reallocate their funds toward lower credit-worthy marginal borrowers, potentially compromising their financial stability. Instead, my findings suggest that specialized banks can effectively increase their revenues while simultaneously mitigating losses, indicating a more prudent lending approach.

The rest of the paper is structured as follows. Section 2 presents the data and the approach that I use to measure the main variables of interest. The micro level results and the empirical methodology discussion are reported in Section 3. Section 4 examines the bank level implications on income performances and delinquencies. Section 5 reports the aggregate implications on sector lending and economic activity. The model is presented in 6. Section 7 concludes.

2. Data and measurement

To measure banks' industry specialization and study how influence bank-sector provision around monetary policy shocks, I rely on a sample of U.S. syndicated loans matched with bank and firms characteristics for the period between 1990 quarter 1 to 2016 quarter 4. In the following section I first describe the sample construction, describe the different measures of specialization, monetary policy changes, and other economic variables of interest that I employ throughout the analysis and finally summarize the sample characteristics.

2.1. Data

In this paper, I combine several data sources: LPC Dealscan, Small Business Administration 7(a) loans data, FR Y-9C reports, Compustat firm-level data, industry-level data coming from the Bureau of Economic Analysis (BEA). My primary data sources come from LPC Dealscan and FR Y-9C reports which I use to obtain information on US business loans and bank industry exposure, while the latter is used to obtain bank-level characteristics for US bank holding companies (BHC). In the absence of bank data on all credit disaggregated by sectoral markets, I focus on a sample of matched banks to the syndicated market as it covers the vast majority of commercial credit in US (Chodorow-Reich, 2014;

Giannetti and Saidi, 2019; Iyer et al., 2022).

Dealscan Loan-level data: I collect loan-level information on syndicated credit from Dealscan data. The dataset contains detailed information for syndicated commercial business loans, including, in particular, loan amounts, pricing, maturity, banks involved in the syndicate and sector characteristics of the borrower at SIC level.

Syndicated lending, though representing a fraction of total banks' lending, significantly accounts for the total volume of credit generated and outstanding at bank level Chodorow-Reich (2014); Giannetti and Saidi (2019). In the past two decades, syndicated lending is about half of total commercial and industrial (C&I) lending volumes, and therefore it is often used to assess bank lending policies Giannetti and Saidi (2019); Ivashina and Scharfstein (2010). On top of it, Dealscan is particularly useful in my setting as syndicated loans are particularly large and the incentive to share risk across the bank syndicate for firms in the sector of specialization is salient. As previous studies point out (Chodorow-Reich, 2014; Giannetti and Saidi, 2019), the main advantage of studying syndicated loans is that a group of banks (the syndicate) co-finance a single borrower where the lead lender generally retains the highest share of the loan and is in charge of the active management while participants are usually not in direct contact with the borrower, but merely supply credit. Compared to other types of bank loans, syndicated loans are on average larger in volume and issued to larger borrowers. This overlapping portfolio setting allows me to exploit different levels of sectoral exposure of each syndicate member.

To harmonize the SIC codes with BEA information at the NAICS level, I convert SIC codes into NAICS ones. I first marge Compustat firm-level balance sheet information on loan level characteristics using (Chava and Roberts, 2008) linking table which matched Dealscan loans (facilities) from 1987 to 2016 to have a perfect map between SIC codes and NAICS codes for matched firms. For the remaining instances I make use of the CENSUS linking table and Fort and Klimek (2016) linking table.

To match Dealscan lender to BHC characteristics I use Schwert (2018)'s linking table and augmented it with the one available from Gomez et al. (2021). Both tables identify the BHC for Dealscan lenders, in particular, the Schwert (2018)'s one identifies the BHC of all DealScan lenders with at least 50 loans or $10 billion loan volume in the matched DealScan-Compustat sample. As Compustat doesn't share a common identifier with the FR Y-9C reports matching the CRSP identifier (`permno`) with the bank's ID (`RSSD9001`) to get a linkage for each matched lender. Following Giometti and Pietrosanti (2022) I define a bank to be the BHC, not the individual Dealscan lender identifier. As most loans in the sample are syndicated, the same loans will be associated with one or more banks.

Consistently with other studies, in order to dissect the effect of aggregate shock on credit supply I retain information for both participant and lead arrangers (Chodorow-Reich, 2014; Doerr and Schaz, 2021; Gomez et al., 2021) and focus on all completed loans issued in the US. Even though lead lenders are more relevant for pricing, as already discussed, the focal point of the analysis is a bank's credit supply, including both lead arrangers and participants provides a better picture of the syndicated loan market and reduces sample selection bias. To identify the lead arranger(s) and participants I follow the procedure outlined in Chakraborty et al. (2018) which is based on a scoring ranking exploiting the role of each lender in the syndicate in the spirit of Bharath et al. (2011). I finally restrict the sample of loans origination between 1991 and 2016 since the coverage is sparse before and as I lose the initial years to define banks' specialization shares as it will be clear from Section 2.2. Most importantly, to measure banks specialization, I use the whole sample of observation (1987-2016), this choice does not affect the results. For the empirical analysis, I further restrict the sample to loans whose borrowers have headquarters in the US (Compustat Foreign Incorporation Code), whenever this information is available. In the empirical analysis, I also drop from the sample all loans to financial corporations, utilities and public sector companies.

The unit of observation of the analysis is the loan facility at the quarterly level. Since in my analysis, the main dependent variable is the volume of credit outstanding between the bank and sector at each quarter, I aggregate all facility-level information at the BHC level. Lastly, I match each loan with the end-of-quarter bank information.

The matched sample yields a maximum of 85,586 facilities originated by 147 banks involving 19,430 non-financial, of which 7,247 are Compustat firms, spanning from the first quarter of 1991 to the last quarter of 2016. A median bank in my sample has five loan originations per sector in a given quarter and is connected to roughly 80 firms (65 from Compustat).

Bank-level data: I use financial data on banks from the FR Y-9C reports. The data includes balance sheet information at the quarterly level for all bank holding companies (BHC) located in the United States with at least $500 million in assets. Because these reports are available at the end of every quarter, I match the origination date of the loan deal with the relevant quarter. For example, I match all syndicated loans that were originated from April 1st to June 30th with the second en of quarter of that year of the FR Y-9C reports.

Small Business Lending loans: part of the analysis makes use of Small Business Administration (SBA) 7(a) loans data to measure industry specialization at origination. The 7(a) program provides guarantees for small business loans and represents the SBA's largest funding program, which is also a relevant source of credit for small businesses. In 2017, SBA 7(a) originated more than 60,000 loans totaling $25.45 billion (Di and Pattison, 2022), covering roughly 10% of SBA lending reported in the Community Reinvestment Act. These SBA loans are of particular importance for small businesses, and in certain industries where SBA lending is common. To be eligible for a 7(a) loan, the borrower must run a for-profit small business that meets SBA industry-specific size standards.

The program, is of particular interest for the analysis as it targets credit-constrained firms. Lenders are obligated to meet the 'credit elsewhere' condition by providing documentation that explains why the borrower was unable to secure a loan under favorable terms without the SBA guarantee. Additionally, they must assess the personal assets of any individuals who possess over 20% ownership in the small business. SBA-backed loans are versatile and can serve various purposes, including funding working capital, supporting business growth and expansions, acquiring existing businesses or franchises, purchasing commercial real estate, or refinancing existing debt.

Private lenders, predominantly commercial banks but also including credit unions and other non-bank lenders, are the main providers of funding for SBA 7(a) loans. These lenders make most decisions regarding the loans, following SBA underwriting rules such as maximum interest rates and borrower requirements. In return, the SBA offers a partial guarantee of 75-85% of the loan amount, depending on its size[5].

Despite the guarantees, thorough screening remains crucial. The SBA's program caters to less creditworthy borrowers who couldn't secure loans under standard terms. While guarantees are partial, the SBA continuously monitors portfolio performance, and it can revoke Preferred Lender status for poor risk management or seek payment for the guaranteed portion in case of lender-related defaults. Hence banks are willing maintain a proper risk-assessment behavior in their lending decisions.

This data set contains loan-level information on the identity, address, city, and industry of the borrowers and corresponding lenders identifier as well as loan characteristics such as total amount, amount of the SBA's loan guarantee, initial interest rate, approval date, loan status (performing/default) and jobs supported by each loan. The dataset includes information on the charge-off amount and date on its loan guarantee, a loan is charge-off. Following Granja et al. (2022) and Di and Pattison (2022), I exclude canceled loans from the analysis because cancellation may be at the initiative of the borrower.

Monetary policy shock I borrow high-frequency monetary policy shocks from Gürkaynak et al. (2005). This series measures monetary shocks using the high-frequency movements in the Federal Funds futures (Kuttner, 2004; Cochrane and Piazzesi, 2002; Gürkaynak et al., 2005; Nakamura and Steinsson, 2018) and construct the shock as follows

$$\varepsilon_t = \frac{D}{D-t}\left(\text{ffr}_{t+\Delta^+} - \text{ffr}_{t-\Delta^-}\right) \tag{1}$$

where t is the time of the monetary announcement, ffr_t is the implied Fed Funds Rate from a current-month Federal Funds future contract at time t, Δ_+, and Δ_-control the size of the time window around the announcement, while the first term is a standard time adjustment for the fact that Federal Funds futures contracts settle on the average effective overnight Federal Funds rate. The window is set as $\Delta_- = 10$ minutes before the announcement and $\Delta_+ = 20$ minutes after the announcement. My time series is equivalent to the one The shock series begins in January 1990, when the Fed Funds futures market opened, and ends in December 2016[6]. Following the literature I aggregate the high-frequency shocks to the quarterly frequency (and yearly frequency for the SBA data) in order to merge them with

[5] Lenders pay the SBA a fee based on loan features and the guaranteed amount.
[6] The series was made available in Jarociński and Karadi (2020).

my data.

2.2. Measuring bank specialization

In the following section, I detail how banks' sectoral specialization is defined and the main assumptions used to design the measure.

I construct the main variable of interest at the bank-sector level. Bank's sector specialization is defined as the ratio of total loans i granted by bank b to all firms in sector s at time t relative to the bank's total credit granted:

$$Specialization_{b,s,t} = \frac{Loan\ outstanding\ _{b,s,t}}{\sum_s\ Loan\ outstanding\ _{b,s,t}} := s_{b,s,t} \tag{2}$$

where $Loan_{b,i,s,t}$ is the loan outstanding credit granted (outstanding and newly generated) by bank b to firm f in sector s at quarter t. This measure is analogous to the one of Paravisini et al. (2023); Blickle et al. (2021).

I face two main data limitations with respect to variable construction: (i) one is the availability of the loan shares that each arranger supplies within a loan (ii) and the other is to correctly measure the exposure to each industry from retained loan shares. To tackle the first issue, I follow Blickle et al. (2020) and estimate the shares for each loan across the syndicate exploiting loan level information, I detail the procedure in subsection A[7].

For the latter, I exclude term loans B because banks tend to sell those loans after origination since they are specifically structured for institutional investors. I then assume that loans are retained in the bank portfolio until maturity, excluding thus all loans that mature within the quarter (Giannetti and Saidi, 2019; Gomez et al., 2021). I merge loan data with Bureau of Economic Analysis (BEA) industry-level data and define aggregate loans using BEA industry classification, which comprises 71 industries based on NAICS codes.

As robustness I also use an alternative measure of specialization as defined by:

$$Excess\ Specialization_{b,s,t} = \frac{Loan\ outstanding\ _{b,s,t}}{\sum_s\ Loan\ outstanding\ _{b,s,t}} - \frac{Loan\ outstanding\ _{s,t}}{\sum_s\ Loan\ outstanding\ _{s,t}} \tag{3}$$

The measure captures the "excess" specialization of a bank in a sector as it reflects the degree to which a bank is over-invested relative to the "optimal" industry weight in the market (Blickle et al., 2021). This measure is not bounded at 0 and can take negative values. Moreover, tails are less likely

[7]The common practice in the literature is to equally weigh the missing shares per loan across the syndicate if the information is not available, while (Chodorow-Reich, 2014; Giannetti and Saidi, 2019; Doerr and Schaz, 2021), which has been show to overstates actual shares reported for a matched sample with the FR Y-14 Q archive.

to distort estimation attempts. Using this measure any over-investment is treated in the same way, regardless of whether the ideal diversified portfolio weight in the industry has a low or high degree of investment share in the economy.

To create a measure of specialization at the bank level I construct banks' HHI index using the shares on each industry from Equation 2.

$$HHI_{b,s} = \sum_{j=1}^{J} (s_{b,s,t})^2 \tag{4}$$

Higher values of a bank indicate low diversification (all credit goes to borrowers from one sector or concentrated portfolio), while lower values reflect increasing diversification of banks' loan portfolios across industries.

2.3. Evidence of specialization & summary statistic

This section provides evidence of the main trends in industry specialization in my matched sample as well as summary statistics for the final dataset.

I first show evidence of the pervasive feature of banks' industry specialization (Blickle et al., 2021). As shown in Figure 1 the average (weighted) share of C&I loans, in my sample, devoted to the top industry is roughly 15%. They comprise more than 20% of the bank's loan portfolio, together with the second industry share, while the average share devoted to all other industry is marginal (Blickle et al., 2021). Overall Figure 1a, tells that the banks in my sample only have one or two preferred industries, which remain stable over time.

Measuring banks' industry specialization with banks-sector share can, however, be biased by the prominence of certain industry in the market. To better gauge the extent of banks' specialization and address this point, I compare the average banks' HHI portfolio with the one of the market in the same spirit as in Giometti and Pietrosanti (2022). I show in Figure 1b that banks' specialization is not a mere product of industry concentration: according to this evidence, banks' portfolios are far more concentrated and less diversified than those of the market. Banks' portfolio concentration is on average twice as large as the one of the market as can been seen by the ratio of the two. This highlights two facts: first the average bank is more concentrated than the market and second not all banks are lending to every industry in the same way.

Finally, Table 1 provides the summary statics for the main variable of interest and controls used in the analysis. The first section reports information at the loan level, From the second to the fourth section I present bank-sector level moments and bank-level moments respectively, which is the main level of the analysis. In the table, I show the main measures of specialization and the "excess" specialization. At the bank sector level, the average degree of specialization for the dealscan sample is around 3%, while the one for small business lending data is considerably higher. However I show in Figure A.4 that in the matched sample, there is high correlation between the Dealscan measure and the corresponding one in the SBA dataset.

Of course, this measure of specialization is driven down by all those sectors in which the bank is not specialized as can be seen from panel (a) in Figure 1. The measure of excess specialization shows a considerable right fat tail distribution, which again is evidence of the wide degree of variation of specialization across banks and industries. Bank-level variables come from the matched sample for banks and the Dealscan panel in my analysis where income variables such as *ROA*, *chargeoffrate* and *provision for loan and lease losses rate* are annualized and scaled to percentages. The remainder of the tables describes the information at the sector and aggregate level. The industry asset redeployability index is constructed using data from Kim and Kung (2017), which measures the pledgeability of an asset or its ability to serve as collateral for the average asset in the industry. In the next session, I study how a monetary policy cuts affects banks' credit supply for banks with different levels of industry specialization.

3. Empirical results: bank-sector lending around monetary policy change

In this section, I explore the effect of the interaction between bank specialization and monetary policy on credit supply. Motivated by the previous evidence, I examine how changes in bank lending at the bank-sector level are influenced by banks' specialization conditional on a monetary policy rate cut.

When the interest rate decrease, a bank encounters a trade-off in its portfolio investment strategy: it can further expand lending in sectors where it has more exposure, leveraging its information advantage in specialized sectors. This action, however, increases its vulnerability to industry-specific shocks. Conversely, the bank can opt to reduce its exposure and diversify its portfolio, capitalizing on the low-rate environment, potentially raising its overall systemic exposure (Goetz et al., 2016; Chu et al., 2020).

I show that upon a cut in monetary policy, bank specialization is associated with significantly higher credit supply towards the sector in which the bank is specialized in (higher exposure). I interpret this evidence as indicative of two facts: average banks specialization is a good approximation for the marginal response for different degree of banks' specialization. Second, that bank exploit their lending advantages coming from lower marginal costs and information advantages which are sector-specific and allocate more credit towards their sector of experience.

To reach these conclusions, I compare the difference in the credit growth volume of outstanding business loans by each bank in each sector as a function of the bank's specialization around changes in monetary policy cuts. To make sure that my results are not driven by sporadic changes in the main explanatory variable, I take a slow-moving lag of my measure of specialization over a three-year horizon to avoid being of the same duration as the observed loan maturity in the sample (roughly 4 years). I

Table 1:
Summary statistics

	Mean	SD	p25	p50	p75	Obs
Loan level						
Loan amount (millions)	38.64	80.60	10.91	22.06	42.91	178,098
Loan maturity (months)	46.99	21.60	36.00	60.00	60.00	178,098
Loans originated per bank-sector	8.61	8.78	3.00	5.00	11.00	178,098
Number of firms per bank-sector cluster	6.16	6.70	2.00	4.00	8.00	178,098
Bank-Sector level						
$\Delta(loan)_{b,s,t}$	0.02	0.24	-0.01	-0.01	0.03	172,769
$Specialization_{b,s}^{t\to t-12}$	0.03	0.06	0.01	0.01	0.03	172,769
$Ex.\ Spec._{b,s}^{t\to t-12}$	0.01	0.06	-0.00	0.00	0.01	172,769
$Mkt\ share_{b,s}^{t\to t-12}$	0.02	0.03	0.00	0.01	0.02	172,769
Bank-Sector level (SBA sample) - yearly						
$\Delta(loan)_{b,s,t}(SBA)$	0.02	1.37	-0.80	0.01	0.83	69,348
$Specialization_{b,s}^{t\to t-3}(SBA)$	0.12	0.18	0.02	0.06	0.14	69,348
$Mkt\ share_{b,s}^{t\to t-3}(SBA)$	0.01	0.03	0.00	0.00	0.01	69,348
Bank level						
$HHIb,t^{t\to t-12}$	0.20	0.24	0.05	0.10	0.24	6,836
$HHIb,t^{t\to t-12}Lead\ bank$	0.35	0.28	0.09	0.28	0.54	5,201
$ROA_{b,t}$	1.03	0.72	0.79	1.11	1.38	6,733
Loan loss provision$_{b,t}$	0.46	0.58	0.13	0.29	0.56	6,885
Δ*Delinquency rate*$_{b,t}$	-0.00	0.00	-0.00	-0.00	0.00	6,830
Charge off rate$_{b,t}$	0.69	0.81	0.22	0.43	0.84	6,885
Δ*Mkt.Cap*$_{b,t}$	0.04	0.18	-0.04	0.04	0.13	6,058
Bank size	9.53	1.55	8.47	9.28	10.53	6,885
Bank equity ratio	0.09	0.03	0.07	0.09	0.10	6,885
Bank security ratio	0.21	0.10	0.14	0.20	0.26	6,885
Bank deposit ratio	0.66	0.19	0.60	0.71	0.79	6,885
Sector level - yearly						
Asset redeployability$_{s,t}$	0.41	0.15	0.33	0.42	0.49	1,625
Δ*gross output*$_{s,t}$	0.02	0.06	-0.00	0.03	0.05	1,625
Δ*value added*$_{s,t}$	0.02	0.10	-0.01	0.02	0.06	1,625
Δ*Employment (indexed 2012)*$_{s,t}$	0.01	0.05	-0.02	0.01	0.03	1,625
$\Delta TFP_{s,t}$	0.00	0.04	-0.01	0.00	0.02	1,625
Aggregate level						
ε_t	-0.00	0.00	-0.00	-0.00	0.00	104
Δffr_t	0.00	0.00	-0.00	0.00	0.00	104

This table provides summary statistics on loan, bank, sector and aggregate characteristics of the sample studied. The sample represents all U.S. syndicated loans that are matched with a valid bank in the dataset. For the bank-sectoral information banks are required to have supplied credit into two distinct quarters for each sector. Bank-level income variables (ROA, provision of loan loss rate and charge-off rate) are annualized and transformed into percentage points. The data covers the period from 1991q1 until 2016q4.

construct my main outcome variable aggregating all the loans outstanding between the bank and a sector at the quarterly level to have sensible variation and enough issuance frequency (Acharya et al., 2018, 2019), this clustering approach also has been used by Degryse et al. (2019), who show that it leads to similar results as the firm fixed effects approach, and, importantly, does not create any bias in the estimation. I present further robustness using loan-level information and bank-firm fixed effect in Appendix B.

3.1. Bank specialization and monetary policy: bank-sector outcomes

Bank specialization: My baseline specification tests how banks' portfolio reacts to an easing of monetary policy, specifically it tests how the loan supply varies at the bank-sector level at different degrees of industry specialization upon a rate cut. I estimate the impulse response of bank-sector loan growth using the local projections, the reduced form model reads as follows:

$$\begin{aligned}\overbrace{\log \ell_{b,s,t+h} - \log \ell_{b,s,t-1}}^{\textit{Change in credit}} = \alpha^h_{s,t} + \alpha^h_{b,t} + \alpha^h_{s,b} + \\ \beta^h_1 \times \textit{ Specialization }^{t-1\to t-12}_{b,s} + \beta^h_2 \times \varepsilon + \beta^h_3 \times \varepsilon \times \textit{ Specialization }^{t-1\to t-12}_{b,s} + \\ \gamma^h_b X_{b,t-1} + \gamma^h_s X_{s,t-1} + u_{b,s,t+h} \qquad (5)\end{aligned}$$

The dependent variable is the natural logarithm of the loan growth amount from bank b to sector s at time t and measures the degree of growth between the bank and the sector over the quarter. The main explanatory variable of interest is $\beta_3 \times \varepsilon \times \textit{ Specialization }^{t-1\to t-12}_{b,s}$, which captures the interaction between monetary policy change and a lagged 12-quarters rolling average of the specialization measure defined in Equation 2. $X_{s,t}$ is a vector of sector control variable including the sector redeployability index measured as Kim and Kung (2017), 2 lags of change in sectoral gross output changes in sectoral TFP and labour unit (index to 2012 levels) which can affect the sectoral demand side. I also control for time-varying bank-level characteristics captured in the $X_{b,t}$ vector that includes: size, capital ratio, security ratio, deposit ratio, and banks' profitability (ROA) to control for bank supply characteristics that can affect both my outcome variables as well as the explanatory variable.

To disentangle the effect of monetary policy on a bank's supply, the reduced form model is saturated with granular sector-time ($\alpha_{s,t}$), bank-time ($\alpha_{b,t}$) and bank-sector ($\alpha_{s,b}$) fixed effects to control for a broad range of unobserved factors capturing sector-specific demand shock (Khwaja and Mian, 2008; Paravisini et al., 2023), bank-specific credit supply shocks (Jiménez et al., 2014; Giometti and Pietrosanti, 2022) and sector-bank specific unobserved factors. It is worth discussing the purpose of these fixed effects to understand what they do. For instance, some sectors may be differently populated by specialized banks and hence may receive a larger share of their credit from unspecialized lenders. To control for the possibility that loan demand in these sectors grows at a different pace or that firms are deferentially impacted by demand shocks, I include (borrower) sector-by-time fixed effects that absorb any time-varying unobserved sector characteristics as well as local demand shocks. The bank time fixed effects ensure that the relevant coefficients are estimated off variation in specialization within the same bank and across its served sectors and not off variation in the composition of lenders in the economy. I finally double-cluster standard errors at the bank and sector levels.

The identification of the coefficient of interest exploits cross-sectional variation between the same bank across different sectors. Exploring the dynamics upon a monetary policy cut within banking industry specialization, a crucial trade-off faced by specialized banks becomes evident. A bank can load even more over its sectors of interest while increasing the exposure of idiosyncratic shocks upon a rate cut or scale down and diversify and thus raise its systemic aggregate exposure. Depending on the varying strengths of these conflicting aspects, the impact of the interaction β_3 upon monetary policy easing is expected to either yield a positive or negative effect. A positive (negative) sign of β_3 signifies that more specialized banks tend to increase their lending growth (new issuance) relatively more than their less specialized counterparts to their respective sector of interest.

Motivated by existing literature, a bank faces the following tradeoff (Goetz et al., 2016): the specialized banks . Depending on the strength of each of the forces, one should expect a positive or negative effect on the interaction β_3 upon an easing of monetary policy. A positive (negative) sign of β_3 indicates that banks that are more specialized, increase their lending growth (new issuance) relatively more than banks with a lower degree of specialization to their sector of interest. Table 2 summarize the results.

In column (1) of Equation 5, the coefficient on bank specialization is negative and statistically significant. This captures that specialized banks, in general, have lower loan growth than less specialized banks, this however, is not in contrast with previous results on the positive association of specialization on loan volume outstanding (Blickle et al., 2021), as they measure two different objects, one is about relative growth in volume, while the other is about outstanding volume. Moreover, higher specialization can lead to a negative association with the growth rate as negative shocks prompt banks to cut supply in non-core sectors (De Jonghe et al., 2020; Iyer et al., 2022), increasing, mechanically, specialization level. Thus specialization tends to be higher during periods of low economic activity when bank supply is limited creating a negative relationship with the growth rate of credit which is also reinforced by mean reversion.

The coefficient on the interaction β_3 is positive and statistically significant suggesting that, during periods of easing, banks lend more to sectors in which they specialize. In columns 2, 3 and 4 I add different time-varying fixed effects that are less restrictive in terms of fixed effects which shows that my results are robust across specifications and reduces the concerns of demand or supply-driven results. In other terms, this suggests that results are not driven by the selection of unobservables and hence by omitted variables problems nor that unobservable demand of supply shocks are drivers of the results.

Table 2:
Specialization and Bank-Sector loan growth

Effect of $Specialization_{b,s,t}$ on loan growth (Bank-sector)					
	$\Delta loan_{b,s,t}$				
	(1)	(2)	(3)	(4)	(5)
ε_t					1.548
					(1.454)
$Specialization_{b,s}^{t \to t-12}$	-0.828***	-0.575***	-0.842***	-0.606***	-0.529***
	(0.102)	(0.058)	(0.112)	(0.066)	(0.060)
$\varepsilon_t \times Specialization_{b,s}^{t \to t-12}$	32.661**	25.129*	13.886	6.583	9.110
	(13.158)	(12.623)	(11.970)	(11.411)	(10.946)
Sector × Year-Quarter F.E.	✓	✓			
Bank × Year-Quarter F.E.	✓		✓		
Sector F.E.			✓	✓	✓
Bank F.E.		✓		✓	✓
Year-Quarter F.E.				✓	
Sector × Bank F.E.	✓	✓	✓	✓	✓
Clustered Std.Errors	Bank-sector	Bank-sector	Bank-sector	Bank-sector	Bank-sector
Adj. R^2	0.277	0.194	0.160	0.075	0.058
Obs	137,689	137,739	131,265	131,351	137,786

The table reports coefficients and t-statistics (in parenthesis) for the bank lending growth volume to sectors after a monetary policy tightening. The reduced form model tested corresponds to Equation 5. The table presents the responses to a monetary policy easing. The unit of analysis is at the bank-sector quarterly level. The sample consists of syndicated loans originated in the U.S. from 1991q1 until 2016q4. The dependent variable is the log growth amount held by each lender at time t. $Specialization_{b,s}^{t-1 \to t-12}$ is the bank specialization and is defined as 12 quarter slow moving average of the share of total credit granted by a bank b to a specific sector s relative to the bank's total credit. In all specifications, are included different levels of fixed effects as noted in the lower part of the table, from most restrictive version (1) to least (5). $X_{s,t}$ is a vector of sector control variable including the sector rediployability index measured as Kim and Kung (2017), 2 lags of change in sectoral gross output changes in sectoral TFP and labour unit (index to 2012 levels) which can affect the sectoral demand side. $X_{b,t}$ is a vector of bank time-varying characteristics such as size, capital ratio, security ratio, deposit ratio and banks' profitability (ROA) to control for bank supply characteristic that can affect both my outcome variables as well as the explanatory variable. The symbols *,** and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Additionally, I also confirm the widely studied puzzle of monetary policy channels in US in which an easing (tightening) is associated with a decrease (increase) in loan growth in column 5 (Kashyap and Stein, 1995, 2000; Supera, 2023; Greenwald et al., 2020).

Economically, the baseline estimate of column 1 indicates that the average banks specialized in sectors that face a 25 basis points cuts in monetary policy for a standard deviation increase in the specialization measure, the bank-sector volume will see an increase by 50 bps on impact , corresponding to a yearly base of 2%[8]. In alternative specification I make use of less stringent fixed effects that do not control for demand and supply side factors. As can be seen, this reduce the magnitude and the statistical relevance, but do not affect the direction of the estimate. Thus controlling for demand and supply side factors are key to correctly estimate the effect of bank-loan credit volume around monetary policy cuts.

[8] $(0.0025 \times .24 \times 32.661)$

My estimates, however, could still be biased by the mere size of the industry rather than capturing the effect of industry specialization. To address this point I show in Table A.2 that my results are robust to the use of *excessive specialization* measure. This measures is less prone to tails distortion in the estimation. Moreover, by construction, this measures treats any excess over-investment in an industry retrospectively on the "optimal" weights the industry has in the economy. This table shows that moving from more stringent specification to less stringent ones (column 5), the coefficient remains significant. Along with the results of Table 2 this is indicative of two things: (i) controlling for sector demand factors is relevant in the context of monetary policy change as sector demand might move in other directions to supply in the hope of less reliance to their customary bank. (ii) This incentive is more prominent for larger sectors. Finally, I exploit loan level data in Table A.1 in the spirit of Chodorow-Reich (2014); Iyer et al. (2022) and compare two loans arranged by the same banks to different sectors and confirm my previous findings. For this specification I am assuming that loan demand is common across firms in the same sectors. Ideally, having a within bank-time and within firm-time specification would be preferred. Unfortunately, as I work on a sample of very large loans, I do not observe many firms doing multiple deals in the same year-quarter. However, the average number of firms in a sector that originate a loan with my banks is pretty small containing a median of 3 firms, reducing any potential concern.

Overall, the empirical analysis at the bank-sector level confirms that specialization indeed affects the monetary policy transmission and that bank reallocates funds towards their core sector of interest upon an unexpected cut of monetary policy rates. Put differently, specialization increase the responsiveness to monetary policy regimes for banks' sector of specialization.

3.2. Long run effects of bank specialization and monetary policy

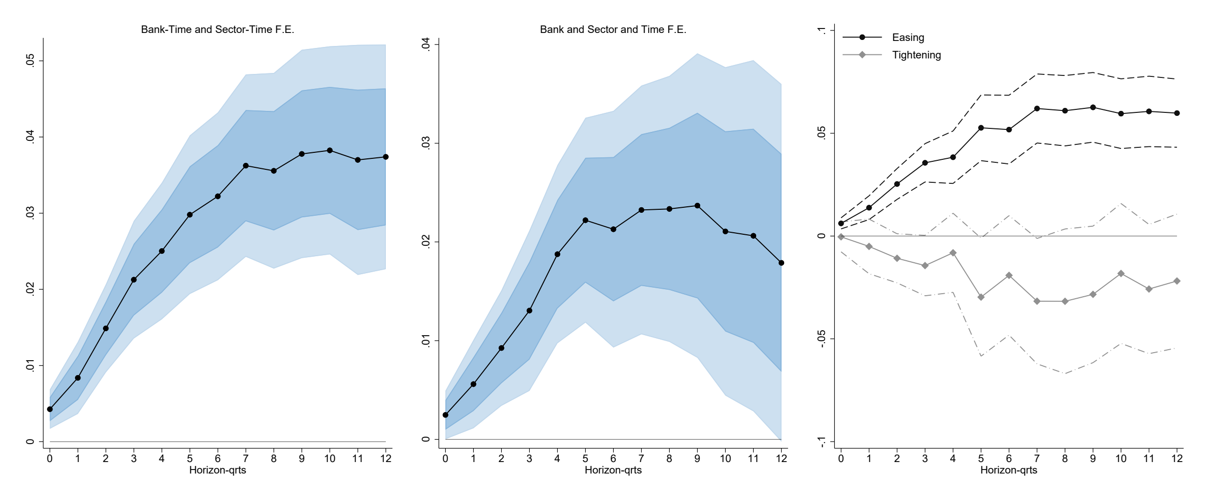
The results so far show that there is an immediate effect on impact, however as evidenced by Kashyap and Stein (1995); Caglio et al. (2022) monetary policy changes have persistent consequences[9]. To study the long-run relations with specialization I employ a similar strategy as in the previous section using local projections (Jordà, 2005) to understand the long-term dynamics of the interactions between monetary policy and banks' specialization. In particular I estimate the impulse responses of banks' with differential degree of specialization upon a 25 bps reduction in in monetary policy shock for a standard deviation increase in specialization following Equation 5, the results are presented in Figure 2.

The left-side figure in Figure 2 depicts the outcome of the most stringent specification using the full fixed effect model, aligning with column (1) in Equation 5[10]. The observed impulse response indicates that, following a monetary policy cut, a bank specializing in a particular industry significantly

[9]Given that there is some lag between the time in which a syndicated loan is contracted and the effective period in which is originated, generally 90 days, it is likely the case that the effects get larger over a bigger horizon than a quarter.

[10]The coefficient is already scaled to a 25 bps cut in monetary policy for a one standard deviation increase in banks' sectoral specialization.

Figure 2:
Impulse response: Bank-Sector Loan growth upon rate cut



Note: Dealscan sample. Impulse response dynamics to a 25 bps cuts in ε_t for a standard deviation increase in $Specialization_{b,s}^{t-1\to t-12}$. The panel reports the conditional estimates for $\beta_3^h \times \varepsilon \times Specialization_{b,s}^{t-1\to t-12}$. The unit of information of the analysis is the loan outstanding at the bank-sector time level. The sample consists of syndicated loans outstanding from 1991q_1 until 2016q_4. The dependent variable is the loan volume (outstanding and originated) held by each lender. Light (dark) blue areas represents 90% (68%) confidence interval used in the panel a and b. Dashed areas represent represents 90% confidence interval used in the panel c. Panel a reports coefficients corresponding to column (1) in table Equation 5, while panel b correspond to column (5) of the same table. Panel c decompose the effect into easing and tightening periods estimated similarly to Equation 5.

amplifies its lending growth toward that industry compared to less specialized banks. This effect is both persistent and economically substantial, peaking at 10 quarters and resulting in a cumulative 4% rise, on a quarterly basis, in the conditional interaction between the bank-sector growth, underscoring the incentive for lenders to expand their portfolio towards their sector of specialization. The central panel displays coefficients corresponding to column (5) in Table 2, qualitatively, the results are unchanged. For robustness, I report the coefficients attached to the excess specialization measures in Figure A.2, which delivers qualitatively and quantitatively the same results.

Moreover, in the rightmost panel, I distinguish between the impacts of easing and tightening in monetary policy: the majority of observed effects originate from periods of monetary policy easing. Conversely, I do not observe any significant impact following a reduction in monetary policy. This outcome is likely attributed to the sample period featuring limited instances of monetary policy tightening, with the bulk of the variance arising from easing periods. However, it's plausible that banks commit to loans and have limited margin for reduction, relying largely on the extensive margin, even though many loans need to be renewed. Consequently, the effect of monetary policy tightening might be compromised in the presence of perfect commitment and loan rollovers.

In conclusion, the results shows that the implication of banks' specialization in the transmission of monetary policy have a persistent and economically relevant effect on banks' portfolio allocation.

3.2.1. Lead arrangers and participants

The current methodology leverages the state of-the-art literature to empirically identify credit supply shocks (Jiménez et al., 2012). It operates under the premise that empirical models saturated with all time variation common across firms within a sector account for credit demand shocks. This approach uses sector fixed-effects to control for endogenous bank-firm matching in the same sector (Khwaja and Mian, 2008). However, recent studies by Paravisini et al. (2023), Herreno (2023), and Altavilla et al. (2022) underscore that this assumption, particularly in the case of specialized banks, might not universally hold without a proper instrument or if the source of the credit supply shock is uncorrelated with bank-specific loan demand. While my context might abide by this, lacking an appropriate exogenous shift in bank credit supply raises concerns in interpreting my results and identifying credit supply shocks.

To address this challenge, I exploit the syndicate structure by comparing credit response around a monetary policy cut for lead arrangers and participants at varying industry specialization levels. The rationale is that confounding factors (credit supply and loan demand correlation), impacting results in the presence of specialization, differ between lead arrangers and participants. As per Degryse et al. (2021), industry specialization levels also influence the syndicate structures. Given that lead arrangers manage and oversee loans, it's more probable that credit supply shocks correlated to bank-specific loan demand are more pronounced for arrangers than participants. By assessing the long-term response through the syndicate structure, I can validate past results and, more importantly, by focusing on participant reactions, alleviate concerns regarding bank-supply and loan demand correlation.

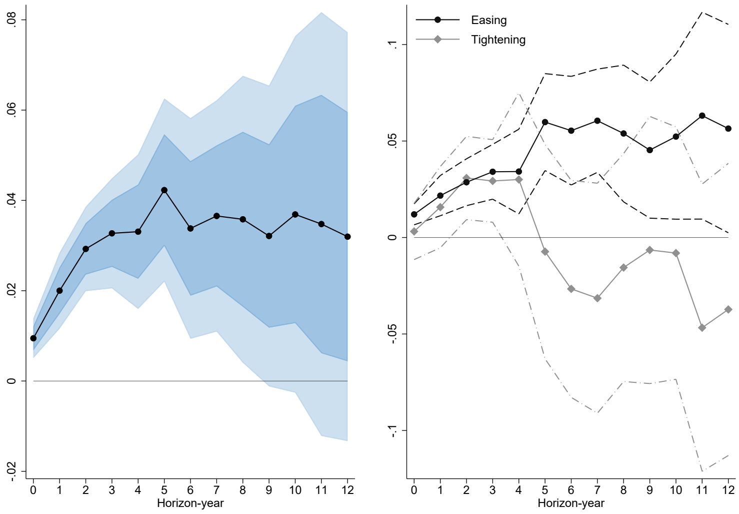
The outcomes for lead lenders and participants are displayed in Figure 3. It shows the impulse response to a 25 bps cut in monetary policy estimated for a standard deviation in industry specialization. I construct the main variable measuring specialization levels for both lead and participant, comparing growth volumes for the corresponding supplied amounts[11].

These outcomes underscore that banks specializing in specific industries exhibit heightened loan growth to corresponding borrowers post a rate reduction, supported by insights gleaned from syndicate structures. This finding aligns with the banks' ability to share information across sectors based on their experiences with similar borrowers, evident in both lead arrangers and participants. This alleviates concerns about credit supply being contingent on sector-specific loan demand. Furthermore, the observed ineffectiveness of monetary policy tightening, as depicted in Figure 2, persists for lead arrangers, emphasizing their limited ability to reduce supply efficiently when rates rise. In contrast, participants possess a higher margin of adjustment, allowing them the choice not to participate in future loans. Overall, these results confirm and reinforce the previous analyses.

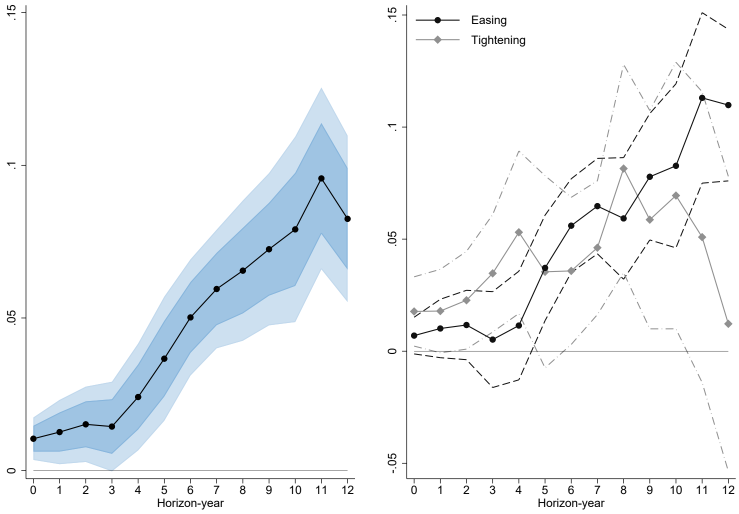
[11]The measure of specialization and the credit growth volume are defined based an all loans outstanding by the lender, whether the lender acts as a lead lender or a syndicate participant, and otherwise.

Figure 3:
Impulse response (lead and particpant): Bank-Sector loan growth upon rate cut

(a) *Credit growth: lead arranger(s)*



(b) *Credit growth: participant(s)*



Note: Dealscan sample. Impulse response dynamics to a 25 bps cuts in ε_t for a standard deviation increase in $Specialization_{b,s}^{t-1\to t-12}$. The panel reports the conditional estimates for $\beta_3^h \times \varepsilon \times Specialization_{b,s}^{t-1\to t-12}$. The unit of information of the analysis is the loan outstanding at the bank-sector time level. The sample consists of syndicated loans outstanding from $1991q_1$ until $2016q_4$. The dependent variable is the loan volume (outstanding and originated) held by each lender. Light (dark) blue areas represents 90% (68%) confidence interval used in the Figure 3a and Figure 3b. Dashed areas represent represents 90% confidence interval used to distinguish between monetary policy easing and tightening effect. Both panels reports coefficients corresponding to column (1) in table Equation 5. The measure of specialization and the credit growth volume are defined based an all loans outstanding by the lender, whether the lender acts as a lead lender (Figure 3a) or a syndicate participant (Figure 3b).

3.3. Robustness and alternative channels

The previous results show the relevance of bank's sectoral specialization for the transmission of monetary policy through their lending supply. One concern is that the results could be driven by other banks' sectoral market structure characteristics, for example, the degree to which a bank has captured an industry (e.g. market concentration). If a bank captures the majority stake in a sector to extract monopoly rents, it may accidentally confound my results. Banks that have a higher stake in the market, have incentive to insulate their captured industry for shock in an attempt to not loose valuable income (Giannetti and Saidi, 2019). In the presence of high market concentration, banks internalize lending spillover and possible systemic effects of their lending behaviour which can potentially alter their portfolio rebalancing upon monetary policy easing. For this reason, high market share banks might have incentives to increase their lending to favour firms in those industries and thus further expand their market share. As banks industry specialization is correlated with industry market share, I verify that my results on specialization hold despite of – and not because of – a bank's role in an industry.

Additionally, a wide body of literature focuses on the relationship between banks' balance sheet characteristic, deposit market power and loan supply. In particular, it could be that banks' specialization is more prominent for smaller and low liquid banks (Giometti and Pietrosanti, 2022; Blickle et al., 2020). If that is the case, banks' specialization captures a lender's financial friction rather than heterogeneity in lending decisions prompted by market structure. For instance, small banks and less liquid banks tend to be more responsive to monetary policy as ease in rates will allow them to raise money more easily (Kashyap and Stein, 2000; Jiménez et al., 2012). To better gauge the effect of specialization teasing out the effect of banks balance sheet characteristics, and market power in a model saturated with industry-time, and bank fixed effects.

To address the above-mentioned concerns, I therefore, include in the baseline specifications the market share of each bank in an industry, which measures the percentage of credit outstanding that a bank has in one industry relative to the total credit supplied to the industry by all banks[12]. In less stringent specifications, I control for banks' characteristics that influence monetary policy such as size (Kashyap and Stein, 1995) and solvency (Kashyap and Stein, 2000; Jiménez et al., 2012) captured by equity and liquidity ratio and deposit market power (Drechsler et al., 2021). Formally, I test the reduced form model presented in Equation 6. The vector $x_{b,t-1}$ contains the full set of alternative mechanisms that I test which are banks' market share, size, equity ratio and liquidity ratio (measured as available for sale securities). The vector $X_{b,t-1}$ self contains the vector $x_{b,t-1}$ while the controls are analogous to

[12]This variable capture the extent to which a bank has captured an industry.

Equation 5.

$$\log \ell_{b,s,t} - \log \ell_{b,s,t-1} = \alpha_{s,t} + \alpha_{b,t} + \alpha_{s,b} +$$
$$\beta_3^h \times \varepsilon_t \times \ Specialization\ _{b,s}^{t-1\to t-12} + \overbrace{\sum_{x\in X} \delta_x \cdot \varepsilon_t \times x_{b,t-1}}^{Alternative\ channels} +$$
$$+ \gamma_{b,s} X_{b,s,t-1} + \gamma_b X_{b,t-1} + \varepsilon_{b,s,t} \quad (6)$$

Table 3 presents the results scaled for a rate cut, estimating Equation 6 which only report the interaction terms coefficients for brevity.

Table 3:
Specialization and Bank-Sector loan growth: robustness

Effect of $Specialization_{b,s,t}$ on loan growth (Bank-sector)			
	$\Delta loan_{b,s,t}$		
	(1)	(2)	(3)
$\varepsilon_t \times Specialization_{b,s}^{t\to t-12}$	31.225**	24.671**	20.485*
	(14.703)	(12.270)	(12.171)
$\varepsilon_t \times Mkt\ share_{b,s}^{t\to t-12}$	48.155	-34.801	-20.475
	(40.178)	(23.881)	(25.881)
$\varepsilon_t \times \beta_b^{Exp.}$		3.541	4.525
		(5.759)	(5.722)
$\varepsilon_t \times \overline{Bank\ equity\ ratio}$		-11.404	
		(20.014)	
$\varepsilon_t \times \overline{Bank\ security\ ratio}$		0.828	
		(7.661)	
$\varepsilon_t \times high\ capital_b$			-0.781
			(1.170)
$\varepsilon_t \times high\ liquidity_b$			2.216*
			(1.235)
Sector × Year-Quarter F.E.	✓	✓	✓
Bank × Year-Quarter F.E.	✓		
Bank F.E.		✓	✓
Sector × Bank F.E.	✓	✓	✓
Clustered Std.Errors	Bank-sector	Bank-sector	Bank-sector
Within R^2	0.284	0.201	0.201
Obs	135,178	135,260	135,260

The table reports coefficients and t-statistics (in parenthesis) for the bank lending growth volume to sectors after a monetary policy tightening. The reduced form model tested corresponds to Equation 6. The table presents the responses to a monetary policy easing. The unit of analysis is at the bank-sector quarterly level. The sample consists of syndicated loans originated in the U.S. from 1991q1 until 2016q4. The dependent variable is the log growth amount held by each lender at time t. $Specialization\ _{b,s}^{t-1\to t-12}$ is the bank specialization and is defined as 12 quarter slow moving average of the share of total credit granted by a bank b to a specific sector s relative to the bank's total credit. In all specifications, are included different levels of fixed effects as noted in the lower part of the table, from most restrictive version (1) to least (3). $X_{b,t}$ is a vector controlling for four lags of the dependent variable. $X_{b,t}$ is a vector of bank time-varying characteristics such as size, capital ratio, security ratio, deposit ratio and banks' profitability (*ROA*) to control for bank supply characteristic that can affect both my outcome variables as well as the explanatory variable. The symbols *,** and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Column (1) provide evidence that my results on the relation between monetary policy cuts and banks' industry specialization is robust to controlling for banks' industry share. As column (1) shows, after a 25 bps decrease in the monetary policy rate, for a one standard deviation increase in banks' specialization (0.06), banks with higher share in an industry increase their lending towards the corresponding sector in the same quarter by 46bps more compared to a bank with a lower share in the sector. A banks' market share increase turns out to be an insignificant factor in shaping the reaction of banks-sector growth upon a rate cut. Most importantly, comparing the R^2 from column (1) in **??** and the corresponding one in Equation 6, there is no sensible increase in variance explained in the model, reducing any concerns on the relevance of banks' market share to be a sensible factor affecting my results and the relative effect of bank specialization is stronger than market share[13]. I take this evidence as a sign that despite contributing to the model's fit, it does not sensibly improve it. Columns (2) and (3) drop the bank-year fixed effects and control for the effect of bank balance sheet characteristic and market power for the transmission of monetary policy[14]. They show that after controlling for the banks' balance sheet characteristic and market power, the result of banks' specialization remains robust and significant. The main coefficient of interest on the interaction term between changes in the rate and specialization remains large and significant. While other banks characteristics do not show statistically significant effects. Overall, Table 3 shows that my results work above and beyond other channels that may confound the results previously presented. Put differently, banks' specialization works beyond banks industry capture (market share) and the so-called balance sheet channel of monetary policy. For robustness, I estimate Equation 6 for the alternative measure of banks' specialization confirming that the baseline findings are both qualitatively and quantitatively nearly identical, the results are shown in Table A.3.

3.4. Financial frictions, bank specialization and monetary policy

This section delves into the interaction between banks' sectoral specialization and financial frictions around changes in monetary policy. In particular, as evidenced in Blickle et al. (2021) and Giometti and Pietrosanti (2022) banks' sectoral specialization is prominent for smaller and less solvent banks Blickle et al. (2021) argue that banks with higher degree of specialization, concentrate their portfolio when they have low capital ratios, suggesting that investing in their sector of specialization is the marginal choice when constrained as it provides better returns. Notably, specialized banks often exhibit lower delinquency rates in their portfolios (Blickle et al., 2021).

As rates decrease, bank may decide to invest even further in their sector of specialization in the presence of low balance sheet ratio as it can relax capital constraints in the future because informational

[13] A 25 bps cut for a standard deviation increase in market share is associated to a positive, though non significant, increase in the volume of credit towards the sector of $48.155 \times 0.0025 \times 0.03 = 36$ bps that is smaller to the effect attached to specialization (46 bps).

[14] Banks' market power is measure as in Drechsler et al. (2021). The variable β^{Exp} measure the sensitivity of banks' interest expenses to change in rates, low value of β^{Exp} corresponds to high degree of market power.

advantage allows them to find better borrowers, despite lowering diversification. Hence improving their returns ex-post. For instance, liquidity poor banks could be more responsive upon a rate cut for a given level of specialization as its marginal choice will lead them to load on their sector of specialization generating higher returns. Therefore one should expect that for a given level of financial friction, banks' specialization amplifies the effect of monetary policy as banks indeed prefer to invest in sectors in which they have some comparative advantage especially in the presence of weak capital ratio.

To test if that is the case, I employ a reduced form model of the following form:

$$
\begin{aligned}
\log \ell_{b,s,t} - \log \ell_{b,s,t-1} = \alpha_{s,t} + \alpha_{b,t} + \alpha_{s,b} + \\
\beta_3 \times \varepsilon_t \times \ \mathit{Specialization}\ _{b,s}^{t-1 \to t-12} + \overbrace{\sum_{x \in X} \delta_x \cdot \varepsilon_t \times x_{b,t-1}}^{\text{Bank friction}} + \\
\overbrace{\sum_{x \in X} \zeta_x \cdot \ \mathit{Specialization}\ _{b,s}^{t-1 \to t-12} \cdot \varepsilon_t \times x_{b,t-1}}^{\text{Bank friction interaction}} + u_{b,s,t} \qquad (7)
\end{aligned}
$$

The interaction between specialization and financial friction is measured by δ_x while the triple interaction effect in ζ_x captures the degree to which for the same level of specialization, banks closer to constraints are more responsive. The main objective is to address if equity and liquidity-poor banks respond more for the same degree of specialization respectively. I compare banks at different degree of specialization in each industry upon a rate cut for the average capital and liquidity ratio observed in a bank in my sample. For ease on interpretation I then separate banks into categories based on whether their capital and liquidity ratio are above the sample median. The results are presented in Table 4.

Column (1) provide evidence that for a given level of specialization, banks with low liquidity and low capital ratio increase even more their lending to the sector of specialization upon a rate cut. This effect is particularly prominent for low liquid bank. It is important to say that in column (1) the coefficient of interest in the triple interaction ζ_x is capturing the relative response of liquidity rich and equity rich banks (as compared to smaller ones) to policy rate changes for different levels of banks' industry specialization. After a 25 bps decrease in the monetary policy rate, for a one standard deviation increase in banks' specialization (0.06), moving from the top quartile of the liquidity distribution (0.26) to the lowest quartile (0.14) is associated to a relative increase in 1.4% in credit towards the sector of specialization[15]. Put it differently, banks with low liquidity ratio are more responsive to monetary policy for a given level of specialization. The relative adjustment of equity and liquidity rich banks for a different levels of specialization estimated through Equation 7 does not allow to understand the overall response of both liquidity (equity) rich and poor banks as it estimates the cross-sectional differences

[15] The effect for a low liquid banks is $(0.0025 \times 0.06 \times [144.36 - 404.864 \times .14]) = 0.013$, while the one for liquidity rich is $(0.0025 \times 0.06 \times [144.36 - 404.864 \times .26]) = 0.006$. Their net difference is an increase in credit of 0.014 decimal points.

Table 4:
Specialization and Bank-Sector loan growth: financial frictions

	Effect of $Specialization_{b,s,t}$ on loan growth (Bank-sector)				
	All banks	Low liquidity banks	High liquidity banks	Low capital banks	High capital banks
	(1)	(2)	(3)	(4)	(5)
$Specialization_{b,s}^{t\to t-12}$	-1.400***	-0.947***	-0.760***	-0.821***	-0.744***
	(0.241)	(0.043)	(0.042)	(0.049)	(0.039)
$\varepsilon_t \times Specialization_{b,s}^{t\to t-12}$	144.362***	67.476***	12.487	56.691**	5.509
	(39.208)	(20.839)	(20.123)	(22.112)	(19.512)
$\varepsilon_t \times Specialization_{b,s}^{t\to t-12} \times \overline{Bank\ equity\ ratio}$	-234.265				
	(243.010)				
$\varepsilon_t \times Specialization_{b,s}^{t\to t-12} \times \overline{Bank\ security\ ratio}$	-404.864***				
	(91.002)				
$Specialization_{b,s}^{t\to t-12} \times \overline{Bank\ equity\ ratio}$	1.304*				
	(0.764)				
$Specialization_{b,s}^{t\to t-12} \times \overline{Bank\ security\ ratio}$	2.046***				
	(0.707)				
Sector × Year-Quarter F.E.	✓	✓	✓	✓	✓
Bank × Year-Quarter F.E.	✓	✓	✓	✓	✓
Sector × Bank F.E.	✓	✓	✓	✓	✓
Clustered Std.Errors	Bank-sector	Bank-sector	Bank-sector	Bank-sector	Bank-sector
Within R^2	0.278	0.332	0.294	0.356	0.291
Obs	137,689	83,489	53,886	49,597	85,827

The table reports coefficients and t-statistics (in parenthesis) for the bank lending growth volume to sectors after a monetary policy tightening. The reduced form model tested corresponds to Equation 7. The table presents the responses to a monetary policy easing. The unit of analysis is at the bank-sector quarterly level. The sample consists of syndicated loans originated in the U.S. from 1991q1 until 2016q4. The dependent variable is the log growth amount held by each lender at time t. $Specialization_{b,s}^{t-1\to t-12}$ is the bank specialization and is defined as 12 quarter slow moving average of the share of total credit granted by a bank b to a specific sector s relative to the bank's total credit. In all specifications I am controlling for four lags of the dependent variable. The symbols *,** and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

across banks balance sheet characteristics. In fact, Equation 7 is saturated with bank-time fixed effects, which span out time-series variation common across the bank. Hence, I additionally estimate the same model separately for all categories based on whether a bank is above of below the median of the empirical distribution. In this way is also easier to interpret the results. Columns (2) and (3) split the sample into low liquid and high liquid banks, the estimate on the interactions of monetary policy and specialization is highly significant for low liquid banks where a standard deviation increase in specialization upon a 25 bps cut is associated to a 10% increase in growth in credit to the sector, while the effect for high liquidity banks, though positive is not statistically significant. Similarly, I find that for low equity capital banks, column (4), specialized banks increase their credit towards the sector of specialization by 85 bps, but the effect for high equity capital banks is non-significant. Overall, Table 3 shows that my results work above and beyond other channels that may confound the results previously presented. Put differently, banks' specialization works beyond banks industry capture (market share) and the so-called balance sheet channel of monetary policy.

These results shows that indeed banks' financial frictions are important drivers in explaining the cross-sectional variation in response for specialized banks. As rate decrease, banks that are more specialized and that have low balance sheet ratios signifying invest in their specialized sector as it becomes the preferable choice when facing constraints. Finally, for robustness, I estimate Equation 7 with the excess measure of specialization. The results are presented in Table A.4 confirming that the baseline findings are both qualitatively and quantitatively nearly identical.

3.5. Small business lending data

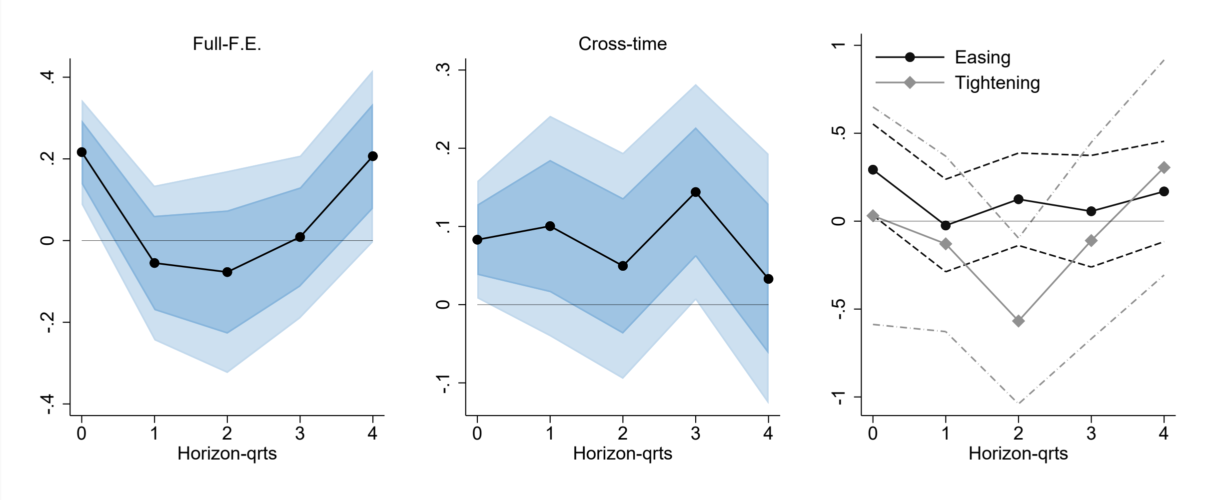
In my core empirical results I exploit US syndicated market loan data from Dealscan. Despite the fact that this dataset covers roughly 50% of US commercial and industrial loans, it targets mainly large firms in the US economy. Therefore my results could not hold outside the syndicated market as the latter is not very representative of the average firm in the US economy. Most importantly, these firms are far from opaque as instead small business are. After all, a specialized bank has greater incentives to use its superior information when the marginal benefits in distinguishing across good and bad borrowers are greatest. As specialized banks are more willing to lend to smaller, and more opaque firms in their industry of specialization (Blickle et al., 2021), I therefore exploit information on bank loans to small businesses and implement the within bank-sector estimation strategy as in the previous analysis. This step is relevant to test whether the specialization channel I previously presented holds in an alternative lending market. In doing so, I study the effect of banks' sectoral specialization on the transmission of monetary policy to the supply of small business lending.

As for section 3.2, I the same local projection specification as in Equation 5 with two key differences: (i) the small business lending dataset has been aggregated at the bank-sector yearly frequency as discussed in section 2.1, second the measure of specialization is internally measured in the small business lending dataset. Figure 4 presents the results of estimating Equation 5 using the information on new small business lending to compute bank specialization with different levels of fixed-effect. The dependent variable is the log of credit growth between the bank and the sector at yearly frequency from 1991 to 2017[16]. The left-most figure, contains the preferred specification with the full set of fixed effects included. It confirms that after a 100 bps cut in the monetary policy rates, banks increase new small business lending growth by more in markets where they are more specialized relative to other markets, controlling for the change in aggregate local lending opportunities. This result is fully consistent with my main results on syndicated lending, more over the magnitudes of this effect is substantially larger. A one standard deviation increase in specialization (0.18) increases lending by 20% per 100 bps decrease in monetary policy rate. Contrary to the syndicated market, this reaction is short lived and the effect is turns to be insignificant after impact.

The panel in the center, I estimate the effect for the model including time, sector and bank fixed effect exploiting both cross-sectional variation as well as time series variation[17]. It confirms the previous results, with the coefficient of interest remaining significant but lowering its magnitude. Again, this

[16]Though the SBA dataset covers also recent years, for consistency I use the same sample period.
[17]In all specification I always control for lags of the dependent variable and for bank-sector fixed effect.

Figure 4:
Impulse response SBA sample: Bank-Sector loan growth upon rate cut



Note: Small Business Lending Administration 7(a) Loan-program sample. Yearly sample. Impulse response dynamics to a 100 bps cuts in ε_t for a standard deviation increase in $Specialization_{b,s}^{t-1\to t-3}(SBA - sample)$. The panel reports the conditional estimates for $\beta_3^h \times \varepsilon \times$ $Specialization\ _{b,s}^{t-1\to t-12}$. The unit of information of the analysis is the loan outstanding at the bank-sector time level. The sample consists of syndicated loans outstanding from $1991q_1$ until $2016q_4$. The dependent variable is the loan volume (outstanding and originated) held by each lender. Light (dark) blue areas represents 90% (68%) confidence interval used in the Figure 3a and Figure 3b. Dashed areas represent represents 90% confidence interval used to distinguish between monetary policy easing and tightening effect. Both panels reports coefficients corresponding to column (1) in table Equation 5. The measure of specialization and the credit growth volume are defined based an all loans outstanding by the lender, whether the lender acts as a lead lender (Figure 3a) or a syndicate participant (Figure 3b).

decrease in the magnitude of the coefficient suggests that sector-year level heterogeneity is a relevant factor to be controlled for in our analyses. As for the long run effect, the graph confirms the short-living effect in this sample. This should not be considered a drawback in my analysis as this dataset targets specifically small and credit constrained firms. The margin of adjustments comes mostly from the extensive ones, as new loans are originated by the bank to firms in the sector and not for instance increase loans to existing customers. Finally the right-most panel disentangles the effect for easing and tightening periods, confirming again that the bulk of the action is coming from easing periods. These finding provides strong evidence that my previous analysis is not specific to the syndicated market. I show that how banks sectoral specialization in small business lending affects the transmission of monetary policy to the growth of new small business lending.

4. Bank Level Results on income and deliquencies

My current findings center on the bank's portfolio allocation and don't delve into the mechanism or the consequences at the bank level resulting from these reallocations. If bank specialization leads to a further concentration of portfolios upon a rate cut, driven by informational advantages, one would expect highly specialized banks to exhibit improved income performance post rate reduction. Given their superior screening and monitoring technologies, they should have the ability to select more reliable clients, potentially resulting in lower delinquencies than less specialized counterparts . This should lead to more stable returns and fewer write-downs (Blickle et al., 2021). Conversely, if specialized banks exhibit a greater reduction in risk aversion compared to non-specialized banks after an easing, one might observe poorer income profitability indices at the bank level. The underlying mechanism of the results is essential. If specialized banks, leveraging their superior screening and monitoring technologies, perform better post rate reduction, it would signify their deliberate allocation of funds towards their sector of expertise, enhancing their income performance while reallocating resources from less advantageous sectors.

In order to test this prediction I use a slow moving average of banks' HHI, a bank-level index of concentration described in Equation 4. The index captures the degree of portfolio concentration at the bank level. The higher, the more the bank loads its investment towards one activity. I then exploit the time-series and cross-sectional information of banks to address how bank concentration influences various measure of income profitability at the bank level upon a monetary policy easing. I then look at the long-run performances of banks as they might be more relevant to test the effect of delinquencies on commercial loans. To test for the long-run consequences of their interplay I make use of local projection methods, in particular, I test the following reduced-form model:

$$Y_{b,t+h} = \alpha_t + \alpha_b + \beta_1^h \times \ HHI_b^{t-1 \to t-12} + \beta_2^h \times \varepsilon_t \times \ HHI_b^{t-1 \to t-12} + \gamma_b X_{b,t-1} + u_{b,t+h} \tag{8}$$

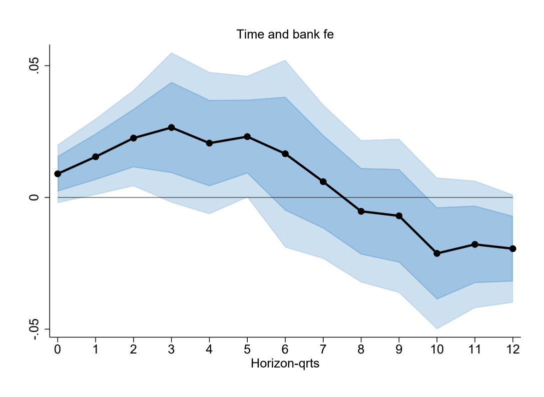
where Y_{t+h} measure either ROA, *loan loss provision*, *charge-off rate*, *deliquency rate* and *market capitalization*. All income variables used in the analysis are annualized and seasonally adjusted as in Drechsler et al. (2017, 2021). The object of interest is the effect of β_2^h, which measures the interaction between a bank's portfolio concentration and monetary policy. In all specification I control for banks' size, capital ratio, liquidity ratio, deposit ratio, C&I ratio and real estate ratio, as well as four lags of the dependent variable, change in gdp change, cpi, monetary policy shock and change in fed funds. I cluster standard errors at the bank level.

Figure 5 reports the impulse response of my measures of income performances to a 25 bps cut in monetary policy rate for a standard deviation increase in banks' HHI at each horizon h.

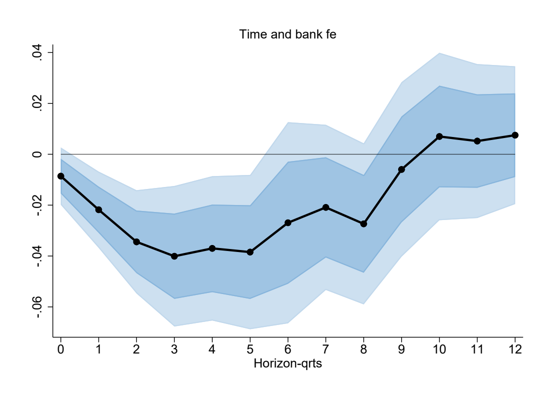
From Figure 5a, the conditional estimate of β_2^h associated to the increase in banks' ROA is positive and significant up to 1 year. Given a 25 bps cut in rates for an standard deviation increase in HHI (0.24) a banks ROA increases by 3 basis points representing a 4% variation in the standard deviation for the corresponding horizon, picking after 2 quarters. Similarly in Figure 5b and in Figure 5c, I find that the IRFs associated to higher levels of concentration are negative and statistically significant representing a

Figure 5:
Impulse response: bank level performances

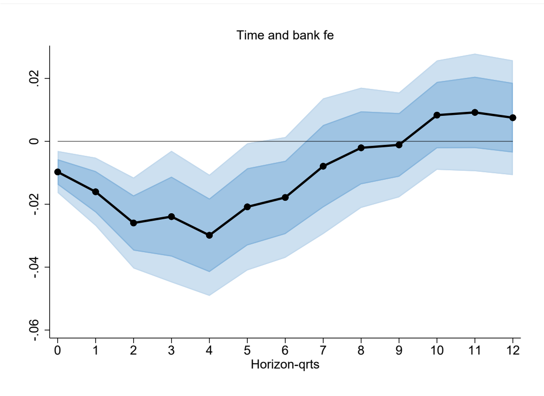
(a) *Banks' ROA*



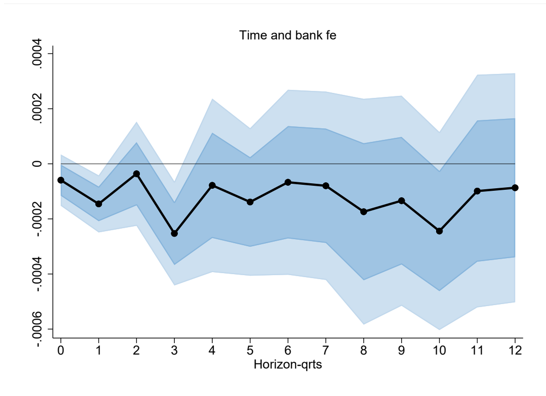
(b) *Banks' Chargeoff*



(c) *Banks' loan loss provision*



(d) *Banks' delinquency rate*



Note: Dealscan sample. Impulse response dynamics to a 25 bps cuts in ε_t for a standard deviation increase in $HHI_b^{t-1 \to t-12}$. The panel reports the conditional estimates for $\beta_2^h \times \varepsilon_t \times HHI_b^{t-1 \to t-12}$. The unit of information of the analysis is the bank time level. The sample consists of matched Dealscan and FR Y-9C bank holding company for the period from $1991q_1$ until $2016q_4$. The dependent variable is the banks' ROA in Figure 5a and chargeoff rate in Figure 5b. Light (dark) blue areas represents 90% (68%) confidence interval. Dashed areas represent represents 90% confidence interval used to distinguish between monetary policy easing and tightening effect. Both panels reports coefficients corresponding to the most saturated model presented in table Equation 8. The measure of banks' concentration are defined based on the syndicate outstanding loan volume at the end of each quarter.

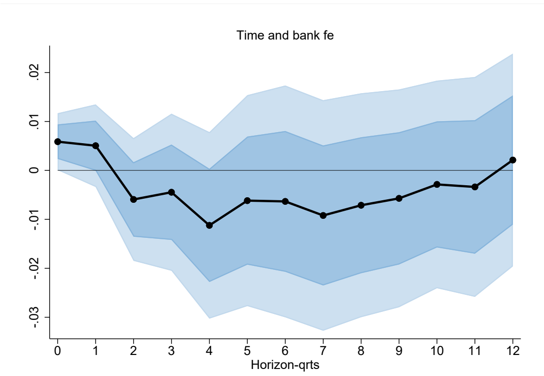
total reduction in chargeoff rate of 4 bps and 3 bps in loan loss provision. These magnitude represents 5% and 5.1% of the total variation in the sample. Finally I compare the cumulative delinquency rate of banks, which measures the cumulative growth of loans accruing or past due over the sample period. The table shows that upon a 25 pbs cut in rates for a standard deviation increase in HHI, the cumulative delinquency rate is reduced by 3 basis points for banks that are relatively more concentrated representing 20% of the variation in the sample for the corresponding horizon.

The previous outcomes confirms that more concentrated banks have the ability to pick better borrowers and thus, ex-post, have superior performance to a less specialized bank. However, the monitoring incentives should be larger for lead arrangers as they are responsible of gathering information about the borrower and generally retain the largest fraction of the loan after origination. I thus, replicate the analysis presented in **??** for lead arrangers. In particular I measure banks' concentration only exploiting lead arrangers shares. In Figure A.5 I not only I confirm the results, but the magnitude and the persistency of the effect is magnitudes larger for all the variables of interest and in particular for cumulative delinquency growth. These evidence suggests that indeed banks with higher degree of portfolio specialization have higher ability in selecting borrowers especially when monitoring incentives are larger (lead arranger).

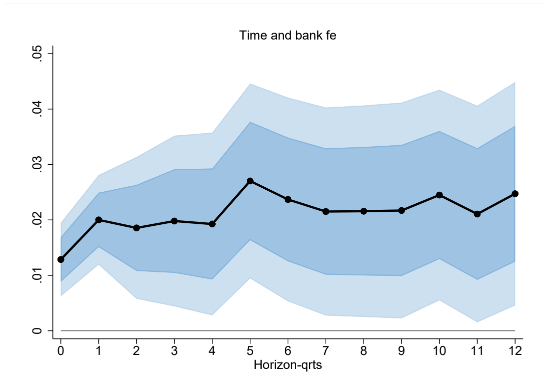
I finally check if these effects are also reflected in banks' market performances comparing their market capitalization growth in Figure 6. I find that banks' industry portfolio concentration measured at the lead arranger level is associated to an cumulative increase in market capitalization of 3% upon a upon a 25 basis point reduction in monetary policy rate, and its cumulative growth is persistent over time. Though, this results is not significant but on impact for the average degree of portfolio concentration in the bank exploiting both lead and participant information.

Figure 6:
Impulse response: market return

(a) *Banks' Mkt Cap*



(b) *Banks' Mkt Cap - HHI lead arranger*



Note: Dealscan sample. Impulse response dynamics to a 25 bps cuts in ε_t for a standard deviation increase in $HHI_b^{t-1 \to t-12}$. The panel reports the conditional estimates for $\beta_2^h \times \varepsilon \times HHI_b^{t-1 \to t-12}$. The unit of information of the analysis is the bank time level. The sample consists of matched Dealscan and FR Y-9C bank holding company for the period from $1991q_1$ until $2016q_4$. The dependent variable is the banks' ROA in Figure 5a and chargeoff rate in Figure 5b. Light (dark) blue areas represents 90% (68%) confidence interval. Dashed areas represent represents 90% confidence interval used to distinguish between monetary policy easing and tightening effect. Both panels reports coefficients corresponding to the most saturated model presented in table Equation 8. The measure of banks' concentration are defined based on the syndicate outstanding loan volume at the end of each quarter.

The results highlighted in this section bring new evidence on the positive effect of specialization via a knowledge spillover effect: as banks can fund themselves at cheaper rates, they redirect the funds towards their portfolio of expertise, but not at the expense of lower risk aversion. Instead, they improve their performances relative to less specialized lenders, which could potentially reduce the overall bank risk. This is particularly relevant for lead arrangers as they monitoring and screening incentives are higher.

In additional robustness check I first confirm that upon a rate cut, the average degree of banks' portfolio concentration increase both in the aggregate as well as exploiting time series variation at the bank level (Figure A.1). I then look for asymmetries in responses of income performances upon rate change for banks at different degree of portfolio concentration in Figure A.1 and focusing on lead arrangers only Figure A.1, finding that indeed there are significant asymmetries in the responses. Higher portfolio concentration appears to be always related to better income performances though the channel through which this happens is very different[18].

5. Sector Level Results on loan growth and aggregate outcomess

In this section I aggregate my data at the sector level and examine whether industry exposed to specialized lenders see an increase in total lending and other real sector outcomes upon a rate cut. My left-hand variables is total commited syndicated credit lending at the sector-quarter level and value added and employment sector-year. Value added and employment are from the integrated BEA and Bureau of Labor Statistics KLEMS data. Given the results presented in Section 3 I expect aggregate mortgage credit supply to be affected by the presence of specialized lenders in a sector. However, differences in lending growth following monetary policy changes may be compensated in a given market between specialized and non-specialized banks. In this case, credit would be reallocated across banks in a sector, but aggregate credit supply would be unaffected.

In this section I therefore analyze the aggregate effects at the sector level. The main right-hand variable is a sector-level presence of specialized lenders, *ISpec*, defined as the weighted average of bank industry specialization in a sector across all banks lending in a given sector, using their lending shares as weights. As for the previous section, I measure my explanatory variable using syndicated loan level data. I then take a slow moving average of my variable of interest to limit any confounding bias. This measure captures the extent to which a sector is served by banks that are specialized in the industry.

I estimate the following local projection:

$$y_{s,t+h} = \alpha_t + \alpha_s + \beta_1^h \times \; ISpec\,_s^{t-1\to t-12} + \beta_2^h \times \varepsilon_t \times \; ISpec\,_s^{t-1\to t-12} + \gamma_s X_{s,t-1} + u_{s,t+h} \tag{9}$$

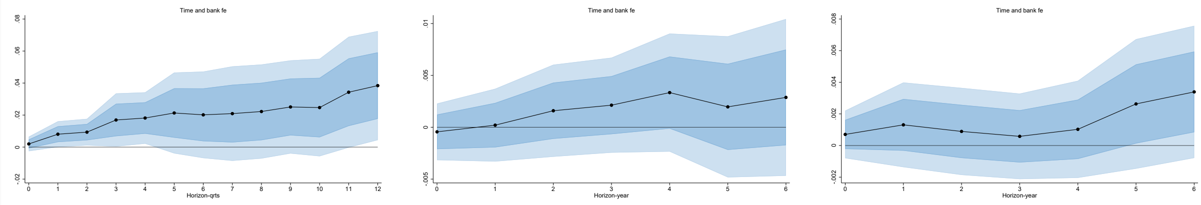
Where $y_{s,t+h}$ is the log growth lending, the log growth in employment, or the log growth in value added in sector s from date $t-1$ to $t+h$. $ISpec\,_s^{t-1\to t-12}$ is the weighted average of banks industry specialization for all banks operating in sector s weighted by their lending shares, α_t and α_s are time and sector fixed effects. I also include sector market concentration interacted with the monetary policy shock, which improves identification by ensuring that I am using variation in the degree of banks

[18] De Jonghe et al. (2021) argues that upon a liquidity freeze banks shift their portfolio towards the lenders that they knw most to protect their stream of revenues, hence this channel might be at work also in this case.

specialization exposure and not coming from sectors captured by few banks. I further controls for sector levels variables that can affect the outcome variable I cluster standard errors at the sector level.

Figure 7:
Impulse response: sector level

(a) *Loan volume* **(b)** *Value added* **(c)** *Employment*



Note: Impulse response dynamics to a 25 bps cuts in ε_t for a standard deviation increase in $ISpec_s^{t-1\to t-12}$. The panel reports the conditional estimates for $\beta_2^h \times \varepsilon_t \times HHI_s^{t-1\to t-12}$. The unit of information of the analysis is the sector time level. The sample consists aggregated sector level information for the period from $1991q_1$ until $2016q_4$. Light (dark) blue areas represents 90% (68%) confidence interval. All panels reports coefficients corresponding to the most saturated model presented in table Equation 9. The measure of Industry exposure to specialized banks are defined based on the syndicate outstanding loan volume at the end of each quarter.

Figure 7 presents the results. Figure 7a reports the benchmark specification using sector lending as the outcome variable. It shows that sectors with higher exposure to specialized banks see an increase in lending relative to other sector upon a rate cut: a one standard deviation increase in $Ispec$ increases lending by 2% per 25 bps cut in rate. The result is statistically significant. Figure 7b and Figure 7c shows the estimates for both value added and employment. Though both panels see an increase in the outcome variable, this results is not statistically significant, this can be the results of reallocation across banks within sector or simply the case that my sample analysis, as it is focused on large firms, is not representative of all the action in the sector.

Overall these results provide evidence that the industry presence of specialized lenders in a market induces increases in real economic activity.

6. Model

In this subsection I provide a simple theoretical setup that helps rationalize the empirical findings presented in the previous sections. In particular the model is used to rationalize the relation between monetary policy to banks' lending specialization and loan supply documented in the main empirical analysis.

Consider a two period economy with a large set of penniless entrepreneurs who are financed by a set of risk-neutral banks supplying loans to each sector $s = 1, 2, \ldots$. Each project requires external finance, which can only come from banks.

Banks have exogenous sector specific monitoring technology, denoted by γ_s drawn from a distribution Γ, with $0 < \gamma_s < 1$. Each bank draws a distinct γ_s for each sector, generating heterogeneous decreasing return across sector for the same bank. This assumption can be easily rationalized in the context of a production function with complementary in the information factor, thus generating the decreasing returns to scale. The heterogeneous returns allows banks to get higher net-revenues on each infra-marginal unit for higher values of γ_s. The bank, in turn, needs to raise funds from outside investors at the exogenous rate R_f.

I further assume that at the beginning of each period a bank in sector s has a stock og preexisting debt commitments that constraint their ability to reduce overall lending total amount lent equal to $L_{s,0}$ assumed to be different across banks and sectors and drawn from a distribution. This $L_{s,0}$ can be thought as long term debt and a fraction δ of it matures each period. The bank has thus $(1-\delta)L_{s,0}$ loans still in operation, and has to decide, the amount of $L_{s,1}$ of loans to lend this period. Therefore, the bank face the following constraint $L_{s,1} \geq (1-\delta)L_{s,0}$. This means that the bank can decide to make new loans in addition to the maturing stock only. This is a convenient way to impose dividend smoothing of revenues of banks (Supera, 2023) and to capture the asymmetries in responses documented in the previous analysis.

The bank's program then reads as:

$$\max_{\{L_{s,1}\}} \sum_s (L_{s,1}^{\gamma_s} - L_{s,1}R_f) \tag{10}$$

$$s.t.$$

$$L_{s,1} \geq (1-\delta)L_{s,0} \ \forall s \tag{11}$$

I define the shadow cost attached to a binding constraint as μ_s.

The optimal scale in each sector is given by:

$$L^*_{s,1} = \begin{cases} \left(\gamma_s R_f^{-1}\right)^{\frac{1}{1-\gamma_s}}, & \text{if } \mu_s = 0 \\ (1-\delta)L_{s,0} & \text{if } \mu > 0 \end{cases} \tag{12}$$

I now distinguish two case, the binding case and the non binding.

Binding constraint: consider the case in which $\mu > 0$. Then irrespective of γ_s the bank cannot scale down its production capacity. In this way I can rationalize the fact that upon a rate increase, banks do not reduce their loan volume.

Non-binding constraint: consider the case in which $\mu = 0$. Then one can show that for given $\gamma_s > \gamma_{s'}$ banks are more specialized in sector γ_s with respect to $\gamma_{s'}$. Formally:

Proposition 1 - Bank specialization: given $\gamma_s > \gamma_{s'}$ the bank will specialize in sector s relative to s'.

Proof of Proposition 1. Consider a bank that invest into two sector γ_s and γ'_s with $\gamma_s > \gamma_{s'}$. Given $L^*_s = \left(\gamma_s R_f^{-1}\right)^{\frac{1}{1-\gamma_s}}$ and $L^*_{s'} = \left(\gamma_{s'} R_f^{-1}\right)^{\frac{1}{1-\gamma_{s'}}}$ and $\partial L^*_s / \partial \gamma_s > 0$, then $L_s / \sum_s L_s > L_{s'} / \sum_s L_s$ then it follows that $L_s^*/L_{s'}^* > 1$. Hence the bank lends more, i.e. is more specialized, in the market in which it has higher marginal returns. □

Proposition 2 - Differential response to R_f: a decrease in R_f leads to a higher relative increase in loan supply by the bank in market γ_s than in the market γ_s' for $\gamma_s > \gamma_s'$

Proof of Proposition 2. Given $\gamma_s > \gamma_s'$, then $\partial L_s^*/\partial R_f < \partial L_{s'}^*/\partial R_f < 0$. □

A bank with $\gamma_s > \gamma_s'$ will increase L_s more with respect to $L_{s'}$ upon a R_f cut.

The results highlighted in the proposition are in line with my empirical findings, most important they provide a rationale for the bank-level improvements of performance as specialized lenders (e.g. banks with higher γ_s) are exploiting their information advantage in return for higher net revenues. The main intuition for such results is that a bank is more specialized in market s as the marginal cost of lending is lower in such market. Also, the bank responds to a reduction in the monetary policy rate R_f by expanding relatively more in the market with higher marginal returns.

Overall this section describes a simplified two-period model with banks facing heterogeneous decreasing returns to scale across sectors due to different monitoring technologies. This model helps to rationalizes the findings that, upon a rate cut, banks expand lending in their sector of specialization due to their marginal advantage in monitoring technologies.

7. Conclusions

The present study investigates the transmission of monetary policy through specialized banks, focusing on bank-sector portfolio response, its implications for bank-level outcomes, and its relation to aggregate outcomes.

My findings reveal that, following a monetary easing, banks that are specialized in a certain sector significantly increase their lending volume to the industry relative to less specialized banks. This effect is mainly driven by monetary policy easing and is robust to measures of bank market concentration. Furthermore, I find that banks with low liquidity ratio and low capital ratios are more responsive to a rate cut for a given level of banks specialization.

By establishing this critical link between industry specialization, financial frictions, and the transmission of monetary policy, my research highlights the importance of considering banks' specific characteristics, including their liquidity levels and degree of specialization, in comprehending the overall response of the banking system pass through to changes in monetary policy.

My results suggest that the banks specialization gives rise to bank-level implications following a rate change. I document how banks with higher portfolio concentration see improved income performances and lower delinquency upon a rate cut compared to more diversified lenders. This results suggests that on the margin, specialized banks exploit their information advantage and select better borrowers.

This reasoning is also corroborated by lead arrangers showing the highest decrease in delinquency and increase in market capitalization for higher level of portfolio concentration following a rate decrease.

Finally my results shows that banks specialization influences aggregate outcomes showing that upon a rate cut, industries that have a higher presence of specialized lenders see an increase in total sectoral lending.

My results are important as the contribute to the understanding of the transmission of monetary policy to lending investigating heterogeneous characteristic of banking market structure: industry specialization. Second, these findings have important policy implications as monetary policy impacts the diversification decisions of banks in industry presence and their risk-taking decisions. By uncovering the dynamics between specialization and monetary policy, this study uncovers how bank portfolio evolves during different monetary policy regimes, shedding light on a previously understudied aspect of the banking industry.

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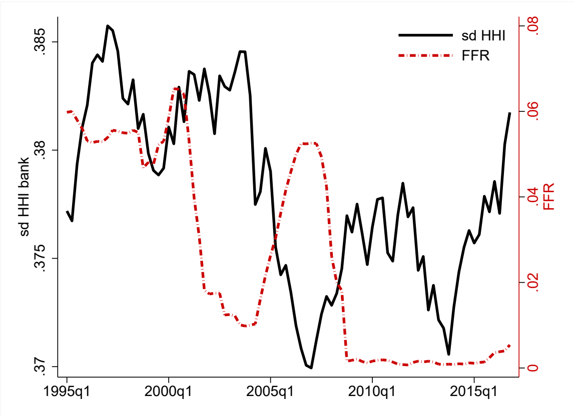
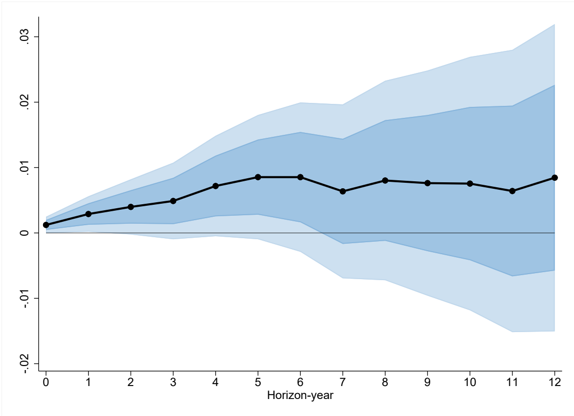
A. Figure appendix

Figure A.1:
Banks HHI evolution around change in rates

(a) *Average HHI dispersion and Fed Funds rates*

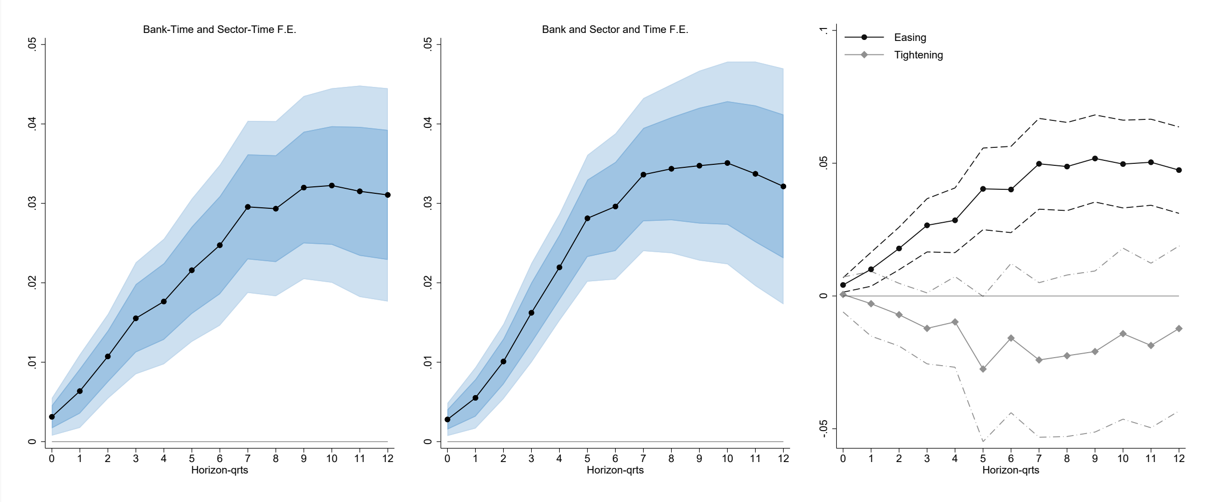


(b) *Banks' cumulative HHI upon shock cut*



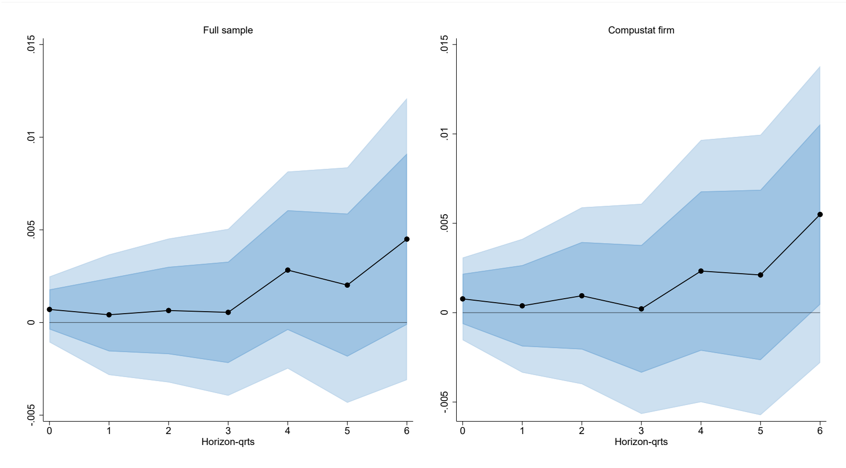
Note: source Dealscan data. Panel a shows the evolution of the standard deviation of banks' HHI (portfolio concentration) and the Fed Funds Rates (FFR) in decimal points. Panel b depicts the impulse response of cumulative banks' HHI portfolio growth around monetary a policy shock cut of 25 bps. The unit of information of the analysis is at the bank time level. The sample consists of the matched banks with an outstanding syndicated loan for the period of 1990q_1 until 2016q_4. The reduced form model corresponds to: $\Delta_h HHI_{b,t+h}^{t \to t-12} = \gamma_b^h + \beta^h \cdot \varepsilon_t + \Gamma_1^h \cdot Z_{b,t-1} + \Gamma_2^h \cdot Z_{t-1} + u_{i,t+h}$. The dependent variable is the cumulative growth of the slow moving average of HHI at the bank level. The vector $\Gamma_1^h \cdot Z_{b,t-1}$ contains bank level controls including 4 lags of the dependent variable, bank level controls (*bank size, capital ratio, and security ratio*) and their interaction with the monetary policy shock, *bank deposit ratio* and *ROA*. The vector $\Gamma_2^h \cdot Z_{t-1}$ contains macro level controls such as 4 lags of the monetary policy shock, change in fed funds rates and change in cpi.

Figure A.2:
Impulse response: Bank-Sector Loan growth upon rate cut - Excess specialization



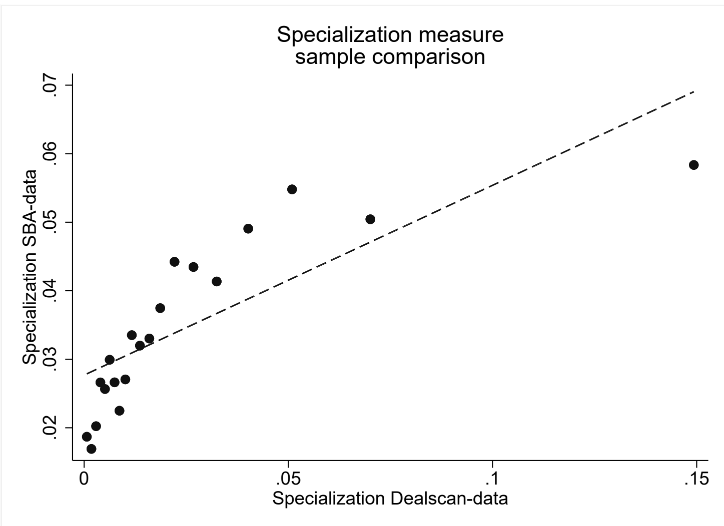
Note: Dealscan sample. Impulse response dynamics to a 25 bps cuts in ε_t for a standard deviation increase in *Excess Specialization* $_{b,s}^{t-1\to t-12}$. The panel reports the conditional estimates for $\beta_3^h \times \varepsilon \times$ *Excess Specialization* $_{b,s}^{t-1\to t-12}$ for the model $\log \ell_{b,s,t+h} - \log \ell_{b,s,t-1} = \alpha_{s,t}^h + \alpha_{b,t}^h + \alpha_{s,b}^h + \beta_1^h \times$ *Excess Specialization* $_{b,s}^{t-1\to t-12} + \beta_2^h \times \varepsilon + \beta_3^h \times \varepsilon \times$ *Excess Specialization* $_{b,s}^{t-1\to t-12} + \gamma_b^h X_{b,t-1} + \gamma_s^h X_{s,t-1} + u_{b,s,t+h}$ The unit of information of the analysis is the loan outstanding at the bank-sector time level. The sample consists of syndicated loans outstanding from 1991q_1 until 2016q_4. The dependent variable is the loan volume (outstanding and originated) held by each lender. Light (dark) blue areas represents 90% (68%) confidence interval used in the panel a and b. Panel a reports coefficients for both publicly and non listed firms, while panel b focus only on a matched sample of Compustat firms.

Figure A.3:
Impulse response: Bank-firm Loan growth upon rate cut



Note: Dealscan sample. Impulse response dynamics to a 25 bps cuts in ε_t for a standard deviation increase in $\textit{Excess Specialization}\ ^{t-1\rightarrow t-12}_{b,s}$. The panel reports the conditional estimates for $\beta^h_3 \times \varepsilon \times \textit{Excess Specialization}\ ^{t-1\rightarrow t-12}_{b,s}$ for the model $\log \ell_{b,s,t+h} - \log \ell_{b,s,t-1} = \alpha^h_{s,t} + \alpha^h_{b,t} + \alpha^h_{s,b} + \beta^h_1 \times \textit{Excess Specialization}\ ^{t-1\rightarrow t-12}_{b,s} + \beta^h_2 \times \varepsilon + \beta^h_3 \times \varepsilon \times \textit{Excess Specialization}\ ^{t-1\rightarrow t-12}_{b,s} + \gamma^h_b X_{b,t-1} + \gamma^h_s X_{s,t-1} + u_{b,s,t+h}$ The unit of information of the analysis is the loan outstanding at the bank-firm at half yearly frequency. The sample consists of syndicated loans outstanding from $1991q_1$ until $2016q_4$. The dependent variable is the loan volume (outstanding and originated) held by each lender. Light (dark) blue areas represents 90% (68%) confidence interval used in the panel a and b. Dashed areas represent represents 90% confidence interval used in the panel c. Panel a reports coefficients corresponding to column (1) in table Equation 5, while panel b correspond to column (5) of the same table. Panel c decompose the effect into easing and tightening periods estimated similarly to Equation 5.

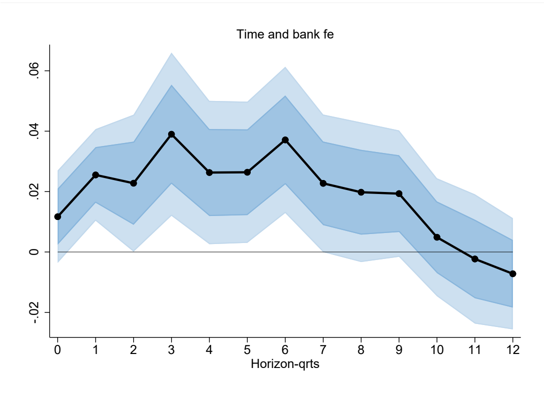
Figure A.4:
SBA and Dealscan specialization comparison



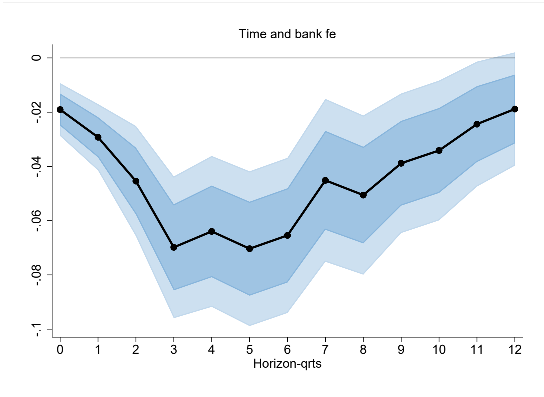
Note: Dealscan and Small Business Lending matched sample. The panel reports a binscatter plot of the correlation between a matched sample of Dealscan lenders and SBA lenders for the period 1991-2016.

Figure A.5:
Impulse response: bank level performances lead arrangers' HHI

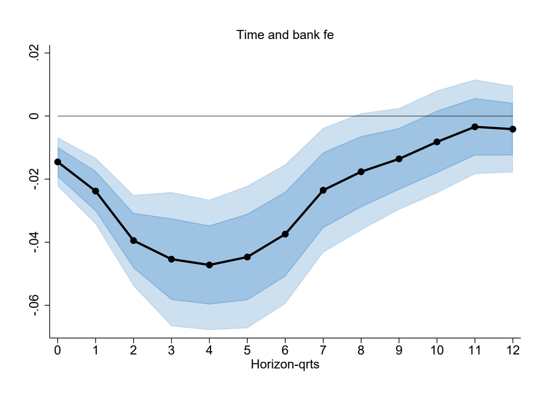
(a) *Banks' ROA*



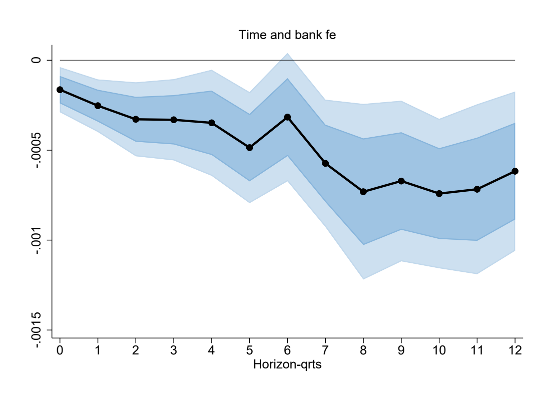
(b) *Banks' Chargeoff*



(c) *Banks' loan loss provision*



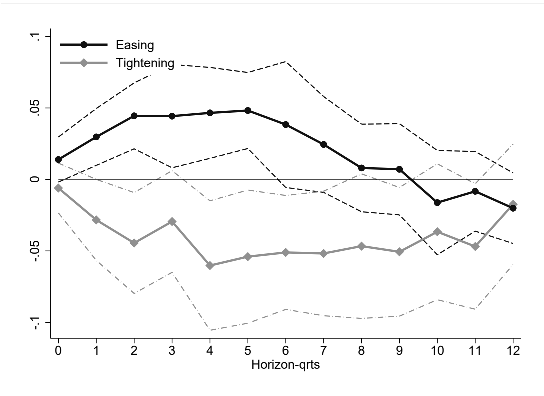
(d) *Banks' delinquency rate*



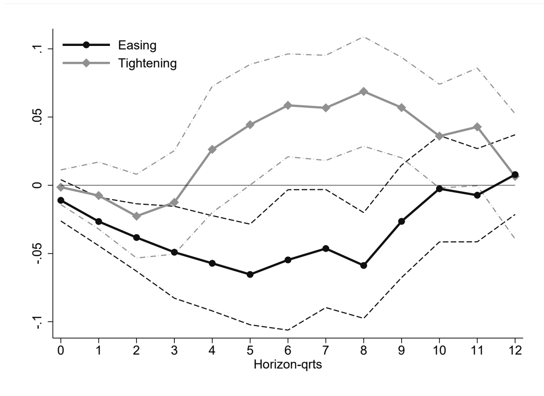
Note: Dealscan sample. Impulse response dynamics to a 25 bps cuts in ε_t for a standard deviation increase in $HHI_b^{t-1\to t-12}$. The panel reports the conditional estimates for $\beta_2^h \times \varepsilon \times HHI_b^{t-1\to t-12}(Lead)$. The unit of information of the analysis is the bank time level. The sample consists of matched Dealscan and FR Y-9C bank holding company for the period from $1991q_1$ until $2016q_4$. The dependent variable is the banks' ROA in Figure 5a and chargeoff rate in Figure 5b. Light (dark) blue areas represents 90% (68%) confidence interval. Dashed areas represent represents 90% confidence interval used to distinguish between monetary policy easing and tightening effect. Both panels reports coefficients corresponding to the most saturated model presented in table Equation 8. The measure of banks' concentration are defined based on the syndicate outstanding loan volume at the end of each quarter.

Figure A.6:
Asymmetric impulse response: bank level performances

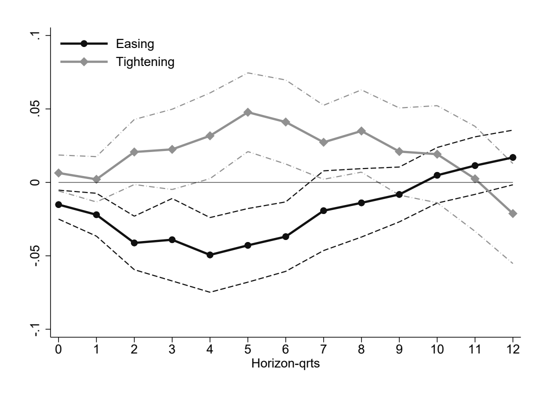
(a) *Banks' ROA*



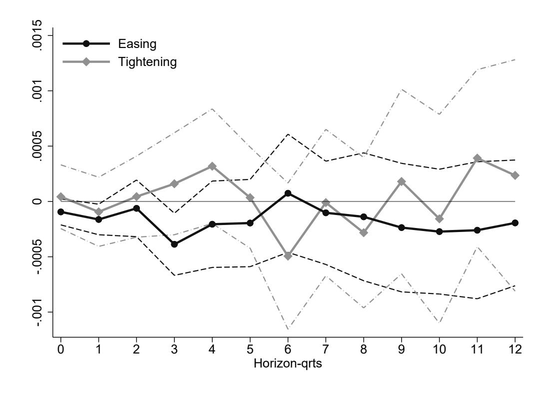
(b) *Banks' Chargeoff*



(c) *Banks' loan loss provision*



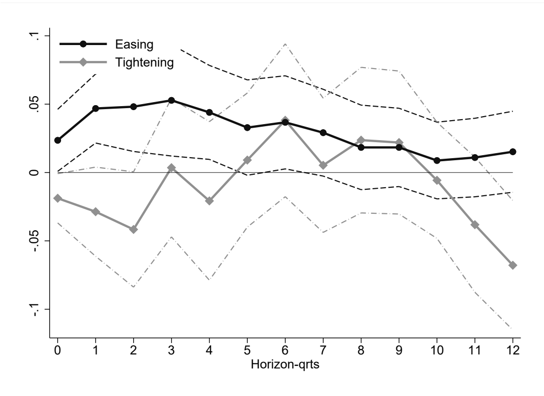
(d) *Banks' delinquency rate*



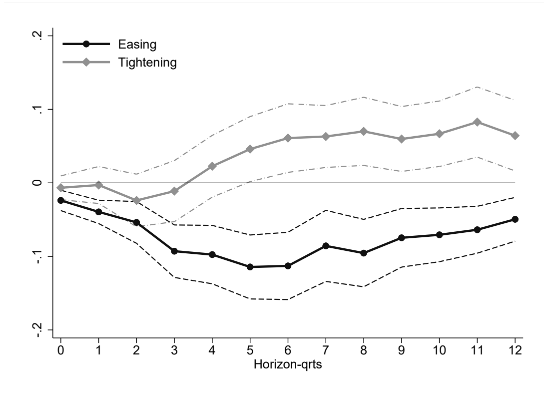
Note: Dealscan sample. Impulse response dynamics to a 25 bps cuts in ε_t for a standard deviation increase in $HHI_b^{t-1\to t-12}$. The panel reports the conditional estimates for $\beta_2^h \times \varepsilon_t \times HHI_b^{t-1\to t-12}$. The unit of information of the analysis is the bank time level. The sample consists of matched Dealscan and FR Y-9C bank holding company for the period from $1991q_1$ until $2016q_4$. The dependent variable is the banks' ROA in Figure 5a and chargeoff rate in Figure 5b. Dashed areas represent represents 90% confidence interval used to distinguish between monetary policy easing and tightening effect. Both panels reports coefficients corresponding to the most saturated model presented in table Equation 8. The measure of banks' concentration are defined based on the syndicate outstanding loan volume at the end of each quarter.

Figure A.7:
Asymmetric impulse response: bank level performances lead arrangers' HHI

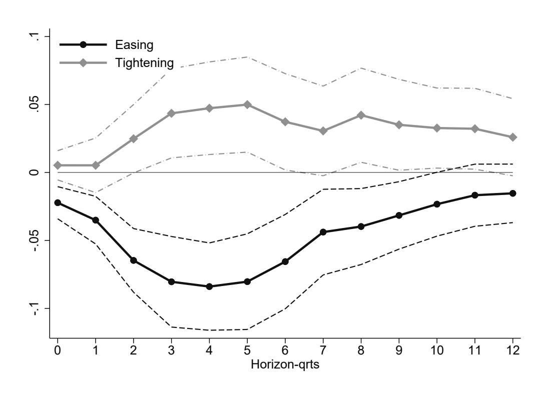
(a) *Banks' ROA*



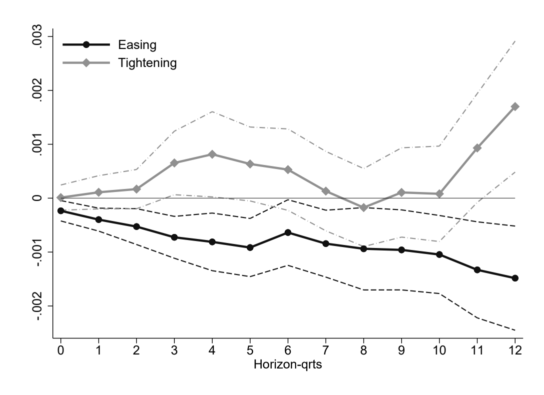
(b) *Banks' Chargeoff*



(c) *Banks' loan loss provision*



(d) *Banks' delinquency rate*



Note: Dealscan sample. Impulse response dynamics to a 25 bps cuts in ε_t for a standard deviation increase in $HHI_b^{t-1 \to t-12}$. The panel reports the conditional estimates for $\beta_2^h \times \varepsilon \times HHI_b^{t-1 \to t-12}(Lead)$. The unit of information of the analysis is the bank time level. The sample consists of matched Dealscan and FR Y-9C bank holding company for the period from $1991q_1$ until $2016q_4$. The dependent variable is the banks' ROA in Figure 5a and chargeoff rate in Figure 5b. Dashed areas represent represents 90% confidence interval used to distinguish between monetary policy easing and tightening effect. Both panels reports coefficients corresponding to the most saturated model presented in table Equation 8. The measure of banks' concentration are defined based on the syndicate outstanding loan volume at the end of each quarter.

B. Table appendix

Table A.1:
Loan level estimates

Effect of $Specialization_{b,s}^{t\to t-12}$ on $log(loan)_{i,b,s,t}$ for an ε_t reduction		
	$log(loan)_{i,b,s,t}$	
	(1)	(2)
ε_t		
$Specialization_{b,s}^{t\to t-12}$	0.786***	
	(0.230)	
$Excess\ Specialization_{b,s}^{t\to t-12}$		0.790***
		(0.225)
$Mkt\ share_{b,s}^{t-1}$	0.987***	0.935***
	(0.297)	(0.287)
$\varepsilon_t \times Specialization_{b,s}^{t\to t-12}$	209.933*	
	(115.280)	
$\varepsilon_t \times Excess\ Specialization_{b,s}^{t\to t-12}$		259.780*
		(137.693)
$\varepsilon_t \times Mkt\ share_{b,s}^{t-1}$	-92.834	-86.398
	(128.345)	(126.945)
Sector × Year-Quarter F.E.	✓	✓
Bank × Year-Quarter F.E.	✓	✓
Sector × Bank F.E.	✓	✓
Clustered Std.Errors	Bank-sector	Bank-sector
Within R^2	0.552	0.554
Obs	128,365	127,867

The table reports coefficients and t-statistics (in parenthesis) for the bank lending growth volume to sectors after a monetary policy tightening. The reduced form model tested corresponds to:

$$\log \ell_{i,b,s,t} = \alpha_{s,t} + \alpha_{b,t} + \alpha_{s,b} + \beta_1 \times \text{ Main Regressor } {}_{b,s}^{t-1\to t-12} + \beta_2 \times \varepsilon_t + \beta_3 \times \varepsilon_t \times \text{ Main Regressor } {}_{b,s}^{t-1\to t-12} + \gamma_i X_{i,t} + u_{i,b,s,t}$$

The table presents the responses to a monetary policy easing. The unit of analysis is at the loan level. The sample consists of syndicated loans originated in the U.S. from 1991q1 until 2016q4. The dependent variable is the log amount supplied by each lender at time t. The *Main Regressor* variable is either the slow moving average of specialization or the slow moving average of excess specialization. In all specifications I am controlling for banks' market share and I included different levels of fixed effects as noted in the lower part of the table to isolate credit supply and demand. $X_{i,t}$ is a vector of loan level controls such as *maturity (months), loan purpose* (indicator for capital purpose) and *loan type* (indicator for credit line, term loan or other). The symbols *,** and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table A.2:
Excess specialization and Bank-Sector loan growth

Effect of *Excess Specialization*$_{b,s,t}$ on loan growth (Bank-sector)					
	$\Delta loan_{b,s,t}$				
	(1)	(2)	(3)	(4)	(5)
ε_t					1.527
					(1.394)
$Excess\ Specialization_{b,s}^{t\to t-12}$	-0.849***	-0.579***	-0.839***	-0.572***	-0.491***
	(0.092)	(0.057)	(0.094)	(0.057)	(0.060)
$\varepsilon_t \times Excess\ Specialization_{b,s}^{t\to t-12}$	34.332**	30.719**	31.356**	22.912*	24.081*
	(13.333)	(13.048)	(12.939)	(12.561)	(12.318)
Sector × Year-Quarter F.E.	✓	✓			
Bank × Year-Quarter F.E.	✓		✓		
Sector F.E.			✓	✓	✓
Bank F.E.		✓		✓	✓
Year-Quarter F.E.				✓	
Sector × Bank F.E.	✓	✓	✓	✓	✓
Clustered Std.Errors	Bank-sector	Bank-sector	Bank-sector	Bank-sector	Bank-sector
Within R^2	0.277	0.194	0.159	0.073	0.057
Obs	137,536	137,604	131,091	131,195	137,634

The table reports coefficients and t-statistics (in parenthesis) for the bank lending growth volume to sectors after a monetary policy tightening. The reduced form model tested corresponds to:

$$\log \ell_{b,s,t} - \log \ell_{b,s,t-1} = \alpha_{s,t} + \alpha_{b,t} + \alpha_{s,b} + \beta_1 \times \ Excess\ Specialization\ {}_{b,s}^{t-1\to t-12} + \beta_2 \times \varepsilon_t + \beta_3 \times \varepsilon_t \times \ Excess\ Specialization\ {}_{b,s}^{t-1\to t-12} + + \gamma_s X_{s,t-1} + \gamma_b X_{b,t-1} + u_{b,s,t}$$

The table presents the responses to a monetary policy easing. The unit of analysis is at the bank-sector quarterly level. The sample consists of syndicated loans originated in the U.S. from 1990q1 until 2016q4. The dependent variable is the log growth amount held by each lender at time t. $Specialization\ {}_{b,s}^{t-1\to t-12}$ is the bank specialization and is defined as 12 quarter slow moving average of the share of total credit granted by a bank b to a specific sector s relative to the bank's total credit. In all specifications, are included different levels of fixed effects as noted in the lower part of the table, from most restrictive version (1) to least (5). $X_{s,t}$ is a vector of sector control variable including the sector rediployability index measured as Kim and Kung (2017), 2 lags of change in sectoral gross output changes in sectoral TFP and labour unit (index to 2012 levels) which can affect the sectoral demand side. $X_{b,t}$ is a vector of bank time-varying characteristics such as size, capital ratio, security ratio, deposit ratio and banks' profitability (*ROA*) to control for bank supply characteristic that can affect both my outcome variables as well as the explanatory variable. The symbols *,** and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table A.3:
Specialization and Bank-Sector loan growth: robustness

Effect of *Excess Specialization*$_{b,s,t}$ on loan growth (Bank-sector)			
	$\Delta loan_{b,s,t}$		
	(1)	(2)	(3)
$\varepsilon_t \times$ *Excess Specialization*$_{b,s}^{t\rightarrow t-12}$	34.674**	30.781**	26.508**
	(15.064)	(12.796)	(12.804)
$\varepsilon_t \times$ *Mkt share*$_{b,s}^{t\rightarrow t-12}$	39.666	-34.550	-21.227
	(37.673)	(22.999)	(25.034)
$\varepsilon_t \times \beta_b^{Exp.}$		3.139	4.192
		(5.745)	(5.714)
$\varepsilon_t \times \overline{\textit{Bank equity ratio}}$		-12.611	
		(20.349)	
$\varepsilon_t \times \overline{\textit{Bank security ratio}}$		0.183	
		(7.475)	
high liquidity$_b \times \varepsilon_t$			2.014
			(1.225)
high capital$_b \times \varepsilon_t$			-0.884
			(1.179)
Sector $\times$ Year-Quarter F.E.	✓	✓	✓
Bank $\times$ Year-Quarter F.E.	✓		
Bank F.E.		✓	✓
Sector $\times$ Bank F.E.	✓	✓	✓
Clustered Std.Errors	Bank-sector	Bank-sector	Bank-sector
Within R^2	0.284	0.200	0.200
Obs	135,152	135,230	135,230

The table reports coefficients and t-statistics (in parenthesis) for the bank lending growth volume to sectors after a monetary policy tightening. The reduced form model tested corresponds to Equation 6. The table presents the responses to a monetary policy easing. The unit of analysis is at the bank-sector quarterly level. The sample consists of syndicated loans originated in the U.S. from 1991q1 until 2016q4. The dependent variable is the log growth amount held by each lender at time t. *Excess Specialization* $_{b,s}^{t-1\rightarrow t-12}$ is the bank specialization and is defined as 12 quarter slow moving average of the share of total credit granted by a bank b to a specific sector s relative to the bank's total credit. In all specifications, are included different levels of fixed effects as noted in the lower part of the table, from most restrictive version (1) to least (3). $X_{b,t}$ is a vector controlling for four lags of the dependent variable. $X_{b,t}$ is a vector of bank time-varying characteristics such as size, capital ratio, security ratio, deposit ratio and banks' profitability (*ROA*) to control for bank supply characteristic that can affect both my outcome variables as well as the explanatory variable. The symbols *,** and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table A.4:
Specialization and Bank-Sector loan growth: financial frictions

	Effect of *Excess Specialization*$_{b,s,t}$ on loan growth (Bank-sector)				
	All banks	Low liquidity banks	High liquidity banks	Low capital banks	High capital banks
	(1)	(2)	(3)	(4)	(5)
$\textit{Excess Specialization}_{b,s}^{t\to t-12}$	-1.397***	-0.982***	-0.787***	-0.838***	-0.760***
	(0.265)	(0.044)	(0.043)	(0.051)	(0.039)
$\varepsilon_t \times \textit{Excess Specialization}_{b,s}^{t\to t-12}$	200.975***	67.176***	19.531	56.646**	5.810
	(54.825)	(22.259)	(20.536)	(22.931)	(20.292)
$\varepsilon_t \times \textit{Excess Specialization}_{b,s}^{t\to t-12} \times \overline{\textit{Bank equity ratio}}$	-494.741**				
	(218.327)				
$\varepsilon_t \times \textit{Excess Specialization}_{b,s}^{t\to t-12} \times \overline{\textit{Bank security ratio}}$	-542.283***				
	(146.930)				
$\textit{Excess Specialization}_{b,s}^{t\to t-12} \times \overline{\textit{Bank equity ratio}}$	1.346*				
	(0.749)				
$\textit{Excess Specialization}_{b,s}^{t\to t-12} \times \overline{\textit{Bank security ratio}}$	1.928**				
	(0.792)				
Sector × Year-Quarter F.E.	✓	✓	✓	✓	✓
Bank × Year-Quarter F.E.	✓	✓	✓	✓	✓
Sector × Bank F.E.	✓	✓	✓	✓	✓
Clustered Std.Errors	Bank-sector	Bank-sector	Bank-sector	Bank-sector	Bank-sector
Within R^2	0.278	0.331	0.296	0.359	0.291
Obs	137,536	83,818	53,472	49,454	85,914

The table reports coefficients and t-statistics (in parenthesis) for the bank lending growth volume to sectors after a monetary policy tightening. The reduced form model tested corresponds to Equation 7. The table presents the responses to a monetary policy easing. The unit of analysis is at the bank-sector quarterly level. The sample consists of syndicated loans originated in the U.S. from 1991q1 until 2016q4. The dependent variable is the log growth amount held by each lender at time t. *Excess Specialization* $_{b,s}^{t-1\to t-12}$ is the bank specialization and is defined as 12 quarter slow moving average of the share of total credit granted by a bank b to a specific sector s relative to the bank's total credit. In all specifications I am controlling for four lags of the dependent variable. The symbols *,** and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

C. Data Appendix

A. Dealscan cleaning

I estimate loan shares in Dealscan ollowing Blickle et al. (2020). A known problem when using syndicated loan level data in Dealscan is that loan share are observed only at origination and the information for most loans is self-reported by the lead arrangers. Syndicate shares at origination are sparsely reported and available for a very small subset of loans where the lead arrangers also report the participant shares at origination (Chodorow-Reich, 2014). These syndicate shares have often been used by researchers to approximate effective bank portfolio shares post-origination. However, Blickle et al. (2020) shows that the lender composition changes post origination – most importantly for loans that are sold to institutional lenders. This can create potential bias in the estimation of banks exposure to each industry. By comparing reported loan share in

To circumvent this issue, I make use of an approximation procedure for post-origination loan shares based use a matched data set at the loan-lender level that merges Dealscan and SNC. They use the loan information available from Dealscan to directly predict the lender shares observed at the first observation in SNC, which instead tracks post-origination loan share. The regression used in their set-up works as follows:

$$\textit{Share at first observation }(SNC)_{i,l} = \beta_0 + \beta_1 \cdot X_{i,l} + \beta_2 \cdot X_l + u_{i,l} \tag{13}$$

Where i denotes the loan and l the lender, $X_{i,l}$ is a set of loan-lender characteristic (e.g. position in the syndicate ...) and X_l are loan characteristics which are observable in Dealscan.

The files are available at Kristian Blickles's web page. To approximate loan ownership post-origination is enough to use their available estimated regression coefficients for the Equation 13 to get an approximation of the post-origiantion loan holdings by banks which participate in the syndicate. They show that this approximation performs better than commonly used loan-shares estimation like pro-rata rules (Giannetti and Laeven, 2012; Saidi and Streitz, 2021; Doerr and Schaz, 2021) or the structure of the syndicate (Chodorow-Reich, 2014).

Another issue when using Dealscan data comes from the loan amendments. A loan can be amended through its life-time (even multiple times), these amendments affect both the maturity as well as the quantity supplied. To reduce the bias in my sample, I thus make use of the `facility amendement` file and correct the loan maturity and volume over its life-time.

B. SBA loan data cleaning

The Small Business Lending dataset (SBA) contains a list of all SBA-guaranteed loans under the 7(a) program from 1991 to 2022. The data are publicly available at U.S. small business lending administration. I perform basic cleaning procedure and drop all observations with missing industry information (`naicscode`), loan volume (`grossapproval`), borrower state (`borrstate`) and project state (`projectstate`). I then drop all those loans that were not originated in U.S. territory, by keeping only the 50 states and DC.

I finally collapse my datasets at the bank-sector yearly level dimension as loan origination are sparsely reported at quarterly frequency. To ensure that a bank's specialization is not adversely affected by isolated exposure to a particular sector, I have excluded any bank-sector observations in cases where the bank has served that specific sector only once. To calculate the slow-moving average of specialization, I require that, for each bank-sector-year observation, there must be a minimum of two non-missing observations in the preceding three years. Any calculation in which I make use of the specialization-distribution is calculated only non missing observations.

C. Variable definition

This section display the source and the variable definition employed in the text as well as its unit.

Table A.5: ***Variable definitions and sources***

Variable Name	Unit	Source	Definition	Frequency
Sector-bank level				
$\Delta(loan)_{s,t+h}$	Decimal	Dealscan	Log difference real outstanding loans between a bank and a sector (base 2012 US dollars).	Quarterly
$Specialization_{b,s}^{t \to t}$	Decimal	Dealscan	Fraction of outstanding loans between the bank and the sector to total bank's outstanding loans.	Quarterly
$Specialization_{b,s}^{t \to t-12}$	Decimal	Dealscan	Slow moving average of bank specialization.	Quarterly
$Excess\ Specialization_{b,s}^{t \to t}$	Decimal	Dealscan	Fraction of outstanding loans between-sector to total bank-outstanding loans net of fraction of loans to sector to total outstanding loans.	Quarterly
$Excess\ Specialization_{b,s}^{t \to t-12}$	Decimal	Dealscan	Slow moving average of excess specialization.	Quarterly
$Mkt\ share_{b,s}^{t \to t}$	Decimal	Dealscan	Fraction of outstanding loans between the bank and the sector to total sector outstanding volume.	Quarterly
$Mkt\ share_{b,s}^{t \to t-12}$	Decimal	Dealscan	Slow moving average of bank-market share.	Quarterly
Bank level				
Bank size	Decimal	FR Y-9C	log(BHCK2170): log of banks's assets	Quarterly
Bank equity ratio	Decimal	FR Y-9C	BHCK3210/BHCK2170: equity capital to assets	Quarterly
Bank security ratio	Decimal	FR Y-9C	Securities/BHCK2170: ratio of securities to assets. Securities are defined as BHCK0390 or as BHCK1754 + BHCK1773 due to change in reporting.	Quarterly
Bank deposit ratio	Decimal	FR Y-9C	(BHDM6631 + BHDM6636)/BHCK2170: total deposit to equity.	Quarterly
Bank ROA	Percent	FR Y-9C	Lagged BHCK4340/BHCK3368 $\times$ 400: annualized net income over quarterly average assets.	Quarterly
Bank HHI	Decimal	Dealscan	Bank HHI based on $Specialization_{b,s}^{t \to t}$	Quarterly
Bank HHI$^{t \to t-12}$	Decimal	Dealscan	Slow moving average of bank's HHI	Quarterly
Bank provision for loan and lease losses	Decimal	FR Y-9C	BHCK4230/BHCK3368: loan loss provision to quarterly average assets.	Quarterly
Bank chargeoffrate	Percent	FR Y-9C	(BHCK4635-BHCK4605)/BHCK2122 $\times$ 400 Net loan loss provision over net loans annualized.	Quarterly
Bank delinquency rate	Decimal	FR Y-9C	(past 90 days loans + non-accruals)/BHCK2122 sum of loans past due 90 days and non accruing loans over net loans, past 90 loans are measured as BHCK1407 or BHCK5525 while non accruals are measured as BHCK1403 or BHCK5525 due to change in reporting.	Quarterly