DEUTSCHE BUNDESBANK EUROSYSTEM

Discussion Paper

Deutsche Bundesbank
No 35/2026

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DOI https://doi.org/10.71734/DP-2026-35
ISBN 978-3-98848-094-1
ISSN 2941-7503

When Nonbanks Dampen and When They Amplify: A Yield-Curve View of the Nonbank Lending Channel*

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June 27, 2026

Abstract

We show that the nonbank lending channel is yield-curve dependent. Using German credit register data and a within-firm identification, we find that nonbanks dampen monetary tightening after short-end surprises but amplify it after medium- and long-end surprises. Financial service institutions drive this sign reversal: they expand through a bank capital reallocation channel at the short end but contract at longer segments. Insurers partly offset this pattern, expanding after medium- and long-end surprises as duration-driven solvency gains support their lending capacity. The aggregate nonbank response therefore depends both on the yield-curve segment affected and on the composition of the nonbank sector.

Keywords: Nonbank lending channel; Monetary policy transmission; Yield curve; Credit allocation; Nonbank financial intermediation

JEL Classification: E52, G21, G22, G23

*We thank seminar and conference participants at the Deutsche Bundesbank Research Seminar Series, the ChaMP Special Workstream 1 NBFI Workshop, the 2026 CEBRA Annual Meeting, the 15th MoFiR Workshop on Banking, IFABS London 2026, the RGS Doctoral Conference, and the FEBRI PhD Conference at the University of Groningen for helpful comments and suggestions. This project is part of the ECB's ChaMP Research Network. The views expressed in this paper are those of the authors and do not necessarily represent the views of the Deutsche Bundesbank.

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1. Introduction

Since the global financial crisis, nonbank financial institutions (NBFIs) have become increasingly important providers of credit to euro area firms, challenging the long-standing dominance of traditional banks (European Central Bank, 2021). This shift is particularly pronounced in Germany, a country historically known for its bank-centered financial system. Between 2002 and 2023, nonbanks' share of total financial assets increased from 22 percent to 42 percent (Figure 1). Understanding how the rise of nonbank intermediation affects monetary policy transmission has therefore become central for macroeconomic stabilization and financial stability.

Recent evidence suggests that nonbanks expand credit when banks retrench after monetary tightening, thereby weakening the traditional bank lending channel (Cucic and Gorea, 2026; Elliott et al., 2022, 2024; Xiao, 2020). This evidence, however, largely identifies monetary tightening through short-rate surprises. That focus may miss an important dimension of the nonbank lending channel. Many nonbank financial institutions are exposed not only to the cost of short-term funding, but also to movements in medium- and long-term rates through duration risk, asset and liability valuations, maturity-transformation incentives, and regulatory solvency constraints. This raises our central question: does the nonbank lending channel depend on the segment of the yield curve through which monetary policy is transmitted?

To answer this question, we collect quarterly supervisory data from the Deutsche Bundesbank's credit register covering 2019:Q1–2023:Q4. The data include credit exposures and lender-reported supervisory default probabilities (PDs) of borrowers, covering all banks and major nonbank intermediaries. We merge these data with supervisory bank balance-sheet information, insurer solvency measures, and firm-level characteristics. Our identification strategy uses high-frequency monetary policy surprises from Altavilla et al. (2019), measured within narrow windows around ECB Governing Council announcements. We decompose these surprises into three orthogonal components that capture policy news moving the short end, the medium end, and the long end of the yield curve. Following Khwaja and Mian (2008), we identify credit supply effects using within-firm variation, comparing how the same firm's borrowing from banks and nonbanks changes after each type of surprise.

Our results show that the prevailing view that nonbanks dampen monetary policy transmission is incomplete; their responses instead vary systematically across yield-curve segments and nonbank types. Following a one-standard-deviation short-end surprise, nonbanks expand credit by 0.32 percent relative to banks, consistent with a dampening effect. This expansion is driven by financial service institutions (FSIs), primarily leasing and factoring companies, which increase credit by 0.87 percent relative to banks, while insurers do not significantly

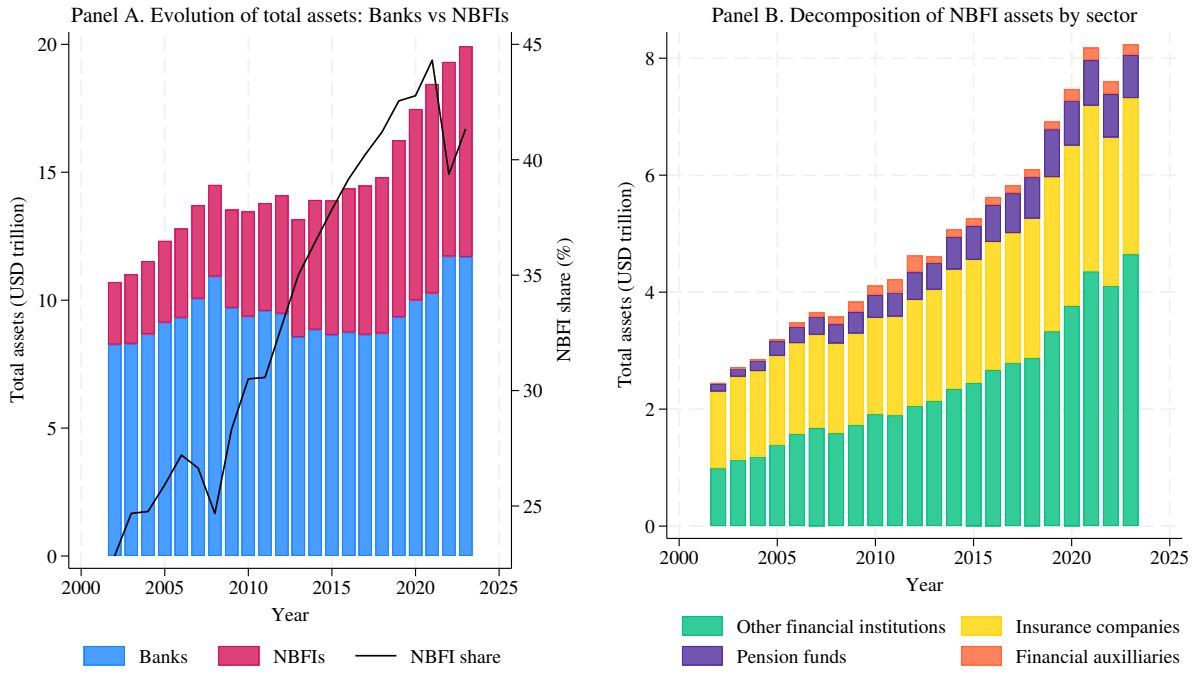


FIGURE 1. EVOLUTION OF TOTAL ASSETS FOR BANKS AND NONBANK FINANCIAL INSTITUTIONS IN GERMANY OVER THE 2002–2023 PERIOD

Source: Financial Stability Board (2024) and own calculations. The NBFI share is calculated as the ratio of the NBFI sector's asset value to the combined total assets of banks and NBFIs.

expand. In contrast, following medium- and long-end surprises, nonbanks contract by 0.36 and 0.34 percent relative to banks, respectively, amplifying rather than dampening policy transmission. This contraction reflects sharp FSI retrenchment, while insurers expand at the medium and long end.

We then investigate the balance-sheet mechanisms underlying these heterogeneous responses. For FSIs, short-end surprises operate through a bank capital reallocation channel: because short-term funding costs adjust quickly while loan income adjusts only gradually (Alessandri and Nelson, 2015), short-end surprises compress bank margins and erode capital buffers. Capital-constrained banks respond by tilting lending toward FSIs, which carry lower supervisory default probabilities than non-financial firms, consistent with economizing on regulatory capital. Medium- and long-end surprises do not activate this channel. Higher term premia raise the expected return to maturity transformation and bank profitability (Minoiu et al., 2025) rather than compressing margins, weakening the capital-economizing motive. As a result, bank exposure to FSIs contracts relative to non-financial firms.

For insurers, by contrast, medium- and long-end surprises operate through a duration-driven solvency channel. Because insurers' liabilities are typically longer-dated than their

assets (Koijen and Yogo, 2022), higher medium- and long-term rates reduce the present value of liabilities by more than that of assets, thereby improving solvency ratios. These solvency gains then translate into lending expansion.

These heterogeneous responses have implications for credit allocation and aggregate dynamics. Because FSIs disproportionately serve small- and medium-sized enterprises (SMEs) and carbon-intensive firms while insurers lend primarily to large firms, the yield-curve segment affected by monetary policy determines which borrowers gain or lose credit access. At the firm level, firms with pre-existing nonbank relationships receive more total credit after short-end surprises but less after medium- and long-end surprises, consistent with nonbanks offsetting bank contraction at the short end and reinforcing it at longer horizons of the yield curve. Aggregating these firm-level effects, the differential nonbank response corresponds to roughly 10.7 billion euros of additional firm credit following a one-standard-deviation short-end surprise, and 18.0 and 15.9 billion euros less following medium- and long-end surprises, respectively.

To the best of our knowledge, we are the first to provide systematic evidence that the nonbank lending channel is yield-curve dependent, linking distinct yield-curve segments to intermediary-specific balance-sheet channels. While our identification relies on German credit register data, the mechanisms we document depend on institutional features that are not unique to Germany, though whether the pattern extends to other financial systems remains an open empirical question. One implication, scoped to our setting, is that policy tools operating further out the yield curve may meet less nonbank offset (and thus achieve more durable credit tightening) than short-rate tools. Our findings suggest that as nonbanks gain market share, their institutional composition will increasingly shape both the aggregate and distributional consequences of monetary policy.

The rest of this paper proceeds as follows. Section 2 reviews the literature on the nonbank lending channel and positions our contribution. Section 3 describes the institutional setting. Section 4 presents our data. Section 5 reports results on heterogeneous lending responses. Section 6 investigates the underlying mechanisms. Section 7 examines implications for credit allocation and aggregate dynamics. Section 8 concludes.

2. Literature Review

As nonbank financial institutions have become major providers of credit (Financial Stability Board, 2024), researchers have proposed a new monetary policy transmission mechanism: the nonbank lending channel. This channel posits that nonbanks may expand credit when banks retrench following monetary tightening, thereby dampening the effectiveness of the traditional bank lending channel (Bernanke and Blinder, 1988; Kashyap and Stein, 1995,

2000).

A prominent mechanism emphasized in the literature is the deposit channel. Drechsler et al. (2017) show that banks with greater deposit market power experience larger deposit outflows when policy rates rise. Xiao (2020) documents that these outflows migrate to money market funds, which channel liquidity to downstream nonbank lenders such as finance companies and broker-dealers. Together, these studies highlight that deposit reallocation within the financial system can shape the relative funding conditions of banks and nonbanks around monetary tightening.

Recent work identifies additional funding-based mechanisms. Using comprehensive lender balance-sheet data, Cucic and Gorea (2026) show that contractionary monetary shocks reduce long-term debt funding for banks while increasing it for nonbanks, and that the nonbank response is stronger among nonbanks that rely more on long-term debt funding ex ante. Haque et al. (2025) trace the intermediation chain from banks to Business Development Companies (BDCs) to ultimate borrowers. They show that banks increase lending to BDCs during monetary tightening, enabling BDCs to maintain credit supply. These findings illustrate how (bank) funding of nonbank intermediaries can affect the transmission of monetary policy to the real economy.

Heterogeneity Within the Nonbank Sector. Evidence on heterogeneity within the nonbank sector is mixed. Some papers emphasize that nonbanks' responses vary with business model and funding structure. For example, Hodge and Weber (2023) show that responses differ across intermediaries that depend on short- versus long-term funding, and Hodula and Libich (2023) document that asset responses differ across broad nonbank groupings (e.g., Other Financial Intermediaries versus investment funds). At the same time, other work finds less differentiated responses across nonbank categories. Xiao (2020), for instance, estimates responses separately across nonbank categories and finds broadly similar directional patterns, while Cucic and Gorea (2026) only find heterogeneous nonbank responses in the consumer segment and not in the corporate segment.

Our Contribution. Despite these contributions, the empirical literature provides limited guidance on whether the nonbank lending channel depends on the segment of the yield curve through which monetary policy is transmitted. Most studies focus on policy surprises that primarily move the short end of the yield curve; Appendix Table F.1 shows that even micro-level evidence using lender-borrower data overwhelmingly concentrates on short-end surprises. Holm-Hadulla et al. (2023) take a step toward addressing this gap by examining both short- and long-rate surprises. They show that investment funds respond similarly to banks following short-rate surprises but contract more sharply following long-rate surprises. While suggestive, three aspects of their analysis leave open questions that our study addresses. First, they focus

on investment funds, leaving open whether other nonbank intermediaries exhibit different yield-curve sensitivities. Second, they use sector-level data, which cannot separate credit supply from credit demand (Degryse et al., 2019; Jiménez et al., 2012; Khwaja and Mian, 2008). Third, their long-rate movements are not orthogonalized with respect to short-rate movements, leaving open whether the observed differences reflect distinct yield-curve segments or correlated rate changes.

We address these limitations using German credit register data that cover both bank and nonbank lending at the lender-borrower level. Our within-firm identification strategy isolates credit supply from credit demand while allowing a direct comparison of lending responses across banks and six nonbank types. We decompose high-frequency monetary policy surprises into orthogonal components that primarily move the short end, the medium end, and the long end of the yield curve, and we test whether different nonbank intermediaries respond differently across these segments.

A second contribution is that we connect yield-curve-segment shocks to intermediary-specific balance-sheet mechanisms. We focus on two channels. The first is a bank capital reallocation channel for FSIs. De Jonghe et al. (2020) show that banks facing funding shocks reallocate credit toward lower-risk borrowers. Wang et al. (2025) extend this logic to bank-nonbank relationships, documenting that capital-constrained banks shift lending toward nonbank intermediaries that carry lower risk weights under Basel regulation. Both studies show that bank balance-sheet pressure can alter the composition of lending toward lower-risk or less capital-intensive exposures, but neither examines whether the strength of this reallocation channel depends on the segment of the yield curve affected by monetary policy.[1]

This distinction is important because shocks to different parts of the yield curve need not generate the same incentives for capital-constrained banks to rebalance their portfolios. Alessandri and Nelson (2015) show that because short-term funding costs adjust quickly while loan income adjusts only gradually, increases in short rates compress bank net interest margins and erode the retained earnings that buffer bank capital. This pressure provides a motive to economize on regulatory capital by reallocating toward lower-risk borrowers such as FSIs. Longer-horizon rates and term premia, by contrast, raise bank profitability rather than compressing margins (Minoiu et al., 2025). The capital-economizing motive that drives reallocation toward FSIs at the short end is therefore absent at the medium and long end. This channel thus predicts that the bank-to-FSI expansion is specific to short-end surprises and concentrated among less-capitalized banks, a prediction we test using heterogeneity in bank capital positions.

[1]The same is true of other studies documenting nonbank lending expansion following bank capital shocks, including Irani et al. (2021), Bednarek et al. (2025), and Lee et al. (2024), all of which focus on regulatory shocks that unambiguously tighten bank capital.

The second is a duration-driven solvency channel for insurance corporations. Under mark-to-market solvency regulation, increases in medium- and long-term rates can improve insurers' solvency when liabilities are longer-dated than assets, potentially relaxing regulatory constraints on credit supply. Prior work has shown that insurers manage duration gaps through portfolio rebalancing in bond markets (Domanski et al., 2017) and that their long-horizon liability structures enable countercyclical investment behavior during market stress (Timmer, 2018). However, this literature studies insurers as investors in securities markets, not as lenders to the real economy. Whether duration-driven solvency dynamics affect insurers' credit supply to firms, and whether this creates a distinct channel of monetary policy transmission, has not been examined. The extension is not immediate: securities holdings can be adjusted rapidly through market transactions, whereas lending relationships involve origination costs, screening, and contractual commitments that may constrain the translation of solvency gains into credit supply. This channel predicts a stronger response among insurers with more negative duration gaps, a prediction we test using the difference between life and non-life insurers.

3. Institutional Setting

This section describes the institutional setting. Our analysis exploits two features of the German financial system: a credit register that comprehensively captures lending by both banks and nonbanks, and a diverse nonbank sector whose balance-sheet structures create heterogeneous exposures to different segments of the yield curve. Section 3.1 describes the financial institutions subject to credit register reporting and the regulatory criteria that determine reportable exposures. Section 3.2 defines our classification of banks and nonbanks and characterizes the two nonbank types central to our analysis: FSIs and insurance corporations.

3.1. Classification of Financial Institutions in the Credit Register

Figure 2 illustrates the financial institutions subject to credit register reporting under Section 14 of the German Banking Act (Kreditwesengesetz, KWG). These can be classified into two broad categories: credit institutions and nonbanks. Within the category of credit institutions, a distinction is made between universal banks and other credit institutions. Universal banks comprise three types of institutions, which together form what is commonly referred to as Germany's three-pillar banking system: commercial banks, savings banks, and cooperative banks. In contrast, other credit institutions represent a more heterogeneous category that includes mortgage banks, specialized credit institutions (also referred to as special-purpose banks), building and loan associations, and other credit institutions such as guarantee banks

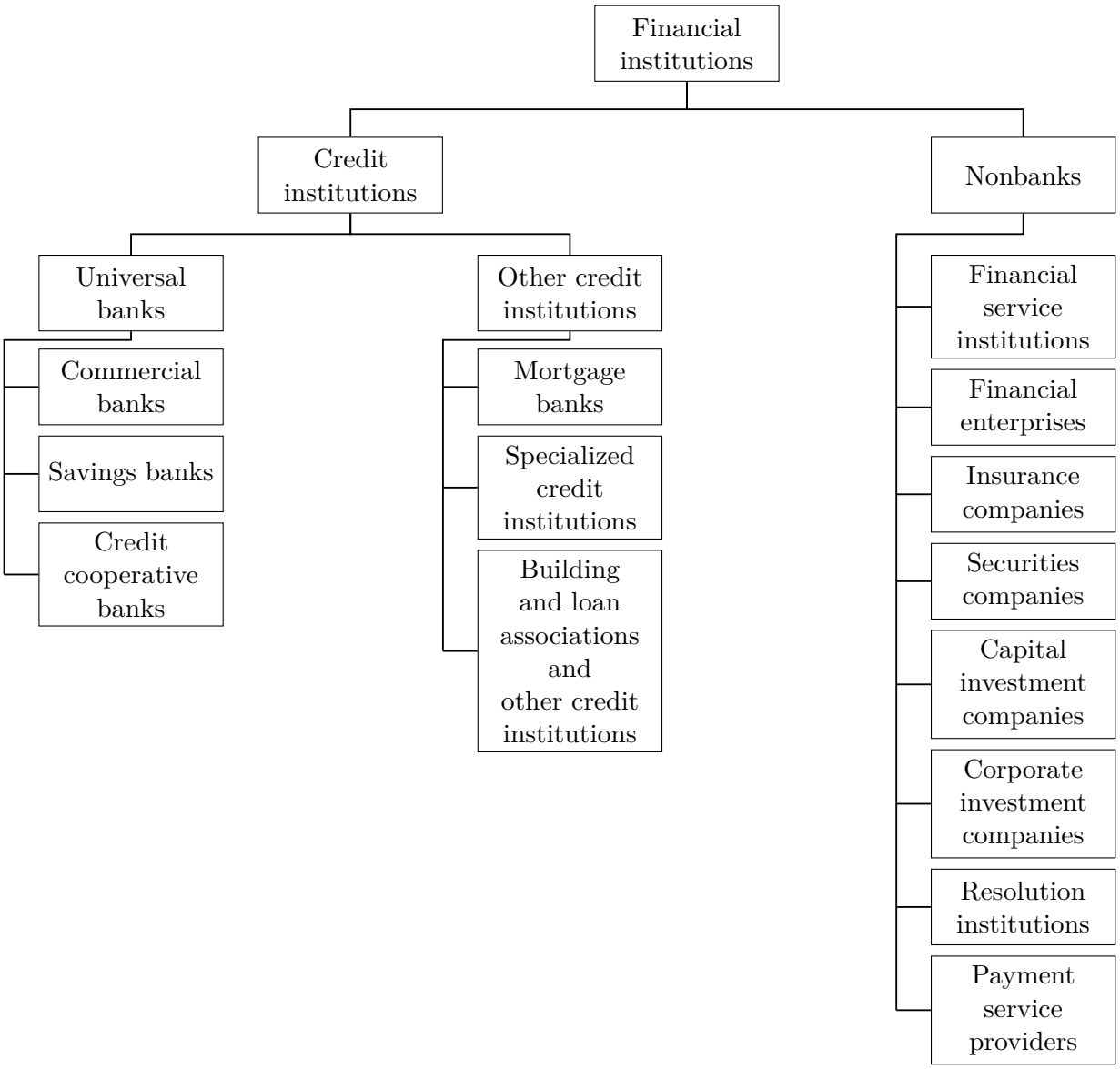


FIGURE 2. CLASSIFICATION OF FINANCIAL INSTITUTIONS IN THE CREDIT REGISTER

and housing companies with saving facilities.

Beyond credit institutions, several types of nonbank financial institutions are also subject to credit register reporting. These include financial service institutions, financial enterprises, insurance companies, securities companies, capital investment companies, corporate investment companies, resolution institutions, and payment service providers. Importantly, these nonbank financial institutions appear in the credit register both as lenders and as borrowers. This dual coverage allows us to observe both nonbank lending to non-financial firms and bank lending to nonbanks, which is central to our identification of the bank capital reallocation channel in Section 6. The inclusion of these entities in the credit register highlights the broad scope of financial sector oversight in Germany and ensures that credit exposures are

systematically captured across the entire financial intermediation system. Such comprehensive coverage of both lender and borrower sides of the financial intermediation system is, to our knowledge, a unique feature of the Deutsche Bundesbank's credit register.

Under the current version of Section 14 of the KWG, these financial institutions must report to the credit register if their exposure to a borrower, or the combined exposure to a group of connected borrowers (the borrower unit), exceeds one million euros at least once during the quarterly reporting period.[2] Once this threshold is met, lenders are required to report exposures to each single member of the borrower unit. As such, the effective threshold is lower than one million euros. Credit exposures include both balance-sheet assets (such as loans, bonds, shares, and participations) and off-balance-sheet items (such as guarantees, credit derivatives, and loan commitments).

Throughout this paper, we exclude specialized credit institutions and public mortgage banks, as these institutions operate under distinct regulatory frameworks and possess risk profiles that differ markedly from those of universal banks. We also exclude three nonbank categories whose credit register exposures do not represent credit supply decisions: resolution institutions (mandated to wind down legacy assets), payment service providers, and equity holding companies. Finally, the study is confined to non-financial borrowers and lenders in Germany that are not in liquidation.

3.2. Defining Banks and Nonbanks

Credit institutions in the credit register are classified according to Section 1(1) of the KWG, which defines them as entities conducting banking business either commercially or at a scale requiring a commercially organized business operation. This definition is broad, encompassing entities that may engage exclusively in lending even without deposit-taking capacity.

For this study, the ability to accept deposits is a crucial distinction. As outlined in Section 2, a key mechanism of the nonbank lending channel involves deposit reallocation from banks to nonbanks. We therefore adopt the Capital Requirement Regulation (CRR) definition, classifying a financial institution as a bank only if it qualifies as a monetary financial institution (MFI)—that is, it both accepts deposits and grants credit. Nonbanks are defined as financial institutions that do not qualify as MFIs. This classification ensures that our "bank" category captures institutions exposed to the deposit channel of monetary policy.

In practice, this means that we create an additional category of nonbanks, which we term non-MFI credit institutions. This category includes KWG-defined credit institutions that

[2]The KWG defines a borrower unit (Kreditnehmer) as a group of legally or economically connected entities in which one entity exercises direct or indirect control over the others. Such control is presumed in cases of financial consolidation under the German Commercial Code, profit transfer agreements, or majority ownership. Additionally, partnerships, corporations, and corporate groups as defined by the German Stock Corporation Act are considered a single borrower unit.

do not hold a deposit license, such as guarantee banks and other credit institutions with partial banking concessions. These entities belong entirely to the category of "other credit institutions" shown in Figure 2 but are classified as nonbanks in our analysis because they lack deposit-taking capacity.

Among the nonbank types listed in Section 3.1, two are central to our empirical analysis: FSIs and insurance corporations. Together, these account for the majority of nonbank credit exposure in our sample (see Table 2). These two nonbank types differ markedly in their funding structures and regulatory frameworks. As we explore in Section 6, these differences generate heterogeneous responses to different yield-curve segments. Appendix A provides detailed regulatory descriptions of all nonbank types.

FSIs include primarily leasing and factoring companies, which provide credit to non-financial corporations. Unlike banks, FSIs cannot accept deposits and are not eligible for central bank funding. They rely heavily on bank funding: in our credit register data, 85 percent of FSI borrowing is sourced from banks. FSIs are regulated under the KWG but are not subject to CRR capital requirements, giving them greater balance-sheet flexibility than banks.

Insurance companies commonly provide credit through promissory notes to corporations and public-sector entities (as discussed in Bednarek et al., 2025). They are regulated under Solvency II, which requires marking both assets and liabilities to market. A key distinction exists between life and non-life insurers. Life insurers hold long-dated liabilities, including annuities, pension obligations, and guaranteed return products that extend decades into the future. Non-life insurers, including property, casualty, and health insurers, hold shorter-duration liabilities tied to claims that typically settle within one to three years.

4. Data

4.1. Data Sources

We construct a comprehensive panel dataset at the lender-firm-quarter level by integrating multiple data sources. Our baseline dataset is derived from the Bundesbank's credit register, which we enrich with firm-level financial and environmental characteristics, bank- and insurer-level balance-sheet data, and monetary policy surprises. Below, we describe each data source and its role in the construction of the empirical dataset.

Lender-Firm-Level Data. We collect supervisory lender-firm-level data on credit exposures (see Section 3.1 for the definition) and lender-reported one-year-ahead PDs from the Deutsche Bundesbank's credit register for the period from 2019:Q1 to 2023:Q4. We restrict the sample to this period because a 2019 reform expanded credit register reporting requirements,

generating an asymmetric break in reported exposures between 2018:Q4 and 2019:Q1 that firm-time fixed effects cannot absorb.[3]

For our analyses, we take the natural logarithm of the exposure measure and use it as the main dependent variable in different specifications, following the convention in the nonbank lending channel literature (e.g., Cucic and Gorea, 2026; Elliott et al., 2022, 2024). The PDs are used to construct a firm-level measure of credit risk. Specifically, for each firm and in each quarter, we compute the median PD across all lenders and classify a firm as "high risk" if its median PD exceeds the cross-sectional median in that quarter. This binary risk indicator is used to examine whether the lending behavior of nonbanks differs from that of banks along the intensive margin of borrower risk in response to monetary policy.

Firm-Level Data. Firm-level financial data with a yearly frequency are obtained from Orbis for the period 2018–2023. We collect data on total assets, number of employees, and operating revenues. These variables are used to compute a measure of firm size based on the European Commission's definition, which classifies firms as SMEs if they employ fewer than 250 persons and have either an annual turnover not exceeding 50 million euros or an annual balance sheet total not exceeding 43 million euros.[4] We match this firm-level data to the credit register by merging it via the combination of the trade register number and the issuing local court.[5] In cases where firms lack this information, we use their legal entity identifier.

To measure corporate environmental risk, we retrieve industry-level Scope 1 emissions scaled by gross value added for Germany over the 2018–2022 period from Eurostat. These emissions are reported at the two-digit NACE code level and are expressed in grams per euro of gross value added (in chain-linked volumes, base year 2010). An industry is classified as "green" if its Scope 1 emission intensity falls below the median for that year.[6]

Bank-Level Data. We obtain end-of-quarter balance-sheet information for all domestic MFIs from the Deutsche Bundesbank's supervisory dataset. These data include variables

[3]The 2019 reform required lenders to report additional items including loan commitments and securities held in the trading portfolio as part of their credit exposures, leading to mechanical increases in reported exposures across lender-firm relationships in 2019:Q1.

[4]Source: https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX:32003H0361.

[5]In Germany, the trade register number is not unique across all companies. This is because each local court (Amtsgericht), is responsible for issuing trade register numbers, and their numbering systems are independent. As a result, two different companies could end up being assigned the same trade register number, but they would be registered in different local courts. This is why to identify a firm we use the combination of trade register number and the issuing local court.

[6]We also collect firm-level Scope 1 emissions from the ETS, ISS, and Refinitiv Eikon and construct an analogous firm-level green indicator. However, we use industry-level emissions as our primary measure because they provide coverage for the vast majority of firms in the credit register. In the regressions shown in Section 7.1, firm-level classifications yield coefficients with consistent signs but reduced significance due to substantially lower coverage (15,511 firm-quarter observations versus about 11.4 million for the industry measure).

such as total assets, core capital ratios, capital adequacy ratios, and non-performing loan (NPL) ratios. To limit the influence of occasional outliers, we winsorize both capital ratios at the 2nd and 98th percentiles. The core capital ratio plays a central role in our bank capital reallocation analysis: we exploit cross-sectional variation in capital ratios to test whether banks with tighter capital positions reallocate lending toward specific (nonbank) borrower types following shocks to different segments of the yield curve.

To explore whether deposit funding dynamics contribute to heterogeneity in banks' credit supply responses, we also collect monthly deposit rate and volume data from the Bundesbank's MFI Interest Rate Statistics. Following Drechsler et al. (2017), we construct bank-specific deposit-spread betas that capture each bank's deposit market power. Banks with higher betas adjust deposit rates more slowly following policy rate changes and may therefore face larger deposit outflows after tightening, thus constraining their lending capacity. We use these measures in supplementary analyses of bank heterogeneity. Appendix C.2 provides details on the deposit data, deposit-spread beta construction, and results. Both datasets are linked to the credit register using internal bank identifiers provided by the Bundesbank.

Insurer-Level Data. We obtain quarterly solvency ratios for insurance corporations from the Bundesbank's supervisory dataset, which collects regulatory filings under the Solvency II framework. The solvency ratio, defined as eligible own funds relative to the solvency capital requirement, captures insurers' regulatory capital position. We use these data to examine whether duration-driven solvency dynamics drive insurers' lending responses across the yield curve.

Monetary Policy Data. Our measures of monetary policy surprises come from the Euro Area Monetary Event-Study Database (EA-MPD) developed by Altavilla et al. (2019), which features intraday changes in risk-free overnight index swap (OIS) rates with different maturities measured around a narrow time-window for each Governing Council meeting since 1999. We retrieve data from the so-called monetary policy event window, which captures changes in the OIS rates from 20 minutes before the press release to 20 minutes after the press conference.

The rationale for using high-frequency data is that, within a short time-window, observed changes in risk-free OIS rates are primarily driven by the policy announcement itself, making them a standard proxy for monetary policy news that is less likely to be contaminated by non-policy macroeconomic developments outside the meeting window. These OIS rate changes are often referred to as monetary policy surprises, in the sense of unexpected revisions in market pricing of the policy path at the corresponding maturity.

To capture shocks to the short end of the yield curve, we use changes in the one-month OIS rate, which Altavilla et al. (2019) identify as a strong proxy for the so-called Target surprise.

To identify shocks to the medium end of the yield curve, we follow the methodology of Gürkaynak et al. (2021) and estimate the Forward Guidance (or Path) surprise by regressing the change in the two-year OIS rate on the one-month OIS rate and taking residuals. Lastly, to capture shocks to the long end of the yield curve, we construct a measure of the Quantitative Tightening surprise by regressing the 10-year OIS rate on the two-year and one-month OIS rates and taking the residuals. By construction, the three measures are mutually orthogonal and isolate innovations to distinct segments of the yield curve.

Throughout the paper, we refer to shocks to the short end of the yield curve as Target surprises, shocks to the medium end as Forward Guidance (FG) surprises, and shocks to the long end as Quantitative Tightening surprises, following naming conventions in the monetary policy literature (Braun et al., 2025; Gürkaynak et al., 2005; Swanson, 2021). At the same time, following Miranda-Agrippino and Nenova (2022), we interpret each factor as capturing the combination of meeting-related shocks that lead market participants to revise rate expectations at the corresponding maturity, rather than as cleanly identified discrete policy instruments. The FG factor, for example, may combine explicit guidance with signaling effects of asset purchases; the QT factor captures residual long-rate movements beyond those transmitted from shorter maturities. Nevertheless, our main empirical findings concern shocks to different yield-curve segments and do not rely on a one-to-one mapping between factors and specific policy instruments.

To match the quarterly frequency of our data, we follow the convention in the literature on monetary policy surprises and take the cumulative sum of the surprises over each quarter (e.g., Bu et al., 2021; Cloyne and Hürtgen, 2016; Coibion, 2012; Romer and Romer, 2004). Finally, for robustness checks, we incorporate Krippner's (2013) euro area shadow policy rate, which provides a continuous measure of the policy stance when nominal rates are near the lower bound.

4.2. Descriptive Statistics

Table 1 presents summary statistics for the main variables used in our empirical analysis. The sample spans 2019:Q1 to 2023:Q4 and comprises 15.7 million lender-firm-quarter observations, covering 945,926 unique firms and 2,909 lenders (1,519 banks and 1,390 nonbanks). Variable definitions are provided in Appendix Table B.1.

Panel A reports summary statistics at the lender-firm-quarter level. Nonbanks display a higher mean credit exposure than banks (5.2 million euros versus 3.2 million euros) but a similar median, suggesting that nonbank exposures are subject to more extreme values relative to banks. Nonbanks also report a higher average probability of default at 3.8 percent compared to 2.9 percent for banks, indicating a relatively riskier credit profile among firms borrowing from nonbanks.

Table 1. Summary Statistics

Variables	N	Mean	Median	SD	p25	p75
Panel A. Lender-firm-quarter level						
Full sample						
Exposure (mill. €)	15,705,599	3.39	0.98	30.85	0.16	2.00
PD (%)	6,667,714	2.92	0.36	13.42	0.15	1.10
Banks						
Exposure (mill. €)	14,295,780	3.21	0.98	26.67	0.18	2.00
PD (%)	6,459,785	2.89	0.35	13.48	0.15	1.10
Nonbanks						
Exposure (mill. €)	1,409,819	5.20	0.88	58.21	0.06	2.06
PD (%)	207,929	3.82	0.70	11.41	0.29	2.68
Panel B. Firm-quarter level						
Total credit (mill. €)	11,549,279	4.58	0.86	156.46	0.14	1.88
Nonbank share (%)	11,549,279	4.81	0.00	19.98	0.00	0.00
Firm PD (%)	5,634,343	2.93	0.39	13.38	0.15	1.10
High-risk firm	5,634,343	0.48	0	0.50	0	1
SME	1,330,911	0.85	1	0.36	1	1
Green industry	11,386,208	0.69	1	0.46	0	1
Panel C. Bank-quarter level						
Assets (mill. €)	25,986	5,650.50	1,271.36	35,803.06	415.70	2,882.85
Core capital ratio (%)	26,255	16.71	15.65	4.24	14.08	17.92
Capital adequacy ratio (%)	26,255	20.31	18.59	6.40	16.78	21.29
Non-performing loan ratio (%)	18,066	1.52	0.97	7.80	0.49	1.55
Deposit-spread beta	3,829	0.85	0.58	3.12	0.37	0.88
Deposit growth (%)	3,800	7.90	1.41	170.11	−0.33	3.34
Panel D. Insurer-quarter level						
Solvency ratio	4,846	3.59	2.96	2.13	2.00	4.50
Panel E. Monetary policy						
Target (basis points)	20	2.70	0.55	5.86	−0.21	5.00
FG (basis points)	20	−0.19	−0.43	6.18	−2.53	0.96
QT (basis points)	20	−0.66	−0.82	2.29	−1.99	1.32

Notes: This table reports summary statistics over 2019:Q1–2023:Q4 for the main variables used in the study. SD denotes standard deviation. Variable definitions are provided in Appendix Table B.1.

Panel B shows that, despite the growth of nonbank lending, banks remain the dominant source of credit for German firms. At the firm-quarter level, the average nonbank share is 4.8 percent, and the median is zero, indicating that more than half of firm-quarter observations do not involve any nonbank credit exposure. Among firms matched to Orbis, 85 percent qualify as SMEs under the European Commission definition.

Panels C and D report bank- and insurer-level characteristics. Panel C indicates that

Table 2. Sector-Quarter Summary Statistics

Financial sector	Exposure (bill. €)	Exposure share (%)	Lender count
Credit institutions	2,278.57	86.20	1,373.75
Financial service institutions	42.71	1.61	207.85
Financial enterprises	5.95	0.23	253.30
Insurance companies	294.62	11.14	458.60
Securities companies	11.33	0.41	13.50
Capital investment companies	3.29	0.12	40.30
Non-MFI credit institutions	7.67	0.29	26.35

Notes: This table reports mean credit exposure, market share, and lender count by lender type at the sector-quarter level over 2019:Q1–2023:Q4.

the German banking system is dominated by relatively small institutions with high average capital adequacy ratios (20.3 percent). The average deposit-spread beta of 0.85 indicates incomplete pass-through of policy rates to deposit rates: on average, banks in our sample raise their deposit rates by only 15 basis points for every 100-basis-point increase in the euro short-term rate (€STR). Panel D shows that, with an average solvency ratio of 359 percent, German insurers maintain substantial buffers above the 100 percent regulatory minimum under Solvency II.

Panel E focuses on the monetary policy surprises. Target surprises average 2.7 basis points with a standard deviation of 5.9. FG and QT surprises average −0.2 and −0.7 basis points, with standard deviations of 6.2 and 2.3 basis points, respectively. Appendix Figure B.1 traces the evolution of these surprises over the sample period.

Table 2 decomposes credit exposure at the sector-quarter level. The nonbank sector accounts for 13.8 percent of the total exposure.[7] Within the nonbank sector, insurance corporations are the largest segment, accounting for 11.1 percent of total exposure (approximately 81 percent of nonbank exposure) while FSIs account for 1.6 percent of total exposure (approximately 12 percent of nonbank exposure). Together, these two segments represent over 90 percent of nonbank credit intermediation.

Panel A in Figure 3 plots cumulative credit growth since 2019:Q1 for banks and nonbanks. Nonbank lending has grown faster than bank lending over the sample period. Panel B decomposes this pattern by nonbank type, focusing on the two largest segments. FSIs drive the aggregate nonbank expansion, displaying substantially higher cumulative growth than both banks and insurers. Insurance corporations, by contrast, exhibit growth rates more comparable to banks.

Appendix Table B.2 examines firm heterogeneity in financing structure. Riskier firms,

[7]The aggregate nonbank share of 13.8 percent is broadly comparable to other markets. Cucic and Gorea (2026) report an average nonbank share of approximately 8 percent in Danish corporate credit markets over 2003–2018, similar to the 9 percent share of US syndicated lending documented by Elliott et al. (2022).

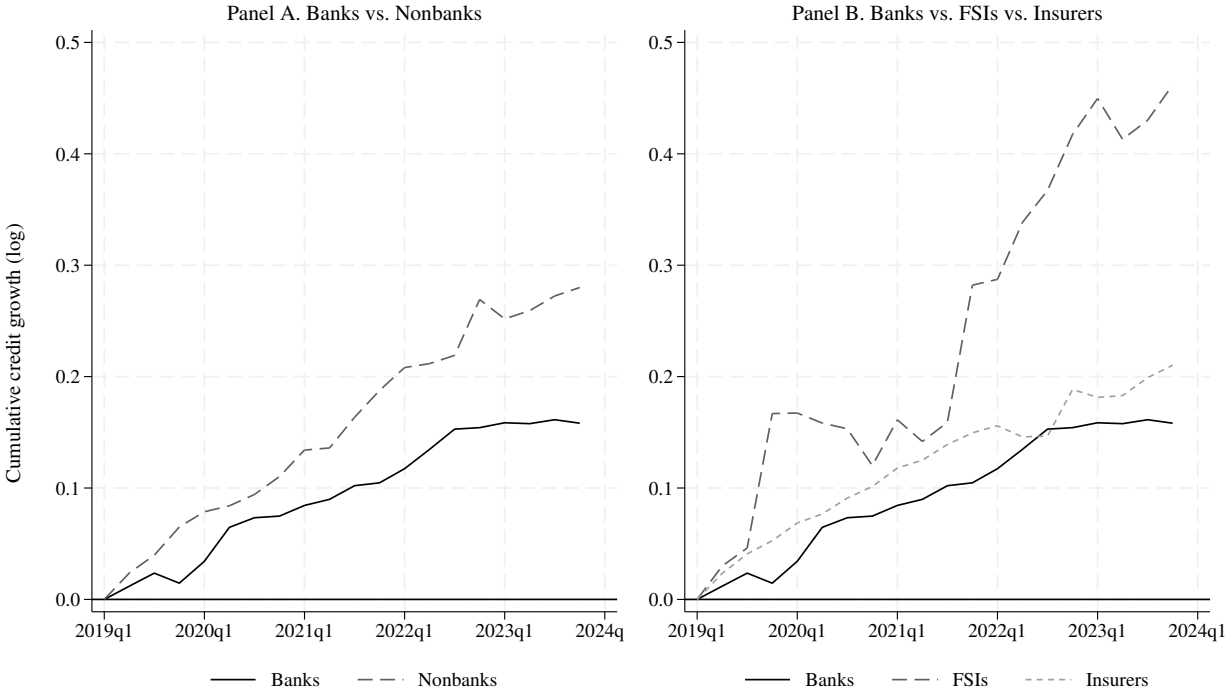


FIGURE 3. CUMULATIVE CREDIT GROWTH BY LENDER TYPE

Notes: This figure plots cumulative credit growth by lender type since 2019:Q1. Credit growth is computed by aggregating total exposure across all lender-firm relationships within each lender type per quarter, then calculating the log change relative to 2019:Q1. Panel A compares banks and nonbanks. Panel B compares banks to financial service institutions (FSIs) and insurance corporations.

SMEs, and firms in brown industries all exhibit higher nonbank shares, potentially reflecting more constrained access to bank credit.

5. Nonbank Responses to Monetary Policy

This section examines how nonbank credit supply responds to monetary policy surprises affecting different segments of the yield curve. We first describe our empirical strategy in Section 5.1. We then document two main findings. First, the aggregate nonbank response varies along the yield curve: nonbanks expand relative to banks following short-end surprises but contract following medium- and long-end surprises (Section 5.2). Second, this aggregate pattern masks substantial heterogeneity: FSIs and insurance corporations respond in opposite directions to each type of surprise (Section 5.3).

5.1. Empirical Strategy

Assessing how nonbanks shift their credit supply in response to different yield-curve movements requires overcoming one main identification challenge, namely isolating credit supply from credit demand effects, as tighter monetary policy can simultaneously affect both through distinct channels. On the demand side, the firm balance-sheet channel posits that firms may delay or reduce investment as higher interest rates increase financing costs, lower collateral values, and weaken expectations about investment returns. This deterioration in firms' creditworthiness increases the external finance premium and suppresses credit demand (Bernanke and Gertler, 1995; Kiyotaki and Moore, 1997). On the supply side, the bank lending channel suggests that monetary tightening reduces banks' reserves and constrains their ability to extend new loans, directly contracting credit supply.

Identification Strategy. To isolate credit supply effects, our identification strategy follows Khwaja and Mian (2008). We include firm-quarter fixed effects and compare credit supplied by banks and nonbanks to the same firm in the same quarter. This absorbs all time-varying firm-level demand shocks, including changes in creditworthiness, investment opportunities, and macroeconomic exposure. We further include lender fixed effects to control for time-invariant differences across financial institutions such as business model, risk appetite, and average lending capacity. The identifying assumption is that, within a firm-quarter, demand for external finance is common across lenders; under this assumption, differential changes in exposure between banks and nonbanks reflect credit supply responses.

A potential concern is anticipatory borrowing: firms may shift borrowing across lenders ahead of expected policy changes. We address this concern by using high-frequency monetary policy surprises measured in narrow windows around ECB Governing Council announcements (Altavilla et al., 2019). Because these surprises capture unanticipated revisions in meeting-related policy news, systematic demand-side reallocation in anticipation of policy is unlikely to explain our results.

Sample Characteristics. The within-firm identification restricts the sample to multi-lender borrowers. Appendix Table B.3 compares these firms to single-lender borrowers. Multi-lender borrowers are larger (mean exposure 21 million versus 1.5 million euros), less likely to be SMEs (70 versus 94 percent), and have substantially higher nonbank shares (14.2 versus 3.0 percent). Risk profiles are similar across both groups. While our baseline results speak most directly to these larger, more diversified borrowers, we show in Section 5.2 that results are robust to including single-lender borrowers using industry-location-time (ILT) fixed effects, following Degryse et al. (2019).

Empirical Framework. We estimate the following model:

Table 3. Nonbank Lending Channel

Dependent variable	Log exposure		
	(1) Target	(2) FG	(3) QT
Nonbank × MP	0.32**	−0.36**	−0.34**
	(0.13)	(0.17)	(0.17)
Constant	5.21***	5.22***	5.21***
	(0.21)	(0.21)	(0.21)
Observations	6,001,921	6,001,921	6,001,921
R^2	0.69	0.69	0.69
Lender FE	Yes	Yes	Yes
Firm-quarter FE	Yes	Yes	Yes

Notes: The dependent variable is the natural logarithm of the lender-firm-quarter credit exposure. Coefficients (and standard errors) are multiplied by 100 and represent approximate percentage changes in exposure. *Nonbank* is an indicator variable taking value one if the lender is a nonbank financial institution and zero if the lender is a bank. *MP* denotes the one-quarter-lagged, standardized monetary policy surprise: the Target surprise in column 1, the Forward Guidance surprise in column 2, and the Quantitative Tightening surprise in column 3. Standard errors, clustered at the lender-firm level, are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

$$\ln(\text{Exposure}_{l,f,t}) = \alpha_{f,t} + \delta_l + \beta_1(\text{Nonbank}_l \times \text{MP}_{t-1}) + \varepsilon_{l,f,t} \tag{1}$$

where $\ln(\text{Exposure}_{l,f,t})$ is the log of total exposure of lender l to firm f in quarter t; $\alpha_{f,t}$ are firm-quarter fixed effects; δ_l are lender fixed effects; Nonbank_l is an indicator taking value one for nonbanks and zero for banks; MP_{t-1} is the lag of one of the three monetary policy surprises as discussed in Section 4.1; β_1 is the coefficient of interest and captures the financing reaction of nonbanks relative to banks following an unexpected policy tightening surprise. Following Cucic and Gorea (2026), we cluster standard errors at the lender-firm level in our baseline specifications.[8]

5.2. Aggregate Nonbank Responses to Yield-Curve Movements

Table 3 reports estimates of equation (1) for the three monetary policy surprises. Column 1 shows that a one-standard-deviation Target surprise increases nonbank credit exposure by 0.32 percent relative to banks.[9] Per basis point, this implies approximately 0.06 percent —

[8]Our results are robust to alternative clustering choices (Appendix Table E.3).

[9]One potential explanation for the bank contraction relative to nonbanks following Target surprises is the deposit channel (Drechsler et al., 2017). Banks with greater deposit market power may experience larger deposit outflows when policy rates rise, as depositors reallocate toward higher-yielding alternatives. Comparing banks with above- and below-median deposit-spread betas, we find that both groups contract

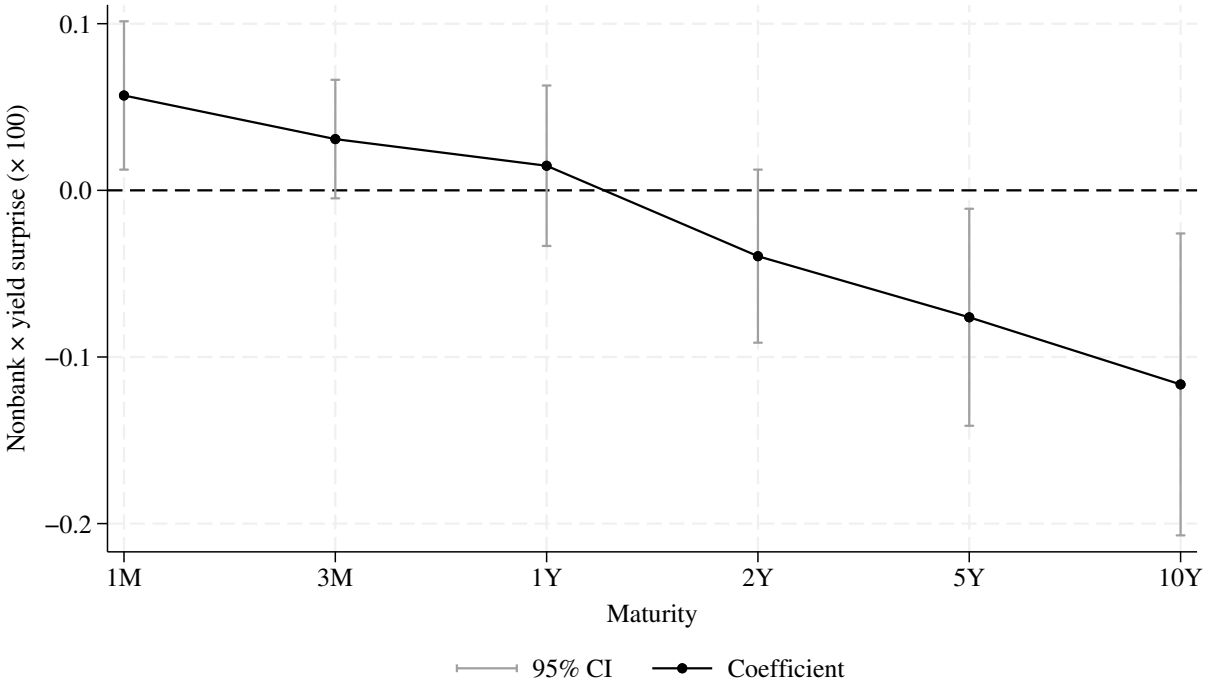


FIGURE 4. AGGREGATE NONBANK CREDIT RESPONSE ACROSS THE YIELD CURVE

Notes: This figure plots the coefficient β_1 from equation (1) estimated separately for lagged OIS surprises at different maturities. Surprises are not orthogonalized and not standardized. Coefficients (and standard errors) are multiplied by 100 and represent approximate percentage changes in exposure relative to banks. Bars represent 95% confidence intervals.

slightly lower compared to the 0.10–0.13 percent range found by Elliott et al. (2022, 2024) in syndicated loan markets.[10]

Columns 2 and 3 reveal a pattern not documented in prior work. Following medium- and long-end surprises (FG and QT), nonbanks contract relative to banks by 0.36 and 0.34 percent per standard deviation, respectively. This pattern is robust to including single-lender borrowers using ILT fixed effects, alternative monetary policy measures, and clustering schemes (Appendix Tables E.1 to E.3). These findings suggest that the nonbank lending channel depends particularly on the segment of the yield curve affected by monetary policy.

Figure 4 illustrates this directly. We estimate equation (1) separately using changes in (non-orthogonalized) OIS surprises at maturities from 1 month to 10 years. The nonbank coefficient declines monotonically: positive and significant at the short end, approximately

relative to nonbanks after Target surprises, but high-beta banks contract more, in line with the prediction of the deposit channel. However, direct evidence that high-beta banks experience larger deposit outflows is limited in our sample. Full results are reported in Appendix C.2.

[10] Cucic and Gorea (2026) report a larger effect (0.51 per basis point) in Denmark using annual data. The annual frequency may capture cumulative effects within a year, leading to stronger responses.

Table 4. Nonbank Lending Channel: Nonbank Heterogeneity

Dependent variable	Log exposure		
	(1) Target	(2) FG	(3) QT
FSI × MP	0.87***	−1.14***	−1.35***
	(0.20)	(0.26)	(0.27)
Financial enterprise × MP	−1.67*	−0.77	0.43
	(1.00)	(1.10)	(1.13)
Capital investment company × MP	−0.49	1.44	0.17
	(2.25)	(2.94)	(3.33)
Insurer × MP	−0.25*	0.59***	0.37*
	(0.14)	(0.19)	(0.19)
Securities company × MP	−3.85	2.42	3.25
	(2.60)	(2.94)	(3.77)
Non-MFI credit institution × MP	0.37	−0.52	1.56***
	(0.42)	(0.48)	(0.50)
Constant	5.21***	5.22***	5.21***
	(0.21)	(0.21)	(0.21)
Observations	6,001,921	6,001,921	6,001,921
R^2	0.69	0.69	0.69
Lender FE	Yes	Yes	Yes
Firm-quarter FE	Yes	Yes	Yes

Notes: The dependent variable is the natural logarithm of the lender-firm-quarter credit exposure. Coefficients (and standard errors) are multiplied by 100 and represent approximate percentage changes in exposure. The reported coefficients capture the differential lending response of each nonbank type relative to banks (the reference group). *MP* denotes the one-quarter-lagged, standardized monetary policy surprise: the Target surprise in column 1, the Forward Guidance surprise in column 2, and the Quantitative Tightening surprise in column 3. Standard errors, clustered at the lender-firm level, are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

zero at 1 year, and increasingly negative at longer maturities.

What drives this sign reversal? As outlined in Section 3, the nonbank sector comprises institutions with fundamentally different balance-sheet structures, funding sources, and regulatory frameworks. In the next section, we decompose the aggregate response by nonbank type to identify which institutions drive the aggregate pattern and to explore whether different types exhibit distinct responses to yield-curve movements.

5.3. Heterogeneous Responses Across Nonbank Types

Table 4 decomposes the aggregate nonbank response by institution type. The results reveal that FSIs drive the aggregate pattern documented in Section 5.2. FSIs expand by 0.87 percent relative to banks following a one-standard-deviation Target surprise, and contract by 1.14 and 1.35 percent following FG and QT surprises, respectively. All three coefficients are highly

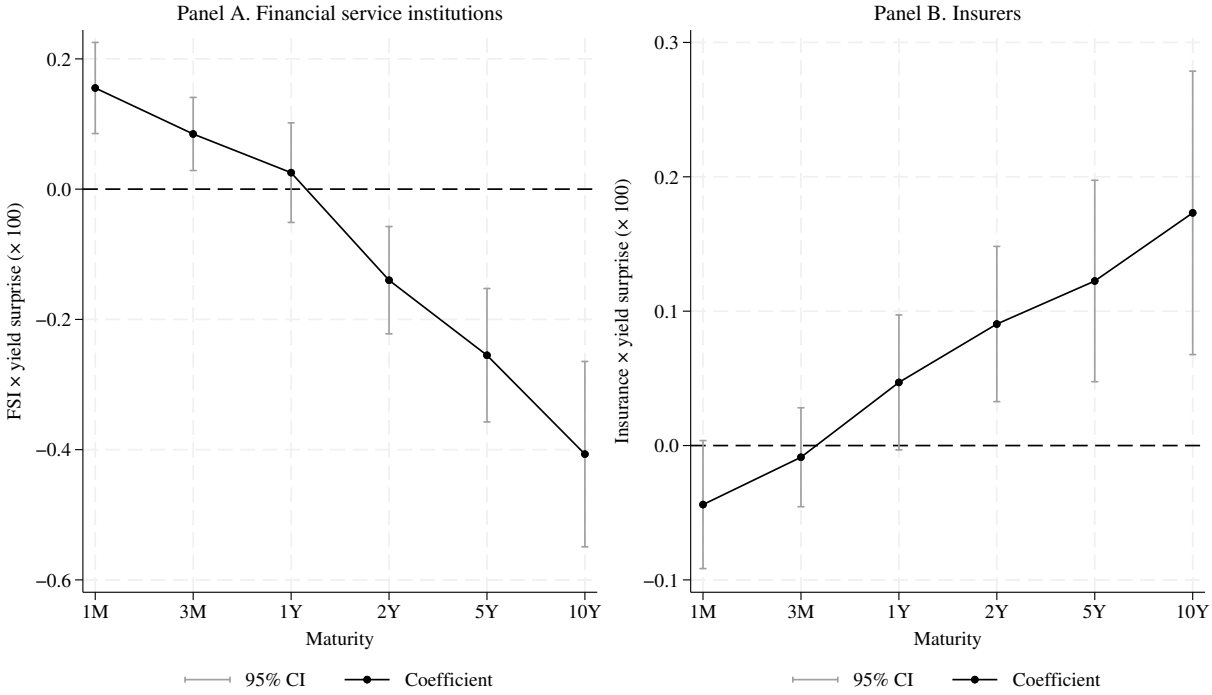


FIGURE 5. NONBANK CREDIT RESPONSE ACROSS THE YIELD CURVE BY LENDER TYPE

Notes: This figure plots lender-type-specific responses to lagged OIS surprises at different maturities. Surprises are not orthogonalized and not standardized. Coefficients (and standard errors) are multiplied by 100 and represent approximate percentage changes in exposure relative to banks. Bars represent 95% confidence intervals.

significant.

Insurance corporations display the opposite pattern at the medium and long end. They expand by 0.59 percent following FG surprises and by 0.37 percent following QT surprises. The latter estimate is close to the 5% significance threshold ($p = 0.054$), whereas the Target response is less precisely estimated ($p = 0.071$). The opposing responses of FSIs and insurers to the same surprises reveal a second dimension of heterogeneity beyond the yield-curve pattern documented in Figure 4.

Figure 5 illustrates these divergent responses across the full maturity spectrum. For FSIs, the coefficient declines monotonically along the yield curve: positive and significant at 1 month and 3 months, approximately zero at 1 year, and increasingly negative and significant from 2 years onward. For insurers, the pattern reverses: approximately zero at the short end, then positive and significant across all longer maturities. These opposing responses suggest that yield-curve movements affect FSIs and insurers through fundamentally different mechanisms, which we examine in Section 6.

The remaining nonbank categories, namely financial enterprises, capital investment companies, securities companies, and non-MFI credit institutions, display mixed or insignificant

responses, consistent with their smaller role in credit intermediation (together accounting for less than 10 percent of nonbank exposure).

Summary. Our results reveal two dimensions of heterogeneity in the nonbank lending channel. First, the aggregate nonbank response varies along the yield curve: nonbanks expand relative to banks following short-end surprises but contract following medium- and long-end surprises. Second, this aggregate pattern masks opposing responses by FSIs and insurers to each type of surprise. Whether nonbanks dampen or amplify monetary policy transmission therefore depends jointly on the yield-curve segment affected by policy and the composition of the nonbank sector.

6. Mechanisms

Section 5 documented two dimensions of heterogeneity in nonbank responses to monetary policy: variation along the yield curve and variation across nonbank types. We now investigate the balance-sheet channels underlying these patterns. Section 6.1 examines the bank capital reallocation channel for FSIs. Section 6.2 examines the duration-driven solvency channel for insurers.

6.1. FSI Channel: Bank Capital Reallocation

Section 5.3 showed that FSIs, primarily leasing companies and factoring firms, drive the aggregate nonbank response to monetary policy: they expand relative to banks following Target surprises but contract following FG and QT surprises. Unlike insurers, FSIs do not hold long-duration assets or liabilities that create mechanical exposure to yield-curve movements. Rather, their lending capacity depends heavily on bank funding: in our credit register data, 85 percent of FSI borrowing is sourced from banks, compared to 48 percent for insurers. This bank dependence suggests that variation in bank funding supply is likely to transmit directly into FSI lending capacity.

We hypothesize that bank capital constraints mediate this transmission at the short end of the yield curve. As discussed in Section 2, short-term funding costs adjust quickly while loan income adjusts only gradually (Alessandri and Nelson, 2015). Target surprises therefore raise banks' current funding costs without a matching contemporaneous increase in interest income, compressing margins and eroding capital buffers. One way for capital-constrained banks to adjust is to reallocate credit toward borrowers with lower default probabilities, thereby economizing on regulatory capital (Wang et al., 2025). FSIs are natural candidates for such reallocation: in our data, their mean default probability is 1.54 percent versus 2.93 percent for

non-financial firms, which is consistent with lower capital charges.[11] Moreover, because FSIs on-lend to the corporate sector, banks can maintain indirect exposure to the real economy, in line with Acharya et al.'s (2024) transformation view. By contrast, FG and QT surprises primarily move longer-horizon rates and term premia rather than current short-term funding costs. These surprises therefore need not generate the same contemporaneous squeeze on bank margins, and the capital-driven reallocation motive should be weaker following them.

To test these predictions, we examine whether banks adjust the composition of their lending toward FSI borrowers after monetary policy surprises, and whether these adjustments vary with bank capitalization. We estimate the following specification at the bank-borrower-quarter level:

$$\begin{aligned}\ln(\text{Exposure}_{l,b,t}) = \delta_{l,t} + \gamma_b \\ + \sum_k \Big[\beta_{1k}\Big(\text{Type}_{k,b} \times \text{MP}_{t-1}\Big) + \beta_{2k}\Big(\text{Type}_{k,b} \times \text{Capital}_{l,t-1}\Big) \\ + \beta_{3k}\Big(\text{Type}_{k,b} \times \text{MP}_{t-1} \times \text{Capital}_{l,t-1}\Big)\Big] + \varepsilon_{l,b,t}\end{aligned} \tag{2}$$

where $\delta_{l,t}$ denotes bank-quarter fixed effects, γ_b denotes borrower fixed effects, and $\text{Type}_{k,b}$ are indicators for each borrower type (FSI, insurer, and other NBFI), with non-financial firms as the omitted category. $\text{Capital}_{l,t-1}$ is the lagged bank core (Tier 1) capital ratio. The bank-quarter fixed effects absorb all time-varying bank characteristics, including overall quarterly lending levels. The specification thus identifies within-bank compositional shifts: how the same bank, in the same quarter, reallocates its portfolio across borrower types in response to monetary policy surprises. The coefficient of interest is β_{3k}, which captures whether the effect of monetary policy surprises on bank lending to borrower type k (relative to non-financial firms) varies with bank capitalization. In the main text, we focus on the FSI coefficients; the full set of borrower-type interactions is reported in Appendix Table C.1.

Table 5 reports the results. Panel A conditions on bank capital. The triple interaction term is negative (-0.33) and statistically significant at the 1 percent level, indicating that the compositional shift toward FSIs following short-end surprises is concentrated among less-capitalized banks. Figure 6 visualizes this heterogeneity by plotting the marginal effect of the Target surprise on bank lending to FSI borrowers at different percentiles of the bank capital distribution: banks in the bottom quartile of core capital increase lending to FSIs by 0.75 percent, while well-capitalized banks exhibit no significant response. By contrast, the corresponding interactions for FG and QT surprises are statistically insignificant, implying no evidence that medium- and long-end surprises induce capital-constrained banks to reallocate

[11] The difference in mean PDs (1.39 percentage points) is statistically significant ($t = 7.25$, $p < 0.001$). A variance ratio test confirms that FSI default probabilities are also significantly less dispersed ($F = 2.32$, $p < 0.001$).

Table 5. Bank Lending to NBFIs: The Role of Bank Capital

Dependent variable	Log exposure		
	(1) Target	(2) FG	(3) QT
Panel A. Conditional on bank capital			
FSI borrower × MP	5.38***	−4.23	−4.37*
	(1.99)	(2.61)	(2.48)
FSI borrower × Bank capital	1.87**	1.84**	1.87**
	(0.80)	(0.80)	(0.80)
FSI borrower × MP × Bank capital	−0.33***	0.24	0.19
	(0.13)	(0.17)	(0.16)
Constant	−60.88***	−60.88***	−60.88***
	(0.12)	(0.12)	(0.12)
Observations	14,566,743	14,566,743	14,566,743
R^2	0.86	0.86	0.86
Bank-quarter FE	Yes	Yes	Yes
Borrower FE	Yes	Yes	Yes
Panel B. Unconditional			
FSI borrower × MP	0.21	−0.72*	−1.07**
	(0.31)	(0.40)	(0.43)
Constant	−57.98***	−57.98***	−57.98***
	(0.11)	(0.11)	(0.11)
Observations	14,893,904	14,893,904	14,893,904
R^2	0.86	0.86	0.86
Bank-quarter FE	Yes	Yes	Yes
Borrower FE	Yes	Yes	Yes

Notes: The dependent variable is the natural logarithm of the bank-borrower-quarter credit exposure. The sample includes all bank lending relationships with non-financial firms and NBFIs as borrowers. Coefficients (and standard errors) are multiplied by 100 and represent approximate percentage changes in exposure. *FSI borrower* is an indicator variable for borrowers that are financial service institutions, with non-financial firms as the reference category. *MP* denotes the one-quarter-lagged, standardized monetary policy surprise: the Target surprise in column 1, the Forward Guidance surprise in column 2, and the Quantitative Tightening surprise in column 3. In Panel A, *Bank capital* is the lagged regulatory Tier 1 capital ratio (winsorized at the 2nd and 98th percentiles). Panel B reports the unconditional effect of each surprise on bank lending to FSI borrowers without conditioning on bank capital. Standard errors, clustered at the bank-borrower level, are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

toward FSIs. The capital-driven reallocation channel is specific to the short end of the yield curve.

Panel B reports the effect of each surprise on bank lending to FSIs without conditioning on bank capital. Following FG and QT surprises, bank exposure to FSIs contracts relative to non-financial firms by 0.72 and 1.07 percent, respectively. For Target surprises, the unconditional effect is insignificant (0.21 percent), reflecting the offsetting heterogeneity

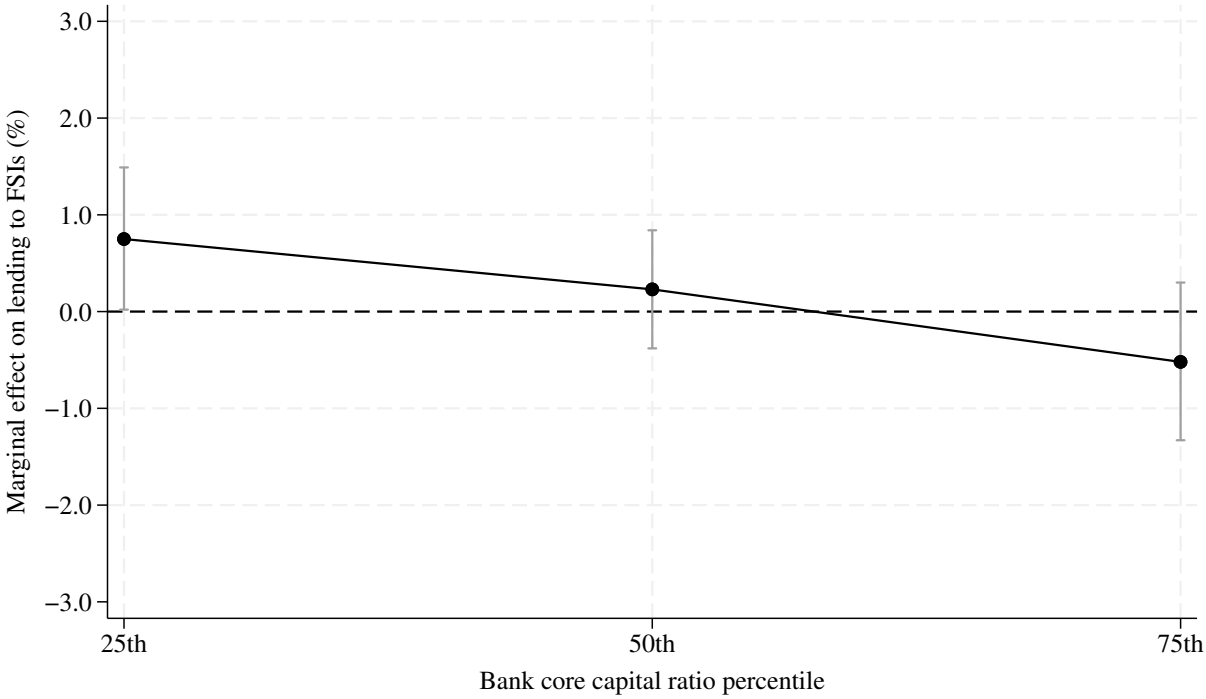


FIGURE 6. BANK LENDING TO FSIS BY BANK CORE CAPITAL POSITION

Notes: This figure plots the marginal effect of Target surprises on bank lending to FSI borrowers (relative to non-financial firms) at the 25th, 50th, and 75th percentiles of the bank core capital ratio distribution. Estimates are derived from equation (2). The marginal effect of Target on bank lending to FSIs at capital percentile p is: $\beta_{1,FSI} + \beta_{3,FSI} \times \text{Capital}_p$. Bars represent 95% confidence intervals based on standard errors clustered at the bank-borrower level. Full regression results are reported in Appendix Table C.1.

documented in Panel A: low-capital banks expand toward FSIs while well-capitalized banks do not. Given that 85 percent of FSI borrowing is sourced from banks, these bank-to-FSI exposures represent a key funding margin for FSI lending capacity. The patterns in bank-to-FSI lending match the FSI lending responses documented in Section 5.3: at the short end, the bank capital reallocation channel actively redirects capital-constrained banks' lending toward FSIs (Panel A); at the medium and long end, this channel is not active and bank exposure to FSIs contracts relative to non-financial firms (Panel B). Appendix Figure C.1 shows that the main patterns are robust to using the capital adequacy ratio rather than the core capital ratio.

6.2. Insurance Channel: Duration Gap and Solvency

While the bank capital reallocation channel operates at the short end of the yield curve, insurers respond through a different balance-sheet mechanism at the medium and long end. Section 5.3 showed that insurers expand lending following medium- and long-end surprises.

We now examine whether this pattern is consistent with a duration-driven solvency channel. Under mark-to-market solvency regulation, when liabilities are longer-dated than assets (a negative duration gap) a rise in medium- and long-term rates reduces the present value of liabilities by more than that of assets, thereby improving solvency. This channel then consists of two links: (i) medium- and long-end surprises improve solvency for insurers with negative duration gaps; (ii) these solvency gains relax regulatory constraints and translate into lending expansion.

We do not observe insurer-level duration gaps directly. We therefore proxy duration-gap exposure using the distinction between life and non-life insurers. Life insurers hold long-dated liabilities (annuities, pension obligations, guaranteed-return products) and typically maintain negative duration gaps, with liability durations exceeding asset durations (Koijen and Yogo, 2022). Non-life insurers hold shorter-duration liabilities tied to claims that typically settle within one to three years.

Solvency Ratio Response to Yield-Curve Movements. Under the channel, increases in medium- and long-term rates should improve life insurers' solvency ratios more than those of non-life insurers, while short-end movements (which have a much smaller effect on the present value of long-dated liabilities) should not generate differential solvency responses.[12]

We test these predictions by estimating:

$$\Delta\text{Solvency ratio}_{i,t} = \mu_i + \theta_t + \beta_1(\text{Life insurer}_i \times \text{MP}_{t-1}) + \varepsilon_{i,t} \tag{3}$$

where $\Delta\text{Solvency ratio}_{i,t}$ denotes the quarterly change in the solvency ratio of insurer i; μ_i denotes insurer fixed effects; θ_t captures quarter fixed effects; Life insurer_i equals one for life insurers, and zero for non-life and health insurers. Standard errors are clustered at the insurer level.

Table 6 reports the results. Following a one-standard-deviation FG surprise, life insurers experience solvency improvements 20.5 percentage points larger than non-life insurers, equivalent to approximately 5.7 percent of the mean solvency ratio (359 percent). Given that the regulatory minimum is 100 percent, this represents an economically meaningful improvement in regulatory capital. The effect for QT surprises is similarly large (16.5 percentage points). For Target surprises, there is no differential response, consistent with short-end movements having limited effects on long-dated liabilities. These results support the first link: medium- and long-end surprises improve the regulatory capital position of life insurers relative to

[12]Appendix Table B.4 reports characteristics by insurer type. Life insurers account for 50 percent of total insurance sector credit exposure and maintain higher average solvency ratios than non-life insurers (484 versus 312 percent).

Table 6. Solvency Ratio Response to Yield-Curve Movements

Dependent variable	Δ Solvency ratio		
	(1) Target	(2) FG	(3) QT
Life insurer × MP	−0.019	0.205***	0.165***
	(0.024)	(0.039)	(0.034)
Constant	0.008***	0.005***	0.0077***
	(0.000)	(0.001)	(0.000)
Observations	4,395	4,395	4,395
R^2	0.078	0.094	0.089
Insurer FE	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes

Notes: The dependent variable is the quarterly change in solvency ratio (eligible own funds divided by solvency capital requirement) in levels. Life insurer equals one for life insurers, zero for non-life and health insurers. *MP* denotes the one-quarter-lagged, standardized monetary policy surprise: the Target surprise in column 1, the Forward Guidance surprise in column 2, and the Quantitative Tightening surprise in column 3. Standard errors, clustered at the insurer level, are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

non-life insurers.

Solvency and Lending. We next test whether duration exposure translates into lending responses. If the duration-driven solvency channel operates as hypothesized, life insurers, which experience larger solvency gains from medium- and long-end movements (Table 6), should expand lending more following FG and QT surprises.

We estimate the following specification on the subsample of insurance corporations:

$$\ln(\text{Exposure}_{l,f,t}) = \gamma_f + \delta_l + \beta_1 \text{MP}_{t-1} + \beta_2 \left(\text{Life insurer}_l \times \text{MP}_{t-1}\right) + \varepsilon_{l,f,t} \tag{4}$$

where γ_f denotes firm fixed effects and δ_l denotes lender fixed effects. Because firms rarely borrow from multiple insurers within the same quarter, firm-quarter fixed effects are not feasible in this subsample. We therefore employ firm fixed effects to absorb time-invariant firm characteristics. We return to the identifying assumptions this entails below.

Table 7 reports the results. Life insurers expand by 0.75 percent relative to non-life insurers following FG surprises and by 0.88 percent following QT surprises. For Target surprises, life insurers contract relative to non-life insurers (−0.56 percent), consistent with the evidence in Table 6 that Target surprises do not generate the solvency relief that underpins the channel. The FG and QT coefficients are consistent with the channel's central prediction: life insurers, which receive the larger solvency relief, expand lending more following medium- and long-end surprises.

Table 7. Insurance Lending Responses: Life vs. Non-Life Insurers

Dependent variable	Log exposure		
	(1) Target	(2) FG	(3) QT
MP	0.29***	−0.44***	−0.67***
	(0.05)	(0.07)	(0.07)
Life insurer × MP	−0.56***	0.75***	0.88***
	(0.08)	(0.12)	(0.12)
Constant	83.25***	83.27***	83.25***
	(0.26)	(0.26)	(0.26)
Observations	538,747	538,747	538,747
R^2	0.86	0.86	0.86
Lender FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes

Notes: The dependent variable is the natural logarithm of the lender-firm-quarter credit exposure. Coefficients (and standard errors) are multiplied by 100 and represent approximate percentage changes in exposure. MP denotes the one-quarter-lagged, standardized monetary policy surprise: the Target surprise in column 1, the Forward Guidance surprise in column 2, and the Quantitative Tightening surprise in column 3. *Life insurer* equals one for life insurers, zero for non-life and health insurers. Standard errors, clustered at the lender-firm level, are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

A potential concern is that firm fixed effects absorb only time-invariant firm characteristics, so that the comparison could in principle reflect differences in the credit demand of life- versus non-life-insurer clients rather than supply-side solvency effects. Two features of the evidence weigh against this interpretation. First, the first link is identified entirely on insurer balance sheets: the solvency response in Table 6 is an insurer-side outcome that does not depend on borrower demand. Second, a demand-based explanation would require that firms borrowing from life insurers exhibit systematically stronger credit demand responses to FG and QT surprises (but not to Target surprises) relative to firms borrowing from non-life insurers, so that insurer-type client demand would have to vary with the yield-curve segment in precisely the way the supply-side solvency mechanism predicts. Such a configuration is difficult to motivate from the demand side alone. As further corroboration, conditioning lending on insurers' predetermined (two-quarter-lagged) solvency changes yields a consistent pattern (Appendix Table C.2): insurers with larger prior solvency gains expand lending more following FG and QT surprises, tying the response to a supply-side balance-sheet variable rather than to insurer type alone.

Summary. Taken together, the evidence is consistent with a duration-driven solvency channel in insurance lending, linking duration exposure to solvency revaluation and, in turn, to credit supply. Life insurers, which hold long-dated liabilities and typically negative

duration gaps, experience solvency gains following medium- and long-end surprises (Table 6), and they expand lending more following FG and QT surprises (Table 7). Target surprises produce no differential solvency relief and correspondingly no differential lending expansion. These findings align with Timmer (2018), who shows that insurers' long-term liability profiles enable countercyclical investment during market stress.

7. Economic Implications

The previous sections documented that different nonbank types respond to different segments of the yield curve through distinct balance-sheet channels: FSIs expand following Target surprises via bank capital reallocation, while insurers expand following FG and QT surprises via duration-driven solvency gains. We now examine the economic implications of these heterogeneous responses. Section 7.1 analyzes how nonbank credit is allocated across firm types, examining three dimensions of firm heterogeneity: size, emissions intensity, and credit risk. Section 7.2 assesses whether nonbank responses offset or amplify aggregate credit dynamics at the firm level.

7.1. Implications for Credit Allocation

Because FSIs and insurers specialize in different borrowers, their heterogeneous responses imply that the yield-curve segment affected by monetary policy determines which firms gain or lose credit access. We test this by extending the baseline specification to include a triple interaction:

$$\begin{aligned}\ln(\text{Exposure}_{l,f,t}) = \alpha_{f,t} + \delta_l + \beta_1(\text{Nonbank}_l \times \text{Firm type}_{f,t-1}) \\ + \beta_2(\text{Nonbank}_l \times \text{MP}_{t-1}) \\ + \beta_3(\text{Nonbank}_l \times \text{Firm type}_{f,t-1} \times \text{MP}_{t-1}) + \varepsilon_{l,f,t}\end{aligned} \tag{5}$$

where $\text{Firm type}_{f,t-1}$ is replaced by $\text{Green}_{f,t-1}$, $\text{High risk}_{f,t-1}$, or SME_f in separate regressions, which are all indicator variables (see Appendix Table B.1 for the definitions). The coefficient β_3 captures whether nonbanks differentially adjust lending to specific firm types relative to banks following monetary policy surprises.

Firm Size. SMEs face well-documented financing constraints due to information asymmetries and limited collateral (Stiglitz and Weiss, 1981). These constraints make SMEs particularly sensitive to monetary policy: banks reduce lending to small firms following tightening (Kandrac, 2012), and small firms exhibit stronger output responses than large firms (Gertler and Gilchrist, 1994). If nonbank responses differentially affect SME credit access, they may

Table 8. Nonbank Credit Allocation: SMEs vs. Large Firms

Dependent variable	Log exposure		
	(1)	(2)	(3)
	Target	FG	QT
Nonbank × SME	23.50***	23.58***	23.53***
	(2.78)	(2.77)	(2.78)
Nonbank × MP	0.14	−0.04	−0.28
	(0.27)	(0.35)	(0.35)
Nonbank × SME × MP	0.77**	−1.04**	−0.47
	(0.36)	(0.47)	(0.49)
Constant	30.40***	30.40***	30.40***
	(0.47)	(0.47)	(0.47)
Observations	2,059,555	2,059,555	2,059,555
R^2	0.66	0.66	0.66
Lender FE	Yes	Yes	Yes
Firm-quarter FE	Yes	Yes	Yes

Notes: The dependent variable is the natural logarithm of the lender-firm-quarter credit exposure. Coefficients (and standard errors) are multiplied by 100 and represent approximate percentage changes in exposure. *Nonbank* is an indicator variable taking value one if the lender is a nonbank financial institution and zero if the lender is a bank. *MP* denotes the one-quarter-lagged, standardized monetary policy surprise: the Target surprise in column 1, the Forward Guidance surprise in column 2, and the Quantitative Tightening surprise in column 3. *SME* is a time-invariant indicator variable taking value one if a firm is classified as an SME according to the European Commission's definition. Standard errors clustered at the lender-firm level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

either amplify or dampen this transmission channel.

Table 8 reports the results. The level effect (Nonbank × SME) indicates that nonbanks maintain 23.5 percent higher exposure to SMEs relative to large firms compared to banks, consistent with U.S. evidence on the growing role of nonbanks in small business lending (Gopal and Schnabl, 2022). Following Target surprises, nonbanks expand to SMEs by 0.77 percent more than to large firms. Following FG surprises, nonbanks contract from SMEs by 1.04 percent more than from large firms. SMEs thus benefit disproportionately from nonbank expansion after short-end surprises but bear disproportionate adjustment when nonbanks contract after medium-end surprises.

Appendix Table D.1 decomposes these effects by nonbank type. FSIs have substantially higher baseline exposure to SMEs and on average expand after Target surprises while contracting after FG and QT surprises, with these responses similar across firm sizes. Insurers display a different pattern. Following Target surprises, insurers contract on average (-0.69 percent) but do not reduce SME lending, as the SME differential nearly offsets the aggregate contraction. Following FG and QT surprises, insurers expand on average, but this expansion is concentrated among large firms: the net effect on SME lending is close to zero. Thus,

Table 9. Nonbank Credit Allocation: Green vs. Brown Industries

Dependent variable	Log exposure		
	(1) Target	(2) FG	(3) QT
Nonbank × Green	−14.29***	−14.38***	−14.31***
	(1.78)	(1.77)	(1.78)
Nonbank × MP	0.63***	−1.07***	−0.86***
	(0.19)	(0.29)	(0.26)
Nonbank × Green × MP	−0.64**	1.48***	0.95***
	(0.27)	(0.42)	(0.35)
Constant	6.32***	6.33***	6.33***
	(0.27)	(0.27)	(0.27)
Observations	5,941,782	5,941,782	5,941,782
R^2	0.69	0.69	0.69
Lender FE	Yes	Yes	Yes
Firm-quarter FE	Yes	Yes	Yes

Notes: The dependent variable is the natural logarithm of the lender-firm-quarter credit exposure. Coefficients (and standard errors) are multiplied by 100 and represent approximate percentage changes in exposure. *Nonbank* is an indicator variable taking value one if the lender is a nonbank financial institution and zero if the lender is a bank. *MP* denotes the one-quarter-lagged, standardized monetary policy surprise: the Target surprise in column 1, the Forward Guidance surprise in column 2, and the Quantitative Tightening surprise in column 3. *Green* is a one-quarter-lagged lagged indicator variable taking value one if a firm operates in an industry classified as green (i.e., the industry's Scope 1 emission intensity falls below the median for that year). Standard errors clustered at the lender-firm level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

short-end tightening supports SME credit through two channels: FSIs expand without firm-size differentiation despite their structural SME tilt, and insurers do not cut SME exposures. Medium- and long-end movements, by contrast, shift insurer expansion toward large firms.

Industry Emissions. We next examine whether nonbank credit flows differ across firms operating in green and brown industries. We classify firms as "green" if their industry's Scope 1 emissions intensity falls below the annual median, and "brown" otherwise.[13] Table 9 reports the results. Nonbanks have 14.3 percent lower exposure to green industries relative to banks, indicating structural exposure to carbon-intensive sectors. Following Target surprises, nonbank expansion flows primarily to brown industries. Following FG and QT surprises, nonbanks contract overall, but green industries are partially protected from this contraction. Appendix Table D.2 shows that this green protection following FG and QT is driven by FSIs, which contract sharply from brown industries while offsetting this for green industries.

[13]Results are robust to using continuous Scope 1 emission intensities and to the EU regulatory classification of high-climate impact sectors (NACE sections A–H and L) under EU Regulation 2019/2089. See Appendix Table D.3. Firm-level green classifications yield coefficients with consistent signs but reduced significance (untabulated).

Table 10. Nonbank Credit Allocation: High-Risk vs. Low-Risk Firms

Dependent variable	Log exposure		
	(1) Target	(2) FG	(3) QT
Nonbank × High risk	17.83***	17.86***	17.85***
	(1.75)	(1.74)	(1.75)
Nonbank × MP	0.07	−0.04	0.17
	(0.21)	(0.27)	(0.26)
Nonbank × High risk × MP	0.19	−0.29	−0.21
	(0.33)	(0.44)	(0.43)
Constant	15.23***	15.23***	15.23***
	(0.28)	(0.28)	(0.28)
Observations	4,915,771	4,915,771	4,915,771
R^2	0.67	0.67	0.67
Lender FE	Yes	Yes	Yes
Firm-quarter FE	Yes	Yes	Yes

Notes: The dependent variable is the natural logarithm of the lender-firm-quarter credit exposure. Coefficients (and standard errors) are multiplied by 100 and represent approximate percentage changes in exposure. *Nonbank* is an indicator variable taking value one if the lender is a nonbank financial institution and zero if the lender is a bank. *MP* denotes the one-quarter-lagged, standardized monetary policy surprise: the Target surprise in column 1, the Forward Guidance surprise in column 2, and the Quantitative Tightening surprise in column 3. *High risk* is a one-quarter-lagged indicator variable taking value one if a firm's PD is greater than the quarterly cross-sectional median. Standard errors clustered at the lender-firm level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Insurers show no significant differentiation by emissions intensity.

Credit Risk. A potential concern is that nonbank expansion attenuates the risk-taking channel of monetary policy by extending credit to riskier borrowers that banks avoid (Adrian and Shin, 2010; Borio and Zhu, 2012; Dell'Ariccia et al., 2017). Table 10 tests this by classifying firms as high-risk if their probability of default exceeds the quarterly cross-sectional median.[14] Despite nonbanks' structural tilt toward riskier borrowers (17.8 percent higher exposure to high-risk firms relative to banks), the triple interactions are insignificant across the three columns. Nonbanks do not differentially expand toward high-risk firms following any surprise.

This null is consistent with the size and emissions patterns: insurer expansion following FG and QT flows to large, lower-risk firms, while FSI contraction is concentrated in brown, higher-risk industries, mechanically shifting nonbank portfolios toward safer borrowers. It is also consistent with evidence from Denmark (Cucic and Gorea, 2026) and the global syndicated loan market (Albuquerque et al., 2025), and aligns with theoretical predictions

[14]Results are robust to using continuous firm-level PDs and to defining high-risk firms relative to industry-quarter medians. See Appendix Table D.3.

that monetary tightening reduces banks' funding advantage, creating a more level competitive environment where nonbanks face less pressure to adopt riskier strategies (Begenau and Landvoigt, 2022).

7.2. Aggregate Credit Dynamics

The credit allocation results in Section 7.1 documented which firm types benefit or lose from nonbank responses to monetary policy. We now examine a complementary question: do nonbank responses offset or amplify aggregate credit dynamics at the firm level?

Firm-Level Credit and Nonbank Access. We test this by aggregating credit exposures at the firm level and comparing outcomes for firms with and without nonbank relationships. Specifically, we estimate:

$$\begin{aligned}\ln(\text{Total credit}_{f,t}) = \gamma_f + \theta_t + \beta_1 \text{Nonbank relation}_{f,t-1} \\ + \beta_2(\text{Nonbank relation}_{f,t-1} \times \text{MP}_{t-1}) + \varepsilon_{f,t}\end{aligned} \tag{6}$$

where Total credit$_{f,t}$ is the sum of all credit exposures to firm f across all lenders in quarter t, γ_f denotes firm fixed effects, θ_t denotes quarter fixed effects, and Nonbank relation$_{f,t-1}$ is an indicator equal to one if the firm borrowed from at least one nonbank lender in the previous quarter. Using the lag ensures that nonbank access is predetermined relative to the monetary policy surprise. The coefficient β_2 captures whether firms with existing nonbank relationships experience different total credit dynamics following monetary policy surprises. Standard errors are clustered at the firm level.

Table 11 reports the results. The level effect indicates that firms with existing nonbank relationships maintain 41 percent higher total credit on average. More importantly, the interaction reveals asymmetric effects across the yield curve. Following Target surprises, firms with existing nonbank relationships receive 0.79 percent more credit than firms without such relationships. Following FG and QT surprises, the pattern reverses: firms with existing nonbank relationships receive 1.33 and 1.18 percent less credit, respectively. These results are consistent with nonbanks offsetting bank contraction in aggregate at the short end and reinforcing it at longer horizons.

Aggregate Magnitudes. To gauge economic significance, we translate firm-level coefficients into euro terms. For the average firm with an active nonbank relationship (total credit: 31.14 million euros; see Appendix Table B.5), a one-standard-deviation Target surprise implies approximately 246 thousand euros in additional credit relative to firms without nonbank

Table 11. Firm-Level Credit Outcomes and Nonbank Access

Dependent variable	Log total credit		
	(1) Target	(2) FG	(3) QT
Nonbank relation	41.23***	41.29***	41.24***
	(0.76)	(0.76)	(0.76)
Nonbank relation × MP	0.79***	−1.33***	−1.18***
	(0.05)	(0.08)	(0.08)
Constant	−73.80***	−73.79***	−73.79***
	(0.06)	(0.06)	(0.06)
Observations	10,449,252	10,449,252	10,449,252
R^2	0.95	0.95	0.95
Firm FE	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes

Notes: The dependent variable is the natural logarithm of the total firm-level credit exposure (summed across all lenders). Coefficients (and standard errors) are multiplied by 100 and represent approximate percentage changes in total credit. *Nonbank relation* is an indicator equal to one if the firm borrowed from at least one nonbank lender in the previous quarter. *MP* denotes the one-quarter-lagged, standardized monetary policy surprise: the Target surprise in column 1, the Forward Guidance surprise in column 2, and the Quantitative Tightening surprise in column 3. Standard errors, clustered at the firm level, are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

access.[15]

In an average quarter, approximately 43,400 firms maintain active nonbank relationships, representing 1.35 trillion euros in total credit. Aggregating across these firms, the offset following a one-standard-deviation Target surprise amounts to approximately 10.7 billion euros.[16] This represents credit that would have contracted had nonbanks responded identically to banks. For FG and QT surprises, the amplification amounts to approximately 18.0 billion euros and 15.9 billion euros.

We interpret these magnitudes cautiously. The calculations assume uniform effects across firm sizes and do not account for general equilibrium adjustments. Nevertheless, they illustrate that nonbank responses have quantitatively meaningful implications for aggregate credit dynamics. At current nonbank market shares, aggregate effects remain modest relative to total credit. However, nonbank assets in Germany have grown substantially over recent decades (Figure 1). As this trajectory continues, the yield-curve dependence of nonbank responses will become increasingly material.

[15] Calculation: 0.79% × €31.14 million = €246 thousand.
[16] Calculation: 0.79% × €1,350.46 billion = €10.67 billion.

8. Conclusion

The prevailing view holds that nonbanks dampen monetary policy transmission by expanding credit when banks contract. We argue that this characterization is incomplete: the nonbank lending channel is yield-curve dependent. In the aggregate, nonbanks expand relative to banks after short-end surprises, dampening monetary tightening, but contract after medium- and long-end surprises, amplifying it. This aggregate pattern is driven primarily by FSIs, which expand after short-end surprises (when bank capital pressure drives reallocation toward them) and contract after medium- and long-end surprises (where this reallocation motive is absent). Insurers respond through a distinct mechanism that runs partly counter to FSIs: they expand after medium- and long-end surprises, as duration-driven solvency relief relaxes their constraints. Because intermediary responses differ in both sign and yield-curve sensitivity, the same nonbank sector can dampen policy in one segment of the curve and amplify it in another, with the net effect depending on which segment moves and on the composition of the nonbank sector.

Although our identification relies on German credit register data, the mechanisms we document depend on institutional features that are not unique to Germany. Insurance corporations account for roughly 8–15 percent of financial system assets across major advanced economies and operate under similar mark-to-market solvency frameworks (Financial Stability Board, 2024). The bank capital reallocation channel may extend to any jurisdiction where banks fund nonbank lenders that on-lend to the real economy, such as finance companies and structured finance vehicles. Whether these mechanisms operate with similar strength in other financial systems is, however, an open empirical question: cross-country differences in nonbank composition, bank-nonbank funding linkages, and regulatory regimes may alter their quantitative importance, and direct evidence from other jurisdictions is needed.

Our results have implications for monetary policy design. In our setting, conventional rate increases, which move the short end of the yield curve, are partially cushioned by nonbank expansion. By contrast, forward guidance and quantitative tightening surprises, which primarily move medium- and long-term rates, are associated with aggregate nonbank contraction that amplifies bank retrenchment. All else equal, this suggests that policy tools operating further out the yield curve may generate stronger aggregate credit tightening, as they encounter less nonbank offset in firm credit markets.

Our results also have implications for financial stability. Aggregate measures of nonbank credit can conceal important shifts within the sector: for example, insurer expansion alongside FSI contraction, or differential effects on credit supply to SMEs. Such offsetting movements can obscure where credit risk and funding vulnerabilities are accumulating within the nonbank sector. This argues for monitoring NBFIs along dimensions that capture balance-sheet

heterogeneity, including funding structure, asset duration, and regulatory regime, rather than focusing only on aggregate nonbank credit.

More broadly, our results suggest that as nonbank intermediation continues to grow, the effectiveness of monetary policy will depend not only on how much credit nonbanks supply, but on which nonbanks supply it and which segment of the yield curve is affected by monetary policy.

References

Acharya, V. V., Cetorelli, N., and Tuckman, B. (2024). *Where do banks end and NBFIs begin?* (Working Paper No. 32316). National Bureau of Economic Research.

Adrian, T. and Shin, H. S. (2010). Financial intermediaries and monetary economics. In *Handbook of Monetary Economics*, volume 3, pages 601–650. Elsevier.

Agarwal, I., Hu, M., Roman, R. A., and Zheng, K. (2023). *Lending by servicing: Monetary policy transmission through shadow banks* (Working Paper No. 23-14). Federal Reserve Bank of Philadelphia.

Albuquerque, B., Cerutti, E., Firat, M., and Chen, N. (2025). *From banks to nonbanks: macroprudential and monetary policy effects on corporate lending* (Working Paper No. 2025/096). International Monetary Fund.

Alessandri, P. and Nelson, B. D. (2015). Simple banking: profitability and the yield curve. *Journal of Money, Credit and Banking*, 47(1):143–175.

Altavilla, C., Brugnolini, L., Gürkaynak, R. S., Motto, R., and Ragusa, G. (2019). Measuring euro area monetary policy. *Journal of Monetary Economics*, 108:162–179.

Banerjee, R. and Serena, J. M. (2024). Dampening the financial accelerator? Direct lenders and monetary policy. *Journal of Money, Credit and Banking*, 58(4):1017–1049.

Bednarek, P., Briukhova, O., Ongena, S., and Westernhagen, N. v. (2025). Effects of bank capital requirements on lending by banks and non-bank financial institutions. *Journal of Financial Intermediation*, 63:101167.

Begenau, J. and Landvoigt, T. (2022). Financial regulation in a quantitative model of the modern banking system. *The Review of Economic Studies*, 89(4):1748–1784.

Bernanke, B. S. and Blinder, A. S. (1988). Credit, money, and aggregate demand. *American Economic Review*, 78(2):435–439.

Bernanke, B. S. and Gertler, M. (1995). Inside the black box: The credit channel of monetary policy transmission. *Journal of Economic Perspectives*, 9(4):27–48.

Borio, C. and Zhu, H. (2012). Capital regulation, risk-taking and monetary policy: A missing link in the transmission mechanism? *Journal of Financial Stability*, 8(4):236–251.

Braun, R., Miranda-Agrippino, S., and Saha, T. (2025). Measuring monetary policy in the UK: The UK monetary policy event-study database. *Journal of Monetary Economics*, 149:103645.

Bu, C., Rogers, J., and Wu, W. (2021). A unified measure of Fed monetary policy shocks. *Journal of Monetary Economics*, 118:331–349.

Cloyne, J. and Hürtgen, P. (2016). The macroeconomic effects of monetary policy: A new measure for the United Kingdom. *American Economic Journal: Macroeconomics*, 8(4):75–102.

Coibion, O. (2012). Are the effects of monetary policy shocks big or small? *American Economic Journal: Macroeconomics*, 4(2):1–32.

Cucic, D. and Gorea, D. (2026). Nonbank lending and the transmission of monetary policy. *The Review of Financial Studies*, 39(4):966–1014.

De Jonghe, O., Dewachter, H., Mulier, K., Ongena, S., and Schepens, G. (2020). Some borrowers are more equal than others: Bank funding shocks and credit reallocation. *Review of Finance*, 24(1):1–43.

Degryse, H., De Jonghe, O., Jakovljević, S., Mulier, K., and Schepens, G. (2019). Identifying credit supply shocks with bank-firm data: Methods and applications. *Journal of Financial Intermediation*, 40:100813.

Dell'Ariccia, G., Laeven, L., and Suarez, G. A. (2017). Bank leverage and monetary policy's risk-taking channel: Evidence from the United States. *The Journal of Finance*, 72(2):613–654.

Den Haan, W. J. and Sterk, V. (2011). The myth of financial innovation and the great moderation. *The Economic Journal*, 121(553):707–739.

Domanski, D., Shin, H. S., and Sushko, V. (2017). The hunt for duration: not waving but drowning? *IMF Economic Review*, 65(1):113–153.

Drechsler, I., Savov, A., and Schnabl, P. (2017). The deposits channel of monetary policy. *The Quarterly Journal of Economics*, 132(4):1819–1876.

Drechsler, I., Savov, A., and Schnabl, P. (2022). How monetary policy shaped the housing boom. *Journal of Financial Economics*, 144(3):992–1021.

Elliott, D., Meisenzahl, R. R., and Peydró, J.-L. (2024). Nonbank lenders as global shock absorbers: Evidence from US monetary policy spillovers. *Journal of International Economics*,

149:103908.

Elliott, D., Meisenzahl, R. R., Peydró, J.-L., and Turner, B. C. (2022). *Nonbanks, banks, and monetary policy: US loan-level evidence since the 1990s* (Working Paper No. 2022-27). Federal Reserve Bank of Chicago.

European Central Bank (2021). *Non-bank financial intermediation in the euro area: Implications for monetary policy transmission and key vulnerabilities* (Occasional Paper No. 2021/270). European Central Bank.

Financial Stability Board (2024). *Global monitoring report on non-bank financial intermediation 2024*. Financial Stability Board.

Gertler, M. and Gilchrist, S. (1994). Monetary policy, business cycles, and the behavior of small manufacturing firms. *The Quarterly Journal of Economics*, 109(2):309–340.

Gopal, M. and Schnabl, P. (2022). The rise of finance companies and fintech lenders in small business lending. *The Review of Financial Studies*, 35(11):4859–4901.

Gürkaynak, R. S., Kara, A. H., Kısacıkoğlu, B., and Lee, S. S. (2021). Monetary policy surprises and exchange rate behavior. *Journal of International Economics*, 130:103443.

Gürkaynak, R. S., Sack, B., and Swanson, E. (2005). The sensitivity of long-term interest rates to economic news: Evidence and implications for macroeconomic models. *American Economic Review*, 95(1):425–436.

Haque, S. M., Jang, Y. S., and Wang, J. J. (2025). *Indirect credit supply: How bank lending to private credit shapes monetary policy transmission* (Working Paper No. 2025-059). Federal Reserve Board.

Hodge, A. and Weber, A. (2023). *The heterogeneous effects of US monetary policy on non-bank finance* (Working Paper No. 2023/055). International Monetary Fund.

Hodula, M. and Libich, J. (2023). Has monetary policy fueled the rise in shadow banking? *Economic Modelling*, 123:106278.

Holm-Hadulla, F., Mazelis, F., and Rast, S. (2023). Bank and non-bank balance sheet responses to monetary policy shocks. *Economics Letters*, 222:110918.

Irani, R. M., Iyer, R., Meisenzahl, R. R., and Peydró, J.-L. (2021). The rise of shadow banking: Evidence from capital regulation. *The Review of Financial Studies*, 34(5):2181–2235.

Jiménez, G., Ongena, S., Peydró, J.-L., and Saurina, J. (2012). Credit supply and monetary policy: Identifying the bank balance-sheet channel with loan applications. *American Economic Review*, 102(5):2301–2326.

Kandrac, J. (2012). Monetary policy and bank lending to small firms. *Journal of Macroeconomics*, 34(3):741–748.

Kashyap, A. K. and Stein, J. C. (1995). The impact of monetary policy on bank balance sheets. In *Carnegie-rochester conference series on public policy*, volume 42, pages 151–195. Elsevier.

Kashyap, A. K. and Stein, J. C. (2000). What do a million observations on banks say about the transmission of monetary policy? *American Economic Review*, 90(3):407–428.

Khwaja, A. I. and Mian, A. (2008). Tracing the impact of bank liquidity shocks: Evidence from an emerging market. *American Economic Review*, 98(4):1413–1442.

Kiyotaki, N. and Moore, J. (1997). Credit cycles. *Journal of Political Economy*, 105(2):211–248.

Koijen, R. S. and Yogo, M. (2022). The fragility of market risk insurance. *The Journal of Finance*, 77(2):815–862.

Krippner, L. (2013). Measuring the stance of monetary policy in zero lower bound environments. *Economics Letters*, 118(1):135–138.

Lee, H., Lee, S., and Paluszynski, R. (2024). Capital regulation and shadow finance: a quantitative analysis. *Review of Economic Studies*, 91(5):3047–3084.

Milic, D. (2021). The impact of non-banking financial institutions on monetary policy transmission in euro area. *Empirical Economics*, 61(4):1779–1817.

Minoiu, C., Schneider, A., and Wei, M. (2025). *Why Does the Yield Curve Predict GDP Growth?: The Role of Banks* (Working Paper No. 2025-05). Federal Reserve Bank of Atlanta.

Miranda-Agrippino, S. and Nenova, T. (2022). A tale of two global monetary policies. *Journal of International Economics*, 136:103606.

Nelson, B., Pinter, G., and Theodoridis, K. (2018). Do contractionary monetary policy shocks expand shadow banking? *Journal of Applied Econometrics*, 33(2):198–211.

Romer, C. D. and Romer, D. H. (2004). A new measure of monetary shocks: Derivation and implications. *American Economic Review*, 94(4):1055–1084.

Stiglitz, J. E. and Weiss, A. (1981). Credit rationing in markets with imperfect information. *American Economic Review*, 71(3):393–410.

Swanson, E. T. (2021). Measuring the effects of federal reserve forward guidance and asset purchases on financial markets. *Journal of Monetary Economics*, 118:32–53.

Timmer, Y. (2018). Cyclical investment behavior across financial institutions. *Journal of Financial Economics*, 129(2):268–286.

Wang, T., Krainer, J., and Vaghefi, F. (2025). *Bank lending to nonbanks: A robust channel fueled by constrained capital?* (Working Paper No. 5293876). SSRN.

Xiao, K. (2020). Monetary transmission through shadow banks. *The Review of Financial Studies*, 33(6):2379–2420.

Appendix A. Regulatory Framework for Financial Institutions

This appendix outlines the distinctions in primary activities, regulatory frameworks, and supervisory arrangements across the financial institution types included in our sample. Appendix Table A.1 provides a comparative overview of these institutional differences.

Financial Service Institutions. Financial service institutions are defined in Section 1(1a) of the KWG as entities that provide financial services on a commercial basis or at a scale requiring a commercially organized business operation. Their services include financial leasing, factoring, crypto custody business, crypto securities registry, and investment management. These institutions are governed by the KWG and are subject to supervision by the Federal Financial Supervisory Authority (BaFin) and the Deutsche Bundesbank. Financial leasing and factoring institutions are exempt from the capital and liquidity requirements that apply to credit institutions, including own funds requirements under Section 10. There are no minimum capital requirements, though standard company law provisions regarding share capital remain applicable.

Financial Enterprises. Financial enterprises, as defined in Section 1(3) of the KWG, engage in activities such as acquiring equity investments, proprietary trading, and corporate advisory services. Financial enterprises are, in essence, more focused on holding and managing financial assets or offering business advice, rather than directly providing financial services to clients. As such, they do not require BaFin authorization to operate and are generally exempt from direct prudential supervision, unless otherwise designated under Section 3 of the KWG. Nonetheless, under Section 44c of the KWG, BaFin and the Bundesbank can request information and inspect premises to ensure these entities do not stray into unauthorized banking or financial services.

Insurance Companies. Insurance companies' core activities include underwriting various types of insurance policies, managing policyholder funds, and investing in financial instruments to meet future liabilities. A key form of credit they provide is promissory notes

(Schuldscheindarlehen), which are bilateral loan agreements typically issued by corporations, municipalities, or public-sector entities (as discussed in Bednarek et al., 2025).

In Germany, insurance companies are supervised by BaFin under the German Insurance Supervision Act (Versicherungsaufsichtsgesetz) and the Solvency II framework, which establishes risk-based capital requirements to ensure financial stability. Under Solvency II, insurance companies must maintain sufficient capital to cover their risks, with the Solvency Capital Requirement (SCR) reflecting a risk-based assessment of potential losses under adverse scenarios. Additionally, the Minimum Capital Requirement (MCR) sets an absolute minimum threshold below which insurers would be considered non-viable, triggering regulatory intervention.

Securities Companies. Securities companies (Wertpapierinstitute) in Germany operate under the Securities Institutions Act (Wertpapierinstitutsgesetz, WpIG), which transposes the EU Investment Firm Directive (IFD) and works in conjunction with the directly applicable Investment Firm Regulation (IFR).[17] These entities specialize in investment services such as brokerage, portfolio management, proprietary trading, underwriting, and operating trading platforms, distinguishing themselves from credit institutions by abstaining from deposit-taking or large-scale lending. Their core function centers on facilitating market transactions and managing financial assets for clients or proprietary accounts.

The regulatory framework distinguishes between four categories of securities companies based on their size, complexity, and systemic relevance. Class 3 firms, the smallest category, engage in limited activities with minimal systemic risk and are subject to capital requirements calculated as the higher of their permanent minimum requirement (PMR) or fixed overheads requirement (FOR). Class 2 firms, offering a broader range of services, face additional K-factor capital charges to account for risks to clients, markets, and their own operations. Class 1 minus firms, with consolidated assets exceeding 15 billion euros (or 5 billion euros under specific risk criteria), are subject to CRR prudential rules while retaining their securities company status. Class 1 firms, surpassing 30 billion euros in assets, are practically considered credit institutions under the CRR, requiring full banking authorization and compliance with corresponding capital, liquidity, and supervisory standards.[18]

Capital Investment Companies. Capital investment companies, or asset management companies, are entities that manage investment funds, either on an open-ended or closed-ended basis, in accordance with the provisions of the German Investment Code (Kapitalanlagegeset-

[17] EU regulations refer to these financial institutions as investment firms. In this article, we refer to them as securities companies to distinguish them from capital investment companies.

[18] Although Class 1 security companies are treated as CRR credit institutions from a regulatory perspective, we still classify them as nonbanks as they do not hold a deposit-taking license and thus do not qualify as MFIs.

zbuch, KAGB). These companies pool investor capital and manage it in accordance with specified investment strategies. Their activities are subject to extensive regulation to ensure investor protection, market integrity, and financial stability.

The regulatory framework governing capital investment companies in Germany is primarily set out in the KAGB, which aligns with European directives such as the Alternative Investment Fund Managers Directive (AIFMD) and the Undertakings for Collective Investment in Transferable Securities (UCITS) Directive. The KAGB establishes licensing requirements, governance standards, and operational obligations for these entities. BaFin oversees their compliance with regulatory requirements, conducting both solvency and market conduct supervision.

To obtain authorization, capital investment companies must meet minimum capital requirements, which vary depending on their structure. Internal asset management companies must have an initial capital of at least 300,000 euros, whereas external asset management companies are required to have at least 125,000 euros. Furthermore, firms managing investment assets exceeding 250 million euros must hold additional own funds amounting to 0.02 percent of the value exceeding this threshold, subject to a maximum cap of 10 million euros.

Beyond initial capital requirements, capital investment companies must maintain adequate ongoing own funds to ensure financial stability and operational soundness. These funds must always meet the minimum thresholds set by European directives such as the AIFMD and UCITS Directive (i.e., own funds equivalent to one quarter of their preceding year's fixed overheads). The required capital levels may be adjusted by BaFin based on the scale and complexity of a firm's business activities. Additionally, asset management companies are required to hold liquidity in the form of liquid assets or short-term instruments that can be quickly converted into bank deposits.

Non-MFI Credit Institutions. This category includes KWG-defined credit institutions that do not hold a deposit license, such as guarantee banks (Bürgschaftsbanken) and other credit institutions with partial banking concessions. Guarantee banks provide credit guarantees to SMEs that lack sufficient collateral, enabling them to obtain bank financing. These entities are classified as credit institutions under the KWG but do not qualify as MFIs under the CRR because they do not accept deposits. In our analysis, they are classified as nonbanks.

Table A.1. Regulatory Framework and Capital Requirements for Banks and Nonbanks in Germany

Institution	Primary activity	Regulation	Capital requirements	Central bank access	Supervisor
Credit institutions					
Monetary financial institutions	Deposit-taking, lending	KWG (CRR/CRD)	Risk-based capital (CRR); leverage ratio; liquidity (LCR, NSFR)	Yes	BaFin, Bundesbank, ECB (for systemically important)
Nonbanks					
Financial service institutions	Factoring, leasing, investment management	KWG	None	No	BaFin, Bundesbank
Financial enterprises	Equity acquisition, property leasing	KWG	None	No	BaFin
Insurance companies	Life, non-life, reinsurance	VAG (Solvency II)	Risk-based (SCR, MCR)	No	BaFin
Securities companies	Securities trading, advice, underwriting	WpIG (MiFID II, IFR, IFD); CRR/CRD for Class 1	Min. capital (all); K-factors (Class 2); CRR (Class 1)	Class 1 only	BaFin, Bundesbank
Capital investment companies	Fund management (UCITS, AIFs)	KAGB (UCITS, AIFMD)	Initial and ongoing capital	No	BaFin
Non-MFI credit institutions	Guarantee banks, credit institutions with partial concessions	KWG	None	No	BaFin, Bundesbank

Appendix B. Data

B.1. Variable Definitions

Table B.1. Variable Definitions

Variable	Definition
Panel A. Lender-firm level	
Exposure	Total credit exposure of lender l to firm f in quarter t, including balance-sheet items (loans, bonds, shares) and off-balance-sheet items (guarantees, credit derivatives), in millions of euros
PD	One-year-ahead probability of default (%) reported by lender l for firm f
Panel B. Firm level	
Total credit	Total credit exposure of firm f in quarter t, summed across lenders, in millions of euros
Nonbank share	Nonbank credit as percentage of total firm credit in quarter t (%)
Firm PD	Median PD across all lenders for firm f in quarter t (%)
High-risk firm	Indicator equal to one if Firm PD exceeds the cross-sectional median in quarter t
SME	Indicator equal to one if a firm has fewer than 250 employees and either annual turnover $\leq$ €50 million or balance sheet total $\leq$ €43 million (European Commission definition)
Green industry	Indicator equal to one if a firm operates in an industry where Scope 1 emissions scaled by gross value added fall below the median in year t
Nonbank relation	Indicator equal to one if a firm borrowed from at least one nonbank lender in quarter $t-1$
Panel C. Bank and insurer level	
Nonbank	Indicator equal to one if a lender is not a monetary financial institution (MFI) and zero if it is
Assets	Bank total assets, in millions of euros
Core capital ratio	Tier 1 capital as a percentage of risk-weighted assets (%)
Capital adequacy ratio	Total regulatory capital (Tier 1 + Tier 2) as a percentage of risk-weighted assets (%)
Non-performing loan ratio	Non-performing loans as a percentage of total gross loans (%)
Deposit-spread beta	Bank-specific sensitivity of deposit spreads to changes in €STR
Deposit growth	Quarterly percentage change in total deposit volumes (%)
Solvency ratio	Eligible own funds relative to the solvency capital requirement. Defined for insurers only.
Panel D. Monetary policy	
Target	Cumulative quarterly change in 1-month OIS rate within monetary policy event window (20 min before press release to 20 min after press conference), in basis points
FG	Cumulative quarterly residual from regression of 2-year OIS change on 1-month OIS change, in basis points
QT	Cumulative quarterly residual from regression of 10-year OIS change on 1-month and 2-year OIS changes, in basis points

Notes: All monetary policy variables are standardized (mean zero, standard deviation one) for regression analysis. Sample period: 2019:Q1–2023:Q4.

B.2. Additional Summary Statistics

Table B.2. Firm Characteristics by Firm Type

Variables	Low risk	High risk	SME	Large	Brown industry	Green industry
N firm-quarters	2,944,718	2,689,625	1,133,671	197,240	3,575,379	7,810,829
Total credit (mill. €)	10.32	4.30	4.71	66.66	3.51	5.09
Nonbank share (%)	2.55	5.26	11.89	18.97	7.53	3.63
Firm PD (%)	0.19	5.93	3.19	2.61	3.86	2.47
SME	0.76	0.83	1.00	0.00	0.88	0.82
Green industry	0.70	0.61	0.51	0.62	0.00	1.00
Number of lenders	1.70	1.57	1.57	5.66	1.40	1.34

Notes: This table reports mean firm characteristics by firm type at the firm-quarter level over 2019:Q1–2023:Q4. Variable definitions are provided in Appendix Table B.1.

Table B.3. Comparison of Multi-Lender and Single-Lender Firms

Variables	Full sample	Multi lender	Single lender
N firm-quarters	11,549,279	1,845,688	9,703,591
Total credit (mill. €)	4.58	20.98	1.46
Nonbank share (%)	4.81	14.19	3.03
Firm PD (%)	2.93	2.94	2.93
SME	0.85	0.70	0.94
Green industry	0.69	0.63	0.70
Number of lenders	1.36	3.25	1.00

Notes: This table reports mean firm characteristics for multi-lender and single-lender borrowers over 2019:Q1–2023:Q4. Multi-lender firms constitute the estimation sample for specifications using firm-quarter fixed effects. Variable definitions are provided in Appendix Table B.1.

Table B.4. Insurance Company Characteristics by Type

Variables	Life insurers	Non-life insurers	Other insurers
N lender-quarters	4,056	3,363	1,753
Mean exposure (mill. €)	727.36	602.72	522.12
Median exposure (mill. €)	119.53	35.11	62.48
Mean share of insurance exposure (%)	50.04	34.35	15.61
Mean solvency ratio	4.84	3.12	2.96
Median solvency ratio	4.05	2.46	2.68

Notes: Notes: This table reports characteristics of insurance corporations by type at the lender-quarter level over 2019:Q1–2023:Q4. Non-life insurers include property, casualty, and health insurers. Other insurers include reinsurers and social security funds. Share of insurance exposure is the percentage of total insurance sector credit. Variable definitions are provided in Appendix Table B.1.

Table B.5. Firm Characteristics by Nonbank Access

Variables	Full sample	With nonbank access	Without nonbank access
N firm-quarters	11,549,279	863,905	10,685,374
Total credit (mill. €)	4.58	31.14	2.43
Nonbank share (%)	4.81	64.32	0.00
Firm PD (%)	2.93	3.53	2.88
SME	0.85	0.69	0.90
Green industry	0.69	0.53	0.70
Number of lenders	1.36	3.50	1.19

Notes: This table reports mean firm characteristics by nonbank access status at the firm-quarter level over 2019:Q1–2023:Q4. A firm has nonbank access if it borrowed from at least one nonbank lender in the previous quarter. Variable definitions are provided in Appendix Table B.1.

B.3. Monetary Policy Surprises

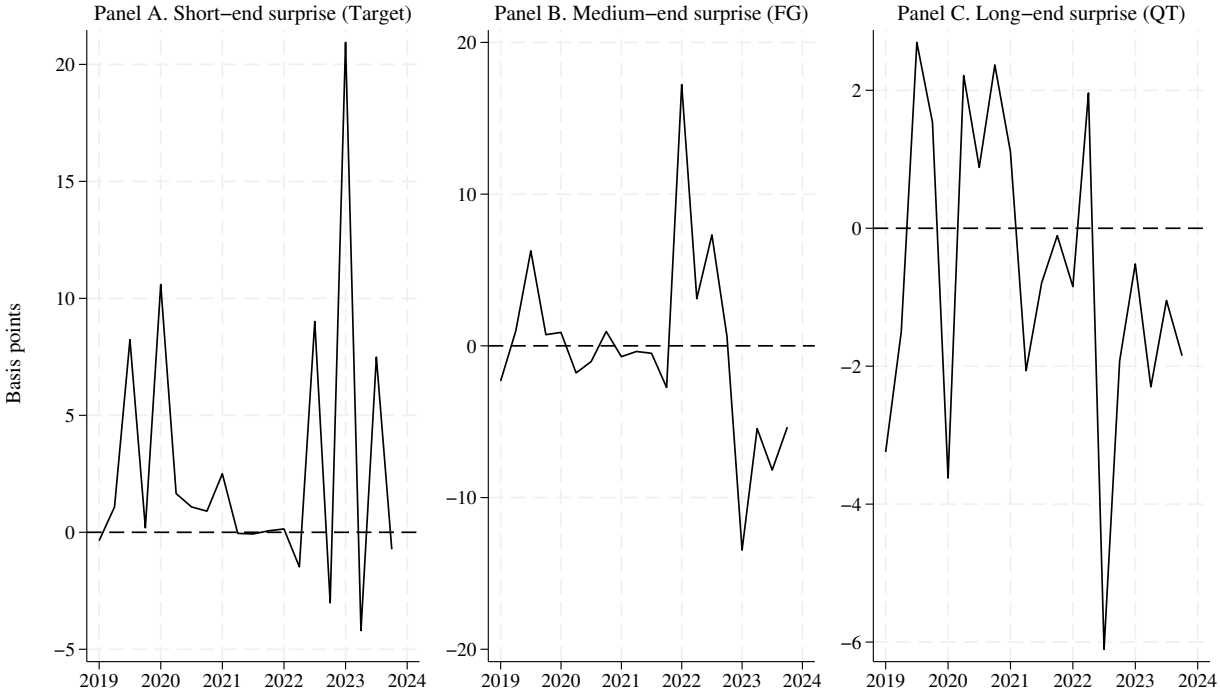


FIGURE B.1. MONETARY POLICY SURPRISES

Appendix C. Mechanisms Details

C.1. Bank Capital Reallocation Channel

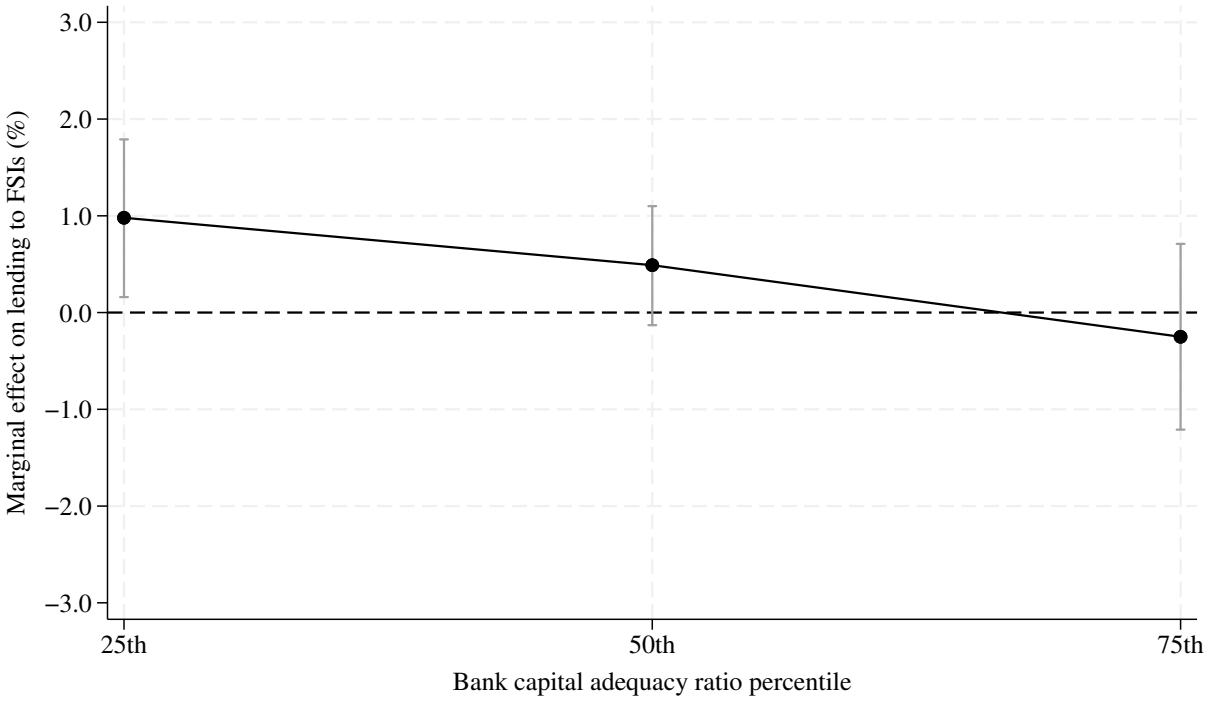


FIGURE C.1. BANK LENDING TO FSIS: ROBUSTNESS USING CAPITAL ADEQUACY RATIOS

Notes: This figure plots the marginal effect of Target surprises on bank lending to FSI borrowers (relative to non-financial firms) at the 25th, 50th, and 75th percentiles of the bank capital adequacy ratio distribution. Estimates are derived from equation (2) using capital adequacy ratios rather than core capital ratios. The marginal effect of Target on bank lending to FSIs at capital percentile p is: $\beta_{1,FSI} + \beta_{3,FSI} \times \text{Capital}_p$. Bars represent 95% confidence intervals based on standard errors clustered at the bank-borrower level.

Table C.1. Bank Lending to NBFIs: The Role of Bank Capital

Dependent variable	Log exposure		
	(1)	(2)	(3)
	Target	FG	QT
FSI borrower × MP	5.38***	−4.23	−4.37*
	(1.99)	(2.61)	(2.48)
Insurer borrower × MP	0.59	11.73***	−0.08
	(2.27)	(3.44)	(3.44)
Other NBFI borrower × MP	−0.01	0.10	−0.38
	(0.56)	(0.77)	(0.75)
FSI borrower × Bank capital	1.87**	1.84**	1.87**
	(0.80)	(0.80)	(0.80)
Insurer borrower × Bank capital	0.43	0.46	0.45
	(0.87)	(0.88)	(0.87)
Other NBFI borrower × Bank capital	0.01	−0.01	0.02
	(0.26)	(0.26)	(0.26)
FSI borrower × MP × Bank capital	−0.33***	0.24	0.19
	(0.13)	(0.17)	(0.16)
Insurer borrower × MP × Bank capital	−0.03	−0.69***	−0.07
	(0.14)	(0.22)	(0.22)
Other NBFI borrower × MP × Bank capital	0.00	−0.03	−0.02
	(0.04)	(0.05)	(0.05)
Constant	−60.88***	−60.88***	−60.88***
	(0.12)	(0.12)	(0.12)
Observations	14,566,743	14,566,743	14,566,743
R^2	0.86	0.86	0.86
Bank-quarter FE	Yes	Yes	Yes
Borrower FE	Yes	Yes	Yes

Notes: The dependent variable is the natural logarithm of the bank-borrower-quarter credit exposure. The sample includes all bank lending relationships with non-financial firms and NBFIs as borrowers. Coefficients (and standard errors) are multiplied by 100 and represent approximate percentage changes in exposure. *FSI borrower*, *Insurer borrower*, and *Other NBFI borrower* are indicator variables for each borrower type, with non-financial firms as the reference category. *Bank capital* is the lagged regulatory Tier 1 capital ratio (winsorized at the 2nd and 98th percentiles). *MP* denotes the one-quarter-lagged, standardized monetary policy surprise: the Target surprise in column 1, the Forward Guidance surprise in column 2, and the Quantitative Tightening surprise in column 3. Standard errors, clustered at the bank-borrower level, are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table C.2. Insurance Lending and Realized Solvency Changes

Dependent variable	Log exposure		
	(1) Target	(2) FG	(3) QT
ΔSolvency	0.02	0.02	−0.00
	(0.08)	(0.08)	(0.09)
MP	0.17***	−0.32***	−0.41***
	(0.04)	(0.06)	(0.06)
ΔSolvency × MP	−0.12	0.19*	0.17**
	(0.09)	(0.10)	(0.07)
Constant	72.63***	72.64***	72.64***
	(0.25)	(0.25)	(0.25)
Observations	428,816	428,816	428,816
R^2	0.89	0.89	0.89
Lender FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes

Notes: The dependent variable is the natural logarithm of the lender-firm-quarter credit exposure. Coefficients (and standard errors) are multiplied by 100 and represent approximate percentage changes in exposure. Sample restricted to insurance corporations. Δ *Solvency* denotes the quarterly change in solvency ratio lagged two quarters, and thus predetermined relative to both the monetary policy surprise and the lending decision. *MP* denotes the one-quarter-lagged, standardized monetary policy surprise: the Target surprise in column 1, the Forward Guidance surprise in column 2, and the Quantitative Tightening surprise in column 3. Standard errors, clustered at the lender-firm level, are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

C.3. Deposit Channel of Monetary Policy

This appendix provides details on the deposit channel analysis. The deposit channel posits that banks' exposure to monetary policy depends on their deposit market power (Drechsler et al., 2017). Banks with greater market power maintain higher deposit spreads but face larger deposit outflows when policy tightens, forcing them to contract lending. Nonbanks, immune to deposit outflows, may expand by filling the gap left by retrenching banks or by receiving funds displaced from bank deposits through money-market funds (Xiao, 2020).

Data. We collect monthly deposit rate and volume data from the Bundesbank's MFI Interest Rate Statistics. This dataset is based on a stratified sample of 240 MFIs, selected to ensure representativeness across bank categories and regions, with the largest institutions from each stratum being chosen. It covers roughly 70 percent of the total German deposit business. Following Drechsler et al. (2017), we focus on deposit rates for new businesses, which refer to interest rates on newly negotiated agreements between banks and customers during the reporting month. These rates are reported separately for household and non-financial corporate deposits and across four maturity buckets (overnight, up to one year, one to two years, and over two years), resulting in eight distinct deposit rate categories. For each

category, we compute a deposit spread by subtracting the corresponding deposit rate from the euro short-term rate (€STR). To align with the quarterly structure of the credit register, we retain the last monthly observation of each quarter.

Deposit-Spread Beta Estimation. We proxy a bank's deposit market power by its deposit-spread beta, which measures the sensitivity of the bank's deposit spread to changes in the short-term policy rate. We estimate deposit-spread betas separately for each of the eight deposit products by running the following regression at the bank level:

$$\Delta\text{Deposit spread}_{i,t}^{j} = \psi_i + \sum_{\tau=0}^{3} \beta_{i,\tau}\, \Delta\text{€STR}_{t-\tau} + \varepsilon_{i,t} \tag{C.1}$$

where ΔDeposit spread$_{i,t}^{j}$ is the quarterly change in the deposit spread for product j of bank i; ψ_i is a bank-specific intercept; and Δ€STR$_{t-\tau}$ is the change in €STR from quarter τ to t. The three lags allow the effect to unfold over a full year. We sum the estimated $\beta_{i,\tau}$ coefficients to obtain a product-specific beta, winsorize at the 5th and 95th percentiles, and average across products to obtain a single bank-level deposit-spread beta.[19] A higher beta indicates that a bank raises deposit rates more slowly following policy tightening, reflecting greater deposit market power but also greater vulnerability to deposit outflows. Banks above the median are classified as high-beta. This approach follows closely Drechsler et al.'s (2017; 2022) methodology.

Deposit Flow. Table C.3 tests whether high-beta banks experience larger deposit outflows. Following a one-standard-deviation Target surprise, deposit growth is 6.51 percentage points lower at high-beta banks relative to low-beta banks. The direction aligns with theoretical predictions; however the estimate is statistically insignificant, likely reflecting limited statistical power, as deposit volume data are available for approximately 200 banks.

Lending Responses. To test whether the deposit channel is a potential mechanism behind the nonbank lending channel, we compare the lending responses of low- and high-beta banks, relative to nonbanks. Specifically, we estimate the following regression model using lender-firm-level data:

$$\begin{aligned}\ln(\text{Exposure}_{l,f,t}) = \alpha_{f,t} + \delta_l + \beta_1(\text{Low-}\beta\text{ bank}_l \times \text{Target}_{t-1}) \\ + \beta_2(\text{High-}\beta\text{ bank}_l \times \text{Target}_{t-1}) + \varepsilon_{l,f,t}\end{aligned} \tag{C.2}$$

where Low-β bank$_l$ and High-β bank$_l$ are indicators for low- and high-beta banks, with

[19] Results are robust to alternative winsorization thresholds for deposit-spread betas, including no winsorization and winsorization at the 1 and 2 percent levels.

Table C.3. Deposit Outflows and Bank Exposure to Monetary Policy via the Deposit Channel

Dependent variable	Deposit growth (%)
High-β × Target	−6.51
	(7.19)
Constant	8.09***
	(0.15)
Observations	3,737
R^2	0.10
Bank FE	Yes
Quarter FE	Yes

Notes: The dependent variable is the growth rate in deposit volumes. *High-β* is a dummy equal to one for banks with deposit-spread betas above the cross-sectional median. *Target* is the one-quarter-lagged standardized Target surprise, retrieved from the Euro Area Monetary Event-Study Database by Altavilla et al. (2019). Standard errors, clustered at the bank level, are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

nonbanks as the omitted category. The deposit channel predicts $\beta_2 < \beta_1 < 0$: both bank types contract relative to nonbanks, but high-beta banks contract more.

Table C.4 reports the results. Column 1 includes firm-quarter fixed effects. Both coefficients are negative, and high-beta banks contract more than low-beta banks (−0.54 versus −0.34 percent). The difference is significant at the 10 percent level ($t = -1.65$). Column 2 replaces firm-quarter with ILT fixed effects, which allows inclusion of single-lender borrowers and substantially expands sample size. The coefficients increase in magnitude (−0.80 and −0.57 percent), and the difference becomes highly significant ($t = -3.78$).

Robustness. To ensure that the deposit-spread beta does not simply reflect other bank characteristics correlated with differential sensitivity to monetary policy, we conduct robustness checks using three alternative classifications: capital adequacy, asset quality, and size. For each bank-quarter, we construct lagged indicator variables identifying (i) low-capital (high-capital) banks as those with a capital ratio below (above) the bottom quartile of the cross-sectional distribution, (ii) high-NPL (low-NPL) banks as those with a nonperforming loan (NPL) ratio above (below) the top quartile, and (iii) small (large) banks as those with total assets below (above) the bottom quartile in the previous quarter.[20] We then interact these indicators with the lagged target surprise and estimate the relative credit supply response, always compared to nonbanks. To ensure comparability across results, we restrict the sample to the same lender-firm-quarter observations as in column 2 of Table C.4; nevertheless, results remain robust when using the full sample.

[20]Results remain qualitatively similar when defining bank characteristics using medians rather than quartiles of the cross-sectional distribution.

Table C.4. Deposit Channel: Bank Contraction and Nonbank Expansion

Dependent variable	Log exposure	
	(1)	(2)
	Firm-quarter FE	ILT FE
Low-β × Target	−0.34**	−0.57***
	(0.16)	(0.09)
High-β × Target	−0.54***	−0.80***
	(0.17)	(0.09)
Constant	7.49***	−57.63***
	(0.29)	(0.25)
Observations	3,329,257	8,922,809
R^2	0.72	0.26
Lender FE	Yes	Yes
Firm-quarter FE	Yes	
ILT FE		Yes
Test of coefficient equality		
t-statistic	−1.65	−3.78

Notes: The dependent variable is the natural logarithm of the lender-firm-quarter credit exposure. Coefficients (and standard errors) are multiplied by 100 and represent approximate percentage changes in exposure. *Low-β* is a dummy equal to one for banks with deposit-spread betas below the cross-sectional median; High-β is a dummy equal to one for banks with deposit-spread betas above the cross-sectional median. The omitted category is nonbanks. Target is the one-quarter-lagged standardized target surprise, retrieved from the Euro Area Monetary Event-Study Database by Altavilla et al. (2019). ILT FE denotes industry-location-time fixed effects. Standard errors, clustered at the lender-firm level, are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table C.5 reports the results. In all cases, both bank types contract relative to nonbanks, but coefficient equality tests fail to reject the null: $t = -0.55$ for capital, $t = -0.96$ for NPL ratio, and $t = 0.21$ for size. This indicates that deposit-spread beta captures a distinct mechanism, namely exposure to deposit funding pressure, rather than proxying for capitalization, asset quality, or scale.

Table C.5. Robustness: Deposit Channel of Monetary Policy

Dependent variable	Log exposure		
	(1)	(2)	(3)
	High vs. low capital	High vs. low NPL	Large vs. small
High-capital bank × Target	−0.66***		
	(0.09)		
Low-capital bank × Target	−0.71***		
	(0.11)		
Low-NPL bank × Target		−0.34***	
		(0.10)	
High-NPL bank × Target		−0.48***	
		(0.17)	
Large bank × Target			−0.69***
			(0.09)
Small bank × Target			−0.59
			(0.48)
Constant	−60.20***	−60.39***	−49.79***
	(0.34)	(0.48)	(2.52)
Observations	8,706,153	7,445,199	8,869,029
R^2	0.26	0.27	0.26
Lender FE	Yes	Yes	Yes
ILT FE	Yes	Yes	Yes
Test of coefficient equality			
t-statistic	−0.55	−0.96	0.21

Notes: The dependent variable is the natural logarithm of lender-firm-quarter credit exposure. Coefficients and standard errors are multiplied by 100 and represent approximate percentage changes in exposure. *High-capital bank* (*Low-capital bank*) is a lagged indicator equal to one if the bank's capital adequacy ratio is above (below) the bottom quartile of the cross-sectional distribution in a given quarter. *Low-NPL bank* (*High-NPL bank*) is a lagged indicator equal to one if the bank's nonperforming loan (NPL) ratio is below (above) the top quartile. *Small bank* (*Large bank*) is a lagged indicator equal to one if the bank's total assets are below (above) the bottom quartile. The omitted category is nonbanks. *Target* is the one-quarter-lagged standardized target surprise, retrieved from the Euro Area Monetary Event-Study Database by Altavilla et al. (2019). ILT FE denotes industry-location-time fixed effects. Standard errors, clustered at the lender-firm level, are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Appendix D. Nonbank Credit Allocation

D.1. Allocation by Lender Type

Table D.1. Nonbank Credit Allocation by Lender Type: SMEs vs. Large Firms

Dependent variable	Log exposure		
	(1)	(2)	(3)
	Target	FG	QT
FSI × SME	42.03***	42.09***	42.04***
	(3.77)	(3.77)	(3.77)
Insurer × SME	−5.48	−5.38	−5.44
	(3.88)	(3.87)	(3.88)
FSI × MP	0.90**	−1.03**	−1.07**
	(0.39)	(0.50)	(0.50)
Insurer × MP	−0.69**	1.43***	0.75**
	(0.28)	(0.37)	(0.37)
FSI × SME × MP	0.90	−0.70	−1.29*
	(0.56)	(0.73)	(0.77)
Insurer × SME × MP	0.83**	−1.49***	−0.91*
	(0.39)	(0.53)	(0.54)
Constant	30.88***	30.88***	30.88***
	(0.46)	(0.46)	(0.46)
Observations	2,059,555	2,059,555	2,059,555
R^2	0.66	0.66	0.66
Lender FE	Yes	Yes	Yes
Firm-quarter FE	Yes	Yes	Yes

Notes: The dependent variable is the natural logarithm of the lender-firm-quarter credit exposure. Coefficients (and standard errors) are multiplied by 100 and represent approximate percentage changes in exposure. The omitted category is banks. *FSI* is an indicator variable taking value one if the lender is a financial service institution. *Insurer* is an indicator variable if the lender is an insurance company. Other nonbank categories are included in the regressions but omitted from the table. *MP* denotes the one-quarter-lagged, standardized monetary policy surprise: the Target surprise in column 1, the Forward Guidance surprise in column 2, and the Quantitative Tightening surprise in column 3. *SME* is a time-invariant indicator variable taking value one if a firm is classified as an SME according to the European Commission's definition. Standard errors clustered at the lender-firm level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table D.2. Nonbank Credit Allocation by Lender Type: Green vs. Brown Industries

Dependent variable	Log exposure		
	(1)	(2)	(3)
	Target	FG	QT
FSI × Green	−10.87***	−10.91***	−10.85***
	(2.42)	(2.41)	(2.42)
Insurer × Green	−20.36***	−20.40***	−20.37***
	(2.50)	(2.50)	(2.50)
FSI × MP	1.09***	−2.05***	−2.26***
	(0.29)	(0.44)	(0.40)
Insurer × MP	−0.11	0.25	0.19
	(0.20)	(0.29)	(0.27)
FSI × Green × MP	−0.50	1.99***	1.79***
	(0.43)	(0.66)	(0.56)
Insurer × Green × MP	−0.27	0.57	0.19
	(0.28)	(0.41)	(0.38)
Constant	6.32***	6.33***	6.33***
	(0.27)	(0.27)	(0.27)
Observations	5,941,782	5,941,782	5,941,782
R^2	0.69	0.69	0.69
Lender FE	Yes	Yes	Yes
Firm-quarter FE	Yes	Yes	Yes

Notes: The dependent variable is the natural logarithm of the lender-firm-quarter credit exposure. Coefficients (and standard errors) are multiplied by 100 and represent approximate percentage changes in exposure. The omitted category is banks. *FSI* is an indicator variable taking value one if the lender is a financial service institution. *Insurer* is an indicator variable if the lender is an insurance company. Other nonbank categories are included in the regressions but omitted from the table. *MP* denotes the one-quarter-lagged, standardized monetary policy surprise: the Target surprise in column 1, the Forward Guidance surprise in column 2, and the Quantitative Tightening surprise in column 3. *Green* is a lagged indicator variable taking value one if a firm operates in an industry classified as green (i.e., the industry's Scope 1 emission intensity falls below the median for that year). Standard errors clustered at the lender-firm level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table D.3. Nonbank Credit Allocation: Robustness to Alternative Definitions

Dependent variable	Log exposure		
	(1)	(2)	(3)
	Target	FG	QT
Panel A. Industry emissions: EU high-climate impact classification			
Nonbank × Green	15.64***	15.60***	15.62***
	(2.19)	(2.19)	(2.19)
Nonbank × MP	0.39***	−0.54***	−0.36*
	(0.15)	(0.20)	(0.20)
Nonbank × Green × MP	−0.27	0.65*	0.13
	(0.28)	(0.37)	(0.38)
Constant	4.36***	4.37***	4.36***
	(0.24)	(0.24)	(0.24)
Observations	6,001,921	6,001,921	6,001,921
R^2	0.69	0.69	0.69
Lender FE	Yes	Yes	Yes
Firm-quarter FE	Yes	Yes	Yes
Panel B. Credit risk: industry-quarter relative risk			
Nonbank × High risk	11.84***	11.85***	11.83***
	(1.65)	(1.64)	(1.65)
Nonbank × MP	0.24	−0.00	0.27
	(0.20)	(0.25)	(0.25)
Nonbank × High risk × MP	0.06	−0.30	−0.83*
	(0.34)	(0.45)	(0.44)
Constant	15.84***	15.85***	15.85***
	(0.26)	(0.26)	(0.26)
Observations	4,915,771	4,915,771	4,915,771
R^2	0.67	0.67	0.67
Lender FE	Yes	Yes	Yes
Firm-quarter FE	Yes	Yes	Yes

Notes: The dependent variable is the natural logarithm of the lender-firm-quarter credit exposure. Coefficients (and standard errors) are multiplied by 100 and represent approximate percentage changes in exposure. *Nonbank* is an indicator variable taking value one if the lender is a nonbank financial institution and zero if the lender is a bank. *MP* denotes the one-quarter-lagged, standardized monetary policy surprise: the Target surprise in column 1, the Forward Guidance surprise in column 2, and the Quantitative Tightening surprise in column 3. Panel A defines high-climate impact sectors following the EU Low Carbon Benchmarks Regulation (EU 2019/2089), which identifies industries with significant energy consumption and greenhouse gas emissions (NACE sections A–H and L). Panel B defines high-risk firms as those with PD above the industry-quarter median. Standard errors, clustered at the lender-firm level, in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Appendix E. Robustness: Baseline Results

Table E.1. Nonbank Lending Channel: Robustness to Single-Lender Borrowers Inclusion

Dependent variable	Log exposure		
	(1)	(2)	(3)
	Target	FG	QT
Nonbank × MP	0.66***	−0.89***	−0.91***
	(0.08)	(0.11)	(0.11)
Constant	−66.58***	−66.57***	−66.58***
	(0.19)	(0.19)	(0.19)
Observations	15,697,723	15,697,723	15,697,723
R^2	0.21	0.21	0.21
Lender FE	Yes	Yes	Yes
ILT FE	Yes	Yes	Yes

Notes: The dependent variable is the natural logarithm of the lender-firm-quarter credit exposure. Coefficients (and standard errors) are multiplied by 100 and represent approximate percentage changes in exposure. *Nonbank* is an indicator variable taking value one if the lender is a nonbank financial institution and zero if the lender is a bank. *MP* denotes the one-quarter-lagged, standardized monetary policy surprise: the Target surprise in column 1, the Forward Guidance surprise in column 2, and the Quantitative Tightening surprise in column 3. ILT FE stands for industry-location-time fixed effects. Standard errors, clustered at the lender-firm level, are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table E.2. Nonbank Lending Channel: Robustness to Alternative Monetary Policy Measures

Dependent variable	Log exposure			
	(1) Shadow rate	(2) ΔShadow rate	(3) €STR	(4) Δ€STR
Nonbank × MP	0.55***	0.83***	0.90***	2.30***
	(0.15)	(0.30)	(0.21)	(0.69)
Constant	5.26***	5.17***	5.15***	5.11***
	(0.21)	(0.21)	(0.21)	(0.21)
Observations	6,001,921	6,001,921	6,001,921	6,001,921
R^2	0.69	0.69	0.69	0.69
Lender FE	Yes	Yes	Yes	Yes
Firm-quarter FE	Yes	Yes	Yes	Yes

Notes: The dependent variable is the natural logarithm of lender-firm-quarter credit exposure. Coefficients and standard errors are multiplied by 100 and represent approximate percentage changes in exposure. *Nonbank* is an indicator equal to one if the lender is a nonbank financial institution and zero if the lender is a bank. *MP* denotes the one-quarter-lagged monetary policy variable: Krippner's (2013) euro area shadow rate in column 1, its quarterly change in column 2, the €STR in column 3, and its quarterly change in column 4. Standard errors, clustered at the lender-firm level, are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table E.3. Nonbank Lending Channel: Robustness to Alternative Standard Error Clustering

Dependent variable	Log exposure		
	(1)	(2)	(3)
	Target	FG	QT
Panel A. Firm-level clustering			
Nonbank × MP	0.32***	−0.36**	−0.34**
	(0.12)	(0.16)	(0.17)
Constant	5.21***	5.22***	5.21***
	(0.00)	(0.00)	(0.00)
Observations	6,001,921	6,001,921	6,001,921
R^2	0.69	0.69	0.69
Lender FE	Yes	Yes	Yes
Firm-quarter FE	Yes	Yes	Yes
Panel B. Lender-level clustering			
Nonbank × MP	0.32	−0.36	−0.34
	(0.27)	(0.40)	(0.39)
Constant	5.21***	5.22***	5.21***
	(0.00)	(0.00)	(0.00)
Observations	2,590,930	2,590,930	2,590,930
R^2	0.69	0.69	0.69
Lender FE	Yes	Yes	Yes
Firm-quarter FE	Yes	Yes	Yes
Panel C. Lender-level clustering with ILT FE			
Nonbank × MP	0.66**	−0.89**	−0.91**
	(0.28)	(0.41)	(0.38)
Constant	−66.58***	−66.57***	−66.58***
	(0.00)	(0.00)	(0.00)
Observations	15,697,723	15,697,723	15,697,723
R^2	0.21	0.21	0.21
Lender FE	Yes	Yes	Yes
ILT FE	Yes	Yes	Yes

Notes: The dependent variable is the natural logarithm of the lender-firm-quarter credit exposure. Coefficients (and standard errors) are multiplied by 100 and represent approximate percentage changes in exposure. *Nonbank* is an indicator variable taking value one if the lender is a nonbank financial institution and zero if the lender is a bank. *MP* denotes the one-quarter-lagged, standardized monetary policy surprise: the Target surprise in column 1, the Forward Guidance surprise in column 2, and the Quantitative Tightening surprise in column 3. ILT FE stands for industry-location-time fixed effects. Standard errors are reported in parentheses: in Panel A clustered at the firm level and in Panels B and C clustered at the lender level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Appendix F. Literature

Table F.1. Literature on the Nonbank Lending Channel

Authors	Period	Geographic scope	Level of observation	MP instrument	Mechanism	Effect
Den Haan and Sterk (2011)	1954–1978, 1984–2008	USA	Aggregate	Short-rate	–	Dampen
Nelson et al. (2018)	1966–2007	USA	Aggregate	Short-rate	–	Dampen
Xiao (2020)	1995–2012	USA	Lender	Short-rate	Deposit	Dampen
Milic (2021)	1999–2019	Euro area	Sector	Short-rate	–	Strengthen
Elliott et al. (2022)*	1990–2011	USA	Syndicated loan	Short-rate	–	Dampen
Drechsler et al. (2022)	2002–2006	USA	County	Short-rate	Deposit	Dampen
Agarwal et al. (2023)*	2012–2018	USA	Lender	Short-rate	Mortgage servicing	Dampen
Hodge and Weber (2023)*	1990–2019	USA	Sector	Short-rate	–	Mixed
Hodula and Libich (2023)	1999–2019	Euro area	Sector	Short-rate	–	Dampen
Holm-Hadulla et al. (2023)	2003–2020	Euro area	Sector	Short-rate + Long-rate	–	Strengthen
Elliott et al. (2024)	1990–2018	Global (except USA)	Syndicated loan	Short-rate	–	Dampen
Banerjee and Serena (2024)	1997–2017	USA	Syndicated loan	Medium-rate	–	Dampen
Haque et al. (2025)*	2012-2023	USA	Lender-borrower	Short-rate	Bank funding	Mixed
Cucic and Gorea (2026)	2003–2018	Denmark	Lender-borrower	Short-rate	Long-term debt	Dampen
This paper	2019–2023	Germany	Lender-borrower	Multiple yield-curve segments	Duration, capital	Mixed

Notes: This table summarizes empirical studies on the nonbank lending channel of monetary policy. MP instrument indicates whether the study examines short-rate, medium-rate, or multiple yield-curve segments. Mechanism indicates whether the study tests a specific transmission channel. Effect indicates whether nonbank responses dampen, strengthen, or show mixed effects on monetary policy transmission. Working papers are marked with an asterisk.