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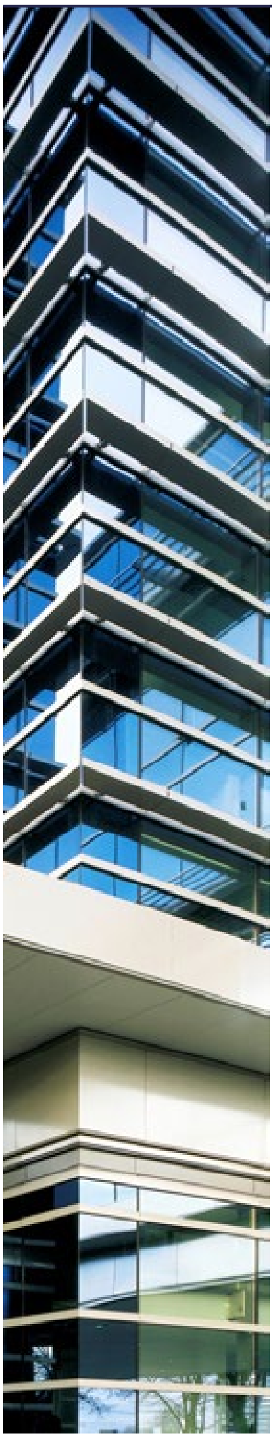
BANK SPECIALIZATION AND THE TRANSMISSION OF EURO AREA MONETARY POLICY



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ChaMP

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Challenges for Monetary Policy Transmission in a Changing World Network (ChaMP)

This paper contains research conducted within the network "Challenges for Monetary Policy Transmission in a Changing World Network" (ChaMP). It consists of economists from the European Central Bank (ECB) and the national central banks (NCBs) of the European System of Central Banks (ESCB).

ChaMP is coordinated by a team chaired by Philipp Hartmann (ECB), and consisting of Diana Bonfim (Banco de Portugal), Margherita Bottero (Banca d'Italia), Emmanuel Dhyne (Nationale Bank van België/Banque Nationale de Belgique) and Maria T. Valderrama (Oesterreichische Nationalbank), who are supported by Gonzalo Paz-Pardo and Jean-David Sigaux (both ECB), 7 central bank advisers and 8 academic consultants.

ChaMP seeks to revisit our knowledge of monetary transmission channels in the euro area in the context of unprecedented shocks, multiple ongoing structural changes and the extension of the monetary policy toolkit over the last decade and a half as well as the recent steep inflation wave and its reversal. More information is provided on its website.

Bank Specialization and the Transmission of Euro Area Monetary Policy*

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September 23, 2025

Abstract

Bank lending is a key factor in the transmission of monetary policy to the real economy. Using granular loan data on the euro area, I analyze how bank specialization interacts with the effects of monetary policy on credit. I first document that bank lending in the euro area is characterized by a substantial degree of specialization. That is, banks tend to be over-exposed to borrowers in certain industries and of certain size. I also find that higher specialization is generally associated with more favorable lending conditions. Most importantly, banks partly insulate their preferred borrowers from the consequences of monetary policy. In particular, they adjust interest rates and lending relatively less strongly for borrowers from groups in which they specialize. My findings suggest that bank specialization is relevant for the aggregate and distributional consequences of monetary policy.

Keywords: Bank specialization, Bank lending, Monetary policy, AnaCredit

JEL Classification: E51, E52, G21

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1 Introduction

The credit channel is generally regarded as an important factor in the transmission of monetary policy. According to this view, changes in policy rates transmit to real economic activity indirectly by affecting the availability of bank credit. To determine how exactly the availability corporate credit changes in response to monetary policy, the literature has often separately considered the role of bank or firm characteristics (see, e.g., Kashyap and Stein, 2000 and Anderson and Cesa-Bianchi, 2024). In this paper, I analyze the interaction between banks and their borrowers in the form of bank specialization as a new feature affecting the transmission of monetary policy. Bank specialization is defined as the over-proportional exposure of banks to particular borrower groups.

I first highlight key patterns of specialization by euro area banks in borrower industry and size and assess the implications of specialization for borrowing conditions. I then turn to the main research question: What is the role of bank specialization for monetary policy transmission to interest rates and credit supply? This research question is evaluated in the context of a local projections-instrumental variable analysis. To calculate bank specialization and assess its interaction with monetary policy, I rely on comprehensive credit register data from AnaCredit. My sample covers loans to euro area firms exceeding EUR 25,000 between mid-2020 and mid-2024.

Using this data, I first document that bank specialization by borrower industry and size is a widespread phenomenon among euro area banks. More concretely, close to all banks specialize in one or two categories within the respective dimension. Moreover, I document strong heterogeneity in the importance of specializing banks for credit intermediation across borrower categories. The average degree of specialization varies considerably across banks and is generally less pronounced among larger lenders. Finally, specialization is broadly associated with lower interest rates, larger loan amounts, longer maturities and higher collateral shares. In the US context, Blickle et al. (2025) document similar relationships. They argue that banks pass on the benefits of superior screening and monitoring that is associated with specialization to their borrowers.

As also argued by Blickle et al. (2025), informational advantages in monitoring and screening are a key reason why banks choose to specialize. These advantages in mitigating information asymmetries are traditionally attributed to long-term lending relationships with individual borrowers (see, e.g., Rajan, 1992). At the same time, specialization may emerge indirectly through regional focus if a bank's home region is dominated by borrowers from a specific group. While the findings in the first part of my analysis are generally consistent with established theories of bank specialization, the focus of this paper lies in examining its implications.

Specifically, the main objective of this paper is to analyze the role of bank specialization for monetary policy transmission. To this end, I conduct a local projections-instrumental variable (LP-IV) analysis using high frequency identified monetary policy shocks as in Altavilla et al. (2019). The impulse responses to these monetary policy shocks suggest that banks change interest rates several basis points less strongly for borrowers in industries or size categories in which they are specialized. Specialization is even more relevant for the response of credit volumes. For instance, the monetary policy induced change in credit among borrowers in the highest industry specialization quartile is only half as strong as the average response.

Generally speaking, banks appear to insulate borrowers from industries and size categories in which they specialize from monetary policy induced changes in interest rates and credit. This result is consistent with De Jonghe et al. (2020) who argue that banks reallocate credit towards industries where they specialize in response to negative funding shocks. My findings suggest that similar behavior is also relevant in the context of monetary policy.

Using a simple regression analysis of the evolution of interest rates and credit during the ECB's 2022/23 monetary policy tightening, I show that the marginal effects of specialization on interest rates are primarily driven by differences in the treatment of new borrowers (the extensive margin). In contrast, the marginal effects of specialization on the reductions in credit can be mainly attributed to differences among existing borrowers (the intensive margin). Insulating high-specialization groups from credit reductions therefore primarily benefited existing borrowers while potential new borrowers profited from an attenuated pass-through to interest rates.

Finally, I explore wider implications of banks' dampened policy pass-through to borrower groups in which they specialize as well as the associated effective reallocation of credit to these borrowers. Specifically, I document that monetary policy leads to a weaker effect on credit in industries that are dominated by specializing banks. Moreover, I show that the share of credit to specializing banks increases after contractionary monetary policy.

Related Literature The analysis in this paper primarily relates to previous work on bank specialization and its implications for firm financing.

On a general level, this paper builds on a long-standing literature on the costs and benefits of loan portfolio concentration. In a seminal contribution, Diamond (1984) emphasizes the risk-reducing advantages of diversification. Empirically, Shim (2019) shows that more diversified loan portfolios are indeed associated with lower bank insolvency risk. In contrast, theoretical work by Winton (1999) and empirical evidence in Acharya et al. (2006) and Böve et al. (2010) suggests that specialization improves loan screening and monitoring, which may outweigh potential risks from portfolio concentration. More recently, Beck et al. (2022) find that higher specialization is associated lower individual bank risk and systemic risk. My paper does not aim to directly contribute to this debate but focuses on the implications of bank specialization for firm financing. However, I draw on the existing theories of loan portfolio concentration to interpret the key results.

In providing a detailed account of bank specialization patterns, my analysis strongly builds on Blickle et al. (2025). That paper also provides the basis for parts of my methodology as well as the measurement of bank specialization. My analysis differs in that it considers specialization in the euro area. Furthermore, my data allows me to also include smaller banks in the analysis and consider specialization according to firm size. Other relevant contributions on the implications of bank specialization are Paravisini et al. (2023), considering the role of specialization in Peruvian export markets, and Iyer et al. (2022), exploring the role of credit by specializing banks in the context of industry-specific shocks.

In the euro area context, this paper is most strongly related to De Jonghe et al. (2020), who consider the role of bank specialization for credit reallocation after funding shocks using Belgian credit register data. My analysis differs in that it explicitly considers changes in credit in response to economy-wide monetary policy shocks for the entire euro area. Bank specialization among Belgian banks has also been considered in the context of innovation (Degryse et al., 2025), Zombie lending (De Jonghe et al., 2025) and in its interaction with credit relationships (Cabossioras and Tielens, 2024). Using the same euro area data as in my analysis, Simoens and Tamburrini (2025) find that specialized banks are better at predicting borrower default, highlighting the role of specialization in providing informational advantages to banks. In the context of Portugal, Bonfim et al. (2024) study specialization in new firms as a novel dimension of bank specialization. Finally, Duquerroy et al. (2022) analyze the implications of local bank specialization in industries for small firms' access to credit in France. In contrast to these contributions, my analysis applies to the euro area as a whole and explicitly studies monetary policy.

This paper also connects with the literature on the role of credit for the transmission of monetary policy, going back to Bernanke and Gertler (1995) and Kashyap and Stein (1995). In this context, it particularly relates to previous work on the role of bank characteristics for the transmission of monetary policy to credit. This includes papers looking at bank liquidity and size (Kashyap and Stein, 2000), leverage (Dell'Ariccia et al., 2017), the degree of loan fixation (Altunok et al., 2024), and exposure to interest rate risk (Gomez et al., 2021). My paper analyzes specialization as a new factor in shaping monetary policy transmission via banks. In doing so, I go beyond considering specialization as a characteristic at the bank level. Instead, I explicitly condition on the degree of specialization that characterizes particular bank-borrower group pairs, which allows for estimating within-bank effects.

Methodologically, my analysis draws from a growing literature that studies micro-level responses to macroeconomic shocks (Almuzara and Sancibrián, 2024). Important contributions using local projections to evaluate the firm-level effects of monetary policy shocks include Ottonello and Winberry (2020), Cloyne et al. (2023) and Anderson and Cesa-Bianchi (2024).

To summarize, the contribution of my paper to the existing literature is twofold. First, it provides a comprehensive overview of bank specialization in the entire euro area and how it matters for firm financing conditions. Second, it analyzes the role of specialization for the transmission of monetary policy to interest rates and credit supply.

Outline The remainder of the paper is structured as follows. Section 2 defines bank specialization and describes the data used in the analysis. Section 3 presents key patters of bank specialization and explores how specialization relates to credit conditions. Section 4 contains the main local projection analysis of the role of specialization for monetary policy transmission. Finally, Section 5 presents additional results and Section 6 concludes.

2 Data and Methodology

In this section, I lay out the main measure of bank specialization and describe the data used to compute bank specialization for the euro area.

2.1 Specialization Measure

Following Blickle et al. (2025), I compute specialization as the difference between the weight of a borrower group in a given bank's loan portfolio relative to the weight of this borrower group in the economy as a whole. More concretely, I measure *excess specialization* of a given bank b in category s at time t as follows:

$$Specialization_{b,s,t} \equiv \frac{LoanAmount_{b,s,t}}{\sum_s LoanAmount_{b,s,t}} - \frac{\sum_b LoanAmount_{b,s,t}}{\sum_b \sum_s LoanAmount_{b,s,t}} \quad (1)$$

The first term on the right hand side represents the share of category s in the bank b's loan portfolio while the second term represents the share of category s in total lending in the economy. The measure of bank specialization therefore measures the relevance of category s for bank b relative to the relevance of category s in overall credit markets. In this sense, it accurately measures the degree of *over-proportional* exposure of bank b in category s.[1]

Bank b is perfectly diversified in category s if the value of excess specialization is zero. Moreover, as highlighted by Cabossioras and Tielens (2024), positive excess specialization by bank b in category s must be offset by negative excess specialization by this bank in other categories. Similarly, positive specialization by bank b in category s must be met by negative specialization in this category by other banks.

I calculate specialization by bank as opposed to legal entity or banking group to account for the fact that decisions on lending to certain borrowers are usually made at this lower level and not by the parent company. Moreover, I relate bank lending shares to the respective shares in the country of the bank as opposed to the euro area as a whole to account for segmentation of credit markets across euro area countries. The data on outstanding credit used to compute (1) is described in the following subsection.

[1] Over-proportional exposure of banks to certain borrowers is sometimes also measured by *relative specialization*, defined as the ratio of the two terms on the right hand side of (1) (see, e.g., Paravisini et al., 2023). In Appendix C, I provide a brief discussion on the implications of measuring over-proportional exposure by relative as opposed to excess specialization.

2.2 Data Description and Sample Selection

For the majority of the analysis, I use data from AnaCredit, a confidential credit register maintained by the European System of Central Banks. The data includes monthly loan-level information on corporate lending by euro area banks, including a large set of creditor, debtor and loan characteristics. Although loans of all amounts are present in the data, banks are only required to report loans that exceed EUR 25,000 in total exposure. Therefore, I will focus on these loans for the purpose of my analysis.

I apply a number of manipulations to the data to arrive at my final data set. First, I include only Euro-denominated lending to non-financial corporations. To ensure a clean correspondence of loans according to borrower category, I exclude loans with multiple debtors. In the interest of loan homogeneity, I focus on three credit instrument classes for my analysis, namely credit lines, revolving credit and other loans.

I then apply the following additional sample selection steps in accordance with Kosekova et al. (2025). First, I remove firms that have active syndicated loans in a given month or are otherwise associated with multiple creditors. The reason is that AnaCredit only contains information on the euro area banks in a given syndicated loan, irrespective of their role in the credit arrangement. Moreover, I exclude firms that are in default in the sense that they have defaulted on any of their active loans in the present month. This ensures that my results are not confounded by highly risky loans or firms with complex banking relationships induced by bankruptcy proceedings. I focus on domestic loans only. Finally, also following Kosekova et al. (2025), I exclude values above the 0.01% level for the number of employees, annual turnover, and balance sheet total on the debtor level. On the instrument level, I exclude values of the outstanding amounts less of equal to 0 and above the 0.01% level. The degree of reduction in terms of number of loans and loan volume implied by these sample selection steps are summarized in Appendix A.

To measure total loan exposure, outstanding loan amounts are calculated as the sum of the respective nominal values outstanding on and off balance sheet. The final loan-level data includes around 6 million loans from more than 2000 banks per month. As an illustration, summary statistics on a cross section of the data in July 2020 are provided in Table 1. The loan level data is used to compute bank specialization separately for each month between July 2020 and September 2024.

3 Bank Specialization in the Euro Area

In this section, I provide stylized facts on bank specialization in the euro area. This includes illustrations of key specialization patterns as well as a regression analysis on the relationship between specialization and selected loan characteristics.

Table 1: Summary Statistics for Credit Outstanding in 2020-07

Country	No. of banks	No. of loans	Total loan volume (EUR bn)				Loan volume (EUR thousands)			Rate
			All	Other loans	Credit lines	Revolving credit	Mean	Median	S.d.	(weighted mean), %
AT	389	163084	114.48	45.27	41.24	27.97	701.99	177.68	2529.15	4.48
BE	38	285440	112.03	33.96	61.11	16.96	392.49	107.96	1568.68	3.51
CY	12	9843	6.14	4.78	1.36	0.00	624.15	129.94	2239.04	5.50
DE	755	1029616	579.80	70.65	482.82	26.33	563.12	97.43	2074.33	2.97
EE	9	6863	7.12	6.89	0.12	0.10	1037.04	136.82	4216.17	6.01
ES	120	891286	256.44	138.99	37.33	80.13	287.72	71.66	1670.07	4.31
FI	135	128707	79.39	70.92	7.20	1.27	616.80	96.40	2723.77	4.39
FR	161	2465200	604.97	379.17	218.03	7.77	245.40	89.24	931.65	2.71
GR	16	78347	41.09	10.06	17.10	13.93	524.49	103.94	2708.04	5.84
IE	14	28478	12.44	10.01	0.59	1.83	436.84	76.63	2444.02	5.09
IT	204	855045	288.65	280.11	2.16	6.39	337.59	85.73	1549.64	4.96
LT	20	10793	8.47	4.10	3.56	0.81	784.51	96.30	3308.99	6.15
LU	33	10014	11.61	6.49	4.53	0.58	1158.93	269.40	4170.88	3.98
LV	12	6021	4.41	3.68	0.31	0.42	732.67	104.13	3015.36	6.03
MT	12	4234	3.94	0.26	3.60	0.08	931.46	221.33	2806.23	4.85
NL	28	68319	136.23	116.89	14.07	5.27	1994.08	255.70	5696.95	3.34
PT	112	196188	49.45	23.14	15.10	11.22	252.07	69.33	1127.58	5.26
SI	13	16109	7.21	0.53	4.36	2.32	447.85	106.67	1577.65	4.81
SK	18	29931	9.85	0.72	7.97	1.17	329.18	67.47	1659.87	4.84
Euro Area	2101	6283518	2333.74	1206.63	922.56	204.55	371.41	89.90	1692.70	3.63

Note. Summary statistics of credit to NFC outstanding in the euro area as of July 2020. Only includes credit lines, revolving credit and other loans with total exposure above EUR 25,000. Excludes syndicated credit, project finance and credit to debtors currently in default.

3.1 Specialization Patterns

I first present graphical illustrations of key patterns of bank specialization in the euro area along the two dimensions considered throughout this paper, i.e., borrower industry and size.[2] Borrower industry is measured at the two-digit NACE level and size according to the common EU definition.[3]

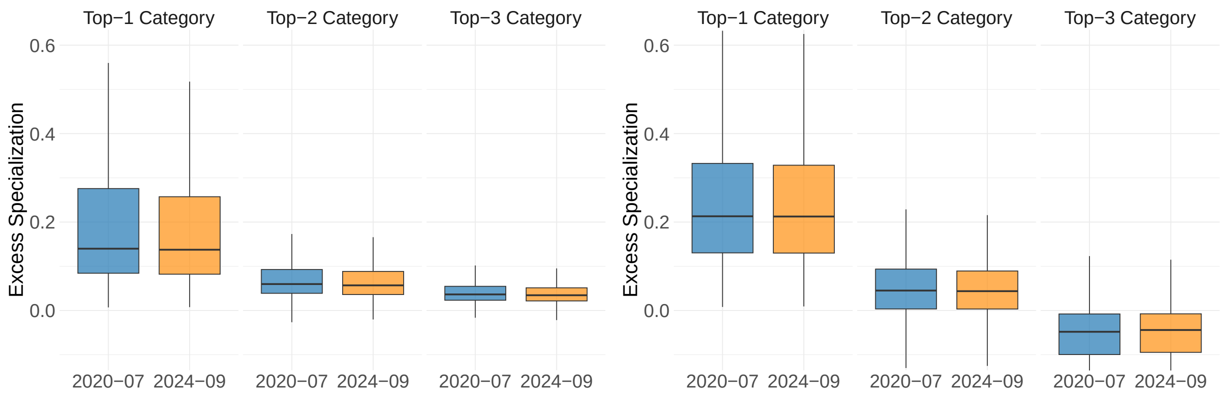
Figure 1 contains box plots representing the distribution of specialization in industry (left panel) and size category (right panel) across banks at the beginning and end of my sample. For each bank and month, I identify the three most preferred categories, i.e. those with the highest values of excess specialization as defined in (1). Each box plot then shows the distribution of banks' excess specialization values for each rank at different dates.

For both industry and size category specialization, there is almost no difference in the respective box plots between the beginning and at the end of my sample. This means that the overall degree of specialization stayed roughly constant within the sample period considered. Note that this does not necessarily imply that specialization remained constant within each bank. Figure 1 also indicates that banks tend to specialize primarily in one or two top categories. Excess specialization in top-1 categories is generally clearly positive. However, specialization in top-2 categories and even more so top-3 categories is already close to zero. This means that banks' exposure in the third most preferred industry is already largely in line with the economy wide exposure. Put differently, banks only have

[2] Similar illustrations for specialization according to borrower location are provided in Appendix B.4.
[3] That is, in accordance with the Annex to Commission Recommendation 2003/361/EC.

non-negligible positive specialization in one to two categories. Because there are only four size categories, the values for the third most preferred size class are generally negative. The box plots in Figure 1 also reveal that for close to all banks, excess specialization in their most preferred industry or size category is positive. Conversely, this means that there are almost no banks in my sample that are fully diversified in the sense that their lending share in their top category aligns with the economy wide share.

FIGURE 1: EXCESS SPECIALIZATION IN TOP CATEGORIES



(a) Specialization by Industry

(b) Specialization by Firm Size

Note. Distribution across banks of excess specialization values in the respective top categories in July 2020 and September 2024. Panel (a) represents specialization in top industries and panel (b) in top size classes.

In Appendix B.1, I show that specialization in top categories is also very relevant when weighted by loan amounts. Overall, 29.5 per cent of all credit is extended to the banks' respective top industries and 43.7 per cent to top size categories.

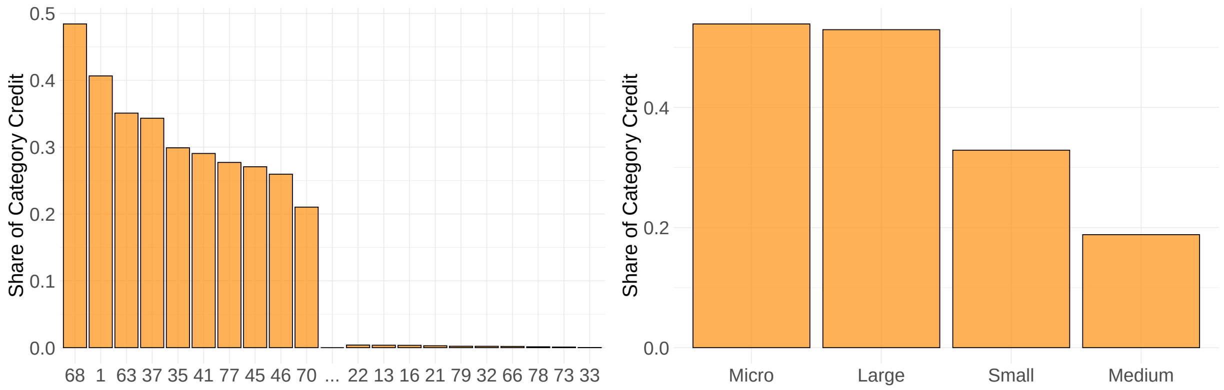
Taking a different perspective, Figure 2 now sheds light on which borrower categories are primarily affected by specialization. The figure shows the specialization intensity for each specialization dimension under consideration. Specifically, it depicts the share of credit within a category that is extended by banks for which that particular category is the most preferred one. The left panel in Figure 2 shows that there is a large degree of heterogeneity in specialization intensity across industries. In industries with NACE-Codes 68 and 1, close to half of all credit is originated by banks for which this industry is most preferred.[4] On the other hand, in industries with NACE-Codes 73 and 33, the share of specialized credit is close to zero.[5] The right panel shows that more than 50 per cent of credit to micro and large borrowers comes from firms which specialize in these size groups, while this figure is less than 20 per cent for medium sized borrowers. Therefore, credit in some borrower categories is heavily dominated by specializing banks while in others,

[4]The NACE-Codes represent *Real estate activities* (NACE code 68) and *Crop and animal production, hunting and related service activities* (1).

[5]These are *Advertising and market research* (73), and *Repair and installation of machinery and equipment* (33)

specializers do not play an important role.[6]

FIGURE 2: SPECIALIZATION INTENSITY BY CATEGORY



(a) Industries (b) Size Categories

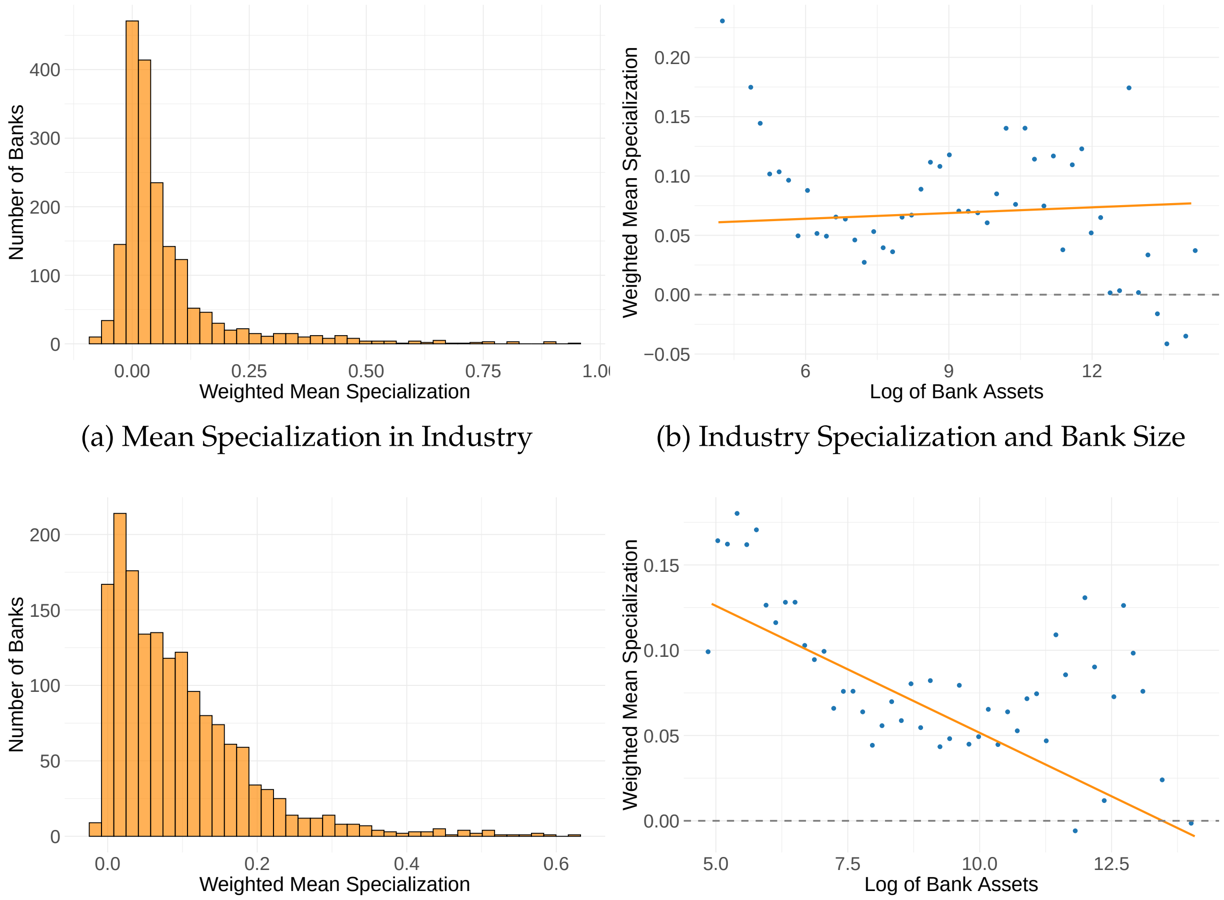
Note. Specialization intensities for different industries (left panel) and size categories (right panel) in July 2020. Specialization intensity is defined as the share of total credit within a given category that comes from banks for which this particular category is the most preferred one.

Similarly, there are differences in the degree of specialization on the bank side. Figure 3 illustrates the distribution of specialization at the bank level as well as the relationship between specialization and bank assets. Specialization at the bank level is measured by the volume-weighted mean of specialization values across the different industries or size categories that a bank lends to. This measure is high if a large share of a bank's lending accrues to categories in which the bank is particularly specialized. The left column panels in the figure point towards some degree of variation in the degree of specialization across banks. Most banks have positive mean specialization values, indicating that borrower groups with high specialization values are also relevant for lenders in terms of absolute volume. The right column panels indicate that high reliance on categories with high specialization is broadly associated with smaller bank size, measured by total assets. Data on bank assets is obtained from the database of individual balance sheet items (iBSI) compiled by the ECB. The relationship between specialization and bank assets appears to be fairly linear when considering specialization in size categories (panel(d)) while for industry specialization, bank size makes a difference mostly for very large or very small banks (panel (b)).

To shed more light on the relationship between specialization and bank characteristics, Table 2 shows the results of fixed effects regressions of mean specialization on a variety of different bank indicators. These indicators are also computed from iBSI data. The regressions confirm the negative relationship between bank size and mean specialization which seems to be nonlinear for industry specialization. In addition, higher liquidity is associated with higher mean specialization while higher loan and securities shares are associated

[6] In section 5, I explicitly analyze the role of heterogeneity in specialization intensity for the transmission of monetary policy.

FIGURE 3: BANK-LEVEL SPECIALIZATION AND RELATIONSHIP WITH BANK SIZE



(a) Mean Specialization in Industry

(b) Industry Specialization and Bank Size

(c) Mean Specialization in Size

(d) Size Specialization and Bank Size

Note. Distribution of mean specialization across banks (left panels) and relationship between mean specialization and total assets (right panels). Mean specialization is computed as the volume-weighted mean of excess specialization values within a given bank. Scatter plots are binned by bank assets.

with lower specialization. There is also a negative relationship between the deposit ratio and mean specialization in industry.

In the appendix, I illustrate additional stylized facts on bank specialization in the euro area. First, Appendix B.2 shows that specialization is a feature in all euro area economies, although the intensity differs somewhat across countries. Second, illustrations in Appendix B.3 indicate that, despite the negative relationship between mean specialization and bank size, specialization is not only a feature of small lenders, possibly focusing on certain geographical regions, but generally also prevalent among large banks. Third, Appendix B.4 illustrates pronounced regional specialization among euro area banks. Fourth, Appendix B.5 explores differences in specialization intensities in industries across countries. Finally, the chosen definition of specialization (1) might imply relatively high values of excess specialization in industries that are very small (see explanations in Appendix C). However, the illustrations in Appendix B.6 show that specialization is also very prevalent

TABLE 2: MEAN SPECIALIZATION AND BANK CHARACTERISTICS

	Mean Industry Specialization		Mean Size Specialization	
	(1)	(2)	(3)	(4)
Log(Assets)	-0.0101		-0.0208***	
	(0.0080)		(0.0030)	
Dummy Large		-0.0941***		-0.0232
		(0.0217)		(0.0200)
Capital Ratio	0.0320	0.0432	-0.0949	0.1235
	(0.0807)	(0.0881)	(0.0734)	(0.0990)
Liquidity Ratio	0.0782**	0.0643*	0.0848**	0.1162***
	(0.0307)	(0.0314)	(0.0310)	(0.0279)
Deposit Ratio	-0.1654***	-0.1661***	-0.0301	0.0234
	(0.0160)	(0.0324)	(0.0274)	(0.0266)
Loan Share	-0.2529***	-0.2835***	-0.1354**	-0.0844
	(0.0732)	(0.0647)	(0.0627)	(0.0553)
Securities Share	-0.5131***	-0.5366***	-0.3147***	-0.2811***
	(0.0757)	(0.0708)	(0.0708)	(0.0562)
Fixed Effects	Country, Month			
R-squared	0.12777	0.13917	0.17947	0.11275
Observations	2,761	2,761	2,595	2,595

Standard errors in parentheses
* p<0.1, ** p<0.05, *** p<0.01

Note. Estimation results of regressing volume-weighted mean specialization on bank characteristics. Bank size is either captured by the log of total assets (columns (1) and (3)) or a dummy variable for the top 5 per cent (within month) of bank assets (columns (2) and (4)). Standard errors are clustered at the country level.

in larger, one digit NACE sectors.[7]

3.2 Specialization and Credit Conditions

So far, I documented that specialization is widespread among euro area banks. I now shed more light on the implications of specialization for borrowers' credit conditions. More concretely, I analyze whether credit conditions are systematically different for firms when they borrow from a bank that specializes in their respective category.

3.2.1 Regression Specification

To assess how specialization relates to credit conditions, I focus exclusively on newly issued loans. The reason is that specialization can only affect loan terms that are determined at the time when a particular specialization level is observed. A loan is considered as newly issued if its origination date lies within the same month as the reporting date. To assess how specialization matters for borrowers, I aggregate the loan level data to the bank-firm level. Loan specific variables are captured as value-weighted averages across loans within

[7]Large banks tend to be highly specialized also in terms of sectors. This alleviates the concern that high industry specialization by large banks is driven by the fact that they generally cater a larger variety of market segments and might therefore exhibit high specialization values in some very small industries.

each bank-firm pair. On the resulting panel of newly issued loans, I estimate the following equation:

$$\begin{aligned} CreditCondition_{b,f,i,s,n,t} = \alpha_{b,t} + \alpha_{i,s,t} + \beta_1 Spec_{b,i,t} + \beta_2 Spec_{b,s,t} + \gamma_1 RegShare_{b,n} \\ + \gamma_2 MktShare_{b,i,t} + \gamma_3 MktShare_{b,s,t} + \gamma_3 Rel_{f,b} + \Gamma X_{f,t} + e_{b,f,i,s,n,t} \end{aligned} \quad (2)$$

where $CreditCondition_{b,f,i,s,n,t}$ stands for credit conditions on new loans granted by bank b to firm f from industry i, size category s, and region n at time t. The credit conditions I consider are average interest rate, maturity, collateral share as well as the total amount of credit by bank-firm pair. To correctly attribute differences in credit conditions to the relevant dimension of specialization, I simultaneously include both specialization measures. Specifically, $Spec$ is a stand-in for different measures of excess specialization by bank b in the respective industry or size category, explained in more detail below.

Specialization along the two dimensions may be not only be correlated with each other at the firm level but also related to regional focus. For instance, a bank might be highly specialized in a particular region which is also home to many firms from a single sector which in turn tend to be of a particular size. In this case, a large degree of specialization in both dimensions for a given bank-firm pair might simply be a by-product of the bank's regional focus. I control for this potential correlation by including $RegShare_{b,n}$, which denotes the share of lending by bank b that accrues to region n.

I follow Blickle et al. (2025) in also adding market shares and bank-firm relationship as controls to the regression. First, a high degree of specialization indicates that a bank is heavily invested in a certain borrower group which may also be associated with a large market share in that group. I therefore include $MktShare$ variables which denote the market shares of bank b in the respective industry and size category. Moreover, a high degree of specialization may mechanically arise if a given bank has close relationships with a few borrowers from a certain category. In this case, the β coefficients would capture the effect of bank-firm relationships rather than specialization. To account for the relationship between banks and certain borrowers, I add the variable $Rel_{f,b}$ as a control. It is defined as the number of months in which firm f has taken out a new loan from bank b during the sample period under consideration.

I also add bank-time and industry-size-time fixed effects. This way, I account for unobserved time-varying bank characteristics as well as unobserved factors that are common across firms in the same industry-size group. The β-coefficients therefore capture the within bank and within industry-size group variation in credit conditions conditional on the degree of specialization. Finally, $X_{f,t}$ includes additional firm-level variables which are likely related to credit conditions. Besides the weighted average of probability of default, this includes interest rate, loan amount, maturity or collateral share depending on the respective dependent variables under consideration.

3.2.2 Regression Results

I now present regression results of estimation equation (2), first for interest rate and credit amount and then for maturity and collateral share. For each dependent variable, I include various columns that differ according to the way in which specialization is captured. To account for heterogeneity in the importance of bank-firm pairs, all regression results are weighted by credit amounts.

Interest Rates and Loan Amounts Table 3 shows the results of estimating equation (2) where the dependent variable is the interest rate in per cent (columns (1) - (5)) and log credit amount (column (6) - (10)).

TABLE 3: ROLE OF SPECIALIZATION FOR INTEREST RATES AND CREDIT AMOUNTS

	Interest Rate					Log Credit Amount				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Industry Spec	-0.0500***		-0.0295***	-0.0493***	-0.0496***	0.136***		0.175***	0.133***	0.136***
	(0.00697)		(0.0103)	(0.00695)	(0.00695)	(0.0146)		(0.0174)	(0.0148)	(0.0146)
Q2 Industry Spec		0.0313***					0.0305***			
		(0.00740)					(0.00947)			
Q3 Industry Spec		-0.00664					0.122***			
		(0.00821)					(0.0102)			
Q4 Industry Spec		-0.0789***					0.137***			
		(0.00976)					(0.0113)			
Top Industry			-0.0522***					-0.0988***		
			(0.0148)					(0.0143)		
Size Spec	-0.00259	-0.00321	-0.00278		0.00756*	-0.0269***	-0.0241***	-0.0272***		-0.0369***
	(0.00336)	(0.00331)	(0.00337)		(0.00385)	(0.00748)	(0.00737)	(0.00750)		(0.00877)
Q2 Size Spec				0.0136*					-0.0253**	
				(0.00781)					(0.0126)	
Q3 Size Spec				-0.0311***					-0.00978	
				(0.00777)					(0.0122)	
Q4 Size Spec				-0.0181*					-0.0257*	
				(0.0100)					(0.0149)	
Top Size Category					-0.0325***					0.0321***
					(0.00653)					(0.0112)
Fixed effects	Industry-Size-Month, Bank-Month									
Controls	Market Shares, Regional Share, Relationship PD, Rate or Amount, Maturity, Collateral Share									
R-squared	0.832	0.832	0.832	0.832	0.832	0.555	0.554	0.555	0.554	0.555
Observations	3993676	3993676	3993676	3993676	3993676	3993676	3993676	3993676	3993676	3993676

Standard errors in parentheses
* p<0.1, ** p<0.05, *** p<0.01

Note. Results of estimating equation (2) with interest rate in per cent or the log credit amount as the dependent variable. Columns differ in how specialization is captured. *Spec* is (standardized) excess specialization computed as in (1), *Q2* to *Q4* represent dummy variables for the respective quartile of the within-country distribution of specialization. *Top <Category>* is a dummy variable for the borrower belonging to the highest specialization category of its lender. Standard errors are clustered at the firm and time level.

The estimation results in column (1) refer to a specification where specialization is captured by the continuous values of excess specialization along industry and size category. Specialization values are standardized such that one unit corresponds to one standard deviation of the distribution of excess specialization within my sample (corresponding to an excess specialization value of around 0.15). The coefficient on *Industry Spec* indicates that a one standard deviation higher value of excess specialization in industry is associated with a 5 basis point lower interest rate. This negative relationship between industry specialization and interest rates is highly significant. In contrast, the coefficient estimate on size category specialization is close to zero and statistically insignificant.

To zoom in on the relationship between industry specialization and interest rates, column (2) considers the effects of discrete levels of excess specialization. Specifically, it shows the result of estimating regression (2) including dummy variables for different quartiles of the within-country distribution of excess specialization. The lowest quartile serves as the reference group. Compared to the first quartile, interest rates among bank-firms in the second quartile are around 3 basis points higher. However, in the highest quartile, interest rates are 8 basis points lower. The bulk of the negative relationship between industry specialization and interest rates estimated in column (1) is thus accounted for by the difference between bank-firm pairs subject to very high specialization and all other bank-firm pairs.

Do the results in columns (1) and (2) merely reflect the effect of higher degree of specialization or is there an additional effect when a borrower belongs to a bank's most preferred industry? This question is addressed in columns (3) which relates interest rates to a dummy variable taking the value one if i is the most preferred industry for bank b in period t. To accurately measure the additional effects of belonging to the top industry, this specification controls for the value of industry (and size) specialization. The coefficient on *Top Industry* indicates that, for a given degree of specialization, belonging to a bank's top industry implies a 5.24 basis point lower interest rate on average. Belonging to a top industry therefore has an additional effect on interest rates beyond the mere effect of higher specialization among top industries. The coefficient on industry specialization remains statistically significant even with the top industry dummy included but is lower compared to the estimate in column (1).

Columns (4) and (5) show regression results analogous to columns (2) and (3) now estimating the effects of different measurements of size specialization while still controlling for industry specialization. Although significant, the coefficient estimates on quartiles of the size specialization distribution do not point towards a clear relationship between size specialization and interest rates. This is consistent with the insignificant coefficient estimates on the continuous measure of size specialization in columns (1) to (3). However, there does appear to be some effect of belonging to a bank's top size category as indicated by column (5). For a given degree of size specialization, interest rates are on average 3.22 basis points lower when a firm belongs to a bank's most preferred size category. When accounting for top size categories, the coefficient on the continuous measure of size specialization is positive and significant at the 10 per cent level but small in magnitude.

Columns (6) to (10) show the results of estimating equation (2) where the dependent variable is the log amount of new credit granted to firm f by bank b at time t. Again, the effects of industry specialization are generally more pronounced than those of size specialization. First, column (6) indicates that a one standard deviation higher level of industry specialization is associated with a close to 15 per cent higher credit amount. The coefficient estimate on size specialization is negative and statistically significant at the 10 per cent level although its magnitude is relatively small. Column (7) suggests that there is a jump in the relationship between industry specialization an loan amounts. Specifically, lending volumes appear to be similar among bank-firm pairs in quartiles 1 and 2 and, at a much higher level, among firms in quartiles 3 and 4. Column (8) shows that there is an additional effect of top category specialization on loan amounts. Somewhat surprisingly, this additional effect is negative implying that for a given degree of specialization, belonging to a bank's top category implies a *lower* average loan amount.

Size specialization is much less important for the determination of average credit volumes. The regression including specialization quartiles in column (9) does not imply a significant relationship between size specialization and credit amount. Column (10) suggests that, controlling for the degree of specialization, being in a bank's top size category is associated with a larger amount of credit. However, the magnitude of the effect of top specialization is much lower compared to the effects of industry specialization.

Maturity and Collateral Share Similar to before, Table 4 contains the regression results of estimating equation (2) where the dependent variable is maturity in months (columns (1) - (5)) or the share of collateral (columns (6) - (10)).

TABLE 4: ROLE OF SPECIALIZATION FOR MATURITY AND COLLATERAL SHARE

			Maturity					Collateral Share		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Industry Spec	3.476***		3.369***	3.500***	3.472***	0.0413***		0.0435***	0.0415***	0.0413***
	(0.334)		(0.364)	(0.330)	(0.334)	(0.00607)		(0.00727)	(0.00613)	(0.00606)
Q2 Industry Spec		0.442					0.0445***			
		(0.430)					(0.00731)			
Q3 Industry Spec		0.966**					0.0418***			
		(0.442)					(0.00729)			
Q4 Industry Spec		2.697***					0.0325***			
		(0.455)					(0.00658)			
Top Industry			0.271					-0.00567		
			(0.629)					(0.0105)		
Size Spec	1.117***	1.205***	1.118***		1.031***	-0.000780	0.000199	-0.000801		-0.000651
	(0.142)	(0.141)	(0.142)		(0.174)	(0.00284)	(0.00286)	(0.00284)		(0.00286)
Q2 Size Spec				-0.0906					0.0151**	
				(0.432)					(0.00720)	
Q3 Size Spec				2.066***					0.00157	
				(0.362)					(0.00722)	
Q4 Size Spec				2.857***					-0.00899	
				(0.420)					(0.00822)	
Top Size Category					0.276					-0.000413
					(0.317)					(0.00556)
Fixed effects	Industry-Size-Month, Bank-Month									
Controls	Market Shares, Regional Share, Relationship PD, Rate, Amount, Maturity or Collateral Share									
R-squared	0.541	0.541	0.541	0.541	0.541	0.363	0.363	0.363	0.363	0.363
Observations	3993676	3993676	3993676	3993676	3993676	3993676	3993676	3993676	3993676	3993676

Standard errors in parentheses
* p<0.1, ** p<0.05, *** p<0.01

Note. Results of estimating equation (2) with maturity in months or collateral share as the dependent variable. Columns differ in how specialization is captured. *Spec* is (standardized) excess specialization computed as in (1), *Q2* to *Q4* represent dummy variables for the respective quartile of the within-country distribution of specialization. *Top <Category>* is a dummy variable for the borrower belonging to the highest specialization category of its lender. Standard errors are clustered at the firm and time level.

According to the regression results in columns (1) to (5), specialization is positively related to loan maturity. Specifically, a one standard deviation higher value of excess specialization is associated with 3.5 months longer maturity of newly issued loans. Column

(2) shows that this relationship is primarily driven by the difference in maturity between the largest specialization quartile of bank-firm pairs and all others quartiles. Moreover, maturity only relates to the magnitude of specialization with no additional effect of being in a bank's top industry (column (3)). The role of size specialization for maturity is very similar to that of industry specialization (columns (4) and (5)) although the magnitudes of coefficient estimates are generally smaller.

Finally, columns (6) to (10) relate collateral shares to specialization. Only industry specialization appears to matter for collateral shares. Specifically, the coefficient estimate of industry specialization in column (6) is positive and significant, suggesting that banks ask for more collateral from firms in industries where they specialize. Intuitively, banks might be more efficient in monitoring the value of collateral in these industries which gives them an incentive to use this margin of adjustment to compensate for default risk (e.g. as opposed to higher interest rates). Column (7) shows that the relationship between specialization and collateral is driven by the difference between the lowest quartile of specialization and the rest.

To conclude, specialization is broadly associated with lower interest rates, larger credit volumes, longer maturities and higher collateral shares of newly issued loans. While the data implies a relatively clear relationship between these credit conditions and the degree of industry specialization, the additional effects of belonging to a top industry are ambiguous. Except for maturities, size specialization generally appears to be less important in determining credit conditions on new loans. At the same time, belonging to the top size category is associated with lower interest rates and larger loan amounts.

My findings are consistent with what Blickle et al. (2025) find for bank lending in the United States. Their interpretation can also be applied here: Banks have informational advantages in terms of screening and monitoring borrowers from groups in which they specialize. Borrowers are able to extract some of the rents from these informational advantages in the form of more favorable credit conditions.

4 Specialization and Monetary Policy Transmission

In this section, I investigate how specialization interacts with the effects of monetary policy. More concretely, I analyze whether, in response to monetary policy, banks adjust interest rates and credit supply more or less strongly among groups in which they are highly specialized.

4.1 Dynamic Consequences of Monetary Policy Shocks

I first analyze how bank specialization interacts with the effects of identified monetary policy shocks, now using data on outstanding credit at the bank-industry and at the bank-size category level. Estimations on the effects of monetary policy are based on a panel local projections-instrumental variable (LP-IV) approach (see Jordà, 2005 and Stock and Watson, 2018). Following Jordà et al. (2015), I interpret the LP-IV estimations in terms of a two-stage leans squares regression framework. In what follows, I first comment on the identification of monetary policy shocks, the baseline regression specifications and the first stage regression results. I then present impulse responses associated with monetary policy shocks.

4.1.1 Monetary Policy Shocks and Local Projection Specifications

In my local projection estimations, I instrument the policy rate by a monetary policy shock derived from high frequency monetary policy surprises. These surprises are taken from the Euro Area Monetary Policy Event-Study Database (EA-MPD) as described in Altavilla et al. (2019). The authors analyze changes in a wide range of different yields around ECB policy announcement to extract four types of monetary policy surprises capturing different aspects of policy implementation. As conventional monetary policy was most relevant during the time period covered by my sample, I use the *Target* factor in my analysis. Due to the short time dimension of my data, my shock series is based on relatively few monetary policy surprises, mostly covering the ECB's most recent monetary tightening episode.[8]

I aggregate my data to the bank-industry level when estimating interactions with industry specialization and to the bank-size category level when estimating interactions with size specialization. I here present the specifications used to estimate responses to monetary policy on the bank-industry level data. Regression specifications based on bank-size category data are analogous to these.

First, I estimate the average effects of monetary policy using the following equation.

$$\Delta CreditCondition_{b,i,t+h,t-1} = \alpha_b + \alpha_i + \beta_h^{avg} \Delta R_t + \Gamma_{1h} Z_{b,i,t-1} + \Gamma_{2h} Z_{b,i,t-1} \Delta R_t + \sum_{k=1}^{4} \Gamma_{3h,k} Y_{t-k} + e_{b,i,t+h} \quad (3)$$

where $\Delta CreditCondition_{b,i,t+h,t-1}$ stands for the change between months $t-1$ and $t+h$ in either the interest rate (on outstanding loans) or the log real credit amount (adjusted for inflation using the HCPI) of bank b and industry i. Monetary policy is captured by the change in the policy rate ΔR_t. To allow for an interpretation in terms of causal effects, ΔR_t is instrumented by the externally identified monetary policy shock.

The vector $Z_{b,i,t-1}$ includes industry specialization, industry market share as well as average size specialization and size market share within the respective bank-industry pair. As is common practice in the local projection literature, I also include four lags of the

[8] Policy surprises are directly associated with ECB policy announcement dates which occur every six weeks. I follow the literature and aggregate these to a monthly frequency by a simple assignment of each surprise to the month in which it occurs. The resulting shock series is depicted in Appendix A.

respective dependent variable and the shock in the regression (see, Almuzara and Sancibrián, 2024). Moreover, I control for broader macroeconomic conditions by including lags of industrial production and inflation collected in the vector Y_{t-k}. I also include bank and industry fixed effects to control for permanent differences in changes of credit conditions. In equation (3), the sequence of coefficient estimates $\{\beta_h^{avg}\}_{h=0}^H$ captures the average response of interest rates and credit outstanding to an exogenous change in the policy rate.

The next set of regression equations estimates the interaction of monetary policy with specialization. Although equation (3) already controls for such interactions, I use a different specification to estimate the marginal effect of higher specialization on monetary policy responses:

$$\begin{aligned}\Delta CreditCondition_{b,i,t+h,t-1} = \alpha_b + \alpha_i + \alpha_{c,t} + \beta_h^{int} Spec_{b,i,t-1}\Delta R_t \\ + \Gamma_{1h} Z_{b,i,t-1} + \Gamma_{2h} Z_{b,i,t-1}\Delta R_t + e_{b,i,t+h} \quad (4)\end{aligned}$$

The advantage of this specification is that I can now include country-time fixed effects denoted by $\alpha_{c,t}$. I thereby flexibly account for any variation that affects all observations within a country in a given month. This may include cross-country differences in the responsiveness to monetary policy shocks as well as country-specific shocks. As the fixed effects absorb all aggregate variation, I can no longer estimate the effects of ΔR_t (or the macro controls) in itself which is why these variables are dropped from the estimation equation.

The variable $Spec_{b,i,t-1}$ denotes specialization of bank b in industry i at time $t-1$, captured in two different ways. First, I account for the degree of specialization using a dummy variable indicating if excess specialization is among the highest quartile of the within-country distribution. In this case, β_h^{int} represents the differential response at horizon h of interest rates and credit amount for bank-industry pairs with high levels of specialization relative to the rest. Second, I similarly estimate the differential response among bank-industry pairs where i is the most preferred industry for bank b using the corresponding dummy variable. In the this case, the degree of excess specialization is included in the control vector $Z_{b,i,t-1}$.

First Stage Regression Results Before turning to the dynamic consequences of monetary policy shocks, I comment on the first stage regression results of my instrumental variable approach. The first stage consists of regressing the policy rate proxy on the monetary policy shock and all the controls used in the second stage regression. The regression results for the first stage regression on equation (3) for $h = 0$ when the dependent variable is the log credit amount are presented in Table 5. I consider different policy rate proxies.

As expected, the coefficients on the shock are positive and significant for all policy rate proxies, indicating that a positive shock leads to an increase in the policy rate. However, the F-statistic is by far the largest for the one month EURIBOR rate. Moreover, the R-

TABLE 5: FIRST STAGE REGRESSION RESULTS

	1m EURIBOR	3m EURIBOR	1m OIS
	(1)	(2)	(3)
Alt. Target	2.497***	1.952***	2.054***
	(0.462)	(0.605)	(0.570)
F-statistic	27.70	20.86	14.73
R-squared	0.378	0.269	0.251
Observations	279114	279114	279114

Standard errors in parentheses
* p<0.1, ** p<0.05, *** p<0.01

Note. First stage regression results of IV regressions using the Target factor from Altavilla et al., 2019 for different policy rate proxies. Results are based on estimating (3) when $h = 0$ on bank-size level data where the dependent variable is log credit amount.

squared is also relatively high, suggesting that the shock explains a lot of the variation in the policy rate. In light of these first stage regression results, the remainder of the analysis will be based on the one month EURIBOR rate instrumented by the *Target* shock from Altavilla et al. (2019).

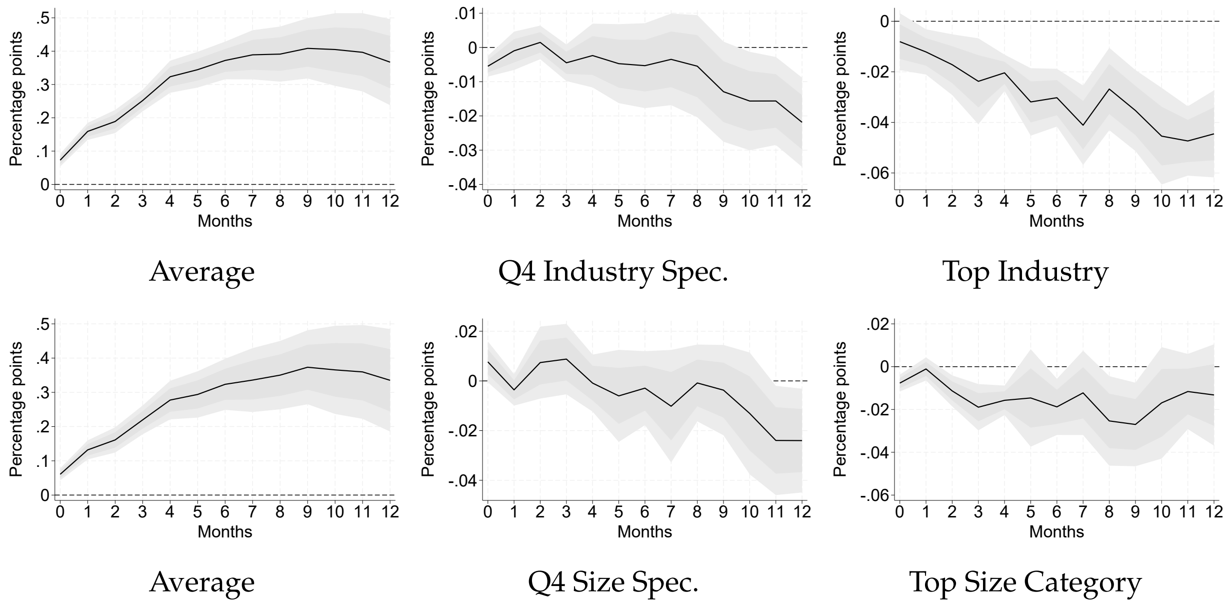
4.1.2 Impulse Responses

I now present the main results of estimating specifications (3) and (4) above, namely the dynamic consequences of changes in the policy rate instrumented by monetary policy shocks. All figures show responses to a monetary policy shock associated with a 25 basis points change in the policy rate where coefficient estimates are weighted by loan amounts. Building on the analysis in Almuzara and Sancibrián (2024), confidence intervals are based on clustered standard errors at the month level.

Interest Rates Figure 4 summarizes the effects of exogenous changes in the policy rate on interest rates. The top row contains the results associated with industry specialization, i.e. estimates from regressions (3) and (4) on data aggregated to the bank-industry level. The bottom row similarly contains results on size category specialization. The first column shows the average interest rate response estimated using equation (3). Column 2 shows the differential interest rate response for bank-category pairs within the highest quartile of specialization, estimated using equation (4). Similarly, the third column contains the differential response for most preferred categories.

As expected, the average interest rate responses estimated from the two different specifications are very similar to each other. Specifically, an exogenous increase in the policy rate by 25 basis points induces an increase in interest rates on outstanding loan of around 40 basis points 12 months after the shock. This implies a more than one-to-one

FIGURE 4: MONETARY POLICY EFFECTS ON INTEREST RATES



Note. Dynamic consequences of an exogenous 25bp increase in the policy rate on interest rates. Based on estimating equations (3) and (4) using data aggregated at bank-industry (top row) and bank-size category (bottom row) level. Column one shows the average response of interest rates and columns two and three interactions with the top quartile dummy of specialization and the top category dummy respectively. Gray bars represent 68 and 90 per cent confidence intervals based on clustered standard errors by month.

pass-through of policy rates to corporate lending rates.[9]

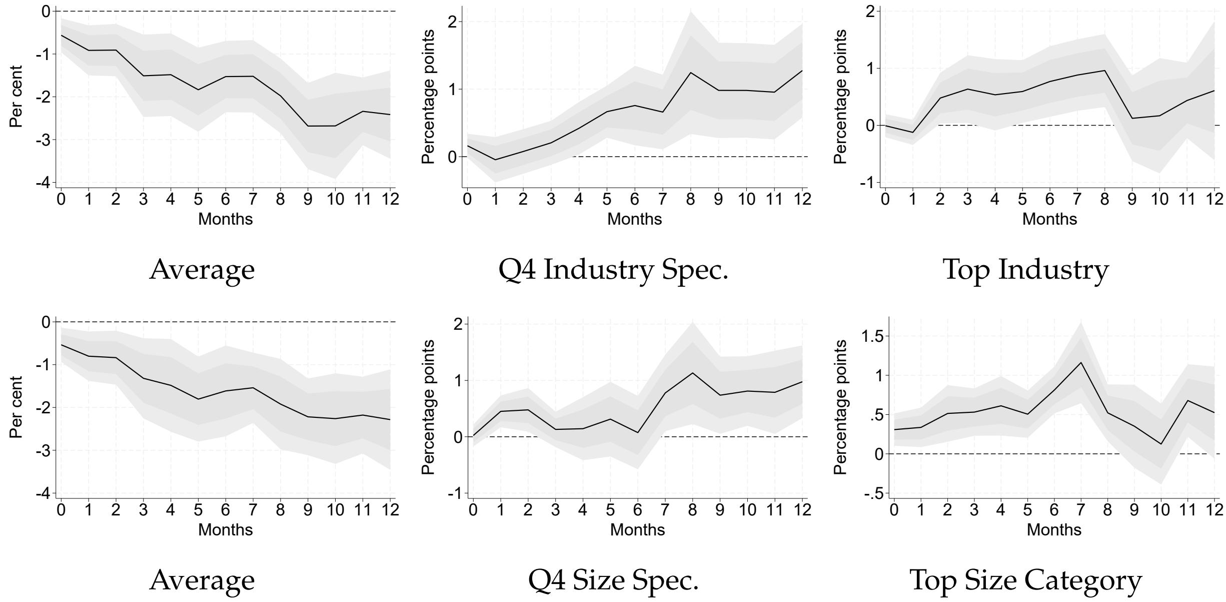
Column 2 shows that higher industry specialization tends to have a dampening effect on interest rate pass-through, especially at long horizons. Specifically, over one year after the shock, interest rates increase by two basis points less for bank-industry or bank-size category pairs characterized by high specialization. The estimation results in column 3 show that being in a bank's top industry has a relatively sizable additional effect. In particular, for a given degree of specialization, banks raise interest rates up to 4 basis points less in top industries and 2 basis points less in top size categories.[10]

Credit Amount Figure 5 shows the dynamic consequences of a monetary policy shock on the amount of credit outstanding. Analogously to Figure 4, the top row contains results associated with industry specialization and the bottom row results associated with size specialization.

[9]This is likely driven by the fact that the sample period includes a sequence of relative large positive shocks (see Appendix A). This in turn implies that the shock produces an average dynamic change in the policy rate that is higher than the impact effect (corresponding local projection results are available upon request). It is therefore not surprising that corporate interest rates change by more than the impact effect of the shock.

[10]In Section 3, I argue that informational advantages may imply that banks require more collateral in industries where they specialize. Collateral shares might also be relevant in the context of monetary policy. In particular, in response to tighter monetary policy, banks may counteract the relative interest rate decreases in groups where they specialize by asking for more collateral. However, using a simple regression of collateral share effects averaged over a 12 month horizon, I find no significant differential responses of collateral shares in groups where banks specialize (see Appndix C).

FIGURE 5: MONETARY POLICY EFFECTS ON CREDIT AMOUNT



Note. Dynamic consequences of an exogenous 25bp increase in the policy rate on log credit amount. Based on estimating equations (3) and (4) using data aggregated at bank-industry (top row) and bank-size category (bottom row) level. Column one shows the average response of credit and columns two and three interactions with the top quartile dummy of specialization and the top category dummy respectively. Gray bars represent 68 and 90 per cent confidence intervals based on clustered standard errors by month.

The first column shows that a 25 basis point increase in the policy rate leads to an average reduction in credit of just over 2 per cent one year after the shock. Over the same horizon, the credit reduction is more than one percentage point weaker for bank-industry and bank-size category pairs in the highest specialization quartile as shown in column 2. Moreover, column 3 implies that there is a significant additional dampening effect of up to one percentage point associated with being in a bank's top industry or size category.

The results of the local projection estimations suggest that the pass-through of policy rates is less pronounced for industries and size categories characterized by high levels of specialization. Also, there is a substantial additional effect of being in a bank's top industry or size category.

Banks therefore appear to insulate borrowers in industries and size categories where they specialize from the interest rate increases and credit reductions induced by monetary policy. This finding is consistent with De Jonghe et al. (2020) who document that banks reallocate credit towards industries in which they specialize in response to an adverse funding shock. The reallocation of credit implied by these findings may have wider implications for the pass-through of monetary policy to certain groups of borrowers. I test two of theses implications further below.

4.2 Robustness

I now provide a number of robustness checks on the baseline results presented in Figures 4 and 5. For a clearer exposition, these robustness checks are based on the responses to an exogenous change in the policy rate averaged over a 12 month horizon. In particular, I estimate single regressions in the spirit of specifications (3) and (4), replacing the sequence of forward changes by their means over horizons 0 to 12. Because my impulse responses generally have the same sign over all horizons, standard significance tests on the coefficient estimates are informative about the overall effects of monetary policy. The baseline results of this regression exercise as well as regression tables containing detailed results of the robustness analysis are presented in Appendix C.

I start by altering the thresholds for capturing specialization. Specifically, I alternatively define the degree of specialization to be represented by dummies for the highest decile and above median instead of only the highest quartile of the within-country distribution. I find that there is some dampening effect of high industry and high size specialization for most of the cutoffs used. The dampening effect on interest rates is most pronounced for specialization above the median. In contrast, the differential effect on credit is only significant for specialization in the top quartile or the top decile (for industry specialization).

I also check if my baseline results are driven by certain countries. To this end, I estimate regressions where I exclude either of the four countries with the highest amount of outstanding credit, one at a time. These countries are France, Germany, Spain and Italy. My results are generally robust to these country exclusions. However, there are some differences in terms of magnitude and statistical significance worth noting. The estimated interaction effects have the highest magnitude when excluding Germany, which indicates that insulating high specialization groups is less pronounced in this country. Conversely, the estimates take relatively low values of even become insignificant when excluding France or Spain which indicates that the baseline results are strongly driven by bank behavior in these two countries. The estimated coefficients on top category interactions are generally more robust to country exclusions. However, for some configurations, excluding France and Spain again reduces the magnitude of the estimates or leads to insignificance.

Next, I explore if the dampening effects of high specialization are more pronounced among certain *groups* of countries. Specifically, I estimate regressions on subsamples including only observations from large economies, Core economies, countries in Central and Eastern Europe (CEE), or economies characterized by high credit market concentration.[11] There is a fairly large degree of variation between these country groups. Insulating behavior by banks is generally more pronounced among large economies, especially in

[11] *Large* includes only France, Germany, Italy and Spain and *Core* includes Germany, France, The Netherlands, Austria, Belgium, Finland and Luxembourg. The *Central and Eastern European* economies that are part of the euro area are Slovakia, Slovenia, Estonia, Latvia and Lithuania. *High concentration* refers to economies where the HHI index of bank credit market concentration is above the 75th percentile of the cross-sectional distribution across countries.

terms of credit amount. The dampening effect on credit amount is also more pronounced in economies with high credit market concentration although this is not generally the case in the context of interest rates. There is also no clear pattern when considering Core or CEE economies (in the latter case possibly due to a relatively small sample size). In some configurations, the estimated interaction effects are stronger than in the complete sample while in others, the interaction effects are weaker or even have opposite signs.

Next, I check if the baseline results on industry specialization are driven by specific sectors by excluding either of the four largest one digit NACE sectors. These are Real Estate (L), Manufacturing (C), Wholesale and Retail Trade (G) and Construction (F). My results are largely robust to sector exclusions. However, the interaction effects of high specialization and top industry on credit outstanding is no longer significant when manufacturing is excluded, pointing towards a strong role for this sector in producing the baseline results. In contrast, the interactions effect of high specialization on interest rates is only significant when manufacturing or construction are excluded indicating that insulating high specialization borrowers is less pronounced in the respective sectors.

In section 3.1, I argue that specialization is also a prevalent feature among large banks. To see if lenders of different size equally insulate borrowers from high specialization groups, I rerun the estimations above, additionally interacting specialization with a dummy capturing banks in the highest quintile of their respective country's distribution of bank assets. The estimation results suggest that large banks generally tend to show similar behavior compared to their smaller counterparts. If anything, they insulate their high specialization or preferred groups less strongly in terms of interest rates but somewhat more in terms of credit.

Next, I check whether my baseline results are robust to using alternative monetary policy surprises. Specifically, I rerun my estimations setting the policy rate to the three month EURIBOR rate instrumented by the monetary policy shock series constructed using monetary surprises from Zlobins (2025). The approach builds on the high frequency surprises by Altavilla et al. (2019) but ensures they do not depend on their own lags and imposes additional sign restrictions. The results on interest rate responses are very similar to those in the baseline analysis. The interaction coefficients of size specialization on credit outstanding are also positive and significant. However, the alternative shock does not have a significant effect on average credit outstanding and there is no significant interaction with either of the industry specialization measures.

Conventional monetary policy again became the main policy tool of the ECB only in the middle of my sample. To account for this, I provide additional results on the effects of quantitative easing shocks. Specifically, I estimate the effects of shocks based on the QE factor in Altavilla et al. (2019) on interest rates and credit averaged over a 12 months using data from July 2020 to June 2022. In line with the estimated responses to conventional monetary policy, banks appear to insulate credit to groups where they specialize from the effects of QE. This is again consistent with the reallocation of credit following adverse funding shocks documented in De Jonghe et al. (2020). I find no significant differential effect of interest rates.

Finally, I investigate whether there is any asymmetry between the effect of contractionary and expansionary monetary policy. To this end, I additionally interact the policy rate and its interaction with specialization with a dummy variable taking the value one if the monetary policy shock is expansionary. The coefficient estimates on these interactions are all insignificant, indicating that there is no difference between the effects of contractionary and expansionary monetary policy. However, given the coverage of my sample, the baseline results reflect the effects of monetary policy during a period of monetary policy tightening. This means that "expansionary" monetary policy shocks essentially reflect weaker than expected rate *increases*. The results on asymmetry in the effects of monetary policy should therefore be interpreted with caution.

5 Extensions and Additional Results

The previous findings suggest that firms are insulated from the consequences of monetary policy shocks when they borrow from specializing banks. In this section, I provide extensions on these baseline results. First, I investigate whether the marginal effects of higher specialization can be attributed to adjustments among existing or new borrowers, i.e. to changes at the intensive or the extensive margin. Second, I ask whether industries and size categories that are dominated by highly specialized banks experience weaker adjustments in credit supply after monetary policy. Third, I estimate the effects of monetary policy on the importance of specializing banks in a given industry or size category.

5.1 Extensive vs. Intensive Margin Adjustment

In this section, I analyze whethethe baseline results reflect differences in adjustments among existing borrowers (the intensive margin) or among new borrowers (the extensive margin). I do so in the context of a simple regression exercise that analyzes the evolution of interest rates and credit during the ECB's recent monetary tightening episode. I simultaneously control for specialization in industry and size category by aggregating my data on outstanding loans to the bank-industry-size level.

The general approach is as follows: I assess whether specialization played a role for how credit evolved during monetary tightening by conditioning on the degree of specialization at the outset of the hiking episode. More concretely, I estimate different regression equations in the spirit of the following specification

$$\Delta CreditCondition_{b,i,s,t-1,t+h} = \alpha_b + \alpha_{i,s} + \delta_1 Tightening_t + (\beta_1 Spec_{b,i,t-1} + \beta_2 Spec_{b,s,t-1} + \gamma_1 MktShare_{b,i,t-1} + \gamma_2 MktShare_{b,s,t-1}) * Tightening_t + e_{b,i,s,t}, \quad (5)$$

where $\Delta CreditCondition_{b,i,s,t-1,t+h}$ stands for the change between months $t-1$ and $t+h$ in either the interest rate or the log real credit amount. Equation (5) therefore regresses the change in interest rates and credit outstanding going forward on current values of the regressors. In this sense, it is conceptually similar to estimating local projections based on policy shocks.

However, in this part of the analysis, I do not estimate the effects of an externally identified monetary policy shock. Instead, to capture monetary policy tightening, I include $Tightening_t$ as a dummy variable which takes the value one if t corresponds to July 2022, i.e. if the time horizon of the change in $CreditCondition$ coincides with the ECB's tightening cycle. The coefficient on $Tightening_t$ therefore captures how the evolution of interest rates and credit after July 2022 differed to the evolution over alternative time periods (a similar approach is used in Coglianese et al., 2025). The estimation results therefore only represent statistical relationships without permitting any causal interpretation. To capture the entire monetary policy tightening cycle up to the end of 2023, I set $h = 18$. The alternative time period includes observations where t is September 2020 to avoid any overlap with the period of monetary policy tightening.

The remaining regressors are defined the same way as in equation (2). Because I aggregate my data to the bank-industry-size level, I no longer include firm controls or regional shares. However, I do include a similar set of fixed effects as before, namely bank and industry-size fixed effects. To the extent that borrowers within a certain industry-size group behave similarly in terms of credit demand, $\alpha_{i,s}$ serves as a credit demand control permitting an interpretation of β_1 as capturing predominantly effects of changes in credit supply (see Degryse et al., 2019). Moreover, I account for differences in the evolution of credit conditions across countries by including country dummies when estimating the interaction effects of specialization with $Tightening$.

The regression setup allows me to conveniently isolate intensive margin effects by constructing two different aggregates for credit outstanding in a given bank-industry-size group. The first group aggregate is formed across firms that the respective bank lends to in both periods, $t-1$ and $t+h$. In this case, $\Delta CreditCondition_{b,i,s,t-1,t+h}$ captures the change in credit conditions among existing borrowers, i.e. the intensive margin of credit adjustment.[12] The second aggregate is formed across all of the bank's borrowers during the sample period, i.e., it additionally includes credit to firms which the bank only lends to in one of the two periods. In this case, $\Delta CreditCondition_{b,i,s,t-1,t+h}$ captures the change in credit conditions among existing borrowers as well as the consequences of lending more or less or at different rates to new borrowers. That is, this measure captures both the intensive

[12]This is a fairly crude measure of existing borrowers, which only considers outstanding credit at the beginning and end of the time horizon. As such, the measure equally includes continuous holdings of the same loans, additional loans to existing borrowers, rollovers of maturing loans, or even repeated but interrupted lending relationships. As a result, my estimation results are uninformative about the mechanisms behind any differential treatment within the group of existing borrowers (e.g. through different terms on new loans to existing borrowers or through re-negotiations of existing credit). A more in-depth analysis of these mechanisms is beyond the scope of this exercise.

margin and the extensive margin change in credit conditions.

To assess the contribution of the intensive margin adjustment, I compare the results from the baseline regression where the dependent variable is the overall change in credit conditions to those obtained from a regression using the change in credit conditions among existing borrowers. I separately consider the evolution of interest rates and credit amount.

Interest Rates Table 6 shows the interaction of specialization with the evolution of interest rates on all credit (columns (1) to (5)) and on credit to existing borrowers (columns (6) to (10)). As before, specialization is captured either by a dummy variable for the highest quartile of the distribution of specialization or by a top category dummy. Again, all regression results are weighted by loan amounts.

The coefficient estimates for interest rates on all credit, presented in columns (1) to (5), are qualitatively in line with the implications of the local projections analysis presented in Figure 4. The coefficient estimate on $Tightening_t$ presented in columns (1) show that interest rates on outstanding credit rose substantially (around 2.18 percentage points) more during monetary tightening compared to the period following September 2020. Moreover, interest rates rose by close to nine basis points less for bank-industry-size groups in the highest quartile of industry specialization (column (2)).[13] There is also a significant interaction with the top industry dummy. In particular, banks raised interest rates around 10 basis points less in their respective top specialization industries (controlling for the magnitude of specialization). Finally, interactions with size specialization are insignificant, suggesting that banks did not particularly favor size categories in which they specialized when raising interest rates.

The main objective of the regression analysis is to assess the contribution of intensive margin adjustments in giving rise to these results. To this end, columns (6) to (10) show results on the evolution of interest rates on credit to existing borrowers during monetary tightening.

First, the coefficient estimate on $Tightening_t$ in column (6) implies that interest rates on credit to existing borrowers rose by 1.97, which is somewhat lower than the estimate for interest rates on all credit. All regressions are value weighted which is why the estimated coefficients for all credit can broadly be interpreted as the weighted average of the respective estimates for existing and new borrowers. The vast majority of credit (around 83 per cent) accrues to existing borrowers. Therefore banks must have raised interest rates for new borrowers very strongly in order to produce the relatively larger increase in interest rates on all credit reported in column (1).

Different to the regression results on all credit, column (7) shows that banks did not increase interest rates significantly less for existing borrowers in high specialization indus-

[13] This is substantially lower than the interaction effect estimated in column (1), excluding country dummies. Hence, there appears to be a high degree of cross-country heterogeneity in interest rate pass-through that is falsely attributed to specialization when country dummies are omitted.

TABLE 6: CHANGE IN INTEREST RATES: EXTENSIVE VS. INTENSIVE MARGIN

	Interest Rate - All Borrowers					Interest Rate - Existing Borrowers				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Tightening	2.176***					1.967***				
	(0.0718)					(0.0723)				
(HighSpec in Industry)*(Tightening)	-0.434***	-0.0898***				-0.380***	-0.0175			
	(0.0557)	(0.0235)				(0.0568)	(0.0230)			
(HighSpec in Size)*(Tightening)			-0.0396					-0.0519		
			(0.0426)					(0.0417)		
(Top Industry)*(Tightening)				-0.109**					-0.0677	
				(0.0458)					(0.0453)	
(Top Size)*(Tightening)					-0.0528					-0.0752**
					(0.0385)					(0.0380)
(Spec in Industry)*(Tightening)			-0.0138	0.00202	-0.0147			0.00609	0.0163	0.00546
			(0.0130)	(0.0157)	(0.0131)			(0.0128)	(0.0157)	(0.0128)
(Spec in Size)*(Tightening)	-0.0144	-0.00784		-0.0101	0.00999	-0.0190	-0.0133		-0.0186	0.0101
	(0.0353)	(0.0157)		(0.0151)	(0.0196)	(0.0363)	(0.0156)		(0.0150)	(0.0197)
Fixed effects	Industry-Size, Bank									
Country Dummies	No	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes
R-squared	0.736	0.834	0.834	0.834	0.834	0.717	0.834	0.834	0.834	0.834
Observations	269533	269533	269533	269533	269533	254156	254156	254156	254156	254156

Standard errors in parentheses
* p<0.1, ** p<0.05, *** p<0.01

Note. Results of estimating equation (5) where the dependent variable is the change in interest rates for all borrowers (columns (1) - (5)) and among only existing borrowers (columns (6) - (10)). Columns differ in how specialization is captured. *Tightening* is a dummy t being July 2022, i.e. the start of the tightening cycle. *HighSpec* a dummy variable for specialization being in the highest quartile of its within-country distribution. *Top <Category>* is a dummy variable for the respective borrower belonging to the highest specialization category of its lender. *Spec* is the continuous (standardized) measure of excess specialization. Standard errors are clustered at the industry-size and bank level.

tries. This suggests that the muted rate increase in rates reported in column (2) is driven by banks charging lower rates on new borrowers from high specialization industries. Because of the relatively low share of new borrower credit, this discount on interest rates for new borrowers in high specialization industries must have been quite substantial. A similar conclusion can be drawn from the coefficient estimates on the interaction with top industry. In particular, the insignificant coefficient in column (9) implies that the muted increase in interest rates in top industries observed for all credit is driven by strong differences between interest rates charged to new borrowers from different industries. As for all credit, the interaction coefficients on size specialization among existing borrowers are generally insignificant. However, interest rates increased significantly less for existing borrowers in top size categories as shown in column (10).

Overall, the muted increase in interest rates on credit to high specialization industries appears to be exclusively driven by banks differentiating strongly between high and low specialization industries when handing out credit to new borrowers. In contrast, there was no significant marginal effect of high specialization on interest rates among existing borrowers.

Credit Outstanding Table 7 now shows the results of estimating equation (5) where the dependent variables are the log-change in total credit outstanding and the log-change in credit to existing borrowers. Again the estimates on total credit outstanding in columns (1) to (5) are qualitatively in line with the local projection results presented above. Specifically, the change in credit outstanding was substantially (16.7 percentage points) lower over the 18 month period following July 2022 as shown in column (1). At the same time, column (2) shows that banks reduced credit by 4.5 percentage points less in industries and by 6.6 percentage points less in size categories where they were highly specialized. The coefficients on interactions with the top category dummy are insignificant.

TABLE 7: CHANGE IN CREDIT OUTSTANDING: EXTENSIVE VS. INTENSIVE MARGIN

	Credit Outstanding - All Borrowers					Credit Outstanding - Existing Borrowers				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Tightening	-0.167***					-0.0801***				
	(0.0106)					(0.00751)				
(HighSpec in Industry)*(Tightening)	0.0530***	0.0448***				0.0392***	0.0274***			
	(0.0133)	(0.0126)				(0.00961)	(0.00938)			
(HighSpec in Size)*(Tightening)			0.0662***					0.0682***		
			(0.0160)					(0.0119)		
(Top Industry)*(Tightening)				0.00936					0.0214	
				(0.0240)					(0.0184)	
(Top Size)*(Tightening)					-0.0233					-0.00509
					(0.0166)					(0.0129)
(Spec in Industry)*(Tightening)			0.0109*	0.00819	0.00942			-0.00114	-0.00398	-0.000901
			(0.00639)	(0.00832)	(0.00613)			(0.00465)	(0.00614)	(0.00461)
(Spec in Size)*(Tightening)	0.0397***	0.0366***		0.0362***	0.0450***	0.0244***	0.0207***		0.0243***	0.0262***
	(0.0111)	(0.0110)		(0.0104)	(0.0137)	(0.00569)	(0.00552)		(0.00532)	(0.00730)
Fixed effects	Industry-Size, Bank									
Country Dummies	No	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes
R-squared	0.164	0.180	0.180	0.180	0.180	0.112	0.120	0.121	0.120	0.120
Observations	269955	269955	269955	269955	269955	254549	254549	254549	254549	254549

Standard errors in parentheses
* p<0.1, ** p<0.05, *** p<0.01

Note. Results of estimating equation (5) where the dependent variable is the log-change in total credit (columns (1) - (5)) and the log-change in credit to existing borrowers (columns (6) - (10)). Columns differ in how specialization is captured. *Tightening* is a dummy t being July 2022, i.e. the start of the tightening cycle. *HighSpec* a dummy variable for specialization being in the highest quartile of its within-country distribution. *Top <Category>* is a dummy variable for the respective borrower belonging to the highest specialization category of its lender. *Spec* is the continuous (standardized) measure of excess specialization. Standard errors are clustered at the industry-size and bank level.

The estimation results on changes in credit to existing borrowers are presented in columns (6) to (10). First, banks reduced credit to these borrowers by around 8 percentage points, only half as much as the reduction in total credit. This implies that the change in total credit primarily occurred through severe reductions in credit to new borrowers.[14] The reduction in credit to existing borrowers in industries with high specialization was muted by only 2.7 percentage points. The interaction effect of industry specialization for total credit was therefore strongly driven by difference in the allocation of credit to new borrowers. At the same time, the magnitude of the interaction coefficient in relation to the average response is higher for existing borrowers which in turn points towards a weaker

[14]A simple back-of-the-envelope calculation helps putting the estimates into perspective. The average share of credit to existing borrowers out of total credit was 83 per cent in July 2022. This means that the contribution of intensive margin adjustment to the reduction in total credit was around $-0.08 * 0.83 = -0.0664$, leaving around 10 percentage points explained by changes in credit to new borrowers. To produce such a sizable contribution to changes in total credit despite the relatively low relevance of new borrowers, there must have been a substantial relative fall in credit to this group, specifically, $-0.1/0.17 = -0.58$ or 58 percentage points.

dampening effect in relation to the average response among new borrowers.

High specialization in size categories played an even stronger role, dampening the reduction in credit after mid-2022 by 6.6 percentage points. This is almost identical to the dampening effect among existing borrowers although this figure is much larger when related to the average credit reduction in this group. In turn, this implies that the marginal effect of specialization among new borrowers was slightly weaker in absolute terms and much smaller in relation to the average reduction in credit in this group. In line with the results on credit outstanding to all borrowers, there was no significant marginal effect of top industry or top size category on the change in credit to existing borrowers.

Generally speaking, insulating high specialization industries from credit reductions took place both among new and existing borrowers. However, in relation to the average reduction in credit, this type of shielding was substantially more pronounced among existing borrowers.

What do the estimation results of this simple regression analysis tell us about the drivers behind the estimated responses to monetary policy shocks presented in the previous section? To some extent, banks also shielded their existing borrowers from overall increases in interest rates and reductions in credit. That is, the average changes in interest rates and credit outstanding can in large parts be attributed to adjustments along the extensive margin. At the same time, there are qualitative differences between the drivers of marginal effects of specialization on interest rates and credit amounts. In relation to the average increase in interest rates, the dampening effect of belonging to a high specialization group was much stronger among new borrowers. In fact nearly all of the marginal effect of specialization on interest rate changes can be attributed to adjustments at the extensive margin. In contrast, the dampening effect of high specialization on reductions in credit outstanding was much more pronounced among existing borrowers (when compared to the average credit reduction). This means that the shielding of high specialization industries from credit reductions can largely be attributed to adjustments at the intensive margin.

5.2 Specialization Intensity and Policy Effectiveness

Banks reduce credit relatively less in industries or size categories in which they specialize. A potential direct consequence is that credit contracts less within categories that are dominated by banks with high levels of specialization in the respective groups. I now explicitly test the empirical validity of this implication.

To this end, I reduce my data to the industry-size category level and explore the marginal effects of higher specialization intensity on monetary policy responses. I simultaneously consider two measures of specialization intensity. First, the share of credit in a given category and country that is originated by banks with a high level of excess specialization in that category. Specialization is assumed to be high if it lies within the highest quintile of the respective country-specific distribution. Although somewhat arbitrary, this cutoff makes sure that I capture banks with substantial levels of specialization without being too restrictive. The mean share of high specialization credit is 25.7 per cent for industries and 11.6 per cent for size categories. As a second measure of specialization intensity, I consider the average magnitude of excess specialization that this credit by highly specialized banks is subject to.

To assess the role of specialization intensity for the transmission of monetary policy to credit, I estimate local projections similar to the ones specified above. In particular, I run the following regressions

$$\begin{aligned}\Delta Credit_{i,s,c,t+h,t-1} = \alpha_{i,s} + \alpha_{c,t} + \left(\beta_{1h}^{int} HighspecShare_{i,c,t-1} + \beta_{2h}^{int} HighspecShare_{s,c,t-1}\right)\Delta R_t \\ + \left(\beta_{3h}^{int} HighspecMean_{i,c,t-1} + \beta_{4h}^{int} HighspecMean_{s,c,t-1}\right)\Delta R_t \\ + \Gamma_{1h} Z_{i,s,c,t-1} + \Gamma_{2h} Z_{i,s,c,t-1}\Delta R_t + e_{i,s,c,t+h} \quad (6)\end{aligned}$$

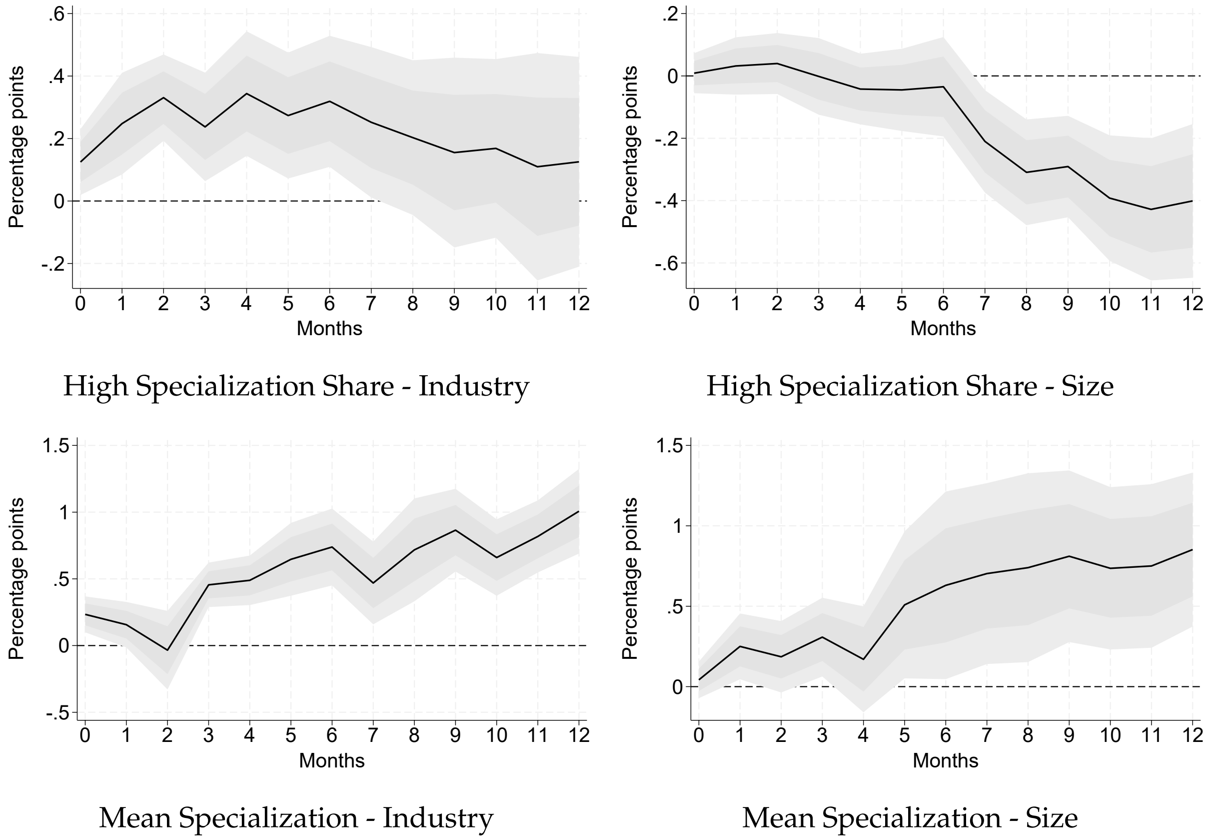
The dependent variable $Credit_{i,s,c,t+h,t-1}$ denotes the log change in credit outstanding to borrowers in industry i, size category s and country c between periods $t-1$ and $t+h$. The regressors $HighspecShare_{i,c,t-1}$ and $HighspecShare_{s,c,t-1}$ are the shares of credit originated by banks with high specialization. Similarly, $HighspecMean_{i,c,t-1}$ and $HighspecMean_{s,c,t-1}$ are the weighted means of excess specialization that this credit by specializing banks is subject to. Taken together, these four regressors are meant to reflect specialization intensity in industry i and size category s. The interaction coefficients β_{1h}^{int} to β_{4h}^{int} are the main coefficients of interest. They capture the marginal effects of higher degrees of specialization intensity on the credit response to monetary policy.

As before, monetary policy is captured by changes in the one month EURIBOR rate instrumented by the *Target* factor from Altavilla et al. (2019). To isolate the effects of specialization intensity, the vector $Z_{i,s,c,t-1}$ includes measures of market concentration, specifically, the country-specific Herfindahl-Hirschman index of bank competition in industry i or size category s. It also includes weighted means of maturity, collateral share and probability of default as well as four lags of the dependent variable. $\alpha_{i,s}$ and $\alpha_{c,t}$ are fixed effects as before.

The volume-weighted coefficient estimates of β_{1h}^{int} to β_{4h}^{int} for different horizons are presented in Figure 6. More specifically, the top left panel shows the marginal effect of a ten percentage point higher share of high industry-specialization credit on the effect of a 25 basis point shock to the policy rate. The top right panel equivalently shows the marginal effect of a ten percentage point higher share of high size-specialization credit. The bottom panels show the corresponding marginal effects of one unit higher mean specialization in industry and size (among high-specialization credit).

The top left panel of Figure 6 indicates, that a higher share of credit by banks specializing in the respective industry generally dampens the credit reduction associated with a

FIGURE 6: SPECIALIZATION INTENSITY AND POLICY EFFECTIVENESS



Note. Marginal effects of higher specialization intensity on the response of log credit to an exogenous 25bp increase in the policy rate. Based on coefficient estimates β_{1h}^{int} to β_{4h}^{int} from equation (6). For the top panels, coefficient estimates are scaled to represent the marginal effect of a ten percentage points higher share of high specialization credit. Gray bars represent 68 and 90 per cent confidence intervals based on clustered standard errors by month.

monetary policy shock. This dampening effect peaks at 0.3 percentage points after six months and is statistically significant up to seven months after the shock. Somewhat counter-intuitively, the top right panel suggests that in the case of size specialization, a higher share *amplifies* the reductions in credit at very long horizons. The bottom panels show that in the context of both industry and size category, the degree of specialization matters for monetary policy transmission. For a given share of credit by specializing banks, there is a significant additional dampening effect if this credit is subject to a higher magnitude of specialization.

Generally speaking, specialization intensity appears to have a dampening effect on the effects of monetary policy on credit. This has two potential policy implications. First, it means that some borrowers may be less affected by monetary policy simply because they operate in a certain industry or belong to a certain size category where specialization is particularly pronounced. Second, it suggests that monetary policy may generally be less effective when the most relevant industries or size categories in an economy are characterized by intense specialization.

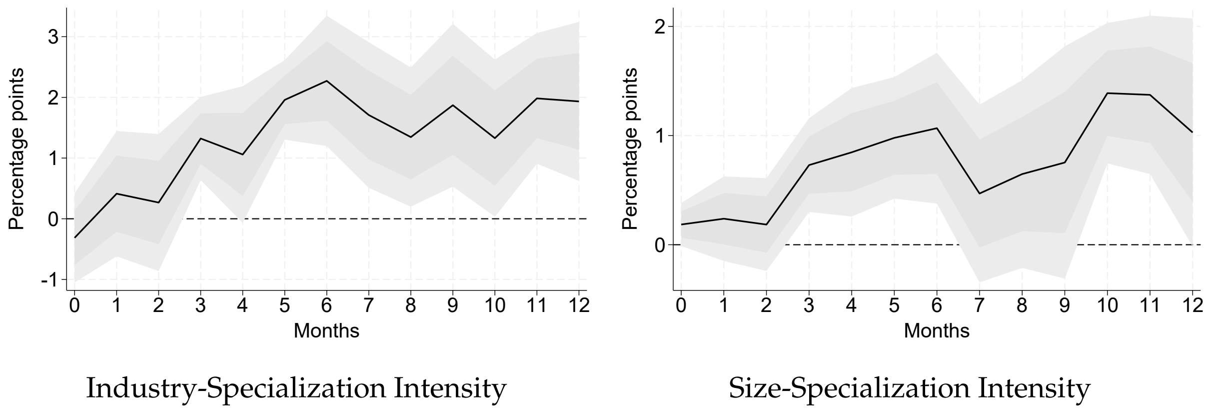
5.3 Monetary Policy Effects on Specialization Intensity

The second implication of banks insulating high specialization industries from changes in credit is that contractionary (expansionary) monetary policy shocks raise (reduce) the fraction of credit in the hands of specializing banks. To explicitly test this implication, I estimate equations in the spirit of (6) above. However, I now set the change in high specialization shares as dependent variables. Specifically, I estimate:

$$\Delta HighspecShare_{i,c,t-1,t+h} = \alpha_{i,s} + \alpha_c + \beta_{1h}^{sint}\Delta R_t + \Gamma_{1h}Z_{i,s,c,t-1} + \Gamma_{2h}Z_{i,s,c,t-1}\Delta R_t + \sum_{k=1}^{4}\Gamma_{3h,k}Y_{c,t-k} + e_{i,s,c,t+h} \quad (7)$$

where all the variables are defined as before and $Z_{i,s,c,t-1}$ includes high specialization shares in $t-1$. The main coefficient of interest is β_{1h}^{sint}, tracing the effect of exogenous changes in the policy rate on the share of credit originated by highly specialized banks. The coefficient estimates associated with a 25bp change in the policy rate are depicted in Figure 7.

FIGURE 7: MONETARY POLICY EFFECTS ON SPECIALIZATION INTENSITY



Note. Effects of an exogenous 25bp increase in the policy rate on specialization intensity. Based on coefficient estimates β_{1h}^{sint} from equation (7). Gray bars represent 68 and 90 per cent confidence intervals based on clustered standard errors by month.

Consistent with my previous finding, contractionary monetary policy is estimated to lead to an increase in specialization intensity. In particular, panel (a) shows that the share of credit intermediated by banks that are highly specialized in the respective industry increases on average by 2 percentage points around six months after the shock and remains elevated until the end of the time horizon considered. Panel (b) shows a similar effect of monetary policy on the share of credit by banks specialized in the respective size category. This effect is statistically significant but somewhat smaller than the effect on industry-specialization intensity, peaking at just over one percentage point one year after the shock.

The results presented in Figure 7 confirm the implications of my previous results. Faced with a monetary tightening, banks reduce credit relatively less in industries and size categories where they are highly specialized. This effective reallocation of credit leads to an increase in the share of credit intermediated by highly specialized banks.

6 Conclusion

In this paper, I explore the role of bank specialization for euro area monetary policy. Specialization is defined as over-proportional exposure of banks to borrowers from certain industries or of certain size. I find that this kind of specialization is highly prevalent among euro area banks and that banks offer more favorable loan terms to borrowers from groups in which they specialize. This is consistent with the idea that specialization is associated with informational advantages in screening and monitoring that borrowers benefit from (see Blickle et al., 2025).

To assess how specialization interacts with monetary policy, I estimate the effects of high frequency identified monetary policy shocks using panel local projections. I find that specialization appears to dampen the pass-through of monetary policy to corporate lending rates and credit volumes. Specifically, banks adjust interest rates and lending less strongly to borrowers in groups where they specialize. I also provide extensions to these baseline findings. First, I argue that in the context of interest rate pass-through, the marginal effect of specialization primarily stems from adjustments at the extensive margin while the intensive margin is more relevant for the effects on credit outstanding. Second, I show that industries dominated by specializing banks are generally less affected by monetary policy. Lastly, contractionary monetary policy leads to an increase in the share of credit by specializing banks.

I find no evidence for asymmetry in how specialization interacts with contractionary or expansionary monetary policy shocks. However, this result should be interpreted with caution, as the analysis is based on data covering an exceptionally strong monetary tightening cycle. For the same reason, all of the estimated effects likely represent upper bounds and may not generalize to periods of more gradual monetary tightening or monetary easing. Future research incorporating data from both monetary easing and tightening would provide a more comprehensive understanding of the role of specialization for monetary policy transmission.

My results suggest that heterogeneity in monetary policy responses across firms might not only depend on their own balance sheet characteristics as often considered in the literature (see, e.g., Ottonello and Winberry, 2020) but also on the degree of specialization among banks they borrow from. More work is still required to verify the empirical relevance of these potential implications. Specifically, a promising avenue for future research would be to look at potential real effects of specialization through differential access to credit for firms. This could be done by considering the interaction of specialization with firm growth, investment and market shares.

Finally, my analysis is silent on the underlying causes of the insulating behavior of banks that is key for interaction between bank specialization and monetary policy transmission. One potential driver might be the presence of concentration risk associated with higher specialization. Specifically, banks might pass on the adverse effects of monetary tightening less to their preferred categories to avoid defaults in areas where they are heavily exposed. An alternative reason for the reallocation of credit to preferred borrower groups might be that the informational advantage of specialization documented by Simoens and Tamburrini (2025) becomes more relevant during monetary tightening when firm prospects generally deteriorate. An explicit empirical investigation of these or other potential mechanisms is also left for future research.

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Appendix

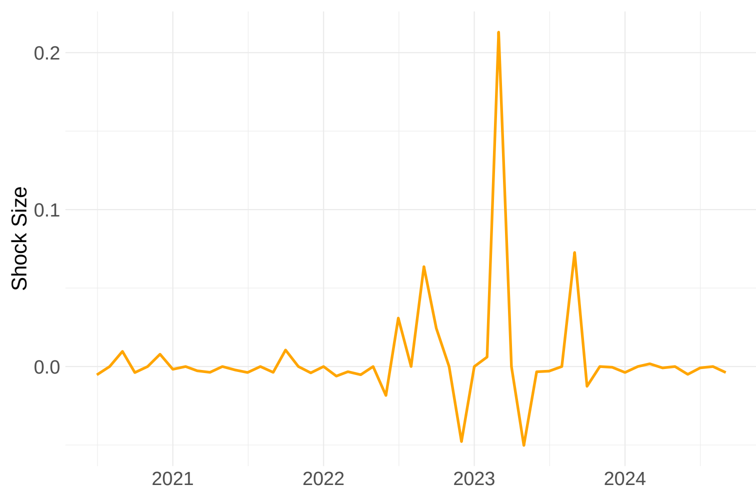
A Data

TABLE A.1: IMPLICATIONS OF SELECTION FOR SAMPLE SIZE IN 2020-07

Country	Loan number after selection (% of initial)				Loan volume after selection (% of initial)			
	No syndicated loans	Loan types	No default firms	Domestic only	No syndicated loans	Loan types	No default firms	Domestic only
AT	83.75	73.38	70.87	68.20	74.34	59.69	58.00	51.50
BE	99.34	86.52	84.19	83.21	89.36	81.37	79.43	71.95
CY	99.63	60.66	41.02	40.46	95.23	72.18	57.28	53.06
DE	90.30	77.54	75.76	75.12	73.78	59.44	58.53	56.87
EE	98.92	66.02	64.74	64.69	89.63	70.30	69.35	69.16
ES	98.93	90.42	84.16	84.09	85.90	80.02	75.69	74.99
FI	96.12	79.26	76.61	76.51	90.99	86.02	84.09	83.76
FR	98.31	88.35	84.98	84.93	83.30	75.51	73.54	73.10
GR	96.12	93.68	81.99	81.92	72.00	66.82	55.35	55.12
IE	97.10	44.43	42.94	40.91	75.22	53.17	51.03	36.56
IT	96.61	54.62	50.56	50.54	79.82	49.07	44.89	44.64
LT	99.09	52.28	50.46	50.38	91.18	67.58	65.75	65.42
LU	69.07	55.50	53.96	30.83	50.03	37.89	37.31	13.48
LV	99.39	85.81	83.28	82.57	93.20	78.98	76.08	72.55
MT	97.25	51.45	45.97	45.42	92.97	55.73	50.32	48.07
NL	98.72	30.09	29.18	28.52	91.78	45.26	44.45	40.61
PT	99.52	83.68	76.83	76.77	95.73	80.53	71.66	71.58
SI	97.40	71.04	67.84	67.62	70.93	61.35	59.32	58.05
SK	99.03	57.75	55.53	55.46	83.22	40.41	39.33	37.80
Euro Area	96.46	76.50	72.67	72.33	80.39	64.27	61.69	59.63

Note. Effect of sample selection as described in the main text on loan numbers and volumes. Columns contain the number of loans and volumes remaining after successively applying sample selections in per cent of the initial total.

FIGURE A.1: MONETARY POLICY SHOCK SERIES



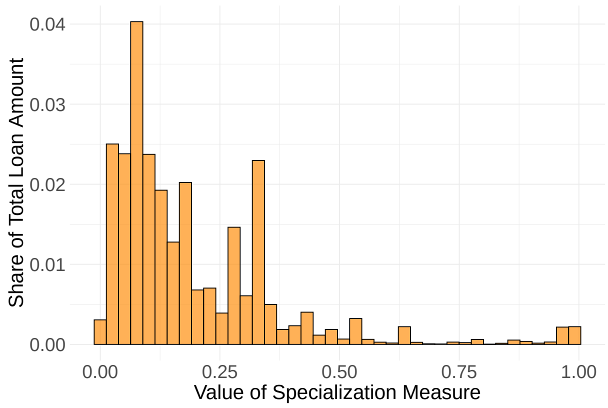
Note. Monetary policy shocks used as instruments in the local projection estimations. Based on the *Target* factor of monetary policy surprises as derived in Altavilla et al. (2019). Surprises are assigned to the respective month in which they occur.

B Specialization Patterns

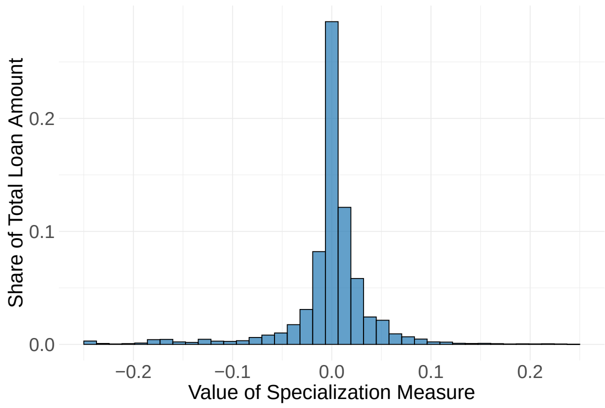
B.1 Specialization Weighted by Credit Amount

Figure B.1 conveys the relevance of specialization in top categories in terms of loan amounts. In all four panels, the histograms depict shares of total credit subject to particular bins of the distribution of excess specialization values. The left panels depicts specialization among the respective top categories and the right panels show specialization in all other categories. In a given row, the total height of the bars in the left panel represent the total share of top category credit and the total height in the right panel represents the total share of non-top category credit. The two totals in each row sum up to one. According to the figure, specialization is relevant also in terms of credit amounts.

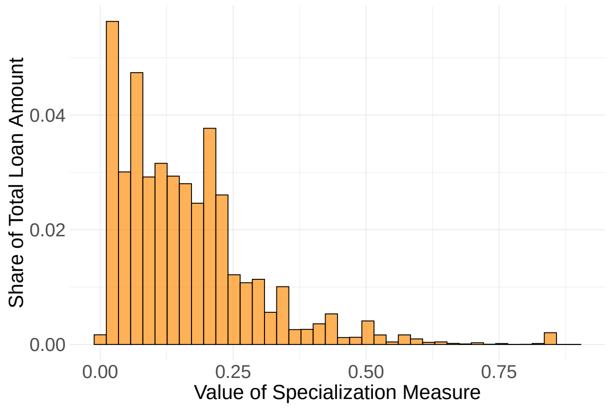
FIGURE B.1: EXCESS SPECIALIZATION WEIGHTED BY CREDIT AMOUNT



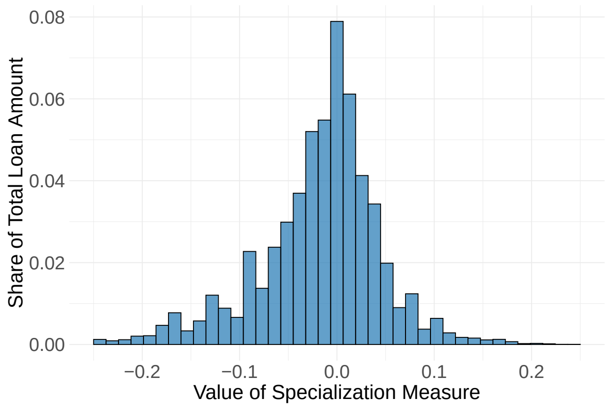
(a) Top Industry



(b) Other Industries



(c) Top Size Category

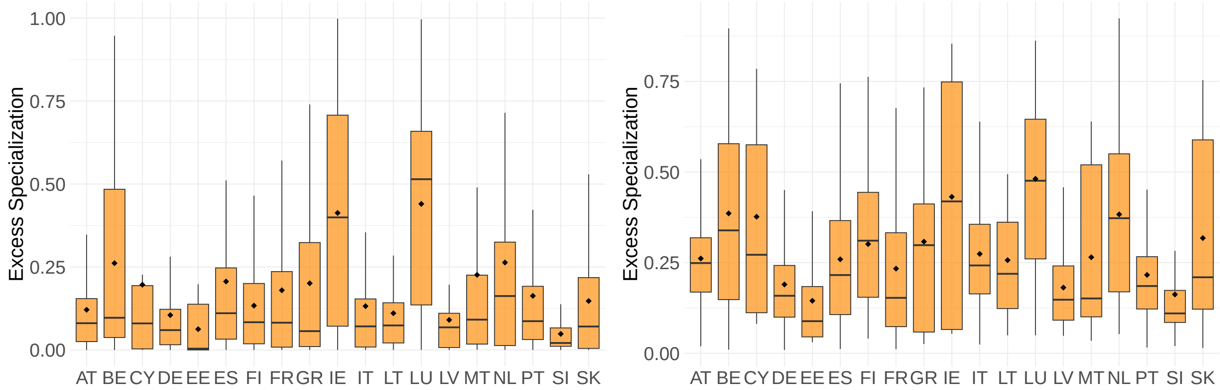


(d) Other Size Categories

Note. Shares of total credit subject to different degrees of specialization in July 2020. Left panels show only banks' top industries and right panels show all other categories. Bars represent shares of total credit, such that the height of all bars in a given row adds op to one.

B.2 Specialization by Country

FIGURE B.2: EXCESS SPECIALIZATION BY COUNTRY

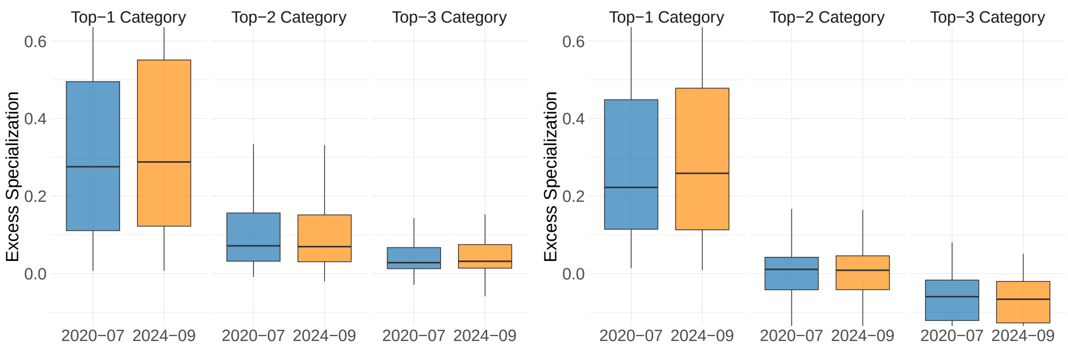


(a) Top Industry (b) Top Size Category

Note. Distribution across banks of excess specialization in respective top categories in July 2020 separately for each country. Diamonds represent mean specialization levels.

B.3 Specialization among Large Banks

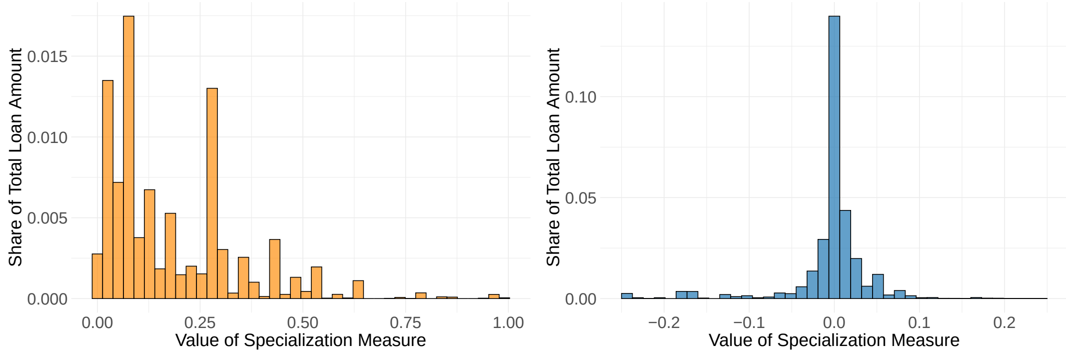
FIGURE B.3: EXCESS SPECIALIZATION IN TOP CATEGORIES - LARGE BANKS



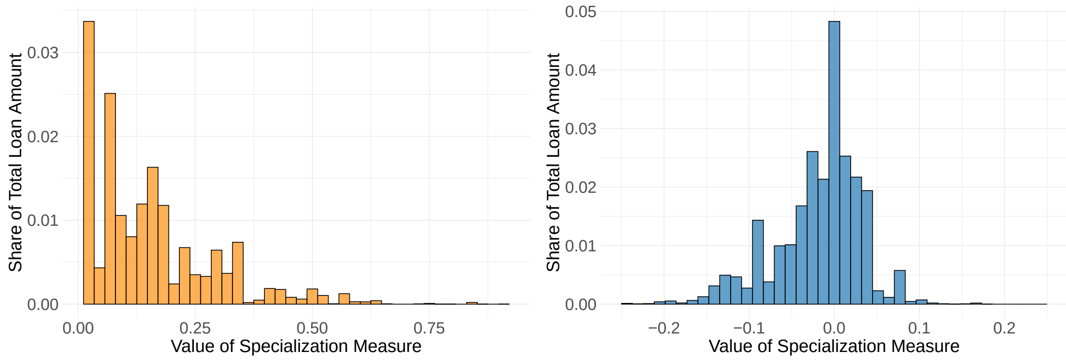
(a) Specialization by Industry (b) Specialization by Firm Size

Note. Distribution across large banks of excess specialization in respective top categories in July 2020 and September 2024. Banks are classified as large if their assets are above the 90th percentile of the cross sectional distribution within the respective country.

Figure B.4: Excess Specialization Weighted by Credit Amount - Large Banks



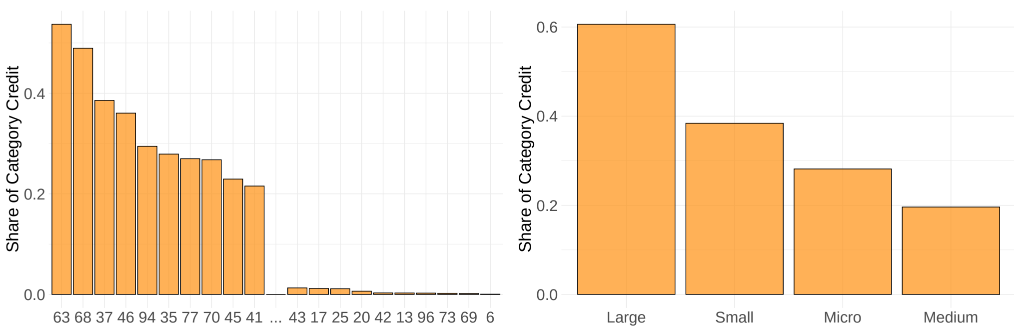
(a) Top Industry (b) Other Industries



(c) Top Size Category (d) Other Size Categories

Note. Shares of total credit subject to different degrees of specialization in July 2020 among large banks. Banks are classified as large if their assets are above the 90th percentile of the cross sectional distribution within the respective country. Left panels show only bank's top categories and right panels show all other categories. Bars represent shares of total credit so the height of all bars in a given row adds op to one.

Figure B.5: Specialization Intensity by Category - Large Banks

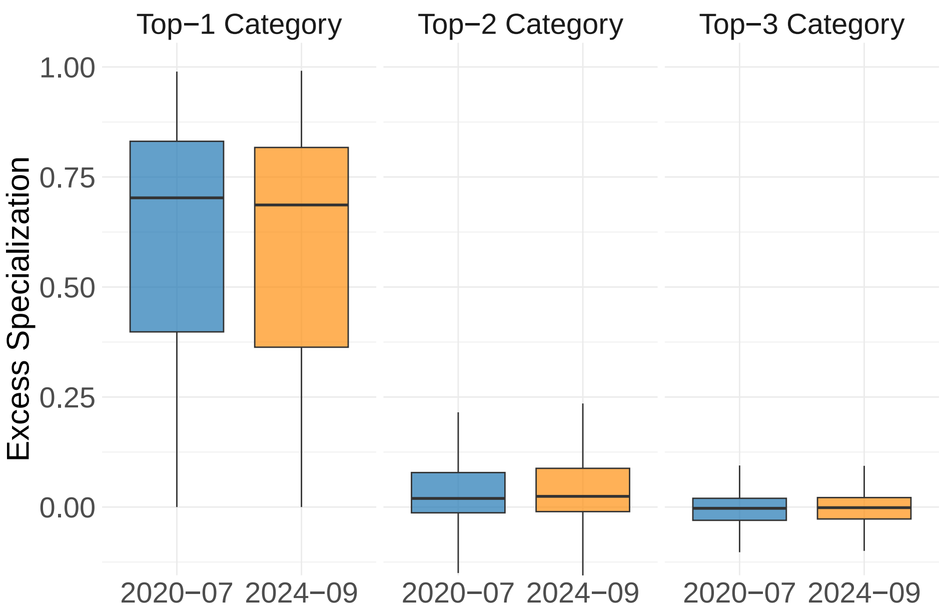


(a) Industries (b) Size Categories

Note. Specialization intensities for different industries (left panel) and size categories (right panel) in July 2020 among large banks. Banks are classified as large if their assets are above the 90th percentile of the cross sectional distribution within the respective country. Specialization intensity is defined as the share of total credit within a given category that comes from banks for which this particular category is the most preferred one.

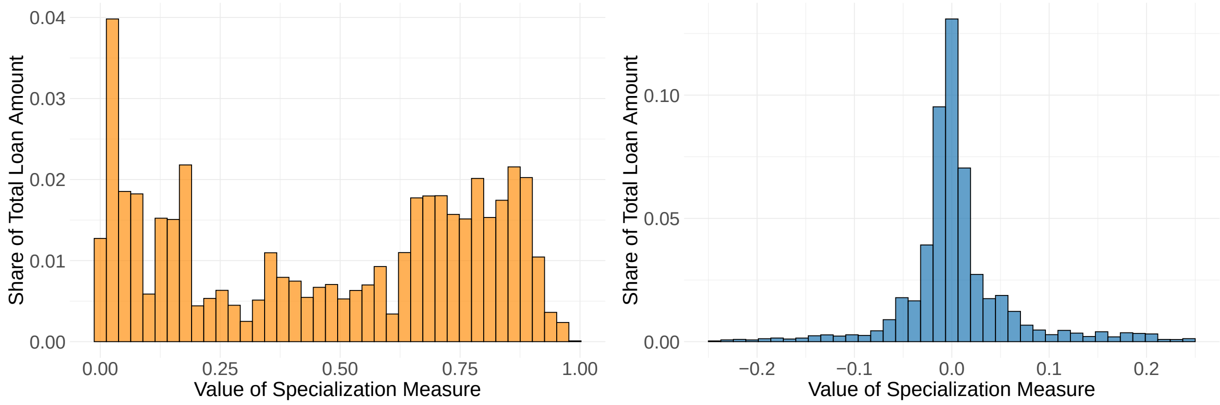
B.4 Regional Specialization

FIGURE B.6: EXCESS SPECIALIZATION BY REGION



Note. Distribution across banks of excess specialization in top NUTS2-regions in July 2020 and September 2024.

FIGURE B.7: WEIGHTED EXCESS SPECIALIZATION BY REGION



(a) Top Region

(b) Other Regions

Note. Shares of total credit subject to different degrees of regional specialization in September 2024. Left panel shows only banks' top NUTS2-regions and right panel shows all other regions. Bars represent shares of total credit so the height of all bars adds op to one.

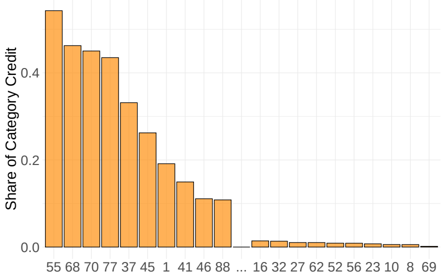
B.5 Specialization Intensity by Country

Figure B.8 depicts specialization intensities in industries for the eight largest euro area economies. Specialization intensity is defined as the share of credit within an industry that is originated by banks for which that particular industry is the most preferred one. An industries that does not appear in a graph is not the most preferred one for any bank in the respective country.

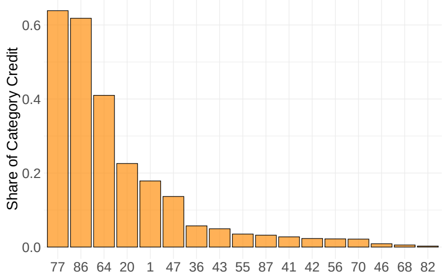
There are notable differences in specialization intensities across countries, which are hidden from the aggregate figure presented in the main text. First, there is substantial variability in the number of industries that are preferred by banks, even between credit markets that can be considered to be of roughly similar size (such as France and Italy). Moreover, there are large differences in the shares of credit originated by specializers in the respective most specialization-intensive industries. In the Netherlands, close to 80 per cent of credit in the most specialization-intensive industry comes from specializers, while the figure is only around 30 per cent in Italy.

The industries that are characterized by the highest specialization intensities are often quite different across countries. For instance, credit to firms in Agriculture (NACE code 1) is dominated by specializing banks in France, Portugal and, to some extent, Germany. On the other hand, specializers play a limited role for agricultural lending in Italy and Spain and in the Netherlands, it is not the most preferred industry for any bank. Conversely, Real Estate (NACE code 68) is strongly dominated by specializers in the Netherlands, France, Germany and Austria but much less so in Belgium and Spain.

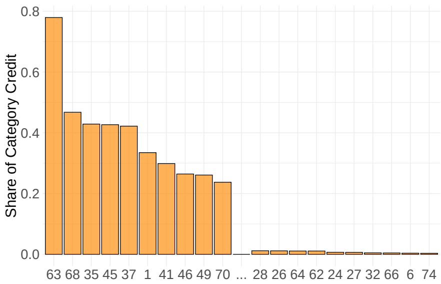
FIGURE B.8: SPECIALIZATION INTENSITY IN INDUSTRIES - COUNTRY COMPARISON



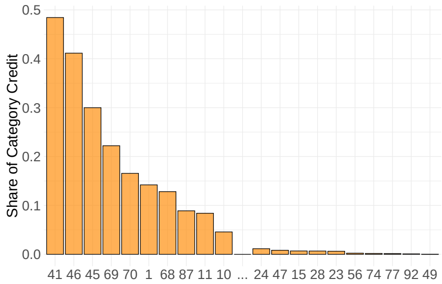
(a) Austria



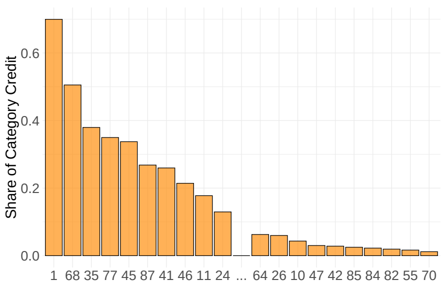
(b) Belgium



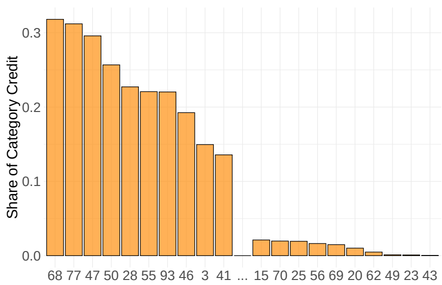
(c) Germany



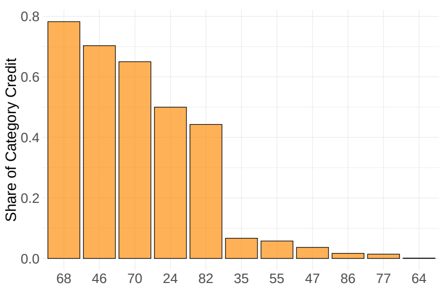
(d) Spain



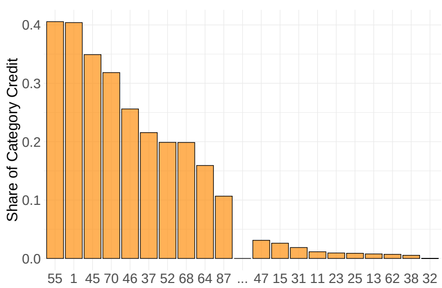
(e) France



(f) Italy



(g) Netherlands

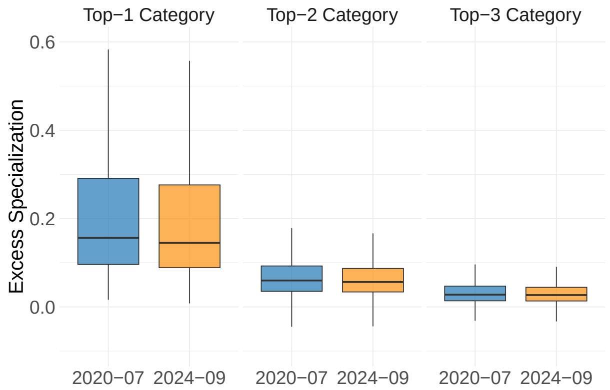


(h) Portugal

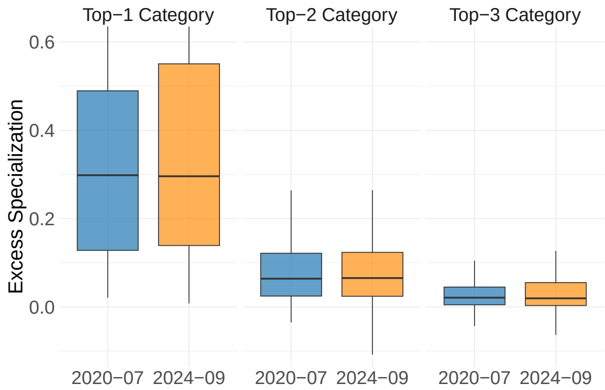
Note. Specialization intensities in industries in July 2020 separately for different countries. Specialization intensity is defined as the share of total credit within a given industry that comes from banks for which this particular industry is the most preferred one.

B.6 Sector Specialization

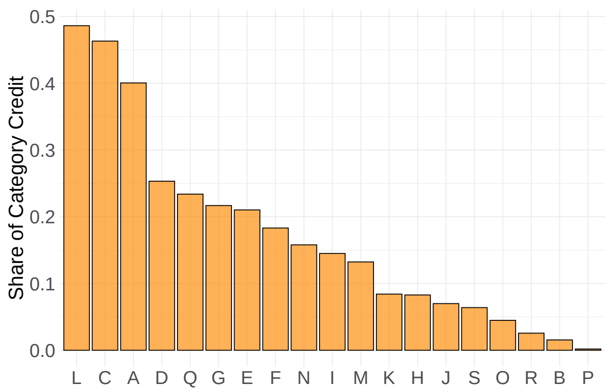
FIGURE B.9: PATTERNS OF EXCESS SPECIALIZATION IN SECTORS



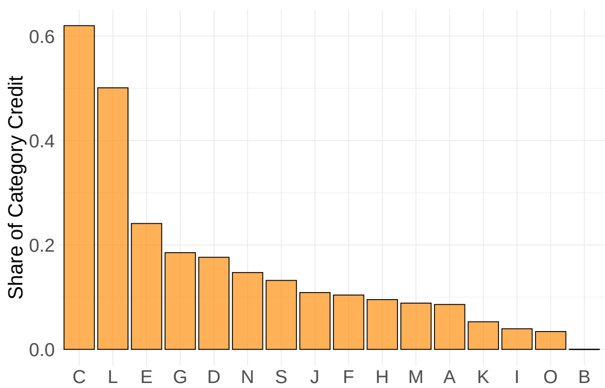
(a) All Banks



(b) Large Banks



(c) All Banks



(d) Large Banks

Note. Specialization patterns in sectors (one-digit NACE) for all banks (left column) and large banks (right column). Banks are classified as large if their assets are above the 90th percentile of the cross sectional distribution within the respective country. The top row depicts the distribution across banks of excess specialization in respective top categories in July 2020 and September 2024. The bottom row depicts specialization intensities for different sectors in July 2020.

C Robustness

C.1 Excess vs. Relative Specialization

Throughout my analysis, I define specialization as the difference between the share of a borrower group in a bank's credit portfolio and the share of this group in the economy's total credit. However, parts of the literature use the ratio of these two terms as an alternative measure of bank specialization (see e.g. Paravisini et al., 2023). That is, using the same notation as in equation (1), they define *relative specialization* as:

$$RelSpecialization_{b,s,t} \equiv \frac{\frac{LoanAmount_{b,s,t}}{\sum_s LoanAmount_{b,s,t}}}{\frac{\sum_b LoanAmount_{b,s,t}}{\sum_b \sum_s LoanAmount_{b,s,t}}} \tag{C.8}$$

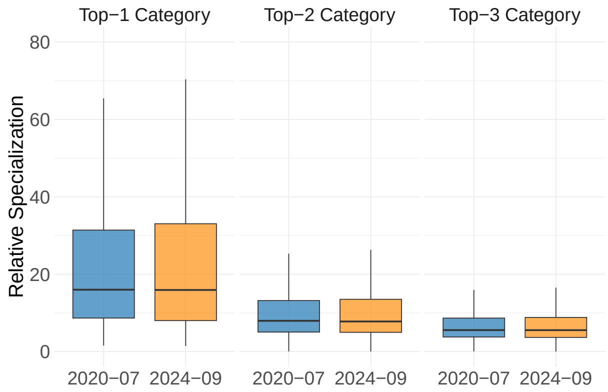
The most important difference between excess specialization and relative specialization (C.8) is that the latter is much more sensitive to the economy-wide share of credit. To fix ideas, consider a bank that lends 5 per cent of its portfolio to Industry A and 30 per cent to industry B. The share of Industry A credit in the economy is 1 per cent while the corresponding share of Industry B is 26 per cent. In this case, the bank has excess specialization of 4 percentage points in both industries. However, the relative specialization is 5 in Industry A and only 1.15 in Industry B.

In a sense, relative specialization is therefore a more accurate measure of over-exposure in a certain industry. After all, lending 5 per cent to a very small industry is much more noteworthy than lending 30 per cent to an industry that is generally quite important. At the same time, as the above example shows, a bank can incur a very high relative specialization even if its own overall credit exposure to this category is relatively small. In this case, we would not necessarily expect this category to play a special role in the bank's lending decisions despite its large relative specialization value.[15]

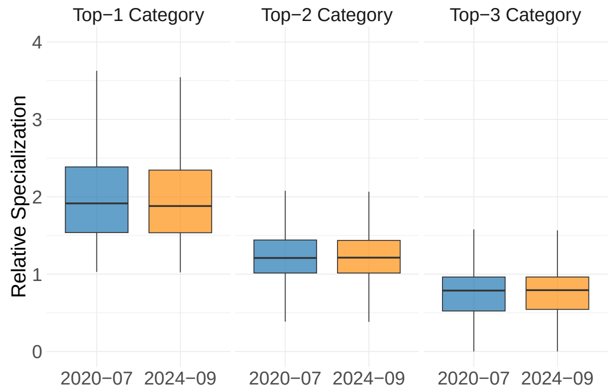
In the context of my analysis, this sensitivity to total industry credit means that some bank-category pairs are characterized by very large degrees of relative specialization which makes this measure hard to interpret. As highlighted by Blickle et al. (2025), relative specialization is therefore characterized by very large right tails. To illustrate this, Figure C.1 contains a box-plots of relative specialization in top industries and size categories analogous to Figure 1 in the main text. The median relative specialization in bank's top industries depicted in the left panel is around 18 while the whiskers of the box plot go up to 70, indicating extreme levels of relative specialization among the top industries. Moreover, even the top 3 industry has a median relative specialization of more than five. This means that banks are far away from perfect diversification in these industries, contrasting with the results on excess specialization in Figure 1.

[15] In fact, several contributions define specialization simply as the exposure of a bank to a certain borrower group without adjusting in any way to economy-wide shares, implicitly assuming that the absolute exposure matters most for banks' decisions.

FIGURE C.1: RELATIVE SPECIALIZATION IN TOP CATEGORIES



(a) Specialization by Industry



(b) Specialization by Firm Size

Note. Distribution across banks of *relative* specialization in respective top categories in July 2020 and September 2024. Panel (a) represents top industries and panel (b) top size classes.

However, as explained above, high relative specialization values may equally reflect a relatively low exposure to small industries. In this case, the very high relative specialization values may refer to industries that account for very little credit overall. In fact, the share of total lending that accrues to top relative specialization industries is only 3.8 per cent, comparing to 29.5 per cent for excess specialization. This suggests that the top relative specialization industries are indeed predominantly small industries.

In contrast, the analogous results on relative specialization in size depicted in the right panel of Figure C.1 are much more in line with those on excess specialization. The reason is that there are no very small size categories which drive up relative specialization values compared to excess specialization. Accordingly, credit to most preferred size categories measured by relative specialization accounts for 42 per cent in total credit, which is comparable to the 43.7 per cent in the case of excess specialization.

Most importantly, using relative as opposed to excess specialization also has different implication in terms of the observations identified by the dummy variables for high specialization and top categories used in may part of my analysis. Specifically, in September 2024, out of all bank-industry pairs falling within the fourth quartile of the excess specialization distribution, around 75 per cent also fell within the highest quartile of the respective distribution of relative specialization. However, for the reasons outlined above, out of the bank-industry pairs identified as most preferred when measured by excess specialization, only 8.5 per cent were also ranked highest when measured by relative specialization. Also consistent with the discussion above, the choice of specialization measure is much less decisive in the context of size specialization where the corresponding figures are 92 and 93 per cent.

C.2 Benchmark: Average Responses

As a benchmark, Tables C.1 and C.1 show the results of estimating specifications (3) and (4) where the sequences of forward changes on the left hand side are replaced by their means over horizons 0 to 12.

TABLE C.1: AVERAGE RESPONSES AND SIZE SPECIALIZATION

	Interest Rate			Credit Outstanding		
	(1)	(2)	(3)	(4)	(5)	(6)
Policy Rate	1.047***			-0.0554**		
	(0.173)			(0.0217)		
(Policy Rate)*(High Spec.)		-0.0253			0.0243*	
		(0.0325)			(0.0126)	
(Policy Rate)*(Top)			-0.0649*			0.0255***
			(0.0336)			(0.00689)
R-squared	0.507	0.0275	0.0284	0.0196	0.0144	0.0162
Observations	274837	274837	274837	273893	273893	273893

Standard errors in parentheses
* p<0.1, ** p<0.05, *** p<0.01

Note. Results of estimating equations (3) and (4) where the dependent variable is the average change in interest rates or credit. $(PolicyRate) * (HighSpec.)$ and $(PolicyRate) * (Top)$ refer to interactions of the policy rate with the top quartile dummy of excess size specialization and the top size category dummy respectively.

TABLE C.2: AVERAGE RESPONSES AND INDUSTRY SPECIALIZATION

	Interest Rate			Credit Outstanding		
	(1)	(2)	(3)	(4)	(5)	(6)
Policy Rate	1.200***			-0.0674***		
	(0.148)			(0.0199)		
(Policy Rate)*(High Spec.)		-0.0328			0.0251**	
		(0.0235)			(0.0123)	
(Policy Rate)*(Top)			-0.122***			0.0223*
			(0.0284)			(0.0112)
R-squared	0.421	0.0191	0.0204	0.0197	0.0207	0.0189
Observations	2677357	2677357	2677357	2668778	2668778	2668778

Standard errors in parentheses
* p<0.1, ** p<0.05, *** p<0.01

Note. Results of estimating equations (3) and (4) where the dependent variable is the average change in interest rates or credit. $(PolicyRate) * (HighSpec.)$ and $(PolicyRate) * (Top)$ refer to interactions of the policy rate with the top quartile dummy of excess industry specialization and the top industry dummy respectively.

The coefficient estimates in the tables are in line and comparable to the impulse responses depicted in Figures 4 and 5. The effect of monetary policy on interest rates is positive while the effect on credit is negative. The responses of interest rates and credit are generally muted for higher specialization and top categories.

C.3 Robustness of Baseleine Results

Tables C.3 to C.13 contain the results of robustness checks as described in the main text. In the tables, the column "baseline" correspond to the benchmark results presented above.

TABLE C.3: ROBUSTNESS - ALTERNATIVE SPECIALIZATION THRESHOLDS

	Interest Rate			Credit Outstanding		
	Baseline	D10	> median	Baseline	D10	> median
Industry Specialization						
(Policy Rate)*(High Spec)	-0.0328	-0.0398	-0.0411*	0.0251**	0.0260**	-0.00230
	(0.0235)	(0.0344)	(0.0210)	(0.0123)	(0.0105)	(0.0106)
Size Specialization						
(Policy Rate)*(High Spec)	-0.0253	-0.0156	-0.0540**	0.0243*	-0.0179	0.0176
	(0.0325)	(0.0260)	(0.0235)	(0.0126)	(0.0163)	(0.0151)

Standard errors in parentheses
* p<0.1, ** p<0.05, *** p<0.01

Note. Results of estimating equation (4) where the dependent variable is the average change in interest rates or credit. In the respective columns, $(PolicyRate) * (HighSpec.)$ refers to interactions of the policy rate with dummy variables for excess size specialization in the top quartile (Baseline), the top decile (D10) and above the median (> median).

TABLE C.4: ROBUSTNESS - COUNTRY EFFECTS OF INDUSTRY SPECIALIZATION

	Baseline	excl. FR	excl. DE	excl. ES	excl. IT
Interest Rate					
(Policy Rate)*(High Spec)	-0.0328	0.00807	-0.0550*	-0.0453	-0.0374
	(0.0235)	(0.0160)	(0.0317)	(0.0294)	(0.0253)
(Policy Rate)*(Top)	-0.122***	-0.103***	-0.122***	-0.126***	-0.130***
	(0.0284)	(0.0256)	(0.0183)	(0.0321)	(0.0319)
Credit Outstanding					
(Policy Rate)*(High Spec)	0.0251**	0.0171*	0.0374**	0.0131	0.0265**
	(0.0123)	(0.00861)	(0.0181)	(0.0125)	(0.0123)
(Policy Rate)*(Top)	0.0223*	0.0138	0.0283	0.00759	0.0252***
	(0.0112)	(0.0127)	(0.0254)	(0.00719)	(0.00882)

Standard errors in parentheses
* p<0.1, ** p<0.05, *** p<0.01

Note. Results of estimating equation (4) where the dependent variable is the average change in interest rates or credit. $(PolicyRate) * (HighSpec.)$ and $(PolicyRate) * (Top)$ refer to interactions of the policy rate with the top quartile dummy of excess industry specialization and the top industry dummy respectively. The columns refer to estimations where different countries are excluded one at a time.

TABLE C.5: ROBUSTNESS - COUNTRY EFFECTS OF SIZE SPECIALIZATION

	Baseline	excl. FR	excl. DE	excl. ES	excl. IT
Interest Rate					
(Policy Rate)*(High Spec)	-0.0253	-0.0312	-0.0546*	-0.0285	-0.0261
	(0.0325)	(0.0228)	(0.0300)	(0.0387)	(0.0337)
(Policy Rate)*(Top)	-0.0649*	0.0267	-0.0957**	-0.0762**	-0.0789**
	(0.0336)	(0.0207)	(0.0388)	(0.0350)	(0.0330)
Credit Outstanding					
(Policy Rate)*(High Spec)	0.0243*	0.0154	0.0290**	0.0127	0.0294**
	(0.0126)	(0.0161)	(0.0124)	(0.0104)	(0.0117)
(Policy Rate)*(Top)	0.0255***	0.0265**	0.0236***	0.0253***	0.0196*
	(0.00689)	(0.0114)	(0.00812)	(0.00648)	(0.0102)

Standard errors in parentheses
* p<0.1, ** p<0.05, *** p<0.01

Note. Results of estimating equation (4) where the dependent variable is the average change in interest rates or credit. $(PolicyRate) * (HighSpec.)$ and $(PolicyRate) * (Top)$ refer to interactions of the policy rate with the top quartile dummy of excess size specialization and the top size category dummy respectively. The columns refer to estimations where different countries are excluded one at a time.

TABLE C.6: ROBUSTNESS - COUNTRY GROUPS AND INDUSTRY SPECIALIZATION

	Baseline	Large	Core	CEE	High HHI
Interest Rate					
(Policy Rate)*(High Spec)	-0.0328	-0.0319	-0.0333	-0.0867	-0.00972
	(0.0235)	(0.0300)	(0.0340)	(0.0686)	(0.0138)
(Policy Rate)*(Top)	-0.122***	-0.130**	-0.125**	-0.267***	-0.0785
	(0.0284)	(0.0481)	(0.0485)	(0.0770)	(0.0488)
Credit Outstanding					
(Policy Rate)*(High Spec)	0.0251**	0.0300*	0.0125	-0.0737***	0.0424**
	(0.0123)	(0.0169)	(0.0146)	(0.0244)	(0.0158)
(Policy Rate)*(Top)	0.0223*	0.0402**	0.00461	0.0713*	0.0593*
	(0.0112)	(0.0178)	(0.00557)	(0.0413)	(0.0339)

Standard errors in parentheses
* p<0.1, ** p<0.05, *** p<0.01

Note. Results of estimating equation (4) where the dependent variable is the average change in interest rates or credit. $(PolicyRate) * (HighSpec.)$ and $(PolicyRate) * (Top)$ refer to interactions of the policy rate with the top quartile dummy of excess industry specialization and the top industry category dummy respectively. The columns refer to estimations focusing on different subsamples where only specific groups of countries are included. *Large* includes only France, Germany, Italy and Spain and *Core* includes Germany, France, The Netherlands, Austria, Belgium, Finland and Luxembourg. *CEE* includes Central and Eastern European economies that are part of the euro area, specifically Slovakia, Slovenia, Estonia, Latvia and Lithuania. *High HHI* refers to countries where the HHI index of bank credit market concentration is above the 75th percentile of the cross-sectional distribution across countries.

TABLE C.7: ROBUSTNESS - COUNTRY GROUPS AND SIZE SPECIALIZATION

	Baseline	Large	Core	CEE	High HHI
Interest Rate					
(Policy Rate)*(High Spec)	-0.0253	0.00459	-0.00874	-0.155*	-0.0659***
	(0.0325)	(0.0381)	(0.0446)	(0.0809)	(0.0229)
(Policy Rate)*(Top)	-0.0649*	-0.0947	-0.112**	0.0230	0.0332
	(0.0336)	(0.0563)	(0.0456)	(0.0822)	(0.0197)
Credit Outstanding					
(Policy Rate)*(High Spec)	0.0243*	0.0364**	0.0212**	-0.0535	0.0404
	(0.0126)	(0.0158)	(0.00946)	(0.0670)	(0.0268)
(Policy Rate)*(Top)	0.0255***	0.0316***	0.0233**	-0.0500*	0.0244
	(0.00689)	(0.00882)	(0.00919)	(0.0293)	(0.0156)

Standard errors in parentheses
* p<0.1, ** p<0.05, *** p<0.01

Note. Results of estimating equation (4) where the dependent variable is the average change in interest rates or credit. $(PolicyRate) * (HighSpec.)$ and $(PolicyRate) * (Top)$ refer to interactions of the policy rate with the top quartile dummy of excess industry specialization and the top industry category dummy respectively. The columns refer to estimations focusing on different subsamples where only specific groups of countries are included. *Large* includes only France, Germany, Italy and Spain and *Core* includes Germany, France, The Netherlands, Austria, Belgium, Finland and Luxembourg. *CEE* includes Central and Eastern European economies that are part of the euro area, specifically Slovakia, Slovenia, Estonia, Latvia and Lithuania. *High HHI* refers to countries where the HHI index of bank credit market concentration is above the 75th percentile of the cross-sectional distribution across countries.

TABLE C.8: ROBUSTNESS - BROAD SECTOR EFFECTS AND INDUSTRY SPECIALIZATION

	Baseline	excl. L	excl. C	excl. G	excl. F
Interest Rate					
(Policy Rate)*(High Spec)	-0.0328	-0.0373	-0.0471*	-0.0246	-0.0383*
	(0.0235)	(0.0294)	(0.0267)	(0.0175)	(0.0204)
(Policy Rate)*(Top)	-0.122***	-0.0850**	-0.104***	-0.109**	-0.128***
	(0.0284)	(0.0376)	(0.0267)	(0.0431)	(0.0312)
Credit Outstanding					
(Policy Rate)*(High Spec)	0.0251**	0.0270*	0.0142	0.0228*	0.0272*
	(0.0123)	(0.0134)	(0.0109)	(0.0123)	(0.0140)
(Policy Rate)*(Top)	0.0223*	0.0296**	0.0140	0.0264*	0.0217*
	(0.0112)	(0.0132)	(0.00979)	(0.0147)	(0.0115)

Standard errors in parentheses
* p<0.1, ** p<0.05, *** p<0.01

Note. Results of estimating equation (4) where the dependent variable is average change in interest rates and credit. $(PolicyRate) * (HighSpec.)$ and $(PolicyRate) * (Top)$ refer to interactions of the policy rate with the top quartile dummy of excess industry specialization and the top industry category dummy respectively. The columns refer to estimations where different (one-digit NACE) sectors are excluded one at a time.

TABLE C.9: ROBUSTNESS - LARGE BANKS

	Interest Rate		Credit Outstanding	
	High Spec.	Top Group	High Spec.	Top Group
Industry Specialization				
(Policy Rate)*(Spec)	-0.0556**	-0.105***	0.0176	0.0149
	(0.0229)	(0.0298)	(0.0146)	(0.0170)
(Policy Rate)*(Spec)*(Large Bank)	0.0374**	-0.0294***	0.0124	0.0130
	(0.0158)	(0.00747)	(0.0179)	(0.0343)
Size Specialization				
(Policy Rate)*(Spec)	-0.0502*	-0.117***	0.0381*	0.0248*
	(0.0272)	(0.0385)	(0.0199)	(0.0143)
(Policy Rate)*(Spec)*(Large Bank)	0.0387	0.0726***	-0.0214	0.00100
	(0.0331)	(0.0222)	(0.0189)	(0.0240)

Standard errors in parentheses
* p<0.1, ** p<0.05, *** p<0.01

Note. Results of estimating equation (4) where the dependent variable is the average change in interest rates or credit. $(PolicyRate) * (Spec.)$ refers to interactions of the policy rate with the top quartile dummy of excess specialization or the top category dummy. $(PolicyRate) * (Spec.) * (LargeBank)$ refers to the additional interaction with a dummy for banks in the highest quintile of the within country distribution of bank assets.

TABLE C.10: ROBUSTNESS - ALTERNATIVE MP SHOCK SERIES

	Interest Rate			Credit Outstanding		
	(1)	(2)	(3)	(4)	(5)	(6)
Policy Rate	1.233***			0.0199		
	(0.199)			(0.0360)		
(Policy Rate)*(High Size Spec.)		0.0573			0.0167*	
		(0.0350)			(0.00943)	
(Policy Rate)*(Top Size)			-0.139***			0.0261**
			(0.0332)			(0.0117)
R-squared	0.544	0.0264	0.0279	0.0139	0.0137	0.0157
Observations	274837	274837	274837	273893	273893	273893

Standard errors in parentheses
* p<0.1, ** p<0.05, *** p<0.01

	Interest Rate			Credit Outstanding		
	(1)	(2)	(3)	(4)	(5)	(6)
Policy Rate	1.148***			-0.00986		
	(0.242)			(0.0305)		
(Policy Rate)*(High Industry Spec.)		-0.0224			0.00265	
		(0.0200)			(0.0139)	
(Policy Rate)*(Top Industry)			-0.0897**			0.00826
			(0.0428)			(0.0135)
R-squared	0.440	0.0196	0.0211	0.0181	0.0201	0.0184
Observations	2677357	2677357	2677357	2668778	2668778	2668778

Standard errors in parentheses
* p<0.1, ** p<0.05, *** p<0.01

Note. Results of estimating equations (3) and (4) where the dependent variable is the average change in interest rates or credit. Based on the three month EURIBOR rate instrumented by the monetary policy shock from Zlobins (2025). $(PolicyRate) * (HighSpec.)$ and $(PolicyRate) * (Top)$ refer to interactions of the policy rate with the top quartile dummy of excess specialization and the top category dummy respectively. The top table shows results on size specialization, the bottom table refers to industry specialization.

TABLE C.11: ADDITIONAL RESULT - EFFECTS OF QE SHOCKS

	Interest Rate			Credit Outstanding		
	(1)	(2)	(3)	(4)	(5)	(6)
QE Shock	0.376			-0.248		
	(0.227)			(0.158)		
(QE Shock)*(High Size Spec)		0.0284			0.303***	
		(0.0599)			(0.0799)	
(QE Shock)*(Top Size)			-0.0847			0.203***
			(0.0662)			(0.0340)
R-squared	0.548	0.571	0.571	0.346	0.377	0.379
Observations	134348	134348	134348	133707	133707	133707

Standard errors in parentheses
* p<0.1, ** p<0.05, *** p<0.01

	Interest Rate			Credit Outstanding		
	(1)	(2)	(3)	(4)	(5)	(6)
QE Shock	0.410*			-0.237		
	(0.204)			(0.171)		
(QE Shock)*(High Industry Spec)		-0.0347			0.283*	
		(0.0637)			(0.145)	
(QE Shock)*(Top Industry)			-0.0828			-0.107
			(0.0656)			(0.118)
R-squared	0.343	0.355	0.355	0.179	0.188	0.186
Observations	1293024	1293024	1293024	1285423	1285423	1285423

Standard errors in parentheses
* p<0.1, ** p<0.05, *** p<0.01

Note. Results of estimating equations (3) and (4) where the change in the policy rate is replaced with a QE shock derived using the QE factor from Altavilla et al. (2019). The sample is restricted to the time period before July 2022. $(QEShock) * (HighSpec.)$ and $(QEShock) * (Top)$ refer to interactions of the QE shock with the top quartile dummy of excess specialization and the top category dummy respectively. The top table shows results on size specialization, the bottom table refers to industry specialization.

TABLE C.12: ADDITIONAL RESULT - RESPONSE OF COLLATERAL SHARES

	Size Specialization			Industry Specialization		
	(1)	(2)	(3)	(4)	(5)	(6)
Policy Rate	0.0521***			0.0268*		
	(0.0168)			(0.0138)		
(Policy Rate)*(High Spec)		-0.0126			-0.00150	
		(0.0229)			(0.00733)	
(Policy Rate)*(Top)			-0.0188			-0.0146
			(0.0318)			(0.0261)
R-squared	0.0314	0.0290	0.0291	0.0337	0.0320	0.0315
Observations	273374	273374	273374	2667022	2667022	2667022

Standard errors in parentheses
* p<0.1, ** p<0.05, *** p<0.01

Note. Results of estimating equations (3) and (4) where the dependent variable is the weighted average of collateral shares. $(QEShock) * (HighSpec.)$ and $(QEShock) * (Top)$ refer to interactions of the QE shock with the top quartile dummy of excess specialization and the top category dummy respectively. Columns (1) to (3) show results on size specialization, columns (4) - (6) refer to industry specialization.

TABLE C.13: ADDITIONAL RESULT - RESPONSE ASYMMETRY

	Size Specialization				Industry Specialization			
	Interest Rate		Credit Outstanding		Interest Rate		Credit Outstanding	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Policy Rate	1.066***		-0.0557**		1.219***		-0.0678***	
	(0.153)		(0.0209)		(0.122)		(0.0189)	
(Policy Rate)*(Exp)	0.233		-0.00740		0.304		-0.0111	
	(0.531)		(0.0498)		(0.534)		(0.0536)	
(Policy Rate)*(High Spec)		-0.0226		0.0289***		-0.0346		0.0314***
		(0.0331)		(0.0101)		(0.0215)		(0.0102)
(Policy Rate)*(High Spec)*(Exp)		0.0326		0.0550		-0.0158		0.0553
		(0.0333)		(0.0377)		(0.0577)		(0.0341)
R-squared	0.507	0.0275	0.0196	0.0144	0.422	0.0191	0.0197	0.0207
Observations	274837	274837	273893	273893	2677357	2677357	2668778	2668778

Standard errors in parentheses
* p<0.1, ** p<0.05, *** p<0.01

Note. Results of estimating equations (3) and (4) accounting for potential asymmetries in the effects of monetary policy. $(PolicyRate) * (Exp)$ and $(PolicyRate) * (HighSpec) * (Exp)$ refer to interactions of the policy rate and specialization interactions with a dummy variable for expansionary monetary policy shocks. Columns (1) to (4) show results on size specialization, columns (5) - (8) refer to industry specialization.