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

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Job Market Paper

This version: June 2023

Abstract

This study uses U.S. syndicated loan data to examine the impact of banks' sectoral market specialization on portfolio rebalancing and credit supply in response to monetary policy easing. The findings highlight a core result: a decrease in the federal funds rate leads to a significant increase in bank lending towards their specialized industries, resulting in a long-lasting portfolio reallocation. Banks' financial frictions are crucial factors reinforcing these lending patterns. Specialized lenders exhibit amplified liquidity concerns, while concentrated banks benefit from their informational advantages, leading to improved profitability and lower deliquencies. Importantly, the findings indicate that banks do not decrease their risk aversion in this process. These effects are economically significant, with credit supply growth between banks and their specialized sectors increasing by 1.5% (quarterly based) after a one standard deviation decrease in policy rates, peaking at 10 quarters which underscores the lasting impact of the lending increase. Overall, these results highlight the role of a bank's sectoral specialization in the transmission of monetary policy and its enduring effects on the economy and the reciprocal relationship between changes in monetary policy regimes and the behavior of specialized banks.

Keywords: Monetary policy; Bank specialization; Bank lending

JEL Classification codes: E51; E52; E44; G21

*Email: gianmarco.ruzzier@upf.edu. I am indebted to Andrea Caggese, Christian Eufinger, Filippo Ippolito, Dmitry Kuvshinov, Andrea Polo and Björn Richter for their constant guidance and extensive feedback. I also thank Priit Jenas, Luigi Falasconi and seminar participants of UPF Finance seminar and BSE PhD Jamboree for their useful comments and discussions. All remaining errors are my own.

1 Introduction

Banks play a vital role in the allocation of credit and the smooth functioning of the financial system and the real economy. Their intermediation capacity and credit provision are crucial for the transmission of monetary policy. In particular, an extensive literature studies how banks' balance sheet heterogeneity and market power affect monetary policy transmission to the real economy (Kashyap & Stein 1995, Jiménez et al. 2012, Drechsler et al. 2017). One relevant form of heterogeneity is banks' different presence in distinct industries, industry specialization (Blickle et al. 2021, Giometti & Pietrosanti 2022), as it affects banks' sector-specific information gathering and their reaction to shocks and policies (De Jonghe et al. 2020, Iyer et al. 2022). While much of the literature has examined the role of industry shocks and the subsequent reallocation of credit from specialized banks to firms, limited evidence exists regarding the impact of credit reallocation following aggregate shocks and, most prominently, the role of banks' industry specialization in the transmission of monetary policy.

This paper aims to fill this gap by providing a comprehensive analysis of the interaction between banks' industry specialization and its response to monetary policy changes. Specifically, I examine the effects of credit reallocation, at the bank-sector level, within a bank's portfolio for more or less specialized lenders, shedding light on the implications of these dynamics. Firstly, I find that banks increase their lending significantly more in sectors where they have a higher level of specialization following an easing of monetary policy. Most importantly, I provide robust evidence of the enduring impact of banks' sectoral specialization on the transmission of monetary policy, with the strongest response observed approximately two years following a decrease in monetary policy rates. This sustained effect is characterized by a substantial increase in banks' credit volume towards their specialized industries, indicating the lasting influence of sectoral specialization on lending behavior. Moreover, I find that this response is particularly pronounced among low-liquid banks that exhibit a greater degree of specialization, aligning with the notion of reduced financial frictions resulting from interest rate decreases. Secondly, I explore the implications of bank specialization and declining interest rates at the bank level, demonstrating that banks with higher levels of industry specialization experience an improvement in their overall income performance, accompanied by a simultaneous decrease in delinquency rates.

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. By showing that in response to lower interest rates banks rebalance their portfolio towards the sector in that they invested more, I supply further evidence of the imperfect transmission of monetary policy. Secondly, I show the fact that banks have sectoral-specific knowledge advantage does not diminish their attitude towards risk highlighting the positive relationship between industry specialization and banks' financial stability in the context of declining interest rates.

This study employs U.S. syndicated loan-level data from Dealscan to address the research question. Syndicated loan-level data involve multiple lenders jointly providing credit to a borrower. Dealscan collects information at origination such as amount, counterparts and industry information. The final dataset covers the period from 1990 to 2016 at a quarterly frequency. The data encompasses 60 industries based on the BEA industry classification, excluding sectors such as FIRE (Finance, Insurance, and Real Estate), utilities, and public sector companies. Loan-level data is complemented with comprehensive information on banks, firms and industry characteristics. Within this dataset, I construct a measure of banks' sector specialization based on the fraction of outstanding credit assigned to a specific sector relative to a lender's total credit portfolio at each point in time (Paravisini et al. 2023, Blickle et al. 2021). This measure captures the extent to which banks concentrate their lending activities in specific sectors and the importance of a sector for a bank enabling an analysis of the implications of sector-specific lending behaviour.

The main empirical findings can be summarized as follows. My data reveal compelling evidence of a systematic reallocation of credit by banks in response to changes in monetary policy rates. Specifically, I find robust evidence that banks increase lending to firms in their specialized industries relative to other sectors following a decrease (increase) in monetary policy rates. The magnitude of this reallocation is substantial, with a 100 basis point decrease in the Fed Funds rates corresponding to an approximate 60 basis point (b.p.) increase in lending volume towards the banks' sectors of specialization. In annual terms, this increase represents 2.3 percent or a fifth of the quarterly growth volume, illustrating the notable impact of monetary policy on banks' lending behaviour. Employing a Local Projection approach Jordà (2005), I document consistent evidence of the long-run effect of the interplay between banks' sectoral specialization and monetary policy. In particular, a one standard deviation decrease in monetary policy rates results in an increase in cumulative growth between the bank and the sector that peaks at around two years, with banks increasing their credit volume towards their specialized industries by approximately 150 b.p. Importantly, my findings confirm that this reallocation channel operates independently from banks-sector interconnections driven by market shares (Giannetti & Saidi 2019) and extends beyond the previously studied channels of monetary policy transmission through banks' balance sheets (Jiménez et al. 2012, 2022).

I further delve into the implications of the previous findings by examining the extent to which industry specialization amplifies or mitigates banks' financial frictions. As specialized banks tend to be smaller and have lower equity ratios (Blickle et al. 2021), it is likely that banks' frictions would be amplified in the presence of a higher degree of specialization. My results provide evidence of a strong interaction between lenders' industry specialization and banks' frictions. Specifically, I find that low-liquid banks with a high degree of specialization exhibit the most pronounced responsiveness to monetary policy. These banks increase their lending volume to a greater extent compared to liquidity-rich banks, indicating that the impact of monetary policy on banks' lending behaviour is more pronounced among specialized banks that face greater financial frictions.

Additionally, I explore the implications of 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. My particular focus is on examining whether banks with higher levels of concentration tend to exhibit reduced risk aversion, potentially leading to an exacerbation of risky behaviour. This is motivated by the notion that the industry-specific knowledge accumulated by these banks in the credit market may incentivize them to shirk their costly monitoring duties, especially when the opportunity cost of funds is reduced (Degryse et al. 2021). However, contrary to expectations, the results do not provide significant support for an increase in risk-taking behaviour among highly concentrated banks. In fact, the findings indicate that, over the cross-section of banks, those with higher levels of concentration experience an increase in return on assets (ROA) and a reduction in loan loss provision of 2 basis points in response to a one standard deviation reduction in the funding rate. This corresponds to a 4 percent total variation in loan loss provision. These results offer empirical support for the underlying mechanism of my previous findings, suggesting that specialized banks while expanding their lending portfolios to their top sectors, allocate credit towards safe firms without compromising their lending standards. The knowledge-specific advantage possessed by these specialized banks appears to contribute to their ability to navigate the lending landscape successfully.

Throughout the analysis, I make use of several approaches to address potential concerns that the increase in lending to the sector of specialization could be driven by credit demand prompted by a decrease in interest rates. Though challenging to control for all observed and unobserved sector and bank heterogeneity, I exploit the disaggregated nature of the data and saturate the bank sector level regression with granular bank-time, firm-time and bank-firm fixed effects that help us isolate credit supply and demand effects at the loan (bank-sector) level (Khwaja & Mian 2008, Jiménez et al. 2012). Additionally, I incorporate restrictive bank-sector fixed effects in all my specifications. This approach helps isolate the variation within the same bank-sector combination over time, effectively controlling for time-invariant portfolio-composition effects and potential endogenous matching issues. Furthermore, I also make use of unexpected monetary shocks measured as in (Jarociński & Karadi 2020). By employing these monetary shocks as an exogenous source of variation, I mitigate the potential influence of any information released prior to the actual rate change. Importantly, my results remain robust across these different strategies. Whether employing direct proxy strategies or employing standard IV regression with monetary policy shocks, I consistently observe the same empirical patterns and draw similar conclusions.

To the best of my knowledge, this paper is the first to focus on identifying how banks' sectoral specialization interacts with monetary policy. 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 & 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 the prominent role of balance sheet channels such as size Kashyap & Stein (1995) and balance sheet characteristic Kashyap & 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 amplifies banks' financial frictions.

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 & 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 & Pietrosanti (2022), Iyer et al. (2022), Di & 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 favourable monetary policy shocks hit banks, they react by funnelling credit towards their sector of specialization. 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 & 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 loan loss provisions. 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.

Finally, my paper adds to the recent literature on local-mortgage market concentration and monetary policy Casado & Martinez-Miera (2023). While this literature 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. 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.

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 results from the estimation and additional analyses are presented in Section 3. Section 4 concludes.

2 Data and measurement

To measure banks' industry specialization and study its influence on monetary policy transmission, 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, FR Y-9C reports, Compustat and 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 & Saidi 2019, Iyer et al. 2022).

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 & 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 & Saidi (2019), Ivashina & 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 & 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 & 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 & 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 & 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 & 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. I also drop from the sample all loans to 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.

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.

Firm-level data I extract firm-level balance sheet information from Compustat at a quarterly frequency for the sample of publicly listed firms in the U.S. The data contains detailed industry activity information for each firm and is used to extract NAICS code for the matched sample of Dealscan and Compustat firms.

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).

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:

$$Specialization_{b,s,t} = \frac{\sum_{i=1}^{I} Loan_{b,i,f,s,t}}{\sum_{s=1}^{S}\sum_{i=1}^{I} Loan_{b,i,f,s,t}} := s_{b,s,t} \tag{1}$$

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 the common practice in the literature and equally weigh the missing shares per loan across the syndicate if the information is not available, while, in case of complete information in Dealscan, I make use of the exact loan portions (Chodorow-Reich 2014, Giannetti & Saidi 2019, Doerr & Schaz 2021). 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 & 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:

$$Excess\ Specialization_{b,s,t} = \frac{\sum_{i=1}^{I} Loan_{b,i,f,s,t}}{\sum_{s=1}^{S}\sum_{i=1}^{I} Loan_{b,i,f,s,t}} - \frac{\sum_{s=1}^{S}\sum_{i=1}^{I} Loan_{b,i,f,s,t}}{\sum\sum_{s=1}^{S}\sum_{i=1}^{I} Loan_{b,i,f,s,t}} \tag{2}$$

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 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 1.

$$HHI_{b,s} = \sum_{j=1}^{J} (s_{b,s,t})^2 \tag{3}$$

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 statisic

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. As shown in Figure 1 the average share of assets 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 (Blickle et al. 2021). In the same spirit of Giometti & Pietrosanti (2022) I show that banks' specialization is not a mere product of industry concentration: as specialization may capture an industry's prominence rather than a bank's policy, I compare in Panel (b) the average concentrations of banks and industries. According to this evidence, banks' portfolios are far more concentrated and less diversified than those of the market. I further bring evidence of the issuance cyclicality for specialized borrowers. Panel (c) plots the fraction of newly generated loans by banks that are in the top (bottom) quartile of the quarterly-lagged specialization measure, while Panel (d) studies the dynamics of the volume of credit. Approximately 20% of the final sample of syndicated loans originated in the United States over the sample period were initiated by highly specialized lenders and picked 30% at the height of the global financial crisis, confirming that during busts, specialized lenders tend to increase their lending towards their core sectors relatively more than the bottom specialized lenders(Iyer et al. 2022, De Jonghe et al. 2020). The share and the volume of business loans made by specialized lenders has nevertheless fluctuated substantially over time. The main takeaway is that lending from specialized lenders is very much correlated to the business cycle, and as that, it has huge consequences for the overall credit allocation. The evidence above shows the relative importance of industry specialization. As banks develop information advantage in certain industries where it is more specialized, adverse liquidity shocks will heterogeneously impact their portfolio, requiring a rebalancing effort.

Table 1 provides the summary statics for the main variable of interest and controls used in the analysis. The first panel reports information at the bank-sector level, 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 is around 4%, with a sensible variable considering the mean.

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 & 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 tightening affects banks' credit supply.

3 Empirical results

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 first examine how banks' industry specialization mediates the relation between monetary policy changes and changes in bank lending at the bank-sector level. This highlights the non-randomness in the portfolio reallocation between banks and sectors. I show that upon an easing in monetary policy, bank specialization is associated with significantly higher credit supply towards the sector in which banks invested most. I interpret this evidence as support for explanations of bank spe-

Figure 1:
Banks portfolio concentration

(a) (b) (c) (d)

Note: Panel a shows the average (weighted) loan portfolio concentration, which is measured as the share of loans to an 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. I split the sample by the yearly median for banks with high and low values of bank diversification, Panel c represents the volume of newly issued credit in every quarter by the top (bottom) quartile banks in the lagged-quarterly specialization distribution, the shaded lines are the fraction of the number of loans originated for each quartile while the other represents the fraction with respect to the volume. In Panel d I repeat the same exercise for Panel c, but looking instead at loan volume origination.

cialization based on lending advantages coming from lower marginal costs and information advantages which are sector-specific. Upon loan origination after easing, one should expect stronger banks performance if banks' specialization is associated with lower marginal costs and higher lending advantages. To test this hypothesis, I then look at banks' outcomes for

Table 1:
Summary statistics

	Mean	SD	p25	p75	Obs
Sector-bank level					
$\Delta(loan)_{s,t}$	0.03	0.26	-0.01	0.04	181,389
$Specialization_{b,s}^{t\rightarrow t-12}$	0.04	0.09	0.01	0.04	182,123
$Excess\ Specialization_{b,s}^{t\rightarrow t-12}$	0.02	0.08	-0.00	0.01	182,123
$p75.Spec_{b,s}^{t-1}(Indicator)$	0.26	0.44	0.00	1.00	181,389
$Mkt\ share_{b,s}^{t\rightarrow t-12}$	0.03	0.06	0.00	0.04	182,123
Bank level					
Bank size	9.55	1.54	8.49	10.54	7,080
Bank equity ratio	0.09	0.03	0.07	0.10	7,079
Bank security ratio	0.21	0.10	0.14	0.26	7,069
Bank deposit ratio	0.66	0.19	0.60	0.79	7,073
Bank ROA	1.05	0.78	0.79	1.39	7,080
Bank HHI	0.21	0.25	0.06	0.24	7,080
Bank provision for loan and lease losses	0.51	0.64	0.14	0.62	7,080
Bank chargeoffrate	0.71	0.88	0.20	0.86	7,077
Bank delinquency rate	0.01	0.01	0.00	0.01	7,077
Sector level					
$Asset\ redeployability_{s,t}$	0.39	0.13	0.33	0.48	6,198
$\Delta gross\ output_{s,t}$	0.02	0.06	-0.00	0.05	6,198
$\Delta value\ added_{s,t}$	0.02	0.09	-0.01	0.06	6,198
$\Delta TFP_{s,t}$	0.00	0.04	-0.01	0.02	6,198
Aggregate level					
R_t	0.030	0.025	0.002	0.053	108
ΔR_t	0.001	0.005	-0.001	0.001	108
$M.P.\ shock\ _t$	0.019	0.076	-0.022	0.040	108

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 1990q1 until 2016q4.

highly concentrated portfolio lenders, where I show that concentrated banks have higher revenue performances and suffer fewer delinquencies on loans.

The purpose of my analysis is to compare the difference in the volume of business loans outstanding by each bank in each sector as a function of the bank's specialization around changes in monetary policy captured by reductions in fed funds. 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). To construct my main outcome variable, I aggregate 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.

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 over the degree of industry specialization. I estimate the following reduced form model:

$$\overbrace{\log \ell_{b,s,t+h} - \log \ell_{b,s,t-1}}^{\text{Change in credit}} = \alpha_{s,t} + \alpha_{b,t} + \alpha_{s,b} + \beta_1^h \times \ Specialization\ _{b,s}^{t-1\to t-12} + \beta_2^h \times \Delta R_t + \beta_3^h \times \Delta R_t \times \ Specialization\ _{b,s}^{t-1\to t-12} + \gamma_b^h X_{b,t-1} + \gamma_s^h X_{s,t-1} + \varepsilon_{b,s,t+h} \quad (4)$$

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 $\beta_3 \times \Delta R_t \times \ Specialization\ _{b,s}^{t-1\to t-12}$, which captures the interaction between monetary policy change and a lagged 12-quarters rolling average of the specialization measure defined in Equation 1. $X_{s,t}$ is a vector of sector control variable including the sector redeployability index measured as Kim & 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 & Mian 2008, Paravisini et al. 2023), bank-specific credit supply shocks (Jiménez et al. 2014, Giometti & 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.

Motivated by existing literature, a bank faces the following tradeoff (Goetz et al. 2016): the specialized banks can load even more over its sectors of interest while increasing the exposure of idiosyncratic shocks or scale down and diversify and thus raise its systemic aggregate exposure (Chu et al. 2020). 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 I of Equation 4, 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,

Table 2:
Loan growth

Effect of ΔR_t on $Specialization_{b,s}$					
	$\Delta loan_t$				
	(1)	(2)	(3)	(4)	(5)
ΔR_t					-0.746***
					(0.266)
Specialization$_{b,s}^{t\to t-12}$	-0.684***	-0.293***	-0.693***	-0.304***	-0.285***
	(0.059)	(0.029)	(0.061)	(0.033)	(0.031)
$\Delta R_t \times$ Specialization$_{b,s}^{t\to t-12}$	14.379***	9.022***	10.987***	7.427***	6.249***
	(3.831)	(1.937)	(3.406)	(2.099)	(1.878)
Sector $\times$ Year-Quarter F.E.	✓	✓			
Bank $\times$ Year-Quarter F.E.	✓		✓		
Sector F.E.			✓	✓	✓
Bank F.E.		✓		✓	✓
Year-Quarter F.E.				✓	
Sector $\times$ Bank F.E.	✓	✓	✓	✓	✓
Clustered Std.Errors	Bank-sector	Bank-sector	Bank-sector	Bank-sector	Bank-sector
R^2	0.20	0.13	0.12	0.05	0.04
Obs	176,053	176,467	176,070	176,484	176,484

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:

$$\log Outstanding\ Credit_{b,s,t} - \log Outsanding\ Credit_{b,s,t-1} = \alpha_{s,t} + \alpha_{b,t} + \alpha_{s,b} + \beta_1 \times\ Specialization\ _{b,s}^{t-1\to t-12} + \beta_2 \times \Delta R_t + \beta_3 \times \Delta R_t \times\ Specialization\ _{b,s}^{t-1\to t-12} + + \gamma_s X_{s,t-1} + \gamma_b X_{b,t-1} + \varepsilon_{b,s,t+h}$$

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 restrive version (1) to least (5). $X_{s,t}$ is a vector of sector control variable including the sector rediployability index measured as Kim & 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.

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. 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 & 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 reduction of 100 basis points in fed funds rates, will increase their lending by 2.3% on impact on a yearly base ($14.78 \times 0.04 \times 1 \times 4$). To ensure that the estimates are not driven by expected monetary policy changes, that might affect deferentially the speed and volume at which banks incur in origination, I provide in Table A1 a specification using unexpected monetary policy shocks identified as in (Jarociński & Karadi 2020). The results are qualitatively and quantitatively unchanged, similar when using the excess specialization measures in Table A2 corroborating the previous results. 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. Put differently, specialization increase the responsiveness to monetary policy regimes.

3.2 Long run effects of bank specialization and monetary policy: bank-sector outcomes

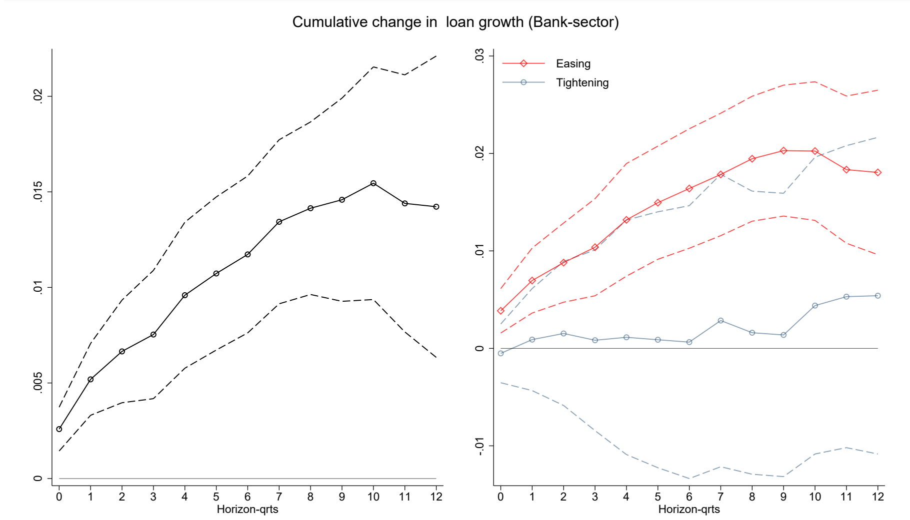
The results so far show that there is an immediate effect on impact, however as evidenced by Kashyap & Stein (1995), Caglio et al. (2022) monetary policy changes have persistent consequences. To study the long-run relations with specialization I employ a similar strategy as in the previous section using local projections (Jordà 2005) to understand the long-term dynamics of specialization which estimate the following local projection model:

$$\log \mathit{Outstanding\ Credit}_{b,s,t+h} - \log \mathit{Outsanding\ Credit}_{b,s,t-1} = \alpha_{s,t+h} + \alpha_{b,t+h} + \alpha_{s,b} + \\ \beta_1 \times \ \mathit{Specialization}\ _{b,s}^{t-1 \to t-12} + \beta_2 \times \Delta R_t + \beta_3 \times \Delta R_t \times \ \mathit{Specialization}\ _{b,s}^{t-1 \to t-12} + \\ + \gamma_s X_{s,t-1} + \gamma_b X_{b,t-1} + \varepsilon_{b,s,t+h} \quad (5)$$

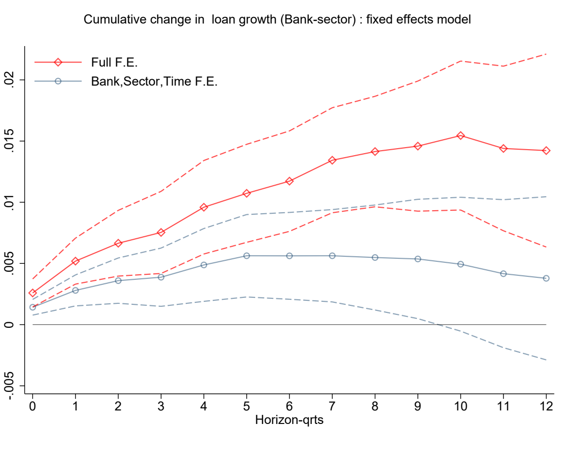
Given that there is some lag between the time in which a syndicated loan is contracted and the effective period in which is originated, generally 90 days, it is likely the case that the effects get larger over a bigger horizon than a quarter. To avoid those outcomes to be affected by the demand or supply side, I estimate the model in Equation 5 with the most stringent fixed effect specification corresponding to column (1) of Table 2. The results are presented in Figure 2.

Panel (a) shows the outcome of Equation 5 upon a standard deviation shock for the average

Figure 2:
Loan growth local projections: monetary easing



(a)



(b)

Note: Panel a reports coefficients and 90% confidence interval. 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 1990q1 until 2016q4. The reduced form model corresponds to:

$$\log \mathit{Outstanding\ Credit}_{b,s,t+h} - \log \mathit{Outsanding\ Credit}_{b,s,t-1} = \alpha_{s,t+h} + \alpha_{b,t+h} + \alpha_{s,b} + \beta_1^h \times \mathit{Specialization}_{b,s}^{t-1 \to t-12} + \beta_2^h \times \Delta R_t + \beta_3^h \times \Delta R_t \times \mathit{Specialization}_{b,s}^{t-1 \to t-12} + \gamma_s X_{s,t-1} + \gamma_b X_{b,t-1} + \varepsilon_{b,s,t+h}$$

The dependent variable is the loan volume (outstanding and originated) held by each lender. The table reports the local projection coefficients for $\beta_3^h \times \Delta R_t \times \mathit{Specialization}_{b,s}^{t-1 \to t-12}$ at horizon h for the full saturated model (bank-time, firm-time and sector-bank fixed effect). All the estimates are based on a one standard deviation shock for the average banks' specialization average, which in the sample corresponds to 0.04 of the total loan portfolio. Panel (a) plots the results for a change in the fed funds rate, while panel (b) plots the results comparing the β_3^h for the corresponding model in column (1) in Table 2 in red and column (5) in Table 2.

bank[1]. It picks at around 10 quarters and is economically significant: after 2 and half years the cumulative growth is around 1.5% higher, at the quarterly frequency, in the portfolio of specialization, again showing the reallocation incentive in the lending portfolio. In addition, I separate the effects of monetary policy changes into positive and negative ones: most of the results are driven by monetary policy easing, but the effect of monetary policy tightening remains unclear and, likely, not well identified, as most of the changes in monetary policy were coming from easings rather than tightenings during the period studied. Finally in panel (b) I report the equivalent comparison for column (1), in red, and column (5) in Table 2. In conclusion, the model shows that the effects of specialization on banks' portfolios have a long-run effect upon and easing and return to their original mean around 3 years after the shock. As in the previous section the robustness in Figure A1 and Figure A2 delivers qualitatively the same message and shows that results are not driven by expected monetary policy change or rather than mismeasurement in the main explanatory variable.

3.3 Alternative channels

So far the analysis showed that banks' specialization distorts the transmission of monetary policy. However, one concern regarding these first findings is that they could be driven by other banks' sectoral market structure characteristics or other bank characteristics that may affect the transmission of monetary policy to loan supply and could be correlated with local market specialization. In particular, banks' sectoral market share could confound my results (Giannetti & Saidi 2019, Iyer et al. 2022). In the presence of high market concentration, banks internalize lending spillover and possible systemic effects of their 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. Alternatively, banks' specialization might be a pure artefact of market concentration as banks have a high industry market share and thus concentrated portfolios. This would suggest that the observed effect of bank specialization on credit supply might simply reflect a bank's willingness to gain market share in an industry.

Additionally, a wide body of literature focuses on the relationship between banks' solvency and loan supply. In particular, it could be that banks' specialization is driven by small and less

[1]The coefficient is already scaled for the standard deviation of the monetary policy change in the sample and the specialized mean of the bank observed in the data.

liquid banks which are close to constraints. 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 & Stein 2000, Jiménez et al. 2012).

To address the above-mentioned concerns, I 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 as well as other well-known banks' characteristics that influence monetary policy such as size (Kashyap & Stein 1995) and solvency (Kashyap & Stein 2000, Jiménez et al. 2012) captured by equity and liquidity ratio. Formally, I test the following reduced form model:

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

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 Equation 4. Table 3 presents the results which only report the interaction coefficients for brevity.

In Table 3 column 3, I show that my results work above and beyond this channel: similarly to De Jonghe et al. (2020) I find that the effect of market share on growth volume is negative, however, I find a statistically significant interaction of market share and monetary policy suggesting that market concentration push banks to expand their portfolio after a liquidity shock internalizing potential positive spillovers coming from easing of monetary regimes in the aim of favouring their portfolios of firms or increase their market shares. However, banks' specialization maintains its statistical strength and magnitude. Most importantly, the relative effect of bank specialization is stronger than market share: a 100 basis points decrease in policy rates corresponds to an increase of credit volume for the average banks' market share of 1.78% on impact on a yearly base ($14.674 \times 0.03 \times 1 \times 4$), while the effect on banks' specialization is 1.98% ($12.434 \times 0.03 \times 1 \times 4$), which corresponds to roughly a 11% stronger effect of banks' specialization relative to market concentration.

Table 3:
Loan growth: alternative channels

Effect of ΔR_t on $Specialization_{b,s}$				
	$\Delta loan_t$			
	(1)	(2)	(3)	(4)
Specialization$_{b,s}^{t\to t-12}$	-0.684***	-0.725***	-0.610***	-0.238***
	(0.059)	(0.066)	(0.054)	(0.024)
$\Delta R_t \times$ Specialization$_{b,s}^{t\to t-12}$	14.379***	14.085***	12.434***	6.438***
	(3.831)	(3.790)	(3.840)	(1.925)
Lag $\Delta loan_t$		-0.049***		
		(0.004)		
Mkt share$_{b,s}^{t\to t-12}$			-0.854***	-0.896***
			(0.123)	(0.112)
$\Delta R_t \times$ *Mkt share*$_{b,s}^{t\to t-12}$			14.674**	9.374*
			(6.505)	(5.180)
$\Delta R_t \times$ Bank size				-0.524**
				(0.206)
$\Delta R_t \times$ Bank equity ratio				-26.484**
				(10.628)
$\Delta R_t \times$ Bank security ratio				2.628
				(2.693)
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	Bank-sector
R^2	0.20	0.20	0.20	0.13
Obs	176,053	172,088	176,053	176,467

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:

$$\log Outstanding\ Credit_{b,s,t} - \log Outsanding\ Credit_{b,s,t-1} = \alpha_{s,t} + \alpha_{b,t} + \alpha_{s,b} + \\ \beta_1 \times\ Specialization\ _{b,s}^{t-1\to t-12} + \beta_2 \times \Delta R_t + \beta_3 \times \Delta R_t \times\ Specialization\ _{b,s}^{t-1\to t-12} + \\ + \gamma_s X_{s,t-1} + \gamma_b X_{b,t-1} + \varepsilon_{b,s,t+h}$$

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 restrive version (1) to least (5). $X_{s,t}$ is a vector of sector control variable including the sector rediployability index measured as Kim & 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.

Most importantly, the R^2 is not significantly improved from column (1) (baseline results) to column (3), which I take as a sign that despite contributing to the model's fit, it does not sensibly improve it: specialization is not driven by unobserved covariance. This is also confirmed when regressing change in credit supply on previous lags in column (2)[2].

To further cast out doubts on whether my results could be driven by small and less liquid banks I horse race banks specialization to measures of banks' financial constraints and market specialization in column (4). The coefficient on banks' specialization remains positive and significant. The key point arising from column 4 is that bank specialization works on top of standard channels of monetary policy, despite the coefficient being halved, as was the case for column 2 in Table 2, once the model is horse-raced with standard channels of monetary policy the effect is still significant and economically relevant. Moreover, the model reproduces the standard effect of the size and equity channel for the transmission of monetary policy: larger banks expend less as they are less subject to financial frictions as is the case for more equity-rich banks.

To compare the economic significance, it is mostly convenient to compare the effect of a one-standard-deviation increase in the explanatory variables after a 100 basis point reduction. The relative impact of banks' specialization on yearly credit supply is 2.3% while for bank's size and banks' equity is roughly 3.2%, suggesting that banks' frictions are indeed prominent factors that however do not absorb the effect of lenders' industry specialization. Put differently, banks' specialization works beyond the so-called balance sheet channel of monetary policy, though the effect is reduced as the specification cannot control for unobserved bank heterogeneity within the quarter. However, these results could hide potential amplifications between specialization and banks' financial functions which are explored in the following section. Table A3 and Table A4 present the corresponding robustness checks for a monetary policy shock and for the excess specialization measures providing the same qualitative results.

3.4 Amplification of banks' balance sheet channel

In this section, I explore whether and how banks' sectoral specialization amplifies financial frictions. In particular, as evidenced in Blickle et al. (2021) and Giometti & Pietrosanti (2022) banks' sectoral specialization is prominent for smaller and less solvent banks, which could

[2]Results are qualitatively unchanged using higher lags of the dependent variables.

exacerbate current bank's frictions. For instance, liquidity issuance could be reinforced by specialization as those banks are more exposed to idiosyncratic risk which would constrain them more in the presence of adverse shocks. 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. Conversely,

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

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

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, bank frictions are more or less prominent. The main objective is to address if equity or liquidity-rich banks respond more for the same degree of specialization respectively. I thus separate banks into two categories for high and low levels of capital ratio and liquidity ratio based on their historical mean observed in the sample: high liquidity (equity) bank is a dummy equal to a unit if the bank is in the top distribution of the sample ratio. The results are presented in Table 4.

Two key points emerge from the table: (i) for a given level of specialization, liquid banks tend to have a higher net issuance of credit (ii) upon an easing, more liquid banks increase loan growth less than less liquid banks for a given level of specialization. To rationalize the result one should think that in general, the more liquid is the bank, the less it will face financial friction. Thus if specialization is a result of lower marginal costs in certain sectors, the bank can exploit its advantage the further it is from friction. However, when a positive liquidity shock hits the bank, specialized lenders respond more as they are relieved from their solvency constraints and can exploit their marginal advantage as the marginal returns are higher. Most interesting, being a high-liquidity bank more than halves the effect of banks' specialization alone which is captured by β_3. Put differently, for a given level of specialization in an industry, a highly liquid bank increases loan growth by roughly 40% less than low liquidity lenders. To

Table 4:
Loan growth and frictions

Effect of ΔR_t on $Specialization_{b,s}$		
	$\Delta loan_t$	
	(1)	(2)
$\Delta R_t \times$ Specialization$_{b,s}^{t\to t-12}$	15.012***	25.995***
	(3.946)	(7.457)
high capital$_b$ $\times$ Specialization$_{b,s}^{t\to t-12}$	0.020	0.027
	(0.094)	(0.099)
high liquidity$_b$ $\times$ Specialization$_{b,s}^{t\to t-12}$	0.419***	0.439***
	(0.107)	(0.111)
high capital$_b$ $\times$ $\Delta R_t \times$ Specialization$_{b,s}^{t\to t-12}$		-2.541
		(7.062)
high liquidity$_b$ $\times$ $\Delta R_t \times$ Specialization$_{b,s}^{t\to t-12}$		-14.908*
		(7.894)
Sector $\times$ Year-Quarter F.E.	✓	✓
Bank $\times$ Year-Quarter F.E.	✓	✓
Sector $\times$ Bank F.E.	✓	✓
Clustered Std.Errors	Bank-sector	Bank-sector
R^2	0.20	0.20
Obs	176,053	176,053

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

$$\log \ell_{b,s,t} - \log \ell_{b,s,t-1} = \alpha_{s,t} + \alpha_{b,t} + \alpha_{s,b} + \beta_3 \times \Delta R_t \times \ Specialization\ _{b,s}^{t-1\to t-12} + \overbrace{\sum_{x\in X} \delta_x \cdot \Delta R_t \times x_{b,t-1}}^{\textit{Bank friction}} + \overbrace{\sum_{x\in X} \zeta_x \cdot \ Specialization\ _{b,s}^{t-1\to t-12} \cdot \Delta R_t \times x_{b,t-1}}^{\textit{Bank friction interaction}} + \varepsilon_{b,s,t} \quad (8)$$

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. High capital and high liquidity banks are dummy variables based on the bank-sample mean of capital ratio and liquidity ratio. The symbols *,** and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

put this into perspective, following a 100 ppt decrease in the fed fund rate for the average level of specialization for a low liquidity bank, loan growth is increased by 4.15% annually, while for a highly liquid bank is 1.78%[3]. The evidence also shows that while capital requirements might play a role as they both enter with the same sign as the liquidity dummy, they are not

[3] $(25.995 \times 0.04 \times 4) = 4.15$ and $((25.995 - 14.908) \times 0.04 \times 4) = 1.785$.

statistically significant. For robustness, I replicate the analysis with a direct proxy measure of unexpected monetary policy shock in Table A5 and an alternative measure of specialization captured by "excess specialization" in Table A6 as above defined.

Overall, this section provides evidence of the application of standard bank frictions through the specialization channel.

3.5 Bank concentration and monetary policy: bank-level outcomes

So far my results talk about the portfolio allocation of the bank and do not indulge in the mechanism or the bank-level consequences of these reallocations. If, after an easing, specialized banks reduce their risk aversion relative to more non-specialized banks, I should see worse performances in terms of income profitability indices at the bank level. Conversely, if specialized banks have better screening and monitoring technologies, it should be easier for them to select the most trustworthy clients and potentially face lower delinquencies compared to less specialized borrowers (Blickle et al. 2021). This analysis is also revealing of the potential mechanism behind the results: if the monitoring and screening ability is at work, the portfolio reallocation can be reconciled with a flight to quality for more specialized banks that are able to seize and screen better opportunities and thus heavily load on them reallocating resources away from sectors in which their marginal advantage is lower.

In order to test this prediction I use the bank-level index of concentration described in Equation 3, 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 cross-section of banks to address how bank concentration affect 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:

$$Y_{t+h} = \alpha_t + \beta_1^h \times \ HHI_b^{\,t-1 \to t-12} + \beta_2^h \times \Delta R_t \times \ HHI_b^{\,t-1 \to t-12} + \gamma_b X_{b,t-1} + \varepsilon_{b,s,t+h} \tag{9}$$

where Y_{t+h} measure either ROA, *loan loss provision* or *charge-off rate*. All income variables used in the analysis are annualized and seasonally adjusted as in Drechsler et al. (2017, 2021).

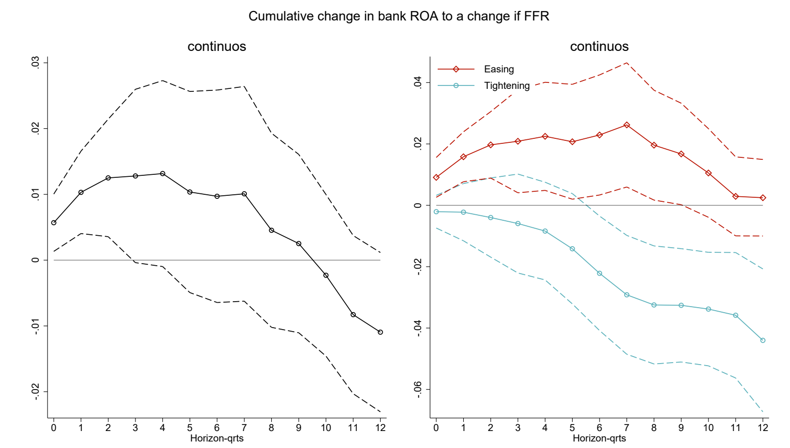
The object of interest is the effect of β_2^h, which measures the interaction between a bank's portfolio concentration and monetary policy. A positive (negative) β_2^h attached to *ROA* means that banks that are more specialized have a relatively better (worse) performance compared to less specialized lenders, similarly a negative (positive) β_2^h denotes a lower (higher) loss provision for those banks, meaning that the extent of expected losses that a bank generates is lower (higher). If specialized banks can indeed select better borrowers due to their screening advantage, then I should see a lower incur in losses and higher profitability. Instead, if those banks chase for risk as rates become relatively lower, then I should expect lower *ROA* and higher delinquencies.

Figure 3 panel a reports the impulse response of *ROA* to a standard deviation decrease in fed funds rates for the average portfolio concentration (0.21) at each horizon h.

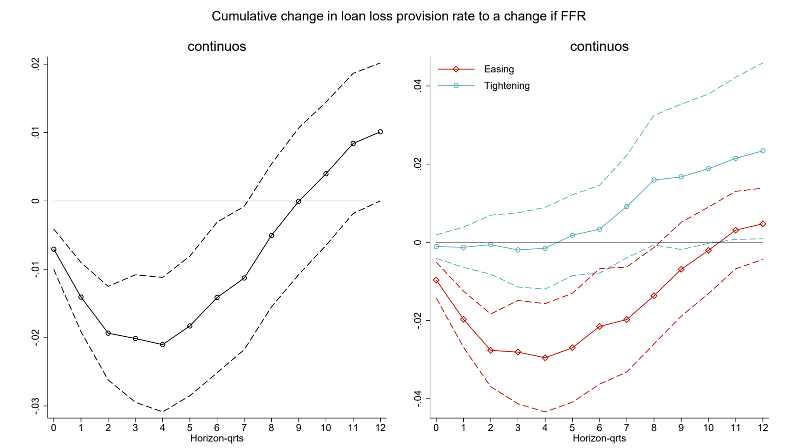
From the panel, the β_2^h is positive and significant up to 1 year, though only marginally economically relevant as the attached coefficient represents a 2 ppt increase in profitability which is only a 1% of the sample mean, however, once I look at the loan loss provision, I see instead that the magnitude is large and the magnitude explains roughly 4% of the overall observed variation. In particular panel b shows that the coefficient is negative, meaning that highly concentrated bank shows a lower loan loss provision in the cross section. This is also confirmed once I look at charge-off rates in Figure A3. Most interestingly, the effect seems to be slightly asymmetric, meaning that these highly concentrated banks perform better both in easing and tightening periods as evidenced in Figure A4 where I use monetary policy shocks. This pattern is consistent with existing literature (Iyer et al. 2022, De Jonghe et al. 2021) which shows that upon a negative shock, specialized banks reach for highly trustworthy borrowers. Overall, this evidence shows that more concentrated banks have the ability to pick better borrowers and thus ex-post have superior performance to a less specialized bank. Ultimately, the effect is also long-lasting again showing the prolonged effects of monetary policy changes.

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 or higher moral hazard. Instead, they improve their performances relative to less specialized lenders, which could potentially reduce the overall bank risk.

Figure 3:
Bank level outcomes: local projections



(a)



(b)

Note: Panel a reports coefficients and 90% confidence interval. The unit of information of the analysis is at the bank-time level. The sample consists of syndicated loans outstanding from 1990q1 until 2016q4. The reduced form model corresponds to:

$$Y_{t+h} = \alpha_t + \beta_1^h \times \ HHI\,_b^{t-1 \to t-12} + \beta_2^h \times \Delta R_t \times \ HHI\,_b^{t-1 \to t-12} + \gamma_b X_{b,t-1} + \varepsilon_{b,s,t+h}$$

The dependent variable is the *ROA* in panel a and loan loss provision in panel b at time $t+h$ observed at the bank level. The table reports the local projection coefficients for $\beta_2^h \times \Delta R_t \times \ Specialization\,_{b,s}^{t-1 \to t-12}$ at horizon h for the full saturated model (bank-time, firm-time and sector-bank fixed effect). All the estimates are based on a one standard deviation shock for the average banks' HHI average, which in the sample corresponds to 0.21. Outcome variables are annualized and seasonally adjusted.

4 Conclusion

The present study investigates the transmission of monetary policy through specialized banks, focusing on the relationship between a monetary policy easing of rates, portfolio reallocation, and its implications for aggregate bank-level outcomes. My findings reveal that, following a monetary easing, banks significantly increase their lending volume to the sectors in which they specialize. Furthermore, the degree of specialization amplifies banks' frictions, as concentrated lending portfolios become more susceptible to liquidity concerns.

By establishing this critical link between industry specialization, financial frictions, and the transmission of monetary policy, my research sheds light on the dynamics of the banking sector during periods of monetary policy adjustments. It 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 to changes in monetary policy.

Notably, my results consistently demonstrate that more concentrated banks, as measured by the Herfindahl-Hirschman Index (HHI) at the lender level, exhibit improved income performance. This finding suggests an optimal allocation of loans to better-performing firms, supporting the notion of a knowledge spillover mechanism.

These results highlight the significance of the identified reallocation channel and provide valuable insights into the broader implications of the interplay between banks' sectoral specialization and monetary policy. By uncovering the dynamics between specialization, financial frictions, and monetary policy, this study contributes to the existing literature and offers important implications for policymakers that can leverage these findings to better understand and address the evolution of credit during different policy regimes, shedding light on a previously understudied aspect of the banking industry.

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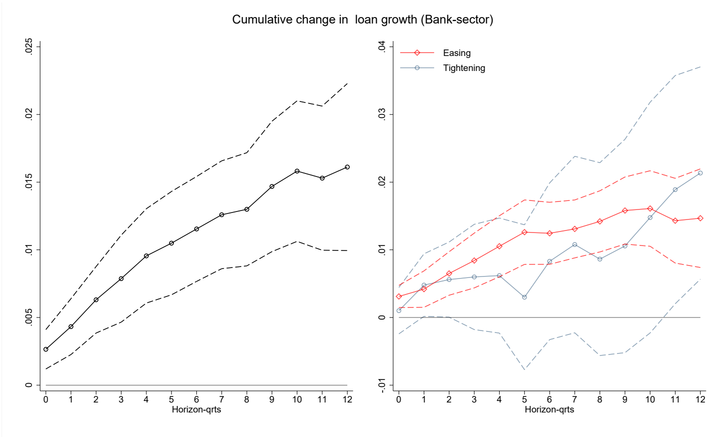
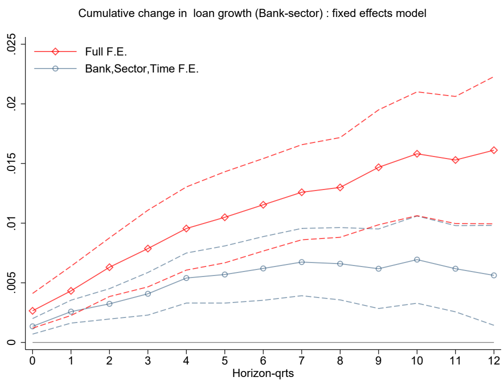
A Appendix

A.1 Figures

Figure A1:
Loan growth local projections unexpected monetary policy shock



(a)



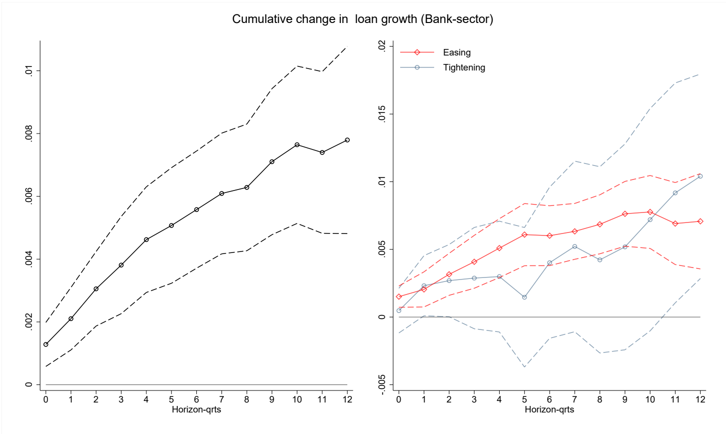
(b)

Note: Panel a reports coefficients and 90% confidence interval. 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 1990q1 until 2016q4. The reduced form model corresponds to:

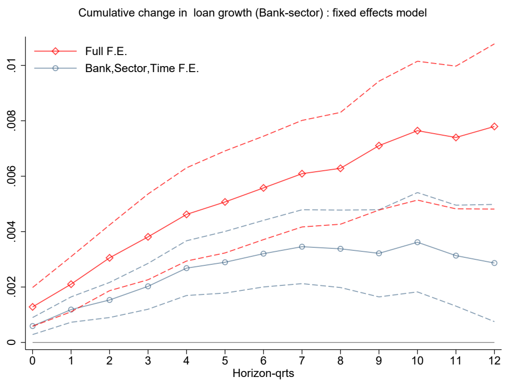
$$\log \textit{Outstanding Credit}_{b,s,t+h} - \log \textit{Outsanding Credit}_{b,s,t-1} = \alpha_{s,t+h} + \alpha_{b,t+h} + \alpha_{s,b} + \beta_1^h \times \textit{Specialization}\,_{b,s}^{t-1 \to t-12} + \beta_2^h \times \Delta R_t + \beta_3^h \times \Delta R_t \times \textit{Specialization}\,_{b,s}^{t-1 \to t-12} + \\ + \gamma_s X_{s,t-1} + \gamma_b X_{b,t-1} + \varepsilon_{b,s,t+h}$$

The dependent variable is the loan volume (outstanding and originated) held by each lender. The table reports the local projection coefficients for $\beta_3^h \times \Delta R_t \times \textit{Specialization}\,_{b,s}^{t-1 \to t-12}$ at horizon h for the full saturated model (bank-time, firm-time and sector-bank fixed effect). All the estimates are based on a one standard deviation shock for the average banks' specialization average, which in the sample corresponds to 0.04 of the total loan portfolio. Panel (a) plots the results for a change in the fed funds rate, while panel (b) plots the results comparing the β_3^h for the corresponding model in column (1) in Table 2 in red and column (5) in Table 2.

Figure A2:
Loan growth local projections unexpected monetary policy shock



(a)



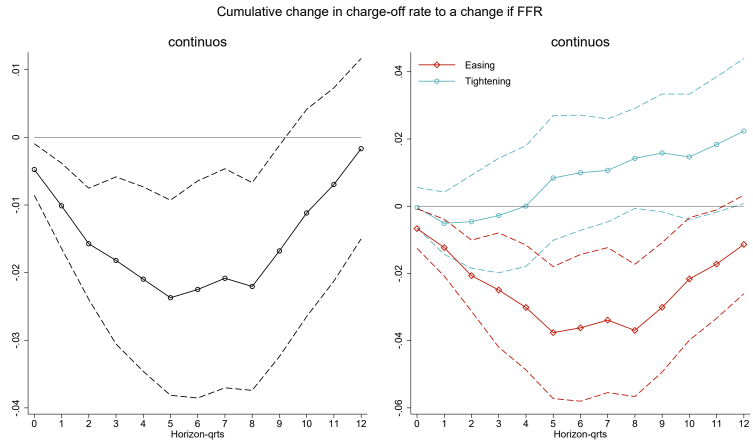
(b)

Note: Panel a reports coefficients and 90% confidence interval. 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 1990q1 until 2016q4. The reduced form model corresponds to:

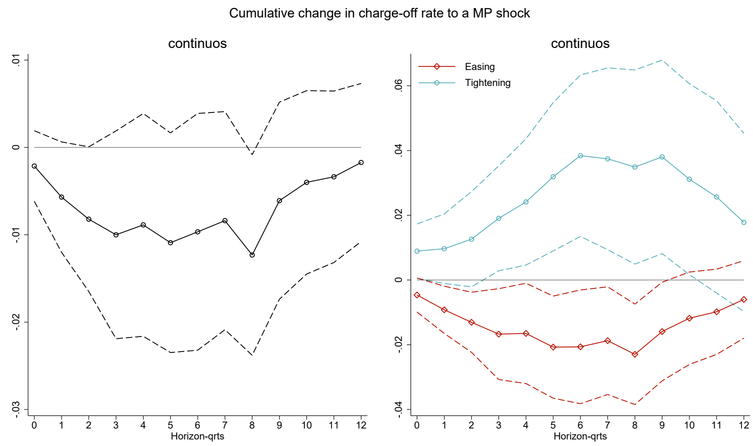
$$\log \mathit{Outstanding\ Credit}_{b,s,t+h} - \log \mathit{Outsanding\ Credit}_{b,s,t-1} = \alpha_{s,t+h} + \alpha_{b,t+h} + \alpha_{s,b} +$$
$$\beta_1^h \times \mathit{Excess\ Specialization}\ _{b,s}^{t-1 \to t-12} + \beta_2^h \times \Delta R_t + \beta_3^h \times \Delta R_t \times \mathit{Excess\ Specialization}\ _{b,s}^{t-1 \to t-12} +$$
$$+ \gamma_s X_{s,t-1} + \gamma_b X_{b,t-1} + \varepsilon_{b,s,t+h}$$

The dependent variable is the loan volume (outstanding and originated) held by each lender. The table reports the local projection coefficients for $\beta_3^h \times \Delta R_t \times$ $\mathit{Specialization}\ _{b,s}^{t-1 \to t-12}$ at horizon h for the full saturated model (bank-time, firm-time and sector-bank fixed effect). All the estimates are based on a one standard deviation shock for the average banks' specialization average, which in the sample corresponds to 0.04 of the total loan portfolio. Panel (a) plots the results for a change in the fed funds rate, while panel (b) plots the results comparing the β_3^h for the corresponding model in column (1) in Table 2 in red and column (5) in Table 2.

Figure A3:
Bank level outcomes: local projections



(a)



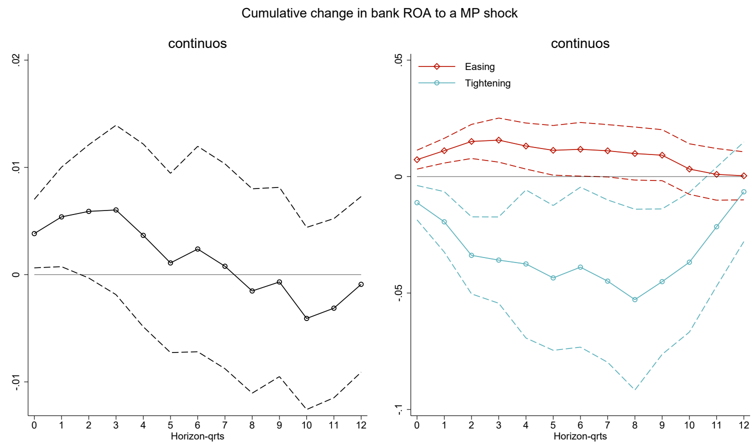
(b)

Note: Panel a reports coefficients and 90% confidence interval. The unit of information of the analysis is at the bank-time level. The sample consists of syndicated loans outstanding from 1990q1 until 2016q4. The reduced form model corresponds to:

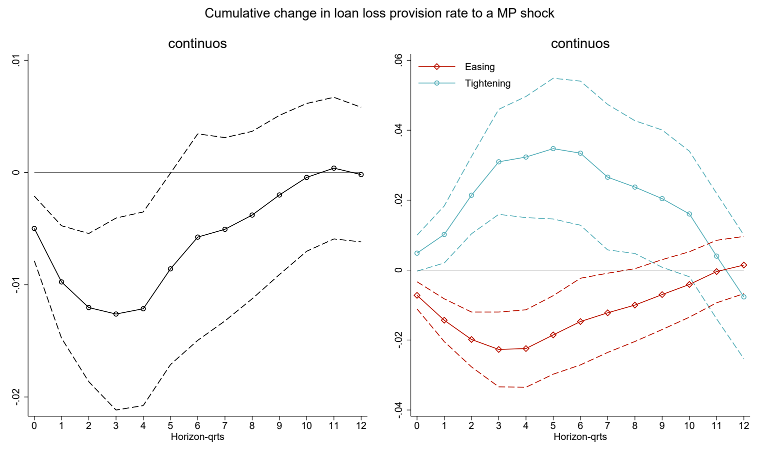
$$Y_{t+h} = \alpha_t + \beta_1^h \times \ HHI_b^{t-1 \rightarrow t-12} + \beta_2^h \times \Delta R_t \times \ HHI_b^{t-1 \rightarrow t-12} + \gamma_b X_{b,t-1} + \varepsilon_{b,s,t+h}$$

The dependent variable is the charge-off rate at time $t+h$ observed at the bank level. The table reports the local projection coefficients for $\beta_2^h \times \Delta R_t \times$ *Specialization* $_{b,s}^{t-1 \rightarrow t-12}$ at horizon h for the full saturated model (bank-time, firm-time and sector-bank fixed effect). All the estimates are based on a one standard deviation shock for the average banks' HHI average, which in the sample corresponds to 0.21. Outcome variables are annualized and seasonally adjusted. Panel a represent the effect of a decrease in the monetary policy rate, while panel b for an unexpected change in monetary policy easing.

Figure A4:
Bank level outcomes: local projections



(a)



(b)

Note: Panel a reports coefficients and 90% confidence interval. The unit of information of the analysis is at the bank-time level. The sample consists of syndicated loans outstanding from 1990q1 until 2016q4. The reduced form model corresponds to:

$$Y_{t+h} = \alpha_t + \beta_1^h \times \ HHI_{b}^{t-1\to t-12} + \beta_2^h \times \Delta R_t \times \ HHI_{b}^{t-1\to t-12} + \gamma_b X_{b,t-1} + \varepsilon_{b,s,t+h}$$

The dependent variable is the ROA in panel a and loan loss provision in panel b at time $t+h$ observed at the bank level. The table reports the local projection coefficients for $\beta_2^h \times \Delta R_t \times \ Specialization_{b,s}^{t-1\to t-12}$ at horizon h for the full saturated model (bank-time, firm-time and sector-bank fixed effect). All the estimates are based on a one standard deviation shock for the average banks' HHI average, which in the sample corresponds to 0.21. Outcome variables are annualized and seasonally adjusted.

A.2 Tables

Table A1:
Loan growth: unexpected monetary policy shocks

Effect of *M.P. shock* $_t$ on $Specialization_{b,s}$					
	$\Delta loan_t$				
	(1)	(2)	(3)	(4)	(5)
M.P. shock $_t$					-0.005
					(0.016)
Specialization$_{b,s}^{t\to t-12}$	-0.692***	-0.294***	-0.705***	-0.307***	-0.290***
	(0.060)	(0.030)	(0.063)	(0.034)	(0.032)
M.P. shock $_t\times$ Specialization$_{b,s}^{t\to t-12}$	0.877***	0.406***	0.879***	0.418***	0.360***
	(0.274)	(0.125)	(0.275)	(0.130)	(0.125)
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
R^2	0.20	0.13	0.12	0.05	0.04
Obs	176,053	176,467	176,070	176,484	176,484

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:

$$\log Outstanding\ Credit_{b,s,t} - \log Outsanding\ Credit_{b,s,t-1} = \alpha_{s,t} + \alpha_{b,t} + \alpha_{s,b} + \beta_1 \times\ Specialization\ _{b,s}^{t-1\to t-12} + \beta_2 \times \Delta R_t + \beta_3 \times \Delta R_t \times\ Specialization\ _{b,s}^{t-1\to t-12} + + \gamma_s X_{s,t-1} + \gamma_b X_{b,t-1} + \varepsilon_{b,s,t+h}$$

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 restrive version (1) to least (5). $X_{s,t}$ is a vector of sector control variable including the sector rediployability index measured as Kim & 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 A2:
Loan growth (Excess Specialization): unexpected monetary policy shocks

Effect of *M.P. shock* $_t$ on *Excess Specialization* $^{t\to t-12}_{b,s}$					
	$\Delta loan_t$				
	(1)	(2)	(3)	(4)	(5)
M.P. shock $_t$					-0.003
					(0.015)
Excess Specialization $^{t\to t-12}_{b,s}$	-0.692***	-0.294***	-0.688***	-0.292***	-0.267***
	(0.060)	(0.030)	(0.061)	(0.031)	(0.030)
M.P. shock $_t\times$ *Excess Specialization* $^{t\to t-12}_{b,s}$	0.880***	0.410***	0.824***	0.387***	0.333***
	(0.273)	(0.127)	(0.278)	(0.129)	(0.119)
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
R^2	0.20	0.13	0.12	0.05	0.04
Obs	176,053	176,467	176,070	176,484	176,484

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:

$$\log \textit{Outstanding Credit}_{b,s,t} - \log \textit{Outsanding Credit}_{b,s,t-1} = \alpha_{s,t} + \alpha_{b,t} + \alpha_{s,b} + \beta_1 \times \textit{ Excess }^{t-1\to t-12}_{b,s} + \beta_2 \times \Delta R_t + \beta_3 \times \Delta R_t \times \textit{ Excess }^{t-1\to t-12}_{b,s} + \gamma_s X_{s,t-1} + \gamma_b X_{b,t-1} + \varepsilon_{b,s,t+h}$$

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* $^{t-1\to t-12}_{b,s}$ 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 restrive version (1) to least (5). $X_{s,t}$ is a vector of sector control variable including the sector rediployability index measured as Kim & 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 A3:
Horse-race: unexpected monetary policy shocks

Effect of *M.P. shock* $_t$ on $Specialization_{b,s}$				
	$\Delta loan_t$			
	(1)	(2)	(3)	(4)
$\text{Specialization}_{b,s}^{t\to t-12}$	-0.692***	-0.732***	-0.617***	-0.240***
	(0.060)	(0.067)	(0.055)	(0.025)
M.P. shock $_t \times$ $\text{Specialization}_{b,s}^{t\to t-12}$	0.877***	0.861***	0.756***	0.357***
	(0.274)	(0.287)	(0.273)	(0.123)
Lag $\Delta loan_t$		-0.049***		
		(0.004)		
$Mkt\ share_{b,s}^{t\to t-12}$			-0.867***	-0.899***
			(0.128)	(0.113)
M.P. shock $_t \times$ $Mkt\ share_{b,s}^{t\to t-12}$			1.048**	0.539
			(0.506)	(0.390)
M.P. shock $_t \times$ Bank size				-0.012
				(0.012)
M.P. shock $_t \times$ Bank equity ratio				0.057
				(0.617)
M.P. shock $_t \times$ Bank security ratio				0.008
				(0.110)
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	Bank-sector
R^2	0.20	0.20	0.20	0.13
Obs	176,053	172,088	176,053	176,467

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:

$$\log \ell_{b,s,t+h} - \log \ell_{b,s,t-1} = \alpha_{s,t} + \alpha_{b,t} + \alpha_{s,b} + \beta_3^h \times \Delta R_t \times \ Specialization\ _{b,s}^{t-1\to t-12} + \sum_{x\in X} \delta_x \cdot \Delta R_t \times x_{b,t-1} + \gamma_b X_{b,t-1} + \varepsilon_{b,s,t} \quad (10)$$

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 restrive version (1) to least (5). $X_{s,t}$ is a vector of sector control variable including the sector rediployability index measured as Kim & 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*) and the main explanatory variable itself 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 A4:
Horse-race (Excess Specialization): unexpected monetary policy shocks

Effect of *M.P. shock* $_t$ on *Excess Specialization* $^{t\to t-12}_{b,s}$				
	$\Delta loan_t$			
	(1)	(2)	(3)	(4)
Excess Specialization $^{t\to t-12}_{b,s}$	-0.692***	-0.733***	-0.618***	-0.236***
	(0.060)	(0.067)	(0.056)	(0.024)
M.P. shock $_t \times$ *Excess Specialization* $^{t\to t-12}_{b,s}$	0.880***	0.866***	0.758***	0.362***
	(0.273)	(0.287)	(0.273)	(0.124)
Lag $\Delta loan_t$		-0.049***		
		(0.004)		
Mkt share $^{t\to t-12}_{b,s}$			-0.866***	-0.906***
			(0.127)	(0.117)
M.P. shock $_t \times$ *Mkt share* $^{t\to t-12}_{b,s}$			1.048**	0.539
			(0.505)	(0.391)
M.P. shock $_t \times$ Bank size				-0.012
				(0.011)
M.P. shock $_t \times$ Bank equity ratio				0.047
				(0.612)
M.P. shock $_t \times$ Bank security ratio				0.011
				(0.110)
Bank C.I. loans to assets				0.060
				(0.051)
Bank R.E. loans to assets				-0.003
				(0.057)
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	Bank-sector
R^2	0.20	0.20	0.20	0.13
Obs	176,053	172,088	176,053	176,467

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:

$$\log \ell_{b,s,t+h} - \log \ell_{b,s,t-1} = \alpha_{s,t} + \alpha_{b,t} + \alpha_{s,b} + \beta_3^h \times \Delta R_t \times \textit{Excess Specialization}\ ^{t-1\to t-12}_{b,s} + \sum_{x\in X} \delta_x \cdot \Delta R_t \times x_{b,t-1} + \gamma_b X_{b,t-1} + \varepsilon_{b,s,t} \quad (11)$$

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* $^{t-1\to t-12}_{b,s}$ 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 restrive version (1) to least (5). $X_{b,t}$ is a vector of bank time-varying characteristics such as size, capital ratio, security ratio, deposit ratio and banks' profitability (*ROA*) and the main explanatory variable itself 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 A5:
Loan growth and frictions: unexpected mp shock

Effect of *M.P. shock* $_t$ on $Specialization_{b,s}$		
	$\Delta loan_t$	
	(1)	(2)
M.P. shock $_t \times$ Specialization$_{b,s}^{t\to t-12}$	0.882***	1.059**
	(0.274)	(0.458)
high capital$_b$ $\times$ Specialization$_{b,s}^{t\to t-12}$	0.025	0.019
	(0.095)	(0.096)
high liquidity$_b$ $\times$ Specialization$_{b,s}^{t\to t-12}$	0.414***	0.427***
	(0.106)	(0.108)
high capital$_b$ $\times$ *M.P. shock* $_t \times$ Specialization$_{b,s}^{t\to t-12}$		0.212
		(0.425)
high liquidity$_b$ $\times$ *M.P. shock* $_t \times$ Specialization$_{b,s}^{t\to t-12}$		-0.458
		(0.397)
Sector $\times$ Year-Quarter F.E.	✓	✓
Bank $\times$ Year-Quarter F.E.	✓	✓
Sector $\times$ Bank F.E.	✓	✓
Clustered Std.Errors	Bank-sector	Bank-sector
R^2	0.20	0.20
Obs	176,053	176,053

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

$$\log \ell_{b,s,t} - \log \ell_{b,s,t-1} = \alpha_{s,t} + \alpha_{b,t} + \alpha_{s,b} +$$

$$\beta_3 \times \Delta R_t \times \ Specialization\ _{b,s}^{t-1\to t-12} + \overbrace{\sum_{x\in X} \delta_x \cdot \Delta R_t \times x_{b,t-1}}^{Bank\ friction} +$$

$$\overbrace{\sum_{x\in X} \zeta_x \cdot \ Specialization\ _{b,s}^{t-1\to t-12} \cdot \Delta R_t \times x_{b,t-1}}^{Bank\ friction\ interaction} + \varepsilon_{b,s,t}$$

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. High capital and high liquidity banks are dummy variables based on the bank-sample mean of capital ratio and liquidity ratio. The symbols *,** and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table A6:
Loan growth and frictions (Excess Specialization)

Effect of *M.P. shock* $_t$ on		
	$\Delta loan_t$	
	(1)	(2)
M.P. shock $_t\times$ *Excessive Specialization*$_{b,s}^{t\to t-12}$	0.885***	1.206**
	(0.272)	(0.459)
high capital b$\times$ *Excessive Specialization*$_{b,s}^{t\to t-12}$	0.031	0.025
	(0.095)	(0.097)
high liquidity b$\times$ *Excessive Specialization*$_{b,s}^{t\to t-12}$	0.411***	0.431***
	(0.105)	(0.108)
high capital b$\times$ *M.P. shock* $_t\times$ *Excessive Specialization*$_{b,s}^{t\to t-12}$		0.227
		(0.450)
high liquidity b$\times$ *M.P. shock* $_t\times$ *Excessive Specialization*$_{b,s}^{t\to t-12}$		-0.700*
		(0.383)
Sector $\times$ Year-Quarter F.E.	✓	✓
Bank $\times$ Year-Quarter F.E.	✓	✓
Sector $\times$ Bank F.E.	✓	✓
Clustered Std.Errors	Bank-sector	Bank-sector
R^2	0.20	0.20
Obs	176,053	176,053

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

$$\log \ell_{b,s,t} - \log \ell_{b,s,t-1} = \alpha_{s,t} + \alpha_{b,t} + \alpha_{s,b} + \beta_3 \times \Delta R_t \times \textit{ Excess Specialization } _{b,s}^{t-1\to t-12} + \overbrace{\sum_{x\in X} \delta_x \cdot \Delta R_t \times x_{b,t-1}}^{\textit{Bank friction}} + \overbrace{\sum_{x\in X} \zeta_x \cdot \textit{ Excess Specialization } _{b,s}^{t-1\to t-12} \cdot \Delta R_t \times x_{b,t-1}}^{\textit{Bank friction interaction}} + \varepsilon_{b,s,t}$$

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. *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. High capital and high liquidity banks are dummy variables based on the bank-sample mean of capital ratio and liquidity ratio. The symbols *,** and *** indicate significance at the 10%, 5%, and 1% levels, respectively.