Specialized banks and the transmission of monetary policy *

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Abstract

Using granular bank-firm data from the Spanish credit register and U.S. syndicated loans, I examine the impact of banks' sectoral specialization on credit supply decisions in response to monetary policy shocks. Following an expansionary monetary policy, banks significantly increase lending to firms in sectors where they specialize. A 25 basis point rate reduction leads specialized banks to increase credit by 1.2-1.4 percentage points more to firms in their sectors of expertise, with effects peaking after one year. This result holds across both the Spanish lending market and the U.S. syndicated one. The mechanism operates through information advantages: the specialization effect is stronger for opaque borrowers, and specialized banks experience lower default rates following monetary easing. These supply decisions have real effects, as firms with greater exposure to specialized lenders exhibit larger increases in investment and profitability during expansionary periods. The findings show that monetary policy transmission varies systematically across sectors depending on the distribution of bank specialization.

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

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1. Introduction

Banks serve a crucial role in the economy through their intermediation functions. Their lending capacity is central to effective monetary policy transmission, as changes in policy rates influence banks' funding costs and subsequently their credit supply decisions. Banks respond heterogeneously to monetary policy changes, with this heterogeneity being central to policy transmission effectiveness (Jiménez et al., 2012; Drechsler et al., 2017). The literature has extensively documented how differences in balance sheet characteristics, such as size, capital adequacy, and deposit funding, drive differential responses to policy shocks (Kashyap and Stein, 1995; Bernanke, 2007; Jiménez et al., 2012; Drechsler et al., 2017; Supera, 2023). However, systematic differences in banks' sectoral portfolio composition have been largely overlooked, despite reflecting sector-specific expertise and potentially creating additional channels for monetary policy transmission.

Banks concentrate substantial portions of their loan portfolios in specific industries, often 15% or more in their preferred sectors (Figure 1)[1], with this concentration reflecting information advantages built through repeated interactions (Blickle et al., 2021; Giometti et al., 2022). Crucially, this pattern is not driven by sectoral prominence in the market (Figure 1b), as banks' average portfolio concentration exceeds market-wide concentration levels. Through concentrated exposure to sectors, banks develop superior industry knowledge and overcome information asymmetries, which impacts credit allocation, loan pricing, security design, and responses to industry-specific shocks (Paravisini et al., 2023; De Jonghe et al., 2020; Iyer et al., 2022). Despite these widespread specialization patterns and their impact on banking outcomes, little is known about how banks' sectoral specialization shapes monetary policy transmission.

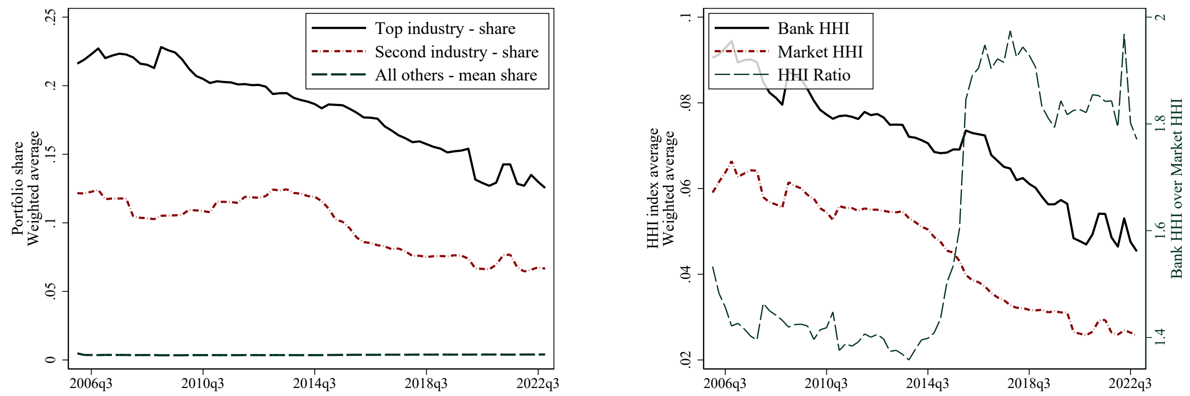
Using detailed loan-level data from Spanish credit registers and U.S. syndicated loan markets, I show that banks' industry specialization explains banks' heterogeneous credit supply responses to identified monetary policy shocks. This differential response operates through information advantages that become amplified during monetary policy easing:

[1] This pattern is confirmed in Blickle et al. (2021) using the FR Y-14Q archive, which tracks all C&I loans over \$1 million for stress-tested U.S. banks, as well as in the U.S. syndicated loan market (Figure A1).

(i) effects are concentrated among borrowers subject to higher information frictions, (ii) specialized banks experience lower default rates following policy easing, and (iii) firms borrowing from specialized banks achieve better subsequent performance. Rather than engaging in indiscriminate risk-taking as documented in the search-for-yield literature (Jiménez et al., 2014; Martinez-Miera and Repullo, 2017), specialized banks can identify creditworthy borrowers more efficiently than competitors, allowing profitable expansion in their areas of expertise without proportionally increasing risk. These patterns hold across diverse institutional settings, from the Spanish banking system to the U.S. syndicated lending markets.

Figure 1:
Banks portfolio concentration patterns - Spain

(a) ***Average share allocated to sectors*** **(b)** ***Average Banks' and Market HHI***



Note: Figure 1a shows the bank's average (weighted) share of loans allocated to each industry at a given point in time, for banks in the Spanish Credit Register (CIR). Data are 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. Industries are identified using 3-digit CNAE codes, that distinguishes 272 different industries. Figure 1b 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 of all banks' portfolios, where the weight is the fraction of a bank's volume over the total market, as in Giometti et al. (2022).

To examine the role that bank specialization plays in monetary policy transmission, I employ two complementary datasets that provide comprehensive evidence across different institutional settings. My primary analysis uses granular data from the Spanish credit register covering all outstanding loans exceeding 6,000 euros extended by credit institutions operating in Spain from 2006Q1 to 2022Q4. I first measure a bank's industry exposure as the share of a bank's credit allocated to a specific sector relative to a bank's total credit portfolio (Blickle et al., 2021; Iyer et al., 2022), where an industry is narrowly identified using 3-digit CNAE codes. I then define banks' specialization in a given industry as an indicator variable of whether the banks' exposure to each sector is in the top quartile of sectoral specialization in a given year (Paravisini et al., 2023). I use this specialization indicator as my key explanatory variable to examine differential credit supply responses to monetary policy shocks. I complement these loan data with comprehensive information on firm characteristics. For external validity, I rely on data from the U.S. syndicated loan market covering 1990Q1 to 2018Q4, applying the same specialization measures to bank-sector lending relationships, where a sector is identified using 2-digit SIC codes. For both datasets, I identify monetary policy shocks purged from the central bank's assessment of the economic outlook following Jarociński and Karadi (2020).

My empirical analysis using Spanish credit register data examines how specialized banks respond differently to monetary policy shocks compared to non-specialized banks. I employ local projections following Jordà (2005) to estimate the dynamic evolution of bank-firm credit growth in response to monetary policy shocks. I find that after an unexpected policy rate decrease, specialized banks exhibit relatively higher credit growth compared to non-specialized banks. A 25 basis point unexpected rate decrease leads specialized banks to increase credit by 1.2 percentage points more than non-specialized banks during the subsequent year. These differential responses are not driven by other bank characteristics that could generate information advantages, such as geographical specialization or industry market share, nor by relationship lending effects that recent literature has shown to influence monetary policy transmission (Cahn et al., 2024; Cao et al., 2025).

This differential response reflects an information advantage mechanism that contrasts with the standard risk-taking explanation for bank responses to monetary policy. When policy rates decline, banks may face pressure to maintain stable net interest margins (Drechsler et al., 2017, 2023), creating incentives that typically lead to increased risk-taking as banks search for yield (Jiménez et al., 2014; Martinez-Miera and Repullo, 2017;

Granja et al., 2022). However, banks' sector-specific knowledge enables lenders to identify creditworthy borrowers more efficiently than competitors in their areas of expertise (Blickle et al., 2025), allowing profitable expansion in these sectors through superior borrower selection rather than indiscriminate lending. I provide evidence supporting this information advantage mechanism, exploiting the fact that specialized banks' advantages are strongest where information frictions are most severe. I find three key results: (i) effects are concentrated among informationally opaque borrowers, with specialized banks increasing credit by 2 percentage points more than non-specialized banks when lending to opaque firms following a 25 basis point easing, (ii) specialized banks experience 5-7 basis points lower default rates during expansionary periods, indicating superior borrower screening, and (iii) the increase in lending is primarily focused on firms with better profitability outcomes, both confirming enhanced selection capabilities rather than indiscriminate risk-taking or zombie lending.

At the firm level, I further show that firms borrowing predominantly from specialized banks experience a 0.1 percentage point higher investment rate and 0.1 percentage point higher profitability following monetary policy easing for a standard deviation increase in firms' exposure, confirming that the differential credit supply translates into improved real outcomes.

I replicate the analysis using data from the U.S. syndicated loan market covering 1990Q1 to 2018Q4 for external validity across different institutional settings. Despite substantial differences in market structure, with syndicated lending involving multiple banks per transaction and serving larger, less opaque borrowers, I find consistent evidence that specialized banks increase lending more in their sectors of expertise following monetary policy easing. To estimate the differential responses, I construct a panel at the bank-sector-quarter level and study the evolution of credit volumes for specialized lenders in response to monetary policy changes. A 25 basis point rate reduction leads specialized banks to increase lending to their specialized sectors by 2.5 percentage points more than non-specialized banks, with effects persisting for approximately eight quarters.

Leveraging bank-level data from the matched syndicated loan data with FR Y-9C bank holding company reports, I examine bank-level performance outcomes upon an unexpected monetary policy rate cut to test whether the specialization effect operates through information advantages or indiscriminate risk-taking. I measure portfolio concentration using the Herfindahl-Hirschman Index of banks' sectoral exposures, where higher concentration indicates greater specialization. Banks with more concentrated portfolios exhibit relatively superior performance following monetary easing, with higher return on assets and lower loan loss provisions and delinquencies. This combination of increased profitability and reduced credit risk is consistent with specialized banks leveraging information advantages to select higher-quality borrowers, rather than engaging in indiscriminate credit expansion.

These results confirm that sectoral specialization represents a significant channel of monetary policy transmission that operates across different institutional settings and, crucially, that monetary policy transmission is market dependent. Overall, lenders have increased responsiveness in their sector of specialization, channeling credit to firms within those industries. The evidence suggests a redirection of loans toward high-quality projects with lower defaults, enhancing overall banking performance, and toward higher profitable firms.

I employ several approaches to address concerns that the differential lending responses could be driven by credit demand rather than bank supply factors. I saturate the bank-firm level specifications with granular bank-time and firm-time fixed effects to control for a range of unobserved firm time-varying factors (Khwaja and Mian, 2008; Jiménez et al., 2012; Paravisini et al., 2023). The bank-time fixed effects control for time-varying heterogeneity at the bank level, including funding conditions that can be affected by monetary policy changes, while exploiting variation across each bank's portfolio allocation decisions (Paravisini et al., 2023). The firm-time fixed effects absorb all firm-specific demand shocks, including those potentially correlated with monetary policy changes, exploiting variation within firms with multiple bank relationships. I thus compare the credit growth of the same bank across different firms in distinct sectors while controlling for unobservable demand heterogeneity. This granular identification approach is enabled by the comprehensive coverage of the Spanish credit register, while the U.S. analysis employs bank-sector-time specifications appropriate for syndicated loan data. These results remain robust when employing less restrictive fixed effects specifications, such as industry-location-size-time and sector-time fixed effects (Degryse et al., 2019), confirming the strength of the specialization channel across different identification strategies and showing that these effects reflect a supply-side phenomenon rather than differential demand across borrowers.

These findings contribute to both the monetary policy transmission and bank specialization literature by demonstrating how sectoral expertise shapes banks' credit allocation responses to policy changes through information advantages rather than indiscriminate risk-taking.

Existing studies show that banks' balance sheet heterogeneity (size, capital, and liquidity) drives differential responses to monetary policy, as smaller and less capitalized banks benefit more from reduced funding costs during easing periods (Kashyap and Stein, 1995, 2000; Jiménez et al., 2012, 2022). Recent research has emphasized the deposit channel of monetary policy transmission, where banks' market power affects their ability to attract and retain deposits during policy changes, influencing their credit supply decisions (Drechsler et al., 2017; Supera, 2023). My paper extends this literature by identifying sectoral specialization as an additional driver of heterogeneous responses that complements existing balance sheet and funding channels. The specialization effects remain significant even after controlling for all time-varying bank characteristics, suggesting information advantages provide an independent transmission mechanism.

A substantial literature documents that specialized banks concentrate lending in specific industries, investing in information acquisition that affects both loan volumes and contract terms (Diamond and Rajan, 2011; Blickle et al., 2021; Giometti et al., 2022; Blickle et al., 2025). When sectors experience negative shocks, specialized banks act as shock absorbers, increasing lending to affected sectors relative to non-specialized banks, thereby reducing procyclicality for borrowers in those sectors (Paravisini et al., 2023; Iyer et al., 2022). I contribute to this literature by showing that specialized banks amplify their exposure to preferred sectors during monetary easing, increasing procyclicality by concentrating credit allocation toward their areas of expertise. This differential response operates through information advantages, with effects concentrated among informationally opaque borrowers where specialized banks' sector-specific knowledge provides the greatest comparative advantage.

My findings also speak to the risk-taking channel of monetary policy transmission. The standard risk-taking hypothesis suggests that monetary easing, or other aggregate economy-wide expansionary conditions, leads banks to extend credit to riskier, marginal borrowers as they search for yield in a low-rate environment (Jiménez et al., 2014; Martinez-Miera and Repullo, 2017; Granja et al., 2022). While De Jonghe et al. (2020) find evidence supporting this mechanism during a wholesale funding crisis, where banks with higher exposure to affected borrowers increased lending to riskier firms, my results reveal the opposite pattern during monetary policy easing. Rather than deteriorating lending standards, specialized banks exhibit improved performance with lower delinquency rates and higher returns, suggesting they exploit information advantages to identify higher-quality borrowers within their sectors of expertise. This evidence suggests that bank specialization can create exceptions to the standard risk-taking channel, where information advantages enable profitable credit expansion without increased risk.

finally, my work relates to Casado and Martinez-Miera (2023), who examine how banks' geographic specialization in local mortgage markets affects monetary policy transmission. My paper differs in three important ways: I focus on sectoral rather than geographic specialization, analyze commercial rather than mortgage lending, and provide comprehensive evidence for the information advantage mechanism through borrower opacity effects, bank performance outcomes, and firm-level real effects. These differences are crucial because commercial lending involves higher information asymmetries and monitoring costs than standardized mortgage products, making it a more direct test of information-based advantages in specialized lending.

The rest of the paper is structured as follows. Section 2 presents the data and the approach that I use to measure the main variables of interest. The empirical methodology and the bank-firm level evidence from the Spanish Credit Register are reported in Section 3, along with the empirical evidence consistent with the plausible mechanism underlying the main results. Section 4 examines the firm aggregate implications on investment and profitability. I present the external validity results for the U.S. syndicated loan market in Section 5 Section 6 concludes.

2. Data and Measurements

To examine how banks' sectoral specialization shapes monetary policy transmission, I employ two complementary datasets that provide comprehensive evidence across different institutional settings. My primary analysis uses granular data from the Spanish credit register (CIR) covering all outstanding loans exceeding 6,000 euros extended by credit institutions operating in Spain from 2006Q1 to 2022Q4, matched with firm-level information from *Central de Balances* (CB). For external validity, I rely on U.S. syndicated loan data for the period 1990Q1 to 2018Q4, matched with bank holding company regulatory reports. In the following sections, I describe the construction of each dataset, explain how I measure banks' sectoral specialization and identify monetary policy shocks, and summarize the key sample characteristics that enable my identification strategy.

2.1. Data

Spanish credit register (CIR): Information on outstanding quarterly loan volumes for bank-firm pairs comes from the *Central de Información de Riesgos* (CIR). The CIR is a confidential supervisory dataset maintained by the Banco de España as part of its role overseeing the Spanish financial system. It provides detailed monthly information on all loans exceeding 6,000 euros extended by credit institutions operating in Spain, including loan terms (e.g., amount, maturity, collateralization) and identifiers for both the lender and the borrowing firm. This low reporting threshold ensures comprehensive coverage of lending activity, including to small firms and defaulted loans.

In this paper, I focus on commercial and industrial loans granted by commercial banks, savings banks and credit unions, while excluding lending by non-bank institutions. I further restrict the sample to loans made to Spanish-incorporated non-financial firms. Despite these filters, the data capture approximately 95% of the total volume of bank debt in Spain and, on average, 88% of bank loans with valid sector and location identifiers. Most importantly, the data distinguishes between committed and used credit. I use the sum of committed credit to measure specialization and as my outcome variable. This reduces concerns that my results are driven by demand-side factors rather than supply.

For the empirical analysis, I constructed a quarterly panel covering the period from 2006Q1 to 2022Q4.

The CIR's granularity is essential for addressing two critical identification challenges. First, the panel structure allows for the precise tracking of the evolution of credit relationships between banks and firms. Second, the detailed loan- and borrower-level information allows me to separate loan supply from demand using saturated fixed effects specifications, following Khwaja and Mian (2008) and Jiménez et al. (2012). The final sample consists of over 59 million observations with a valid match with the CB dataset. I complement this sample with firms' accounting balance sheet information.

Spanish Central de Balances (CB): The Central de Balances is a firm-level dataset provided by the Banco de España that contains the detailed annual accounting and financial statements of Spanish firms. The sample is constructed to ensure representativeness across firm size, sector, and region. The dataset includes balance sheets, income statements, and cash flow data, covering variables such as investment, sales, employment, profitability, and leverage.

In this paper, I focus on non-financial corporations with valid identifiers that can be matched to the credit register, with a valid sector and province identifier. While not fully comprehensive, the CB provides a rich and internally consistent panel that is well suited for analyzing firm-level outcomes over time. It also allows me to study the interaction between credit dynamics and real firm variables, such as investment and output, around monetary policy shocks. For data quality, I further exclude non-for-profit firms, foreign entities and firms own by the local or national government. I finally exclude firms with 0 employees, sales or assets.

The quarterly bank-firm-level panel is matched with firms' balance sheet information from the previous end-of-year to account for the different time frequencies of these two data sources.

For the purpose of my analysis, I define a sector using 3-digit CNAE codes, which represent the Spanish implementation of the European NACE (Nomenclature of Economic Activities) classification system. This classification provides 272 distinct industry categories, offering sufficient granularity to capture meaningful sectoral specialization patterns while maintaining adequate sample sizes within each industry ensuring sufficient specificity (e.g., distinguishing between different types of manufacturing) and statistical power for identification.

Dealscan Loan-level data: For the external validity, I rely on syndicated loan-level data from U.S. In the absence of an equivalent credit registry for the U.S. case, I focus on a sample of matched banks to the syndicated market. Syndicated lending, though representing a fraction of total banks' lending, significantly accounts for the vast majority of credit volume generated and outstanding balances at bank level Chodorow-Reich (2014); Giannetti and Saidi (2019)[2]. 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.

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. This allows me to exploit the structure of the syndicate and create a quasi-credit register for the U.S. at the bank-sector level where I overcome the relative sparse origination at the quarterly level with the large variation across the syndicate. As most loans in the sample are syndicated, the same loans will be associated with one or more banks. This portfolio setting allows me to exploit different levels of sectoral exposure of each syndicate member. I allocate loan shares over the syndicate following Blickle et al. (2020). I provide further details in the allocation of loan volume across the syndicate in A.6.

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 [3] to borrowers headquartered in the US excluding loans to financial corporations, utilities and public sector companies. To identify the lead arranger(s) and participants,

[2]In the past two decades, syndicated lending was 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).

[3]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.

I follow Chakraborty et al. (2018)[4] and restrict the sample of loans origination between 1990Q1 and 2018Q4 since the coverage is sparse before 1990.

For the empirical analysis, I aggregate the estimated outstanding volume of all at the bank-sector quarter level, where the lender is defined as the bank holding company.

Bank-level data: Bank Holding Company level information comes 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 end of quarter of that year of the FR Y-9C reports.

To match Dealscan lender to the bank holding company (BHC) in the FR Y-9C reports, I use Schwert (2018)'s linking table augmented with the one 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.

The matched sample yields a maximum of 85,586 facilities originated by 147 matched banks involving 19 thousand non-financial firms, spanning from the first quarter of 1990 to the last quarter of 2018.

Monetary policy shock: I use high-frequency monetary policy shocks constructed following the methodology of Jarociński and Karadi (2020). A key advantage of this approach for my analysis is that it provides consistent shock identification for both European Central Bank (ECB) and Federal Reserve policies, enabling comparable analysis across my Spanish and U.S. datasets.

The approach builds on earlier high-frequency identification strategies (Cochrane and Piazzesi, 2002; Kuttner, 2004; Gürkaynak et al., 2005; Nakamura and Steinsson, 2018) but extends them by addressing the confounding role of central bank information shocks. While traditional methods may conflate monetary policy surprises with changes in the

[4] Chakraborty et al. (2018) develop a scoring ranking exploiting the role of each lender in the syndicate in the spirit of Bharath et al. (2011).

central bank's economic outlook, Jarociński and Karadi (2020) use a factor-augmented VAR framework to separate pure monetary policy shocks from information effects.

I use the monetary policy component that isolates unexpected interest rate changes orthogonal to central bank information[5]. The original series is measured at daily frequency using changes in the implied ECB rates from overnight index swap rates around ECB policy announcements for Europe, and changes in implied Federal Funds rates from futures contracts around FOMC announcements for the U.S.

I aggregate the daily series to quarterly frequency following Gertler and Karadi (2015) and Ottonello and Winberry (2020). Specifically, I weight the high-frequency measures to account for the timing of policy announcements within each quarter. For each high-frequency measure ϵ_{t_k} observed on day t_k, I assign a weight $\nu_k = q_k/Q_k$, where q_k represents the number of days remaining in the quarter after the announcement and Q_k is the total number of days in that quarter. I then construct the weighted quarterly measure of monetary policy shock for quarter t, denoted as ε_t:

$$\varepsilon_t = \sum_{t_k \in Q_{t-1}} (1 - \nu_k)\epsilon_{t_k} + \sum_{t_k \in Q_t} \nu_k \epsilon_{t_k}$$

where Q_t represents the set of days with monetary policy announcements in quarter t. This weighting scheme accounts for the fact that an announcement occurring late in quarter $t-1$ may have substantial effects on economic variables in quarter t, while an announcement occurring late in quarter t may have relatively limited impact on that same quarter's economic outcomes.

2.2. Measuring bank specialization

In the following section, I detail the construction of my measure of banks' sectoral specialization.

I construct the main variable of interest at the bank-sector level. Bank's exposure to each sector is defined as the ratio of total loans i granted by bank b to all firms in sector s

[5] The shock series for Europe and US are available at https://marekjarocinski.github.io/jkshocks/jkshocks.html. The European series builds on the methodology developed in Altavilla et al. (2019).

at time t relative to the bank's total credit granted:

$$Specialization_{b,s,t} = \frac{Loan\ outstanding\ _{b,s,t}}{\sum_s\ Loan\ outstanding\ _{b,s,t}} := s_{b,s,t} \tag{1}$$

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

I then define the main variable of interest $Top - Spec._{b,s,t}$ as an indicator variable of whether the bank's exposure to each sector is in the top quartile of sectoral specialization. Formally $Top - Spec._{b,s,t}$ is defined as:

$$Top - Spec._{bs,t} = \mathbf{I}\{Specialization_{b,s,t} \geq p^{75}_{s,t}\} \tag{2}$$

This indicator approach captures whether a bank is specialized relative to other banks in the market at a given time, focusing on banks with meaningful sectoral concentration rather than marginal differences in exposure. The top-quartile threshold ensures I identify banks with substantial specialization while maintaining sufficient variation for identification (Paravisini et al., 2023). This binary classification also facilitates the interpretation of economic magnitudes and aligns with the theoretical notion that information advantages require significant sectoral focus rather than incremental exposure differences.

For the Spanish CIR data, I implement this measure directly using outstanding loan volumes at the bank-firm-quarter level. I use 3-digit CNAE codes, providing 272 distinct industry categories that offer sufficient granularity to capture meaningful specialization patterns while maintaining adequate sample sizes. The comprehensive coverage and detailed loan-level information in the CIR enables precise measurement of banks' sectoral exposures without the data limitations present in other contexts.

For the U.S. syndicated loan market, I adapt this approach to overcome two key data limitations: missing loan shares within syndicates and loan retention patterns. I estimate loan shares following Blickle et al. (2020)[6], detailed in Section A.6, exclude Term Loans B

[6]This approach improves upon the common practice in the literature (Chodorow-Reich, 2014; Giannetti and Saidi, 2019; Doerr and Schaz, 2021) of equally weighting the missing shares across the syndicate,

that banks typically sell post-origination, and assume loans are retained in bank portfolios until maturity (Giannetti and Saidi, 2019; Gomez et al., 2021). I use 2-digit SIC codes (83 industry groups) reflecting the more concentrated nature of syndicated lending[7].

2.3. Firm Exposure to Specialized Lenders

To measure a firm's exposure to specialized lenders, I construct a weighted average of the specialization level of all banks from which the firm borrows. Specifically, for each firm f at time t, I calculate:

$$\text{Firm-Spec-Exposure} f, t = \sum_{b' \in \mathcal{B}_f} \omega_{b',f,t} \times Top - Spec._{b',s,t} \tag{3}$$

where $\mathcal{B}_f$ is the set of banks lending to firm f, $\omega_{b',f,t} = \frac{\text{Loan} b,f,t}{\sum b' \in \mathcal{B}_f \text{Loan} b',f,t}$ represents the share of firm f's total bank debt from bank b at time t, and $Top - Spec._{b,s,t}$ is the indicator variable identifying whether bank b is in the top quartile of specialization in firm f's sector. This measure captures the extent to which a firm's credit relationships are concentrated among banks that specialize in its sector, weighted by the importance of each bank in the firm's funding structure. This weighted approach accounts for the relative importance of each lending relationship in the firm's capital structure. Using the indicator variable for top-quartile specialization rather than continuous specialization measures ensures to capture relationships with banks that have substantial information advantages in the firm's sector. The resulting firm-level measure ranges from 0 to 1, with higher values indicating greater exposure to specialized lenders, and can be interpreted as the share of a firm's bank debt that comes from banks with specialized knowledge of its industry.

Summary statistic for the variables included in the sample are available in Table 1.

The Spanish sample comprises nearly 60 million bank-firm quarterly observations spanning 2006Q1-2022Q4, a period characterized by significant firm deleveraging, seen in

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which has been shown to overstate actual shares when compared with matched samples from the FR Y-14 Q archive.

[7]To ensure consistency in my estimated shares for the Dealscan sample, I drop the first 3 years of observations for each bank-sector pair to ensure convergence in the estimated shares. This effectively reduces the sample coverage to January 1990 until December 2018.

Table 1:
Summary Statistics - Spain Sample

Panel A - Spain				
	Mean (1)	St. Dev. (2)	p25 (3)	p75 (4)
Bank-Firm level				
$\Delta loan_{b,f,t-1\to t}$	-0.027	0.234	-0.080	0.000
$\Delta loan_{b,f,t-1\to t+4}$	-0.096	0.518	-0.325	0.010
$Rel.Intensity_{b,f}^{t-20\to t-1}$	0.442	0.376	0.092	0.859
$Num\ Banks\ by\ Firm_{f,t}$	3.631	3.794	1.000	4.000
Bank-Sector level				
$Top\text{-}Spec_{b,s,t1}$	0.243	0.429	0.000	0.000
$Top\text{-}Spec_{b,s,t1}^{Geo}$	0.574	0.495	0.000	1.000
$Mkt.Share_{b,s,t-1}$	0.013	0.036	0.000	0.006
$Num\ Sec.\ by\ Banks_{b,t}$	161.877	68.143	118.000	217.000
Observations	59,392,810			

Panel B - Spain				
	Mean (1)	St. Dev. (2)	p25 (3)	p75 (4)
Firm level				
$Inv.Rate_{f,t}$	0.048	0.132	0.000	0.035
$Sales\ to\ Asset_{f,t}$	1.226	1.277	0.231	1.756
$Wage\ to\ Asset_{f,t}$	0.324	0.391	0.088	0.394
$ROA_{f,t}$	0.001	0.146	-0.016	0.046
$Capital\ growth_{f,t}$	-0.005	1.756	-0.139	0.028
$Sales\ growth_{f,t}$	-0.010	0.602	-0.174	0.180
$Asset\ growth_{f,t}$	0.023	0.296	-0.074	0.110
$Log\ of\ Asset_{f,t}$	6.096	1.670	5.028	7.084
$FirmSpec.Exposure_{f,t-1}$	0.211	0.364	0.000	0.265
Observations	7,613,656			

This table provides summary statistics at two levels: bank-firm quarter level and firm year level for the Central de Información de Riesgos (CIR) and Central de Balances (CB) matched sample from Spain. The sample includes all matched bank-firm pairs with valid non-financial company sector codes. It is restricted to banks that serve more than one sector per quarter and to sectors with more than one bank serving them. Panel A presents bank-firm data from the matched CIR and CB dataset for the sample period 2006Q1-2022Q4. Panel B presents firm-year level data from the CB dataset for the same period, containing firm-year observations.

the average quarterly credit growth (-2.7%) and yearly credit growth (-9.6%). The data reveal substantial multiple banking relationships, with firms borrowing from an average of 3.6 banks simultaneously. Bank specialization is prevalent, with 25% of relationships involving banks in the top quartile of sectoral specialization, consistent with the quartile-based definition. At the firm level, the challenging economic environment is reflected in modest investment rates (4.8% of assets), near-zero profitability, and negative average growth in sales and capital. Notably, firms' average exposure to specialized lenders reaches 21.1%, underscoring the importance of bank specialization in credit allocation during this deleveraging cycle.

I report similar summary statistics for the syndicated loan data in Table A1. The US syndicated loan sample comprises 147 banks serving an average of 44 sectors each over 1990Q1-2018Q4. The market exhibits sparse origination at this level of frequency, with banks originating an average of 3.6 loans per bank-sector-quarter and serving approximately 2.6 firms per cell. Quarterly credit growth averages 3.7% at the bank-sector level, reflecting the more stable economic environment compared to the Spanish deleveraging period.

3. Specialization and Lending Around Monetary Policy Change

In this section, I examine how the interaction between bank specialization and monetary policy affects credit supply. Specifically, I analyze the evolution of credit around monetary policy variations, conditional on banks' sector-level degree of specialization.

I document that following monetary policy cuts, bank specialization is associated with higher credit supply towards sectors in which the bank is specialized. This finding suggests that banks exploit their informational and operational advantages, reflected in lower screening and monitoring costs, by concentrating credit allocation toward sectors where they possess superior information sets. The effect is particularly pronounced for informationally opaque borrowers, where banks' sector-specific knowledge provides a greater comparative advantage in overcoming information asymmetries and reducing adverse selection costs.

Furthermore, I provide evidence that specialized banks experience a lower likelihood of non-performing loans (NPLs) following monetary policy easing, consistent with their superior ability to identify creditworthy borrowers within their areas of expertise. This result supports the hypothesis that specialization enables banks to engage in more informed risk-taking, rather than indiscriminate credit expansion, following accommodative monetary policy shocks (Jiménez et al., 2014; Martinez-Miera and Repullo, 2017).

3.1. Bank-Firm Credit Responses

I examine how bank-firm credit growth responds heterogeneously to monetary policy shocks conditional on banks' sectoral specialization. Specifically, I estimate how credit growth $\Delta Loan_{b,f,t+h}$ at horizon $h \geq 0$ varies with the interaction between bank b's specialization indicator in sector s and monetary policy shocks at time t.

I employ a panel regression local projection framework (Jordà, 2005), where I regress the cumulative change in log loan volumes, $\Delta Loan_{b,f,t+h} \equiv \log(Loan)_{b,f,t+h} - \log(Loan)_{b,f,t-1}$, on the interaction between bank specialization measured at $t-1$ and the monetary policy shock at t, alongside individual specialization and a set of firm level controls.

The primary identification challenge lies in isolating credit supply effects from confounding demand and bank-heterogeneity factors. On the demand side, monetary policy may directly affect firms' investment opportunities and borrowing needs, leading to loan quantity changes unrelated to bank specialization (Khwaja and Mian, 2008; Degryse et al., 2019). For instance, if specialized banks disproportionately lend to firms in sectors that are more responsive to monetary policy variation, observed credit growth could reflect firm demand rather than bank supply responses.

On the supply side, monetary policy may affect banks heterogeneously through channels unrelated to specialization, such as differences in size, funding structure, or capital adequacy (Kashyap and Stein, 1995; Dell'Ariccia et al., 2008; Jiménez et al., 2012; Drechsler et al., 2017). If specialized banks systematically differ along these dimensions, the estimated specialization effect could confound bank-level heterogeneity with sector-specific expertise.

To address these identification concerns, I exploit the granular structure of Spanish credit register (CIR) data and employ saturated fixed effects specifications following the approach of Jiménez et al. (2012) and Jiménez et al. (2014). This within-bank, within-firm identification strategy simultaneously compares: (i) loan growth by the same bank across firms in different sectors, and (ii) loan growth for the same firm across different lenders. This identification controls for unobserved firm-level demand shocks (through firm-time fixed effects) and bank-level supply shocks unrelated to specialization (through bank-time fixed effects), allowing me to identify the differential impact of specialization on credit supply responses to monetary policy (Paravisini et al., 2023; Blickle et al., 2021; Giometti et al., 2022). The implied identifying assumption is that banks face homogeneous demand (e.g., face the same change in lending opportunities). This approach follows the methodology of Khwaja and Mian (2008), requiring firms to borrow from multiple banks to be included in the estimation. To this end, in a less stringent specification, I include sector-time fixed effects or industry-location-size-time (ILS-time) fixed effects. Where in the latter I create ten bins based on firms' assets following Degryse et al. (2019). When using these less restrictive specifications, the identifying assumption is that firms within the same sector-location-size-time cell face similar demand conditions, allowing for identification through within-cell variation in bank specialization.

I estimate the following baseline dynamic panel regression specification using local projections:

$$\begin{aligned}\Delta\text{Loan}_{b,f,t+h} = \alpha^{i}_{f,t+h} + \alpha_{b,t+h} + \beta^{h}_{1}\text{Top-Spec.}_{\cdot b,s,t-1} + \beta^{h}_{2}\varepsilon_t \times \text{Top-Spec.}_{\cdot b,s,t-1} \\ + \omega'_h X_{f,t-1} + \Omega'_h \varepsilon_t \times Z_{f,t-1} + u_{b,f,t+h} \quad (4)\end{aligned}$$

where $h = 0, 1, \ldots, H$ denotes the forecast horizon. The specification includes $\alpha^{i}_{f,t+h}$ representing alternatively, time and firm, industry-location-size-time or firm-time fixed effects that absorb all firm-specific demand shocks (including those correlated with monetary policy), while $\alpha_{b,t+h}$ represents bank-time fixed effects that control for all bank-specific supply factors unrelated to sectoral specialization.

The key coefficient of interest is β^{h}_{2}, which captures the differential effect of monetary policy shocks ε_t on credit growth for banks with high sectoral specialization ($Top-Spec._{\cdot b,s,t-1}$) relative to less specialized banks. The specialization indicator is measured at the end of period $t-1$ to ensure predetermined treatment status.

In the baseline model, I include two sets of control variables. The vector $X_{f,t-1}$ contains firm-level characteristics measured in the last quarter of the previous year: log assets, return on assets (ROA), asset tangibility, liquidity ratio, and leverage. These controls address concerns that results might be driven by systematic differences in firm riskiness between specialized and non-specialized bank portfolios.

The vector $Z_{f,t-1}$ includes firm log assets and leverage, interacted with the monetary policy shock ($\varepsilon_t \times Z_{f,t-1}$). This interaction term controls for heterogeneous firm-level sensitivities to monetary policy conditional on financial characteristics, following Gertler and Gilchrist (1993), Ottonello and Winberry (2020), Cloyne et al. (2020), and Fabiani et al. (2024). This ensures that the specialization effects are not confounded with well-documented firm-level heterogeneity in monetary policy transmission.

Standard errors are two-way clustered at the bank and sector level to account for correlation in residuals across all bank-firm relationships within a bank, as well as across all bank-firm relationships within a sector.

In the tables, a positive ε_t stands for a tightening monetary policy shock. The coefficient of interest in Equation 4 is β_2^h, which captures how a bank's sectoral specialization affects its credit provision to individual firms following a *contractionary* monetary policy shock at horizon h. Thus, a negative estimate of β_2^h will imply that banks that are specialized in a given sector before a contractionary monetary policy shock experience a relatively weaker growth in credit over the horizon h, and conversely, a relatively stronger credit growth after an expansionary shock.

Finally, to show that the findings on Top-Spec.$_{b,s,t-1}$ explaining heterogeneous response to credit supply are not driven by other bank-market structure characteristics or simply by relationship lending, I extend Equation 4 to:

$$\begin{aligned}\Delta Loan_{b,f,t+h} &= \alpha^i_{f,t+h} + \alpha_{b,t+h} + \beta_1^h \, Top\text{-}Spec._{\ b,s,t-1} + \beta_2^h \varepsilon_t \times Top\text{-}Spec._{b,s,t-1} + \\ \Gamma'_h X_{b,s,t-1} &+ \Theta'_h \varepsilon_t \times X_{b,s,t-1} + \gamma_1^h Rel.Intensity_{b,f}^{t-20\to t-1} + \gamma_2^h \varepsilon_t \times Rel.Intensity_{b,f}^{t-20\to t-1} + \\ &\omega'_h X_{f,t-1} + \Omega'_h \varepsilon_t \times X_{f,t-1} + u_{b,f,t+h} \quad (5)\end{aligned}$$

The vector $X_{b,s,t-1}$ contains banks' market structure characteristics that can affect the response of credit following a monetary policy shock. The vector includes the measure of bank's market share in a given sector Mkt.Share$_{b,s,t-1}$ and geographic specialization indicator $Top-Spec^{geo}_{b,prv,t-1}$ (Casado and Martinez-Miera, 2023), where the latter identifies banks in the top quartile of geographic specialization at a given point in time. The geographic identifier is the province (prv) [8]. This control ensures that the effect of industry specialization are not driven by banks' geographic footprint. The control for banks' sectoral market share, measured as the share of banks credit to a sector over the sectoral total outstanding credit addresses the concern that results might be driven by market concentration rather than information-based specialization. Banks with dominant market positions in particular industries may have different incentives than specialized banks without lower market power to extend credit. As Giannetti and Saidi (2019) suggest, banks with high market share might insulate their captured industries from shocks to preserve valuable income streams. In the presence of high market concentration, banks internalize lending spillovers and potential systemic effects, which could alter their portfolio decisions following a monetary policy easing. Such lenders might strategically increase lending to these industries to maintain or expand their market dominance, independent of any information advantages. Finally, the regression controls for relationship lending ($Rel.Intensity_{b,f}^{t-20\rightarrow t-1}$) measure as the outstanding loan volume between the bank and firm for the past five years over the firm's volume for the last five years as in Bharath et al. (2011). Controlling for relationship lending, ensure that the results are not driven by banks acquiring information over a specific firm.

The estimation sample covers the period 2006Q1 to 2022Q4. To ensure robust identification and avoid the influence of extreme outliers, I require banks to have outstanding balances in at least two sectors per quarter and include only sectors with at least two active banks per quarter.

3.1.1. Panel Regression Estimates

I first present results from estimating Equation 4 in Table 2, reporting point estimates for the annual growth rate in credit ($h = 3$). This horizon captures the fact that credit

[8] Spain has 52 provinces. The reason to use provinces instead of municipalities is twofold. First, it allows the fact that both branches and firms might operate across distinct areas with respect to narrowly defined municipalities to maintain a fair comparison in terms of the number with respect to sectors. Second, it reduces concerns in the banks' exposure distribution at the municipality level, which may not be well defined in many small and sparsely populated municipalities. Using municipalities (more than 1000) or regions (17) will induce an unfair comparison between the clustering unit of analysis.

Table 2:
Bank-Firm Credit volume Evolution Around Monetary Policy Change

	$\Delta loan_{f,t+3\rightarrow t-1}$					
	(1)	(2)	(3)	(4)	(5)	(6)
$Top-Spec_{b,s}^{t-1}$	0.010**	0.007*	0.013***	0.010**	0.009**	0.012**
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)
JK shock $\times$ $Top-Spec_{b,s}^{t-1}$	-21.422***	-5.448*	-23.645***	-5.808**	-5.898**	-4.835**
	(7.189)	(3.041)	(7.281)	(2.335)	(2.400)	(1.965)
Firm Controls	✓	✓	✓	✓	✓	
Time F.E.	✓					
Firm F.E.	✓	✓				
Sector-Time F.E				✓		
ILS -Time F.E.			✓		✓	
Firm-Time F.E.						✓
Bank F.E.	✓		✓			
Bank-Time F.E.		✓		✓	✓	✓
Clustered Std.Errors	Bank-Sector	Bank-Sector	Bank-Sector	Bank-Sector	Bank-Sector	Bank-Sector
R^2	0.127	0.138	0.114	0.052	0.124	0.367
Obs	29,046,444	29,046,123	28,551,618	29,118,136	28,551,290	26,270,900

The table reports coefficients and t-statistics (in parenthesis) for the bank lending growth volume to firm after a monetary policy change (e.g. contractionary). The reduced form model tested corresponds to Equation 4. The unit of analysis is at the bank-firm quarterly level. The sample consists of outstanding loan volumes between January 2006 to December 2022. The dependent variable is the log growth amount held by each lender at time t. *Top-Spec.* $_{b,s,t-1}$ is the bank specialization identifying banks in the top quartile of sectoral specialization at a given point in time. In all specifications, are included different levels of fixed effects are included as noted in the lower part of the table, from the least restrictive version (1) to the most (6). The symbols *,** and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

adjustments following monetary policy shocks may take several quarters to fully materialize.

The table presents different specifications with progressively more stringent fixed effects combinations. Columns (4), (5), and (6) all include bank-time fixed effects, controlling for time-varying heterogeneity within banks. Across these three columns, I progressively narrow the within-cell variation used to control for firm demand-side factors, moving from sector-time fixed effects to firm-time fixed effects. Column (6), which includes both firm-time and bank-time fixed effects, represents the most conservative specification that exploits only within-firm and within-bank variation over time.

Consistent with previous work (Paravisini et al., 2023; Giometti et al., 2022; Blickle et al., 2020; Iyer et al., 2022), I find a positive unconditional effect of specialization on firm credit growth ($\beta_1^{h=3} > 0$). This indicates that specialized banks provide more credit to firms in their sectors of specialization, absent monetary policy shocks[9].

Across all specifications, the point estimates for $\beta_2^{h=3}$ are negative and statistically significant, indicating that specialized banks increase credit supply relatively more than non-specialized banks following expansionary monetary policy shocks. Focusing on the most stringent specification in Column (6), the economic magnitude is substantial: following a 25 basis point rate cut, banks increase credit supply by approximately 1.21 percentage points more to firms in sectors where they are specialized, relative to firms in non-specialized sectors.

This effect persists despite controlling for all firm-specific demand factors, through firm-time fixed effects, and bank-specific supply factors unrelated to specialization, through bank-time fixed effects). Importantly, the coefficient estimates differ between specifications with and without bank-time fixed effects, highlighting the importance of controlling for time-varying bank characteristics that could bias the results. The inclusion of bank-time fixed effects is crucial for isolating the specialization effect from other bank-level factors. However, when focusing on specifications that include bank-time fixed effects (columns 4-6), the coefficient remains stable across different levels of demand controls—from sector-time to firm-time fixed effects. This stability demonstrates that, once bank-level heterogeneity is properly controlled for, firm demand factors are not heavily impacting the estimates, providing further confidence in the identification of the specialization channel.

A critical question is whether these results reflect the information advantage associated with specialization or other confounding factors that are sector or geographical dependent. Table 3 addresses this concern by including additional interaction terms to control for alternative mechanisms as outlined in Equation 5.

The results presented in Table 3 confirm the robustness of the specialization effect: upon a monetary policy easing shock, specialized banks increase credit more in their sectors of expertise. For this analysis, I employ the most stringent specification with firm-time and bank-time fixed effects and compare the bank specialization channel against alternative mechanisms. I sequentially add controls for geographic specialization, bank

[9]Column (6), which contains firm-time fixed effects, which can be interpreted as measuring credit growth to individual firms, rather than capturing expanded lending toward the sector more broadly as in the other columns.

Table 3:
Bank-Firm Credit volume Evolution Around MP Change - Covariates

	$\Delta loan_{f,t+3\rightarrow t-1}$			
	(1)	(2)	(3)	(4)
$Top - Spec_{b,s}^{t-1}$	0.012**	0.011***	0.017***	0.014***
	(0.005)	(0.004)	(0.006)	(0.004)
$Top - Spec_{b,prv}^{t-1}$	0.009***			0.014***
	(0.002)			(0.002)
$Mkt.Share_{b,s,t1}$		0.035		0.077
		(0.044)		(0.056)
$Rel.Intensity_{b,f}^{t-20\rightarrow t-1}$			-0.131***	-0.133***
			(0.014)	(0.014)
JK shock × $Top - Spec_{b,s}^{t-1}$	-4.850**	-5.613***	-5.029**	-5.786***
	(1.973)	(1.959)	(2.011)	(2.036)
JK shock × $Top - Spec_{b,prv}^{t-1}$	0.335			0.508
	(1.381)			(1.488)
JK shock × $Mkt.Share_{b,s,t1}$		25.081		22.927
		(16.061)		(15.970)
JK shock × $Rel.Intensity_{b,f}^{t-20\rightarrow t-1}$			4.561	4.315
			(4.391)	(4.455)
Firm-Time F.E.	✓	✓	✓	✓
Bank-Time F.E.	✓	✓	✓	✓
Clustered Std.Errors	Bank-Sector	Bank-Sector	Bank-Sector	Bank-Sector
R^2	0.367	0.367	0.370	0.370
Obs	26,270,814	26,270,900	26,270,900	26,270,814

The table reports coefficients and t-statistics (in parenthesis) for the bank lending growth volume to firm after a monetary policy change (e.g. contractionary). The reduced form model tested corresponds to Equation 5. The unit of analysis is at the bank-firm quarterly level. The sample consists of outstanding loan volumes between January 2006 to December 2022. The dependent variable is the log growth amount held by each lender at time t. *Top-Spec.* $_{b,s,t-1}$ is the bank specialization identifying banks in the top quartile of sectoral specialization at a given point in time. In all specifications, are included firm-time and bank-time fixed as noted in the lower part of the table. The symbols *,** and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

sectoral market share, and relationship intensity across columns. Finally, in Column (4) I simultaneously control for all bank-sector and bank-firm characteristics.

The interaction between monetary policy and sectoral specialization remains economically and statistically significant across all specifications, even after controlling for these alternative channels. The economic magnitude is stable across specification: in the most comprehensive specification (Column 4), a 25 basis point rate reduction is associated with a 1.4 percentage point relative increase in credit volume between specialized banks and firms in their sectors of expertise.

The coefficients on market share interactions, geographic specialization, and relationship lending are not statistically significant. This suggests that the observed effects stem primarily from information advantages arising from repeated interactions with firms in specific sectors, rather than from market power or alternative forms of information acquisition. Put it differently, the specialization channel dominates these alternative mechanisms in explaining heterogeneous responses to monetary policy, though the coefficient signs align with previously documented results (Hachem, 2011; Cahn et al., 2024; Cao et al., 2025).

3.1.2. Local Projection Estimates

Having established the stability of coefficients under alternative fixed effects specifications, Figure 2 presents the main results from the local projection analysis using the most saturated specification with bank-time and firm-time fixed effects. For ease of interpretation, all results are scaled to represent responses to a 25 basis point monetary policy reduction.

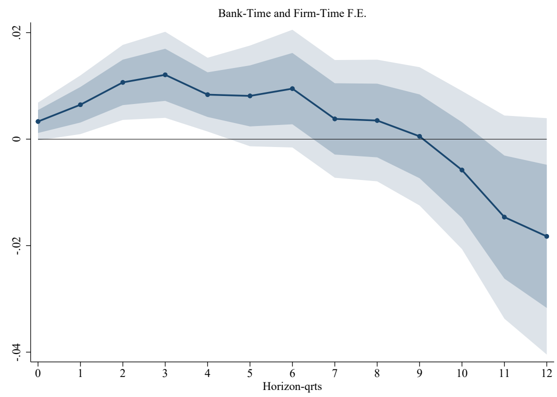
Figure 2a plots the scaled point estimates for β_2^h to a 25 basis point reduction alongside 90% and 68% confidence intervals from the baseline specification (Equation 4). The positive estimates indicate that specialized banks increase credit supply more than non-specialized banks following monetary policy easing, with the effect materializing immediately upon the shock.

The largest differential response occurs approximately one year after the shock, where specialized banks increase credit by about 1.2 percentage points more than non-specialized banks following a 25 basis point rate reduction. This represents a substantial economic magnitude given typical cumulative yearly credit growth rates. The effect gradually dissipates thereafter, consistent with temporary portfolio rebalancing rather than permanent structural changes. As shown in Figure A2, the response heterogeneity remains substantial under alternative specifications using sector-time or industry-location-size-time fixed effects.

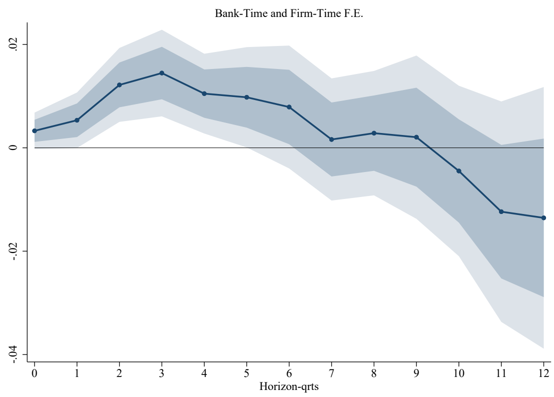
Figure 2b presents estimates from the extended specification (Equation 5) that simultaneously controls for bank-sector characteristics, geographic specialization and sectoral market share, and bank-firm relationship intensity. The inclusion of these controls does not diminish the specialization effect. If anything, the point estimates are slightly larger,

Figure 2:
Evolution in Bank-Firm Credit Volume around MP Change

(a) *No Covariates*



(b) *With Covariates*



Note: Spain credit register sample. Unit of observation: bank-firm quarter. Impulse response dynamics to a 25 bps cut in ε_t. Point estimates, 90% and 68% confidence intervals for β_2^h from estimating specifications Equation 4 and Equation 5 containing bank-time and firm-time fixed effects. The outcome variable is the change in log credit between the bank-firm pair at a given horizon h. Covariates included in Figure 2b are the bank's market share, the bank's geographic specialization, and relationship lending. Confidence intervals based on two-way clustered standard errors at the bank and sector level. The sample consists of outstanding quarterly loan volume between a bank-firm for the period from 2006q_1 until 2022q_4. Lighter areas represent 90% confidence interval. The measure of banks' specialization, *Top-Spec.* $_{b,s,t-1}$, identifies banks in the top quartile of sectoral specialization at a given point in time.

with peak effects reaching 1.4 percentage points after one year.

The dynamic pattern plotted in the two panels reveals two key features of the specialization channel. First, the response is immediate, suggesting that specialized banks can quickly identify and act on opportunities in their sectors of expertise following monetary easing. Second, the peak impact occurs after four quarters, indicating that full portfolio rebalancing takes time as banks evaluate projects and firms adjust their investment plans. The gradual fade thereafter suggests that the advantage is temporary. I further show in Figure A3 that the response heterogeneity remains unchanged under alternative specifications using sector-time or industry-location-size-time fixed effects.

Overall, these findings support the hypothesis that sectoral specialization provides information advantages that enable more responsive credit supply during monetary policy cycles, beyond what can be explained by alternative bank-level channels documented in prior literature (Jiménez et al., 2012; Drechsler et al., 2017; Supera, 2023).

3.2. Inspecting the Underlying Mechanisms

While the previous analysis shows that specialized banks respond more strongly to monetary policy shocks, the cross-sectional variation in banks' sectoral exposure reflects endogenous decisions and past realizations. Although using predetermined specialization measures and extensive controls for alternative bank and firm characteristics reduces concerns about identification, further evidence on the specific mechanisms improves the interpretation of the results.

To this end, I explore whether the differential response of specialized banks operates through the information advantage channel (Blickle et al., 2025). When policy rates decline, banks may face pressure to maintain stable net interest margins (Drechsler et al., 2017, 2023), creating incentives to expand lending while preserving profitability, especially those with little deposit market power. This environment typically leads to increased risk-taking as banks search for yield (Jiménez et al., 2014; Martinez-Miera and Repullo, 2017). However, if specialized banks possess superior information about firms in their sectors of expertise, their sector-specific knowledge should enable them to identify creditworthy borrowers more efficiently than competitors (Blickle et al., 2025), allowing profitable expansion through superior borrower selection rather than indiscriminate lending.

To validate this information advantage mechanism, I examine three dimensions of bank and borrower behavior. First, I investigate whether the specialization effects are concentrated among informationally opaque firms, where information asymmetries are most severe and specialized knowledge should provide the greatest comparative advantage (Blickle et al., 2025; Casado and Martinez-Miera, 2023). Second, I analyze whether specialized banks exhibit lower ex-post default rates during expansionary periods, which would indicate more informed lending decisions rather than the indiscriminate risk-taking typically associated with monetary easing. Third, I examine whether firms receiving credit from specialized banks during expansionary periods demonstrate better subsequent performance, consistent with more efficient capital allocation toward higher-quality projects.

3.2.1. Information Sensitivity and Credit Allocation

To test whether specialized banks' differential response operates through information advantages, I examine heterogeneous effects across firm opacity. I construct a firm-level opacity measure based on discretionary accruals, which capture the degree of information asymmetry between firms and lenders.

Discretionary accruals reflect management's accounting choices and are less persistent than cash flows in predicting future earnings (Bhattacharya et al., 2013; López-Espinosa et al., 2017). Firms with extreme discretionary accruals have poor earnings quality, making it harder for lenders to assess their true financial condition. If specialized banks possess superior information about firms in their sectors, their advantage should be most pronounced when lending to opaque firms where information asymmetries are severe.

Following Leuz et al. (2003), I measure discretionary accruals as:

$$Disc.Acc._{f,t} = \frac{|ACC_{f,t}|/Assets_{f,t-1}}{|CFO_{f,t}|/Assets_{f,t-1}} \tag{6}$$

where $ACC_{f,t}$ represents firms' total accruals and $CFO_{f,t}$ is cash flow from operations[10]. To reduce noise from year-to-year variation, I use a three-year moving average and define opacity relative to sector-year medians:

$$Opaque_{f,t} = \mathbf{I}\{Disc.Acc._{f,t} \geq p^{50}_{s,t}\} \tag{7}$$

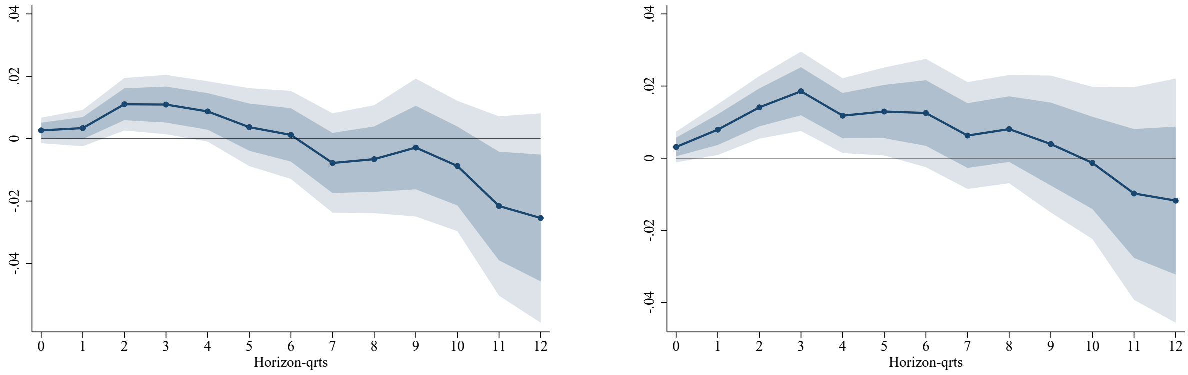
This sector-year normalization accounts for systematic differences in accruals across industries while identifying firms that are relatively opaque within their sectors.

I use the firm-level one-year lagged opacity indicator from Equation 7 to estimate two separate local projection regressions, one for the subsample of opaque firms and another for non-opaque firms, using the fully saturated specification from Equation 5 with bank-time and firm-time fixed effects. This split-sample approach yields distinct coefficients $\beta_2^{h,opaque}$ and $\beta_2^{h,non-opaque}$ that capture how specialized banks' differential response to monetary policy varies across firm types.

[10] Firm-level variables from CBI have a yearly frequency, hence t represent the end of year observation.

Figure 3:
Opaque and Non Opaque Credit Volume Response around MP Change

(a) *Non Opauqe Firms Sample* **(b)** *Opaque Firms Sample*



Note: Spain credit register sample. Unit of observation: bank-firm quarter. Impulse response dynamics to a 25 bps cut in ε_t for non-opaque and opaque firms. Point estimates, 90% and 68% confidence intervals for $\beta_2^{h,non-opaque}$ and $\beta_2^{h,opaque}$ from estimating specifications Equation 5 containing bank-time and firm-time fixed effects. The outcome variable is the change in log credit between the bank-firm pair at a given horizon h. Covariates included in Figure 2b are the bank's market share, the bank's geographic specialization, and relationship lending. Confidence intervals based on two-way clustered standard errors at the bank and sector level. The sample consists of outstanding quarterly loan volume between a bank-firm for the period from 2006q_1 until 2022q_4. Lighter areas represent 90% confidence interval. The measure of banks' specialization, *Top-Spec.* $_{b,s,t-1}$, identifies banks in the top quartile of sectoral specialization at a given point in time.

If specialized banks possess superior information advantages, the specialization effect should be stronger for opaque firms where information asymmetries are most severe. Formally, we expect $|\beta_2^{h,opaque}| > |\beta_2^{h,non-opaque}|$.

The results in Figure 3 support this prediction. Figure 3a presents estimates for non-opaque firms ($\beta_2^{h,non-opaque}$), while Figure 3b shows results for opaque firms ($\beta_2^{h,opaque}$). The specialization effect is larger and more persistent for opaque borrowers: specialized banks increase credit by 2 percentage points more than non-specialized banks when lending to opaque firms upon a 25 basis points easing shock, with effects gradually fading after six quarters. In contrast, the effect for non-opaque firms is both smaller in magnitude and less persistent, confirming that information advantages drive the differential response to monetary policy. Results remain robust when using the raw opacity indicator without smoothing, as shown in Figure A4.

3.2.2. Credit Quality: Non-Performing Loans

Monetary easing typically increases banks' risk-taking behavior, as compressed interest margins incentivize the search for yield (Jiménez et al., 2014; Martinez-Miera and Repullo, 2017). However, if specialized banks possess superior information about borrowers in their sectors of expertise, they should be able to expand credit while maintaining better risk outcomes relative to non-specialized banks.

I examine default rates following monetary policy easing for specialized and unspecialized lenders. I construct a panel where the dependent variable is a binary indicator equal to one if a bank-firm pair experiences a first default, defined as a loan falling at least 90 days behind on payments (Blanco et al., 2023, 2024). The sample is restricted to bank-firm relationships with no prior defaults to ensure I capture first-time default events. Details on variable construction are provided in Section A.5.

I estimate the bank-firm likelihood of experiencing a first default over horizons $h = 3, 4, 8$ quarters, since NPL effects may appear with a lag:

$$\mathbb{1}NPL_{f,t+h} = \alpha_f^i + \alpha_{b,t+h} + \beta_1^h \text{Top-Spec.}_{b,s,t-1} + \beta_2^h \varepsilon_t \times \text{Top-Spec.}_{b,s,t-1} + \omega_h' X_{f,t-1} + \Omega_h' \varepsilon_t \times Z_{f,t-1} + u_{b,f,t+h} \quad (8)$$

The specification mirrors Equation 4. The timing structure ensures that defaults observed at $t + h$ result from lending decisions made at time $t + h - 1$ or earlier.

The coefficient β_2^h captures the differential default probability for specialized banks relative to non-specialized banks following a "contractionary" monetary policy shocks. A positive estimate for β_2^h indicates that specialized banks experience relatively lower default rates during expansionary periods, consistent with superior screening ability that allows them to expand credit without proportionally increasing risk upon rate compression.

The results in Table 4 provide evidence consistent with specialized banks maintaining better risk outcomes during monetary easing. Across horizons $h = 3, 4, 8$, the coefficient β_2^h is positive, indicating that specialized banks experience lower default rates during expansionary periods relative to non-specialized banks. The economic magnitude is

Table 4:
Bank-Firm NPL Evolution Around Monetary Policy Change

	$\mathbb{1}NPL_{b,f,t+3}$			$\mathbb{1}NPL_{b,f,t+4}$			$\mathbb{1}NPL_{b,f,t+8}$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$Top-Spec_{b,s}^{t-1}$	0.000**	0.000	0.000***	0.000**	0.000	0.000**	0.000***	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
JK shock $\times$ $Top-Spec_{b,s}^{t-1}$	0.277***	0.251**	0.147	0.240**	0.156	0.032	-0.014	-0.039	0.196*
	(0.092)	(0.120)	(0.101)	(0.101)	(0.135)	(0.090)	(0.151)	(0.113)	(0.109)
Firm F.E	✓			✓			✓		
Firm-Time F.E.			✓			✓			✓
ILS-Time F.E.		✓			✓			✓	
Bank-Time F.E.	✓	✓	✓	✓	✓	✓	✓	✓	✓
Clustered Std.Errors	Bank-Sector	Bank-Sector	Bank-Sector	Bank-Sector	Bank-Sector	Bank-Sector	Bank-Sector	Bank-Sector	Bank-Sector
R^2	0.104	0.099	0.474	0.115	0.103	0.490	0.136	0.114	0.535
Obs	32,529,520	32,006,366	31,172,245	30,400,493	29,865,323	28,799,152	22,988,828	22,463,886	20,581,072

The table reports coefficients and t-statistics (in parentheses) for the bank-firm NPL likelihood following a contractionary monetary policy shock. The reduced form model corresponds to Equation 8. The unit of analysis is at the bank-firm quarterly level. The sample consists of outstanding loan relationships comprising only first-ever defaults or non-defaulting relationships between January 2006 and December 2022. The dependent variable is a binary indicator equal to one if a bank-firm pair experiences a first default, defined as a loan falling at least 90 days behind on payments. *Top-Spec.* $_{b,s,t-1}$ identifies banks in the top quartile of sectoral specialization at a given point in time. All specifications include bank-time fixed effects and different firm fixed effects as noted in the lower part of the table. The symbols *,** and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

substantial: estimates range from five to seven basis points lower default probability for a 25 basis point easing shock.

While the results are robust across different fixed effects specifications, comparing firm fixed effects (Columns 1, 4, 7) with industry-location-size-time and firm-time alternatives, statistical significance varies across specifications. This likely reflects the identification challenges in the sample, when Spanish firms were deleveraging heavily and default rates were historically low, reducing both sample variation and statistical power.

Nevertheless, the positive sign for β_2^h and economic magnitude across specifications suggest that specialized banks' information advantages enable more prudent risk-taking during expansionary periods, supporting the information channel over indiscriminate credit expansion.

3.2.3. Specialization and Firm Performance

Monetary policy easing may lead banks with concentrated lending to extend credit to low-productive firms, particularly through evergreening existing loans (e Castro et al., 2024; De Jonghe et al., 2021). Therefore if accommodative monetary policy reduces banks' screening and monitoring incentives, lenders should increase credit more to unprofitable firms upon an easing. However, if specialized banks possess superior information about borrowers in their sectors of expertise, they should allocate credit more efficiently, extending loans to firms with stronger future performance prospects.

To test this prediction, I examine whether specialized banks increase lending to firms that subsequently have better performance, conditional on monetary policy shocks. I regress quarterly bank-firm credit growth on the triple interaction between bank specialization, monetary policy shocks, and firms' future ROA growth:

$$\begin{aligned}\Delta\text{Loan}_{b,f,t} = \alpha_{f,t} + \alpha_{b,t} + \beta_1\text{Top-Spec.}_{b,s,t-1} + \beta_2\varepsilon_t \times \text{Top-Spec.}_{b,s,t-1} \\ + \beta_3\text{Top-Spec.}_{b,s,t-1} \times \Delta\text{ROA}_{y\to y+k} + \beta_4\varepsilon_t \times \text{Top-Spec.}_{b,s,t-1} \times \Delta\text{ROA}_{y\to y+k} \\ + \omega' X_{f,t-1} + \Omega'\varepsilon_t \times Z_{f,t-1} + u_{b,f,t} \quad (9)\end{aligned}$$

where $\Delta\text{ROA}_{y\to y+k}$ represents the change in firm ROA from year y to year $y+k$, with $k = 1, 2, 3$ years. The coefficient of interest is β_4, which captures whether specialized banks' differential response to monetary policy varies with firms' subsequent performance.

I use quarterly credit growth, rather than cumulative growth over multiple quarters, to isolate the current allocation decision and avoid mechanical correlation between extended credit accumulation and subsequent firm performance. This timing choice is motivated by the immediate credit response documented in Figure 2 and ensures that the lending decision temporally precedes the performance measurement.

The results are shown in Table 5. Across specifications, I observe an unconditionally positive relation between specialization and a firm's increase in ROA in the subsequent year, in line with specialization being related to better screening and monitoring ability. In Column (1) the triple interaction between specialization, monetary policy, and the difference in in firm's $ROA_{t\to t+1}$ (one year after origination) is negative. This means that upon an expansionary monetary policy, specialized banks increase credit relative more to future profitable firms. I observe that these results are stronger in magnitude and significance in Column (3). The results provide mild evidence that specialized banks increase credit to better-performing firms during monetary easing. While the coefficients

Table 5:
Credit Evolution around MP Change and Future Firms Performance

	$\Delta loan_{f,t \to t-1}$		
	(1) Post: 1 year	(2) Post: 2 year	(3) Post: 3 year
$Top - Spec_{b,f,t-1}$	0.003**	0.003*	0.003*
	(0.001)	(0.001)	(0.002)
JK shock $\times$ $Top - Spec_{b,f,t-1}$	-0.844	0.051	-0.056
	(1.119)	(1.143)	(0.932)
$Top - Spec_{b,f,t-1} \times \Delta ROA_{f,t \to t+1}$	0.001***		
	(0.000)		
$Top - Spec_{b,f,t-1} \times \Delta ROA_{f,t \to t+2}$		0.001***	
		(0.000)	
$Top - Spec_{b,f,t-1} \times \Delta ROA_{f,t \to t+3}$			0.001***
			(0.000)
JK shock $\times$ $Top - Spec_{b,f,t-1} \times \Delta ROA_{f,t \to t+1}$	-0.119		
	(0.298)		
JK shock $\times$ $Top - Spec_{b,f,t-1} \times \Delta ROA_{f,t \to t+2}$		-0.415	
		(0.397)	
JK shock $\times$ $Top - Spec_{b,f,t-1} \times \Delta ROA_{f,t \to t+3}$			-0.653*
			(0.364)
Firm-Time F.E.	✓	✓	✓
Bank-Time F.E.	✓	✓	✓
Clustered Std.Errors	Bank-Sector	Bank-Sector	Bank-Sector
R^2	0.300	0.297	0.291
Obs	16,539,605	14,070,229	12,046,474

The table reports coefficients and t-statistics (in parentheses) for the bank-firm quarterly credit growth after a monetary policy shock (e.g. contractionary). The reduced form model corresponds to Equation 9. The unit of analysis is at the bank-firm quarterly level. The sample consists of outstanding loan relationships between January 2006 and December 2022. *Top-Spec.* $_{b,s,t-1}$ identifies banks in the top quartile of sectoral specialization at a given point in time. All specifications include bank-time fixed effects and different firm fixed effects as noted in the lower part of the table. The symbols *,** and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

are not consistently significant across all specifications, they are directionally consistent with the information advantage hypothesis and notably inconsistent with evergreening or zombie lending patterns.

To formalize the intuition underlying these empirical findings, I develop a simple theoretical framework in Appendix Section A.1. The model features banks with heterogeneous screening abilities across sectors that optimally allocate credit to maximize profits. Banks with superior screening technology in particular sectors naturally specialize in those areas due to higher marginal returns. Crucially, when funding costs decrease, banks optimally expand lending most in their sectors of comparative advantage, rationalizing the main empirical findings through sector-specific information advantages.

3.3. Robustness Tests

The main finding that specialized banks increase credit relatively more in sectors where they are specialized remains robust across alternative empirical specifications.

In the baseline analysis, I use monetary policy shocks that are purged of information about the economic outlook, isolating pure monetary policy stance changes (Nakamura and Steinsson, 2018; Jarociński and Karadi, 2020). As a robustness check, I re-estimate the main specifications using standard high-frequency monetary policy surprises around ECB policy announcements, following Gürkaynak et al. (2005)[11]. These alternative shocks are constructed as the first principal component of surprise changes in overnight index swaps with maturities of 1, 3, 6 months, and 1 year during policy announcement windows. Figure A5 presented in Section A.4.3, shows that the main findings are largely unchanged, confirming that the specific shock identification strategy does not drive the main results.

To verify that the results are robust to alternative specialization measures, I re-estimate Equation 4 using different definitions of bank specialization. Table A2 in Section A.4.6 reports point estimates for the annual growth rate in credit ($h = 3$) for a monetary policy shock (e.g. contractionary).

Columns (1) and (2) construct the specialization indicator using a slow-moving average of banks' sectoral exposure over the previous 12 quarters ($Top.Spec_{b,s}^{t-12 \to t-1}$) to reduce the influence of temporary changes in banks' exposure. The results are qualitatively and quantitatively similar to the baseline findings in Table 2.

Columns (3) and (4) employ the excess specialization measure of Blickle et al. (2025), constructed as the difference between a bank's observed exposure to sector s and the sector's weight in the aggregate loan portfolio. This measure adjusts for the fact that certain sectors are naturally larger or more bank-intensive than others. While this concern is partially addressed in my baseline specification through industry-location-size-time or

[11] The shock series is available at Marek Jarocinski - Shocks ECB.

firm-time fixed effects, the excess specialization measure provides an additional robustness check. The continuous measure yields results consistent with the baseline: a 25 basis point rate reduction is associated with a 50 basis point increase in credit for a standard deviation increase in excess specialization (0.06).

Columns (5) and (6) show similar effects using a slow-moving average of the excess specialization measure. Columns (7) and (8) fix excess specialization at its mean over 2006Q1-2011Q4, reducing the sample to observations after 2012Q1. Finally, columns (9) and (10) fix excess specialization at the full-sample average, yielding the strongest results in terms of both statistical significance and economic magnitude for both the conditional monetary policy interaction and the unconditional specialization effect.

I further verify that my results are not driven by the specific sample period by restricting the analysis to 2006Q1-2018Q4 and re-estimating the specification in Equation 5 including all covariates. This subsample excludes the most recent ECB policy measures. The results are presented in Figure A6 in Section A.4.4. The local projection estimates over this restricted period yield qualitatively similar results to those in Figure 2, though with lower statistical significance. This reduction in precision likely reflects the more limited variation in monetary policy shocks during 2006-2018. Despite the reduced statistical power, the economic pattern remains consistent: specialized banks continue to increase credit more to firms in their sectors of specialization following monetary easing, with similar magnitudes to the full-sample results.

Finally, I verify that the results are robust to alternative clustering methods. The baseline specification employs two-way clustering at the bank and sector levels to account for correlation in residuals across all bank-firm relationships within a bank and across all bank-firm relationships within a sector. However, since the treatment (specialization) varies at the bank-sector-time level, clustering at bank-time and sector levels provides an alternative approach that allows for correlation within banks over time while maintaining the sectoral correlation structure.

Figure A7 in Section A.4.5 presents results using this alternative clustering approach for the full specification with covariates (Equation 5), including bank-time and firm-time fixed effects. The main findings are largely unaffected by the clustering method and, if anything, show increased statistical significance under the alternative clustering approach, confirming the robustness of the specialization effects.

4. Firm-Level Evidence: Borrowing from Specialized Banks around Monetary Policy variation

To examine whether banks' differential credit responses translate into real economic outcomes, I analyze how firms' performance varies with their exposure to specialized lenders around monetary policy changes. This firm-level perspective complements the bank-level evidence by testing whether the increased credit supply from specialized banks generates meaningful real effects for borrowing firms.

The empirical approach relates firms' real and financial outcomes to their exposure to specialized lenders around monetary policy changes. For each firm, I construct an exposure measure that captures the weighted proportion of its bank borrowing coming from specialized lenders and estimate the following specification:

$$y_{f,t} = \beta_1 Firm - Spec.Exposure_{f,t-1} + \beta_2 \varepsilon_t \times Firm - Spec.Exposure_{f,t-1} + \\ \omega' \times X_{f,t-1} + \Omega' \varepsilon_t \times Z_{f,t-1} + u_{f,t} \quad (10)$$

where $y_{f,t}$ measures either the yearly investment rate, sales to assets, wage to assets, or ROA. All outcome variables are normalized by firm assets to ensure comparability across firm sizes, with investment rates scaled by lagged assets to capture flow-to-stock relationships. All firms' variables are at an annual frequency, as are the monetary policy shocks, which are aggregated at the yearly frequency using the weighted methodology described in Section 2.1.

The vector $X_{f,t-1}$ includes firm-level controls: lag of log of assets, firm's ROA, liquid asset ratio, leverage ratio, tangible asset ratio, and the firm's geographic exposure, which measures the predetermined weighted proportion of credit coming from geographically specialized banks. The vector $Z_{f,t-1}$ contains the interaction of monetary policy shocks with firm-level variables, including lag log of assets, leverage, and the firm's exposure to geographically specialized banks.

The specification includes firm fixed effects to control for time-invariant firm characteristics, as well as sector-time and province-time fixed effects to account for industry and geographic demand fluctuations. While this specification cannot fully control for firm-specific demand effects, unlike the bank-firm analysis, the inclusion of these fixed effects mitigates concerns about systematic differences across firms and industries. The results should be interpreted as evidence that differential credit supply from specialized banks translates into real economic effects, complementing the bank-level identification strategy.

Standard errors are clustered at the firm level. The coefficient of interest is β_2, which measures firms' differential sensitivity to monetary policy based on their exposure to sectorally specialized banks after a monetary policy shock (e.g. contractionary shocks). A negative β_2 indicates that upon monetary policy easing, firms with greater exposure to specialized banks experience larger increases in their outcome variables compared to less exposed firms. Table 6 presents the results of this analysis using annual firm-level data from the Spanish Central de Balances (CB) database from 2006 to 2022.

The results show heterogeneity in firms' responses to monetary policy based on their exposure to specialized lenders. The coefficients on the interaction term $\varepsilon_t \times$ Firm-Spec.Exposure$_{f,t-1}$ are negative and statistically significant for investment rate (Column 1) and ROA (Column 4). This indicates that following an expansionary monetary policy shock, firms with greater exposure to specialized lenders experience larger increases in investment and profitability. In terms of magnitudes, a 100 basis points ease shock relates to a 0.1 percentage point higher investment rate and firms' ROA, respectively. These magnitudes are economically relevant: the 0.1 percentage point effects represent approximately 2% relative increase in investment rates (relative to the 4.8% sample mean). The economic pattern remains consistent for the wage bill (Column 3), though statistical significance is reduced due to a smaller sample size from limited reporting.

These results provide suggestive borrower-level evidence that firms borrowing from specialized banks not only receive more credit during monetary easing but also translate this credit into relatively better real outcomes. The findings align with the bank-level

Table 6:
Conditional Response to Monetary Policy Change and Firm's Exposure

	$Inv.Rate_{f,t}$	$Sales_{f,t}$	$Wage_{f,t}$	$ROA_{f,t}$
	(1)	(2)	(3)	(4)
$Firm$ - $Spec.Exposure_{f,t-1}$	0.001***	0.000	-0.001	0.000
	(0.000)	(0.001)	(0.001)	(0.000)
$\varepsilon_t \times Firm$ - $Spec.Exposure_{f,t-1}$	-0.278*	0.715	-0.080	-0.359*
	(0.165)	(0.866)	(0.918)	(0.217)
Firm Controls	✓	✓	✓	✓
Firm F.E.	✓	✓	✓	✓
Sector-Time F.E	✓	✓	✓	✓
Geo -Time F.E.	✓	✓	✓	✓
Clustered Std.Errors	Firm	Firm	Firm	Firm
R^2	0.341	0.854	0.936	0.448
Obs	4,417,530	4,104,663	249,068	3,599,203

The table reports coefficients and t-statistics (in parentheses) for the firms' response to a monetary policy change (e.g. contractionary) depending on the degree of exposure to sectorally specialized lenders. The reduced form model tested corresponds to Equation 10. The unit of analysis is at the firm-year level. The sample consists of firms' yearly balance sheet information in Spain from the end of year 2006-2022. The dependent variable is stated on the top of each columns, all variables are scaled by the end of period firms' assets, apart from investment rates which is scaled by the previous end of year value. $Firm - Spec.Exposure_{f,t-1}$ is the weighted average loan volume share exposure to banks in the top quartile of sectoral specialization at a given point in time. In all specifications, firm fixed effects, sector-time, and province-time fixed effects are included. Firm-level controls include lags of log of assets, leverage, tangibility, and profitability. The table also includes the weighted average loan volume share exposure to banks in the top quartile of geographical specialization at a given point in time, and its interaction with monetary policy. Monetary policy interactions with lags of the log of assets and leverage are also included, though not reported. The symbols *,** and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

evidence presented in Section 3.1, confirming that specialized banks' differential responses to monetary policy may generate meaningful real economic effects for their borrowers. While these results demonstrate that differential credit supply from specialized banks translates into real economic effects, they cannot definitively establish whether this occurs through information advantages, relationship effects, or simply greater credit availability. However, they align with the mechanism presented in Section 3.2.

5. External Validity: U.S. Syndicated Loans Evidence

To examine whether the specialization effects documented in Spain generalize across different institutional settings and market structures, I study the relationship between bank specialization and monetary policy transmission using data from the U.S. syndicated loan market. This analysis provides external validity by testing the core findings in a different lending environment characterized by arm's-length syndicated lending rather than relationship-based bank lending, where firms are larger, less opaque and have alternative sources funding if needed.

The framework remains the same as in the Spanish context: when the interest rates decrease, banks face portfolio allocation decisions between leveraging sector-specific expertise or diversifying risk exposure. However, the syndicated loan context offers a distinct testing ground where information advantages may manifest differently due to the market-based nature of loan origination and the presence of multiple lenders per transaction.

Using bank-sector-quarter level data from the syndicated loan market, I examine whether specialized banks increase lending more in their sectors of expertise following a rate cut.

The results align with the Spanish findings: credit supply increases more for specialized banks in their sectors of expertise following monetary policy easing. This pattern is consistent with the information advantage mechanism, where yield compression increases the value of sector-specific knowledge, enabling specialized banks to expand credit to creditworthy borrowers while maintaining superior performance outcomes relative to diversified competitors.

5.1. Bank-Sector Responses in Syndicated Lending

I estimate the sensitivity of bank-sector credit growth to monetary policy easing conditional on banks' industry specialization. Due to data limitations in the syndicated loan sample, I aggregate all outstanding loans between a bank and sector at quarterly frequency to ensure sufficient variation and issuance frequency within each bank-sector pair (Acharya et al., 2018, 2019). This aggregation approach yields similar estimates to firm-level fixed effects without introducing estimation bias, as demonstrated in Degryse et al. (2019) and in Table 2.

I estimate local projections on bank-sector loan growth $\Delta \text{Loan}_{b,s,t-1\to t+h}$ at horizons

$h = [0, \ldots, 12]$ quarters using the following specification:

$$\Delta \text{Loan}_{b,s,t+h} = \alpha_{s,t+h} + \alpha_{b,t+h} + \beta_1^h \, \textit{Top-Spec.}_{b,s,t-1} + \beta_2^h \varepsilon_t \times \textit{Top-Spec.}_{b,s,t-1} + \\ \theta_h' X_{b,s,t-1} + \Theta_h' \varepsilon_t \times X_{b,s,t-1} + \psi_h' \sum_{k \in \{t-4,t-1\}} \Delta \text{Loan}_{b,s,k} + u_{b,s,t+h} \quad (11)$$

The dependent variable is the log growth in loan volume from bank b to sector s at time t. The key coefficient of interest is β_2^h, which captures the differential response of specialized banks to monetary policy changes. Local projection estimates are scaled to represent responses to a 25 basis point rate reduction.

The vector $X_{b,s,t-1}$ includes bank-sector characteristics that might affect the relationship between specialization and monetary policy response, particularly the bank's market share within the sector (measured as bank b's credit to sector s relative to total sectoral credit). The term $\sum_{k \in \{t-4,t-1\}} \Delta \text{Loan}_{b,s,k}$ includes four lags of the dependent variable to account for persistence in bank-sector lending patterns and control for pre-existing trends that might confound the monetary policy response.

The specification includes different fixed effects: sector-time effects ($\alpha_{s,t+h}$) control for sector-specific demand shocks and economic conditions (Khwaja and Mian, 2008; Paravisini et al., 2023), while bank-time effects ($\alpha_{b,t+h}$) control for bank-specific credit supply factors (Jiménez et al., 2014; Paravisini et al., 2023; Giometti et al., 2022). This saturation approach isolates variation in specialized banks' differential responses to monetary policy from confounding demand and supply factors. Standard errors are two-way clustered at the bank and sector levels.

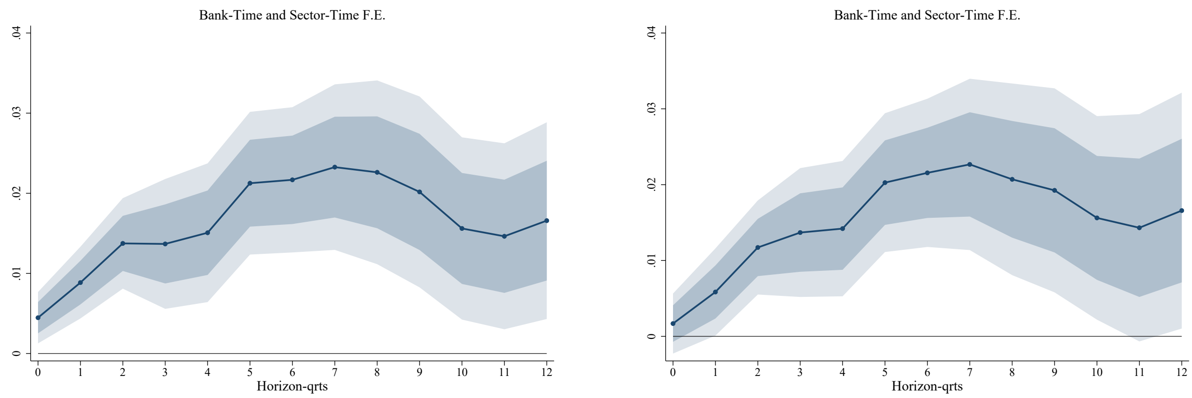
The identification strategy exploits cross-sectional variation in how the same bank responds across different sectors, combined with time-series variation in each bank-sector pair. The sample covers 1990Q1 to 2018Q4. To ensure robust estimation, I require banks to have originated multiple loans per sector and exclude banks with exposure to only one sector over the sample period.

Table A3 in the appendix presents coefficient estimates for one-year credit growth following monetary policy shocks across different fixed effects specifications.

The dynamic responses are shown in Figure 4.

Figure 4:
Evolution in Bank-Sector Credit Volume around MP Change

(a) *No sector covariates cross-terms* **(b)** *With sector covariates cross-terms*



Note: US syndicated loan sample. Impulse response dynamics to a 25 bps cut in ε_t. Unit of observation: bank-sector quarter. Point estimates, 90% and 68% confidence intervals for β_2^h from estimating specifications Equation 11 without controls (Figure 4a) and with controls (Figure 4b), including bank-time and sector-time fixed effects. The outcome variable is the change in log credit between the bank-sector pair at a given horizon h. Covariates included in $X_{b,s,t-1}$ in Equation 11 for Figure 4b are the bank's market share and the interaction with monetary policy. All specifications include 4 lags of the dependent variable. Confidence intervals based on two-way clustered standard errors at the bank and sector level. The sample consists of estimated outstanding quarterly loan volume between a bank sector for the period from $1990q_1$ until $2018q_4$. Lighter areas represent represents 90% confidence interval. The measure of banks' specialization, *Top-Spec.* $_{b,s,t-1}$, identifies banks in the top quartile of sectoral specialization at a given point in time.

Figure 4a presents results from the baseline specification with bank-time and sector-time fixed effects and four lags of the dependent variable, without additional bank-sector controls.

The impulse responses confirm that specialized banks significantly increase credit in their sectors of expertise following monetary easing. After a 25 basis point rate cut, banks in the top quartile of specialization increase lending to these sectors by an additional 2.5 percentage points compared to less specialized banks. This portfolio reallocation is persistent, beginning immediately and reaching peak impact around 8 quarters after the shock.

The more persistent effects compared to the Spanish case likely reflect differences in syndicated loan characteristics, including longer origination processes[12] and different

[12]Typically, it takes 90 days from the syndication process to the effective origination of a loan.

borrower profiles, as well as the aggregated nature of the bank-sector analysis. The effect remains robust when controlling for market share interactions (Figure 4b), confirming that the specialization effect operates through information advantages rather than market power.

These findings demonstrate that the main results generalize beyond the Spanish relationship banking context to the U.S. syndicated loan market, supporting the external validity of the main results.

5.2. Bank-Level Portfolio Response

Unlike in the Spanish case, loan-level delinquencies cannot be examined in the syndicated loan setting. To provide additional evidence for the information advantage mechanism, I study bank-level performance outcomes following monetary policy changes. If specialized banks exploit informational advantages during easing periods, they should exhibit improved bank-level performance metrics through superior borrower selection and risk management (Blickle et al., 2021). Conversely, if credit expansion reflects search-for-yield behavior (Martinez-Miera and Repullo, 2017), bank performance should deteriorate due to increased risk-taking without corresponding screening improvements.

To measure portfolio concentration, I construct the Herfindahl-Hirschman Index (HHI) using each bank's sectoral loan shares:

$$HHI_{b,s} = \sum_{s'=1}^{S} (Specialization_{b,s',t})^2 \tag{12}$$

where $Specialization_{b,s',t}$ represents bank b's lending share to sector s' at time t. Higher HHI values indicate greater portfolio concentration, while lower values reflect diversification across industries. While HHI measures overall concentration rather than specialization in a specific sector, the two concepts are related: banks with high sectoral specialization typically exhibit higher concentration levels.

I match the U.S. syndicated loan data with FRY-9C regulatory reports covering bank holding companies from 1990Q1-2018Q4, providing direct measures of bank-level performance and risk metrics. To assess how portfolio concentration affects performance following monetary policy changes, I estimate local projections over horizons $h = [0, \ldots, 12]$ quarters:

$$y_{b,t+h} = \alpha_{t+h} + \alpha_b + \beta_1^h \ HHI_{\ b,t-1} + \beta_2^h \varepsilon_t \times \ HHI_{\ b,t-1} + \gamma_b X_{b,t-1} + u_{b,t+h} \tag{13}$$

where $y_{b,t+h}$ represents various bank performance measures, including ROA, loan loss provisions, charge-off rates, and delinquency rates. The specification includes time fixed effects α_{t+h} to absorb time-varying factors common across banks and bank fixed effects α_b to control for unobservable bank characteristics that may confound the results.

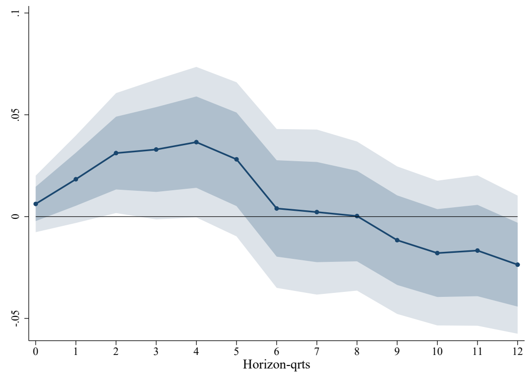
All performance variables are annualized and seasonally adjusted following Drechsler et al. (2017, 2021). For ease of interpretation, all results are scaled to represent responses to a 25 basis point rate cut for a one standard deviation increase in HHI. The vector $X_{b,t-1}$ controls for bank characteristics including size, capital ratio, liquidity ratio, deposit ratio, commercial and industrial (C&I) loan ratio, and real estate loan ratio, as well as four lags of the dependent variable.

The coefficient β_2^h captures how portfolio concentration relates to bank performance following monetary policy shocks. If information advantages drive specialized banks' behavior, we expect more concentrated banks to outperform diversified banks following easing periods. Standard errors are clustered at the bank level. Due to the inclusion of four lags, the effective sample covers 1991Q1-2018Q4.

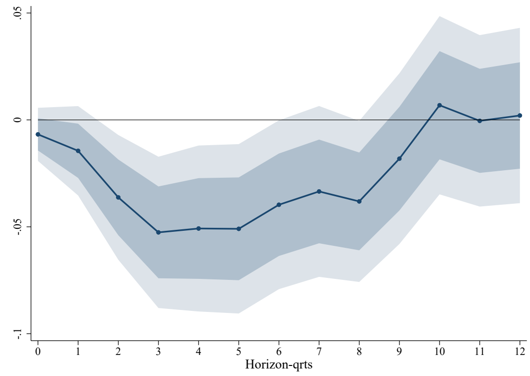
Figure 5 reports the impulse responses of different performance measures following a 25 basis point rate cut for a one standard deviation increase in banks' HHI concentration. Across all measures, bank performance improves with the degree of portfolio concentration: banks with more concentrated portfolios perform significantly better than their diversified counterparts following monetary easing. The results are statistically significant and economically meaningful, consistent with concentrated banks exploiting information advantages rather than engaging in indiscriminate risk-taking. Examining Figure 5a, the conditional estimate β_2^h for ROA is positive and statistically significant for up to one year, consistent with the patterns observed at the bank-sector level. Following a 25 basis point

Figure 5:
Impulse response to rate cut: bank level performances

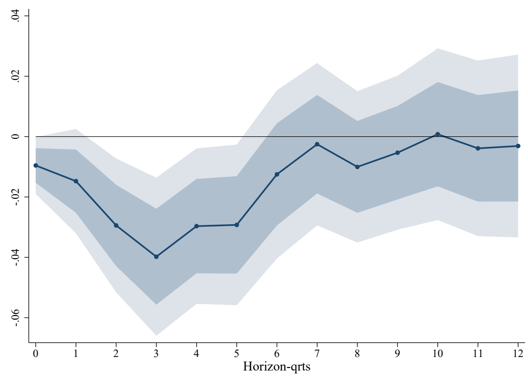
(a) *Banks' ROA*



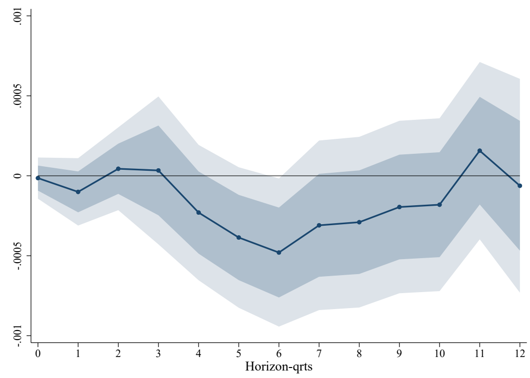
(b) *Banks' Chargeoff*



(c) *Banks' loan loss provision*



(d) *Banks' delinquency rate*



Note: Matched Dealscan and FRY-9C sample. Unit of observation: bank quarter. Impulse response dynamics to a 25 bps cut in ε_t for a standard deviation increase in $HHI_{b,t-1}$. The panel reports the conditional estimates for β_2^h for the interaction term $\varepsilon_t \times HHI_b^{b,t-1}$. The sample consists of matched Dealscan and FR Y-9C bank holding company for the period from $1991q_1$ until $2018q_4$. The dependent variable is the banks' ROA in Figure 5a and charge-off rate in Figure 5b. Light (dark) blue areas represent 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 13. The measure of banks' concentration is defined based on the syndicate outstanding loan volume at the end of each quarter.

rate cut, a one standard deviation increase in HHI (0.24) relates to a 3 basis point increase in bank ROA, representing a 4% increase relative to the sample standard deviation and peaking around four quarters.

The performance improvements extend beyond profitability to asset quality metrics. Figure 5b and Figure 5c present impulse responses for charge-off rates and loan loss provisions. Higher concentration levels are associated with statistically significant reductions in both measures: a 25 basis point expansionary shock combined with a one standard deviation increase in portfolio concentration relates to lower charge-off rates of 5 basis points and loan loss provisions of 4 basis points. These effects represent approximately 5% of the total sample variation and peak around four quarters after the shock. The banks' increase in ROA performance is explained by a relative improvement in delinquencies, consistent with the informational advantage channel.

Finally, I examine cumulative delinquency rates, measured as the fraction of loans past due 90^{+} days, plus nonaccrual loans relative to total loans net of allowances. Following a 25 basis point rate cut, banks with a one standard deviation higher HHI experience a 5 basis point reduction in cumulative delinquency rates, representing 20% of the sample variation for the corresponding horizon.

These findings relate to banks with more concentrated portfolios leveraging superior screening and monitoring capabilities to select higher-quality borrowers when interest rates decline. Rather than exploiting lower rates to shift toward riskier borrowers and seize higher yields, concentrated banks appear to effectively use their information advantages to identify the most creditworthy borrowers, resulting in enhanced profitability and reduced loan losses.

While the bank-level analysis cannot fully rule out alternative explanations such as loan evergreening (e Castro et al., 2024), the results align with the mechanism evidence presented in Section 3.2 and support the information advantage hypothesis. The consistency of findings across the Spanish banking system and U.S. syndicated lending shows the broader applicability of the information advantage mechanism across different institutional settings.

6. Conclusion

This study investigates how banks' sectoral specialization affects monetary policy transmission, examining lending decisions at the bank-firm level, their implications for bank performance, and their ultimate effects on firm outcomes.

My empirical analysis reveals a consistent pattern across different institutional settings and data sources. Following monetary easing, banks significantly increase lending to firms in sectors where they specialize relative to non-specialized banks. This finding holds in the comprehensive Spanish credit register and for the subsample of US syndicated loans, suggesting that the specialization channel operates across different financial systems and lending environments. Using granular bank-firm data from Spain with saturated fixed effects, I establish that this effect reflects a supply-side phenomenon rather than differential demand across borrowers.

The mechanism underlying this differential response operates through banks' information advantages. I provide evidence that the specialization effect is stronger for informationally opaque borrowers, where specialized banks' sector-specific knowledge provides a greater comparative advantage. Consistent with superior screening ability, specialized banks experience lower default rates following monetary easing, and their increased lending flows predominantly to firms with better subsequent performance outcomes.

I further show that these supply-side decisions have aggregated benefits for companies borrowing from specialized lenders. Firms with greater exposure to specialized lenders experience larger increases in investment rates and profitability following monetary easing compared to firms borrowing primarily from non-specialized banks, suggesting that specialized banks efficiently channel credit to productive uses.

The findings contribute to understanding heterogeneous monetary policy transmission by highlighting how bank market characteristics drive sector-specific responses to interest rate changes. Unlike previous research focusing on bank balance sheet constraints, this study demonstrates that information-based specialization creates systematic differences in credit supply responses across sectors.

These results carry important policy implications as monetary policy affects not only the overall level of bank lending but also its sectoral allocation through banks' specialization decisions.

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A. Appendix

A.1. 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 static 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 returns across sectors for the same bank. This assumption can be easily rationalized in the context of a production function with complementarity in the information factor, thus generating decreasing returns to scale. The heterogeneous returns allow 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.

The bank's program then reads as:

$$\max_{\{L_{s,1}\}} \sum_s (L_{s,1}^{\gamma_s} - L_{s,1} R_f) \tag{14}$$

The optimal scale in each sector is given by:

$$L_{s,1}^* = \left(\gamma_s R_f^{-1}\right)^{\frac{1}{1-\gamma_s}} \tag{15}$$

Given the optimality condition, 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 static 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.

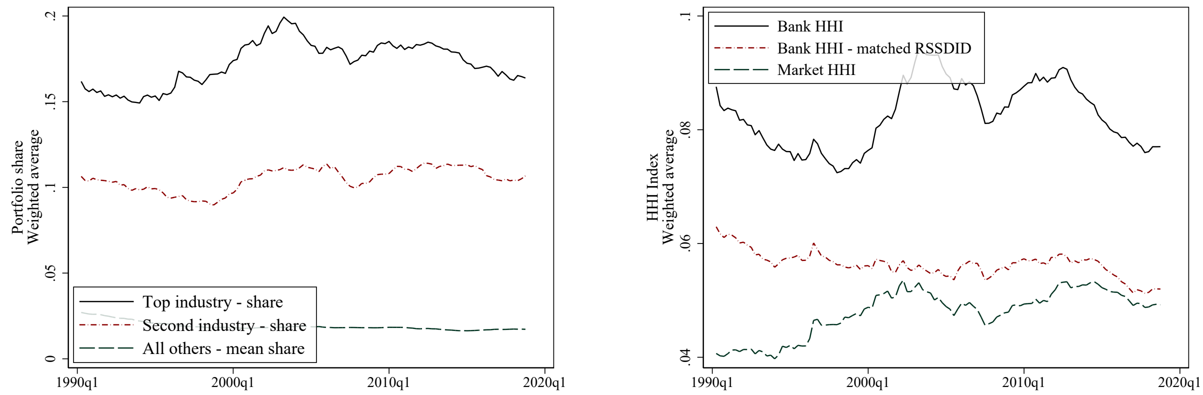
A.2. Aggregate US Evidence In Banks Portfolio Concentration

A.3. Summary Statics for the Syndicated Loan Market

The US syndicated loan sample spans 1990Q1-2018Q4 and includes 154,368 bank-sector quarterly observations from 147 matched bank holding companies. Banks serve an average of 44 sectors each (out of 83 two-digit SIC industry groups), originating 3.6 loans per bank-sector-quarter on average and serving 2.6 unique firms per cell. This concentration creates identification challenges for within-cell estimation strategies, as many bank-sector-quarter cells contain few firms, hence the aggregation at the bank-sector quarter pairs. Bank

Figure A1:
Banks portfolio concentration patterns - US Syndicated Market

(a) ***Average share allocated to sectors: US*** (b) ***Average Banks' and Market HHI: US***



Note: Figure A1a shows the bank's average (weighted) share of loans allocated to each industry at a given point in time, for banks in the US syndicated loan market. Data are 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. Figure A1b 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 of all banks' portfolios, where the weight is the fraction of a bank's volume over the total market, as in Giometti et al. (2022).

specialization is prevalent, with 25% of relationships involving top-quartile specialized lenders. Credit growth is positive on average (3.7% quarterly), contrasting with the Spanish deleveraging environment. At the bank level, the sample includes 7,629 bank-quarter observations with substantial variation in size (mean log assets of 9.6) and performance metrics. Banks exhibit profitability (mean ROA of 1.1%) comparable to other studies with moderate risk-taking: change loan loss provisions averaging 0.49%. The dataset excludes Term Loan B facilities typically sold after origination and estimates loan shares using Blickle et al. (2020) methodology to address missing syndicate information.

A.4. Specialization and Lending Around Monetary Policy Change

A.4.1. Alternative Fixed Effect Specification

This subsection presents robustness tests using less restrictive fixed effects that are sufficient to identify supply-side effects while preserving statistical power and controlling

Table A1:
Summary Statistics - US Sample

Panel A: Syndicated Market - US				
	Mean (1)	St. Dev. (2)	p25 (3)	p75 (4)
Bank-Sector level				
$\Delta loan_{b,s,t}$	0.037	0.210	0.000	0.042
$\Delta loan_{b,s,t+3}$	0.138	0.483	-0.037	0.335
$Top\text{-}Spec_{b,s,t-1}$	0.112	0.316	0.000	0.000
$Num\ Sec.\ by\ Bank_{b,s,t}$	43.376	17.390	31.000	58.000
$Loans\ originated_{b,s,t}$	3.622	4.411	1.000	4.000
$Firm\ in\ Bank\text{-}Sec\text{-}Qtr_{b,s,t}$	2.616	3.250	1.000	3.000
$Firm\ in\ Sec\text{-}Qtr_{b,s,t}$	17.244	15.654	6.000	23.000
Observations	154,368			

Panel B - US				
	Mean (1)	St. Dev. (2)	p25 (3)	p75 (4)
Bank level				
$\log(Asset)_{b,t}$	9.565	1.558	8.505	10.577
$Equity\ Ratio_{b,t}$	0.090	0.030	0.072	0.103
$ROA_{b,t}$	1.054	0.787	0.791	1.391
$C\&I\ Ratio_{b,t}$	0.161	0.083	0.105	0.202
$\Delta ROA_{b,t}$	1.052	0.653	0.799	1.382
$\Delta Chg.\ Off_{b,t}$	0.715	0.791	0.226	0.899
$\Delta Loan\ Loss\ Prov._{b,t}$	0.485	0.582	0.139	0.597
$\Delta Del.\ Rate.\ (p.p.)_{b,t}$	-0.011	0.209	-0.068	0.051
Observations	7,629			

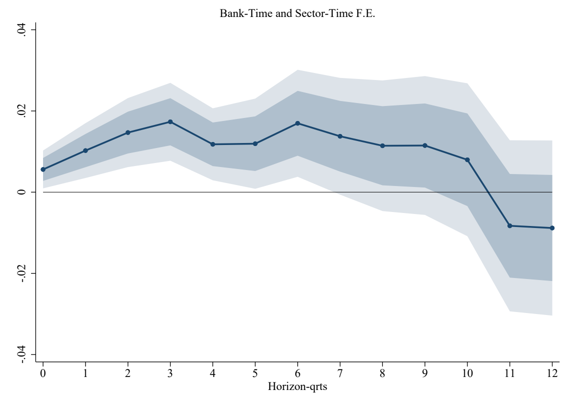
This table provides summary statistics at two levels: bank-sector quarter level and bank quarter level for the matched Dealscan and FR-Y9C dataset. The sample includes all matched bank-sectors pairs with valid non-financial company sector codes. It is restricted to banks that serve more than one sector per quarter and to sectors with more than one bank serving them. Panel A presents bank-sector data from the sample period 1990Q1-2018Q4. Panel B presents bank-quarter level data from the FR-Y9C dataset for the same period, containing. For ease of interpretation, the change in delinquency rate is scaled to reflect percentage points.

for firms' demand. Figure A2 shows coefficient estimates for β_2^h from alternative versions of specification Equation 4 using bank-time with sector-time fixed effects (Figure A2a) and bank-time with industry-location-size-time (ILS-time) fixed effects (Figure A2b).

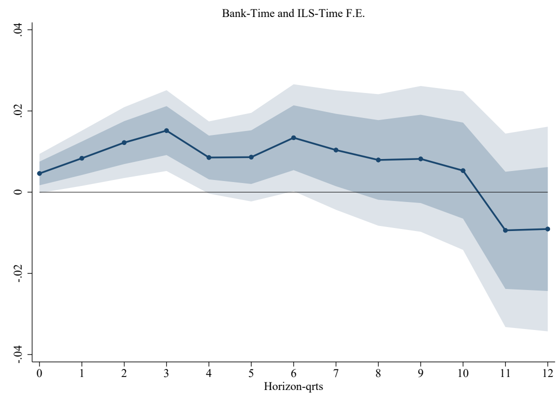
The results confirm that the main findings presented in Figure 2 remain robust under different and less restrictive fixed effects specifications. While these alternatives control for demand factors less stringent than firm-time fixed effects, they yield qualitatively and

Figure A2:
Evolution in Bank-Firm Credit Volume around MP Change

(a) *No Covariates with $\alpha_{b,t}$ and $\alpha_{s,t}$*



(b) *No Covariates with $\alpha_{b,t}$ and $\alpha_{ILS,t}$*



Note: Spain credit register sample. Unit of observation: bank-firm quarter. Impulse response dynamics to a 25 bps cut in ε_t. Point estimates, 90% ans 68% confidence intervals for β_2^h from estimating specifications Equation 4 containing bank-time and sector-time (Figure A2a) or ILS-time fixed effects (Figure A2b). The outcome variable is the change in log credit between the bank-firm pair at a given horizon h. Confidence intervals based on two-way clustered standard errors at bank and sector level. The sample consists of outstanding quarterly loan volume between a bank-firm for the period from $2006q_1$ until $2022q_4$. Lighter areas represent represents 90% confidence interval. The measure of banks' specialization, *Top-Spec.*$_{b,s,t-1}$, identifies banks in the top quartile of sectoral specialization at a given point in time.

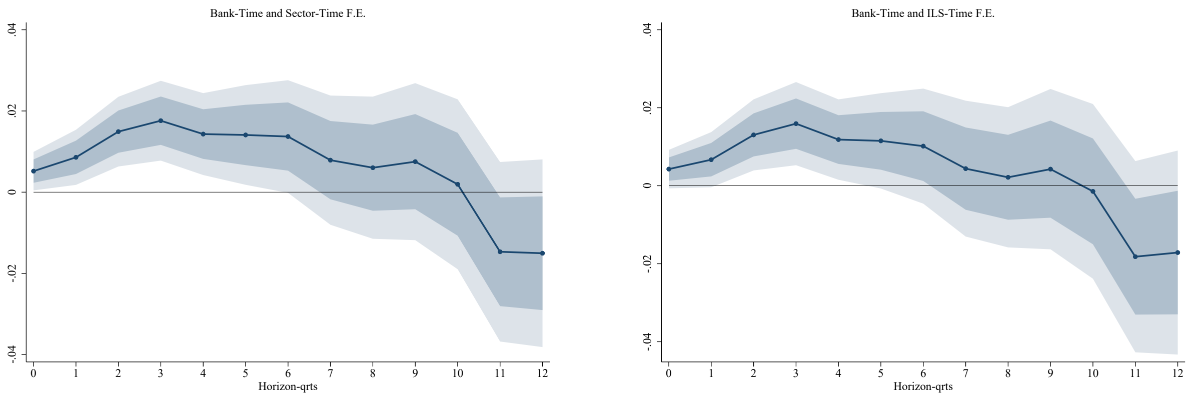
quantitatively similar estimates, consistent with Degryse et al. (2021) who show that more parsimonious specifications can effectively capture supply-side effects in credit registry data.

Figure A3 extends the analysis by including the full set of controls from specification Equation 5, which accounts for alternative transmission channels including geographic specialization, sectoral market share, and relationship lending intensity. Following recent evidence that relationship lending affects monetary policy transmission (Cahn et al., 2024; Cao et al., 2025), these controls ensure the specialization effect is not confounded by other bank-firm relationship characteristics.

The results show stability across specifications: whether using sector-time fixed effects (Figure A3a) or ILS-time fixed effects (Figure A3b), the specialization effects remain economically and statistically significant. Combined with the baseline firm-time fixed effects results (Figure 2b), this evidence indicates that the findings are not sensitive to the specific approach used to control for demand-side factors.

Figure A3:
Credit Volume Evolution around MP Change - With Covariates

(a) *With Covariates and* $\alpha_{b,t}$ *and* $\alpha_{s,t}$ **(b)** *With Covariates and* $\alpha_{b,t}$ *and* $\alpha_{ILS,t}$



Note: Spain credit register sample. Unit of observation: bank-firm quarter. Impulse response dynamics to a 25 bps cut in ε_t. Point estimates, 90% ans 68% confidence intervals for β_2^h from estimating specifications Equation 5 containing bank-time and (Figure A3a) or ILS-time fixed effects (Figure A3b). The outcome variable is the change in log credit between the bank-firm pair at a given horizon h. Confidence intervals based on two-way clustered standard errors at bank and sector level. The sample consists of outstanding quarterly loan volume between a bank-firm for the period from $2006q_1$ until $2022q_4$. Lighter areas represent represents 90% confidence interval. The measure of banks' specialization, *Top-Spec*$._{b,s,t-1}$, identifies banks in the top quartile of sectoral specialization at a given point in time.

A.4.2. Differential Response for (Non) Opaque Borrowers

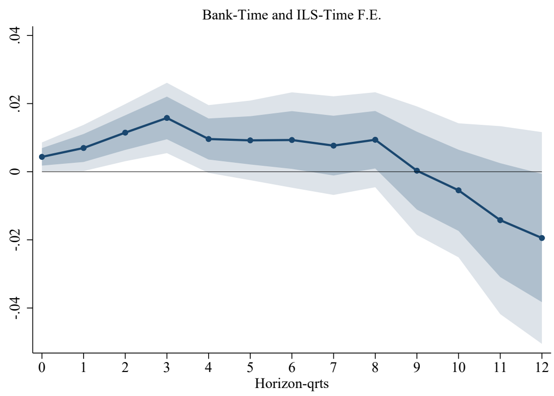
This subsection presents robustness tests for the opacity analysis discussed in Section 3.2. Figure A4 shows estimates for β_2^h from specification Equation 5 using split samples based on firm opacity. Firms are classified as opaque if their discretionary accruals (Equation 6) exceed the sector-year median in the previous year.

The results confirm the patterns documented in the main analysis: specialized banks' differential response is larger for opaque borrowers (Figure A4b) compared to non-opaque firms (Figure A4a). Figure A4b shows that specialized banks' credit growth is larger and more persistent for opaque borrowers, with peak effects reaching approximately 2 percentage points. In contrast, Figure A4a demonstrates that the specialization effect for non-opaque firms is smaller in magnitude and less persistent. These findings using lagged opacity measures are consistent with the main results and confirm that the information advantage mechanism is robust to alternative specifications of borrower transparency.

Figure A4:
Opaque and Non Opaque Credit Volume Response around MP Change

(a) *Lagged Non Opaque Indicator Firms Sample*

(b) *Lagged Opaque Indicator Firms Sample*



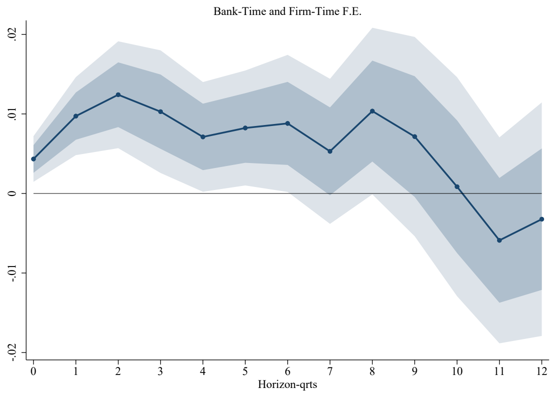
Note: Spain credit register sample. Unit of observation: bank-firm quarter. Impulse response dynamics to a 25 bps cut in ε_t for non-opaque and opaque firms. Point estimates, 90% and 68% confidence intervals for $\beta_2^{h,non-opaque}$ and $\beta_2^{h,opaque}$ from estimating specifications Equation 5 containing bank-time and firm-time fixed effects. The outcome variable is the change in log credit between the bank-firm pair at a given horizon h. Covariates included in Figure 2b are the bank's market share, the bank's geographic specialization, and relationship lending. Confidence intervals based on two-way clustered standard errors at the bank and sector level. The sample consists of outstanding quarterly loan volume between a bank-firm for the period from 2006q_1 until 2022q_4. Lighter areas represent 90% confidence interval. The measure of banks' specialization, *Top-Spec.* $_{b,s,t-1}$, identifies banks in the top quartile of sectoral specialization at a given point in time.

A.4.3. Gürkaynak, Sack and Swanson (2005) Shock Identification

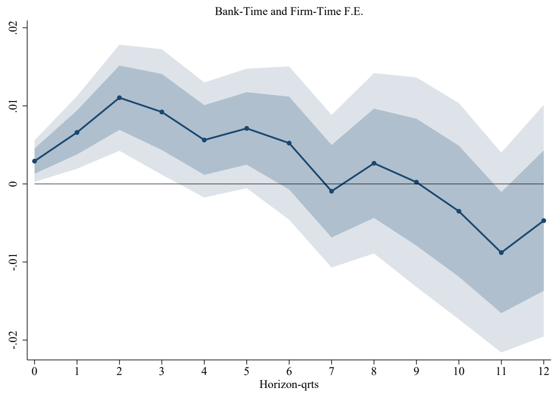
This subsection presents robustness tests using an alternative monetary policy shock identification following the high-frequency approach of Gürkaynak et al. (2005). The alternative shock series is constructed as the first principal component of surprise changes in overnight index swaps with maturities of 1-, 3-, 6-months, and 1-year during narrow event windows around ECB policy announcements, aggregated to quarterly frequency following Ottonello and Winberry (2020).

The results using GSS-type shocks closely align with the baseline findings in terms of both magnitudes and dynamic patterns. Unlike the baseline Jarociński and Karadi (2020) shocks, this approach does not separate pure monetary policy surprises from information effects about economic conditions. The similarity of results across both identification strategies suggests that the specialization effects are robust to different monetary policy shock measures and are not driven by central bank information revelation around policy

Figure A5:
Evolution in Bank-Firm Credit upon Gürkaynak et al. (2005) shock



(a) *No Covariates*



(b) *With Covariates*

Note: Spain credit register sample. Unit of observation: bank-firm quarter. Impulse response dynamics to a 25 bps cut in ε_t. Point estimates, 90% and 68% confidence intervals for β_2^h from estimating specifications Equation 4 and Equation 5, including bank-time and firm-time. The outcome variable is the change in log credit between the bank-firm pair at a given horizon h. Confidence intervals based on two-way clustered standard errors at the bank and sector level. The sample consists of outstanding quarterly loan volume between a bank-firm for the period from $2006q_1$ until $2022q_4$. Lighter areas represent 90% confidence interval. The measure of banks' specialization, *Top-Spec*$_{\cdot b,s,t-1}$, identifies banks in the top quartile of sectoral specialization at a given point in time.

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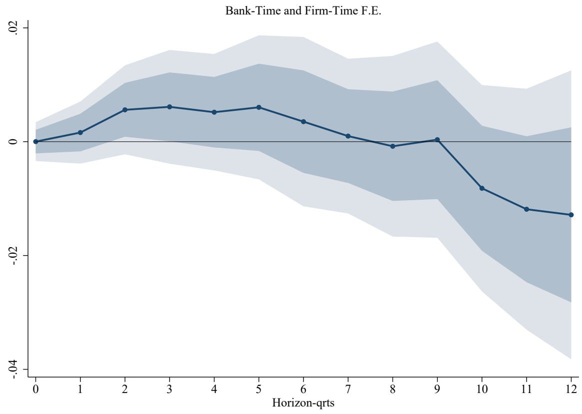
A.4.4. Alternative Sample Period

This subsection presents robustness tests using a restricted sample period that excludes the recent tightening in monetary policy measures. Figure A6 shows results for the 2006Q1-2018Q4 period using the full specification with covariates.

The results using the restricted sample period remain qualitatively consistent with the full-sample findings, though with lower statistical significance and smaller magnitudes. This reduction likely reflects the limited variation in monetary policy during 2006-2018, a period characterized by relatively stable ECB policy compared to the full sample that includes additional variation from the recent monetary policy tightening cycle. Despite the reduced statistical power, the economic pattern persists: specialized banks continue to increase credit more in their sectors of expertise following monetary easing, confirming that the main results are not artifacts of including exceptional policy episodes.

Figure A6:
Evolution in Bank-Firm Credit for 2006Q1-2018Q4



Note: Spain credit register sample. Unit of observation: bank-firm quarter. Impulse response dynamics to a 25 bps cut in ε_t. Point estimates, 90% and 68% confidence intervals for β_2^h from estimating specification Equation 5 including bank-time and firm-time fixed effects. The outcome variable is the change in log credit between the bank-firm pair at a given horizon h. Confidence intervals based on two-way clustered standard errors at bank and sector levels. The sample consists of outstanding quarterly loan volume between bank-firm pairs from 2006Q1 to 2018Q4. Lighter areas represent 90% confidence intervals. The measure of banks' specialization, *Top-Spec.*$_{b,s,t-1}$, identifies banks in the top quartile of sectoral specialization at a given point in time.

A.4.5. Alternative Standard Errors Clustering

This subsection presents robustness tests using alternative clustering methods. Since the treatment (specialization) varies at the bank-sector-time level, clustering at bank-time and sector levels provides an alternative approach that allows for correlation within banks over time while maintaining the sectoral correlation structure.

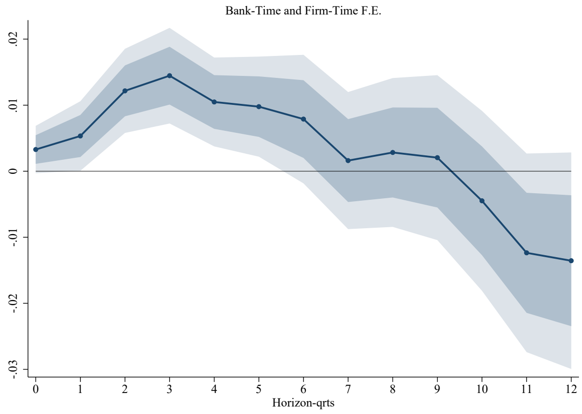
Figure A7 reports estimates for β_2^h from the baseline specification using bank-time and sector clustering instead of the baseline bank and sector clustering approach.

The results remain robust to this alternative clustering approach, with similar magnitudes and statistical significance as the baseline specification.

A.4.6. Alternative Explanatory Variables

This subsection presents robustness tests using alternative measures of bank specialization. Table A2 reports coefficient estimates for $\beta_2^{h=3}$ (annual credit growth) from specification Equation 4 across different specialization measures and fixed effects specifications.

Figure A7:
Evolution in Bank-Firm Credit - Bank-Time and Sector Clustering



Note: Spain credit register sample. Unit of observation: bank-firm quarter. Impulse response dynamics to a 25 bps cut in ε_t. Point estimates, 90% and 68% confidence intervals for β_2^h from estimating specification Equation 4 including bank-time and firm-time fixed effects. The outcome variable is the change in log credit between the bank-firm pair at a given horizon h. Confidence intervals based on two-way clustered standard errors at bank-time and sector levels. The sample consists of outstanding quarterly loan volume between bank-firm pairs from 2006Q1 to 2022Q4. Lighter areas represent 90% confidence intervals. The measure of banks' specialization, *Top-Spec.*$_{b,s,t-1}$, identifies banks in the top quartile of sectoral specialization at a given point in time.

The alternative measures include slow-moving averages of sectoral exposure (to reduce noise from temporary portfolio shifts), excess specialization measures that adjust for sector size in the economy (Paravisini et al., 2023; Blickle et al., 2025), and time-invariant specialization measures constructed using pre-sample averages. These alternatives address potential concerns that the baseline top-quartile indicator might capture mechanical effects related to sector size or temporary exposure changes rather than genuine specialization advantages.

The results demonstrate that the main findings are robust across alternative specialization measures. Whether using continuous excess specialization measures, slow-moving averages, or time-invariant measures, the coefficient estimates remain qualitatively and quantitatively similar to the baseline results. This consistency confirms that the specialization effects are not artifacts of the specific measure construction but reflect differences in banks' sector-specific advantages.

Table A2:
Robustness for Credit Volume Evolution Around Monetary Policy Change

	$Top\text{-}Spec_{b,s}^{t-12\rightarrow t-1}$		$Ex.Spec_{b,s,t-1}$		$Ex.Spec_{b,s}^{t-12\rightarrow t-1}$		$Ex.Spec_{b,s}^{06\rightarrow 11}$		$Ex.Spec_{b,s}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Spec. Measure	0.009**	0.012**	0.169***	0.215***	0.170***	0.217***	0.185***	0.250***	0.200***	0.251***
	(0.004)	(0.005)	(0.045)	(0.058)	(0.049)	(0.059)	(0.052)	(0.053)	(0.041)	(0.051)
JK shock × Spec. Measure	-5.405**	-4.853**	-25.238	-31.373*	-23.331	-26.023*	-40.624**	-28.047	-37.726**	-43.673**
	(2.614)	(2.263)	(16.982)	(16.129)	(15.595)	(15.516)	(19.338)	(18.749)	(15.003)	(17.386)
Firm Controls	✓		✓		✓		✓		✓	
ILS -Time F.E.	✓		✓		✓		✓		✓	
Firm-Time F.E.		✓		✓		✓		✓		✓
Bank-Time F.E.	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Clustered Std.Errors	Bank-Sector	Bank-Sector	Bank-Sector	Bank-Sector	Bank-Sector	Bank-Sector	Bank-Sector	Bank-Sector	Bank-Sector	Bank-Sector
R^2	0.124	0.368	0.125	0.368	0.125	0.368	0.129	0.377	0.125	0.368
Obs	28,410,359	25,262,232	28,551,314	26,270,932	28,410,383	25,262,258	19,369,246	14,640,770	28,555,533	26,277,395

The table reports coefficients and t-statistics (in parenthesis) for the bank lending growth volume to firm after a monetary policy change (e.g. contractionary). The reduced form model tested corresponds to Equation 4. The unit of analysis is at the bank-firm quarterly level. The sample consists of outstanding loan volumes between January 2006 to December 2022. The dependent variable is the log growth amount held by each lender at time t. The explanatory variables interacted with the monetary policy shock (e.g. contractionary) are reported on the top of each column. In all specifications, are included different levels of fixed effects are included as noted in the lower part of the table, from the least restrictive version (1) to the most (6). The symbols *,** and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

A.4.7. Bank-Sector Response in Syndicated Lending

This subsection presents the baseline estimates for U.S. syndicated lending using bank-sector aggregated data. Table A3 reports estimates for specification Equation 11 over a one-year horizon following monetary policy shocks, with coefficients representing a monetary policy change (e.g. contractionary).

Table A3:
Bank-Sector Credit Volume Evolution Around Monetary Policy Change

Effect of Industry specialization in bank's portfolio on				
	$\Delta loan_{b,s,t-1\rightarrow t+4}$			
	(1)	(2)	(3)	(4)
$Top-Spec_{b,s,t1}$	-0.196***	-0.217***	-0.200***	-0.219***
	(0.016)	(0.013)	(0.014)	(0.012)
$\varepsilon_t \times Top-Spec_{b,s,t1}$	-17.604*	-23.905***	-14.607	-19.853***
	(9.685)	(7.494)	(9.469)	(6.928)
Time F.E.	✓	✓	✓	✓
Sector F.E.	✓	✓		
Sector-Time F.E.			✓	✓
Bank F.E.	✓		✓	
Bank-Time F.E.		✓		
Clustered Std.Errors	Bank-sector	Bank-sector	Bank-sector	Bank-sector
Within R^2	0.106	0.333	0.191	0.414
Obs	153,241	153,241	153,241	153,241

The table reports coefficients and t-statistics (in parentheses) for the bank lending growth volume to sectors after a monetary policy change (e.g., contractionary). The reduced form model tested corresponds to Equation 11. The unit of analysis is at the bank-sector quarterly level. The sample consists of syndicated loans originated in the U.S. from 1990q1 until 2018q4. The dependent variable is the log growth amount held by each lender at time t. *Top-Spec.* $_{b,s,t-1}$ is the bank specialization identifying banks in the top quartile of sectoral specialization at a given point in time. In all specifications, are included different levels of fixed effects as noted in the lower part of the table, from the least restrictive version (1) to the most (4). The symbols *,** and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

The interaction coefficient β_2^h is negative and statistically significant across specifications, indicating that specialized banks increase credit more in their sectors of expertise following expansionary monetary policy. The preferred specification (Column 4) shows that a 25 basis point rate reduction is associated with a 1.5% relative increase in lending volume to specialized sectors.

The unconditional specialization coefficient is negative, contrasting with loan-level studies that find positive associations between specialization and outstanding loan volumes

(Blickle et al., 2021; Iyer et al., 2022) and the Spanish evidence in Section 3.1. This difference reflects the bank-sector aggregation level, which confounds intensive and extensive margin effects. Specialized banks may exhibit lower aggregate growth rates due to: (i) mean reversion effects when they reduce lending in non-core sectors during downturns, mechanically increasing measured specialization, (ii) re-compositional effects across firms within a sector, and (iii) the fact that growth rates and outstanding levels measure fundamentally different concepts. 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, the specialization level. This is a limitation of the bank-sector clustering aggregation. Despite this aggregation-level artifact, the key finding remains robust: specialized banks respond differentially to monetary policy in their sectors of expertise, consistent with information advantage mechanisms.

These results on the conditional growth upon monetary policy expansion confirm that the specialization effects documented in the Spanish banking sample extend to U.S. syndicated lending, despite differences in market structure and aggregation levels.

A.5. Measuring probability of default

To estimate the probability of default at the bank-firm level, I follow the methodology proposed by Blanco et al. (2023, 2024), defining a default event as the occurrence of a non-performing loan (NPL) lasting for at least three consecutive months. This criterion distinguishes firms experiencing sustained financial distress from those undergoing temporary liquidity issues. This step results in dropping less than 2% of all NPLs.

In constructing the default indicator, I exclude all observations following the first default event for each bank-firm pair. This approach mitigates potential biases arising from firms with recurrent defaults, ensuring that the estimated default probabilities reflect the onset of financial distress rather than its recurrence (Blanco et al., 2023, 2024).

As a robustness check, I construct an alternative measure that accounts for repeated default episodes. In this specification, I exclude observations following the first default within each distinct default spell, thereby allowing for multiple default episodes per bank-firm pair while still avoiding over-representation of prolonged distress periods.

A.6. Dealscan cleaning

I estimate loan shares in Dealscan following Blickle et al. (2020). A known problem when using syndicated loan-level data in Dealscan is that loan shares 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.

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 setup works as follows:

$$\textit{Share at first observation } (SNC)_{i,l} = \beta_0 + \beta_1 \cdot \mathrm{X}_{i,l} + \beta_2 \cdot \mathrm{X}_l + u_{i,l} \tag{16}$$

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 16 to get an approximation of the post-origination loan holdings by banks that participate in the syndicate. They show that this approximation performs better than commonly used loan-share 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 amendment` file and correct the loan maturity and volume over its lifetime.

Finally, to match the Dealscan identifier to the FR Y-9C, I use two distinct maps from Schwert (2018) and Gomez et al. (2021). Since Schwert (2018) maps Dealscan identifier with Compustat Identifier and given that the latter doesn't share a common identifier with the FR Y-9C reports, I match the CRSP identifier (`permno`) with the bank's ID (`RSSD9001`) to get a linkage for each matched lender.