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Banking System Market Structure and Corporate Credit Patterns

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To Rebecca and my parents

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Abstract

This thesis explores the interplay between financial intermediation and economic conditions. It examines how banks' industry specialization interacts with monetary policies and how collateral value uncertainties shape the lending behaviors of financial intermediaries. The first chapter reveals that banks with industry specialization adjust lending practices significantly in response to monetary policy changes, leveraging sector-specific knowledge to enhance loan performance. The second chapter investigates the effects of collateral value uncertainty on banks' lending decisions, showing that high uncertainty increases banks' real estate lending at the expense of commercial loans, impacting profitability and loan performance. The third chapter demonstrates how firms invest in intangible customer capital to enhance borrowing capacity through unsecured debt. Integrating these insights, the thesis underscores how financial intermediation influences economic outcomes, offering valuable implications for policy and financial practices.

Resum

Esta tesis explora la interacción entre la intermediación financiera y las condiciones económicas, enfocándose en cómo la especialización de los bancos y la incertidumbre del valor del colateral afectan las políticas de préstamo. El primer capítulo muestra que los bancos con especialización industrial ajustan sus prácticas de préstamo en respuesta a cambios en la política monetaria, utilizando su conocimiento sectorial para mejorar el rendimiento de los préstamos. El segundo capítulo revela que la incertidumbre en el valor del colateral incrementa los préstamos inmobiliarios de los bancos, afectando la rentabilidad. El tercer capítulo indica cómo las empresas invierten en capital cliente para aumentar su capacidad de obtener deuda no garantizada. Integrando estos hallazgos, la tesis destaca cómo la intermediación financiera influye en los resultados económicos, ofreciendo implicaciones importantes para la política y las prácticas financieras.

Preface

This thesis investigates the dynamic interactions between financial intermediation and economic conditions, and their consequential impacts on non-financial companies (NFCs). It delves into how financial intermediaries shape the operational and financial contours of firms, focusing on the influence of monetary policies and the uncertainties tied to collateral values. Additionally, the thesis explores the market structure of financial firms and provides insights into how financial frictions affect both NFCs and lenders, ultimately influencing broader economic outcomes. Overall, this thesis provides a rich analysis of the interactions between financial intermediation and the economic decisions and outcomes of non-financial companies (NFCs).

The first chapter studies how banks' industry specialization affects monetary policy transmission and shows how banks leverage their industry-specific knowledge to tailor their lending practices in response to monetary policy changes. This question is important in that monetary policy shapes economic activity by influencing bank's lending decisions, however despite the prominence of banks industry specialization and its consequence on lending outcomes, little is know on how it affect monetary policy transmission. Using detailed U.S. syndicated loan data, the analysis reveals that banks with higher degrees of industry specialization increase their lending relatively more in their sectors of specialization following an expansionary monetary policy shock. Moreover, studying bank-level performance it shows that banks more specialized have relative improved loan performance compared to less specialized banks upon a expansionary monetary policy shock consistent with specialized banks exploiting their informational advantage, gather through industry specialization, to select better borrowers. A simple model featuring lender-level differences in monitoring capacity across sectors can rationalize at the same time different specialization patterns within banks and the observed effect of monetary policy on loan portfolio re-balances. The results provide a new channel through which monetary policy influences the real economy, mediated by the specialized knowledge of financial intermediaries.

The second chapter delves into the dynamics of collateral value uncertainty and its impact on banks' lending decisions, particularly comparing real estate loans and commercial loans. This question is of crucial importance as fluctuation in collateral prices affect banks' behavior, in particular crowding out of commercial lending amid asset price fluctuations. However, little is understood about how ex ante uncertainty in collateral values shapes banks' lending decisions. By examining the response of banks to local collateral value uncertainty, the study uncovers how variations in collateral values affect banks' portfolio decisions and profitability. In particular, it finds that banks with greater exposure to regions with high collateral uncertainty tend to increase their real estate lending with respect to commercial loans. While doing so they retain higher fraction of real estate loans inside their portfolios. The study finds evidence of inefficient holding of real estate loans as bank more exposed to collateral uncertainty suffer from reduced profitability and higher loan delinquencies, thereby highlighting the broader economic implications of collateral price uncertainty on financial stability.

The third chapter explores how firms finance their investment in customer capital—a critical but intangible asset that enhances firms' future revenue potentials but cannot be directly pledged as collateral. This part of the thesis shows a positive correlation between firms' expenditures on customer acquisition and their reliance on unsecured debt. It proposes and empirically validates a model where increased customer capital investment boosts firms' cash flows and market valuations, thereby enhancing their capacity via unsecured financing. The chapter propose a model that rationalize the empirical findings into a framework featuring frictional goods markets in which firms need to invest in marketing spending to attract customers and its subject to financial frictions. This segment of the research underscores the importance of customer capital in corporate financing decisions and its impact on firms' debt structures.

By weaving together these themes, this thesis provides a deeper understanding of how specific attributes of financial intermediation—such as industry specialization and the management of collateral risk—influence lending behaviors and, consequently, the broader economic outcomes.

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Chapter 1

SPECIALIZED BANKS AND THE TRANSMISSION OF MONETARY POLICY:

EVIDENCE FROM THE U.S. SYNDICATED LOAN MARKET

1.1 Introduction

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

Since banks are responsible for selecting credit-worthy borrowers and monitoring loans, they are subject to costly information acquisition. Banks specialize in specific industries due to their information advantage built over repeated interactions with borrowers in similar industries (Blickle et al., 2021; Giometti et al., 2022), resulting in heterogeneous bank presence in distinct industries. Therefore, banks' portfolio is far from diversified, with lenders generally allocating 15% or more of their Commercial and Industrial loans (C&I) into their preferred industry (Figure 1.1a)[1]. Crucially, this pattern is not driven by an industry's prominence in the market (Figure 1.1b). Banks' industry specialization has, then, been shown to significantly impact credit allocation (Paravisini et al., 2023), security design (Giometti et al., 2022) and reaction to shocks (De Jonghe et al., 2020; Iyer et al., 2022). While much of the literature examined the transmission of industry-specific shocks for specialized banks, limited evidence exists concerning the role of specialized banks in the transmission of monetary policy. Does the banks' exposure to specific sectors influence monetary policy transmission? And if so, how? In other words, do banks exploit their informational advantage in reaction to monetary policy shock, and if so, how does this affect the riskiness of their portfolios and aggregate outcomes?

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

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

delinquency rates and higher market capitalization[2]. These findings are consistent with specialized banks exploiting their informational advantage to select better borrowers without compromising monitoring activity. Finally, I document the aggregate sector impact of banks' specialization by aggregating lending volumes at the sector level. Sectors with higher exposure to specialized lenders experience increased lending volumes following a rate reduction.

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

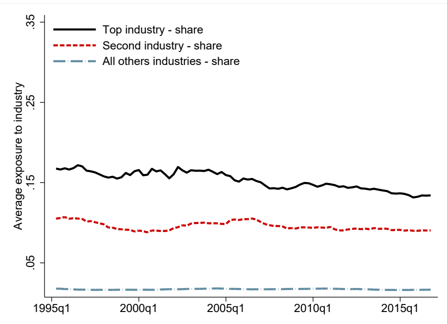
To examine the role that bank specialization plays in the provision of credit supply in the presence of monetary policy changes, I use granular data for bank loans from the US syndicated loan market between 1987 and 2016 at quarterly frequency. Syndicated loan-level data involve multiple lenders jointly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

I identify monetary policy shocks by utilizing high-frequency surprises in interest rate futures contracts within a 30-minute window around the policy, fol-

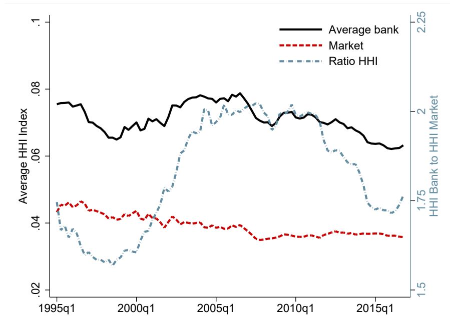
[2] Banks' portfolio concentration measures the overall bank-level degree of specialization, higher levels of industry specialization are associated with higher levels of portfolio concentration.

Figure 1.1:
Banks portfolio concentration

(a) Average share allocated to each industry



(b) Banks' and market average concentration



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

lowing the approach outlined by Gürkaynak et al. (2004) and Gertler and Karadi (2015). This method ensures the isolation of exogenous rate variations from other macroeconomic factors and minimizes potential issues of reverse causality.

The main unit of analysis is the outstanding credit volume at the bank-sector-quarter level. My analysis is subject to a common identification challenge in the empirical banking literature: unobserved changes in industry-level lending opportunities and bank-level heterogeneity could bias my results and prevent identifying the bank's loan supply effect stemming from banks' industry specialization.

I address this identification challenge by exploiting the disaggregated nature of the data and saturating the bank-sector level regression with granular bank-time, sector-time, and bank-sector fixed effects that isolate credit supply and demand effects at the bank-sector level (Khwaja and Mian, 2008; Jiménez et al., 2012), which could otherwise drive my results. I thus compare the credit growth of the same bank across different sectors. The identifying assumption posits that banks face uniform demand across sectors, regardless of their degree of specialization. To reduce any concern on confounding effect between monetary policy and my measure of specialization I employ slow moving averages for my measure of specialization as Paravisini et al. (2023) and Giometti et al. (2022).

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

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

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

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

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

The second set of results explores the implications of banks' specialization at the bank level and its interaction with monetary policy. To quantify the degree of specialization at the bank level, I construct a measure of concentration using the Herfindahl-Hirschman Index (HHI) based on the level of specialization in each industry. According to existing theories and evidence, periods of cheap credit may foster a build-up in risk with potential consequences for the aggregate economy (Granja et al., 2022). Specialized banks can exploit their informational advantage and select high-quality borrowers and seize higher returns (Blickle et al., 2021; Giometti et al., 2022) or instead, as yields are compressed by low rates, they can focus on risky borrowers in their industry of specialization and shirk their costly monitoring duties in the hope of higher returns (Degryse et al., 2021; Eufinger et al., 2022). To answer this question, I look at bank-level income performance and delinquencies for different degrees of portfolio concentration. My findings indicate that banks with higher levels of concentration experience an increase in return on assets (ROA) and a reduction in the charge-off rate of 3 and 4 bps, respectively, in response to a one standard deviation reduction in the funding rate[4].

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

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

These estimates represent 4% (1%) of the standard deviation (mean) and 5% (6%) of the standard deviation (mean) for the observed variation of their respective distributions over the corresponding horizon. These effects are more pronounced and enduring for lead lenders, confirming that specialized banks use their screening capabilities to select better borrowers and increase returns, consistent with the heightened monitoring activity linked to lead arrangers in syndicated lending (Botsch and Vanasco, 2019; Blickle et al., 2020).

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

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

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

Related literature: My results speak to several strands of literature. First, I add to the large literature that studies the role of banks' heterogeneity in the transmission of monetary policy (Kashyap and Stein, 1995, 2000; Jiménez et al., 2012, 2022; Drechsler et al., 2017; Gomez et al., 2021) in particular, they show that weak balance sheet amplifies the transmission of monetary policy. The existing papers highlighted the prominent role of balance sheet channels such as size Kashyap and Stein (1995) and balance sheet characteristic Kashyap and Stein (2000); Jiménez et al. (2012), market structure (Drechsler et al., 2017) and the exposure to interest rate risk (Gomez et al., 2021) in the transmission of monetary policy. I add to this literature by providing compelling evidence on how bank industry specialization works beyond them and acts as a key driver of credit supply responses to fed funds changes. When the central bank lowers interest rates, it promotes banks to increase their lending towards the sectors in which they have specialised as they find them more attractive. In addition, my findings suggest that this channel is amplified by banks' financial frictions. To the best of my knowledge, this paper is the first to focus on identifying how banks' sectoral specialization interacts with monetary policy.

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

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

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

The rest of the paper is structured as follows. Section 1.2 presents the data and the approach that I use to measure the main variables of interest. The micro level results and the empirical methodology discussion are reported in Section 1.3.

Section 1.4 examines the bank level implications on income performances and delinquencies. Section 1.5 reports the aggregate implications on sector lending and economic activity. The model is presented in 1.6. Section 1.7 concludes.

1.2 Data and measurement

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

1.2.1 Data

In this paper, I combine several data sources: LPC Dealscan, Small Business Administration 7(a) loans data, FR Y-9C reports, Compustat firm-level data, industry-level data coming from the Bureau of Economic Analysis (BEA). My primary data sources come from LPC Dealscan and FR Y-9C reports which I use to obtain information on US business loans and bank industry exposure, while the latter is used to obtain bank-level characteristics for US bank holding companies (BHC). In the absence of bank data on all credit disaggregated by sectoral markets, I focus on a sample of matched banks to the syndicated market as it covers the vast majority of commercial credit in US (Chodorow-Reich, 2014; Giannetti and Saidi, 2019; Iyer et al., 2022).

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

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

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

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

Consistently with other studies, in order to dissect the effect of aggregate shock on credit supply I retain information for both participant and lead arrangers (Chodorow-Reich, 2014; Doerr and Schaz, 2021; Gomez et al., 2021) and focus on all completed loans issued in the US. Even though lead lenders are more relevant for pricing, as already discussed, the focal point of the analysis is a bank's credit supply, including both lead arrangers and participants provides a better picture of the syndicated loan market and reduces sample selection bias. To identify the lead arranger(s) and participants I follow the procedure outlined in Chakraborty et al. (2018) which is based on a scoring ranking exploiting the role of each lender in the syndicate in the spirit of Bharath et al. (2011). I finally restrict the sample of loans origination between 1991 and 2016 since the coverage is sparse before and as I lose the initial years to define banks' specialization shares as it will be clear from Section 1.2.2. Most importantly, to measure banks specialization, I use the whole sample of observation (1987-2016), this choice does not affect the results. For the empirical analysis, I further restrict the sample to loans whose borrowers have headquarters in the US (Compustat Foreign Incorporation Code), whenever this information is available. In the empirical analysis, I also drop from the sample all loans to financial corporations, utilities and public sector companies.

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

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

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

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

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

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

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

This data set contains loan-level information on the identity, address, city, and industry of the borrowers and corresponding lenders identifier as well as loan characteristics such as total amount, amount of the SBA's loan guarantee, initial

[5] Lenders pay the SBA a fee based on loan features and the guaranteed amount.

interest rate, approval date, loan status (performing/default) and jobs supported by each loan. The dataset includes information on the charge-off amount and date on its loan guarantee, a loan is charge-off. Following Granja et al. (2022) and Di and Pattison (2022), I exclude canceled loans from the analysis because cancellation may be at the initiative of the borrower.

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

$$\varepsilon_t = \frac{D}{D-t}\left(\mathrm{ffr}_{t+\Delta^+} - \mathrm{ffr}_{t-\Delta^-}\right) \tag{1.1}$$

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

[6]The series was made available in Jarociński and Karadi (2020).

1.2.2 Measuring bank specialization

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

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

$$Specialization_{b,s,t} = \frac{Loan\ outstanding\ _{b,s,t}}{\sum_s\ Loan\ outstanding\ _{b,s,t}} := s_{b,s,t} \tag{1.2}$$

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

I face two main data limitations with respect to variable construction: (i) one is the availability of the loan shares that each arranger supplies within a loan (ii) and the other is to correctly measure the exposure to each industry from retained loan shares. To tackle the first issue, I follow Blickle et al. (2020) and estimate the shares for each loan across the syndicate exploiting loan level information, I detail the procedure in subsection C.1[7].

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

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

which comprises 71 industries based on NAICS codes.

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

$$\textit{Excess Specialization}_{b,s,t} = \frac{\textit{Loan outstanding}_{\ b,s,t}}{\sum_s \textit{Loan outstanding}_{\ b,s,t}} - \frac{\textit{Loan outstanding}_{\ s,t}}{\sum_s \textit{Loan outstanding}_{\ s,t}} \tag{1.3}$$

The measure captures the "excess" specialization of a bank in a sector as it reflects the degree to which a bank is over-invested relative to the "optimal" industry weight in the market (Blickle et al., 2021). This measure is not bounded at 0 and can take negative values. Moreover, tails are less likely 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 1.2.

$$HHI_{b,s} = \sum_{j=1}^{J} (s_{b,s,t})^2 \tag{1.4}$$

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

1.2.3 Evidence of specialization & summary statistic

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

I first show evidence of the pervasive feature of banks' industry specialization (Blickle et al., 2021). As shown in Figure 1.1 the average (weighted) share of C&I loans, in my sample, devoted to the top industry is roughly 15%. They comprise more than 20% of the bank's loan portfolio, together with the second industry share, while the average share devoted to all other industry is marginal (Blickle et al., 2021). Overall Figure 1.1a, tells that the banks in my sample only have one or two preferred industries, which remain stable over time.

Measuring banks' industry specialization with banks-sector share can, however, be biased by the prominence of certain industry in the market. To better gauge the extent of banks' specialization and address this point, I compare the average banks' HHI portfolio with the one of the market in the same spirit as in Giometti et al. (2022).

I show in Figure 1.1b that banks' specialization is not a mere product of industry concentration: according to this evidence, banks' portfolios are far more concentrated and less diversified than those of the market. Banks' portfolio concentration is on average twice as large as the one of the market as can been seen by the ratio of the two. This highlights two facts: first the average bank is more concentrated than the market and second not all banks are lending to every industry in the same way.

Finally, Table 1.1 provides the summary statics for the main variable of interest and controls used in the analysis.

The first section reports information at the loan level, From the second to the fourth section I present bank-sector level moments and bank-level moments respectively, which is the main level of the analysis. In the table, I show the main measures of specialization and the "excess" specialization. At the bank sector level, the average degree of specialization for the dealscan sample is around 3%, while the one for small business lending data is considerably higher. However I show in Figure A.7 that in the matched sample, there is high correlation between the Dealscan measure and the corresponding one in the SBA dataset.

Of course, this measure of specialization is driven down by all those sectors in which the bank is not specialized as can be seen from panel (a) in Figure 1.1. The measure of excess specialization shows a considerable right fat tail distribution, which again is evidence of the wide degree of variation of specialization across banks and industries. Bank-level variables come from the matched sample for banks and the Dealscan panel in my analysis where income variables such as *ROA*, *chargeoffrate* and *provision for loan and lease losses rate* are annualized and scaled to percentages. The remainder of the tables describes the information at the sector and aggregate level. The industry asset redeployability index is constructed using data from Kim and Kung (2017), which measures the pledgeability of an asset or its ability to serve as collateral for the average asset in the industry. In the next session, I study how a monetary policy cuts affects banks' credit supply for banks with different levels of industry specialization.

Table 1.1:
Summary statistics

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

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

1.3 Empirical results: bank-sector lending around monetary policy change

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

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

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

To reach these conclusions, I compare the difference in the credit growth volume of outstanding business loans by each bank in each sector as a function of the bank's specialization around changes in monetary policy cuts. To make sure that my results are not driven by sporadic changes in the main explanatory variable, I take a slow-moving lag of my measure of specialization over a three-year horizon to avoid being of the same duration as the observed loan maturity in the sample (roughly 4 years). I construct my main outcome variable aggregating all the loans outstanding between the bank and a sector at the quarterly level to have sensible variation and enough issuance frequency (Acharya et al., 2018, 2019), this clustering approach also has been used by Degryse et al. (2019), who show that it leads to similar results as the firm fixed effects approach, and, importantly, does not create any bias in the estimation. I present further robustness using loan-level information and bank-firm fixed effect in section B.

1.3.1 Bank specialization and monetary policy: bank-sector outcomes

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

$$\begin{aligned}&\overbrace{\log \ell_{b,s,t+h} - \log \ell_{b,s,t-1}}^{\textit{Change in credit}} = \alpha^h_{s,t} + \alpha^h_{b,t} + \alpha^h_{s,b} + \\ &\beta^h_1 \times \textit{Specialization}\,^{t-1 \to t-12}_{b,s} + \beta^h_2 \times \varepsilon + \beta^h_3 \times \varepsilon \times \textit{Specialization}\,^{t-1 \to t-12}_{b,s} + \\ &\qquad\qquad \gamma^h_b X_{b,t-1} + \gamma^h_s X_{s,t-1} + u_{b,s,t+h} \qquad (1.5)\end{aligned}$$

The dependent variable is the natural logarithm of the loan growth amount from bank b to sector s at time t and measures the degree of growth between the bank and the sector over the quarter. The main explanatory variable of interest is $\beta_3 \times \varepsilon \times \textit{Specialization}\,^{t-1 \to t-12}_{b,s}$, which captures the interaction between monetary policy change and a lagged 12-quarters rolling average of the specialization measure defined in Equation 1.2. $X_{s,t}$ is a vector of sector control variable including the sector redeployability index measured as Kim and Kung (2017), 2 lags of change in sectoral gross output changes in sectoral TFP and labour unit (index to 2012 levels) which can affect the sectoral demand side. I also control for time-varying bank-level characteristics captured in the $X_{b,t}$ vector that includes: size, capital ratio, security ratio, deposit ratio, and banks' profitability (ROA) to control for bank supply characteristics that can affect both my outcome variables as well as the explanatory variable.

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

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

Motivated by existing literature, a bank faces the following tradeoff (Goetz et al., 2016): the specialized banks . Depending on the strength of each of the forces, one should expect a positive or negative effect on the interaction β_3 upon an easing of monetary policy. A positive (negative) sign of β_3 indicates that banks that are more specialized, increase their lending growth (new issuance) relatively more than banks with a lower degree of specialization to their sector of interest. Table 1.2 summarize the results.

In column (1) of Equation 1.5, the coefficient on bank specialization is negative and statistically significant. This captures that specialized banks, in general, have lower loan growth than less specialized banks, this however, is not in contrast with previous results on the positive association of specialization on loan volume outstanding (Blickle et al., 2021), as they measure two different objects, one is about relative growth in volume, while the other is about outstanding volume. Moreover, higher specialization can lead to a negative association with the growth rate as negative shocks prompt banks to cut supply in non-core sectors (De Jonghe et al., 2020; Iyer et al., 2022), increasing, mechanically, specialization level. Thus specialization tends to be higher during periods of low economic activity when bank supply is limited creating a negative relationship with the growth rate of credit which is also reinforced by mean reversion.

The coefficient on the interaction β_3 is positive and statistically significant

Table 1.2:
Specialization and Bank-Sector loan growth

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

The table reports coefficients and t-statistics (in parenthesis) for the bank lending growth volume to sectors after a monetary policy tightening. The reduced form model tested corresponds to Equation 1.5. The table presents the responses to a monetary policy easing. The unit of analysis is at the bank-sector quarterly level. The sample consists of syndicated loans originated in the U.S. from 1991q1 until 2016q4. The dependent variable is the log growth amount held by each lender at time t. *Specialization* $_{b,s}^{t-1\rightarrow t-12}$ is the bank specialization and is defined as 12 quarter slow moving average of the share of total credit granted by a bank b to a specific sector s relative to the bank's total credit. In all specifications, are included different levels of fixed effects as noted in the lower part of the table, from most restrictive version (1) to least (5). $X_{s,t}$ is a vector of sector control variable including the sector rediployability index measured as Kim and Kung (2017), 2 lags of change in sectoral gross output changes in sectoral TFP and labour unit (index to 2012 levels) which can affect the sectoral demand side. $X_{b,t}$ is a vector of bank time-varying characteristics such as size, capital ratio, security ratio, deposit ratio and banks' profitability (*ROA*) to control for bank supply characteristic that can affect both my outcome variables as well as the explanatory variable. The symbols *,** and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

suggesting that, during periods of easing, banks lend more to sectors in which they specialize. In columns 2, 3 and 4 I add different time-varying fixed effects that are less restrictive in terms of fixed effects which shows that my results are robust across specifications and reduces the concerns of demand or supply-driven results. In other terms, this suggests that results are not driven by the selection of unobservables and hence by omitted variables problems nor that unobservable demand of supply shocks are drivers of the results. Additionally, I also confirm the widely studied puzzle of monetary policy channels in US in which an easing (tightening) is associated with a decrease (increase) in loan growth in column 5 (Kashyap and Stein, 1995, 2000; Supera, 2023; Greenwald et al., 2020).

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

My estimates, however, could still be biased by the mere size of the industry rather than capturing the effect of industry specialization. To address this point I show in Table B.2 that my results are robust to the use of *excessive specialization* measure. This measures is less prone to tails distortion in the estimation. Moreover, by construction, this measures treats any excess over-investment in an industry retrospectively on the ”optimal” weights the industry has in the economy. This table shows that moving from more stringent specification to less stringent

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

ones (column 5), the coefficient remains significant. Along with the results of Table 1.2 this is indicative of two things: (i) controlling for sector demand factors is relevant in the context of monetary policy change as sector demand might move in other directions to supply in the hope of less reliance to their customary bank. (ii) This incentive is more prominent for larger sectors. Finally, I exploit loan level data in Table B.1 in the spirit of Chodorow-Reich (2014); Iyer et al. (2022) and compare two loans arranged by the same banks to different sectors and confirm my previous findings. For this specification I am assuming that loan demand is common across firms in the same sectors. Ideally, having a within bank-time and within firm-time specification would be preferred. Unfortunately, as I work on a sample of very large loans, I do not observe many firms doing multiple deals in the same year-quarter. However, the average number of firms in a sector that originate a loan with my banks is pretty small containing a median of 3 firms, reducing any potential concern.

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

1.3.2 Long run effects of bank specialization and monetary policy

The results so far show that there is an immediate effect on impact, however as evidenced by Kashyap and Stein (1995); Caglio et al. (2022) monetary policy changes have persistent consequences[9]. To study the long-run relations with spe-

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

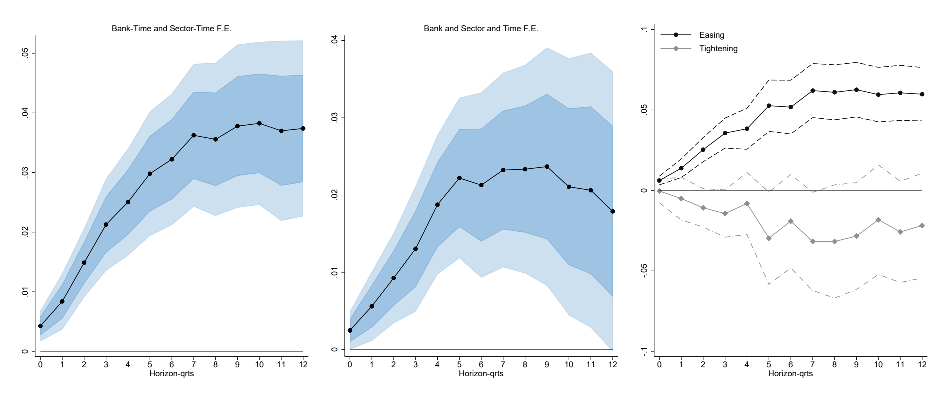
cialization I employ a similar strategy as in the previous section using local projections (Jordà, 2005) to understand the long-term dynamics of the interactions between monetary policy and banks' specialization. In particular I estimate the impulse responses of banks' with differential degree of specialization upon a 25 bps reduction in in monetary policy shock for a standard deviation increase in specialization following Equation 1.5, the results are presented in Figure 1.2.

The left-side figure in Figure 1.2 depicts the outcome of the most stringent specification using the full fixed effect model, aligning with column (1) in Equation 1.5[10]. The observed impulse response indicates that, following a monetary policy cut, a bank specializing in a particular industry significantly amplifies its lending growth toward that industry compared to less specialized banks. This effect is both persistent and economically substantial, peaking at 10 quarters and resulting in a cumulative 4% rise, on a quarterly basis, in the conditional interaction between the bank-sector growth, underscoring the incentive for lenders to expand their portfolio towards their sector of specialization. The central panel displays coefficients corresponding to column (5) in Table 1.2, qualitatively, the results are unchanged. For robustness, I report the coefficients attached to the excess specialization measures in Figure A.2, which delivers qualitatively and quantitatively the same results.

Moreover, in the rightmost panel, I distinguish between the impacts of easing and tightening in monetary policy: the majority of observed effects originate from periods of monetary policy easing. Conversely, I do not observe any significant impact following a reduction in monetary policy. This outcome is likely attributed to the sample period featuring limited instances of monetary policy tightening, with the bulk of the variance arising from easing periods. However, it's plausible that banks commit to loans and have limited margin for reduction, relying largely

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

Figure 1.2:
Impulse response: Bank-Sector Loan growth upon rate cut



Note: Dealscan sample. Impulse response dynamics to a 25 bps cuts in ε_t for a standard deviation increase in $\textit{Specialization}\,_{b,s}^{t-1\to t-12}$. The panel reports the conditional estimates for $\beta_3^h \times \varepsilon \times \textit{Specialization}\,_{b,s}^{t-1\to t-12}$. The unit of information of the analysis is the loan outstanding at the bank-sector time level. The sample consists of syndicated loans outstanding from $1991q_1$ until $2016q_4$. The dependent variable is the loan volume (outstanding and originated) held by each lender. Light (dark) blue areas represents 90% (68%) confidence interval used in the panel a and b. Dashed areas represent represents 90% confidence interval used in the panel c. Panel a reports coefficients corresponding to column (1) in table Equation 1.5, while panel b correspond to column (5) of the same table. Panel c decompose the effect into easing and tightening periods estimated similarly to Equation 1.5.

on the extensive margin, even though many loans need to be renewed. Consequently, the effect of monetary policy tightening might be compromised in the presence of perfect commitment and loan rollovers.

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

Lead arrangers and participants

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

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

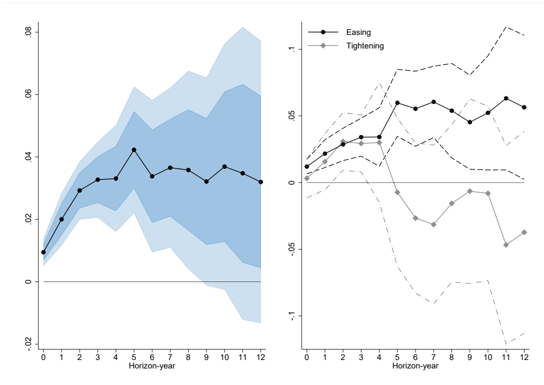
The outcomes for lead lenders and participants are displayed in Figure 1.3. It shows the impulse response to a 25 bps cut in monetary policy estimated for a standard deviation in industry specialization. I construct the main variable measuring specialization levels for both lead and participant, comparing growth volumes for the corresponding supplied amounts[11].

These outcomes underscore that banks specializing in specific industries exhibit heightened loan growth to corresponding borrowers post a rate reduction, supported by insights gleaned from syndicate structures. This finding aligns with the banks' ability to share information across sectors based on their experiences with similar borrowers, evident in both lead arrangers and participants. This alleviates concerns about credit supply being contingent on sector-specific loan demand. Furthermore, the observed ineffectiveness of monetary policy tightening, as depicted in Figure 1.2, persists for lead arrangers, emphasizing their limited ability to reduce supply efficiently when rates rise. In contrast, participants possess a higher margin of adjustment, allowing them the choice not to participate in future loans. Overall, these results confirm and reinforce the previous analyses.

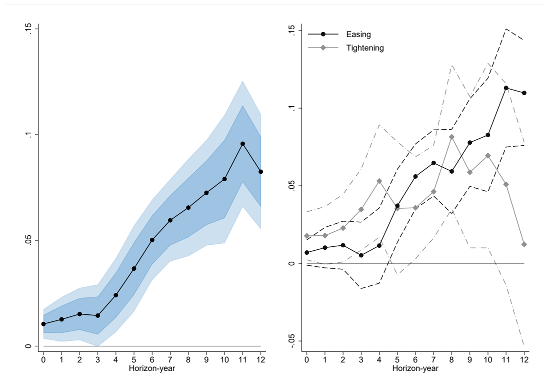
[11]The measure of specialization and the credit growth volume are defined based an all loans outstanding by the lender, whether the lender acts as a lead lender or a syndicate participant, and otherwise.

Figure 1.3:
Impulse response (lead and particpant): Bank-Sector loan growth

(a) Credit growth: lead arranger(s)



(b) Credit growth: participant(s)



Note: Dealscan sample. Impulse response dynamics to a 25 bps cuts in ε_t for a standard deviation increase in $\textit{Specialization}\,_{b,s}^{t-1\to t-12}$. The panel reports the conditional estimates for $\beta_3^h \times \varepsilon \times \textit{Specialization}\,_{b,s}^{t-1\to t-12}$. The unit of information of the analysis is the loan outstanding at the bank-sector time level. The sample consists of syndicated loans outstanding from $1991q_1$ until $2016q_4$. The dependent variable is the loan volume (outstanding and originated) held by each lender. Light (dark) blue areas represents 90% (68%) confidence interval used in the Figure 1.3a and Figure 1.3b. Dashed areas represent represents 90% confidence interval used to distinguish between monetary policy easing and tightening effect. Both panels reports coefficients corresponding to column (1) in table Equation 1.5. The measure of specialization and the credit growth volume are defined based an all loans outstanding by the lender, whether the lender acts as a lead lender (Figure 1.3a) or a syndicate participant (Figure 1.3b).

1.3.3 Robustness and alternative channels

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

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

To address the above-mentioned concerns, I therefore, include in the baseline specifications the market share of each bank in an industry, which measures the percentage of credit outstanding that a bank has in one industry relative to the total credit supplied to the industry by all banks[12]. In less stringent specifications, I control for banks' characteristics that influence monetary policy such as size (Kashyap and Stein, 1995) and solvency (Kashyap and Stein, 2000; Jiménez et al., 2012) captured by equity and liquidity ratio and deposit market power (Drechsler et al., 2021). Formally, I test the reduced form model presented in Equation 1.6. The vector $x_{b,t-1}$ contains the full set of alternative mechanisms that I test which are banks' market share, size, equity ratio and liquidity ratio (measured as available for sale securities). The vector $X_{b,t-1}$ self contains the vector $x_{b,t-1}$ while the controls are analogous to Equation 1.5.

$$\begin{aligned}\log \ell_{b,s,t} - \log \ell_{b,s,t-1} = \alpha_{s,t} + \alpha_{b,t} + \alpha_{s,b} + \\ \beta_3^h \times \varepsilon_t \times \ \mathit{Specialization}\,_{b,s}^{t-1 \to t-12} + \overbrace{\sum_{x \in X} \delta_x \cdot \varepsilon_t \times x_{b,t-1}}^{\text{Alternative channels}} + \\ + \gamma_{b,s} X_{b,s,t-1} + \gamma_b X_{b,t-1} + \varepsilon_{b,s,t} \quad (1.6)\end{aligned}$$

Table 1.3 presents the results scaled for a rate cut, estimating Equation 1.6 which only report the interaction terms coefficients for brevity.

Column (1) provide evidence that my results on the relation between monetary policy cuts and banks' industry specialization is robust to controlling for banks' industry share. As column (1) shows, after a 25 bps decrease in the monetary policy rate, for a one standard deviation increase in banks' specialization (0.06), banks with higher share in an industry increase their lending towards the corre-

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

Table 1.3:
Specialization and Bank-Sector loan growth: robustness

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

The table reports coefficients and t-statistics (in parenthesis) for the bank lending growth volume to sectors after a monetary policy tightening. The reduced form model tested corresponds to Equation 1.6. The table presents the responses to a monetary policy easing. The unit of analysis is at the bank-sector quarterly level. The sample consists of syndicated loans originated in the U.S. from 1991q1 until 2016q4. The dependent variable is the log growth amount held by each lender at time t. *Specialization* $_{b,s}^{t-1\to t-12}$ is the bank specialization and is defined as 12 quarter slow moving average of the share of total credit granted by a bank b to a specific sector s relative to the bank's total credit. In all specifications, are included different levels of fixed effects as noted in the lower part of the table, from most restrictive version (1) to least (3). $X_{b,t}$ is a vector controlling for four lags of the dependent variable. $X_{b,t}$ is a vector of bank time-varying characteristics such as size, capital ratio, security ratio, deposit ratio and banks' profitability (*ROA*) to control for bank supply characteristic that can affect both my outcome variables as well as the explanatory variable. The symbols *,** and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

sponding sector in the same quarter by 46bps more compared to a bank with a lower share in the sector. A banks' market share increase turns out to be an insignificant factor in shaping the reaction of banks-sector growth upon a rate cut. Most importantly, comparing the R^2 from column (1) in Equation 1.5 and the corresponding one in Equation 1.6, there is no sensible increase in variance explained in the model, reducing any concerns on the relevance of banks' market share to be a sensible factor affecting my results and the relative effect of bank specialization is stronger than market share[13]. I take this evidence as a sign that despite contributing to the model's fit, it does not sensibly improve it. Columns (2) and (3) drop the bank-year fixed effects and control for the effect of bank balance sheet characteristic and market power for the transmission of monetary policy[14]. They show that after controlling for the banks' balance sheet characteristic and market power, the result of banks' specialization remains robust and significant. The main coefficient of interest on the interaction term between changes in the rate and specialization remains large and significant. While other banks characteristics do not show statistically significant effects. Overall, Table 1.3 shows that my results work above and beyond other channels that may confound the results previously presented. Put differently, banks' specialization works beyond banks industry capture (market share) and the so-called balance sheet channel of monetary policy. For robustness, I estimate Equation 1.6 for the alternative measure of banks' specialization confirming that the baseline findings are both qualitatively and quantitatively nearly identical, the results are shown in Table B.3.

Finally I estimate the impulse response function for a 25 bps expansionary

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

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

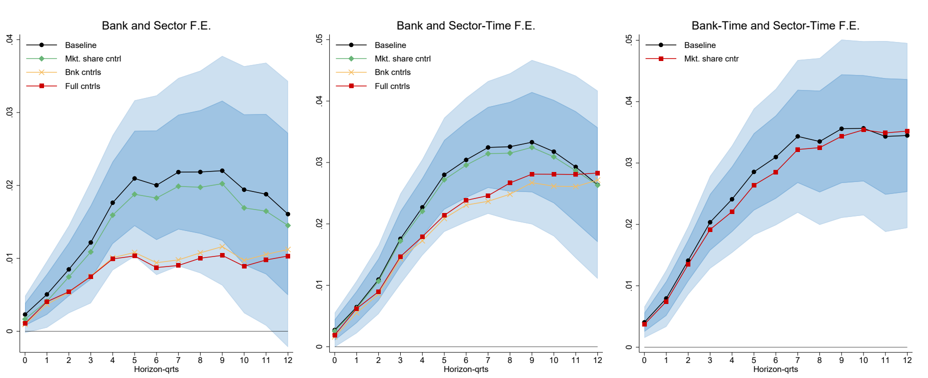
rate shock at different degree of bank industry specialization controlling for the above mentioned alternative channels which allows me to study the long-run relations with specialization. I employ a similar strategy as in the previous section using local projections (Jordà, 2005) to understand the long-term dynamics of the interactions between monetary policy and banks' specialization. The results are presented in Figure 1.4, where the estimates are largely unchanged. In particular the estimates attached to the specialization coefficient interacted with monetary policy is always positive and significant (Figure A.3 and Figure A.4), confirming that even in the long run, bank industry specialization influence monetary policy above and beyond other significant factors affecting monetary policy transmission. Ultimately, banks' market share, despite being positive, is not statistically significant (Figure A.5).

1.3.4 Financial frictions, bank specialization and monetary policy

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

As rates decrease, bank may decide to invest even further in their sector of specialization in the presence of low balance sheet ratio as it can relax capital constraints in the future because informational advantage allows them to find better borrowers, despite lowering diversification. Hence improving their returns

Figure 1.4:
IRF Bank-Sector loan growth - Alternative channels



Note: Dealscan sample. Impulse response dynamics to a 25 bps cuts in ε_t for a standard deviation increase in $\mathit{Specialization}_{b,s}^{t-1\rightarrow t-12}$. The panel reports the conditional estimates for $\beta_3^h \times \varepsilon \times \mathit{Specialization}_{b,s}^{t-1\rightarrow t-12}$ controlling for alternative channels that can affect monetary policy transmission such as bank size, liquidity ratio, equity ratio and bank-sector market share. The unit of information of the analysis is the loan outstanding at the bank-sector time level. The sample consists of syndicated loans outstanding from $1991q_1$ until $2016q_4$. The dependent variable is the loan volume (outstanding and originated) held by each lender. Light (dark) blue areas represents 90% (68%) confidence interval. Panel a reports coefficients corresponding to column (1) in table Equation 1.5, panel b correspond to column (4) of the same table while panel c correspond to column (5) of the same table. The black solid line represents the coefficient of the model in Equation 1.5, while the other solid lines represents the estimates attached to different horse-raced models. Red solid lines display the estimates attached to the interaction effect when all alternative channels are considered.

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

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

$$
\begin{aligned}
\log \ell_{b,s,t} - \log \ell_{b,s,t-1} &= \alpha_{s,t} + \alpha_{b,t} + \alpha_{s,b} + \\
&\beta_3 \times \varepsilon_t \times \textit{Specialization}\,_{b,s}^{t-1 \to t-12} + \overbrace{\sum_{x \in X} \delta_x \cdot \varepsilon_t \times x_{b,t-1}}^{\textit{Bank friction}} + \\
&\overbrace{\sum_{x \in X} \zeta_x \cdot \textit{Specialization}\,_{b,s}^{t-1 \to t-12} \cdot \varepsilon_t \times x_{b,t-1}}^{\textit{Bank friction interaction}} + u_{b,s,t}
\end{aligned} \tag{1.7}
$$

The interaction between specialization and financial friction is measured by δ_x while the triple interaction effect in ζ_x captures the degree to which for the same level of specialization, banks closer to constraints are more responsive. The main objective is to address if equity and liquidity-poor banks respond more for the same degree of specialization respectively. I compare banks at different degree of specialization in each industry upon a rate cut for the average capital and liquidity ratio observed in a bank in my sample. For ease on interpretation I then separate banks into categories based on whether their capital and liquidity ratio are above the sample median. The results are presented in Table 1.4.

Column (1) provide evidence that for a given level of specialization, banks

Table 1.4:
Specialization and Bank-Sector loan growth: financial frictions

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

The table reports coefficients and t-statistics (in parenthesis) for the bank lending growth volume to sectors after a monetary policy tightening. The reduced form model tested corresponds to Equation 1.7. The table presents the responses to a monetary policy easing. The unit of analysis is at the bank-sector quarterly level. The sample consists of syndicated loans originated in the U.S. from 1991q1 until 2016q4. The dependent variable is the log growth amount held by each lender at time t. *Specialization* $_{b,s}^{t-1\to t-12}$ is the bank specialization and is defined as 12 quarter slow moving average of the share of total credit granted by a bank b to a specific sector s relative to the bank's total credit. In all specifications I am controlling for four lags of the dependent variable. The symbols *,** and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

with low liquidity and low capital ratio increase even more their lending to the sector of specialization upon a rate cut. This effect is particularly prominent for low liquid bank. It is important to say that in column (1) the coefficient of interest in the triple interaction ζ_x is capturing the relative response of liquidity rich and equity rich banks (as compared to smaller ones) to policy rate changes for different levels of banks' industry specialization. After a 25 bps decrease in the monetary policy rate, for a one standard deviation increase in banks' specialization (0.06), moving from the top quartile of the liquidity distribution (0.26) to the lowest quartile (0.14) is associated to a relative increase in 1.4% in credit towards the sector of specialization[15]. Put it differently, banks with low liquidity ratio are more responsive to monetary policy for a given level of specialization. The relative adjustment of equity and liquidity rich banks for a different levels of specialization estimated through Equation 1.7 does not allow to understand the overall response of both liquidity (equity) rich and poor banks as it estimates the cross-sectional differences across banks balance sheet characteristics. In fact, Equation 1.7 is saturated with bank-time fixed effects, which span out time-series variation common across the bank. Hence, I additionally estimate the same model separately for all categories based on whether a bank is above of below the median of the empirical distribution. In this way is also easier to interpret the results. Columns (2) and (3) split the sample into low liquid and high liquid banks, the estimate on the interactions of monetary policy and specialization is highly significant for low liquid banks where a standard deviation increase in specialization upon a 25 bps cut is associated to a 10% increase in growth in credit to the sector, while the effect for high liquidity banks, though positive is not statistically significant. Similarly, I find that for low equity capital banks, column (4), specialized banks increase their credit towards the sector of specialization by 85 bps, but the effect for high equity capital banks is non-significant. Overall, Table 1.3 shows that my results work above and beyond other channels that may confound the results previously presented. Put differently, banks' specialization works beyond banks industry capture (market share) and the so-called balance sheet channel of monetary policy.

These results shows that indeed banks' financial frictions are important drivers in explaining the cross-sectional variation in response for specialized banks. As

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

rate decrease, banks that are more specialized and that have low balance sheet ratios signifying invest in their specialized sector as it becomes the preferable choice when facing constraints. Finally, for robustness, I estimate Equation 1.7 with the excess measure of specialization. The results are presented in Table B.4 confirming that the baseline findings are both qualitatively and quantitatively nearly identical.

For completeness I then study the long run implication of these effect using local projection approach (Jordà, 2005) estimating first the following model:

$$\Delta loan_{b,s,t+h} = \left[\beta_1^h \times \ Spec._{b,s}^{t-1\to t-12} + \beta_2^h \times \varepsilon_t \times \ Spec._{b,s}^{t-1\to t-12}\right] |\mathbf{I}_{j=\textit{High Liq.,High Cap.}} \\ + \alpha_{s,t+h} + \alpha_{b,t+h} + \alpha_{s,b} + \gamma_{b,s}^h X_{b,s,t-1} + \epsilon_{b,s,t+h} \quad (1.8)$$

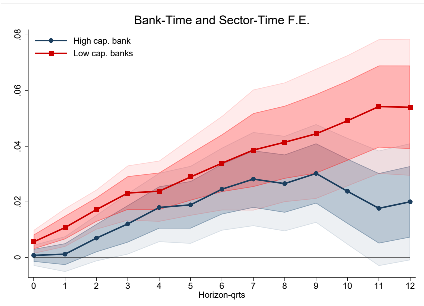
Equation 1.8 estimates a separated regression for weakly capitalized (liquid) and highly capitalized (liquid) banks for different degree of specialization. This model corresponds to comparing columns (4) and (5) in Table 1.4 [16], where highly capitalized banks is a dummy indicating a bank for which its equity ratio is above the median in the sample. The conditional impulse responses are presented in Figure 1.5.

The results suggest that indeed for a given level of specialization, banks that are closer to the constraint are indeed more responsive to monetary policy. This analysis, however, does not tease out the relative impact of the two estimates. To understand the relative impact I estimate the triple interaction model from the

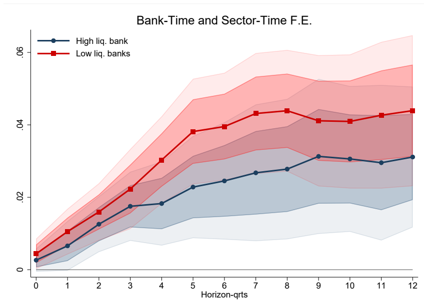
[16] Similarly I repeat the exercise for columns (2) and (3).

Figure 1.5:
IRF Bank-Sector loan growth - Balance sheet channel

(a) Low and High capital banks



(b) Low and High liquid banks



Note: Dealscan sample. Impulse response dynamics to a 25 bps cuts in ε_t for a standard deviation increase in $\mathit{Specialization}_{b,s}^{t-1\to t-12}$ for banks that are highly and lowly capitalized (liquid). The panel reports the separated conditional estimates for $\beta_3^h \times \varepsilon \times \mathit{Specialization}_{b,s}^{t-1\to t-12} | \mathbf{I}_{j=\mathit{High\ Liq.,High\ Cap.}}$. The unit of information of the analysis is the loan outstanding at the bank-sector time level. The sample consists of syndicated loans outstanding from $1991q_1$ until $2016q_4$. The dependent variable is the loan volume (outstanding and originated) held by each lender. Light (dark) areas represents 90% (68%) confidence interval. Panel a reports coefficients corresponding to column (4) and colum (5) in table Table 1.4, panel b correspond to column (2) and (3) of the same table.

following specification:

$$\Delta loan_{b,s,t+h} = \left[Spec._{b,s}^{t-1 \to t-12} + \varepsilon_t \times \ Spec._{b,s}^{t-1 \to t-12} \right] \beta_j^h \otimes \sum_{j=H.L.,H.C.} \mathbf{I}_{j=H.L.,H.\ C.}$$
$$+ \alpha_{s,t+h} + \alpha_{b,t+h} + \alpha_{s,b} + \gamma_{b,s}^h X_{b,s,t-1} + \epsilon_{b,s,t+h} \tag{1.9}$$

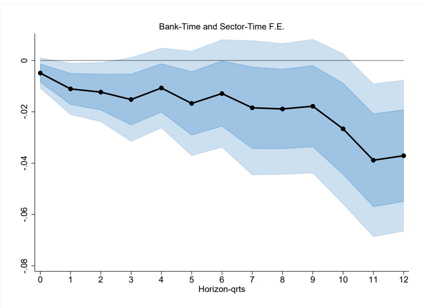
The triple interaction allows to estimate the relative relative response of more capitalize (liquid) banks for a given level of specialization upon an expansionary rate for the horse-raced model when both channels are taken into account. A negative coefficient of $\varepsilon \times$ $Spec._{b,s}^{t-1 \to t-12} \times \mathbf{I} = H.C.$ is telling that for a given level of specialization, highly capitalized banks are less responsinve to an expansionary shock with respect to less capitalized banks. Put it differently, weakly capitalized banks concentrate even further. The results presented in Figure 1.6 confirm this intuition, more over in terms of magnitude they show that for a given level of specialization both highly capitalized banks a liquid banks increase credit to their sector of specialization by 2% less compared to weakly capitalized (liquid) banks.

1.3.5 Small business lending data

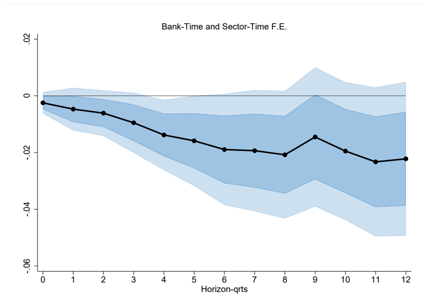
In my core empirical results I exploit US syndicated market loan data from Dealscan. Despite the fact that this dataset covers roughly 50% of US commercial and industrial loans, it targets mainly large firms in the US economy. Therefore my results could not hold outside the syndicated market as the latter is not very representative of the average firm in the US economy. Most importantly, these firms are far from opaque as instead small business are. After all, a specialized bank has greater incentives to use its superior information when the marginal benefits in distinguishing across good and bad borrowers are greatest. As specialized banks are more willing to lend to smaller, and more opaque firms in their industry of

Figure 1.6:
IRF Bank-Sector loan growth - Balance sheet channel

(a) High capital banks



(b) High liquid banks



Note: Dealscan sample. Impulse response dynamics to a 25 bps cuts in ε_t for a standard deviation increase in $\textit{Specialization}_{b,s}^{t-1\rightarrow t-12}$ for banks that are highly and lowly capitalized (liquid). The panel reports the separated conditional estimates for $\beta_3^h \times \varepsilon \times \textit{Specialization}_{b,s}^{t-1\rightarrow t-12} \times \sum_{j=H.L.,H.C.} \mathbf{I}_{j=H.L.,H.C.}$. The unit of information of the analysis is the loan outstanding at the bank-sector time level. The sample consists of syndicated loans outstanding from $1991q_1$ until $2016q_4$. The dependent variable is the loan volume (outstanding and originated) held by each lender. Light (dark) areas represents 90% (68%) confidence interval.

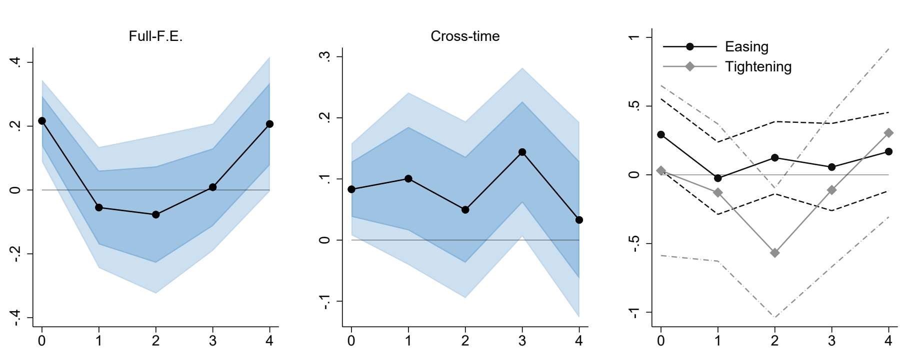
specialization (Blickle et al., 2021), I therefore exploit information on bank loans to small businesses and implement the within bank-sector estimation strategy as in the previous analysis. This step is relevant to test whether the specialization channel I previously presented holds in an alternative lending market. In doing so, I study the effect of banks' sectoral specialization on the transmission of monetary policy to the supply of small business lending.

As for section 1.3.2, I the same local projection specification as in Equation 1.5 with two key differences: (i) the small business lending dataset has been aggregated at the bank-sector yearly frequency as discussed in section 1.2.1, second the measure of specialization is internally measured in the small business lending dataset. Figure 1.7 presents the results of estimating Equation 1.5 using the information on new small business lending to compute bank specialization with different levels of fixed-effect. The dependent variable is the log of credit growth between the bank and the sector at yearly frequency from 1991 to 2017[17]. The left-most figure, contains the preferred specification with the full set of fixed effects included. It confirms that after a 100 bps cut in the monetary policy rates, banks increase new small business lending growth by more in markets where they are more specialized relative to other markets, controlling for the change in aggregate local lending opportunities. This result is fully consistent with my main results on syndicated lending, more over the magnitudes of this effect is substantially larger. A one standard deviation increase in specialization (0.18) increases lending by 20% per 100 bps decrease in monetary policy rate. Contrary to the syndicated market, this reaction is short lived and the effect is turns to be insignificant after impact.

The panel in the center, I estimate the effect for the model including time, sector and bank fixed effect exploiting both cross-sectional variation as well as time

[17]Though the SBA dataset covers also recent years, for consistency I use the same sample period.

Figure 1.7:
Impulse response SBA sample: Bank-Sector loan growth upon rate cut



Note: Small Business Lending Administration 7(a) Loan-program sample. Yearly sample. Impulse response dynamics to a 100 bps cuts in ε_t for a standard deviation increase in $\mathit{Specialization}_{b,s}^{t-1\rightarrow t-3}(SBA - sample)$. The panel reports the conditional estimates for $\beta_3^h \times \varepsilon \times \mathit{Specialization}\,{}_{b,s}^{t-1\rightarrow t-12}$. The unit of information of the analysis is the loan outstanding at the bank-sector yearly level. The sample consists of small business loans origination from 1991 until 2016 end of year. The dependent variable is the loan volume (originated) by each lender. Light (dark) blue areas represents 90% (68%) confidence interval used in the Figure 1.3a and Figure 1.3b. Dashed areas represent represents 90% confidence interval used to distinguish between monetary policy easing and tightening effect. Both panels reports coefficients corresponding to column (1) in table Equation 1.5. The measure of specialization and the credit growth volume are defined based an all loans originated loans by the lender in the small business lending dataset.

series variation[18]. It confirms the previous results, with the coefficient of interest remaining significant but lowering its magnitude. Again, this decrease in the magnitude of the coefficient suggests that sector-year level heterogeneity is a relevant factor to be controlled for in our analyses. As for the long run effect, the graph confirms the short-living effect in this sample. This should not be considered a drawback in my analysis as this dataset targets specifically small and credit constrained firms. The margin of adjustments comes mostly from the extensive ones, as new loans are originated by the bank to firms in the sector and not for instance increase loans to existing customers. Finally the right-most panel disentangles the effect for easing and tightening periods, confirming again that the bulk of the action is coming from easing periods. These finding provides strong evidence that my previous analysis is not specific to the syndicated market. I show that how banks sectoral specialization in small business lending affects the transmission of monetary policy to the growth of new small business lending.

1.4 Bank Level Results on income and deliquencies

My current findings center on the bank's portfolio allocation and don't delve into the mechanism or the consequences at the bank level resulting from these reallocations. If bank specialization leads to a further concentration of portfolios upon a rate cut, driven by informational advantages, one would expect highly specialized banks to exhibit improved income performance post rate reduction. Given their superior screening and monitoring technologies, they should have the ability to select more reliable clients, potentially resulting in lower delinquencies than less specialized counterparts . This should lead to more stable returns and fewer write-downs (Blickle et al., 2021). Conversely, if specialized banks exhibit a greater

[18] In all specification I always control for lags of the dependent variable and for bank-sector fixed effect.

reduction in risk aversion compared to non-specialized banks after an easing, one might observe poorer income profitability indices at the bank level. The underlying mechanism of the results is essential. If specialized banks, leveraging their superior screening and monitoring technologies, perform better post rate reduction, it would signify their deliberate allocation of funds towards their sector of expertise, enhancing their income performance while reallocating resources from less advantageous sectors.

In order to test this prediction I use a slow moving average of banks' HHI, a bank-level index of concentration described in Equation 1.4. The index captures the degree of portfolio concentration at the bank level. The higher, the more the bank loads its investment towards one activity. I then exploit the time-series and cross-sectional information of banks to address how bank concentration influences various measure of income profitability at the bank level upon a monetary policy easing. I then look at the long-run performances of banks as they might be more relevant to test the effect of delinquencies on commercial loans. To test for the long-run consequences of their interplay I make use of local projection methods, in particular, I test the following reduced-form model:

$$Y_{b,t+h} = \alpha_t + \alpha_b + \beta_1^h \times \mathit{HHI}_b^{\,t-1 \to t-12} + \beta_2^h \times \varepsilon_t \times \mathit{HHI}_b^{\,t-1 \to t-12} + \gamma_b X_{b,t-1} + u_{b,t+h} \tag{1.10}$$

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

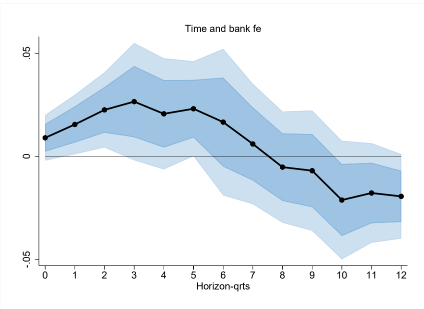
Figure 1.8 reports the impulse response of my measures of income performances to a 25 bps cut in monetary policy rate for a standard deviation increase in banks' HHI at each horizon h.

From Figure 1.8a, the conditional estimate of β_2^h associated to the increase in banks' ROA is positive and significant up to 1 year. Given a 25 bps cut in rates for an standard deviation increase in HHI (0.24) a banks ROA increases by 3 basis points representing a 4% variation in the standard deviation for the corresponding horizon, picking after 2 quarters. Similarly in Figure 1.8b and in Figure 1.8c, I find that the IRFs associated to higher levels of concentration are negative and statistically significant representing a total reduction in chargeoff rate of 4 bps and 3 bps in loan loss provision. These magnitude represents 5% and 5.1% of the total variation in the sample. Finally I compare the cumulative delinquency rate of banks, which measures the cumulative growth of loans accruing or past due over the sample period. The table shows that upon a 25 pbs cut in rates for a standard deviation increase in HHI, the cumulative delinquency rate is reduced by 3 basis points for banks that are relatively more concentrated representing 20% of the variation in the sample for the corresponding horizon.

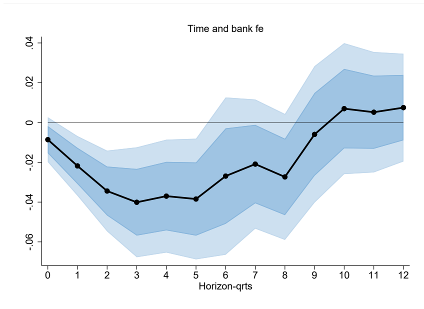
The previous outcomes confirms that more concentrated banks have the ability to pick better borrowers and thus, ex-post, have superior performance to a less specialized bank. However, the monitoring incentives should be larger for lead arrangers as they are responsible of gathering information about the borrower and generally retain the largest fraction of the loan after origination. I thus, replicate the analysis presented in Figure 1.8 for lead arrangers. In particular I measure banks' concentration only exploiting lead arrangers shares. In Figure A.8 I not only I confirm the results, but the magnitude and the persistency of the effect is magnitudes larger for all the variables of interest and in particular for cumulative delinquency growth. These evidence suggests that indeed banks with higher

Figure 1.8:
Impulse response: bank level performances

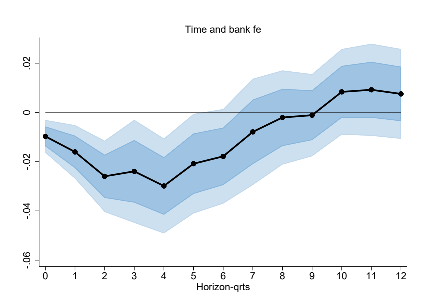
(a) Banks' ROA



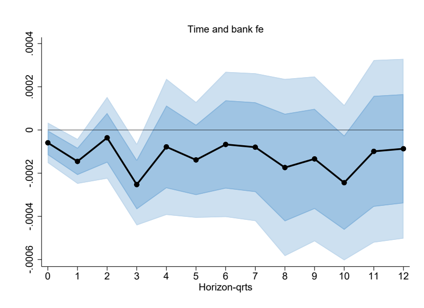
(b) Banks' Chargeoff



(c) Banks' loan loss provision



(d) Banks' delinquency rate



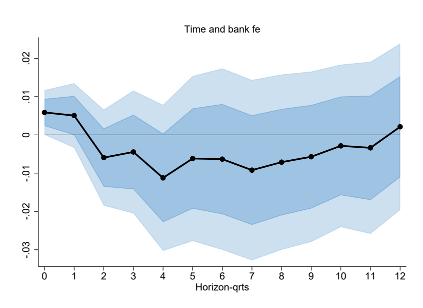
Note: Dealscan sample. Impulse response dynamics to a 25 bps cuts in ε_t for a standard deviation increase in $HHI_b^{t-1\rightarrow t-12}$. The panel reports the conditional estimates for $\beta_2^h \times \varepsilon_t \times HHI_b^{t-1\rightarrow t-12}$. The unit of information of the analysis is the bank time level. The sample consists of matched Dealscan and FR Y-9C bank holding company for the period from $1991q_1$ until $2016q_4$. The dependent variable is the banks' ROA in Figure 1.8a and chargeoff rate in Figure 1.8b. Light (dark) blue areas represents 90% (68%) confidence interval. Dashed areas represent represents 90% confidence interval used to distinguish between monetary policy easing and tightening effect. Both panels reports coefficients corresponding to the most saturated model presented in table Equation 1.10. The measure of banks' concentration are defined based on the syndicate outstanding loan volume at the end of each quarter.

degree of portfolio specialization have higher ability in selecting borrowers especially when monitoring incentives are larger (lead arranger).

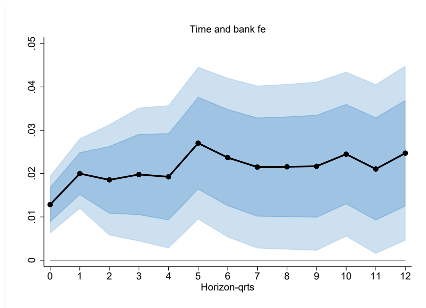
I finally check if these effects are also reflected in banks' market performances comparing their market capitalization growth in Figure 1.9. I find that banks' industry portfolio concentration measured at the lead arranger level is associated to an cumulative increase in market capitalization of 3% upon a upon a 25 basis point reduction in monetary policy rate, and its cumulative growth is persistent over time. Though, this results is not significant but on impact for the average degree of portfolio concentration in the bank exploiting both lead and participant information.

Figure 1.9:
Impulse response: market return

(a) Banks' Mkt Cap



(b) Banks' Mkt Cap - HHI lead arranger



Note: Dealscan sample. Impulse response dynamics to a 25 bps cuts in ε_t for a standard deviation increase in $HHI_b^{t-1\to t-12}$. The panel reports the conditional estimates for $\beta_2^h \times \varepsilon \times HHI_b^{t-1\to t-12}$. The unit of information of the analysis is the bank time level. The sample consists of matched Dealscan and FR Y-9C bank holding company for the period from $1991q_1$ until $2016q_4$. The dependent variable is the banks' ROA in Figure 1.8a and chargeoff rate in Figure 1.8b. Light (dark) blue areas represents 90% (68%) confidence interval. Dashed areas represent represents 90% confidence interval used to distinguish between monetary policy easing and tightening effect. Both panels reports coefficients corresponding to the most saturated model presented in table Equation 1.10. The measure of banks' concentration are defined based on the syndicate outstanding loan volume at the end of each quarter.

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

In additional robustness check I first confirm that upon a rate cut, the average degree of banks' portfolio concentration increase both in the aggregate as well as exploiting time series variation at the bank level (Figure A.1). I then look for asymmetries in responses of income performances upon rate change for banks at different degree of portfolio concentration in Figure A.1 and focusing on lead arrangers only Figure A.1, finding that indeed there are significant asymmetries in the responses. Higher portfolio concentration appears to be always related to better income performances though the channel through which this happens is very different[19].

1.5 Sector Level Results on loan growth and aggregate outcomes

In this section I aggregate my data at the sector level and examine whether industry exposed to specialized lenders see an increase in total lending and other real sector outcomes upon a rate cut. My left-hand variables is total commited syndicated credit lending at the sector-quarter level and value added and employment sector-year. Value added and employment are from the integrated BEA and Bureau of

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

Labor Statistics KLEMS data. Given the results presented in Section 1.3 I expect aggregate mortgage credit supply to be affected by the presence of specialized lenders in a sector. However, differences in lending growth following monetary policy changes may be compensated in a given market between specialized and non-specialized banks. In this case, credit would be reallocated across banks in a sector, but aggregate credit supply would be unaffected.

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

I estimate the following local projection:

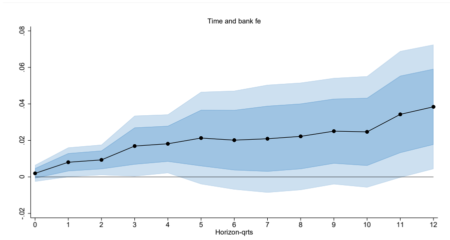
$$y_{s,t+h} = \alpha_t + \alpha_s + \beta_1^h \times \mathit{ISpec}\,_s^{t-1 \to t-12} + \beta_2^h \times \varepsilon_t \times \mathit{ISpec}\,_s^{t-1 \to t-12} + \gamma_s X_{s,t-1} + u_{s,t+h} \tag{1.11}$$

Where $y_{s,t+h}$ is the log growth lending, the log growth in employment, or the log growth in value added in sector s from date $t-1$ to $t+h$. $\mathit{ISpec}\,_s^{t-1 \to t-12}$ is the weighted average of banks industry specialization for all banks operating in sector s weighted by their lending shares, α_t and α_s are time and sector fixed effects. I also include sector market concentration interacted with the monetary policy shock, which improves identification by ensuring that I am using variation in the degree of banks specialization exposure and not coming from sectors captured by few banks. I further controls for sector levels variables that can affect the outcome variable I cluster standard errors at the sector level.

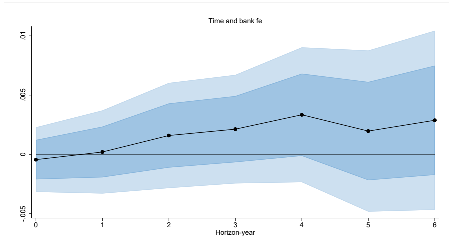
Figure 1.10 presents the results. Figure 1.10a reports the benchmark specifica-

Figure 1.10:
Impulse response: sector level

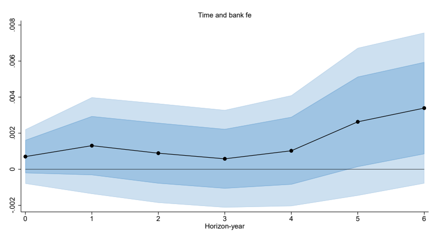
(a) Loan volume



(b) Value added



(c) Employment



Note: Impulse response dynamics to a 25 bps cuts in ε_t for a standard deviation increase in $\mathit{ISpec}\,_s^{t-1\rightarrow t-12}$. The panel reports the conditional estimates for $\beta_2^h \times \varepsilon_t \times \mathit{HHI}\,_s^{t-1\rightarrow t-12}$. The unit of information of the analysis is the sector time level. The sample consists aggregated sector level information for the period from $1991q_1$ until $2016q_4$. Light (dark) blue areas represents 90% (68%) confidence interval. All panels reports coefficients corresponding to the most saturated model presented in table Equation 1.11. The measure of Industry exposure to specialized banks are defined based on the syndicate outstanding loan volume at the end of each quarter.

tion using sector lending as the outcome variable. It shows that sectors with higher exposure to specialized banks see an increase in lending relative to other sector upon a rate cut: a one standard deviation increase in $Ispec$ increases lending by 2% per 25 bps cut in rate. The result is statistically significant. Figure 1.10b and Figure 1.10c shows the estimates for both value added and employment. Though both panels see an increase in the outcome variable, this results is not statistically significant, this can be the results of reallocation across banks within sector or simply the case that my sample analysis, as it is focused on large firms, is not representative of all the action in the sector.

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

1.6 Model

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

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

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

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

The bank's program then reads as:

$$\max_{\{L_{s,1}\}} \sum_s (L_{s,1}^{\gamma_s} - L_{s,1}R_f) \tag{1.12}$$

$$s.t.$$

$$L_{s,1} \geq (1-\delta)L_{s,0} \ \forall s \tag{1.13}$$

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

The optimal scale in each sector is given by:

$$L_{s,1}^* = \begin{cases} \left(\gamma_s R_f^{-1}\right)^{\frac{1}{1-\gamma_s}}, & \text{if } \mu_s = 0 \\ (1-\delta)L_{s,0} & \text{if } \mu > 0 \end{cases} \tag{1.14}$$

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

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

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

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

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

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

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

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

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

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

1.7 Conclusions

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

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

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

My results suggest that the banks specialization gives rise to bank-level implications following a rate change. I document how banks with higher portfolio concentration see improved income performances and lower delinquency upon a rate cut compared to more diversified lenders. This results suggests that on the margin, specialized banks exploit their information advantage and select better borrowers. This reasoning is also corroborated by lead arrangers showing the highest decrease in delinquency and increase in market capitalization for higher level of portfolio concentration following a rate decrease.

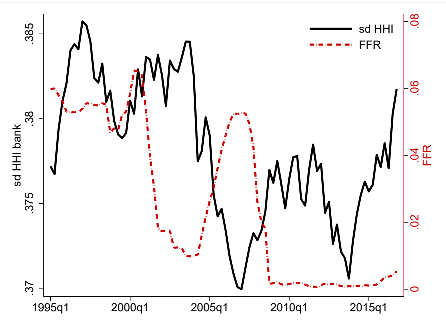
Finally my results shows that banks specialization influences aggregate outcomes showing that upon a rate cut, industries that have a higher presence of specialized lenders see an increase in total sectoral lending.

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

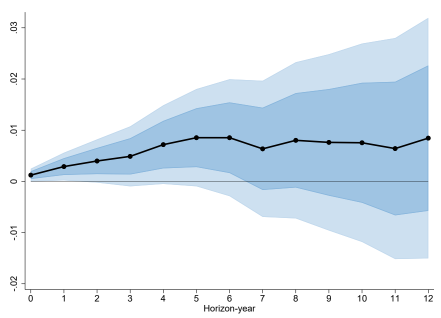
A Figure appendix

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

(a) Average HHI dispersion and Fed Funds rates

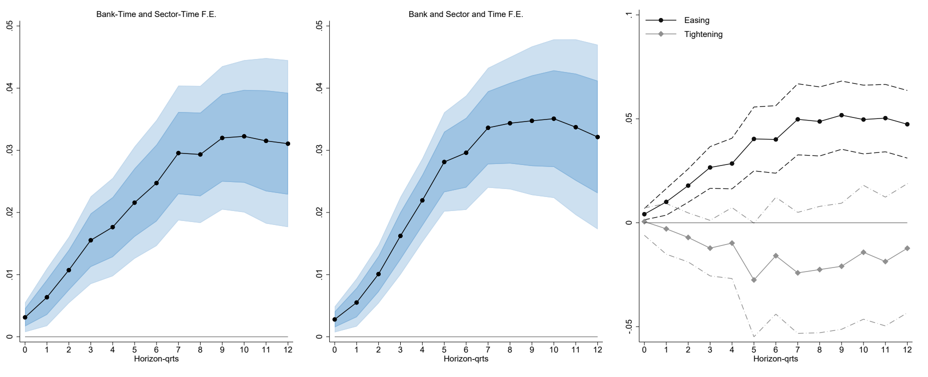


(b) Banks' cumulative HHI upon shock cut



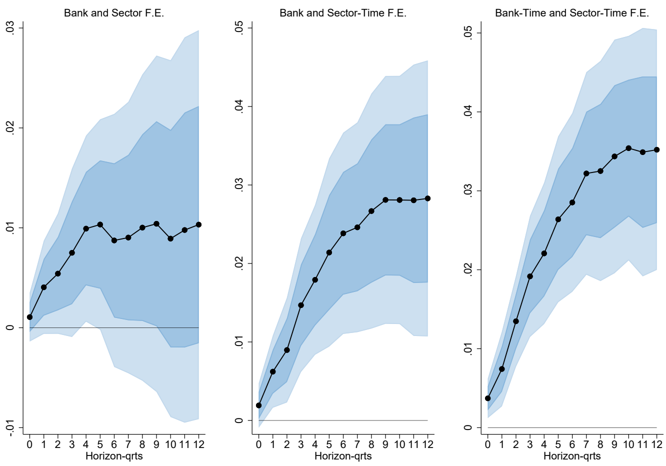
Note: source Dealscan data. Panel a shows the evolution of the standard deviation of banks' HHI (portfolio concentration) and the Fed Funds Rates (FFR) in decimal points. Panel b depicts the impulse response of cumulative banks' HHI portfolio growth around monetary a policy shock cut of 25 bps. The unit of information of the analysis is at the bank time level. The sample consists of the matched banks with an outstanding syndicated loan for the period of $1990q_1$ until $2016q_4$. The reduced form model corresponds to: $\Delta_h HHI^{t\to t-12}_{b,t+h} = \gamma^h_b + \beta^h \cdot \varepsilon_t + \Gamma^h_1 \cdot Z_{b,t-1} + \Gamma^h_2 \cdot Z_{t-1} + u_{i,t+h}$. The dependent variable is the cumulative growth of the slow moving average of HHI at the bank level. The vector $\Gamma^h_1 \cdot Z_{b,t-1}$ contains bank level controls including 4 lags of the dependent variable, bank level controls (*bank size, capital ratio, and security ratio*) and their interaction with the monetary policy shock, *bank deposit ratio* and *ROA*. The vector $\Gamma^h_2 \cdot Z_{t-1}$ contains macro level controls such as 4 lags of the monetary policy shock, change in fed funds rates and change in cpi.

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



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

Figure A.3:
IRF Bank-Sector growth alternative channels

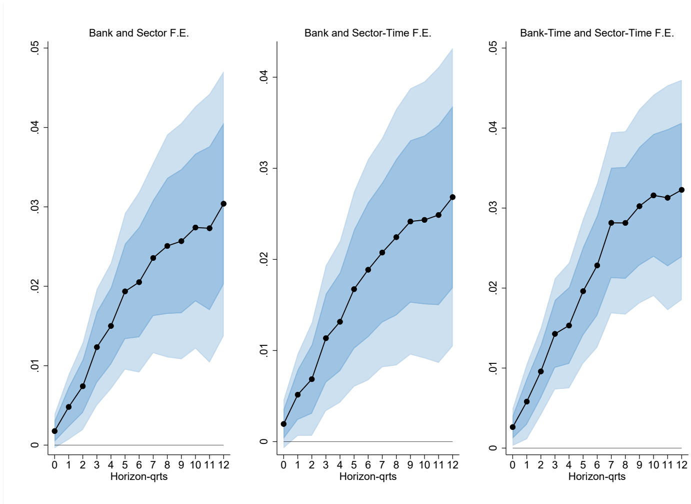


Note: Dealscan sample. Impulse response dynamics to a 25 bps cuts in ε_t for a standard deviation increase in *Specialization* $^{t-1\rightarrow t-12}_{b,s}$. The panel reports the conditional estimates for the model

$$\begin{aligned}\Delta loan_{b,s,t+h} =& \alpha_{s,t+h} + \alpha_{b,t+h} + \alpha_{s,b} + \beta_1^h \times \textit{Spec.}\ ^{t-1\rightarrow t-12}_{b,s} + \beta_2^h \times \textit{Mkt. Share}\ ^{t-1\rightarrow t-12}_{b,s} + \\ & \beta_3^h \times \varepsilon_t \times \textit{Spec.}^{t-1\rightarrow t-12}_{b,s} + \beta_4^h \times \varepsilon_t \times \textit{Mkt. Share}^{t-1\rightarrow t-12}_{b,s} + \\ & \sum_{j\in J} \beta_j^h \times \varepsilon_t \times \textit{Bank controls}_{b,t-1} + \gamma_{b,s}^h X_{b,s,t-1} + \gamma_b^h \times X_{b,t-1} + \\ & \gamma_{s,t}^h \times X_{s,t-1} + \gamma_\varepsilon^h \times \varepsilon_t + \epsilon_{b,s,t+h} \end{aligned} \tag{1.15}$$

reporting only $\beta_3^h \times \varepsilon \times$ *Specialization* $^{t-1\rightarrow t-12}_{b,s}$ controlling for alternative channels that can affect monetary policy transmission such as bank size, liquidity ratio, equity ratio and bank-sector market share. The unit of information of the analysis is the loan outstanding at the bank-sector time level. The sample consists of syndicated loans outstanding from $1991q_1$ until $2016q_4$. The dependent variable is the loan volume (outstanding and originated) held by each lender. Light (dark) blue areas represents 90% (68%) confidence interval. Panel a reports coefficients controlling only for bank and sector fixed effect, panel b control for sector-time fixed effect while panel c reports the most saturated model's estimates. In all regression I control for bank-sector fixed effects and errors are clustered at bank and sector level. The black solid line represents the coefficient of the model in Equation 1.5, while the other solid lines represents the estimates attached to different horse-raced models. Red solid lines display the estimates attached to the interaction effect when all alternative channels are considered.

Figure A.4: **IRF Bank-Sector growth alternative channels - excess specialization**



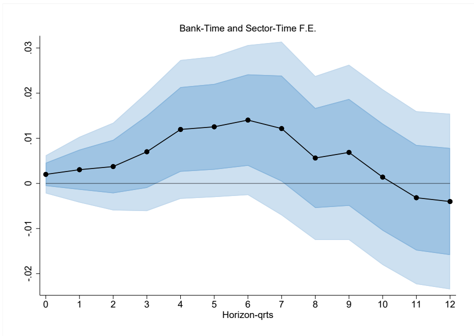
Note: Dealscan sample. Impulse response dynamics to a 25 bps cuts in ε_t for a standard deviation increase in *Specialization* $_{b,s}^{t-1\rightarrow t-12}$. The panel reports the conditional estimates for the model

$$\begin{aligned}\Delta loan_{b,s,t+h} =& \alpha_{s,t+h} + \alpha_{b,t+h} + \alpha_{s,b} + \beta_1^h \times \textit{Exc. Spec.}\ _{b,s}^{t-1\rightarrow t-12} + \beta_2^h \times \textit{Mkt. Share}\ _{b,s}^{t-1\rightarrow t-12} + \\ & \beta_3^h \times \varepsilon_t \times \ \textit{Spec.}_{b,s}^{t-1\rightarrow t-12} + \beta_4^h \times \varepsilon_t \times \ \textit{Mkt. Share}_{b,s}^{t-1\rightarrow t-12} + \\ & \sum_{j\in J} \beta_j^h \times \varepsilon_t \times \textit{Bank controls}_{b,t-1} + \gamma_{b,s}^h X_{b,s,t-1} + \gamma_b^h \times X_{b,t-1} + \\ & \gamma_{s,t}^h \times X_{s,t-1} + \gamma_\varepsilon^h \times \varepsilon_t + \epsilon_{b,s,t+h} \end{aligned} \tag{1.16}$$

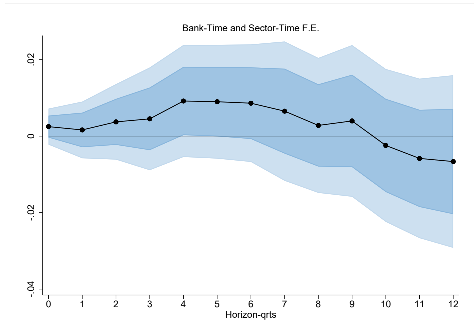
reporting only $\beta_3^h \times \varepsilon \times$ *Specialization* $_{b,s}^{t-1\rightarrow t-12}$ controlling for alternative channels that can affect monetary policy transmission such as bank size, liquidity ratio, equity ratio and bank-sector market share. The unit of information of the analysis is the loan outstanding at the bank-sector time level. The sample consists of syndicated loans outstanding from $1991q_1$ until $2016q_4$. The dependent variable is the loan volume (outstanding and originated) held by each lender. Light (dark) blue areas represents 90% (68%) confidence interval. Panel a reports coefficients controlling only for bank and sector fixed effect, panel b control for sector-time fixed effect while panel c reports the most saturated model's estimates. In all regression I control for bank-sector fixed effects and errors are clustered at bank and sector level. The black solid line represents the coefficient of the model in Equation 1.5, while the other solid lines represents the estimates attached to different horse-raced models. Red solid lines display the estimates attached to the interaction effect when all alternative channels are considered.

Figure A.5: **IRF Bank-Sector growth - bank market share elasticity**

(a) Mkt share estimates



(b) Mkt share estimates

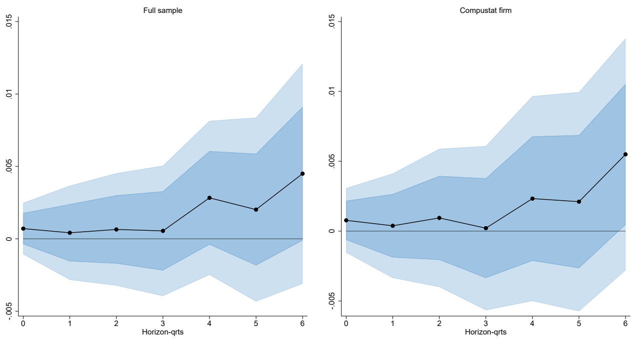


Note: Dealscan sample. Impulse response dynamics to a 25 bps cuts in ε_t for a standard deviation increase in *Mkt. Share* $_{b,s}^{t-1\to t-12}$. The panel reports the conditional estimates for the model

$$\begin{aligned}\Delta loan_{b,s,t+h} =& \alpha_{s,t+h} + \alpha_{b,t+h} + \alpha_{s,b} + \beta_1^h \times \textit{Measure of Spec.}\ _{b,s}^{t-1\to t-12} + \beta_2^h \times \textit{Mkt. Share}\ _{b,s}^{t-1\to t-12} + \\ & \beta_3^h \times \varepsilon_t \times \textit{Measure of Spec.}_{b,s}^{t-1\to t-12} + \beta_4^h \times \varepsilon_t \times \textit{Mkt. Share}_{b,s}^{t-1\to t-12} + \\ & \sum_{j\in J} \beta_j^h \times \varepsilon_t \times \textit{Bank controls}_{b,t-1} + \gamma_{b,s}^h X_{b,s,t-1} + \gamma_b^h \times X_{b,t-1} + \\ & \gamma_{s,t}^h \times X_{s,t-1} + \gamma_\varepsilon^h \times \varepsilon_t + \epsilon_{b,s,t+h} \end{aligned} \tag{1.17}$$

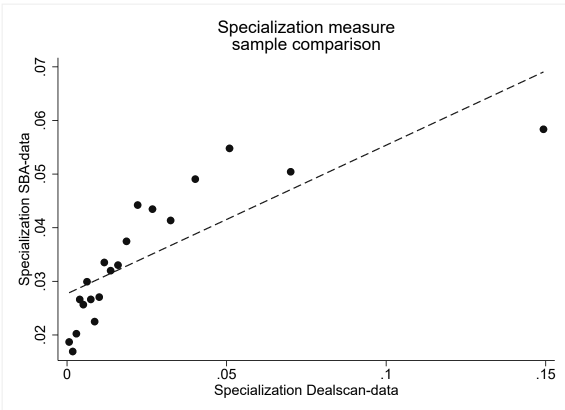
reporting only $\beta_4^h \times \varepsilon \times$ *Mkt Share* $_{b,s}^{t-1\to t-12}$ controlling for alternative channels that can affect monetary policy transmission such as bank size, liquidity ratio, equity ratio and measures of bank-industry specialization. The unit of information of the analysis is the loan outstanding at the bank-sector time level. The sample consists of syndicated loans outstanding from $1991q_1$ until $2016q_4$. The dependent variable is the loan volume (outstanding and originated) held by each lender. Light (dark) blue areas represents 90% (68%) confidence interval. Panel Figure A.5a reports coefficients controlling for bank industry specialization for the most saturated model, while panel Figure A.5b controls for bank excess industry specialization. In all regression I control for bank-sector fixed effects and errors are clustered at bank and sector level. Red solid lines display the estimates attached to the interaction effect when all alternative channels are considered.

Figure A.6:
Impulse response: Bank-firm Loan growth upon rate cut



Note: Dealscan sample. Impulse response dynamics to a 25 bps cuts in ε_t for a standard deviation increase in *Excess Specialization* $_{b,s}^{t-1\to t-12}$. The panel reports the conditional estimates for $\beta_3^h \times \varepsilon \times$ *Excess Specialization* $_{b,s}^{t-1\to t-12}$ for the model $\log \ell_{b,s,t+h} - \log \ell_{b,s,t-1} = \alpha_{s,t}^h + \alpha_{b,t}^h + \alpha_{s,b}^h + \beta_1^h \times$ *Excess Specialization* $_{b,s}^{t-1\to t-12} + \beta_2^h \times \varepsilon + \beta_3^h \times \varepsilon \times$ *Excess Specialization* $_{b,s}^{t-1\to t-12} + \gamma_b^h X_{b,t-1} + \gamma_s^h X_{s,t-1} + u_{b,s,t+h}$ The unit of information of the analysis is the loan outstanding at the bank-firm at half yearly frequency. The sample consists of syndicated loans outstanding from $1991q_1$ until $2016q_4$. The dependent variable is the loan volume (outstanding and originated) held by each lender. Light (dark) blue areas represents 90% (68%) confidence interval used in the panel a and b. Dashed areas represent represents 90% confidence interval used in the panel c. Panel a reports coefficients corresponding to column (1) in table Equation 1.5, while panel b correspond to column (5) of the same table. Panel c decompose the effect into easing and tightening periods estimated similarly to Equation 1.5.

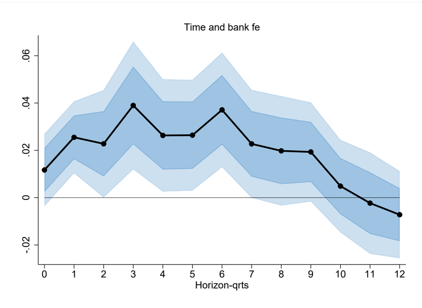
Figure A.7:
SBA and Dealscan specialization comparison



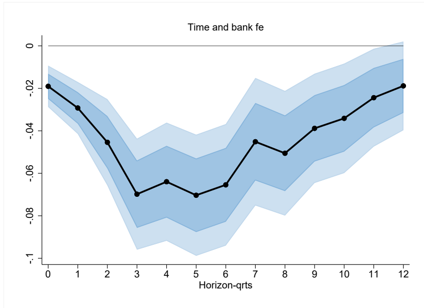
Note: Dealscan and Small Business Lending matched sample. The panel reports a binscatter plot of the correlation between a matched sample of Dealscan lenders and SBA lenders for the period 1991-2016.

Figure A.8:
IRF: bank level performances lead arrangers' HHI

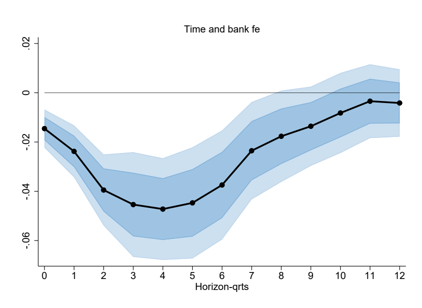
(a) Banks' ROA



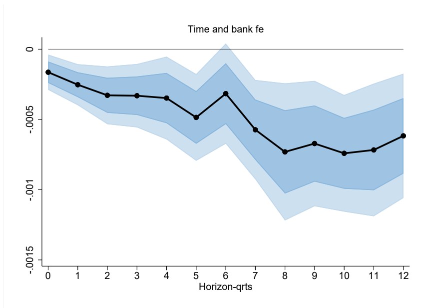
(b) Banks' Chargeoff



(c) Banks' loan loss provision



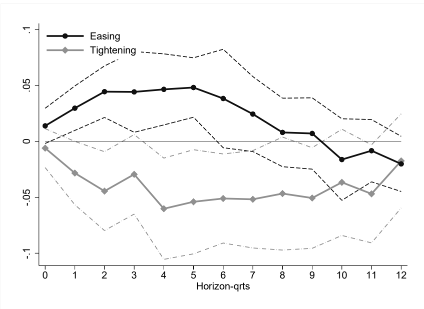
(d) Banks' delinquency rate



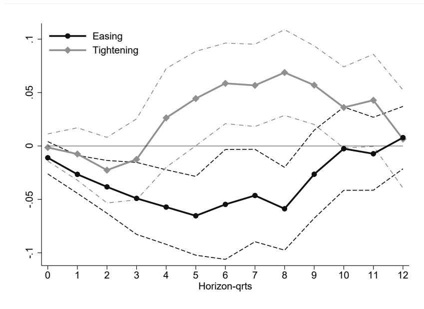
Note: Dealscan sample. Impulse response dynamics to a 25 bps cuts in ε_t for a standard deviation increase in $HHI_b^{t-1\to t-12}$. The panel reports the conditional estimates for $\beta_2^h \times \varepsilon \times HHI_b^{t-1\to t-12}(Lead)$. The unit of information of the analysis is the bank time level. The sample consists of matched Dealscan and FR Y-9C bank holding company for the period from $1991q_1$ until $2016q_4$. The dependent variable is the banks' ROA in Figure 1.8a and chargeoff rate in Figure 1.8b. Light (dark) blue areas represents 90% (68%) confidence interval. Dashed areas represent represents 90% confidence interval used to distinguish between monetary policy easing and tightening effect. Both panels reports coefficients corresponding to the most saturated model presented in table Equation 1.10. The measure of banks' concentration are defined based on the syndicate outstanding loan volume at the end of each quarter.

Figure A.9:
Asymmetric IRF: bank level performances

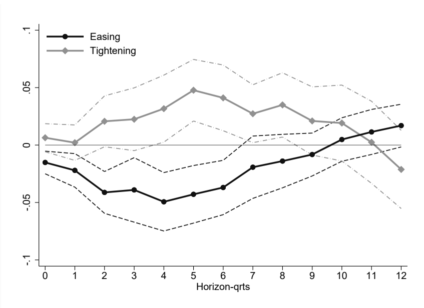
(a) Banks' ROA



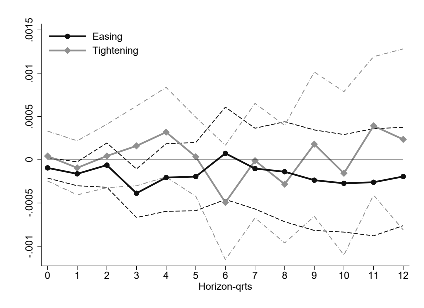
(b) Banks' Chargeoff



(c) Banks' loan loss provision



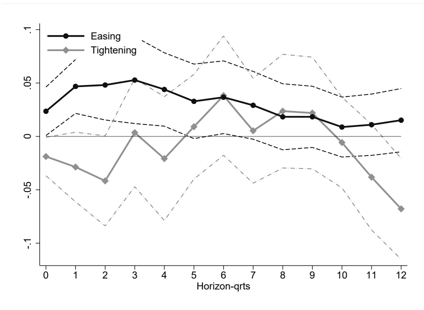
(d) Banks' delinquency rate



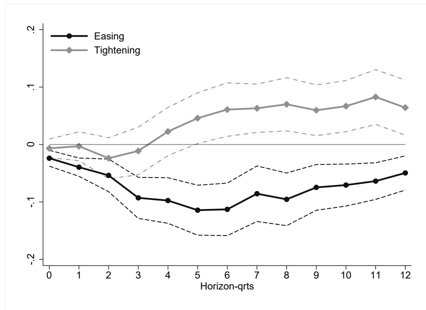
Note: Dealscan sample. Impulse response dynamics to a 25 bps cuts in ε_t for a standard deviation increase in $HHI_b^{t-1\to t-12}$. The panel reports the conditional estimates for $\beta_2^h \times \varepsilon_t \times HHI_b^{t-1\to t-12}$. The unit of information of the analysis is the bank time level. The sample consists of matched Dealscan and FR Y-9C bank holding company for the period from $1991q_1$ until $2016q_4$. The dependent variable is the banks' ROA in Figure 1.8a and chargeoff rate in Figure 1.8b. Dashed areas represent represents 90% confidence interval used to distinguish between monetary policy easing and tightening effect. Both panels reports coefficients corresponding to the most saturated model presented in table Equation 1.10. The measure of banks' concentration are defined based on the syndicate outstanding loan volume at the end of each quarter.

Figure A.10:
Asymmetric IRF: bank level performances lead arrangers' HHI

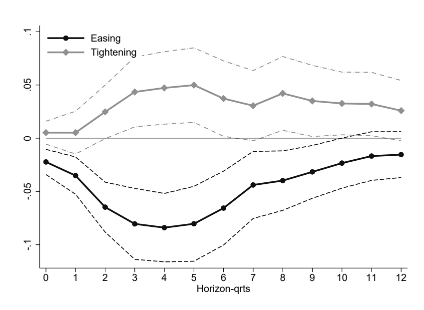
(a) Banks' ROA



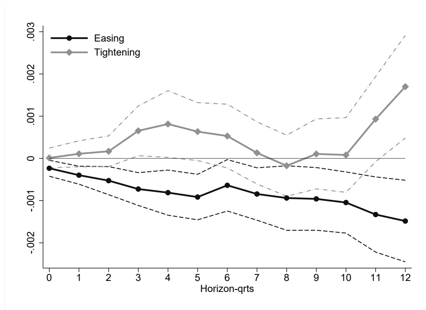
(b) Banks' Chargeoff



(c) Banks' loan loss provision



(d) Banks' delinquency rate



Note: Dealscan sample. Impulse response dynamics to a 25 bps cuts in ε_t for a standard deviation increase in $HHI_b^{t-1\to t-12}$. The panel reports the conditional estimates for $\beta_2^h \times \varepsilon \times HHI_b^{t-1\to t-12}(Lead)$. The unit of information of the analysis is the bank time level. The sample consists of matched Dealscan and FR Y-9C bank holding company for the period from $1991q_1$ until $2016q_4$. The dependent variable is the banks' ROA in Figure 1.8a and chargeoff rate in Figure 1.8b. Dashed areas represent represents 90% confidence interval used to distinguish between monetary policy easing and tightening effect. Both panels reports coefficients corresponding to the most saturated model presented in table Equation 1.10. The measure of banks' concentration are defined based on the syndicate outstanding loan volume at the end of each quarter.

B Table appendix

Table B.1:
Loan level estimates

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

The table reports coefficients and t-statistics (in parenthesis) for the bank lending growth volume to sectors after a monetary policy tightening. The reduced form model tested corresponds to: $\log \ell_{i,b,s,t} = u_{i,b,s,t} + \alpha_{s,t} + \alpha_{b,t} + \alpha_{s,b} + \gamma_i X_{i,t} \beta_1 \times$ *Main Regressor* $_{b,s}^{t-1\to t-12} + \beta_2 \times \varepsilon_t + \beta_3 \times \varepsilon_t \times$ *Main Regressor* $_{b,s}^{t-1\to t-12}$. The table presents the responses to a monetary policy easing. The unit of analysis is at the loan level. The sample consists of syndicated loans originated in the U.S. from 1991q1 until 2016q4. The dependent variable is the log amount supplied by each lender at time t. The *Main Regressor* variable is either the slow moving average of specialization or the slow moving average of excess specialization. In all specifications I am controlling for banks' market share and I included different levels of fixed effects as noted in the lower part of the table to isolate credit supply and demand. $X_{i,t}$ is a vector of loan level controls such as *maturity (months), loan purpose* (indicator for capital purpose) and *loan type* (indicator for credit line, term loan or other). The symbols *,** and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

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

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

The table reports coefficients and t-statistics (in parenthesis) for the bank lending growth volume to sectors after a monetary policy tightening. The reduced form model tested corresponds to: $\log \ell_{b,s,t} - \log \ell_{b,s,t-1} = \alpha_{s,t} + \alpha_{b,t} + \alpha_{s,b} + \beta_1 \times$ *Excess Specialization* $_{b,s}^{t-1\to t-12} + \beta_2 \times \varepsilon_t + \beta_3 \times \varepsilon_t \times$ *Excess Specialization* $_{b,s}^{t-1\to t-12} + + \gamma_s X_{s,t-1} + \gamma_b X_{b,t-1} + u_{b,s,t}$ The table presents the responses to a monetary policy easing. The unit of analysis is at the bank-sector quarterly level. The sample consists of syndicated loans originated in the U.S. from 1990q1 until 2016q4. The dependent variable is the log growth amount held by each lender at time t. *Specialization* $_{b,s}^{t-1\to t-12}$ is the bank specialization and is defined as 12 quarter slow moving average of the share of total credit granted by a bank b to a specific sector s relative to the bank's total credit. In all specifications, are included different levels of fixed effects as noted in the lower part of the table, from most restrictive version (1) to least (5). $X_{s,t}$ is a vector of sector control variable including the sector redeployability index measured as Kim and Kung (2017), 2 lags of change in sectoral gross output changes in sectoral TFP and labour unit (index to 2012 levels) which can affect the sectoral demand side. $X_{b,t}$ 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 B.3:
Specialization and Bank-Sector loan growth: robustness

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

The table reports coefficients and t-statistics (in parenthesis) for the bank lending growth volume to sectors after a monetary policy tightening. The reduced form model tested corresponds to Equation 1.6. The table presents the responses to a monetary policy easing. The unit of analysis is at the bank-sector quarterly level. The sample consists of syndicated loans originated in the U.S. from 1991q1 until 2016q4. The dependent variable is the log growth amount held by each lender at time t. *Excess Specialization* $_{b,s}^{t-1\to t-12}$ is the bank specialization and is defined as 12 quarter slow moving average of the share of total credit granted by a bank b to a specific sector s relative to the bank's total credit. In all specifications, are included different levels of fixed effects as noted in the lower part of the table, from most restrictive version (1) to least (3). $X_{b,t}$ is a vector controlling for four lags of the dependent variable. $X_{b,t}$ is a vector of bank time-varying characteristics such as size, capital ratio, security ratio, deposit ratio and banks' profitability (*ROA*) to control for bank supply characteristic that can affect both my outcome variables as well as the explanatory variable. The symbols *,** and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

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

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

The table reports coefficients and t-statistics (in parenthesis) for the bank lending growth volume to sectors after a monetary policy tightening. The reduced form model tested corresponds to Equation 1.7. The table presents the responses to a monetary policy easing. The unit of analysis is at the bank-sector quarterly level. The sample consists of syndicated loans originated in the U.S. from 1991q1 until 2016q4. The dependent variable is the log growth amount held by each lender at time t. *Excess Specialization* $_{b,s}^{t-1\rightarrow t-12}$ is the bank specialization and is defined as 12 quarter slow moving average of the share of total credit granted by a bank b to a specific sector s relative to the bank's total credit. In all specifications I am controlling for four lags of the dependent variable. The symbols *,** and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

C Data Appendix

C.1 Dealscan cleaning

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

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

$$\textit{Share at first observation } (SNC)_{i,l} = \beta_0 + \beta_1 \cdot \mathrm{X}_{i,l} + \beta_2 \cdot \mathrm{X}_l + u_{i,l} \quad (1.18)$$

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

The files are available at Kristian Blickles's web page. To approximate loan ownership post-origination is enough to use their available estimated regression coefficients for the Equation 1.18 to get an approximation of the post-origiantion loan holdings by banks which participate in the syndicate. They show that this approximation performs better than commonly used loan-shares estimation like pro-rata rules (Giannetti and Laeven, 2012; Saidi and Streitz, 2021; Doerr and Schaz, 2021) or the structure of the syndicate (Chodorow-Reich, 2014).

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

C.2 SBA loan data cleaning

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

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

C.3 Variable definition

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

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

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

Chapter 2

EXPOSURE TO COLLATERAL VALUE UNCERTAINTY AND BANK PORTFOLIO ALLOCATION

Joint with Francisco Amaral

2.1 Introduction

Fluctuations in the value of assets used as collateral to underpin financial transactions shape the supply dynamics of lenders. While much is known about how changes in collateral prices affect banks' behavior, in particular the crowding out of commercial lending amid asset price fluctuations (Chakraborty et al., 2018; Martín et al., 2021), little is understood about how ex-ante uncertainty in collateral values shapes banks' lending decisions.

Using US banks' regional exposure and the local nature of mortgage lending, we investigate the extent to which local house price risk shapes banks' loan portfolios through the collateral channel. While we know that house price risk strongly affects loan terms (Jiang and Zhang, 2022) and that there is considerable regional heterogeneity in housing risk (Amaral et al., 2021), we do not know how this affects banks that are highly exposed to regional housing markets.

We measure collateral value uncertainty as banks' exposure to local house prices and investigate how banks' exposure to collateral uncertainty influences their lending decisions. Exploiting detailed U.S. transaction price data, mortgage information, and small business loans, we document how this exposure shifts bank portfolios towards real estate loans and its implication for banks' profitability. Specifically, we find that higher exposure to collateral uncertainty is associated with an increased origination volume of real estate loans compared to small business loans and higher retention rates of real estate mortgages. Our analysis reveals that banks facing higher collateral uncertainty exhibit higher holding rates and originate more real estate loans while maintaining higher rejection rates compared to less exposed banks. This results in a shift towards real estate loans (RE) that banks retain in their portfolios, rather than securitizing them. Banks inefficiently hold more RE loans in their portfolios, incurring the costs of higher delinquencies. Consistently with this intuition, we find that at the bank level, higher exposure to collateral uncertainty relates to lower profitability (ROE), higher loan loss provisions, and non-performing loans (NPLs), particularly in real estate loans. These findings highlight the detrimental effects of collateral uncertainty on bank performance and portfolio decisions.

To examine the impact of collateral uncertainty on banks, we use transaction-level real estate data from CoreLogic spanning from 1996 to 2017, and we measure collateral uncertainty following Jiang and Zhang (2022). We complement this data with detailed census branch-level information to measure banks' exposure to collateral uncertainty. Our bank-level exposure measures the extent to which lenders are located in areas where collateral value uncertainty is high. To study lender's choices across different types of loans, we collect mortgage loan-level data from the Home Mortgage Disclosure Act (HMDA) for the same period and for small business (SBLs) loans originated in the United States. The HMDA requires most financial institutions to report and disclose detailed information about their mortgage activities, including loan volume, application status, location, and securitization. SBLs data comes from the Community Reinvestment Act (CRA) dataset, which aggregates the annual loan volumes originated by lenders with total assets exceeding $1 billion by the county of the loan recipient. We aggregate this data at the bank-county-year level, creating a comprehensive panel of originated loans across loan types for each entity over time and space. By combining these datasets, we can measure loan volume origination for each bank in a specific county over time, allowing us to analyze the effects of collateral uncertainty on banks' lending decisions.

Examining the drivers of banks' lending practices around varying levels of collateral uncertainty is inherently complex, particularly due to potential biases introduced by concurrent loan demand within a county. These biases can confound attempts to isolate the pure effects of banks' lending behavior. To mitigate this issue, we employ a strategy that leverages within-country variation across banks, bolstering our empirical model with county-year fixed effects. By assuming uniform demand across borrowers within each county, we effectively control for contemporaneous fluctuations in loan demand. This methodological approach allows us to attribute observed changes in lending behavior to banks' responses to collateral uncertainty, enhancing the robustness of our findings. We further exploit the cross-section and the within variation of banks to study the bank-level consequence of lender's decision allowing us to compare similar banks that differ in their exposure to collateral uncertainty.

The main empirical findings of this study are as follows. At the bank-county-year level, we observe that banks more exposed to collateral uncertainty significantly increase their origination of real estate (RE) loans relative to small business loans (SBLs). This effect is both economically substantial and statistically significant. Specifically, a one standard deviation increase in a bank's exposure to collateral uncertainty is associated with a 14.31% relative increase in RE loan volume compared to commercial loans. In practical terms, this represents an increase of approximately $266,000 in favor of real estate loans, given that the mean difference in loan volumes within our sample is $1.862 million. In robustness tests, we further demonstrate that our findings are not driven by lenders reacting to observed price dispersion (i.e., house market volatility exposure) or price level exposure, as documented by Chakraborty et al. (2018). These tests reinforce the validity of our results, highlighting the significant impact of collateral uncertainty on banks' lending decisions.

We then show the mechanism behind our results. While banks face higher collateral uncertainty, they significantly alter their intensive margin of lending of real estate loans. While on the margin lenders increase their originated applications of real estate loans to commercial loans, they increase significantly the volume of originated loans. That is to say, a standard deviation increase in collateral uncertainty exposure is associated with higher lending volume of the order of 14.4% and 15.96% for RE and Conformable Loans Limit (CLL).[1] We further show that this behavior is accompanied by higher retention rates (i.e., loans held on a bank's balance sheet), while banks more exposed have higher rejection rates, in line with Jiang and Zhang (2022). We take this evidence as suggestive that banks shift their lending behavior in favor of real estate loans. However while they doing so, lenders might incur an inefficient retention of mortgage loans as they are harder

[1]The residential mortgage market in the United States is segmented across two markets: the conforming market and the jumbo market. These two markets account for the vast majority of the originated residential mortgages. Conforming mortgages are eligible for purchase by government-sponsored enterprises(GSEs). Jumbo mortgages, alternatively, are not eligible for GSE and are more difficult to securitize

to liquidate in the secondary market, thus exposing banks to potential risk on their balance sheet.

The second set of results, explores thus the bank-level implication of these findings. Our analysis reveals that banks with higher exposure to collateral uncertainty exhibit distinct portfolio behaviors and financial outcomes. Specifically, while these banks demonstrate a higher allocation towards outstanding real estate loans relative to commercial loans at the bank level of an order of 4.44%, we find that the heightened lending activity towards real estate loans is accompanied by lower profitability metrics, such as returns on equity (ROE), and higher levels of non-performing loans (NPLs). In practice, a standard deviation increase in a bank's exposure to collateral uncertainty is related to a 2.2% lower ROE ratio and most importantly with 14% more delinquencies measured by NPLs ratio. This suggests that the heavy allocation towards RE loans also introduces heightened financial risks and necessitates increased provisions for loan losses. These findings underscore the challenges banks face in managing collateral uncertainty.

Building on these findings, our study provides new insights into how banks respond to collateral uncertainty and its implications for their lending strategies. Our results highlight the pronounced shift towards real estate loans among banks facing higher exposure to collateral uncertainty, with substantial increases observed in both residential real estate (RE) loans and Conforming Loans Limits (CLL) and their consequent challenges in maintaining profitability, as evidenced by lower returns on equity (ROE) and elevated levels of non-performing loans (NPLs), particularly within the 1-4 family real estate loan segment. These findings underscore the hurdles that banks face in securitizing these loans ultimately hurting their performances. Our study sheds new light on the financial implication of collateral uncertainty on banks' activity and their broader implications for financial performance and risk management strategies.

Literature review: Our paper is related to several strands of literature. Broadly, our paper fits into the large literature on frictions that affect mortgage credit (Lustig and Van Nieuwerburgh, 2005; Mian and Sufi, 2011; Greenwald et al., 2020; Agarwal et al., 2017; Buchak et al., 2018; Jiang, 2023; Jiang and Zhang, 2022) and its implication for the macro economy (Glaeser and Shapiro, 2003; Piazzesi and Schneider, 2016; Di Maggio and Kermani, 2017; Di Maggio et al., 2017; Mian and Sufi, 2011; Martín et al., 2021; Amaral et al., 2021). Our paper builds on the literature of house price dispersion pioneered by Giacoletti (2021) and analyzes idiosyncratic risk in residential real estate markets. In particular, our paper relates to Jiang and Zhang (2022) showing that collateral value uncertainty, i.e., idiosyncratic house price risks, matters in the U.S. residential real estate market, finding substantial cross-sectional heterogeneity in housing collateral values. They show that house price dispersion interacts with lender incentives and the housing appraisal system, ultimately influencing mortgage credit access: mortgages backed by high-dispersion houses are more likely to be rejected, receive worse rate menus, and have lower LTP ratios.

Our paper contributes to this literature by first showing that this channel is also proper for county-level acceptance rate and, most importantly, reduces securitization rate at the county level, both for conformable loans as well for non-conforming loans. Finally, we show evidence suggesting that lenders face the same constraints that raise deposits in areas with heightened collateral value uncertainty.

Our paper builds on the empirical literature studying the effect of house prices on credit and investment. The evidence on the effect of collateral price fluctuations on investment is mixed so far. Some papers provide evidence for a positive effect through a collateral channel, where higher corporate headquarters prices for listed firms are shown in Chaney et al. (2012). Recently, Adelino et al. (2015)

found evidence of crowding on private home prices for entrepreneurs boosting firm credit. Similarly, Jiménez et al. (2020) argued that Spanish banks could increase their credit supply during the housing boom by relying on mortgage securitization. However, Chakraborty et al. (2018) showed instead that banks that were more exposed to the U.S. housing boom reduced their loans to firms using a sample of large syndicated borrowers, finding evidence for mortgages crowding out corporate credit. Most prominently Martín et al. (2021) showed, focusing on the Spanish economy, that these two channels are not mutually exclusive, as they find that when banks face financial constraints, rising demand for housing initially crowds out non-housing credit. However, as the boom continues, housing credit repayments raise banks' net worth and expand their credit supply, so crowding out gives way to crowding in.

Our paper adds to this literature by decomposing the total effect of house price risks into price fluctuations and the idiosyncratic component. We show in robustness checks that these two components might have opposite directions in the securitization ability of loans and thus can rationalize part of the aforementioned empirical results. Moreover, we contribute to this literature by showing that banks that are most exposed to the latter component face tighter constraints as they are unable to securitize their loans; they inefficiently hold too many real-estate loans to achieve their desired target leverage.

The rest of the paper is structured as follows. Section 2.2 presents our methodology to measure collateral uncertainty and banks' exposure to it and the empirical methodology used in the paper. Section 2.3 presents the various data sources used in the analysis. The results from the estimation and additional analyses are presented in Section 2.4, where we provide bank-county level evidence in Subsection 2.5 and the bank level implication in 2.5.1. We provide a robustness test in Section 2.6. Section 2.7 concludes.

2.2 Methodology and identification

In the following section, we detail how collateral value uncertainty, measured via idiosyncratic house price risk is defined and the main assumptions used to design the measure.

2.2.1 Measuring idiosyncratic house price risk

Following the real estate literature (Kotova and Zhang, 2020), we measure price deviations at the house transaction level as the difference between the transaction price and the expected market value of the property, which is determined using a hedonic regression estimated on signle-family houses sales.[2]

For each county separately, we regress the natural logarithm of the transaction price for property i in year-quarter tq on year-month fixed effects, η_{tm}, year-quarter-zip-code fixed effects, $\kappa_{n,tq}$, and a second-order polynomial function of apartment characteristics (age, square foots, number of rooms and number of bathrooms) interacted with year fixed effects, $f_c(x_i, ty)$:

$$ln(p_{i,tq}) = y_i + \eta_{tm} + \kappa_{n,tq} + f_c(x_i, ty) + u_{i,tq}, \tag{2.1}$$

where $u_{i,tq}$ is a mean-zero error term with variance σ^2. The η_{tm} and $\kappa_{n,tq}$ terms absorb parallel shifts in housing prices in a county and in zip-codes over time, for example due to gentrification. The $f_c(x_i, ty)$ term allows apartments with different observable characteristics x_i to appreciate at different rates: for example, the $f_c(x_i, ty)$ term allows larger apartments to appreciate faster than smaller apartments, or newer apartments to appreciate faster than older apartments. We use an

[2] A very similar approach to estimate the market value is employed in Kotova and Zhang (2020); Buchak et al. (2020).

additive functional form for $f_c(x_i, ty)$:[3]

$$f_c(x_i, ty) = g_c^{sqft}(sqft, ty) + g_c^{yrbuilt}(yrbuilt, ty) + g_c^{romms}(rooms, ty) + g_c^{bathrooms}(bathrooms, ty) \quad (2.2)$$

These functions are interacted second-order polynomials in their constituent components. The squared terms of the polynomial function accommodate the possibility that the effect of size and age on transaction prices may vary along the distribution. For instance, larger apartments might appreciate at a different rate than smaller apartments, and this effect may not follow a monotonic pattern.

The residuals, $u_{i,tq}$ from equation (2.1) quantify the discrepancy between the transaction price and the expected market value of the apartments. Consequently, the squared residuals serve as a measure of price dispersion at the house transaction level.

However, the price dispersion measured in the previous section reflects realized price dispersion. In other words, the residuals, $u_{i,tq}$, from Equation (2.1) are only observed ex-post and thus represent a biased measure of investors' expectations. Therefore, we approximate the information set available to a potential investor about a specific property before purchasing it. We then use the information about other transactions to interpolate the expected price dispersion for the transaction of a specific house. To achieve this, we employ the method introduced in Jiang and Zhang (2022). Using the observable characteristics of the properties and the transaction values of similar properties that were sold in the same period, we obtain a prediction of idiosyncratic price dispersion at the property level. More specifically, we estimate the following regression:

[3] In principle, it would be better to estimate a fully interacted polynomial in all house characteristics. However, as argued by Kotova and Zhang (2020), that is not computationally feasible.

$$u_{i,tq}^2 = g_c(x_i, tq) + \epsilon_{it} \tag{2.3}$$

$$\hat{\sigma}_{i,tq}^2 = \hat{g}_c(x_i, tq), \tag{2.4}$$

where u^2 are the squared residuals estimated from equation 2.1 and $g_c(x_i, tq)$ is a smooth function of observable property characteristics interacted with quarter fixed effects. The characteristics are size, age and location and g is an additive function that takes the form:

$$\begin{aligned} g_c(x_i, tq) = g_c^{sqmt}(tq, sqmt) + g_c^{yrbuilt}(tq, yrbuilt) + \\ g_c^{rooms}(tq, rooms) + g_c^{bathrooms}(tq, bathrooms), \end{aligned} \tag{2.5}$$

where the functions g are second-order polynomials that interact time quarter fixed effects with size and year of construction respectively. We then use the predicted values, $\hat{g}_c(x_i, t)$, as an estimate of the property transaction level predicted price dispersion and take the average idiosyncratic exposure at the county level which we define as $\hat{\sigma}_{c,t}^2$ [4].

2.2.2 Measuring banks' exposure to idiosyncratic house price risk

In the baseline analysis, we define a bank's exposure to house price risk as the branch-deposit volume weighted average to county-level idiosyncratic risk. This approach assumes that banks are significantly exposed to loan demand from firms and households in their core deposit branches, but is less biased than using loan

[4] We estimate $\hat{\sigma}_{i,tq}^2$ using the information set available in each quarter. Subsequently, we create our measure of interest by pooling these quarterly estimates over the year-county pairs.

weights which would instead cofounded by banks' supply decisions. If a bank raises a lot of deposits in an area, then it is likely that its main lending operations are also based in that area. Data on deposit amounts at the branch level for the banks in our sample come from the Federal Deposit Insurance Corporation's (FDIC) Summary of Deposits.

For each bank, we weigh the pre-existing deposit volumes at the county level to obtain a measure of each bank's exposure to idiosyncratic house price risk where it has active deposit-taking activities. The resulting measure of bank exposure to idiosyncratic house price risk is given :

$$\mathit{Exposure}_{b,t} = \sum_{c \in b} \frac{deposit_{c,b,t-1}}{\sum_{c \in b} deposit_{c,b,t-1}} \times \hat{\sigma}^2_{c,t} \tag{2.6}$$

The term $\hat{\sigma}^2_{c,t}$ captures the county time varying idiosyncratic house price risk for 1996 to 2017, while b, c, t define respectively the bank, the county and the time. This bank time-variant measure captures the extent to which each bank is exposed to price uncertainty and ranges from 0 to $+\infty$. For consistency, in our analysis we exclude banks whose branches are located in only one county as they cannot diversify across space.

We also provide several alternative measure of our main explanatory variable, including fixing the deposit share weights across the sample, or taking slow moving average of the deposit share. The idea is to make sure that our results are driven by exposure to house price uncertainty and not by banks decision to move across counties.

2.3 Data

To measure idiosyncratic house prices and study its influence on loan securitization and banks' investment policy we rely on several data sources from the US economy. In the following section we first describe the sample construction, describe the measure of idiosyncratic house price risk, and other economic variables of interest that we employ throughout the analysis and finally summarize the sample characteristics.

Corelogic deed & tax data: We obtain house transaction records in the entire US from 1990 to 2017 from the CoreLogic Deed dataset. The data set reports each house transaction attached to a specific property and provides information on the sale amount, mortgage amount, transaction date, and property location. We merge the transaction records with the CoreLogic Tax records, which contain property characteristics such as year built and square footage. We estimate price dispersion for each house in this merged data set and aggregate it into county-level information. Due to data coverage limitation, we restrict our sample to 1996-2017.

Home Mortgage Disclosure Act (HMDA): The HMDA covers the near universe of U.S. mortgage applications, including both originated, accepted, and rejected applications and in particular whether a loan is sold within a year of origination[5]. We use the HMDA for extensive and intensive margin analysis on mortgage applications and securitization rates.

Community Reinvestment Act (CRA): We obtain small business lending data from the CRA small business loans database provided by the Federal Financial Institutions Examination Council (FFIEC). This data set contains information on the total number and volume of small business loans originated by each report-

[5]Anecdotal evidence shows that In U.S. the majority of loans are sold within a year of origination, moreover the HMDA data are ex-post updated after submissions, which reduce any potential mistake of mismeasurement.

ing financial institution in each U.S. county during a calendar year. For 1996 and 2004, all commercial and savings banks with total assets exceeding $250 million were required to report. Post 2005, the FFIEC raised the mandatory reporting asset size threshold from $250 million to $1 billion. Following this increase in the asset size threshold, the number of banks reporting to the CRA small business lending data set declined by approximately half now tracking around 1,000 institutions. For our regression analysis, we use the entire sample of banks available at any point in time.

FDIC deposit branch data: The data on deposit quantities and branch locations are from the Federal Deposit Insurance Corporation (FDIC). This data covers the universe of U.S. bank branches at an annual frequency from June 1994 to June 2020. The data set has information on branch characteristics such as the parent bank, location, and deposit volume. We use the unique FDIC branch identifier to match it with other data sets at the parent bank.

Call reports data: We employ financial data on banks from the Call Reports. The data includes balance sheet information at the quarterly level for all deposit-insured bank companies located in the United States. Because these reports are available at the end of every quarter, we match the origination year of the loan deal with the final quarter of each year.

The final sample consists of information for the 47 major states in the U.S. country and a total of 1260 counties [6].

Finally, we provide in Table 2.1 the summary statics for the main variable of interest and controls used in the analysis. Rejection and holding rates are heavily skewed, with a heavy right tail and very dispersed, while volume rates are more evenly distributed. Going to bank level measures, our main variable of interest, bank-level collateral uncertainty exposure, is very dispersed, we defer the dis-

[6] The list of states for which we have sufficient data for our estimate procedure are the 51 US territory state and federal district with the exclusion of Alaska, Hawaii, DC, and Connecticut

cussion to section 2.4 where we also present new stylized facts related to these measures. Regarding the remaining variables we observe that NPL ratio and loan loss provisions are close to historical averages, suggesting that despite we cannot the full spectrum of banks, our sample remains representative[7].

[7]In non-tabulated results, we show that the matched county-deposit share accounts for roughly 80% of deposit shares in our banks, also for GSIB banks. Regarding the matched share of HMDA and CRA data, for years post-2000, we are able to match more than 50% of origination volume, while for prior years the share is reduced to below 30% due to sparse information in Corelogic data.

Table 2.1:
Summary statistics

	Mean	SD	Min	Max	p25	p75	Obs
Bank-county level							
Rejection rate$_{b,c,t}$	0.20	0.16	0.00	1.00	0.08	0.27	124,114
Rejection rate CLL$_{b,c,t}$	0.20	0.16	0.00	1.00	0.08	0.28	123,694
Held rate$_{b,c,t}$	0.69	0.26	0.00	1.00	0.48	0.97	124,114
Held rate CLL$_{b,c,t}$	0.67	0.27	0.00	1.00	0.46	0.97	123,694
log(1+amount)$_{b,c,t}$	8.04	1.93	0.00	15.91	6.90	9.26	124,114
log(1+amount CLL)$_{b,c,t}$	7.79	1.95	0.00	15.31	6.67	9.04	124,114
log(1+held amount)$_{b,c,t}$	7.84	1.84	0.00	15.98	6.72	8.97	124,114
log(1+held amount CLL)$_{b,c,t}$	7.51	1.83	0.00	14.81	6.45	8.64	124,114
log(1+SBL amount)$_{b,c,t}$	7.97	1.61	0.34	14.00	7.02	9.07	97,513
log(1+SBL applications)$_{b,c,t}$	3.23	2.12	0.00	11.36	1.61	4.77	124,114
log dif. HMDA-CRA loans$_{b,c,t}$	0.40	1.61	-12.01	8.82	-0.47	1.34	97,513
log dif. CLL HMDA-CRA loans$_{b,c,t}$	0.14	1.72	-12.13	8.71	-0.69	1.13	97,513
log dif. held HMDA-CRA loans$_{b,c,t}$	0.57	1.73	-6.84	10.13	-0.66	1.67	124,114
log dif. held CLL HMDA-CRA appl.$_{b,c,t}$	0.47	1.78	-8.51	10.07	-0.77	1.61	124,114
Bank level							
$\sum_{c\in b} dp.sh._{c,b,t-1}\hat{\sigma}^2_{c,t}$	0.30	0.12	0.00	0.63	0.23	0.38	20,830
$\sum_{c\in b} dp.sh._{c,b}\hat{\sigma}^2_{c,t}$	0.33	0.13	0.00	1.01	0.25	0.42	20,830
ROA$_{b,t}$	0.01	0.01	-0.05	0.03	0.01	0.01	20,593
ROE$_{b,t}$	0.10	0.08	-0.42	0.31	0.06	0.14	20,349
$\frac{NPL}{Loans}_{b,t}$	0.01	0.02	0.00	0.11	0.00	0.02	20,518
$\frac{NPL\ 1\text{-}4\ RE}{REloans}_{b,t}$	0.01	0.02	0.00	0.13	0.00	0.02	19,535
Loan loss prov. %$_{b,t}$	0.32	0.42	0.00	3.32	0.09	0.36	19,575
Log assets$_{b,t}$	6.43	1.51	3.42	14.58	5.43	7.09	20,830
$\frac{Core\ deposits}{Assets}_{b,t}$	0.69	0.10	0.22	0.88	0.63	0.77	20,666
$\frac{Whl\ deposits}{Assets}_{b,t}$	0.15	0.08	0.01	0.45	0.09	0.20	20,613
$\frac{Tier\ 1}{Assets}_{b,t}$	0.09	0.02	0.05	0.31	0.08	0.10	20,406

This table provides summary statistics for bank-county and bank-level characteristics of the studied sample on an annual basis. The sample includes all matched deposit-insured bank companies with more than one active branch in the counties analyzed. To be included in the summary statistics, banks are required to operate in more than one matched county in our sample and be active at the end of each calendar year. Bank-county-level information is sourced from the matched sample of HMDA and CRA data, while bank-level information is obtained from bank Call Reports, SoD, and CoreLogic datasets. The data spans the period from 1996 to 2017. As our analysis requires banks to have at least two consecutive years of observations to measure the exposure variable, the effective sample period begins in 1997. We finally exclude the post-GFC years 2008 and 2009 from our sample.

2.4 Stylized facts

In this section, we present new stylized facts regarding county-level collateral value uncertainty and its implications for loan outcomes, as well as bank-level cross-sectional exposure and persistence in relation to this uncertainty.

We begin by offering additional evidence that collateral value uncertainty is associated with reduced market liquidity, corroborating the findings of Jiang and Zhang (2022). Figure 2.1 illustrates that county-level retention rates, defined as the proportion of loans retained by financial institutions, increase with higher county-level collateral uncertainty.[8] Moreover, we demonstrate that the share of non-bank lenders in a county is inversely related to higher collateral uncertainty.[9]

As noted by Buchak et al. (2018), non-banks typically follow an *originate-to-distribute* model. Their lower presence indicates that these loans are more difficult to securitize, as non-banks are less inclined to hold mortgage loans in their portfolios due to their relatively lower balance sheet capacity compared to traditional banks. This is further evidenced by the higher county-level concentration, suggesting that local presence in these markets is essential to capitalize on potential returns in the loan market.

The results are illustrated in Figure 2.1, where we present county-level binscatter plots for holding rates, shadow bank market share, and the county-level Herfindahl-Hirschman Index (HHI). We measure the holding rate as the number of loan applications held by banks at the end of the year relative to the total number of applications originated.

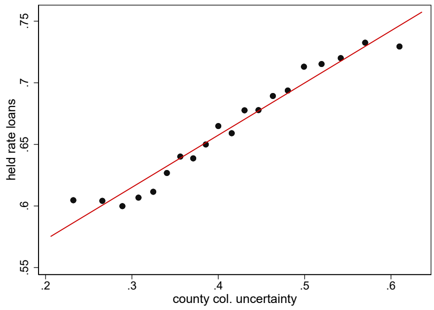
Next, we analyze the variation in exposure to collateral value uncertainty

[8]urther evidence supporting these patterns for both conforming and non-conforming loans is provided in Figure A.1.

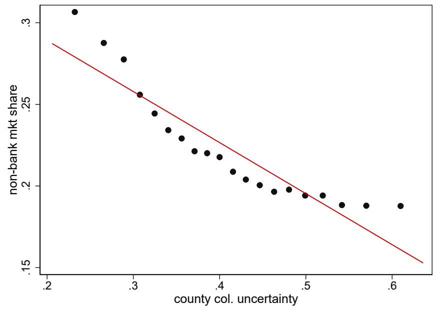
[9]Following Buchak et al. (2018) and Agarwal et al. (2022), we define non-banks as lenders classified as ”independent mortgage banks” or ”independent mortgage banks affiliated with a depository institution” in the HMDA dataset, using the `type` variable as specified in the Avery file.

Figure 2.1:
Collateral uncertainty and liquidity

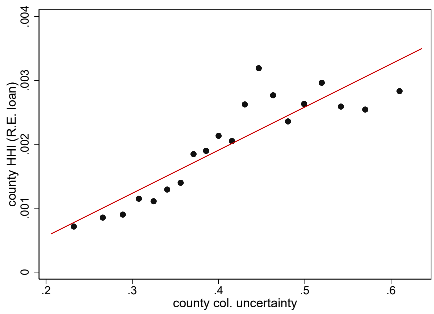
(a) Hold rate



(b) Shadow-bank origination share



(c) County-level concentration

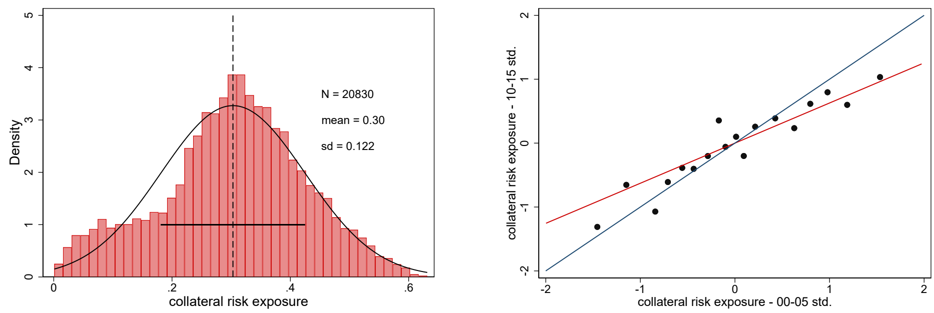


Note: Figure 2.1a plots county-level holding rate for HMDA loans for the period 1996-2017. The graphs plot a binscatter plot on county collateral uncertainty on loans holding rate controlling for year fixed effect. The sample includes annual county-level observations from 1996 to 2017. Figure 2.1b shows the binscatter for the county collateral uncertainty measure on shadow bank loan volume market share controlling for year fixed effect. Figure 2.1c shows the binscatter for the county collateral uncertainty measure on county-level HHI controlling for year fixed effect. The data comes from the matched HMDA and CoreLogic datasets for the period 1996-2017.

across the banks in our sample. This measure captures the extent to which banks are exposed to areas with different collateral uncertainty levels, based on their deposit volume share in a given area.

Figure 2.2:
Stylized facts about banks' collateral uncertainty exposure

(a) Exposure distribution (b) Exposure persistency



Note: Figure 2.2a plots bank-level distribution for our measure of banks' collateral uncertainty exposure over the sample period 1996-2017. Figure 2.2b shows the binscatter for the 5-year average bank-level distribution for the period 2000-2005 against the average distribution for 2010-2015. To obtain the values, we standardized the mean of the 5-year average of banks' collateral uncertainty exposure over the different periods and plotted the corresponding distributions. For the construction of our measure of exposure, we required to have 2 consecutive periods of our collateral exposure measure, thus the first bank-level observation effectively started in 1997. We exclude the GFC years 2008 and 2009 from our sample.

In Figure 2.2, we plot a histogram illustrating the distribution of collateral uncertainty exposure at the bank level for the sample period 1996-2017. The distribution is strongly centered around the mean, but the tails are quite thick, indicating considerable variation in exposure measures across banks. Banks at the 10th percentile of the distribution have an exposure of 0.13, while those at the 90th percentile have an exposure of 0.56.

Although there is significant dispersion in banks' exposure to real estate collateral uncertainty, this dispersion remains very persistent over time. In Figure 2.2b, we plot the average bank-level exposure for the period between 2000 and 2005 against the corresponding period between 2010 and 2015. To ensure comparability over time, we standardize the exposure measure in both periods.[10] We observe a clear positive relationship closely following the 45-degree line, indicating that banks with relatively high exposure at the start of the 2000s also had relatively high levels of exposure at the start of the 2010s. Additionally, the fitted line is very close to the 45-degree line, suggesting that the relative ranking of banks with respect to exposure is highly persistent over time. This persistence suggests that differences in collateral price uncertainty exposure are not driven by time-varying factors, such as bank locations or deposit characteristics in an area. Instead, the dispersion appears to be driven by the persistent characteristics of the local housing stock. To further corroborate this, we show in Figure A.3 that our measure of exposure remains highly persistent across different periods of analysis. In Appendix Figure A.4, we differentiate the persistence across the two components of our exposure measure (e.g., deposit shares and county-level collateral risk). Banks' deposit shares are considerably stickier than county-level collateral uncertainty, further suggesting that the variation is driven by local housing differences.

Overall, this section demonstrates that our measure of collateral uncertainty is related to lower market liquidity and that there is significant heterogeneity in banks' exposure to it. This heterogeneity is ultimately driven by local housing characteristics rather than time-varying factors such as banks' location choices or volatile deposit shares. In the next sections, we examine the relationship between banks' collateral uncertainty exposure and loan outcomes.

[10] We standardize the exposure measure in both periods to have a mean of zero and a standard deviation of one across banks.

2.5 Collateral uncertainty exposure and banks portfolio decision

The county-level evidence in section 2.4 indicates that higher levels of collateral uncertainty are associated with reduced market liquidity of the assets underlying financial transactions. Given the critical role of collateral value in both mortgage and commercial loans and the varying exposure banks have to collateral uncertainty, we formally investigate its impact on banks' decisions regarding mortgage and small business loans (SBLs).

Establishing a direct relationship between real estate collateral uncertainty and SBL loans is challenging due to potential omitted factors, the most significant being local demand. If higher collateral uncertainty or specific county characteristics lead to a decline in local demand, banks' portfolio decisions could simply reflect this heterogeneous demand between mortgages and SBLs. Therefore, to accurately determine the effect of collateral uncertainty on the allocation between real estate and SBL loans, it is essential to control for local demand variations.

We address this issue by analyzing the cross-section of banks within specific counties, exploiting the variation in exposure to local collateral uncertainty at the bank level. Specifically, we compare two different banks within the same county that have differing levels of exposure to our measure of collateral uncertainty.

2.5.1 Cross-Sectional Analysis: Real Estate and Commercial Loans

Our within-county estimation strategy exploits the log differences in the volume of real estate loans compared to small business lending. Both datasets are available at the bank-county level. These two markets are particularly well-suited for our analysis because mortgage loans are highly standardized contracts and typically information-insensitive, relying heavily on the loan-to-value (LTV) ratio and collateral values (Jiang and Zhang, 2022). In contrast, small business lending is a highly illiquid yet economically important form of lending, where collateral values are crucial to backing transactions.

We run the following OLS specification:

$$y_{b,c,t} = \alpha_{b,c} + \alpha_{c,t} + \alpha_b + \beta_1 \times \sum_{c \in b} \frac{deposit_{c,b,t-1}}{\sum_{c \in b} deposit_{c,b,t-1}} \times \hat{\sigma}^2_{c,t} + \Gamma' X_{b,t-1} + \varepsilon_{b,c,t} \quad (2.7)$$

where $y_{b,c,t}$ is the log difference of new real estate to SBL loans by bank b in county c in year t, or any other variable of interest at the bank-county-year level. $\sum_{c \in b} \frac{deposit_{c,b,t-1}}{\sum_{c \in b} deposit_{c,b,t-1}} \times \hat{\sigma}^2_{c,t}$ is the bank-level predicted collateral exposure of bank b in year t, $\alpha_{b,c}$ are bank-county fixed effects, $\alpha_{c,t}$ are county-time fixed effects, and α_b are bank fixed effects. We double-cluster standard errors at the bank and county levels. The key set of controls is the county-time fixed effects, which absorb changes in local lending opportunities common across banks operating in a county c. We also include county-bank fixed effects, which absorb time-invariant characteristics such as local brand effects and any other persistent differences in a bank's relation with a particular county or vice-versa. The bank fixed effects absorb invariant characteristics of the banks that might drive their average lending opportunities. We also include local concentration (Branch-HHI$_{b,c,t}$ as in Drechsler et al. (2017)) to control for local deposit market concentration faced by each bank, which can have repercussions on banks' choice of commercial loans (Supera, 2023). Finally, across all our analyses, we include the following bank-level variables: bank size, tier 1 ratio, core-deposit ratio, wholesale funding ratio, and ROA to control for differences in the condition of banks. We focus on the sample of banks with branches in at least two counties because the coefficient of interest, β_1, could be biased when banks cannot diversify across counties. This means that the sample of banks in our estimation is relatively large as seen in section 2.3.[11] To identify our coefficient of interest, we are effectively exploiting the variation in collateral uncertainty exposure faced by different banks operating within the same county during the same period. By comparing banks with different levels of exposure to local collateral uncertainty within the same county, we can isolate the impact of collateral uncertainty on their lending decisions, controlling for county-wide economic conditions and bank-specific factors.

The results are presented in Table 2.2. Column (1) does not control for local lending opportunities while it controls for persistent differences in banks'-county relations (i.e., $\alpha_{b,c}$). However, it shows that when banks face higher collateral uncertainty exposure, they then increase their proportion of real estate loans to commercial lending, though the results are not statistically significant.

In the most saturated model, where we control for local demand characteristics that drive the relative demand for loans within a county, as shown in Column (2), we find strong and significant results. This demonstrates the importance of accounting for local lending opportunities. Specifically, it shows that banks more exposed to collateral uncertainty will increase their real estate lending relative to small business lending compared to less exposed banks within the same county. A one standard deviation increase in a bank's exposure to collateral uncertainty is associated with a 14.31% increase in the ratio of real estate to commercial loans. [12] This magnitude is both quantitatively and economically significant. Given that the average county difference between real estate loan origination volume and commercial loans is approximately 1.862 million in our sample, this implies that

[11] Our sample of analysis corresponds to the top 90 percentile of the asset distribution of banks in the United States.

[12] Calculated as $\exp(0.12 \times 1.115) - 1 = 0.1431$, where 0.12 is the observed standard deviation of banks' exposure to collateral uncertainty. Given that the unconditional mean of the real estate to commercial loans ratio is $\exp(0.40) \approx 1.49$, the absolute change in the ratio corresponds to $1.49 \times 0.1431 \approx 0.21$.

Table 2.2:
Banks' collateral uncertainty exposure and portfolio choice

Above 1 counties		
	Main dep: log dif. HMDA-CRA loans	
	(1)	(2)
$\sum_{c \in b} dp.sh._{c,b,t-1} \cdot \hat{\sigma}^2_{c,t}$	0.522	1.115***
	(0.446)	(0.426)
Controls	✓	✓
Year and county F.E.	✓	
County-year F.E.		✓
Bank F.E.		✓
Bank-county F.E.	✓	✓
Clustered Std.Errors	Bank county	Bank county
R^2	0.717	0.782
Obs	96,062	96,062

This table provides estimates of the sensitivity of R.E. to C&I small business loans to banks' house price collateral uncertainty exposure. The data are aggregated at the bank-county year level for the sample years 1996 to 2017. We exclude the year of the global financial crisis (2008,2009) from the estimation to make sure that our results are not driven by the bust in real estate and small business loans post-GFC. We further focus on banks that operate in more than one county to make sure that banks can diversify their local opportunities. The table presents the estimate for the following model in Equation 2.7. The level of significance are * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

banks increase their real estate loan exposure by 266 thousand dollars.

Alternatively, their share of real estate to commercial loans moves from 1.49 to 1.7 times the size of small business loans.

We then analyze the extensive margin of lending by considering the log differences in the number of originated applications for held real estate loans compared to small business loans (SBLs). Our focus is on held real estate loan origination rather than total origination because held loans better represent the actual risk retained by banks, providing a clearer picture of a bank's exposure to collateral uncertainty. Total origination figures can be misleading if a substantial portion of the originated loans are sold off, transferring the risk to other entities.

The results are presented in Table 2.3, where we find positive and statistically significant outcomes for both specifications of our analysis.

Table 2.3:
Banks' collateral uncertainty and portfolio choice: applications

Above 1 counties		
	Main dep: log dif. held HMDA-CRA appl.	
	(1)	(2)
$\sum_{c\in b} dp.sh._{c,b,t-1} \cdot \hat{\sigma}^2_{c,t}$	1.095*	1.232**
	(0.602)	(0.530)
Controls	✓	✓
Year and county F.E.	✓	
County-year F.E.		✓
Bank F.E.		✓
Bank-county F.E.	✓	✓
Clustered Std.Errors	Bank county	Bank county
R^2	0.745	0.792
Obs	124,114	124,114

This table provides estimates of the sensitivity of R.E. to C&I small business loan applications to banks' house price collateral uncertainty exposure. The data are aggregated at the bank-county year level for the sample years 1996 to 2017. We exclude the year of the global financial crisis (2008,2009) from the estimation to make sure that our results are not driven by the bust in real estate and small business loans post-GFC. We further focus on banks that operate in more than one county to make sure that banks can diversify their local opportunities. The table presents the estimate for the following model in Equation 2.7. The level of significance are * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Focusing on Column (2), we find that a one standard deviation increase in banks' exposure to collateral uncertainty is associated with a 16% increase in the loan application ratio. [13] These estimates are economically significant, as

[13] Calculated as $\exp(0.12 \times 1.232) - 1 = 0.1593$. Given that the unconditional mean in held originated applications of real estate to commercial loans is $\exp(0.57) \approx 1.76$, the absolute change in the ratio corresponds to $1.76 \times 0.1593 \approx 0.28$.

the application ratio moves from 1.7 to double the size of SBL loans. We find similar results once considering total real estate origination, the results are shown in Table B.1, however, magnitudes are smaller.

2.5.2 Mechanism

To delve deeper into the mechanisms driving the observed relationship between collateral uncertainty and banks' lending decisions, we extend our analysis to include several key metrics: real estate loan rejection rates, holding rates, and volumes, as well as the corresponding metrics for small business lending (SBL). By examining these aspects, we aim to highlight the mechanism through which banks adjust their lending practices and risk management strategies in response to varying levels of collateral uncertainty. Specifically, we analyze whether banks are more likely to reject real estate loan applications, hold a greater proportion of originated real estate loans, and adjust their dollar volume of real estate loans.

Part of our results could be explained by increased risk-taking behavior by banks in favor of real estate loans in pursuit of higher returns when the market becomes less liquid. To test this, we examine whether banks change their rejection rates when facing higher collateral uncertainty. Rejection rates are defined as the number of non-accepted applications out of the total received applications. The results are presented in Table 2.4:

In Column (1) we report the results for the rejection rate on real estate loans. We find that as banks face higher collateral uncertainty exposure, they exhibit higher rejection rates for real estate loans, indicating that they are not reducing their aversion to risk. Specifically, a one standard deviation increase in exposure is associated with an increase of 1.1 percentage points in the rejection rate.[14] Given that the unconditional mean rejection rate is 20%, this increase corresponds

[14] Calculated as $0.12 \times 0.091 = 0.01092$

Table 2.4:
Banks' collateral uncertainty and portfolio choice: mechanism

	Above 1 counties			
	Rejection rate$_{b,c,t}$	*Held rate*$_{b,c,t}$	*log held amount*$_{b,c,t}$	*log held amount CLL*$_{b,c,t}$
	(1)	(2)	(3)	(4)
$\sum_{c\in b} dp.sh._{c,b,t-1} \cdot \hat{\sigma}^2_{c,t}$	0.091***	0.135*	1.205***	1.255***
	(0.033)	(0.073)	(0.384)	(0.383)
Controls	✓	✓	✓	✓
County-year F.E.	✓	✓	✓	✓
Bank F.E.	✓	✓	✓	✓
Bank-county F.E.	✓	✓	✓	✓
Clustered Std.Errors	Bank county	Bank county	Bank county	Bank county
R^2	0.610	0.739	0.870	0.851
Obs	124,114	124,114	124,114	124,114

This table provides estimates of the sensitivity of various real estate loan metrics to banks' exposure to house price collateral uncertainty. The data are aggregated at the bank-county-year level for the sample years 1996 to 2017. We exclude the years of the global financial crisis (2008 and 2009) from the estimation to ensure our results are not driven by the bust in real estate and small business loans post-GFC. We focus on banks that operate in more than one county to ensure they can diversify their local opportunities. Column (1) shows the estimates for the rejection rates of real estate loans. Column (2) presents the estimates for the held rates of real estate loans. Column (3) contains the estimates for the loan volume origination of real estate loans. Column (4) shows the estimates for the held volume origination of real estate loans. The table presents the estimate for the following model in Equation 2.7. The level of significance are * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

to a 5.46% semi-elasticity.[15] This means that a one standard deviation increase in banks' exposure to collateral uncertainty results in a 5.46% increase in the rejection rate relative to the average rejection rate. As banks do not increase their risk-taking on real estate loans, we then look at their holding rates to see if, on the margin, these loans are different across banks with different exposures. The results are presented in Column (2). A one standard deviation increase in a bank's exposure to collateral uncertainty is associated with a 1.62% increase in the held rate of

[15] Calculated as $\frac{0.01092}{0.20} \times 100 = 5.46\%$

real estate loans. [16] Given that the unconditional mean held rate is 0.69, this corresponds to a semi-elasticity of approximately 2.35%.[17] This demonstrates that banks with higher collateral uncertainty exposure tend to hold a slightly higher proportion of real estate loans, confirming that these loans are harder to sell as evidenced in Figure 2.1. However, these facts cannot explain alone the increase in real estate volumes seen in Table 2.2. We thus look at the intensive margin of lending to real estate loans in Column (3) and to conformable loans in Column (4). We use conforming loans as a key segment to highlight the potential role of banks' selection in the market, as the origination of these loans does not require substantial balance sheet capacity for banks. This is because conforming loans are eligible for purchase by government-sponsored enterprises (GSEs), which alleviates the need for banks to retain them on their balance sheets.[18]

We find that on the intensive margin, banks with higher exposure to collateral uncertainty significantly increase their loan origination volume. This effect is pronounced and economically relevant across all loan types, including conforming loans. Specifically, a one standard deviation increase in exposure is associated with a 14.4% and 15.06% increase in loan volume, respectively. These findings suggest a potential crowding out of commercial loans by real estate loans for banks more exposed to collateral uncertainty.

In Table 2.5, we provide a similar analysis for SBLs. We find a moderate increase in loan volume while the number of originated applications remains unchanged. Given the results in Table 2.2, this difference can be attributed to the relative risk profiles and profitability of the two loan types. Real estate loans, particularly in a less liquid market, may offer higher returns compared to SBLs,

[16] $\exp(0.12 \times 0.135) - 1 = 0.0162$

[17] $0.0162/0.69 = 0.0235$

[18] Buchak et al. (2018) and Buchak et al. (2020) show that the vast majority of retention and origination of conforming loans can be explained by banks' balance sheet capacity, where banks with more equity can retain larger loans on their balance sheets.

Table 2.5:
Banks' collateral uncertainty and portfolio choice: SBLs loans

Above 1 counties		
	log(1+SBLs volume)$_{b,c,t}$	*log(1+SBLs app.s)*$_{b,c,t}$
	(1)	(2)
$\sum_{c \in b} dp.sh._{c,b,t-1} \cdot \hat{\sigma}^2_{c,t}$	0.466*	0.544
	(0.250)	(0.336)
Controls	✓	✓
County-year F.E.	✓	✓
Bank F.E.	✓	✓
Bank-county F.E.	✓	✓
Clustered Std.Errors	Bank county	Bank county
R^2	0.910	0.910
Obs	92,517	92,517

This table provides estimates of the sensitivity of various SBL loan metrics to banks' exposure to house price collateral uncertainty. The data are aggregated at the bank-county-year level for the sample years 1996 to 2017. We exclude the years of the global financial crisis (2008 and 2009) from the estimation to ensure our results are not driven by the bust in real estate and small business loans post-GFC. We focus on banks that operate in more than one county to ensure they can diversify their local opportunities. Column (1) shows the estimates for the loan volumes originated. Column (2) presents the estimates for the held rates of real estate loans. The table presents the estimate for the following model in Equation 2.7. The level of significance are * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

prompting banks to allocate more resources towards them. Conversely, SBLs, which generally have higher default rates and lower collateral values, might be less attractive under increased uncertainty. However, this reallocation of resources towards real estate loans comes with a cost of higher retention rates, which might induce potential risk at the bank-level. In the next section, we study the overall bank implication of these patterns.

2.5.3 Bank-level analysis

In the previous section, we analyzed bank-level policies at different levels of exposure to collateral uncertainty by exploiting cross-country heterogeneity among banks. In this section, we examine the bank-level consequences of the previously discussed results. This analysis provides a detailed picture of how banks' portfolios behave in response to changes in collateral uncertainty exposure. It also allows us to verify the robustness of our earlier results on lenders' portfolio policies across real estate and commercial loans using a different dataset, namely the U.S. Call Reports.

First, we use a cross-sectional analysis to demonstrate that banks with higher exposure to collateral uncertainty have a higher fraction of real estate loans, consistent with our previous findings. Second, our evidence indicates that higher exposure to collateral uncertainty is associated with lower income performance. Specifically, we show that higher exposure to collateral uncertainty correlates with lower returns on assets. Additionally, this lower profitability can be explained by higher levels of non-performing loans, particularly those related to 1 to 4 family loans (the same loans analyzed in the HMDA data). This relationship is further confirmed by higher provisions for loan losses.

We reach these conclusions by studying the portfolio performance of these banks at the bank level, as delinquencies are not directly observed in the HMDA or CRA dataset. This is a limitation because current bank policies might take time to reflect on their balance sheets. To address this issue partially, we complement our cross-section with a within-bank analysis to show that collateral uncertainty exposure drives banks' performance, rather than other differences across banks.

We run the following OLS regression, where the unit of observation is now a bank-year:

$$y_{b,t} = \alpha_t + \alpha_b + \beta_1 \times \sum_{c \in b} \frac{deposit_{c,b,t-1}}{\sum_{c \in b} deposit_{c,b,t-1}} \times \hat{\sigma}^2_{c,t} + \Gamma' X_{b,t-1} + \varepsilon_{b,t} \quad (2.8)$$

where $y_{b,t}$ is our bank-level variable of interest component (e.g., R.E. to C&I ratio or ROE) of bank b at date t, α_t and α_b are time and bank fixed effects. We cluster standard errors at the bank level. Our main set of controls includes banks' balance sheet characteristics such as bank size, core deposit ratio, wholesale ratio, lagged ROA, and Tier 1 ratio to control for differences among banks that can drive the dependent variables.

Real estate and commercial loan composition

In Table 2.6, we present the results for the real estate to commercial loan ratios. Consistent with our bank-county level analysis, we show that higher exposure to collateral uncertainty leads to a higher ratio of real estate loans to commercial loans.

Column (1) is the bank-level counterpart of Table 2.2. As previously mentioned, these data are collected from Call Reports, demonstrating that despite our bank-county level estimates not covering the entire banking landscape, they remain fairly representative. The estimated coefficients are qualitatively similar to our earlier estimates on originated loans: a one standard deviation increase in exposure corresponds to an effect of $1.637 \times 0.12 = 0.19644$, which represents a 4.44% increase in outstanding volume compared to the observed mean. Columns (2) and (3) show similar results when comparing family loans to total commercial loans or examining total real estate loans. Nevertheless, the net effect on total real

Table 2.6:
Banks' collateral uncertainty: Real estate to C&I ratio

Above 1 counties			
	$\frac{\textit{RE 1-4 family}}{\textit{SBL loans}}$	$\frac{\textit{RE 1-4 family}}{\textit{CI loans}}$	$\frac{\textit{RE loans}}{\textit{CI loans}}$
	(1)	(2)	(3)
$\sum_{c\in b} dp.sh._{c,b,t-1} \cdot \hat{\sigma}^2_{c,t}$	1.637**	2.017***	1.687*
	(0.819)	(0.557)	(1.019)
Controls	✓	✓	✓
Year F.E.	✓	✓	✓
Clustered Std.Errors	Bank	Bank	Bank
R^2	0.090	0.050	0.052
Obs	15,872	16,132	16,150
Mean Dep.	4.42	2.66	7.38

This table provides estimates of the sensitivity of various real estate to commercial loan metrics to banks' exposure to house price collateral uncertainty. The data are at the bank-year level for the sample years 1996 to 2017. We exclude the years of the global financial crisis (2008 and 2009) from the estimation to ensure our results are not driven by the bust in real estate and small business loans post-GFC. We focus on banks that operate in more than one county to ensure they can diversify their local opportunities and for which we have at least one originated loan in the HMDA data in a given year. Column (1) shows the estimates for the outstanding loan volumes for 1-4 RE loans to SBL loans. Column (2) shows the estimates for the outstanding loan volumes for 1-4 RE loans to total C%I loans. Column (2) shows the estimates for the outstanding loan volumes for total RE loans to total C%I loans. The table presents the estimate for the following model in Equation 2.8. The level of significance are * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

estate is strongly positive.

Banks' profitability

In this subsection, we examine the impact of banks' exposure to collateral uncertainty on their profitability. Our analysis reveals that banks with higher exposure to collateral uncertainty exhibit lower returns on equity (ROE). This decline in profitability is accompanied by an increase in non-performing loans (NPLs), indicating a deterioration in the quality of their loan portfolios. Furthermore, these banks are observed to have higher provisions for loan losses, reflecting their need to account for the increased risk associated with their loan portfolios.

Table 2.7:
Banks' collateral uncertainty: profitability

	Profitability							
	$ROE_{b,t}$		$\frac{NPL}{Loans}_{b,t}$		$\frac{NPL\ 1\text{-}4\ RE}{REloans}_{b,t}$		*Loan loss prov.* $\%_{b,t}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
bank exp. (dep-weight): collateral risk	-0.004	-0.019***	0.003**	0.005***	0.011***	0.012***	0.083***	0.123**
	(0.004)	(0.007)	(0.001)	(0.002)	(0.002)	(0.002)	(0.031)	(0.053)
Controls	✓	✓	✓	✓	✓	✓	✓	✓
Year F.E.	✓	✓	✓	✓	✓	✓	✓	✓
Bank F.E.		✓		✓		✓		✓
Clustered Std.Errors	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank
R^2	0.520	0.658	0.306	0.605	0.191	0.543	0.284	0.503
Obs	18,940	18,940	19,043	19,043	18,055	18,055	18,874	18,874

This table provides estimates of the sensitivity of various metrics of banks' profitability to exposure in house price collateral uncertainty. The data are at the bank-year level for the sample years 1996 to 2017. We exclude the years of the global financial crisis (2008 and 2009) from the estimation to ensure our results are not driven by the bust in real estate and small business loans post-GFC. We focus on banks that operate in more than one county to ensure they can diversify their local opportunities and for which we have at least one originated loan in the HMDA data in a given year. The table presents the estimate for the following model in Equation 2.8. The level of significance are * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

In Table 2.7, we present the results for the banks' profitability analysis. Consistent with the mechanism outlined in subsection 2.5.2, we show that higher exposure to collateral uncertainty leads to lower bank profitability than these loans. A one standard deviation increase in exposure is associated with a reduction in ROE of 2.2% with respect to its sample means. Our results suggest that these loans are inefficiently retained in the bank's portfolio, as it appears that they are harder to securitize. We confirm this intuition by looking and non-performing loans. In Column (3) to Column (6) we see that the more the bank is exposed to collateral uncertainty, the higher their NPLs, the results are even stronger once we focus only on NPLs related to 1-4 family R.E. loans. We measure NPLs out of their outstanding balance, hence Column (4) is purged out by NPLs arising from commercial loans which might be driven by other banks' policies. Overall our estimates suggest that for an increase in one standard deviation in banks' collateral exposure, the 1-4 R.E. NPL ratio increases by 14% which is an economically sizable effect. Moreover, we do not observe huge swings in estimates, suggesting that our results are not driven by unobservable banks' heterogeneity. Similarly, Column (7) and Column (8) we confirm higher provisions for loan losses for more exposed banks, reflecting their need to account for the increased risk associated with their loan portfolios.

Overall these findings underscore the adverse effects of collateral uncertainty on banks' financial health and highlight the importance of effective risk management strategies and well functioning MBS market.

Further results in banks' asset re-composition

In this last section, we examine banks' overall asset composition to see how exposure to collateral uncertainty affects their balance sheet strategies. By investigating various asset categories such as securities, fed funds purchases, cash and coins, and trading securities, we provide further evidence on how banks manage their assets in response to increased risk.

In Table 2.8, we present the results for the banks' asset composition analysis. Our analysis reveals no significant differences in the holdings of securities, fed funds purchases, and cash and coins between banks with varying levels of collateral uncertainty exposure. However, we find that banks with higher exposure to collateral uncertainty tend to hold more trading securities. This can be interpreted

Table 2.8:
Banks' collateral uncertainty: asset re-composition

	Asset composition							
	$\frac{Scrts}{Asset}_{b,t}$		$\frac{Fed\ funds\ prch}{Asset}_{b,t}$		$\frac{Cash}{Asset}_{b,t}$		$\frac{Trading\ assets}{Asset}_{b,t}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
bank exp. (dep-weight): collateral risk	0.018	0.010	-0.008	-0.002	-0.002	0.003	0.017***	0.018***
	(0.017)	(0.014)	(0.006)	(0.006)	(0.003)	(0.005)	(0.004)	(0.006)
Controls	✓	✓	✓	✓	✓	✓	✓	✓
Year F.E.	✓	✓	✓	✓	✓	✓	✓	✓
Bank F.E.		✓		✓		✓		✓
Clustered Std.Errors	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank
R^2	0.120	0.806	0.130	0.652	0.126	0.536	0.141	0.605
Obs	18,957	18,957	18,822	18,822	18,951	18,951	18,341	18,341

This table provides estimates of the sensitivity of various metrics of banks' asset composition to exposure in house price collateral uncertainty. The data are at the bank-year level for the sample years 1996 to 2017. We exclude the years of the global financial crisis (2008 and 2009) from the estimation to ensure our results are not driven by the bust in real estate and small business loans post-GFC. We focus on banks that operate in more than one county to ensure they can diversify their local opportunities and for which we have at least one originated loan in the HMDA data in a given year. The table presents the estimate for the following model in Equation 2.8. The level of significance are * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

as a risk composition or liquidity story: these banks, possibly due to inefficiencies in managing their real estate loan portfolios, might be engaging in a reach-for-yield behavior. By increasing their holdings in trading securities, they may be attempting to compensate for lower returns or higher risks associated with their real estate loans. This shift towards trading assets reflects a strategy to enhance overall portfolio returns in the face of heightened uncertainty and potential inefficiencies in their primary lending activities. Alternatively, banks may increase their holdings in trading securities to diversify their portfolios. By holding a mix of assets, banks can spread risk and potentially stabilize returns, especially when real estate markets are uncertain.

Overall these results show that banks' collateral uncertainty exposure has potential consequences beyond banks' policies between real estate and commercial loans.

2.6 Robustness

2.6.1 Measuring banks exposure to collateral risk

In our main analysis, we measure banks' exposure to collateral uncertainty using deposit shares that vary over time. However, concerns may arise that banks adjust their deposit shares to mitigate exposure to collateral uncertainty. To address this, we conduct several robustness checks using alternative measures of exposure. First, we compute banks' exposure using fixed deposit shares averaged over the entire sample period. This approach assumes that banks' deposit share remains constant while risk comes from time varying collateral uncertainty. We further provide measure exploiting slower-moving average of deposit shares. Second, we explore the sensitivity of our results to changes in the timing of collateral uncertainty shocks. By shifting the timing of these shocks relative to our exposure measures, we assess whether the results are sensitive to the specific timing assumptions.

Table B.2, Table B.3 and Table B.4 presents the results for the real estate to commercial loan ratio under these alternative specifications. We find that our main findings are robust across these different measures of exposure. Quantitatively and qualitatively, the estimated effects remain consistent, indicating that our results are not driven by the specific timing or method of measuring banks' exposure to collateral uncertainty.

2.6.2 Realized price dispersion and price index

Part of our results could still be driven by realized price volatility exposure and not by collateral uncertainty, which means that banks react only to observed price volatility rather than taking inot account ex-ante local characteristic. Alternatively, Chakraborty et al. (2018) provide evidence that banks' exposure to conty price variation induces change in lending behavior crowding out business loans. To further ensure the robustness of our results, we control for observed price dispersion and county-level house price indices. These additional controls account for variations in local market conditions that could influence banks' reactions to collateral uncertainty. By including these controls, we aim to isolate the specific effect of banks' exposure to collateral uncertainty from other local economic factors.

Our analysis in Table B.5 shows that including these controls does not alter our main findings. The sensitivity of the real estate (R.E.) to commercial and industrial (C&I) small business loans ratio to banks' exposure to house price collateral uncertainty remains robust and largely unaltered in magnitudes. Moreover, the magnitude of the uncertainty risk exposure effect is consistently stronger than the effects of price dispersion and county price index, underscoring the primary role of collateral uncertainty in influencing banks' portfolio decisions.

This robustness check affirms that our results are not driven by local price dynamics or broader economic conditions but are instead a direct consequence of banks' responses to collateral uncertainty. The findings highlight the importance of understanding and managing collateral risks in maintaining balanced and stable loan portfolios.

2.7 Conclusion

This paper addresses a critical gap in the existing literature on bank lending practices by examining the impact of collateral uncertainty on banks' portfolio decisions. While previous studies have explored the relationship between housing prices and bank lending, there has been limited focus on how collateral uncertainty specifically influences banks' behavior. We aim to fill this gap by analyzing the effects of collateral uncertainty on real estate and commercial loan ratios at both the bank-county and bank levels. Our analysis also controls for observed price dispersion to ensure that our findings are not confounded by broader economic volatility.

At the bank-county level, we find that higher exposure to collateral uncertainty leads to an increased ratio of real estate loans to commercial loans. This result is consistent across various measures of exposure, including time-varying and fixed deposit shares, slow-moving averages, and different timings of collateral uncertainty. The robustness of our results suggests that banks with higher collateral uncertainty exposure are not merely adjusting their portfolios to mitigate risk but are fundamentally altering their lending practices. These banks exhibit higher loan volumes on real estate loans and holding rates while increasing rejection rates, suggesting a shift in the portfolio composition of loans without increasing risk to new loan origination and potential difficulties in securitizing these loans due to heightened collateral uncertainty.

At the bank level, our findings reveal that banks with greater exposure to collateral uncertainty have lower profitability, as evidenced by lower return on equity (ROE). These banks also report higher levels of non-performing loans (NPLs) and increased provisions for loan losses, particularly for 1 to 4-family loans. This suggests that collateral uncertainty not only affects the composition of banks' loan portfolios but also has significant implications for their overall financial health and risk management practices. The observed increase in trading securities holdings among these banks points to a potential strategy to offset the inefficiencies in their loan portfolios by seeking higher yields in more liquid and tradable assets.

The policy implications of our findings are profound (and yet to be studied) for understanding risk concentration and the stability of the banking sector. The tendency of banks to inefficiently hold onto real estate loans and the lack of diversification in the supply of mortgage-backed securities (MBS) could exacerbate risk concentration in certain areas as well as the banking sector. Future research should explore the long-term impacts of these dynamics on market stability and market concentration to better understand the effectiveness of regulatory interventions in promoting diversification and risk management among banks.

Overall, this paper contributes to a deeper understanding of the mechanisms through which collateral uncertainty affects bank behavior, highlighting the need for comprehensive risk assessment frameworks and proactive regulatory measures to safeguard the stability of the financial system.

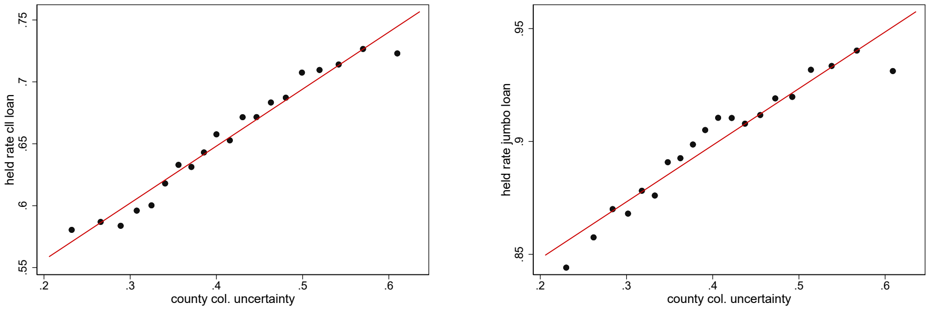
A Figure appendix

A.1 County level collateral uncertainty

Figure A.1:
Collateral uncertainty and liquidity

(a) Hold rate - conformable loans

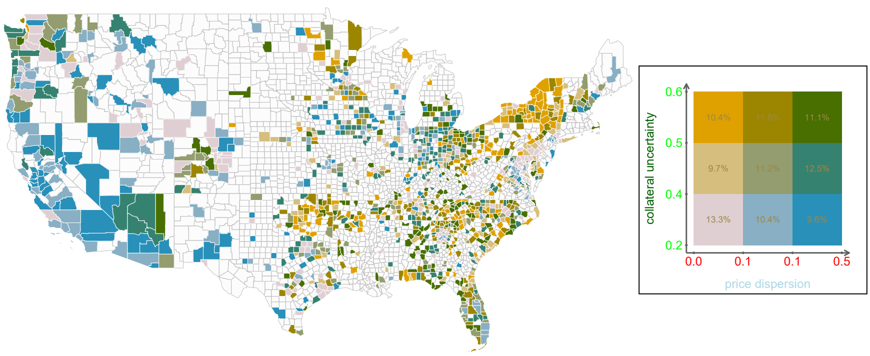
(b) Hold rate - jumbo loans



Note: Figure A.1a plots county-level holding rate for conformable HMDA loans for the period 1996-2017. The graphs plots a binscatter plot on county collateral uncertainty on loans holding rate controlling for year fixed effect. The sample includes annual county level observations from 1996 to 2017. Figure A.1a plots county-level holding rate for non-conformable HMDA loans for the period 1996-2017. The graphs plots a binscatter plot on county collateral uncertainty on loans holding rate controlling for year fixed effect. For each of the variable we define the holding rate as the fraction of held (non) conformable loans out of (non) conformable loans originated. The data comes from the matched HMDA and Corelogic dataset for the period 1996-2017.

A.2 Bank-county collateral exposure

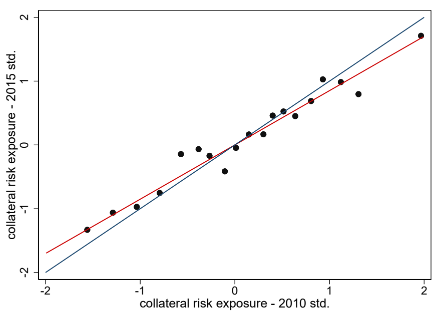
Figure A.2:
Geographic dispersion and price volatility



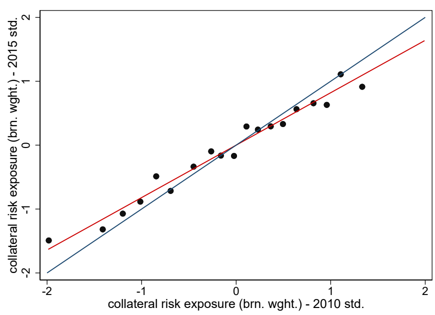
Note: This figure plots the geographical distribution of collateral uncertainty and its relation to price dispersion. The data report the unconditional mean through the sample for each county. The collateral value uncertainty and the price dispersion are estimated at the county level based on transaction-level data from CoreLogic.

Figure A.3:
Persitency in banks' collateral uncertainty exposure

(a) Pesistency - deposit weighted



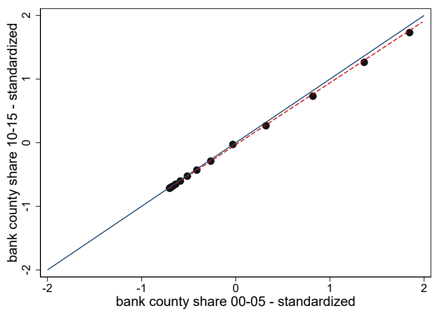
(b) Pesistency - branch weighted



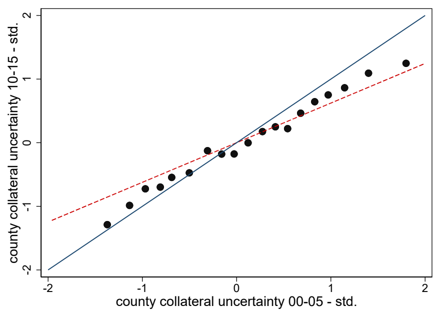
Note: Figure A.3a shows the binscatter for the bank-level distribution for the period 2010 against the average distribution for 2015 were we weighted the banks' exposure by the volume of deposits. Similarly, Figure A.3b shows the binscatter for the bank-level distribution for the period 2010 against the average distribution for 2015, however, weighting it by number of branches. To obtain the values, we standardized the banks' collateral uncertainty exposure over the different periods and plotted the corresponding distributions.

Figure A.4:
persitency in deposit shares and collateral uncertainty

(a) Pesistency - deposit shares



(b) Pesistency - collateral uncertainty



Note: Figure A.4a shows the binscatter for the average bank's branch-level deposit share distribution across two different periods. Similarly, Figure A.4b shows the binscatter for the county-level distribution for the period 2000-2005 the average for 2010-2015, however. To obtain the values, we standardized the banks' collateral uncertainty exposure over the different periods and plotted the corresponding distributions.

B Table appendix

B.1 Bank-county collateral exposure

Table B.1:
Banks' collateral uncertainty and portfolio choice: applications

Above 1 counties		
	Main dep: log dif. HMDA-CRA appl.	
	(1)	(2)
$\sum_{c \in b} dp.sh._{c,b,t-1} \cdot \hat{\sigma}^2_{c,t}$	0.772	0.891*
	(0.525)	(0.468)
Controls	✓	✓
Year and county F.E.	✓	
County-year F.E.		✓
Bank F.E.		✓
Bank-county F.E.	✓	✓
Clustered Std.Errors	Bank county	Bank county
R^2	0.749	0.795
Obs	124,114	124,114

This table provides estimates of the sensitivity of R.E. to C&I small business loans to banks' house price collateral uncertainty exposure. The data are aggregated at the bank-county year level for the sample years 1996 to 2017. We exclude the year of the global financial crisis (2008,2009) from the estimation to make sure that our results are not driven by the bust in real estate and small business loan post GFC. We further focus on banks that operate more than one county to make sure that banks can diversify their local opportunities. The table presents the estimate for the following model in Equation 2.7. The level of significance are * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.2:

Banks' collateral uncertainty exposure robustness

	Above 1 counties					
	(1) log dif. HMDA-CRA loans	(2) log dif. CLL HMDA-CRA loans	(3) log dif. held HMDA-CRA loans	(4) log dif. held CLL HMDA-CRA loans	(5) log dif. held HMDA-CRA appl.	(6) log dif. held CLL HMDA-CRA appl.
$\sum_{c\in b} dp.sh._{c,b,t-1} \cdot \hat{\sigma}^2_{c,t}$	1.115***	1.139***	1.436***	1.530***	1.232**	1.238**
	(0.426)	(0.430)	(0.551)	(0.543)	(0.530)	(0.518)
$\sum_{c\in b} dp.sh._{c,b} \cdot \hat{\sigma}^2_{c,t}$	1.269***	1.351***	1.560***	1.636***	1.800***	1.832***
	(0.379)	(0.397)	(0.453)	(0.469)	(0.478)	(0.490)
$\sum_{c\in b} dp.sh._{c,b,t-1} \cdot \hat{\sigma}^2_{c,t-1}$	0.282	0.233	0.388	0.329	0.146	0.119
	(0.405)	(0.421)	(0.511)	(0.526)	(0.358)	(0.361)
$\sum_{c\in b} dp.sh._{c,b,96\to 05} \cdot \hat{\sigma}^2_{c,t}$	0.351	0.491	-0.240	-0.280	-0.024	-0.063
	(0.550)	(0.603)	(0.642)	(0.733)	(0.470)	(0.472)
$\sum_{c\in b} dp.sh._{c,b,96\to 05} \cdot \hat{\sigma}^2_{c,t-1}$	-0.721	-0.671	-1.028*	-1.308**	0.172	0.071
	(0.544)	(0.572)	(0.565)	(0.648)	(0.430)	(0.421)
$\sum_{c\in b} dp.sh._{c,b,t-3\to t-1} \cdot \hat{\sigma}^2_{c,t}$	1.118***	1.159***	1.499***	1.617***	1.645**	1.661**
	(0.362)	(0.363)	(0.514)	(0.513)	(0.694)	(0.681)
$\sum_{c\in b} dp.sh._{c,b,t-5\to t-1} \cdot \hat{\sigma}^2_{c,t}$	0.910***	0.933***	1.342***	1.468***	1.770***	1.797***
	(0.324)	(0.326)	(0.432)	(0.431)	(0.668)	(0.655)
$\sum_{c\in b} dp.sh._{c,b,t-3\to t-1} \cdot \hat{\sigma}^2_{c,t-1}$	0.881*	0.863*	1.246**	1.267**	1.060**	1.045**
	(0.453)	(0.458)	(0.611)	(0.609)	(0.513)	(0.510)
$\sum_{c\in b} dp.sh._{c,b,t-5\to t-1} \cdot \hat{\sigma}^2_{c,t-1}$	0.746*	0.724*	1.193**	1.260**	1.396**	1.404**
	(0.384)	(0.388)	(0.492)	(0.490)	(0.575)	(0.569)

This table provides estimates of the sensitivity of R.E. to C&I small business loans to banks' house price to different collateral uncertainty measures. The data are aggregated at the bank-county year level for the sample years 1996 to 2017. We exclude the year of the global financial crisis (2008,2009) from the estimation to make sure that our results are not driven by the bust in real estate and small business loan post GFC. We further focus on banks that operate more than one county to make sure that banks can diversify their local opportunities. For measures using deposit shares from the 1996-2005 period, we exclude over half of counties due to data limitations in Corelogic. The table presents the estimate for the following model in Equation 2.7. The level of significance are * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.3:
Banks' collateral uncertainty: robustness R.E. loans

	Above 1 counties								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Rejection rate$_{b,c,t}$	*Rejection rate CLL*$_{b,c,t}$	*Rejection rate jumbo*$_{b,c,t}$	*Held rate*$_{b,c,t}$	*Held rate CLL*$_{b,c,t}$	*Held rate jumbo*$_{b,c,t}$	*log held amount*$_{b,c,t}$	*log held amount CLL*$_{b,c,t}$	*log held amount jumbo*$_{b,c,t}$
$\sum_{c\in b} dp.sh._{c,b,t-1} \cdot \hat{\sigma}^2_{c,t}$	0.091***	0.093***	-0.045	0.135*	0.133*	0.019	1.205***	1.255***	1.734***
	(0.033)	(0.035)	(0.047)	(0.073)	(0.074)	(0.095)	(0.384)	(0.383)	(0.578)
$\sum_{c\in b} dp.sh._{c,b} \cdot \hat{\sigma}^2_{c,t}$	0.046	0.046	0.002	0.082	0.084	-0.022	0.880***	0.955***	0.927**
	(0.037)	(0.038)	(0.046)	(0.065)	(0.065)	(0.073)	(0.279)	(0.299)	(0.420)
$\sum_{c\in b} dp.sh._{c,b,t-1} \cdot \hat{\sigma}^2_{c,t-1}$	0.058	0.060	-0.074*	0.097	0.094	0.017	0.684*	0.664	1.357**
	(0.039)	(0.040)	(0.042)	(0.074)	(0.077)	(0.060)	(0.398)	(0.407)	(0.528)
$\sum_{c\in b} dp.sh._{c,b,96\to 05} \cdot \hat{\sigma}^2_{c,t}$	0.015	0.005	0.052	-0.129	-0.147	-0.152*	0.103	0.039	0.544
	(0.052)	(0.051)	(0.091)	(0.086)	(0.095)	(0.079)	(0.440)	(0.482)	(0.834)
$\sum_{c\in b} dp.sh._{c,b,96\to 05} \cdot \hat{\sigma}^2_{c,t-1}$	-0.014	-0.022	0.030	-0.078	-0.111	0.030	-0.196	-0.377	0.619
	(0.055)	(0.056)	(0.096)	(0.104)	(0.112)	(0.086)	(0.407)	(0.418)	(0.925)
$\sum_{c\in b} dp.sh._{c,b,t-3\to t-1} \cdot \hat{\sigma}^2_{c,t}$	0.081**	0.081**	-0.021	0.149*	0.151*	0.064	1.173***	1.234***	.611***
	(0.036)	(0.037)	(0.045)	(0.078)	(0.078)	(0.092)	(0.392)	(0.391)	(0.553)
$\sum_{c\in b} dp.sh._{c,b,t-5\to t-1} \cdot \hat{\sigma}^2_{c,t}$	0.078**	0.079**	-0.034	0.163**	0.168**	0.061	1.100***	1.176***	1.444***
	(0.034)	(0.035)	(0.040)	(0.073)	(0.073)	(0.082)	(0.366)	(0.362)	(0.523)
$\sum_{c\in b} dp.sh._{c,b,t-3\to t-1} \cdot \hat{\sigma}^2_{c,t-1}$	0.076**	0.077*	-0.073	0.173*	0.174*	0.094	1.147**	1.161***	1.949***
	(0.038)	(0.039)	(0.049)	(0.089)	(0.091)	(0.093)	(0.452)	(0.446)	(0.604)
$\sum_{c\in b} dp.sh._{c,b,t-5\to t-1} \cdot \hat{\sigma}^2_{c,t-1}$	0.077**	0.079**	-0.079*	0.188**	0.194**	0.087	1.127***	1.177***	1.766***
	(0.034)	(0.035)	(0.041)	(0.083)	(0.084)	(0.085)	(0.394)	(0.383)	(0.546)

This table provides estimates of the sensitivity of R.E. to C&I small business loans to banks' house price collateral uncertainty exposure. The data are aggregated at the bank-county year level for the sample years 1996 to 2017. We exclude the year of the global financial crisis (2008,2009) from the estimation to make sure that our results are not driven by the bust in real estate and small business loan post GFC. We further focus on banks that operate more than one county to make sure that banks can diversify their local opportunities. For measures using deposit shares from the 1996-2005 period, we exclude over half of counties due to data limitations in Corelogic. The table presents the estimate for the following model in Equation 2.7. The level of significance are * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.4:
Banks' collateral uncertainty: robustness SBL loans

	Above 1 counties	
	(1)	(2)
	log(1 + SBL loan) $_{b,c,t}$	*log(1 + SBL application)* $_{b,c,t}$
$\sum_{c\in b} dp.sh._{c,b,t-1} \cdot \hat{\sigma}^2_{c,t}$	0.466*	0.544
	(0.250)	(0.336)
$\sum_{c\in b} dp.sh._{c,b} \cdot \hat{\sigma}^2_{c,t}$	-0.149	-0.382
	(0.235)	(0.298)
$\sum_{c\in b} dp.sh._{c,b,t-1} \cdot \hat{\sigma}^2_{c,t-1}$	0.437*	0.971**
	(0.227)	(0.391)
$\sum_{c\in b} dp.sh._{c,b,96\rightarrow 05} \cdot \hat{\sigma}^2_{c,t}$	0.447	-0.062
	(0.307)	(0.674)
$\sum_{c\in b} dp.sh._{c,b,96\rightarrow 05} \cdot \hat{\sigma}^2_{c,t-1}$	0.756**	-0.195
	(0.312)	(0.708)
$\sum_{c\in b} dp.sh._{c,b,t-3\rightarrow t-1} \cdot \hat{\sigma}^2_{c,t}$	0.272	0.025
	(0.223)	(0.291)
$\sum_{c\in b} dp.sh._{c,b,t-5\rightarrow t-1} \cdot \hat{\sigma}^2_{c,t}$	0.184	-0.046
	(0.223)	(0.227)
$\sum_{c\in b} dp.sh._{c,b,t-3\rightarrow t-1} \cdot \hat{\sigma}^2_{c,t-1}$	0.418	0.555
	(0.285)	(0.361)
$\sum_{c\in b} dp.sh._{c,b,t-5\rightarrow t-1} \cdot \hat{\sigma}^2_{c,t-1}$	0.289	0.350
	(0.278)	(0.269)

This table provides estimates of the sensitivity of C&I small business loans to banks' house price collateral uncertainty exposure. The data are aggregated at the bank-county year level for the sample years 1996 to 2017. We exclude the year of the global financial crisis (2008,2009) from the estimation to make sure that our results are not driven by the bust in real estate and small business loan post GFC. We further focus on banks that operate more than one county to make sure that banks can diversify their local opportunities. For measures using deposit shares from the 1996-2005 period, we exclude over half of counties due to data limitations in Corelogic. The table presents the estimate for the following model in Equation 2.7. The level of significance are * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.5:
Banks' collateral uncertainty: dispersion and price index

	Above 1 counties							
	$logdif.HMDA-CRAloans$		*Rejection rate*$_{b,c,t}$		*Held rate*$_{b,c,t}$		*log(1+SBLs volume)*$_{b,c,t}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\sum_{c\in b} dp.sh._{c,b,t-1} \cdot \hat{\sigma}^2_{c,t}$	1.061**	1.069***	0.128**	0.126**	0.252**	0.226**	0.504**	0.528**
	(0.433)	(0.413)	(0.050)	(0.051)	(0.110)	(0.107)	(0.246)	(0.239)
$\sum_{c\in b} dp.sh._{c,b,t-1} \cdot sd(\sigma^2_{c,t-1})$	1.167		-0.031		-0.426*		0.094	
	(0.784)		(0.090)		(0.238)		(0.379)	
$\sum_{c\in b} dp.sh._{c,b,t-1} \cdot p_{c,t}{}^{ind}$		0.002**		0.000		0.000		-0.001*
		(0.001)		(0.000)		(0.000)		(0.000)
Controls	✓	✓	✓	✓	✓	✓	✓	✓
County-year F.E.	✓	✓	✓	✓	✓	✓	✓	✓
Bank F.E.	✓	✓	✓	✓	✓	✓	✓	✓
Bank-county F.E.	✓	✓	✓	✓	✓	✓	✓	✓
Clustered Std.Errors	Bank county	Bank county	Bank county	Bank county	Bank county	Bank county	Bank county	Bank county
R^2	0.785	0.786	0.649	0.649	0.724	0.724	0.909	0.909
Obs	91,400	91,400	91,400	91,400	91,400	91,400	91,400	91,400

This table provides estimates of the sensitivity of R.E. to C&I small business loans and other metrics to banks' house price collateral uncertainty exposure controlling for other realized price dispersion and price index exposure. The data are aggregated at the bank-county year level for the sample years 1996 to 2017. We exclude the year of the global financial crisis (2008,2009) from the estimation to make sure that our results are not driven by the bust in real estate and small business loan post GFC. We further focus on banks that operate more than one county to make sure that banks can diversify their local opportunities. The table presents the estimate for the following model in Equation 2.7. The level of significance are * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

C Data cleaning

C.1 HMDA data

We drop observations for which loan value is strictly below 10 thousand dollars and for which applicant income is missing or below a thousand dollars. We retain information only for one to four-family property type and for conventional loans (i.e. `laon_type` is 1). Finally, we retain information for one of the following three actions: (i) loan originated, (ii) application approved but loan not originated, or (iii) application denied. Other actions represent dubious statuses (e.g. application withdrawn by applicant) or loans purchased by other financial institutions and would amount to double-counting as these loans are reported both by the originating institution and the purchasing institution as explained in Dell'Ariccia et al. (2008). We further drop all observations in which either state or county is missing, 0 or misreported. Finally, we drop all loan purposes that are either 0 or not corresponding to one of the following categories: (i) home purchase, (ii) home improvement, and (iii) refinancing or cash-out refinancing

C.2 FDIC SOD date

For deposit data summary, we exclude all data points originating from the subsequent states: `"AS", "FM", "GU", "MH", "MP", "PR", "PW", "VI","AK", "HI"`. This elimination is justified by the limited availability of collateral uncertainty measures within these regions. Subsequently, we limit our analysis to data from commercial banks, commercial or savings banks, state-chartered and Federal Reserve member banks (`bkclass "N", "NM", "SM"`).

We further refine our dataset by removing observations with zero values for the variables `fipscode`, `depsumbr`, and `rssdid`. Additionally, we discard any observations with missing values for `cert` and `rssdid`.

Lastly, we restrict our analysis to branch service types (`brsertyp`) equal to 11, signifying full-service brick-and-mortar offices.

Merging HMDA with Call Report

To merge banks' balance sheet information with HMDA data we map the HMDA identifier with the RSSD identifier from FRB's NIC constructed by Robert Avery[19]. We drop all observations for which `entity` is 0 as these loans are originated by independent mortgage banks and no further information indicates that the banks are subsidiaries of a commercial bank or thrift [20], in few cases this indicates that the originator was liquidated within the year and we exclude those cases. We match the HMDA ID with the corresponding call report entity holder a the end of each year.

C.3 Corelogic data

In this section, we outline the steps taken to clean the Corelogic data prior to estimating the idiosyncratic price dispersion. First, transactions not involving single-family houses were removed, enhancing comparability across transactions. Second, transactions in package deals—those involving more than one house—were also excluded. Typically, it is not possible to identify the exact price of the individual houses in the package deal. Thirdly, we eliminated full duplicates—transactions sharing identical information across all variables. Subsequently, near-duplicates were also removed; these refer to transactions of the same house occurring on the

[19] The file is available at Neil Bhutta's web page. This dataset contains matching information for all lenders who have ever filed an HMDA report. The HMDA identifier is matched to the corresponding information from the FRB's NIC system and FFIEC or TFR Call Reports for each end-of-year filing. If the filer is a subsidiary of a bank holding company, the filer is matched to the lead (largest) bank of the holding company.

[20] We provide in the appendix a graphical distribution of mortgage banks across the US territory.

same day. Fourthly, transactions flagged as non-arm's length by Corelogic—such as those between relatives—were dropped. Fifthly, any transactions missing critical information, such as price, date, building year, or size, were omitted from the dataset. Additionally, we excluded all transactions financed by the Federal Housing Administration (FHA), Veteran's Administration (VA), or the Farm Service Agency or Rural Housing Service (FSA/RHS). Finally, to mitigate concerns with outliers, we applied a 1% winsorization to transaction prices and square footage of the house for each respective year.

For Corelogic data, we exclude all data points originating from the subsequent states: `"AS", "FM", "GU", "MH", "MP", "PR", "PW", "VI","AK", "HI"` due to limited availability of data within these states. Due to the estimation procedure requirements, the final sample contains 47 states as `"AS","CT"` do not have enough data points.

C.4 Data sources

Summary of Deposits (SoD) data comes from FDIC from 1994 on. Historical SoD comes from Christa Bouwman's web-page for the period 1981-1993.

HMDA data: we retrieved the Historical Data from 1990 to 2013 from National Archives catalog for the corresponding series 2456161. For the years 2014-2016 we use FFIEC-HMDA Flat Data and finally for years 2017 on we use the Three Year National Loan Level Dataset.

CRA small business loans for the period of 1996 to 2017 are available at FFIEC-CRA. Origination data are contained in the `Disclosure Data` under panel `D1-1`. The corresponding `RSSDID` identifier is mapped to each single `respondent_id` via the `Transmittal Data`.

Call Reports data comes from Philipp Schnabl. We retrieve data for Real Estate loans post-2010 from the FFIEC Single Period Report for different schedules and combine with our original dataset. Pre 2010 data are from Chicago FED-Call Report

Chapter 3

CUSTOMER CAPITAL AND THE CROSS SECTION OF CORPORATE BORROWING

Joint with Luigi Falasconi and Lukas Nord

3.1 Introduction

Firms devote substantial resources to growing and maintaining their customer base (Gourio and Rudanko, 2014; Argente et al., 2021; Afrouzi et al., 2020). This investment is evidence of the significant importance of *customer capital* as an asset to the firm and its crucial role in generating sales for firms' products. However, unlike physical assets, a firm's customer base is not easily transferable and hence difficult to pledge directly as collateral to borrow against. The need to grow a customer base and the difficulty of pledging customers as collateral raises the question as to how firms finance their customer capital.

This paper relates firms' investment in their customer base to their financial decisions. Our key intuition is, that as an investment into a firm's customer base increases future cash flows it also increases firms' ability to borrow in uncollateralized debt. We document empirically a positive relationship between US firms' spending on customer acquisition and their issuance of unsecured credit. A simple model economy featuring frictional accumulation of customers and uncollateralized borrowing is able to rationalize the empirical facts.

The first contribution of this paper is to provide novel empirical facts on the relation between customer expenditure and firms' debt policies. We use granular data for US-listed companies between 1981 and 2018 at a yearly frequency from Compustat, allowing us to measure both firms' investment in their customer base and their (un)secured debt. Following the literature (Gourio and Rudanko, 2014; Afrouzi et al., 2020), we measure firms' customer base investment as their Selling, General, and Administrative Expenses (SG&A, non-production costs) over total operating cost -the sum of SG&A and cost of operating goods (COGS)- and divide all debt holdings between secured and unsecured claims (Eisfeldt and Rampini, 2009; Benmelech et al., 2020).

Our first empirical finding is, that firms with higher degrees of customer expense have consistently higher fractions of unsecured debt ratios. Moving from the bottom quartile to the top quartile of customer expenses we observe an increase in the ratio of unsecured credit to total assets of 74 basis points, corresponding to an increase of 4% of the mean. We find similar magnitudes when focussing on the ratio of unsecured debt to total debts, which increases by 2.7 percentage points (4.45% of the mean). Our findings are robust to alternative measures of customer expenditure and the timing of expenses.

Our second empirical result explores the mechanism behind the first finding, by documenting the evolution of cashflows in response to an increase in customer expenses. We find that in the cross-section of firms, higher customer expense predicts higher future firm values as proxied by higher enterprise-value-to-assets

(Tobins' Q) and market-to-book ratios. Exploiting the within firms time series variation, we find that these results hold at the firm level over time, but are short lived and revert back to the mean after 2 years. Our findings also show that sales growth increases by 2.7% and enterprise-value-to-assets by 3.3% points for a standard deviation increase in our measure of customer base investment over a 1-year horizon. These results indicate a close relationship between customer expenses and a firm's cash flows, providing a rationale for the patterns of unsecured debt. Growth in firms' sales and value facilitates their borrowing against cash flows rather than physical collateral, expanding a firm capacity to issue unsecured debt.

Our third empirical result examines the relationship between debt issuance and customer expenses. Based on the proposed mechanism, increasing customer capital expenses should coincide with an increase in firms' debt capacity and steer its debt issuance towards unsecured debt. We find evidence that upon a standard deviation increase in customer expenses, firms increase their debt-issuance-to-assets by 108 basis points increase. This increase in debt is driven by unsecured credit which grows by 7.51 percentage points increase percentage points relative to firms' assets, increasing its overall share. These magnitudes are economically relevant and confirm our previous results. Secured debt issuance increases as well, but the effect is weaker than the increase in unsecured credit and not statistically significant.

The second contribution of this paper is to propose a model that rationalizes the empirical findings. We extend the framework of Afrouzi et al. (2020) to incorporate borrowing. Our framework features frictional goods markets in which firms need to invest in marketing spending to attract customers. Firms are ex-post heterogeneous due to idiosyncratic productivity shocks and (endogenous) differences in the size of their customer base. We assume need to finance part of their variable cost within periods through unsecured credit. Their borrowing is constrained to a fraction of the going concern value of the firm. The setup allows us to study how firms' expenditure on their customer base interacts with their financial decisions.

In the model, the relationship between firms' customer base investment and their borrowing goes both ways. On the one hand, firms' marketing spending is part of their variable cost and as such is constrained by the within-period restriction on firms' borrowing. On the other hand, investment in firms' customer base increases future cash flows and hence the going-concern value, relaxing firms' borrowing constraints.

The model successfully replicates the empirical findings. Under a reasonable set of parameters, our framework generates both the empirical relationship between investment in a customer base and firm (unsecured) debt and the proposed mechanism. In the model, 1. firms with higher marketing spending have higher debt, and 2. firms with higher marketing spending experience a stronger growth in firm value. The relationship between investment in customers and firm value is key in generating the observed patterns, as it allows firms to expand their borrowing in times of high investment into their customer base.

Literature review: Our results speak to several strands of literature. First, we add to the large literature that studies customer acquisition and firms' expenses by relating the non-deployable nature of the customer base to firms' liability structure. Previous literature emphasized the importance of frictions in output markets, such as search frictions in explaining the price setting and firms' customer accumulation (Gourio and Rudanko, 2014; Paciello et al., 2019; Argente et al., 2021; Afrouzi et al., 2020). Our work builds on these previous approaches to study how product market frictions can influence corporate debt structure.

The main literature we contribute to is the one of firms' financial constraints and debt structure. In this regard, recent work has again brought to attention the crucial differences between debt collateralized by physical assets and the one supported by cash flow claims (Donaldson et al., 2019, 2020; Lian and Ma, 2021; Drechsel, 2023). This literature emphasizes the role that firms' cash flow plays in determining a firm's choice among secured and unsecured debt instruments. However, compared to their studies in this paper, we take one step back and try to understand what types of firm's assets are more likely to contribute to firms' cash flow growth and how this translates to firms' choice across debt types.

Our paper is closely related to the work of Kermani and Ma (2023) and Kermani and Ma (2020), which shows that a firm's asset specificity, interacting with debt capacity, shaped debt structure. We contribute to their work by showing how customer capital accumulation relates to specific debt choices, highlighting the tight interactions between customer expenses and firms' going concern value. Our work sheds new light on the interplay between the firms' asset composition and the optimal liability structure when firms build their customer base.

Finally, we contribute to the huge body of literature on firms' financial structure and the choice of debt, e.g. Rauh and Sufi (2010); Rampini and Viswanathan (2020). Compared to these studies in this paper, we explicitly narrow our focus to understanding the mechanisms behind firms' customer capital accumulation and debt choices. The empirical results highlighted in this work relate to Rampini and Viswanathan (2020). They argue that given secured debt is explicitly collateralized, which facilitates enforcement, constrained firms will be more likely to borrow against it. Our work shows that although this channel might be at work, firms with higher customer capital expenses can credibly promise future growing cash flows, which allow them to expand their capacity and, therefore, their marginal choice of debt becomes the one supported by unencumbered assets. By boosting future sales and firms' going concern values, customer expenses allow enterprises to issue more unsecured debt. This effect is large enough to increase overall firms' debt issuance.

The rest of the paper is structured as follows. section 3.2 presents the data and the approach we use to measure the main variables of interest. section 3.3 presents stylized facts about our selling effort measures. The empirical results are presented and discussed in section 3.4, while robustness tests are section 3.5. The model and its parametrization are discussed in section 3.6 and section 3.7 respectively. section 3.8 discuss the model performance and we conclude in section 3.9.

3.2 Data sources and measurement

Since we do not directly observe firms' customer bases, we focus on expenditures related to customer acquisition. Our primary variable of interest captures the extent to which firms engage in customer acquisition activities. To accurately measure this, we normalize these expenditures by overall costs or sales, as detailed later.

We utilize a comprehensive dataset of U.S. publicly listed firms, spanning from 1981 to 2018, which provides detailed information on expenditures related to acquiring and retaining customers. This dataset also includes firm-level data on debt structure, allowing us to distinguish between secured and unsecured debt.

In the following section, we describe the sample construction, outline the various measures of customer expenditure intensity, and present the other economic variables of interest used throughout the analysis. Finally, we summarize the sample characteristics.

3.2.1 Data

In this section, we provide a brief overview of the main data cleaning procedures used. In section C, we provide a detailed explanation of the data construction process.

Our main data source for this paper is Compustat firm-level data, which contains detailed information on firms' balance sheet items for all U.S. publicly traded firms. We use firms' balance sheets to obtain information on debt structure and expenditures for non-financial firms. Although we rely solely on publicly traded firms, they are economically significant as they drive business cycle fluctuations (Crouzet and Mehrotra, 2020). Moreover, Compustat data contains information on firm-level financial statements, including measures of sales, input expenditures, capital stock information, and, most importantly for us, detailed tracking of selling and administrative expenses.

Consistent with other studies (Eisfeldt and Rampini, 2009; Crouzet and Mehrotra, 2020; Ottonello and Winberry, 2020), we focus on U.S.-incorporated firms. We further exclude utilities (SIC codes 4900-4999) due to heavy regulation, and financial firms (SIC codes 6000-6999) because their balance sheets differ significantly from other firms. We also exclude public firms as in Ottonello and Winberry (2020), though they represent a minimal fraction of our sample, these companies are not necessarily engaged in acquiring and maintaining customers. In the following section, we describe the construction of our variable of interest.

3.2.2 Measurements

One main advantage of using the Compustat database is that it reports key measures, although imperfect, to gauge selling effort. We measure firms' selling costs via selling, general, and administrative expenses (SG&A).[1]

The variable SG&A has been used in recent studies to effectively capture firm-level expenses in the sales force (Gourio and Rudanko, 2014; Morlacco and Zeke, 2021; Ptok et al., 2018; Afrouzi et al., 2020). In particular Ptok et al. (2018) clearly

[1]We do not use advertising expenditure since it has two severe limitations: it only captures a narrow subset of total selling costs, and data availability is very limited.

shows that SG&A is very effective in capturing firm-level sales force spending. However, this item includes different expenses that are not directly related to the firm's selling efforts, such as bad debt expenses, payments in pensions and retirement, rents, and expenditures in research and development, among other costs (Chiavari, 2022). Afrouzi et al. (2020) and Ewens et al. (2024) describe in detail the items reported in SG&A and how R&D expenditures are accounted into it. Because of this, we provide robustness checks employing an internally calculated measure of selling effort that controls for these additional costs.

As a benchmark measure, we utilize firm-level under selling, general and administrative expenses (SG&A) over total cost (i.e., the sum SG&A and cost of goods sold (COGS)).[2] We also employ alternative measures used in existing literature, ensuring the robustness of our main findings to the choice of selling cost adopted in the analysis. In section C, we provide a detailed explanation of the different measures and their construction. Throughout the analysis, we will refer to selling expenses and customer-related expenses interchangeably.

The reason for scaling selling expenses with total costs is to capture the intensity at which a firm seeks to build and maintain its customer base. Intuitively, the more a firm spends on customer-related expenses relative to its total costs, the higher the emphasis on customer acquisition and retention. This measure has several advantages over alternative approaches, such as scaling by sales or considering only SG&A.

Firstly, scaling SG&A by total cost provides a more comprehensive view of a firm's expenditure structure. Total cost includes both SG&A and COGS, encompassing all major expense categories. By using total cost as the denominator, we account for the full spectrum of a firm's spending, making our measure a more accurate reflection of the relative importance of customer-related expenses within

[2]Their corresponding labels in Compustat are `xsga` and `cogs`.

the firm's overall cost structure. Secondly, scaling by total cost mitigates potential distortions that could arise from using sales as the denominator. Sales figures can be influenced by external factors such as market conditions, pricing strategies, and demand fluctuations, which may not accurately reflect a firm's strategic focus on customer acquisition and retention. Total cost, on the other hand, is more directly linked to the firm's operational and strategic decisions, providing a clearer picture of how resources are allocated toward customer-related activities. Thirdly, this measure captures the intensity of customer-related spending relative to other costs, offering insights into the firm's strategic priorities. Firms with a higher SG&A-to-total-cost ratio are likely to prioritize customer acquisition and retention more heavily, indicating a strategic emphasis on building and maintaining a robust customer base. This is particularly important for understanding the dynamics of firms' growth strategies and their impact on debt composition and overall financial health. Finally, this approach aligns with our theoretical model that emphasizes the role of marketing and customer acquisition in driving firm value and borrowing capacity.

To analyze the interaction between customer expenses and debt composition, we rely on firm-level balance sheet data. Our focus is to measure secured and unsecured debt. Compustat reports secured debt levels in the item "debt mortgages and other secured debt," available starting from the 1981 fiscal year. The main advantage of using this variable is that on top of mortgages and bank debt, it often includes leases. All these debt products typically require pledging hard collateral. We thus distinguish the share of secured and unsecured debt with respect to total debt as well as the share of secured and unsecured debt with respect to total assets (book value). Total debt is defined as the sum of short-term and long-term debt.

Lastly, as part of our analysis focuses on the relationship between customer expenses and the firm's growth opportunities, we need measures of a firm's future value relative to its current book value. We use two proxies for this: the first is Tobin's Q, constructed as the ratio of the firm's enterprise value over total assets, and the second is the market-to-book ratio.

We present summary statistics for our main variables of interest in the Table 3.1: On average, firms devote roughly 30% of their costs to retaining and acquiring customers, while compared to sales it corresponds to approximately 24%. We find a sensible degree of heterogeneity in firms' selling cost structure in our sample as an interquartile change corresponds to 0.23 points in change of customer expenses. We present further stylized facts about this measure in the next section. We also present summary statistics for our refinement of SG&A, namely $sga/(sga + cogs)_{f,t}$. The procedure to construct the variable is in subsection C.2 Consistently with other studies (Lian and Ma, 2021; Drechsel, 2023; Kermani and Ma, 2020, 2023) we find that secured debt only represents a tiny proportion of firms' debt, roughly 40% on average, while the bulk of firms' debt is represented by unsecured claims (e.g. bonds, credit lines, ...). Overall our sample shows a significant difference across firms, which we will exploit in the next session where we investigate the relationship between firms' customer expenses and debt distribution.

Table 3.1:
Summary Statistics

	Mean	SD	Min	Max	p25	p75	Obs
$\frac{xsga}{xsga+cogs}_{f,t}$	0.28	0.18	0.03	0.97	0.15	0.38	71,675
$\frac{xsga}{sale}_{f,t}$	0.24	0.15	0.02	0.99	0.13	0.32	71,666
$\frac{xsga}{cogs}_{f,t}$	0.57	1.11	0.03	30.82	0.17	0.60	71,675
$\frac{sga}{xsga+cogs}_{f,t}$	0.24	0.17	0.01	0.95	0.11	0.32	71,665
$\frac{sga}{sale}_{f,t}$	0.19	0.12	0.01	0.90	0.09	0.25	71,699
$\frac{sga}{cogs}_{f,t}$	0.44	0.78	0.01	20.73	0.13	0.47	71,665
$\frac{Unsec.debt}{asset}_{f,t}$	0.17	0.17	0.00	0.99	0.02	0.26	72,674
$\frac{Sec.debt}{asset}_{f,t}$	0.11	0.15	0.00	0.86	0.00	0.16	72,674
$\frac{Unsec.debt}{debt}_{f,t}$	0.62	0.37	0.00	1.00	0.27	1.00	72,674
$\frac{\textit{Enterprise value}}{asset}_{f,t}$	1.17	1.24	-0.20	19.75	0.50	1.42	64,618
$\frac{\textit{Market Value}}{asset}_{f,t}$	1.16	1.26	0.03	17.01	0.43	1.41	65,342
$\frac{\Delta Debt}{asset}_{f,t}$	0.00	0.10	-0.36	0.82	-0.03	0.02	65,397
$\frac{\Delta \textit{Unsec. Debt}}{Asset}_{f,t}$	0.01	0.12	-0.65	0.98	-0.02	0.03	66,215
$\frac{\Delta \textit{Sec. Debt}}{Asset}_{f,t}$	0.00	0.09	-0.41	0.56	-0.01	0.00	65,845
$\frac{\Delta \textit{Unsec. Debt}}{Debt}_{f,t}$	0.12	0.94	-1.00	14.33	-0.13	0.11	64,746
$\frac{\Delta \textit{Sec. Debt}}{Debt}_{f,t}$	0.02	0.42	-0.97	5.00	-0.07	0.01	64,375
$\frac{ppent}{asset}_{f,t}$	0.31	0.22	0.00	0.90	0.14	0.44	72,674
$\frac{invetories}{asset}_{f,t}$	0.18	0.15	0.00	0.67	0.04	0.27	72,674
$\frac{cash}{asset}_{f,t}$	0.12	0.14	0.00	0.83	0.02	0.16	72,674
$\frac{debt}{asset}_{f,t}$	0.27	0.21	0.00	1.00	0.11	0.40	72,674
$\textit{log real sales}_{f,t}$	4.92	2.05	-2.75	12.22	3.46	6.31	72,674
$age_{f,t}$	17.35	12.73	1.00	73.00	7.00	25.00	72,674
$\textit{log real asset}_{f,t}$	4.75	2.11	-2.90	12.55	3.23	6.19	72,674

This table provides summary statistics for a sample of US company-listed firms in Compustat on firm-level characteristics of the sample studied. The data covers the period from 1981 until 2018. Firms with leverage exceeding one unit and those with total cost over sales exceeding one unit are excluded from the analysis.

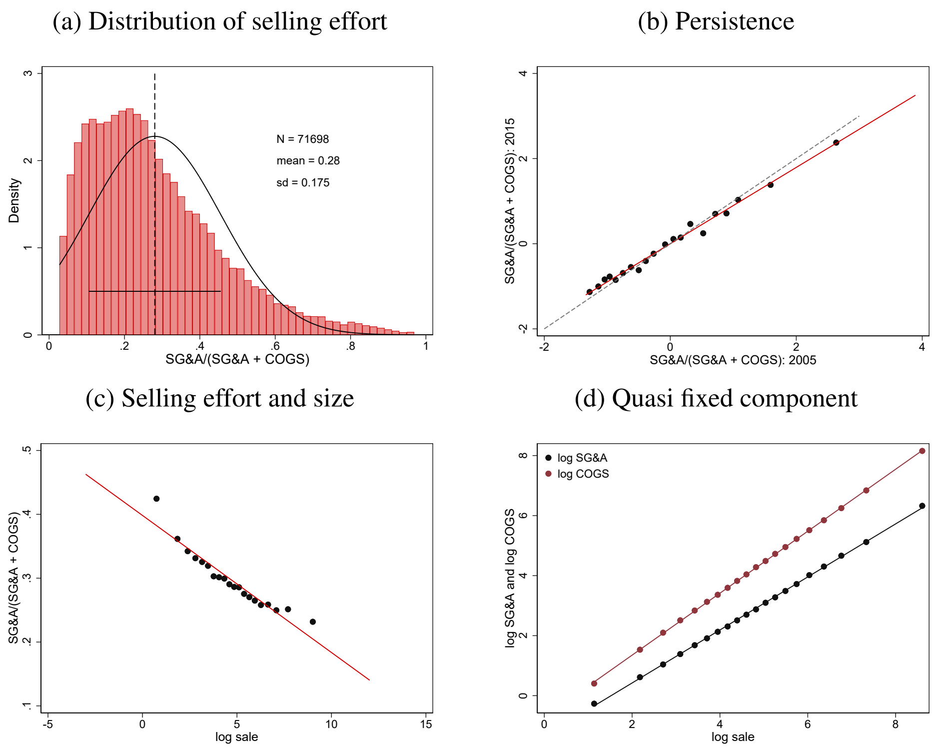
3.3 Stylized facts about selling effort

In this section, we present some stylized facts about the estimated selling effort in US non financial firms and discuss the various results.

We first confirm in Figure 3.1 that the estimated selling effort dispersion has very long tails and presents huge heterogeneity, likely reflecting sectoral specific differences. Because of this, we then study its persistence properties over time. Figure 3.1b plots a binscatter-plot residualized by sector-year fixed effect of firm-level selling effort in 2015 against firm-level selling effort in 2010. Over both time periods, firm-level selling effort in the later year is lined up with the firm-level selling effort earlier year. This suggests that the differences in firm-level selling effort are a persistent feature at the firm level evidence of its quasi-fixed component. We then show in Figure 3.1c that over the firm size distribution selling effort decreases in size as the firm grows larger, consistent with the idea that younger firms have a larger share of selling effort expenses relative to their sales-volume. In Figure 3.1d we plot a binscatter plot of log SG&A and log of COGS against log of sale (i.e., our model equivalent of size). We find that the variability of selling effort to size is driven by a change in COGS rather than SG&A, consistent with Afrouzi et al. (2020). In untabulated results we also find that selling effort is also negatively related to measures of tangibility.

Overall this evidence shows that selling effort distribution is very dispersed and highly persistent driven by the quasi-fixed nature of selling expenditure, showing that firms need to continue investing in acquiring and retaining their customers.

Figure 3.1:
Stylized fact



Note: This figure shows the correlation between firm-level selling effort dispersion and various outcomes. Panel a firm-level selling effort distribution. Panel b plots firm-level selling dispersion measures in 2015 against firm-level selling dispersion in 2005. Panel c plots firm-level selling residualized by sector-year fixed effects against the log of sale. Panel d plots firm-level log SG&A and log COGS volume against the log of sale. The two variables are residualized by sector-year fixed effects. The sample includes annual firm-year observations from 1981 to 2018 whose $\frac{(xsga+cogs)}{sale} \leq 1$ and with leverage below a unit. Source: Compustat.

3.4 Empirical results

In this section, we explore the relationship between a firm's selling effort and its debt structure, policies, and future cash flows. Motivated by previous evidence, we first examine how debt structure changes in relation to the intensity of selling effort. We then investigate its relation to future enterprise values. Lastly, we explore how variations in selling effort relate to debt issuance policies and the composition of debt (i.e., secured and unsecured debt).

Throughout the analysis, we employ the following OLS regression model, where the unit of observation is the firm-year:

$$y_{f,t} = \sum_{j \in J} \alpha_j + \beta_1 \times [\textit{Measure of selling effort}_{f,t}] + \Gamma' X_{f,t} + \varepsilon_{f,t} \qquad (3.1)$$

Here, the dependent variable $y_{f,t}$ measures debt-structure variables, future cash-flow-related metrics, and debt-issuance variables. The variable α_j represents different levels of fixed effects, including sector-year and firm fixed effects where applicable. Our main measure of selling effort is SG&A over total costs (i.e., $xsga/(xsga + cogs)$). The vector $X_{f,t}$ includes firm-level controls relevant to the outcome studied and will be detailed later. Across all specifications, standard errors are double-clustered at the firm and year levels.

3.4.1 Selling effort and debt structure

Exploiting the cross-section of firms, we document that higher levels of customer-related expenses are associated with larger ratios of unsecured borrowing. This pattern holds true within the firm-time dimension as well.

To reach these conclusions, we rely on the reduced form approach presented in Equation 3.1 and compare the share of unsecured debt relative to assets and total debt at different levels of selling effort, controlling for observable characteristics that might influence debt distribution. As observed in section 3.3, firms with high selling effort tend to have lower shares of tangible equity and larger fractions of cash. We control for the share of tangible capital, inventories, cash ratio, and leverage. Additionally, we control for the log of assets, age, and sales. The baseline analysis considers the cross-section of firms with sector-year fixed effects, where a sector is defined by a two-digit SIC code. This allows us to absorb time-varying heterogeneity across firms within a specific sector that might alter debt distribution. Robustness to the inclusion of firm-fixed effects is presented in Appendix section B.

We present the results in Table 3.2:

We observe that higher levels of selling effort are associated with higher ratios of unsecured debt to assets (Column 1) and a higher share of unsecured debt (Column 3), while there is a negative relationship with secured credit to assets (Column 2). The results are economically significant. Moving from the 25^{th} to the 75^{th} percentile of the selling effort distribution per increase in selling effort is associated with a 4% higher ratio of unsecured debt over assets and a 4.45% higher unsecured share over debt.[3] As a robustness check, we compare our model under alternative timing specifications and measures of customer-related expenses in Table B.2, showing that results remain largely unchanged. In particular, examining slow-moving averages suggests that results are not driven by sporadic changes in customer expenditures. Moreover, once controlling for firms' fixed effect in Table B.1 yields similar coefficient magnitudes, indicating that the cross-sectional analysis is less prone to omitted variable bias from unobserved, time-invariant characteristics.

Overall, the takeaway is that, after controlling for tangibility and other observ-

[3]The results are calculated as: $(.38-.15)\times 0.032/0.17 = 0.043$ and $(.38-.15)\times 0.120/0.62 = 0.045$.

Table 3.2:
Selling effort and debt composition

	Debt distribution		
	$\frac{Unsec.\ Debt}{Asset}_{f,t}$	$\frac{Sec.\ Debt}{Asset}_{f,t}$	$\frac{Unsec.\ Debt}{Debt}_{f,t}$
	(1)	(2)	(3)
$\frac{xsga}{xsga+cogs}_{f,t}$	0.032***	-0.032***	0.120***
	(0.006)	(0.006)	(0.020)
Controls	✓	✓	✓
Sector-Year F.E.	✓	✓	✓
Clustered Std.Errors	Firm year	Firm year	Firm year
R^2	0.545	0.463	0.167
Obs	71,698	71,698	71,698

Note: This table presents firm-level panel regression of firms' outstanding debt. Debt is split between secured and unsecured debt. We restrict the sample to all firms whose $\frac{(xsga+cogs)}{sale} \leq 1$ and with leverage below a unit, all the other control variables are normalized by assets. End of period controls (unreported) include tangible capital, inventories and cash ration, leverage the logs of asset, age and sales. Standard errors are clustered by firm and fiscal year. The sample period is 1981-2018 fiscal years for the universe of non-financial firms in Compustat. The level of significance are * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

able characteristics affecting firms' debt structure, companies with higher selling efforts tend to have a debt composition skewed toward unsecured debt, which is typically supported by the firm's cash flows.

3.4.2 Selling effort and firms' growing prospect

In this section we investigate the relationship between customer capital and future firms' growing prospects. We find that firms with higher selling effort levels see their enterprise value to asset and MTB ratio grow more with respect to comparable firms with lower selling effort. Moreover, these firms see heightened cumulative sales growth, showing that higher expenses are related to future firms' performance.

Understanding the dynamics of customer expenditures and firms' growth prospects is crucial for interpreting the previous results. If firms with high selling efforts can credibly promise their creditors higher future prospects, then issuing debt backed by anticipated cash flows, specifically unsecured debt, becomes advantageous. Conversely, if these firms do not demonstrate superior future performance, the results can be explained by standard borrowing constraints, such as a lack of tangible capital (Eisfeldt and Rampini, 2009; Rampini and Viswanathan, 2020). Disentangling these two channels is challenging, especially without detailed bank-firm or bond data to clearly differentiate them. However, by examining firms' growth prospects, we can gather evidence to support one of these explanations.

We thus focus on two measures that proxy for a firm's growing prospect and that are tightly linked to firms' credit access (Greenwald et al., 2020; Lian and Ma, 2021; Drechsel, 2023). In particular, we study the relation between customer expenses and consecutive enterprise to asset value (i.e., Tobin's Q) and MTB both over the cross-section and the within firm time dimension using Equation 3.1 where our independent variable is the end of period selling effort and our controls, same as in Table 3.2 are at the beginning of period and one lag of the dependent variable.[4] Results are presented in Table 3.3

Consistent with our growing prospect hypothesis, the results show that when firms increase their selling effort, they also see their future value increase. In terms of magnitude, an interquartile increase in selling effort is associated with a 9.5% increase in the enterprise to asset ratio with respect to its mean over a one period

[4]The timing assumption is not driving the results, and it is based on our modeling assumption. In un-tabulated results we run the regression with end of period controls, and the results are virtually unchanged.

Table 3.3:
Selling effort and firms' growing prospect

	Cross-section			
	$\Delta \frac{Ent.val}{Assets}_{f,t}$		$\frac{Mkt.val}{Assets}_{f,t}$	
	(1) $t+1$	(2) $t+2$	(3) $t+1$	(4) $t+2$
$\frac{xsga}{xsga+cogs}_{f,t}$	0.487***	0.685***	0.457***	0.637***
	(0.063)	(0.086)	(0.062)	(0.080)
Controls	✓	✓	✓	✓
Sector-Year F.E.	✓	✓	✓	✓
Clustered Std.Errors	Firm year	Firm year	Firm year	Firm year
R^2	0.603	0.441	0.650	0.488
Obs	55,816	50,428	56,632	51,241

Note: This table presents firm-level panel regression. We restrict the sample to all firms whose $\frac{(xsga+cogs)}{sale} \leq 1$ and with leverage below a unit, all the other control variables are normalized by assets. End of period controls (unreported) include tangible capital, inventories and cash ration, leverage the logs of asset, age and sales. Standard errors are clustered by firm and fiscal year. The sample period is 1981-2018 fiscal years for the universe of non-financial firms in Compustat. The level of significance are * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

and with a 9% increase in MTB scaled to the mean.[5]

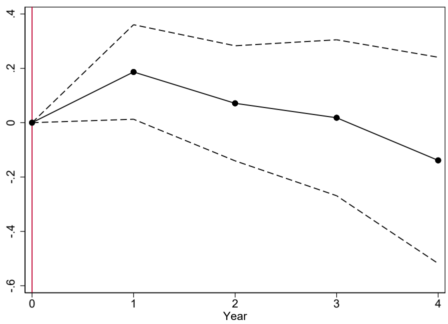
We further provide in Figure 3.3 further evidence of the mechanism for the within-firm model counterpart of Table 3.3. We estimate local projection akin Jordà (2005) for the predicted relation over a 4-year horizon.

These results confirm that the current increase in selling expenses on average relates to future growing prospects, though the effect is short-lived as mean reversion is particularly strong for the variable of analysis as these variables exhibit high volatility and sensitivity to short-term changes. This is of crucial importance

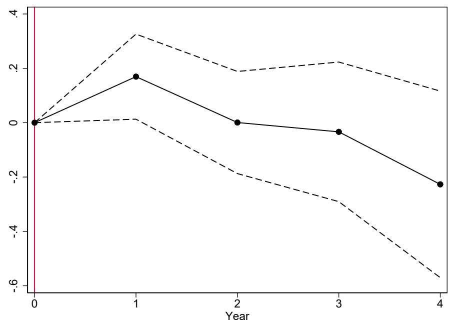
[5]The results are calculated as: $(.38-.15)\times.487/1.17 = 0.095$ and $(.38-.15)\times0.457/1.16 = 0.090$. In percentage points increase we have $(.38-.15)\times.487 = 11.2\%$ and $(.38-.15)\times0.457 = 10.5\%$.

Figure 3.2:
Predicting future growing prospects

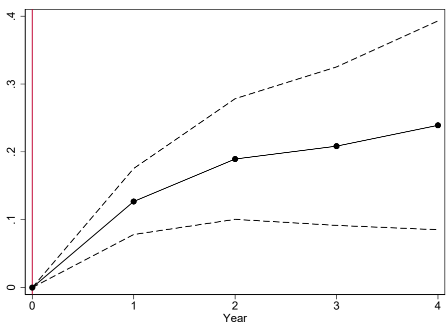
(a) Enterprise value to asset



(b) MTB



(c) Cumulative sales growth



Note: This panel presents firm-level within panel regression of firms' future going prospect. The panel reports OLS coefficient for Equation 3.1. We restrict the sample to all firms whose $\frac{(xsga+cogs)}{sale} \leq 1$ and with leverage below a unit, all the other control variables are normalized by assets. Beginning of period controls (unreported) include tangible capital, inventories and cash ration, leverage the logs of asset, age and sales and lagged dependent variable. Standard errors are clustered by firm and fiscal year. Bands represents 10% confidence bandwidth level. The sample period is 1981-2018 fiscal years for the universe of non-financial firms in Compustat.

for firms as it allows them to credibly promise the investors the future stream of revenues. We report within-firm level estimates in Table B.3. Our findings seem to better suit the fact that high-selling effort firms can pledge higher future cash flows, thus shifting their debt composition toward unsecured claims.

Overall the analysis points towards the fact that these firms' growth prospects are stronger, thus on the margin, the firm should choose a higher level of unsecured claims once they issue new debt. We formally test this hypothesis in the next session.

3.4.3 Selling effort

In this section, we examine whether, upon debt issuance, firms with higher selling efforts increase their proportion of unsecured credit relatively more than secured ones. Our left-hand variables are net debt issuance measured as debt issuance net of repayment over lagged assets, change in unsecured credit to lagged assets, change in secured debt to lagged assets, and change in unsecured debt to lagged debt where a change in debt classes are measured difference in debt across two contiguous periods. According to our previous results, we should expect higher selling effort firms to issue more unsecured claims on the margin compared to secured ones. In this case, we use within-firm analysis to show that selling effort levels are driving firms' debt policy choice, rather than other differences across companies.

We present the results for the within the firm model in Table 3.4. We also present the full specification with cross-sectional estimates in Table B.4.

Column (1) reports the specification using net debt issuance as the outcome variable. It shows that firms with higher selling efforts see an increase in net debt relative to other firms: a one standard deviation increase in selling effort (0.18) increases net debt by 73 bps. The result is statistically significant. This evidence shows that these firms once they access the market, issue more debt compared to lower-selling effort firms. Column (2) adds to the previous analysis focusing on

Table 3.4:
Selling effort and firms' debt policies

	Debt issuance			
	$\frac{\Delta Debt}{lag\ Asset}_{f,t}$	$\frac{\Delta Unsec.\ Debt}{lag\ Asset}_{f,t}$	$\frac{\Delta Sec.\ Debt}{lag\ Debt}_{f,t}$	$\frac{\Delta Unsec.\ Debt}{lag\ Debt}_{f,t}$
	(1)	(2)	(3)	(4)
$\frac{xsga}{xsga+cogs}_{f,t}$	0.042**	0.060***	0.117*	0.417***
	(0.017)	(0.019)	(0.058)	(0.131)
Controls	✓	✓	✓	✓
Sector-Year F.E.	✓	✓	✓	✓
Firm F.E.	✓	✓	✓	✓
Clustered Std.Errors	Firm year	Firm year	Firm year	Firm year
R^2	0.367	0.300	0.281	0.267
Obs	28,868	28,868	28,868	28,868

Note: This table presents firm-level panel regression for firms' debt policies. We restrict the sample to all firms whose $\frac{(xsga+cogs)}{sale} \leq 1$ and with leverage below a unit, all the other control variables are normalized by assets. End of period controls (unreported) include tangible capital, inventories and cash ration, leverage and the logs age and sales. Further controls: lagged log of assets to control for beginning of period assets used to scale right hand variable. Standard errors are clustered by firm and fiscal year. The sample period is 1981-2018 fiscal years for the universe of non-financial firms in Compustat. The level of significance are * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

unsecured debt issuance. A one standard deviation increase in selling effort corresponds to a 108 basis points increase in the net change in unsecured debt over lagged assets. This shows that a substantial volume of the firms' total assets is represented by new uninsured debt claims. To better understand the debt composition we then compare Column (3) and Column (4) where we see the net share of debt scaled by previous debt. The first thing to notice is that both coefficients are positive and significant, meaning that high selling effort firms issue both types of debt in higher volume compared to lower ones, consistent with Column (1). However, on the margin, high selling effort firms issue more unsecured claims. A one standard deviation increase in selling effort corresponds to a 7.51 percentage points increase in the net change in unsecured debt over lagged total debt, while the effect for secured debt is 2 percentage points. Thus high selling effort firms, on the margin, shift their debt issuance to unsecured debt causing the overall debt composition to move away from secured debt. We also investigate alternative measures of selling effort to check the robustness of our results in Table B.5 which confirm qualitatively the previous results.

Overall, we highlight the positive relationship between customer-related expenses and the issuance of unsecured debt. Of course, our results cannot be interpreted as causal without a proper source of exogenous variation, however, we want to stress that given the positive relation between cash flows and customer capital investment, a firm is more likely to shift its debt composition towards unsecured debt to exploit all the benefits from it.

3.5 Robustness

Our analysis is centered on the relationship between selling efforts and customer base due to the well-established link between customer-related expenditures and customer metrics, as detailed by Afrouzi et al. (2020). Direct observations of the customer base are absent in our dataset; however, we employ the methodologies proposed by Ewens et al. (2024) to estimate the accumulation of organizational capital using firm expenditures, which serves as a proxy for the customer base.[6] We aggregate SG&A expenditures following Ewens et al. (2024) and examine variations in debt composition across firms with differing levels of accumulated customer expenditures. We list the results in Table B.6. Consistently with our main findings in Table 3.2, we show that firms with higher accumulated SG&A —reflecting greater customer capital— display a higher propensity for unsecured

[6] Organizational capital indirectly reflects the customer base, predominantly derived from SG&A expenditures, adjusted for R&D expenses.

over secured debt, both as a proportion of total assets and within their debt portfolios.

We further corroborate our main findings with additional robustness checks using alternative categorizations of debt as delineated by Lian and Ma (2021), which distinguishes between cash flow-based debt (CFL), which includes unsecured obligations and secured debt supported by non-tangible collateral such as blanket liens or stock shares, and asset-based debt (ABL), encompassing debts secured by tangible assets like machinery or plants. The results, presented in Table B.7, reveal that this segmentation of debt types yields qualitatively similar patterns to our primary findings, particularly in the dominance of CFL over debt.

In the subsequent section, we will formally introduce a model that encapsulates the dynamics of customer capital accumulation and borrowing constraints.

3.6 Model

This section presents a novel firm dynamics model with endogenous customer acquisition and borrowing constraint that is consistent with our motivational facts. We build on Afrouzi et al. (2020) and incorporate a debt financing problem subject to going-concern constraint similar to Sun and Xiaolan (2019).

3.6.1 Households

A representative household has Greenwood–Hercowitz–Huffman (GHH) preferences over consumption C and labor supply N according to

$$u(C - g(N)).$$

Consumption is split over a unit measure of varieties j. The household consists of a unit measure of buyers i, and each individual buyer only has access to a subset of all available varieties, which is determined endogenously as outlined below. Aggregate consumption is a composite of consumption across varieties and buyers, such that

$$C = \left(\int \int 1_{ij} c_{ij}^{\frac{\mu-1}{\mu}} didj \right)^{\frac{\mu}{\mu-1}},$$

where 1_{ij} is an indicator function equal to one if buyer i has access to variety j and zero otherwise. Denote the share of buyers having access to variety j as s_j, i.e.

$$s_j = \int 1_{ij} di$$

The household maximizes utility by choosing labor supply and consumption of each buyer for each available variety subject to the budget constraint

$$\int \int p_j c_{ij} didj \leq wN + \Pi$$

where p_j is the price for variety j, w is the wage rate, and Π are firms' profits which are rebated lump-sum to the household.

Households' optimal choice for labor satisfies

$$w = g'(N)$$

The optimal allocation of consumption across buyers and varieties is given as

$$c_{ji} = \begin{cases} \left(\frac{p_j}{P}\right)^{-\mu} C & \text{if } 1_{ij} = 1 \\ 0 & \text{if } 1_{ij} = 0 \end{cases}$$

such that total demand for variety j is given by

$$c_j = s_j \left(\frac{p_j}{P}\right)^{-\mu} C$$

where the price index P satisfies

$$P = \left(\int s_j p_j^{1-\mu} dj\right)^{\frac{1}{1-\mu}} .$$

3.6.2 Firms

There is a unit measure of firms, each producing a differentiated variety j. The firm's state vector is characterized by its idiosyncratic productivity z_j, which evolves stochastically over time according to a first-order Markov process, and its customer base s_j. For convenience, we omit the j subscript below.

Firms produce output with production function $f(z, n) = zn^{\alpha}$, where α is the returns to scale and labor n the single input factor. In addition to their labor input, firms choose marketing activity m, paid in units of labor, which allows them to accumulate customers. The next period's customer base depends on current customers and marketing activity and evolves according to the law of motion $s' = h(s, m)$.

Every period, firms exit exogenously at random with probability δ.[7] We assume that exiting firms are replaced by an equal mass of entrants that draw their initial productivity at random from the stationary distribution of z, i.e. we normalize the mass of active firms to one and the distribution of the productivity of active firms to the stationary distribution of z.

Firms need to finance a fraction ϕ of their total wage bill $w(n+m)$ in advance,

[7]We do not allow for endogenous exit. We verify ex-post that no firm in the economy would choose to exit if possible, i.e. we check that firm values are always positive.

by borrowing in within-period debt at interest rate r. Their borrowing is subject to a constraint of the form

$$\phi w(n+m) \leq \theta(1-\delta)\beta \mathrm{E}V(z', s').$$

$\theta > 0$ determines the fraction of their going-concern value a firm is able to pledge as collateral for short term debt.

The dynamic programming problem of the firm can be written as

$$V(z,s) = \max_{y,m} p(s,y)y - w(1+r\phi)(n(z,y)+m) + (1-\delta)\beta \mathrm{E}V(z',s') \tag{3.2}$$

$$\text{s.t. } s' = g(s,m) \tag{3.3}$$

$$\phi w(n(z,y)+m) \leq \theta(1-\delta)\beta \mathrm{E}V(z',s') \tag{3.4}$$

where we have substituted $n(z,y) = \left(\frac{y}{z}\right)^{\frac{1}{\alpha}}$ from the production function and $p(s,y) = \left(\frac{y}{sC}\right)^{\frac{-1}{\mu}} P$ from households' preferences, imposing $c_j = y_j$ in equilibrium.

The firm's optimal choice for output satisfies

$$p(s,y) + p_y(s,y)y - w(1+r\phi)n_y(z,y) - \lambda w \phi n_y(z,y) = 0,$$

with λ the multiplier on the borrowing constraint. Denote $k = w(1+r\phi)n_y(z,y)$ as the firms marginal cost of production and $\Lambda_y = \lambda w \phi n_y(z,y)$ the shadow cost of borrowing to finance one additional unit of output. From above $p_y(s,y)y = -\frac{1}{\mu}p(s,y)$. We can rewrite the optimality condition as

$$p = \frac{\mu}{\mu - 1}(k + \Lambda_y).$$

If the borrowing is not binding ($\lambda_y = 0$), we recover the standard optimal pricing condition with CES preferences, which sets prices as a constant markup over marginal cost of production k, proportionate to the price elasticity μ. Under a binding borrowing constraint, firms still set a constant markup over marginal cost, but these cost now incorporate the shadow value of the binding borrowing constraint Λ_y. The more binding the constraint, the higher is going to be the markup over the pure cost of production, as

$$\frac{p}{k} = \frac{\mu}{\mu - 1}\left(1 + \frac{\Lambda_y}{k}\right) \geq \frac{\mu}{\mu - 1}$$

Firms optimal choice for marketing m satisfies

$$\begin{aligned} & - w(1 + r\phi) + h_m(s, m)(1 - \delta)\beta \mathrm{E}\frac{\partial V(z', s')}{\partial s'} \\ & \qquad\qquad + \lambda\left[-\phi w + \theta h_m(s, m)(1 - \delta)\beta \mathrm{E}\frac{\partial V(z', s')}{\partial s'}\right] = 0 \end{aligned}$$

where the firm optimally trades-off the labor cost of marketing $-w(1+r\phi)$ against the marginal value of gaining future customers $h_m(s, m)(1-\delta)\beta \mathrm{E}\frac{\partial V(z',s')}{\partial s'}$. Again, denote the borrowing wedge in the optimality condition as

$$\Lambda_m = \left[-\phi w + \theta h_m(s, m)\beta \mathrm{E}\frac{\partial V(z', s')}{\partial s'}\right].$$

Whenever the constraint binds (whenever $\lambda > 0$) it has to hold that

$$-\phi w < -\theta h_m(s, m)\beta \mathrm{E}\frac{\partial V(z', s')}{\partial s'} \Rightarrow \Lambda_m < 0$$

as otherwise the firm could relax the constraint by increasing its marketing spending. A binding borrowing constraint ($\lambda > 0$ and $\Lambda_m < 0$) hence implies that

$w(1+r\phi) < h_m(s,m)(1-\delta)\beta \mathrm{E}\frac{\partial V(z',s')}{\partial s'}$, i.e. the benefits of additional marketing outweigh its cost and the firm is forced to choose less than the optimal amount of marketing.

3.6.3 Matching and Equilibrium

Assume that a fraction $(1-\rho)$ of the mass of buyers with access to variety j s_j loses access at the end of each period. Assume further, that all buyers without previous access as well as those who lost access can (re-)match with the firm for the next period. The matching happens in a market where the mass of potential buyers $(1-\rho s)$ is matched with the mass of firms marketing representatives m according to matching technology $M(s,m) = \Gamma\left((1-\rho s)^{\gamma} m^{1-\gamma}\right)$, such that the law of motion for firms customer acquisition is given by

$$h(s,m) = \rho s + M(s,m) = \rho s + \Gamma\left(1-\rho s\right)^{\gamma} m^{1-\gamma}$$

In equilibrium, the labor supplied by households has to equal firms' total demand for production and marketing. Denote $\psi(z,s)$ as the mass of firms with state (z,s). Labor market clearing then requires

$$N = \int\int \psi(z,s)(n(z,y(z,s)) + m(z,s))dzds$$

We do not model the determinantion of the interest rate r explicitly, but assume it is determined based on the optimal problem of a banking sector, which distributes all interest income as profits to households, together with the profits from producing firms. Households' overall profit income is given by

$$\Pi = \int\int \psi(z,s)p(s,y(z,s)y(z,s)dzds - wN$$

3.7 Parametrization

We now calibrate the model and verify that its steady state behavior is consistent with key features of the microdata.

3.7.1 Calibration

For our initial calibration, we exogenously fix a subset of parameters. Second, we choose the remaining parameters in order to match moments in the data.

Table 3.5:
Fixed parameters

Parameter	**Description**	**Value**
Exogenously set		
r_f	Interest rate	0.02
δ	Exit probability	0.06
ρ	Customer retention	0.9
η	Frish elasticity	1
α	Return to scale	0.64
Set to match data		
μ	Price elasticity	5
γ	Matching function elasticity	0.5
Γ	Productivity of matching function	1
θ	Going concern constraint	0.035

Table 3.5 lists the parameters we used in our calibration. The model period is one year, so we set the risk free rate to 2% as our baseline. We borrow the exogenous exit parameter from Lee and Mukoyama (2015). We follow Afrouzi et al. (2020) and set the customer retention parameters, the Frish elasticity, and the return to scale parameters based on their model calibration. We set the price elasticity to 5 such that the steady state observed markup is equivalent to the cost weighted markup observed in our sample (1.25). The key parameter of interest is the going concern one, namely θ. We approximate the going concern value with

its enterprise value and we scale it by its short term debt to closely follow the debt definition used in the model. In the data, the observed mean is 0.035. We provide evidence that aggregate operating expenditures (i.e., the sum of SG&A and COGS), closely track the evolution of short term debt in Figure A.1.

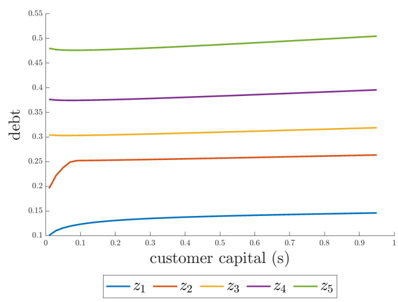
3.8 Model validation

The first two panels in Figure 3.3 analyze firms' decision rules in a steady state and identify a key source of financial heterogeneity across firms, namely customer capital. Firms accumulate customers by additional borrowing. A higher customer base s means higher demand which further boosts the firms value. In our model, more productive firms will be constrained as firms need to finance their input of production in advance. Hence the results in Figure 3.3a. Most importantly, under a binding borrowing constraint, firms still set a constant markup over marginal cost, but these costs now incorporate the shadow value of the borrowing constraint Λ_y. Thus, the more binding the constraint, the higher is going to be the markup over the pure cost of production, hence more productive firms will have higher markups as they are hitting the constraints.

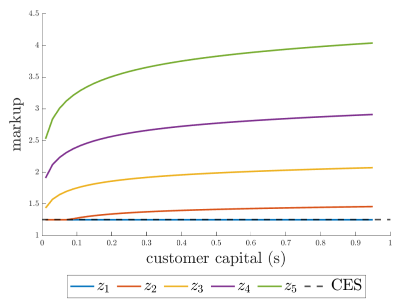
Crucially, the model is able to replicate the key empirical results of our model. In our model, a firm's debt policy is the empirical equivalent of choosing unsecured debt. Higher levels of selling effort intensive firms will have a higher volume of debt over size Figure 3.3c (i.e., employment). The underlying reason for it is that as firms invest in acquiring new customers m, their future values increase Figure 3.3d. The only way to support higher debt volumes is to have higher future value to be pledged. This shows that our model is able to replicate the key features observed in Compustat data.

Figure 3.3:
Model empirical validation

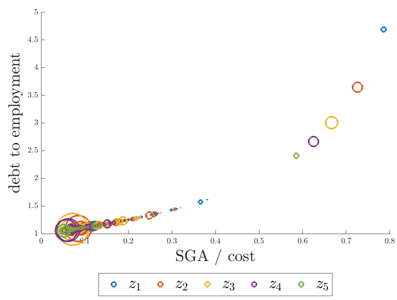
(a) Debt policy



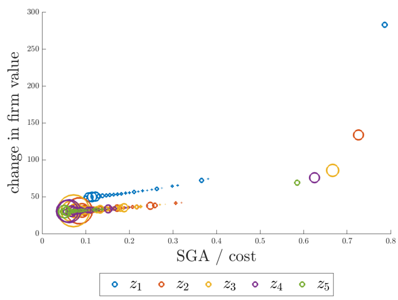
(b) Markup policy



(c) Debt to employment



(d) Firm value to selling effort



Note: This panel presents the model's depiction of firm policy functions, examining the relationship between the debt-to-employment ratio and firms' future value relative to total costs. Figure 3.3a and Figure 3.3b illustrate firm policies across varying levels of productivity. Additionally, Figure 3.3b contrasts these findings against the predictions of the CES function. Figure 3.3c and Figure 3.3d explore the linkage between selling effort and total costs in relation to debt per employee and firms' valuation. The size of each dot in these figures indicates the mass of firms represented, with larger dots denoting a higher concentration of firms in the distribution.

3.9 Conclusion

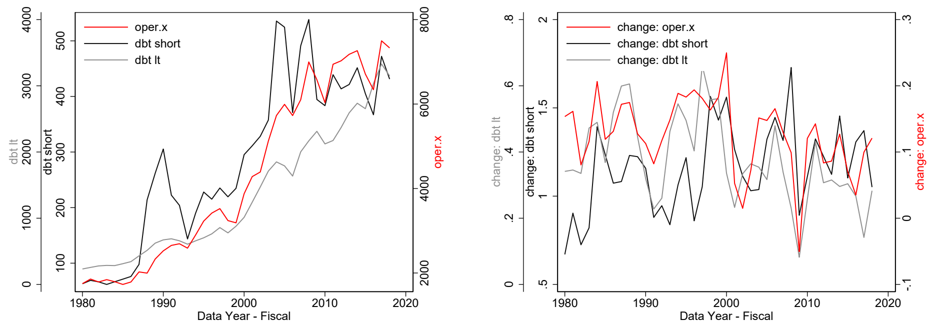
In this study, we explore the relationship between firms' investment in customer capital, their debt structure, and firms' debt policies. Our findings underscore a significant link between firms' intensity in customer expenditure and their debt composition, shedding light on how these expenses shape firms' financial policies. Specifically, our empirical results reveal that firms allocating substantial resources to acquire and maintain their customer base exhibit a pronounced debt composition tilted towards unsecured debt.

We present compelling evidence indicating that such firms leverage their growing concern value to augment their debt capacity, thereby facilitating borrowing against future cash flows rather than traditional physical collateral. Upon issuance, as customer expenses can increase firms' sales, unsecured debt becomes their marginal choice as the same unencumbered assets support it. These insights challenge conventional financial constraint models, highlighting the pivotal role of customer expenses in expanding firms' borrowing capacities. We then build a model of customer capital accumulation with firm financial friction that can match the empirical patterns observed in the data. Our results shed new insights into the relationship between customer capital, debt structure, and firms' financial needs in today's dynamic business landscape.

A Figure appendix

Figure A.1:
Operating expenditure and debt trends

Time series: volumes Time series: change



Note: This panel presents aggregate time series for short debt dynamics and operating expenditures defined as the sum of SG&A and COGS. We restrict the sample to all firms whose $\frac{(xsga+cogs)}{sale} \leq 1$ and with leverage below a unit. The sample period is 1981-2018 fiscal years for the universe of non-financial firms in Compustat. Aggregate time series is based on the sum of outstanding volume at each point in time, while the second panel plots the mean difference of each variable.

B Table appendix

Table B.1:
Customer expenditure and debt composition: within-firm

	Debt distribution					
	$\frac{Unsec.\ Debt}{Asset}_{f,t}$		$\frac{Sec.\ Debt}{Asset}_{f,t}$		$\frac{Unsec.\ Debt}{Debt}_{f,t}$	
	(1) Cross-section	(2) Within	(3) Cross-section	(4) Within	(5) Cross-section	(6) Within
$\frac{xsga}{xsga+cogs}_{f,t}$	0.032***	0.033***	-0.032***	-0.033***	0.120***	0.101***
	(0.006)	(0.011)	(0.006)	(0.011)	(0.020)	(0.032)
Controls	✓	✓	✓	✓	✓	✓
Sector-Year F.E.	✓	✓	✓	✓	✓	✓
Firm F.E.		✓		✓		✓
Clustered Std.Errors	Firm year	Firm year	Firm year	Firm year	Firm year	Firm year
R^2	0.545	0.776	0.463	0.736	0.167	0.579
Obs	71,698	71,698	71,698	71,698	71,698	71,698

Note: This table presents firm-level panel regression of firms' outstanding debt. We restrict the sample to all firms whose $\frac{(xsga+cogs)}{sale} \leq 1$ and with leverage below a unit, all the other control variables are normalized by assets. End of period controls (unreported) include tangible capital, inventories and cash ration, leverage the logs of asset, age and sales. Standard errors are clustered by firm and fiscal year. The sample period is 1981-2018 fiscal years for the universe of non-financial firms in Compustat. The level of significance are * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.2:
Customer expenditure and debt composition: alternative measures

	Debt distribution		
	(1)	(2)	(3)
	$\frac{\text{Unsec. Debt}}{Asset}_{f,t}$	$\frac{\text{Sec. Debt}}{Asset}_{f,t}$	$\frac{\text{Unsec. Debt}}{Debt}_{f,t}$
$\frac{xsga}{xsga+cogs}_{f,t}$	0.032***	-0.032***	0.120***
	(0.006)	(0.006)	(0.020)
$\frac{xsga}{sale}_{f,t}$	0.039***	-0.039***	0.128***
	(0.007)	(0.007)	(0.022)
$\frac{xsga}{cogs}_{f,t}$	0.003***	-0.003***	0.012***
	(0.001)	(0.001)	(0.002)
$\frac{sga}{xsga+cogs}_{f,t}$	0.030***	-0.030***	0.112***
	(0.006)	(0.006)	(0.020)
$\frac{sga}{sale}_{f,t}$	0.040***	-0.040***	0.125***
	(0.008)	(0.008)	(0.025)
$\frac{sga}{cogs}_{f,t}$	0.004***	-0.004***	0.017***
	(0.001)	(0.001)	(0.003)
lag $\frac{xsga}{xsga+cogs}_{f,t}$	0.028***	-0.044***	0.118***
	(0.007)	(0.007)	(0.022)
lag $\frac{xsga}{sale}_{f,t}$	0.036***	-0.050***	0.123***
	(0.008)	(0.008)	(0.026)
lag $\frac{xsga}{cogs}_{f,t}$	0.003**	-0.004***	0.012***
	(0.001)	(0.001)	(0.003)
lag $\frac{sga}{xsga+cogs}_{f,t}$	0.026***	-0.042***	0.107***
	(0.007)	(0.007)	(0.023)
lag $\frac{sga}{sale}_{f,t}$	0.038***	-0.050***	0.117***
	(0.009)	(0.009)	(0.030)
lag $\frac{sga}{cogs}_{f,t}$	0.004**	-0.006***	0.015***
	(0.002)	(0.001)	(0.004)
$\frac{xsga}{xsga+cogs}_{f,t-3\rightarrow t}$	0.030***	-0.047***	0.124***
	(0.007)	(0.007)	(0.022)
$\frac{xsga}{sale}_{f,t-3\rightarrow t}$	0.028***	-0.039***	0.099***
	(0.007)	(0.005)	(0.016)
$\frac{xsga}{cogs}_{f,t-3\rightarrow t}$	0.003***	-0.004***	0.011***
	(0.001)	(0.001)	(0.003)
$\frac{sga}{xsga+cogs}_{f,t-3\rightarrow t}$	0.029***	-0.045***	0.117***
	(0.007)	(0.007)	(0.022)
$\frac{sga}{sale}_{f,t-3\rightarrow t}$	0.034***	-0.044***	0.108***
	(0.008)	(0.006)	(0.018)
$\frac{sga}{cogs}_{f,t-3\rightarrow t}$	0.004***	-0.006***	0.015***
	(0.002)	(0.001)	(0.004)

Note: This table presents firm-level cross-sectional panel regression of firms' outstanding debt. We restrict the sample to all firms whose $\frac{(xsga+cogs)}{sale} \leq 1$ and with leverage below a unit, all the other control variables are normalized by assets. End of period controls (unreported) include tangible capital, inventories and cash ration, leverage the logs of asset, age and sales. Standard errors are clustered by firm and fiscal year. The sample period is 1981-2018 fiscal years for the universe of non-financial firms in Compustat. The level of significance are * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.3:
Customer expenditure and firms' growing prospect-within firm

Within firm				
	$\Delta \frac{Ent.val}{Assets}_{f,t}$		$\frac{Mkt.val}{Assets}_{f,t}$	
	(1)	(2)	(3)	(4)
	$t+1$	$t+2$	$t+1$	$t+2$
$\frac{xsga}{xsga+cogs}_{f,t}$	0.187*	0.071	0.169*	0.001
	(0.106)	(0.129)	(0.095)	(0.114)
Controls	✓	✓	✓	✓
Sector-Year F.E.	✓	✓	✓	✓
Firm F.E.	✓	✓	✓	✓
Clustered Std.Errors	Firm year	Firm year	Firm year	Firm year
R^2	0.711	0.645	0.742	0.672
Obs	54,121	48,716	54,913	49,517

Note: This table presents firm-level within panel regression. We restrict the sample to all firms whose $\frac{(xsga+cogs)}{sale} \leq 1$ and with leverage below a unit, all the other control variables are normalized by assets. End of period controls (unreported) include tangible capital, inventories and cash ration, leverage the logs of asset, age and sales. Standard errors are clustered by firm and fiscal year. The sample period is 1981-2018 fiscal years for the universe of non-financial firms in Compustat. The level of significance are * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B.4:

Selling effort and firms' debt policies

	Debt issuance							
	$\frac{\Delta Debt}{lag\ Asset}_{f,t}$		$\frac{\Delta Unsec.\ Debt}{lag\ Asset}_{f,t}$		$\frac{\Delta Sec.\ Debt}{lag\ Debt}_{f,t}$		$\frac{\Delta Unsec.\ Debt}{lag\ Debt}_{f,t}$	
	(1) Cross-section	(2) Within	(3) Cross-section	(4) Within	(5) Cross-section	(6) Within	(7) Cross-section	(8) Within
$\frac{xsga}{xsga+cogs}_{f,t}$	0.010*	0.042**	0.014**	0.060***	0.056**	0.117*	0.120**	0.417***
	(0.006)	(0.017)	(0.005)	(0.019)	(0.024)	(0.058)	(0.045)	(0.131)
Controls	✓	✓	✓	✓	✓	✓	✓	✓
Sector-Year F.E.	✓	✓	✓	✓	✓	✓	✓	✓
Firm F.E.		✓		✓		✓		✓
Clustered Std.Errors	Firm year	Firm year	Firm year	Firm year	Firm year	Firm year	Firm year	Firm year
R^2	0.119	0.367	0.094	0.300	0.088	0.281	0.075	0.267
Obs	28,868	28,868	28,868	28,868	28,868	28,868	28,868	28,868

Note: This table presents firm-level panel regression for firms' debt policies. We restrict the sample to all firms whose $\frac{(xsga+cogs)}{sale} \leq 1$ and with leverage below a unit, all the other control variables are normalized by assets. End of period controls (unreported) include tangible capital, inventories and cash ration, leverage and the logs age and sales. Further controls: lagged log of assets to control for beginning of period assets used to scale right hand variable. Standard errors are clustered by firm and fiscal year. The sample period is 1981-2018 fiscal years for the universe of non-financial firms in Compustat. The level of significance are * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B.5:
Selling effort and firms' debt policies robustness

	Within firm: debt issuance			
	(1) $\frac{\Delta Debt}{lag\ Asset}_{f,t}$	(2) $\frac{\Delta Unsec.\ Debt}{lag\ Asset}_{f,t}$	(3) $\frac{\Delta Sec.\ Debt}{lag\ Debt}_{f,t}$	(4) $\frac{\Delta Unsec.\ Debt}{lag\ Debt}_{f,t}$
$\frac{xsga}{xsga+cogs}_{f,t}$	0.042**	0.060***	0.117*	0.417***
	(0.017)	(0.019)	(0.058)	(0.131)
$\frac{xsga}{sale}_{f,t}$	0.057***	0.084***	0.189**	0.538***
	(0.018)	(0.022)	(0.076)	(0.155)
$\frac{xsga}{cogs}_{f,t}$	0.001	0.000	-0.001	0.011
	(0.001)	(0.002)	(0.005)	(0.009)
$\frac{sga}{xsga+cogs}_{f,t}$	0.023	0.049***	0.014	0.346***
	(0.016)	(0.018)	(0.059)	(0.116)
$\frac{sga}{sale}_{f,t}$	0.032*	0.059***	0.053	0.381**
	(0.018)	(0.021)	(0.072)	(0.151)
$\frac{sga}{cogs}_{f,t}$	0.002	0.000	-0.007	0.022
	(0.002)	(0.003)	(0.009)	(0.019)

Note: This table presents firm-level panel regression for firms' debt policies under alternative measure of selling effort. We restrict the sample to all firms whose $\frac{(xsga+cogs)}{sale} \leq 1$ and with leverage below a unit, all the other control variables are normalized by assets. End of period controls (unreported) include tangible capital, inventories and cash ration, leverage and the logs age and sales. Further controls: lagged log of assets to control for beginning of period assets used to scale right hand variable. Standard errors are clustered by firm and fiscal year. The sample period is 1981-2018 fiscal years for the universe of non-financial firms in Compustat. The level of significance are * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B.6:
Selling effort and debt composition accumulated SG&A

	Debt distribution					
	$\frac{Unsec.\ Debt}{Asset}_{f,t}$		$\frac{Sec.\ Debt}{Asset}_{f,t}$		$\frac{Unsec.\ Debt}{Debt}_{f,t}$	
	(1) Cross-section	(2) Within	(3) Cross-section	(4) Within	(5) Cross-section	(6) Within
log(accumulated SG&A)$_{f,t}$	0.006***	0.007***	-0.006***	-0.007***	0.020***	0.035***
	(0.001)	(0.002)	(0.001)	(0.002)	(0.005)	(0.008)
Controls	✓	✓	✓	✓	✓	✓
Sector-Year F.E.	✓	✓	✓	✓	✓	✓
Firm F.E.		✓		✓		✓
Clustered Std.Errors	Firm year	Firm year	Firm year	Firm year	Firm year	Firm year
R^2	0.538	0.767	0.463	0.730	0.168	0.575
Obs	69,890	69,890	69,890	69,890	69,890	69,890

Note: This table presents firm-level panel regression of firms' outstanding debt. Debt is split between secured and unsecured debt. We restrict the sample to all firms whose $\frac{(xsga+cogs)}{sale} \leq 1$ and with leverage below a unit, all the other control variables are normalized by assets. End of period controls (unreported) include tangible capital, inventories and cash ration, leverage the logs of asset, age and sales. Standard errors are clustered by firm and fiscal year. The sample period is 1981-2018 fiscal years for the universe of non-financial firms in Compustat. The level of significance are * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B.7:
Selling effort and debt composition CFL and ABL

	Debt distribution					
	$\frac{CFL.\ Debt}{Asset}_{f,t}$		$\frac{ABL.\ Debt}{Asset}_{f,t}$		$\frac{CFL.\ Debt}{Debt}_{f,t}$	
	(1) Cross-section	(2) Within	(3) Cross-section	(4) Within	(5) Cross-section	(6) Within
$\frac{xsga}{xsga+cogs}_{f,t}$	0.013	0.027	-0.012	-0.033	0.084***	0.053
	(0.011)	(0.027)	(0.012)	(0.030)	(0.029)	(0.080)
Controls	✓	✓	✓	✓	✓	✓
Sector-Year F.E.	✓	✓	✓	✓	✓	✓
Firm F.E.		✓		✓		✓
Clustered Std.Errors	Firm year	Firm year	Firm year	Firm year	Firm year	Firm year
R^2	0.618	0.845	0.390	0.733	0.335	0.703
Obs	25,784	25,784	25,784	25,784	25,784	25,784

Note: This table presents firm-level panel regression of firms' outstanding debt. Debt is split between secured and unsecured debt. We restrict the sample to all firms whose $\frac{(xsga+cogs)}{sale} \leq 1$ and with leverage below a unit, all the other control variables are normalized by assets. End of period controls (unreported) include tangible capital, inventories and cash ration, leverage the logs of asset, age and sales. Standard errors are clustered by firm and fiscal year. The sample period is 1981-2018 fiscal years for the universe of non-financial firms in Compustat. The level of significance are * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

C Data appendix

C.1 Data cleaning

In this section we detail the steps followed to clean the sample.

1. We keep consolidate status firm: `cosol = "C"`, retain information for standard format only firms: `datafmt = "STD"`, domestic population firms `popsrc = "D"`, USD currency firms `curcd = "USD"` and finally active or inactive status only `costat: "A","I"`

2. We drop firms whose sic code is in the following categories [4900, 4999], [6000,6799] or [9100,9799)]

3. Upon creation of our variables of interest we then exclude firms with

   - Negative, missing or being zero for the following variables: `at,emp,markup`
   - We then drop firms whose absolute acquisition ratio over assets is above 5%
   - We drop firms observation if for the following variables `sale`, `cogs`, `xsga`, `xopr`, `ppegt`, `ppent` we observe a missing or strictly negative value

C.2 Alternative measures of customer expenditures

As the variable SG&A contains several cost expenditure not strictly related to customer acquisition, we adjusted the variable in the same spirit as Chiavari (2022). Our selling measure is constructed as follows, where the subscript f and t denotes the firm and the time respectively:

$$sga_{ft} = \texttt{xsga}_{ft} - \texttt{xrent}_{ft} - \texttt{xpr}_{ft} - \texttt{recd}_{ft} - \texttt{xrd}_{ft} \tag{3.5}$$

The selling general and administrative expenses have been purged from the expenditure in rents in pensions and retirement, bad debts expenses, and research and development expenses. This variable is a refinement of our baseline `xsga`. The advantage of using this metric instead of advertisement expenses is that the latter it captures more closely expenses designated for advertising purposes.

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