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Monetary policy, central bank information, and bank lending: Evidence from German banks

Sophia List
Norbert Metiu

Deutsche Bundesbank, Wilhelm-Epstein-Straße 14, 60431 Frankfurt am Main,
Postfach 10 06 02, 60006 Frankfurt am Main

Tel +49 69 9566-0

Please address all orders in writing to: Deutsche Bundesbank,
Press and Public Relations Division, at the above address or via fax +49 69 9566-3077

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Sophia List
(Deutsche Bundesbank)

Norbert Metiu
(Deutsche Bundesbank)

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Abstract

This paper examines the impact of monetary policy and central bank information on banks' lending using data on German bank balance sheets from 2002 to 2018. Local projection estimates show that the volume of loans to non-financial corporations declines significantly after a restrictive monetary policy shock that is independent of non-monetary information in central bank announcements. This decline is stronger for relatively small banks with less liquid balance sheets, which have less access to external financing. By contrast, the volume of loans increases significantly following an unexpected monetary policy rate tightening that is associated with favorable information on the economic outlook. This increase is stronger for relatively small banks with more liquid balance sheets, which are better able to boost lending. This insight adds a new dimension to the role of banks in the transmission of central bank policy.

JEL classification: C33; E51; E58; G21

Keywords: Bank lending; Central bank; Credit; Information shock; Monetary policy; Transmission mechanism

*Correspondence: Norbert Metiu, Deutsche Bundesbank, Wilhelm-Epstein-Str. 14, 60431 Frankfurt am Main, Germany. E-mail: sophia.list@bundesbank.de (List); norbert.metiu@bundesbank.de (Metiu). Acknowledgements: We are grateful to Milan Deskar-Skrbic, Refet Gürkaynak, Rainer Haselmann, as well as participants of the 9th Research Workshop of the ECB Monetary Policy Committee Task Force on Banking Analysis for Monetary Policy and seminar participants at the Deutsche Bundesbank for helpful comments and suggestions. We also thank Péter Karádi for providing us the updated shock series from Jarociński and Karádi (2020). Fabian Wassmann provided excellent research assistance. The views expressed in this paper are those of the authors and do not necessarily represent the views of the Deutsche Bundesbank or the Eurosystem.

1 Introduction

Banks play a vital role in the transmission of monetary policy. There is long-standing evidence that changes in the monetary policy rate affect the ability of banks to issue loans and, in turn, the real economy (e.g., Kashyap and Stein, 2000; Ciccarelli et al., 2015). At the same time, when central banks announce a policy rate decision, they also reveal information about their assessment of economic conditions. Recent studies argue that this may produce "information shocks" with distinct macroeconomic implications. Evidence shows, for instance, that the announcement of a rate hike may reflect good news about the economy, which can stimulate economic activity (e.g., Jarociński and Karádi, 2020). The possible presence of such information effects raises the following questions: First, how do monetary policy shocks stripped of information about economic fundamentals affect bank lending? Second, do information shocks have autonomous effects on bank lending?

In this paper, we study the impact of euro area monetary policy and central bank information on German banks' lending to non-financial corporations (NFCs). Germany, which has the largest economy and financial sector in the EU, is particularly suited for our analysis because its financial system is dominated by banks, and bank loans serve as a key source of funding for NFCs. We use a confidential bank-level panel data set that contains quarterly information on German bank balance sheets for the period between 2002 and 2018. The data are collected by the Deutsche Bundesbank and comprise all NFC loans larger than 1.5 million euros extended by banks domiciled in Germany, along with additional balance sheet figures. After adjustments, our sample comprises a balanced panel of over 900 commercial, savings, and cooperative banks that account for nearly 70% of total banking system assets in 2018.

We estimate the dynamic responses of German banks' NFC loans to "pure" monetary policy (PMP) shocks and central bank information (CBI) shocks identified as in Jarociński and Karádi (2020), using bank-level panel local projections (Jordá, 2005; Jordá et al., 2015). This empirical approach combines insights from two strands of literature. One strand examines the impact of monetary policy on the economy in a macroeconometric framework using vector autoregressions (VARs) or local projections (e.g., Ciccarelli et al., 2015; Jarociński and Karádi, 2020; Jordá et al., 2020; Miranda-Agrippino and Ricco, 2021). Macroeconometric models allow tracing out the causal effects of exogenous shocks under appropriate identification assumptions. Following this approach, for instance, Jarociński and Karádi (2020) dissect monetary policy surprises into PMP shocks and CBI shocks by exploiting information inherent in the high-frequency co-movement of interest rates and stock prices within a structural VAR. Another strand of the literature investigates how certain bank balance sheet characteristics influence the monetary transmission mechanism by correlating policy rates with bank loans in a cross-sectional regression at the micro level (e.g., Kashyap and Stein, 2000; Kishan and Opiela, 2000; Jiménez et al., 2012). The use of disaggregated data helps to shed light on heterogeneity and isolate credit supply from potential confounding demand effects.

We find that a positive PMP shock – i.e., an unexpected monetary policy rate tightening that is independent of information about economic fundamentals – leads to a statistically significant reduction in the volume of bank loans to NFCs. The effect is economically meaningful: On average across all banks, the loan volume decreases by around three-quarters of a percentage point one year after a one-standard-deviation positive PMP shock. The effects are relatively persistent, as firms receive nearly one and a half percentage points less credit relative to the pre-shock level three years after the shock.

The negative effects of a restrictive monetary policy shock on bank loans are consistent with several possible mechanisms. First, a policy rate tightening reduces banks' cash flows and increases their indirect costs, which has a negative impact on the supply of new loans. In addition, it reduces banks' net worth as it typically affects the market value of their assets more strongly than their liabilities due to maturity transformation, which also has a negative impact on loan supply (e.g., Boivin et al., 2010; Ciccarelli et al., 2015). At the same time, higher policy rates may also reduce firms' loan demand by raising their borrowing costs (e.g., Bernanke and Gertler, 1995; Ciccarelli et al., 2015). We thus examine separately banks that differ in balance sheet characteristics that mainly influence the supply of credit (see, e.g., Kashyap and Stein, 1995, 2000). The results show that the decline in loans is stronger for relatively *small* banks with *less liquid* balance sheets, which is consistent with the bank lending channel of monetary policy transmission.

At the same time, we find that a positive CBI shock – i.e., an unexpected policy rate tightening that reflects non-monetary information about economic fundamentals – leads to a statistically significant *increase* in the volume of loans extended to non-financial firms. On average across all banks, the loan volume rises by more than one percentage point one year after a one-standard-deviation positive CBI shock. This increase is stronger for relatively *small* banks with *more liquid* balance sheets. Thus, when a policy rate tightening conveys good news about economic fundamentals, smaller and more liquid banks use their extra liquidity to expand business lending. This result adds a new dimension to the role of banks in the transmission of central bank policy. There are at least two potential explanations for why relatively small banks might be more affected by a CBI shock. First, smaller banks might face more information asymmetries because of less resources to monitor economic conditions than larger banks (e.g., Holod and Peek, 2007). The information shock is thus likely to have a higher novelty value for relatively small banks. Second, smaller banks might be more collateral-constrained than larger banks. The rise in collateral values after a positive CBI shock may thus primarily improve financing conditions for relatively small banks, allowing them to extend more loans.

To our best knowledge, this paper is the first to examine the effects of information shocks on bank loans. Our results complement recent evidence that news about economic fundamentals are an important component of monetary policy surprises (e.g., Nakamura and Steinsson, 2018; Cieslak and Schrimpf, 2019; Jarociński and Karádi, 2020; Andrade and Ferroni, 2021; Miranda-Agrippino and Ricco, 2021). Existing studies adopt the idea of a "central bank information" effect, whereby investors' beliefs about the state of the economy adjust in response to the central bank's announcement. For example, Jarociński and Karádi (2020) show by means of a New Keynesian model that the aggregate implications of a CBI shock are consistent with central bank communication about future financial market conditions: The central bank in their model influences private expectations by communicating its knowledge about a future capital-quality shock to the public. Positive news about future capital quality improves bank balance sheets through asset valuation effects. In turn, banks ease credit conditions, which strengthens aggregate demand, and the monetary policy rate tightens in response. Our key result that a positive CBI shock causes an increase in bank loans is consistent with this interpretation of how a CBI shock propagates to the economy.[1] Given this interpretation, our results suggest that communicating positive news about financial conditions can be a useful tool for encouraging the provision of credit to businesses, which might be particularly important during financial stress periods. This complements existing evidence that central bank communication about the state of the financial system influences financial market returns (Born et al., 2014), as well as individuals' expectations and risk-taking behavior (Beutel et al., 2021).

The empirical results hold up to various robustness checks. Above all, we obtain similar estimates when we replace the shock series with the monetary policy "target" surprises estimated by Altavilla et al. (2019) from intraday financial market data, which we split into PMP and CBI surprises using an approach similar to the one in Jarociński and Karádi (2020). Our results are also robust to how we measure bank size and liquidity, to including banks with special tasks as well as mortgage banks and building and loan association into the sample, to clustering standard errors along the cross-section and time dimension, to how we account for outliers in the loan growth data, and to removing the period of the ECB's large-scale quantitative easing program from the sample.

Our paper contributes to a long-standing literature on the bank lending channel. According to the "lending view", a monetary policy rate tightening leads to a reduction in reservable deposits that banks cannot completely offset by other sources of funding due to financial frictions, which may force banks to reduce their supply of loans (e.g., Bernanke and Blinder, 1988; Bernanke and Gertler, 1995; Kashyap and Stein, 1995). Early studies have employed time se-

[1]Other studies argue in favor of a "central bank response to news" effect. For instance, according to Bauer and Swanson (2023), monetary policy announcements may reveal new information about the central bank's policy response function rather than about the state of the economy. They highlight the need to control for macroeconomic and financial variables in the period before the announcement. As our empirical approach controls for pre-announcement information, the effect of an information shock we observe on bank lending is also not inconsistent with this latter interpretation.

ries data to examine the effects of U.S. monetary policy on bank lending (e.g., Bernanke and Blinder, 1992; Kashyap et al., 1993). However, there is no obvious way to disentangle loan supply from potentially confounding loan demand effects using aggregate data. Later studies have instead used disaggregated data to analyze the differential effects of U.S. monetary policy across banks with different balance sheet characteristics, under the assumption that these affect loan supply but not loan demand. Kashyap and Stein (1995) show, for example, that a policy rate tightening has a disproportionately large impact on loan supply by smaller banks, which have less access to external financing. Evidence also shows that banks are more responsive to changes in U.S. monetary policy if they have weaker – i.e., less liquid and undercapitalized – balance sheets (e.g., Peek and Rosengren, 1995; Kashyap and Stein, 2000; Kishan and Opiela, 2000).

We add to a large literature on the bank lending channel outside the United States. The international evidence is less conclusive. For instance, using micro data, Favero et al. (1999) do not find evidence of a significant response of bank loans in France, Germany, Italy, and Spain to a monetary tightening, regardless of bank size. By contrast, Altunbas et al. (2002) find evidence for the bank lending channel in Italy and Spain but none in France and Germany. Ehrmann et al. (2003) emphasize that liquidity plays an important role in the monetary transmission mechanism for euro area countries. De Santis and Surico (2014) find relatively large effects of monetary policy on cooperative and savings banks with lower liquidity and lesser capital in Germany and savings banks with smaller size in Italy, while the effects are generally weaker and more homogeneous in Spain and France. Further evidence for the bank lending channel is found by Gambacorta and Mistrulli (2004) and Gambacorta (2005) for Italian banks, and by Gambacorta and Shin (2018) using a sample of 105 international banks operating in 14 advanced economies. Instead of grouping banks by bank-specific features, some studies disentangle loan supply and demand by exploiting loan variation for firms with multiple banking relationships. For instance, employing bank-firm-level data, Jiménez et al. (2012) show that, consistent with the bank lending channel, Spanish banks with low capital or liquidity are more likely to reject loan applications by firms after an increase in the short-term interest rate. Ivashina et al. (2022) show using data from the Spanish and Peruvian credit register that monetary policy propagates through bank balance sheets differentially across different loan types, and that the results in Jiménez et al. (2012) are mainly driven by cash-flow loans. Using the Spanish data, Jiménez et al. (2014) further document that monetary policy affects not only the volume but also the composition of bank loan supply: a lower overnight rate induces lowly capitalized banks to grant more loan applications to ex ante risky firms. Other studies isolate loan supply effects using data from bank lending surveys. Using survey data, Ciccarelli et al. (2015), for instance, show that the lending channel amplifies the real effects of monetary policy shocks, and Altavilla et al. (2021) document that weak banks not only supply less loans but also face less loan demand following a monetary tightening. Our empirical approach contributes to the existing literature by analyzing the causal effects of exogenous shocks instead of correlating bank loans with policy rates, and by capturing variation across banks and over time within a panel local projection framework.

Our results corroborate existing evidence in favor of a bank lending channel in Germany. For instance, using data on German banking groups, Kakes and Sturm (2002) find that relatively large commercial banks are less sensitive to changes in the policy rate than relatively small credit cooperatives. Using bank-level data for the 1990s, Worms (2003) finds that the bank lending channel in Germany works through banks' liquidity rather than size. Ehrmann and Worms (2004) emphasize the role of liquidity in a comparable sample of German banks, showing that smaller banks are able to cushion the effects of a policy rate tightening by tapping into liquidity in their interbank network, which allows them to diminish possible size-related disadvantages. By contrast, small banks that cannot access the interbank market are more sensitive to policy rate changes. Hülsewig et al. (2006) present evidence in line with the bank lending channel using aggregate data for Germany for the 1991-2003 period. Using disaggregated data for a more recent period between 2008-2018, Imbierowicz et al. (2021) find asymmetric effects of monetary policy on lending by German banks: better capitalized banks lend more after a monetary policy easing but the effects of a tightening are not significant. Finally, a growing number of papers investigate the role of bank lending in the transmission of unconventional monetary policy measures, both in the euro area (e.g., Altavilla et al., 2020; Albertazzi et al., 2021; Altavilla et al., 2021; Peydró et al., 2021) and in Germany (e.g., Bednarek et al., 2021; Paludkiewicz, 2021). The Eurosystem started to purchase securities under its large-scale asset purchase programme (APP) in October 2014. Compared to existing studies, our sample covers a relatively long time period that spans from the public introduction of the euro in 2002 until the end of 2018, allowing us to study the transmission mechanism before and during the APP.

The rest of the paper is organized as follows. Section 2 describes our empirical approach, including the econometric model and the data used. Section 3 reports our main results and robustness checks. Finally, section 4 concludes.

2 Empirical approach

2.1 Econometric model

Let $y_{i,t}$ denote the volume of NFC loans extended by bank i in period $t = 1, \ldots, T$ (in logs and deflated by the German HICP). To examine the dynamic effects of PMP shocks and CBI shocks on banks' NFC loans, we estimate panel local projection regressions (see, e.g., Jordá, 2005; Jordá et al., 2015):

$$\Delta_h y_{i,t-1} = \alpha_{i,h} + \beta_h \xi_t + \sum_{j=1}^{p} \boldsymbol{\gamma}'_{h,j} \boldsymbol{x}_{i,t-j} + \sum_{j=1}^{p} \boldsymbol{\lambda}'_{h,j} \boldsymbol{z}_{t-j} + u_{i,t+h}, \tag{1}$$

where $\Delta_h y_{i,t-1} \equiv y_{i,t+h} - y_{i,t-1}$, and ξ_t is a time series of either PMP shocks or CBI shocks. Moreover, $\boldsymbol{x}_{i,t-j} = [\Delta y_{i,t-j}, \boldsymbol{b}_{i,t-j}]$, where $\Delta y_{i,t-j}$ is the first-difference of log real loans lagged by $j = 1, \ldots, p$ periods, and $\boldsymbol{b}_{i,t-j}$ is a vector of lagged bank-level controls; $\boldsymbol{z}_{t-j} = [\xi_{t-j}, \boldsymbol{m}_{t-j}]$, where ξ_{t-j} controls for any potential serial dependence in the shock series, and $\boldsymbol{m}_{t-j}$ is a vector of lagged macro-level controls; $\alpha_{i,h}$ is a bank-specific fixed effect; and $u_{i,t+h}$ is the projection residual. The coefficients $\{\beta_h\}_{h=1}^{H}$ capture the impulse response function (IRF) of $\Delta_h y_{i,t-1}$ with respect to the shock ξ_t at horizon $h = 1, \ldots, H$. Throughout the paper, we winsorize the growth rate of real loans at the 1$^{\text{st}}$ and 99$^{\text{th}}$ percentile to mitigate the effect of outliers, which may arise, e.g., due to bank mergers. For completeness, we also report non-winsorized results in a robustness check. Equation (1) is estimated by ordinary least squares (OLS) with a lag length set to $p = 4$ quarters. We conduct inference based on Driscoll and Kraay (1998) standard errors. In a robustness check, we show estimates with standard errors clustered by bank and time (see, e.g., Cloyne et al., 2023). Our estimation sample starts in 2002:Q2 and ends in 2018:Q4 (we lose the first quarter in our sample due to taking first-differences). We vary the sample period for the sake of robustness.

2.2 Shock series

To measure the exogenous component of monetary policy and central bank communication, we use time series of PMP shocks and CBI shocks taken from Jarociński and Karádi (2020). Monetary policy in Germany has been conducted at the supranational level within the Eurosystem since 1999, with the ECB setting the key policy rates for the euro area. High-frequency co-movement of short-term interest rates and stock prices in a narrow window around ECB policy announcements allows for the separation of PMP shocks and CBI shocks. A broad range of models predict a negative co-movement between these variables after a monetary policy shock due to the present value effect of interest rate changes. Yet, Jarociński and Karádi (2020) document a positive co-movement after almost half of the policy announcements by the ECB since 1999. They argue that a positive co-movement between interest rates and stock prices in the announcement window can be interpreted as a reflection of an information shock. For instance, a policy rate tightening may signal to market participants that the central bank has a more favorable economic outlook, producing a stock price increase.

In line with these considerations, Jarociński and Karádi (2020) disentangle PMP shocks from CBI shocks using a VAR model that combines monthly variables such as interest rates, prices, economic activity, and financial indicators with variables that reflect high-frequency financial market surprises at the time of monetary policy announcements. They make two assumptions on the announcement surprises. First, announcement surprises are assumed to be affected only by PMP and CBI shocks and not by other shocks. Second, they impose sign restrictions that identify a PMP shock for the euro area from a surprise increase in three-month EONIA swaps and a surprise drop in the Euro Stoxx 50 index, while a CBI shock is identified from a surprise increase in both of these variables in a tight event window around ECB policy announcements. Their identification scheme does not impose any restrictions on the monthly variables. We use the sequence of (median) shocks extracted by Jarociński and Karádi (2020) from their structural VAR for the euro area. Using a shock series identified from a structural VAR allows us to trace the causal effects of such shocks. To match the frequency of the macroeconomic and bank-level data, the shock series are summed at a quarterly frequency as is standard in the literature.

Figure 1 depicts the time series of Jarociński and Karádi (2020) PMP and CBI shocks. During the sample period, larger shocks occurred in recessions than outside of recessions. PMP shocks were predominantly positive and CBI shocks were mainly negative during recessions, while the opposite is true for expansions. Jarociński and Karádi (2020) discuss a number of important euro area information shock events. For instance, the largest negative CBI shock occurred in 2012:Q3. In July 2012, the ECB cut the key policy rates by 25 basis points, reducing the overnight rate to essentially zero. ECB President Draghi explained this move as follows: “Inflationary pressure over the policy-relevant horizon has been dampened further as some of the previously identified downside risks to the euro area growth outlook have materialised. [...] The risks surrounding the economic outlook for the euro area continue to be on the downside. They relate, in particular, to a renewed increase in the tensions in several euro area financial markets and their potential spillover to the euro area real economy."[2] The policy announcement prompted a stock market depreciation of more than two percent, which is consistent with a negative information shock. Notice the emphasis on financial market conditions as a key factor affecting the economic outlook, consistent with the outcomes of the DSGE model in Jarociński and Karádi (2020).

2.3 Control variables

The choice of control variables is in line with earlier studies. Consistent with recent work on the monetary transmission mechanism in the euro area (e.g., Jarociński and Karádi, 2020), we select the following macro-level controls, m_{t-j}, for the German economy: the log-difference of real GDP; the log-difference of the HICP; the difference in the yield on 1-year German

[2]See: Introductory statement to the press conference (with Q&A) by Mario Draghi, President of the ECB, and Vitor Constancio, Vice-President of the ECB, Frankfurt am Main, 5 July 2012.

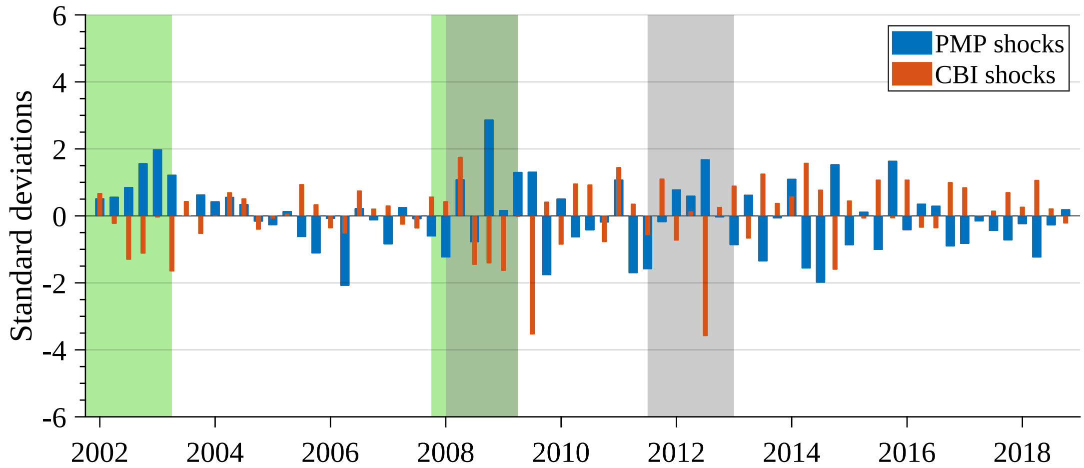


Figure 1: **Jarociński and Karádi (2020) shock series for the euro area, 2002:Q1-2018:Q4**

Note: Pure monetary policy (PMP) shocks (thick blue bars) and central bank information (CBI) shocks (thin red bars) estimated by Jarociński and Karádi (2020). Green shaded areas denote German recession periods dated by the German Council of Economic Experts. Gray shaded areas mark euro area recessions dated by the Euro Area Business Cycle Network. All series are standardized quarterly sums.

federal bonds (Bunds); the Gilchrist and Mojon (2018) NFC credit spread, which is the average spread on the yield of German NFC bonds relative to the yield on Bunds of matched maturities; and a qualitative measure of loan demand for banks domiciled in Germany, obtained from the German responses to the euro area Bank Lending Survey (BLS).[3] We include the corporate credit spread and the loan demand measure to control for factors that influence firms' demand for bank credit at the macro level. Following the micro literature on the bank lending channel (e.g., Jiménez et al., 2012, 2014), we include the following bank-specific variables into the vector $\boldsymbol{b}_{i,t-j}$: the log-difference of bank i's total assets (deflated by the HICP); bank i's return-on-assets ratio, calculated as the ratio of net income to total assets; bank i's liquidity ratio, computed as the ratio of cash and bonds to total assets; and bank i's capital ratio, obtained as the ratio of total equity to total assets.

2.4 Bank balance sheet data

The dependent variable $y_{i,t}$ and the bank-specific control variables $\boldsymbol{b}_{i,t}$ in Equation (1) are based on a large bank-level panel dataset for the period from 2002:Q1 to 2018:Q4. We discuss the dataset and its representativeness for the German banking system in what follows.

[3]We obtain GDP and HICP data from the German Federal Statistical Office (Destatis), Bund yields through Bloomberg, and the BLS responses from the ECB. Credit spreads come from: https://publications.banque-france.fr/en/economic-and-financial-publications-working-papers/credit-risk-euro-area.

2.4.1 Composition of banks in the sample

As at 31 December 2018, the German banking system comprised a total of 1783 credit institutions, of which 1669 banks belong to one of the three main categories: The commercial banking sector (398 banks), the savings banks sector (392 banks) and the cooperative banking sector (879 banks) (see Deutsche Bundesbank, 2019). The group of commercial banks (*Kreditbanken*) comprises three of the largest German banks (*Großbanken*): Deutsche Bank, Commerzbank, and UniCredit Bank. In addition, regional banks (*Regionalbanken*) that typically concentrate on particular geographic regions, private banks that are usually small and specialized in particular activities, and a small set of branches of foreign banks also form part of the commercial bank sector. The savings bank sector includes savings institutions (*Sparkassen*) and five federal state banks (*Landesbanken*), as well as the savings institutions' securities services provider, DekaBank. The cooperative bank sector comprises a large number of small credit cooperatives with local function (collectively referred to as *Volksbanken* and *Raiffeisenbanken*), and their central institution, DZ Bank, which also serves retail and corporate customers. Other types of banks (114 banks as at Dec. 31, 2018), in addition, include mortgage banks (*Realkreditinstitute*), building and loan associations (*Bausparkassen*), and banks with special tasks such as development banks (e.g., the KfW banking group). The commercial and savings bank sectors account for 40% and 26% of total banking system assets, respectively, the cooperative bank sector holds a smaller, but still substantial, asset share of 12%, while the remaining banks hold 22% (as of 2018; see Deutsche Bundesbank, 2022).

We use quarterly data on individual bank balance sheets covering a large part of the German banking system. We obtain data on loans to NFCs from the German credit register for 1524 banks that account for 96% of total assets in 2018. All banks domiciled in Germany are required to report NFC loans exceeding the threshold of €1.0 million to the Bundesbank. The reporting threshold was €1.5 million before 2015. We aggregate the volume of loans extended by each bank to NFCs in each quarter. We also obtain confidential data from the Bundesbank on banks' balance sheet statistics and income statements, including data on total assets, liquid assets (cash and bonds), total equity, and net income at the bank level.

We adjust our data to obtain a balanced and consistent sample, which is a prerequisite for estimating the local projections defined in Equation (1). First, we only include loans larger than €1.5 million, as this was the reporting threshold for most of the sample period. Second, we do not include foreign subsidiaries of German banks. Third, we use a balanced panel including only banks for which we have loan-level data and balance sheet information over the whole sample period. Adjusting the dataset to a balanced sample leaves us with 940 banks that account for 72% of total 2018 assets.

Figure 2 shows the composition of the balanced sample, as measured by total assets, total loans to NFCs, and the number of banks included. The asset composition in the balanced sample reflects that of the overall banking system, as described above. The balanced sample includes relatively few, but on average larger, commercial banks (65 banks). The sample also contains a large number of savings institutions and the five federal state banks that account for a substantial share of total assets (379 banks), as well as a large number of relatively small cooperative banks (469 banks). Finally, there are eight mortgage banks, eight building and loan associations, and eleven banks with special tasks, which we exclude from the final sample because of their rather specific business models (see also Kakes and Sturm, 2002). For completeness, we include these institutions in a robustness check. After these adjustments, the final sample comprises 913 banks that account for 67% of total banking system assets in 2018.

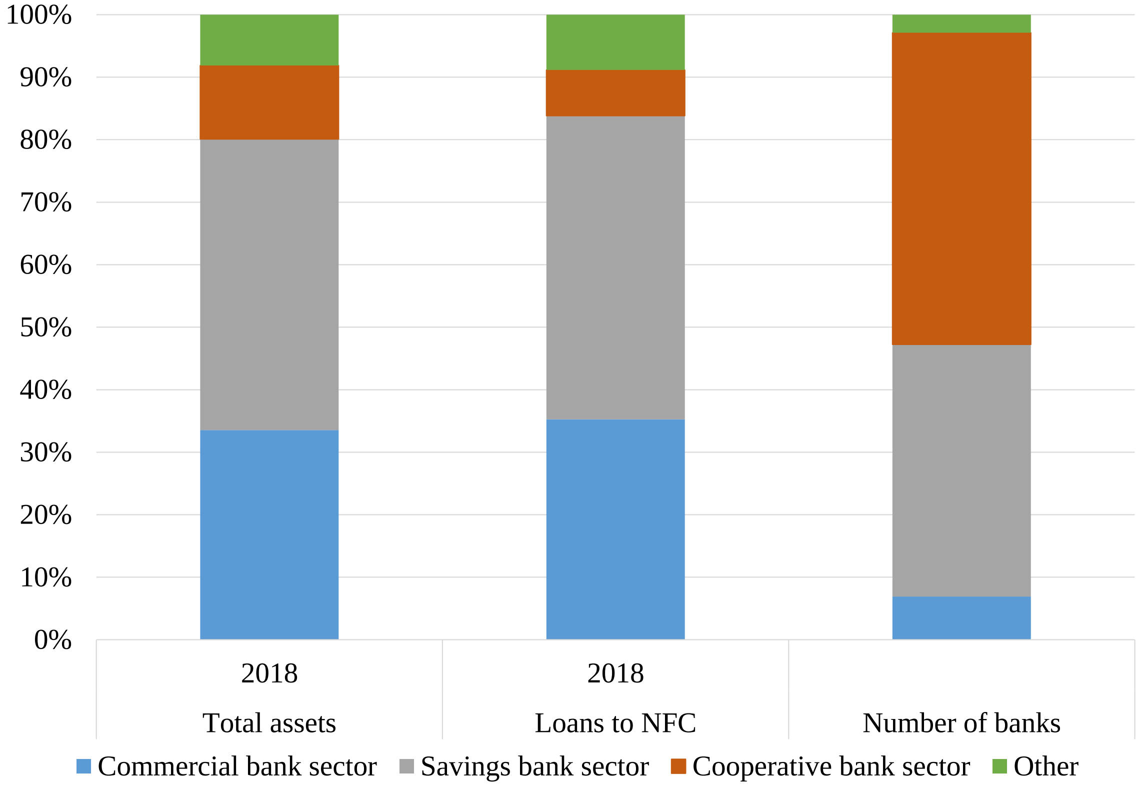


Figure 2: **Composition of banks in the sample, 2018**

Note: This figure depicts the composition of banks in the sample by total assets, loans to non-financial corporations, and the number of banks in 2018 (940 in total). Banks are categorized into the commercial bank sector, the savings bank sector, the cooperative bank sector, and other banks (including mortgage banks, building and loan associations, and banks with special tasks).

Figure 3 depicts the time series of NFC loans extended by the banks in our sample, aggregated by type of bank. Throughout the sample period, the total volume of NFC loans increased two-and-a-half-fold from around €400 billion in 2002 to over €1 trillion in 2018. Germany experienced a recession between 2001:Q1 and 2003:Q2 mainly owing to domestic structural issues and another one between 2008:Q1-2009:Q2 due to the global financial crisis.[4] The recessions of the early and late 2000s have left a stronger mark on commercial and savings bank loans, while loans extended by credit cooperatives appear to be less prone to cyclical fluctuations. The 2010s have seen an expansion in NFC loans by all types of banks.

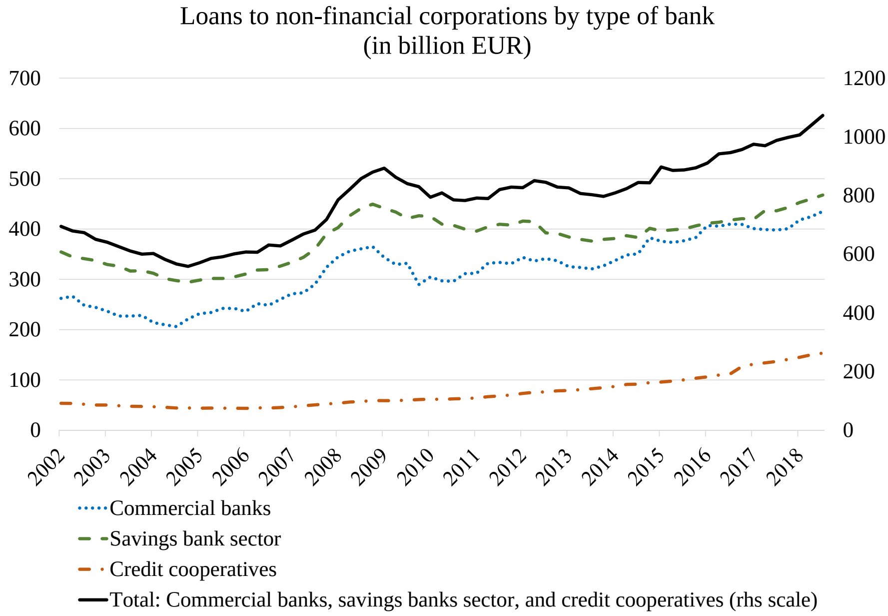


Figure 3: **Loans to non-financial corporations aggregated by bank type**

Note: Loans to non-financial corporations extended by the banks in our sample, aggregated by bank type. Total loans are the sum of loans extended by commercial banks, savings and federal state banks, as well as credit cooperatives (measured on the right-hand side scale). All values are expressed in billion euros (at current prices).

Table 1 reports summary statistics for some key balance sheet figures. The values reported are averages for each bank over the period 2002-2018. The volume of total assets averages at around €6.7 billion (in 2018 prices) for the banks in our sample, with a standard deviation of around €58.6 billion. The asset volume of commercial banks (roughly €45.1 billion) is, on average, more than seven times larger than that of savings banks (roughly €6.2 billion) and around 25 times larger than that of cooperative banks (roughly €1.8 billion). The volume of NFC loans averages at around €925 million over the sample period, or about 14% of the average asset volume. The NFC loan volume amounts to, on average, around €5.5 billion (≈ 13% of total assets) for commercial banks, approximately €1.1 billion (≈ 17% of total assets) for savings banks, and about €169.8 million (≈ 10% of total assets) for cooperative banks. The average growth rate of business loans is 1.6% quarter-on-quarter, with a standard deviation of

[4]See the business cycle turning-point dates published by the German Council of Economic Experts at https://www.sachverstaendigenrat-wirtschaft.de/en/topics/business-cycles-and-growth/konjunkturzyklus-datierung.html.

Variable	Mean	Std. dev.	p25	Median	p75
Total assets (€mn)	6669.31	58605.25	611.78	1150.50	2308.07
NFC loans (€mn)	925.02	6041.60	39.82	101.47	276.06
ΔNFC loans (%)	1.59	1.49	0 .63	1.47	2.51
Capital ratio (%)	8.77	1.99	7.73	8.62	9.61
Liquid assets (%)	20.55	9.36	14.34	19.01	25.46

Table 1: **Summary statistics**

Note: The table reports summary statistics for the banks in the sample. The variables are: the volume of total assets (in €mn at 2018 prices, deflated by the HICP); the volume of NFC loans (in €mn at 2018 prices, deflated by the HICP); the log first-difference of the real loan volume (in %, winsorized at the 1^{st} and 99^{th} percentile); the ratio of capital to total assets (in %); and the ratio of liquid assets (bonds and cash) to total assets (in %). Values are averaged for each bank over the 2002:Q1-2018:Q4 period.

1.5%. Commercial banks and cooperative banks have a somewhat higher average loan growth ($\approx$ 2.1%) than savings banks ($\approx$ 0.8%). On average across banks and time, capital makes up around 8.8% of total assets, and liquid assets (cash and bonds) account for around 20.6% of total assets. Banks do not markedly differ in their average capital and liquidity position, regardless of business model.

2.4.2 Composition of borrowers in the sample

Figure 4 shows a breakdown of bank loans in our sample by borrowing sector at the end of 2018.[5] With 33%, by far the largest share of loans in our sample goes to firms that perform real estate activities, including buying and selling of own real estate, rental and operating of own or leased real estate, and real estate activities on a fee or contract basis (NACE code: L). Smaller but still substantial shares of loans – of between 10% and 16% – go to firms supplying utlilities including electricity, gas, steam and air-conditioning supply, water supply, sewerage, waste management and remediation (NACE code D and E), firms in the manufacturing sector (NACE code: C), as well as firms offering professional, scientific, technical, administration and support service activities (NACE code: M and N). Moreover, the wholesale and retail trade, repair of motor vehicles and motorcycles sector (NACE code: G) and the transportation and storage sector (NACE code: H) account for 9% and 7% of loans, respectively, while the construction sector (NACE code F) accounts for 3% of loans in our sample. The remaining sectors in our sample include accommodation and food service activities (NACE code: I), information and communication (NACE code: J), human health services, residential care and

[5] To study the composition of banks' NFC loan portfolio, we aggregate the loans of each bank by the economic sector to which the borrower belongs using the Nomenclature of Economic Activities (NACE) classification, which is the standard European nomenclature of productive economic activities. For details, see: https://nacev2.com/en.

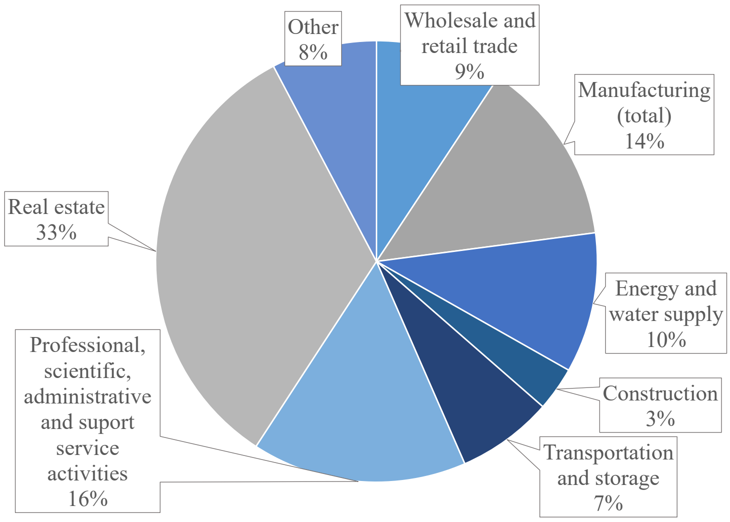


Figure 4: **Composition of loan portfolio by borrowing sector, 2018:Q4**

Note: This figure depicts the composition of bank lending by borrowing sector in 2018:Q4. Borrowing sectors are classified according to their NACE classification. The sectors grouped within the category *Other* are: Information and communication, human health and social work activities, arts, entertainment and recreation, accommodation and food services as well as other services. The figure is based on our adjusted dataset, i.e. incorporating only loans by the commercial bank sector, savings bank sector, and cooperative bank sector.

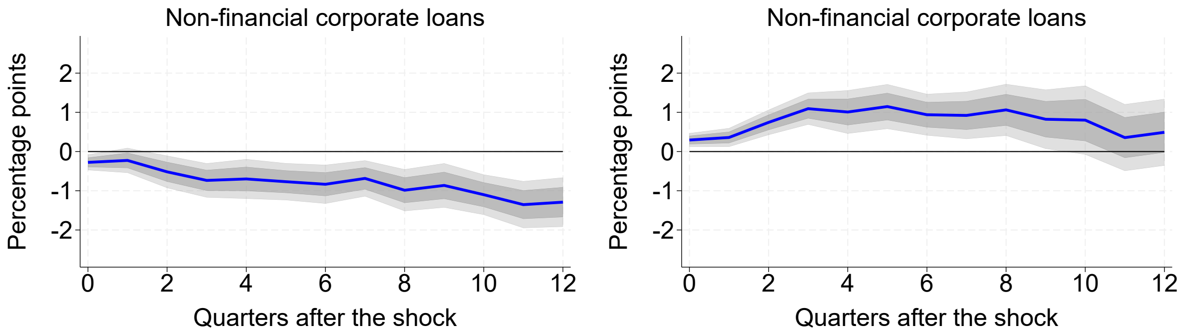
social work activities (NACE code: Q), arts, entertainment and recreation (NACE code: R), and other services (NACE code: S). These together account for 8% of bank loans.

3 Results

3.1 Average effects across all banks

We first estimate the impact of PMP shocks and CBI shocks on NFC loans for the entire sample of banks. Figure 5 (left panel) depicts the impulse responses of NFC loans to a positive, one-standard-deviation PMP shock – that is, an interest rate hike that coincides with a drop in stock prices around policy announcements –, estimated with the local projections approach. The shock leads to a statistically significant reduction in bank lending on impact. On average across all banks, the volume of business loans decreases by around three-quarters of a percentage point one year after the shock.[6] The estimated effects are relatively persistent: banks continue to lend nearly one and a half percentage points less to non-financial firms three years after the shock. The persistence of the effects is comparable to the persistent response of the volume and lending standards for bank loans to enterprises to monetary policy shocks in structural VARs (e.g.,

[6]For comparison, the PMP shock leads to a drop in German real GDP of nearly three-quarters of a percentage point one year after the shock (see Figure A.1 in the Appendix).



PMP shock **CBI shock**

Figure 5: **Impulse responses for all banks**

Notes: Responses of German banks' non-financial corporate loans to a positive, one-standard-deviation pure monetary policy (PMP) shock (left panel) and central bank information (CBI) shock (right panel), identified as in Jarociński and Karádi (2020). Average effects for all banks in the sample (N = 913). Loan growth is winsorized at the 1$^{\text{st}}$ and 99$^{\text{th}}$ percentile. Shaded areas represent the 68% (dark gray) and 90% (light gray) confidence intervals based on Driscoll and Kraay (1998) standard errors.

Bernanke and Blinder, 1992; Ciccarelli et al., 2015; Miranda-Agrippino and Ricco, 2021). A long-lasting decline in loans is consistent with evidence that banks typically respond to higher policy rates in the short term by selling liquid assets and in the longer term by reducing their loan holdings, as the stock of loans is difficult to change quickly (e.g., Bernanke and Blinder, 1992).

Figure 5 (right panel) shows the impulse responses of NFC loans to a positive, one-standard-deviation CBI shock – i.e., an interest rate tightening and a concurrent increase in stock prices around policy announcements. Bank lending expands on impact in a statistically significant manner. On average across all banks, the loan volume increases by about one percentage point one year after the shock. The impulse response is hump shaped, and loans return gradually back to the baseline level after two years.[7] Thus, the CBI shock stimulates the provision of bank loans, which adds an informational dimension to the bank lending channel.

3.2 Effects for banks grouped by balance sheet characteristics

We estimate the effects of PMP and CBI shocks separately for groups of banks that differ in bank-specific characteristics, which are assumed to only influence loan supply and not loan demand (in line with, e.g., Kashyap and Stein, 1995, 2000; Kishan and Opiela, 2000).[8] We first split the sample by asset size. In particular, we compute the average asset volume of each

[7]For comparison, the CBI shock leads to a gradual increase in German real GDP, reaching nearly one and a half percentage points above the baseline level three years after the shock (see Figure A.1 in the Appendix).

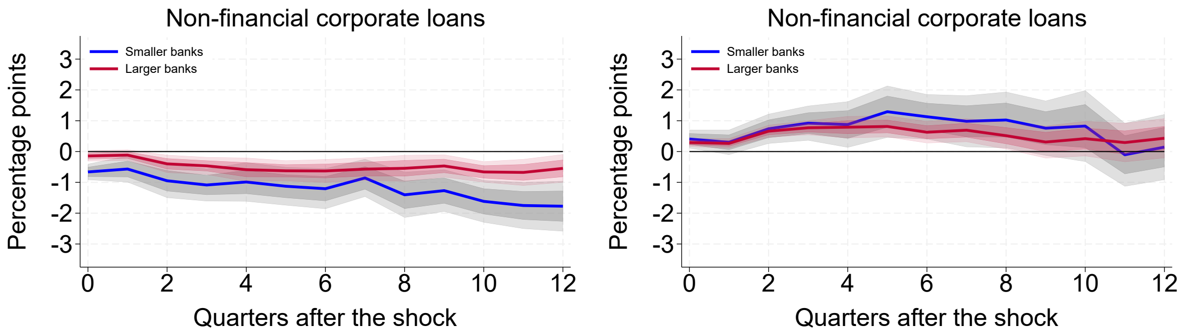
[8]One could also control for demand effects at the individual loan/firm level, but this would restrict the sample to firms with multiple banking relationships (see, e.g., Khwaja and Mian, 2008; Jiménez et al., 2012, 2014).

bank in our sample over time, yielding an average asset volume distribution across banks. We then estimate the effects of PMP and CBI shocks separately for banks that fall into the lower quartile (small banks) and the upper quartile (large banks) of the asset volume distribution. Second, we split the sample by banks' liquidity position using a similar procedure. Finally, we jointly consider the role of size and liquidity.

Figure 6 shows the impulse responses obtained for the 25% smallest and the 25% largest banks by total assets. A positive PMP shock leads to a significantly stronger decrease in the volume of NFC loans extended by relatively small banks. The loans extended by smaller banks significantly decrease by around one half of a percentage point on impact. By contrast, the loans of relatively large banks barely contract on impact. The loan volume of smaller banks continues to decrease over the projection horizon by around one percentage point after one year and close to two percentage points after three years. The reduction in the loan volume of larger banks is more modest over the projection horizon, and the strongest decrease of around one half of a percentage point occurs within the first year after the shock. Hence, relatively small banks that have worse access to external finance are more responsive to PMP shocks than larger banks, consistent with a bank lending channel of monetary policy transmission (see, e.g., Kashyap and Stein, 1995, 2000).

A positive CBI shock leads to a significant increase in the volume of NFC loans, which is more pronounced for banks with a less sizable balance sheet than for larger banks. The volume of loans extended by smaller banks rises on impact, and it reaches its peak of around 1.25 percentage points five quarters after the shock. The loan volume of relatively large banks increases by only up to about 0.75 percentage points two quarters after the shock, and it then gradually declines to the baseline level. A potential explanation for this relatively more modest increase is that relatively small banks might face more information asymmetries than larger banks (see, e.g., Holod and Peek, 2007). Hence, the economic news conveyed by the CBI shock is likely to have higher novelty value for smaller banks that might have less resources to monitor economic conditions than larger banks. Another potential explanation is that smaller banks might be more collateral-constrained in their access to external finance than larger banks. The rise in collateral values after a positive CBI shock may thus primarily improve financing conditions for smaller banks.

Next, we group banks by their liquidity position. Figure 7 shows the impulse responses for banks with the 25% lowest and the 25% highest ratios of liquid assets (cash and bonds) to total assets, on average, over the sample period. Liquidity seems to mainly matter for the transmission of CBI shocks. A PMP shock causes a drop in NFC loans of similar magnitude and persistence for banks with less liquid balance sheets and for more liquid banks. Even though effects tend to be somewhat more modest for more liquid banks, especially in the first two years after the shock, the median effects fall within the same 68% confidence bands for



PMP shock **CBI shock**

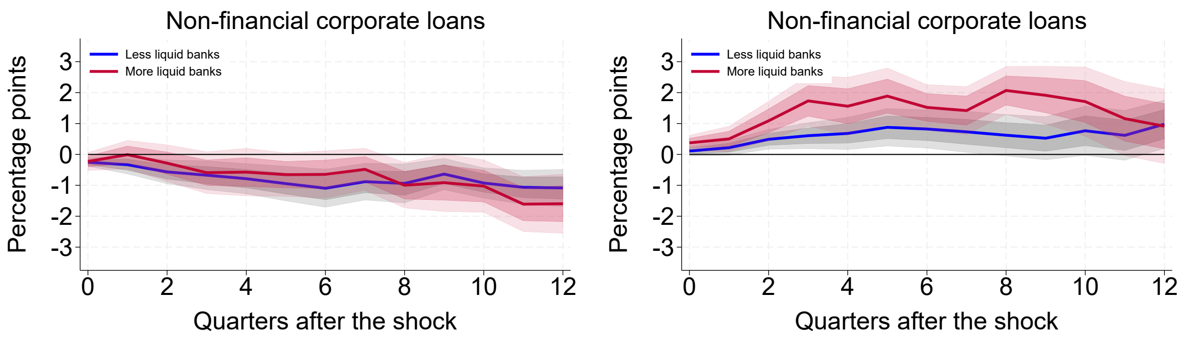
Figure 6: **Impulse responses for banks grouped by total assets**

Notes: Responses of German banks' non-financial corporate loans to a positive, one-standard deviation pure monetary policy (PMP) shock (left) and a central bank information (CBI) shock (right), identified as in Jarociński and Karádi (2020). Effects for banks with the 25% lowest total asset volume (blue). Effects for banks with the 25% highest total asset volume (red). Loan growth is winsorized at the 1^{st} and 99^{th} percentile. Shaded areas represent the 68% (dark shaded) and 90% (light shaded) confidence intervals based on Driscoll and Kraay (1998) standard errors.

the most part. At the same time, banks that hold more liquid assets use their extra liquidity to expand their business lending significantly more strongly after a positive CBI shock than less liquid banks. The increase in the volume of loans made by banks with more liquid balance sheets is more than twice as large and more persistent than that of less liquid banks.

The asymmetric effects across banks that differ in their liquidity position are more pronounced when we focus on the subsample of relatively small banks. A positive PMP shock leads to a significant and relatively persistent decrease in the loan volume of *smaller* banks with *less liquid* balance sheets, while there are hardly any effects on the loans of smaller and more liquid banks (see Figure 8). The volume of loans made by relatively small and less liquid banks also decreases more strongly after a PMP shock than the loan volume of loans extended by less liquid banks with larger balance sheets, which hardly moves after the shock (see Figure 9). Hence, the business loans of smaller and more liquidity-constrained banks are more responsive to PMP shocks, corroborating earlier evidence in favor of a bank lending channel of monetary policy in Germany (e.g., Kakes and Sturm, 2002; Ehrmann and Worms, 2004).

A positive CBI shock leads to a significant and relatively persistent increase in the volume of loans extended by *smaller* banks with *more liquid* balance sheets, while the loans of smaller and less liquid banks do not respond significantly, and even tend to decrease over time (see Figure 8). A positive CBI shock also has positive but somewhat more modest effects on the volume of loans extended by more liquid banks with larger balance sheets (see Figure 9). While more liquid assets make larger banks equally able to boost lending after a CBI shock, they may face less information asymmetries or might be less collateral-constrained than smaller banks,



PMP shock **CBI shock**

Figure 7: **Impulse responses for banks grouped by liquidity**

Notes: Responses of German banks' non-financial corporate loans to a positive, one-standard deviation pure monetary policy (PMP) shock (left) and a central bank information (CBI) shock (right), identified as in Jarociński and Karádi (2020). Effects for banks with the 25% lowest ratio of liquid assets (bonds and cash) to total assets (blue). Effects for banks with the 25% highest ratio of liquid assets to total assets (red). Loan growth is winsorized at the 1^{st} and 99^{th} percentile. Shaded areas represent the 68% (dark shaded) and 90% (light shaded) confidence intervals based on Driscoll and Kraay (1998) standard errors.

as discussed before. Hence, information shocks induce smaller banks with more liquid balance sheets to particularly boost lending to firms. These results empirically support the interpretation of the CBI shock put forth by Jarociński and Karádi (2020) as a positive news shock about the state of financial conditions, which encourages bank lending to firms.

3.3 Robustness

We conduct a battery of robustness checks. First, we replace the shock series by the monetary policy target surprises derived by Altavilla et al. (2019) from high-frequency data. Target surprises capture intraday variation in short-maturity overnight indexed swap (OIS) rates within a tight event window around ECB press releases attributable to the shift in market expectations due to the policy decisions announced in the press release. They can thus best be understood as monetary policy shocks that primarily move the short-end of the yield curve. Target surprises are available at a daily frequency between January 3, 2002 and September 13, 2018.[9]

We split the daily target surprises into PMP and CBI surprises using an approach similar to the "poor man's sign restrictions" in Jarociński and Karádi (2020). In particular, we sum up the daily target surprises within each quarter after eliminating those ECB press release days on which target surprise and the Euro Stoxx 50 index move in the same direction in the 15-

[9]We retrieved the daily target surprise series from the website of Refet S. Gürkaynak (http://refet.bilkent.edu.tr/research.html). Daily target surprises are identified up to scale, they are thus scaled by Altavilla et al. (2019) such that they have unit effect on the one-month OIS rate in the press release window.

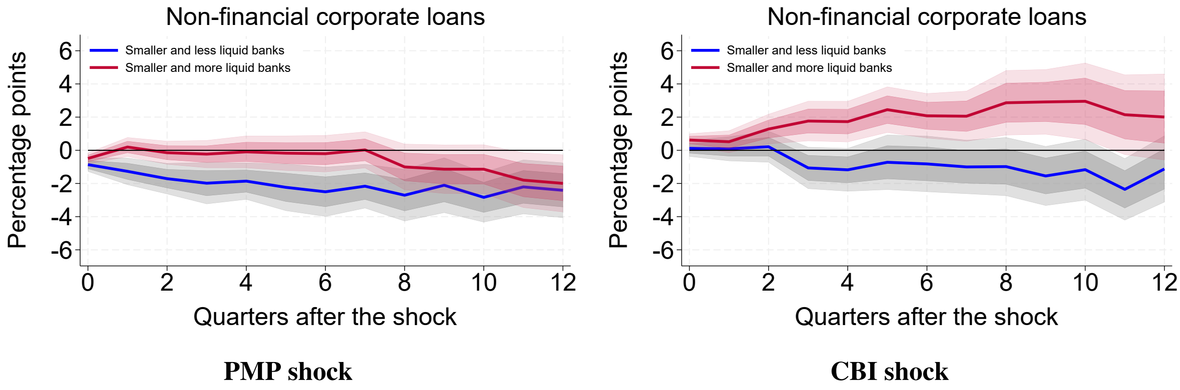


Figure 8: **Impulse responses for smaller banks grouped by liquidity**

Notes: Responses of German banks' non-financial corporate loans to a positive, one-standard deviation pure monetary policy (PMP) shock (left) and a central bank information (CBI) shock (right), identified as in Jarociński and Karádi (2020). Effects for banks with the 25% lowest asset volume and liquidity ratio (blue). Effects for banks with the 25% lowest asset volume and the 25% highest liquidity ratio (red). Loan growth is winsorized at the 1^{st} and 99^{th} percentile. Shaded areas represent the 68% (dark shaded) and 90% (light shaded) confidence intervals based on Driscoll and Kraay (1998) standard errors.

minute-long press release window.[10] We obtain CBI surprises from the ECB press release days on which the target surprise and the Euro Stoxx 50 index move in the same direction in the press release window. Figure A.2 in the Appendix depicts the Altavilla et al. (2019) PMP and CBI target surprise series. There is a positive correlation between PMP target surprises and Jarociński and Karádi (2020) PMP shocks (with a correlation coefficient of $\rho = 0.49$), and CBI target surprises are positively correlated with Jarociński and Karádi (2020) CBI shocks ($\rho = 0.43$). Large positive PMP target surprises and large negative CBI target surprises occurred during recessions. For instance, the largest negative CBI target surprise coincides with the largest negative CBI shock in 2012:Q3.

The results obtained when using the PMP and CBI target surprise series are in line with the baseline results (see Figure A.3 in the Appendix). On average across all banks, a positive PMP target surprise leads to a significant decrease in loans, although the effects are more delayed compared to those of a PMP shock (Figure A.3; top left). Consistent with the baseline results, a PMP target surprise has particularly adverse effects on the loans of less liquid banks with smaller balance sheets (Figure A.3; bottom left). On average across all banks, a positive CBI target surprise leads to a significant and hump-shaped increase in bank lending, which is in line with the effects obtained with the Jarociński and Karádi (2020) CBI shock series (Figure A.3; top right). Moreover, this increase is stronger for more liquid banks with smaller balance sheets (Figure A.3, bottom right).

[10] Intraday changes in the Euro Stoxx 50 index are the median quotes in the ten minutes after minus the median quotes in the ten minutes before the press release window (see Altavilla et al., 2019).

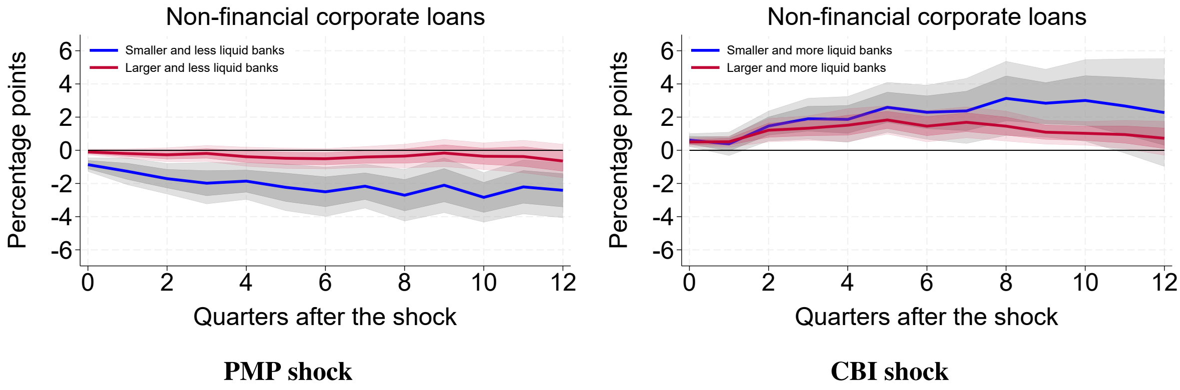


Figure 9: **Impulse responses for small vs. large banks grouped by liquidity**

Notes: Responses of German banks' non-financial corporate loans to a positive, one-standard deviation pure monetary policy (PMP) shock (left) and a central bank information (CBI) shock (right), identified as in Jarociński and Karádi (2020). Effects for banks with the 25% largest total asset volume and the 25% lowest liquidity ratio (blue). Effects for banks with the 25% largest total asset volume and the 25% highest liquidity ratio (red), on average, over the sample period. Loan growth is winsorized at the 1^{st} and 99^{th} percentile. Shaded areas represent the 68% (dark shaded) and 90% (light shaded) confidence intervals based on Driscoll and Kraay (1998) standard errors.

Second, we assess the robustness to the composition of banks in the sample. Our baseline results are not sensitive to the inclusion of banks with special tasks as well as mortgage banks and building and loan associations into the sample (see Figure A.4). We also obtain comparable results when we distinguish between banks that belong to the commercial bank sector, the savings bank sector, and the cooperative bank sector. The results for savings banks and credit cooperatives are closely in line with the estimates obtained for the entire sample of banks (see Figures A.5 and A.6). Due to the smaller sample size, we split the sample of commercial banks along the median asset size and liquidity ratio. The effects for commercial banks are less precisely estimated, but they are consistent with the baseline results (see Figure A.7).[11]

Third, we study how robust our results are to different monetary policy regimes. As discussed above, the overnight rate in euro area money markets reached the zero lower bound (ZLB) in 2012:Q3. To distinguish the effects prior to the ZLB from those during the ZLB, we reformulate the local projection model in Eq. (1) as follows:

$$\Delta_h y_{i,t-1} = \alpha_{i,h} + D_{ZLB}\beta_h\xi_t + (1 - D_{ZLB})\beta_h\xi_t + \sum_{j=1}^{p} \boldsymbol{\gamma}'_{h,j}\boldsymbol{x}_{i,t-j} + \sum_{j=1}^{p} \boldsymbol{\lambda}'_{h,j}\boldsymbol{z}_{t-j} + u_{i,t+h}, \quad (2)$$

where the impulse response coefficients β_h are interacted with a dummy variable D_{ZLB}, which takes the value of one between 2012:Q4-2018:Q4 and is equal to zero otherwise; all else remains unchanged. On average, bank loans respond similarly to a PMP shock before and during

[11]We omit the largest banks from the sub-samples to not distort sub-sample medians and quartiles.

the ZLB period, although the effects are more persistent and become stronger over the projection horizon during the ZLB episode (Figure A.8; top left). However, when focusing on the sub-sample of relatively small banks, we find that our baseline results are robust (i.e., PMP shocks disproportionally affect smaller and less liquid banks), and they are driven mainly by the sequence of PMP shocks in the pre-ZLB sample period; the effects are not statistically significant in the ZLB sample (Figure A.8; middle and bottom left). At the same time, bank loans are, on average, significantly more responsive to CBI shocks during the ZLB period and hardly move after a CBI shock in the pre-ZLB sample (Figure A.8; top right). Again, we find that our baseline results are robust (i.e., CBI shocks disproportionally affect smaller and more liquid banks), and information shocks play a significant role during the ZLB period (Figure A.8; middle and bottom right).

Large-scale asset purchases constitute another change in the conduct of monetary policy. The Eurosystem started to purchase securities under its large-scale Asset Purchase Programme (APP) in October 2014. We study the effects before and during the APP period by replacing D_{ZLB} in Eq. (2) with a dummy variable D_{APP}, which takes the value of one between 2014:Q4-2018:Q4 and is equal to zero otherwise. We find that PMP shocks do not have statistically significant average effects on bank loans during the APP period, while the average effects are significantly negative in the pre-APP sample (Figure A.9; top left). This carries over to the effects estimated for the subsample of smaller and less liquid banks (Figure A.9; middle left). While imprecisely estimated, CBI shocks have more front-loaded effects during the APP period, while their effects are more persistent in the pre-APP period, especially for smaller and more liquid banks (Figure A.9; right).

Fourth, we group banks by their capital ratios. When looking at the entire sample of banks, we do not find any asymmetries in the effects of PMP and CBI shocks across banks with different degrees of capitalization (see Figure A.10). When focusing on the sub-sample of smaller banks, we still do not find differences in the transmission of PMP shocks to bank loans across less and more capitalized banks. However, our estimates indicate that the loans of smaller and less capitalized banks strongly increase after a CBI shock, while the shock has hardly any impact on the loans of smaller and more capitalized banks. Communicating positive news about fundamentals can thus particularly stimulate business lending by less capitalized banks.

Fifth, we investigate the robustness to some econometric modelling choices. One such aspect is the statistical inference on impulse responses. Specifically, we compute confidence intervals with heteroscedasticity-consistent standard errors that are clustered along the bank and time dimension. The estimated confidence intervals are wider when using two-way clustered standard errors, but the estimated effects continue to retain their statistical significance at the same level (see Figure A.11). Another model parameter is the percentile at which we winsorize loan growth to account for potential outliers. The results are nearly identical to the baseline estimates when we do not winsorize the loan growth data (see Figure A.12), or when we winsorize loan growth at the 10$^{\text{th}}$ and 90$^{\text{th}}$ percentile (see Figure A.13).

Finally, we consider two variable measurement choices. We obtain robust results when measuring liquidity by the ratio of bonds to total assets (see Figure A.14). Moreover, we investigate how sensitive our results are to how we measure bank size, by estimating the effects separately for banks with a small and large NFC loan portfolio, on average, over the sample period. In particular, for each bank in our sample, we compute the average volume of NFC loans over time, yielding a loan volume distribution across banks. We then split the sample into small banks (i.e., banks that fall into the firts quartile of the loan volume distribution) and large banks (i.e., banks in the fourth quartile of the distribution), and compute impulse responses by local projection separately for the two subsamples. The asymmetric effects of PMP and CBI shocks are more pronounced when we split the sample by average NFC loan volume instead of total assets (see Figure A.15).

3.4 Effects for different borrowing sectors

In order to assess how PMP and CBI shocks affect the composition of the loan portfolio, we estimate the effects on loans grouped by borrowing sector. For this purpose, we use the information on individual borrowers to aggregate the loans of each bank by the sector to which the borrower belongs based on the NACE classification. Cross-sectional heterogeneity in the estimated effects of PMP and CBI shocks also exists across borrowing sectors. Figure 10 displays the effects of a positive PMP shock on bank loans grouped by the economic sector to which the borrowers belong on the left-hand panel. Effects are shown for the three sectors with largest share of loans that go to each sector in descending order as well as the sum of the remaining sectors (based on 2018 data).

The volume of loans decreases significantly after a PMP shock in all of the sectors displayed here. Lending to sectors that receive the largest share of lending, namely the real estate services sector (which received 33% of all loans in 2018) and the professional, scientific, technical, administration and support service activities sector (16% of loans in 2018) decreases by around one percentage point within a year after the shock, and the effects persist for several years. The impact of a PMP shock on the manufacturing sector (14% of loans in 2018) and the aggregate of the remaining sectors is initially weaker, but firms in these sectors receive around two to three percentage points less bank loans at their trough within three years after the shock. Taken together, our results indicate that PMP shocks lead to a broad-based contraction in loans to NFCs across sectors.

The right-hand panel of Figure 10 shows the sectoral responses to a positive CBI shock. After a CBI shock, banks extend significantly more loans to firms in the real estate services sector (by around 3 percentage points at the peak) and the professional, scientific, technical, administration and support service activities sector (by about 1.5 percentage points at the peak). Lending to manufacturing firms also increases significantly (by approximately 1 percentage point at the peak). The effect of a CBI shock on lending to the remaining sectors is less pronounced as it increases slightly but the significant effect does not persist for long. This heterogeneity in the change in lending across borrowing sectors may reflect a reallocation within banks' loan portfolios after an information shock.

4 Conclusion

There is long-standing evidence that monetary policy affects bank loan supply and the real economy through a bank lending channel. This paper adds a new dimension to the bank lending channel by considering the role of central bank communication. Monetary policy announcements disclose non-monetary information about the state of the economy, which has distinct macroeconomic implications. Yet little is known about how the supply of bank credit responds to an exogenous tightening in the monetary policy rate that is independent of non-monetary information in central bank communication, and whether central bank information has autonomous effects on bank lending. We present novel evidence on these issues, obtained using micro-level data on German bank balance sheets for the period 2002-2018.

We obtain two main findings. First, a conventional tightening in the policy rate leads to a significant decrease in the volume of bank loans to non-financial corporations. In line with the bank lending channel of monetary policy, the decrease is stronger for relatively small banks with less liquid balance sheets, which are likely to have more difficulty with raising external funding. Second, we find that a policy rate tightening due to an information shock leads to a significant increase in the volume of non-financial business loans. The increase is stronger for relatively small banks with more liquid balance sheets, which can use the extra liquidity to make loans to the corporate sector. By documenting the impact of information shocks on bank lending, we empirically corroborate earlier theoretical work showing that central bank information shocks are consistent with news about the state of financial conditions.

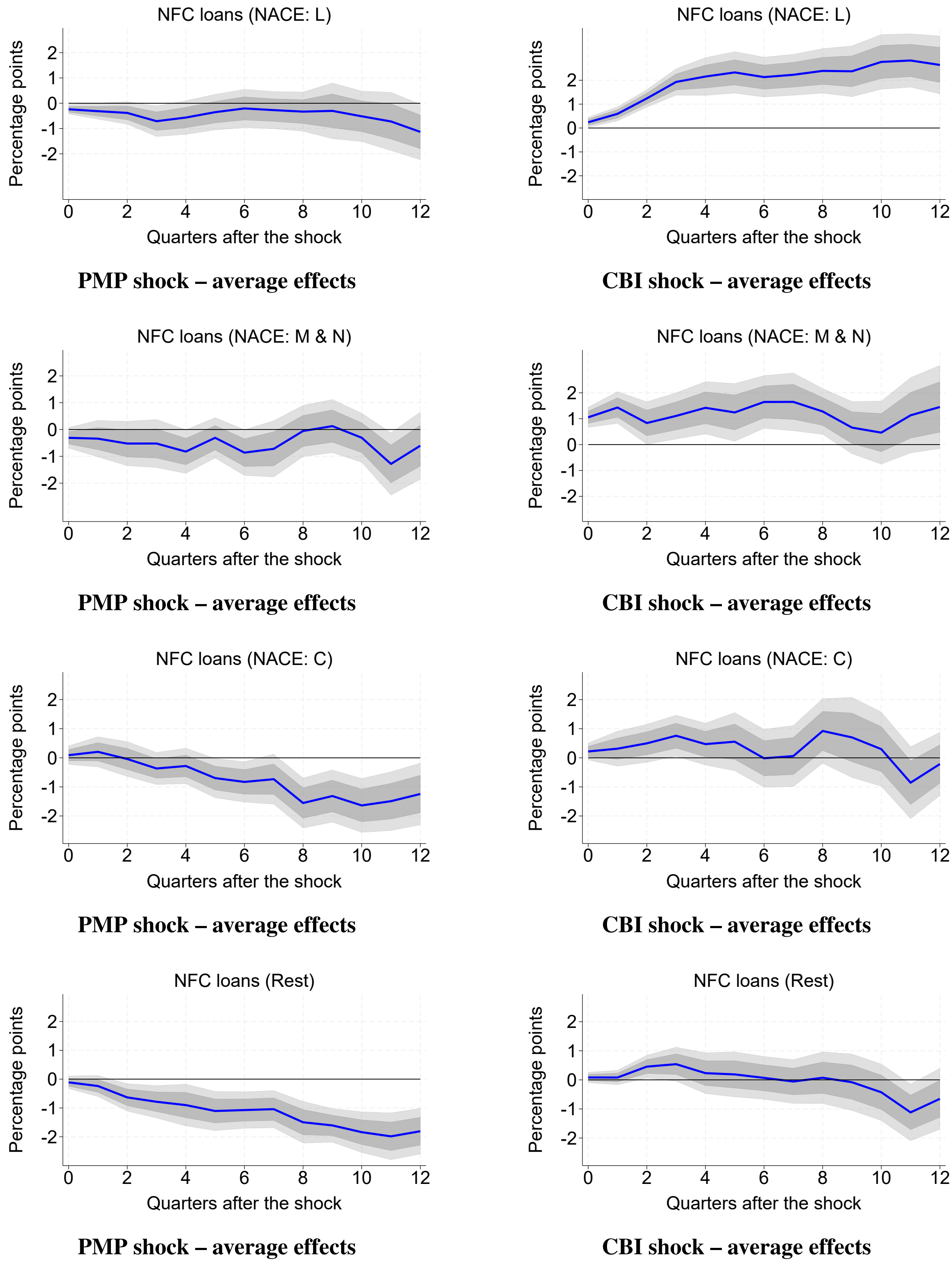


Figure 10: **Impulse responses of bank loans by borrowing sector**

Notes: Responses of bank loans made to firms grouped by sector to a positive, 1-std.-dev. PMP shock (left) and CBI shock (right), identified as in Jarociński and Karádi (2020). Loans are aggregated over to the following sectors: real estate activities (NACE code: L), professional, scientific, technical, administration and support service activities (NACE code: M and N), manufacturing firms (NACE code: C) and all other sectors. Average effects for all banks. Loan growth is winsorized at the 1st and 99th percentile. 68% (dark shaded) and 90% (light shaded) confidence intervals based on Driscoll and Kraay (1998) standard errors.

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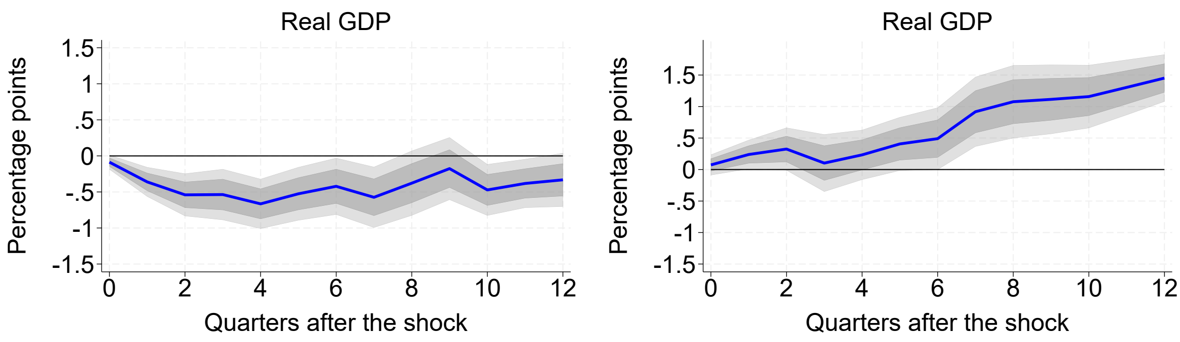
A Additional Figures



PMP shock **CBI shock**

Figure A.1: **Impulse responses of real GDP**

Notes: Responses of German real GDP to a positive, one-standard-deviation pure monetary policy (PMP) shock (left panel) and central bank information (CBI) shock (right panel), identified as in Jarociński and Karádi (2020), estimated using local projections. Shaded areas represent the 68% (dark gray) and 90% (light gray) confidence intervals based on Driscoll and Kraay (1998) standard errors.

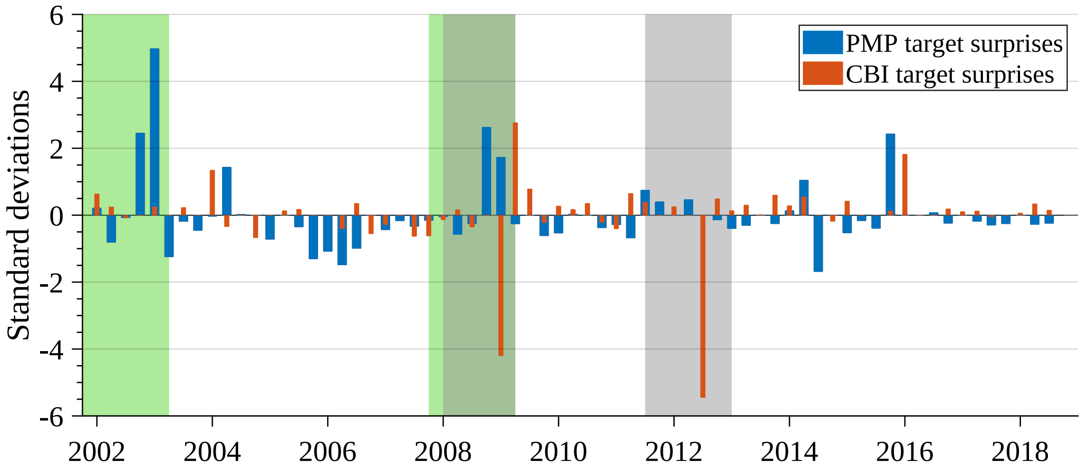
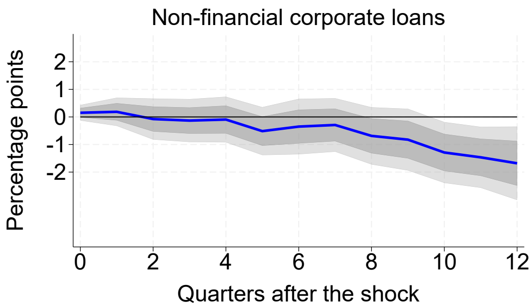
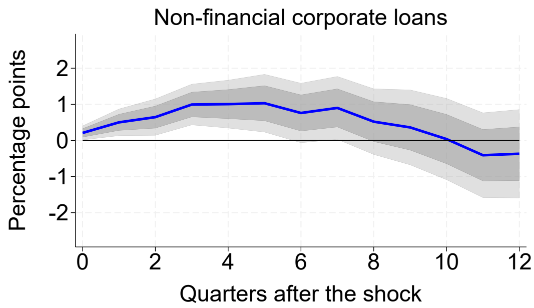


Figure A.2: **Altavilla et al. (2019) shock series for the euro area, 2002:Q1-2018:Q3**

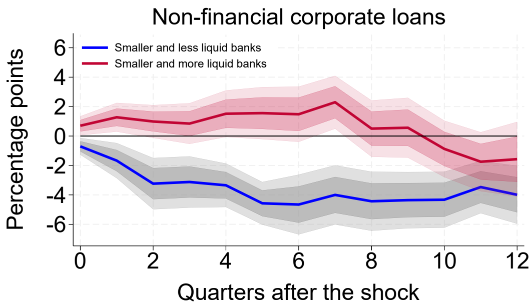
Note: Monetary policy target surprises estimated by Altavilla et al. (2019), split into PMP surprises (thick blue bars) and CBI surprises (thin red bars). PMP surprises: sum of the daily target surprises within each quarter after eliminating those ECB press release days on which the target surprise and the Euro Stoxx 50 index move in the same direction in the press release window; CBI surprises: sum of the daily target surprises on the ECB press release days on which the target surprise and the Euro Stoxx 50 index move in the same direction in the press release window. Green shaded areas denote German recession periods dated by the German Council of Economic Experts. Gray shaded areas mark euro area recessions dated by the Euro Area Business Cycle Network. All series are standardized quarterly sums.



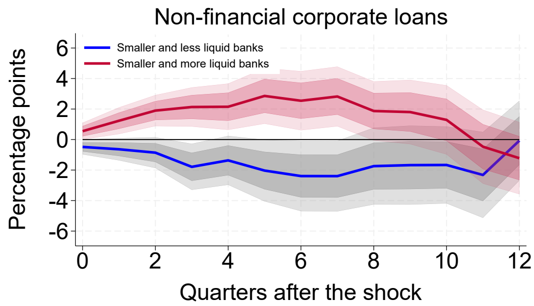
PMP surprise – average effects



CBI surprise – average effects



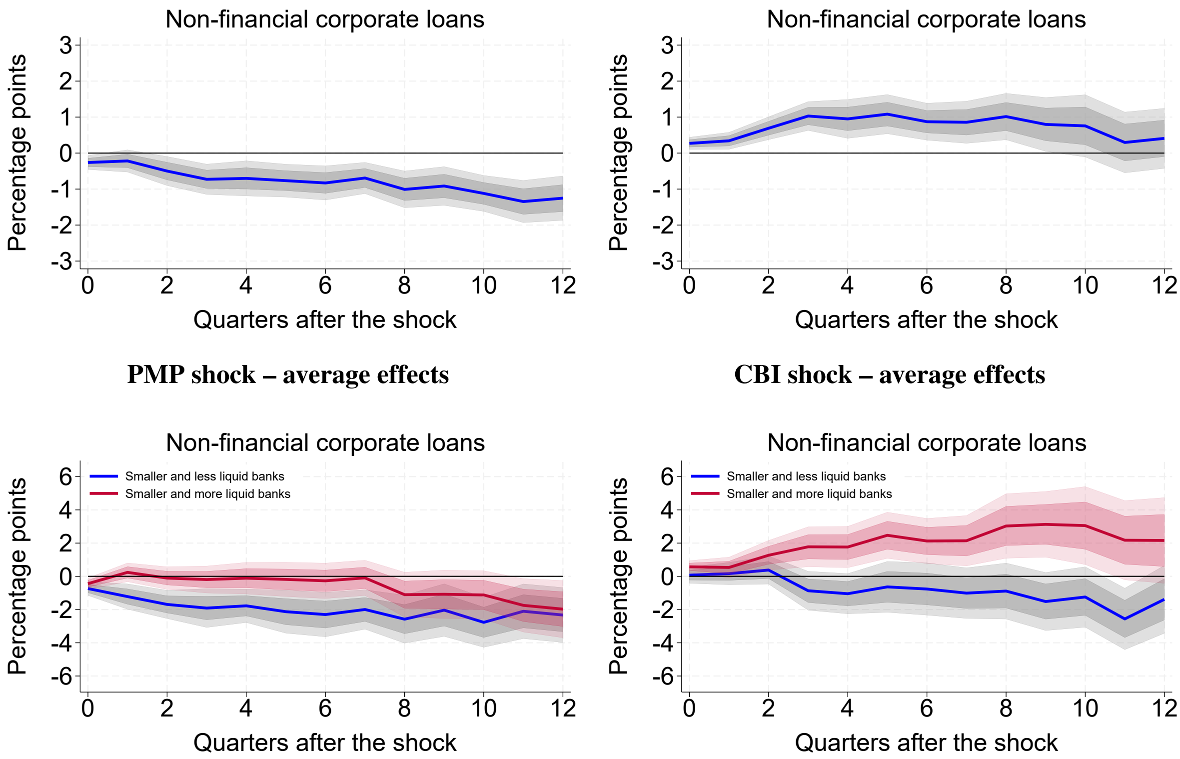
PMP surprise – smaller banks split by liquidity



CBI surprise – smaller banks split by liquidity

Figure A.3: **Impulse responses using the Altavilla et al. (2019) target surprise series**

Notes: Responses of NFC loans to a positive, 1-std.-dev. PMP target surprise (left) and CBI target surprise (right), derived from Altavilla et al. (2019). Top panel: Average effects for all banks. Bottom panel: Effects for the 25% smallest banks with the 25% lowest ratio of liquid assets to total assets (blue) and 25% smallest banks with the 25% highest liquidity ratio (red). Loan growth is winsorized at the 1$^{\text{st}}$ and 99$^{\text{th}}$ percentile. 68% (dark shaded) and 90% (light shaded) confidence intervals based on Driscoll-Kraay standard errors.

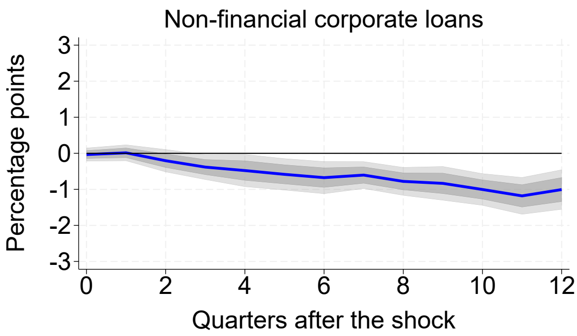


PMP shock – average effects **CBI shock – average effects**

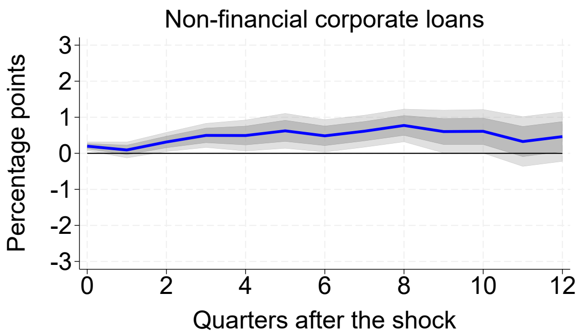
PMP shock – smaller banks split by liquidity **CBI shock – smaller banks split by liquidity**

Figure A.4: **Impulse responses with data including other banking groups**

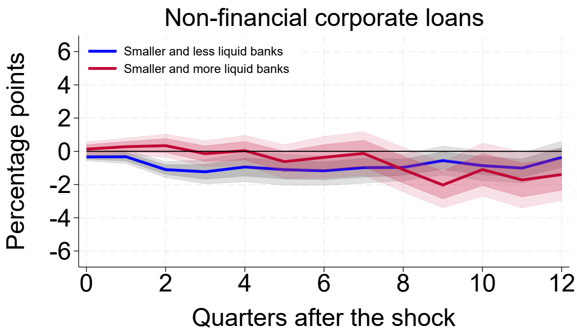
Notes: Responses of NFC loans to a positive, 1-std.-dev. PMP shock (left) and CBI shock (right), identified as in Jarociński and Karádi (2020). Top panel: Average effects for all banks, including banks with special tasks, mortgage banks and building and loan associations (N=940 banks). Bottom panel: Effects for the 25% smallest banks with the 25% lowest ratio of liquid assets to total assets (blue) and 25% smallest banks with the 25% highest liquidity ratio (red). Loan growth is winsorized at the 1^{st} and 99^{th} percentile. 68% (dark shaded) and 90% (light shaded) confidence intervals based on Driscoll-Kraay standard errors.



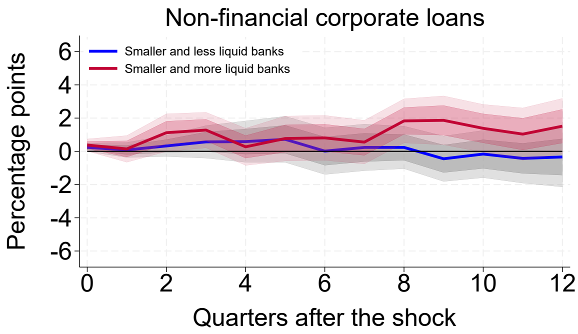
PMP shock – average effects



CBI shock – average effects



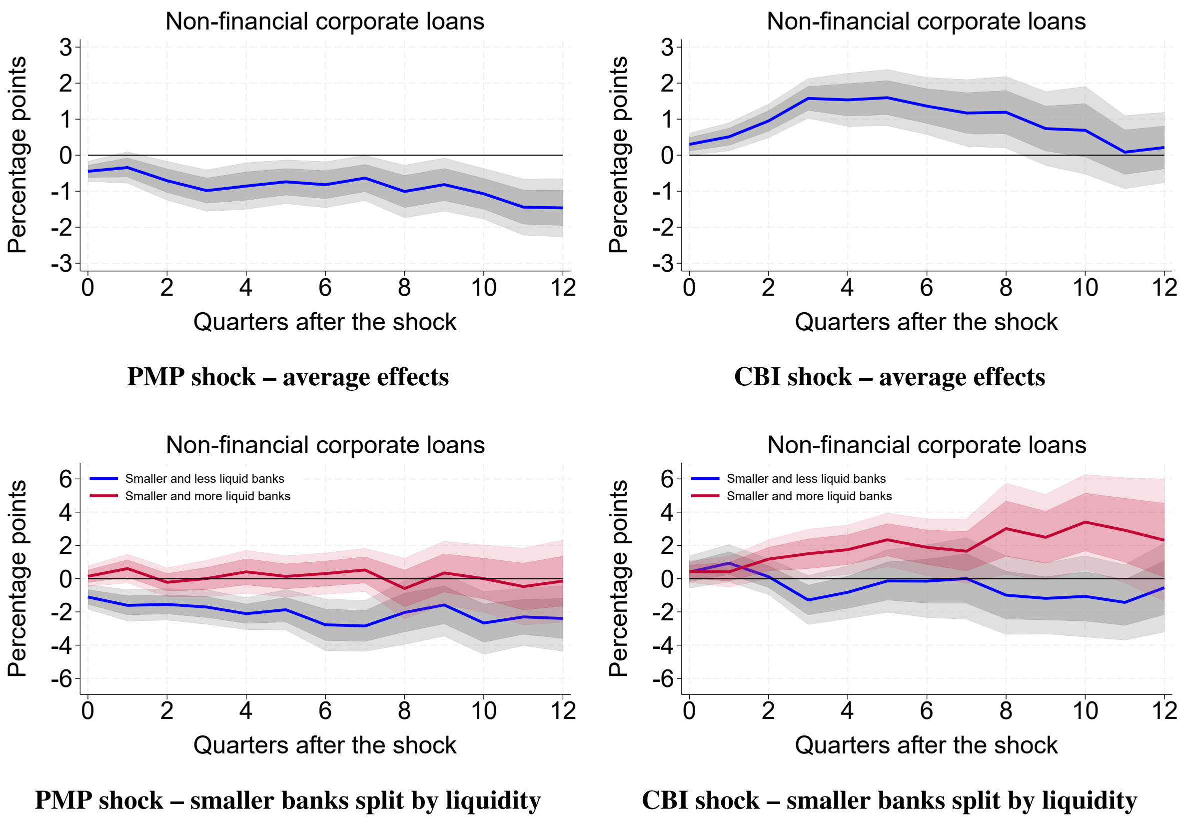
PMP shock – smaller banks split by liquidity



CBI shock – smaller banks split by liquidity

Figure A.5: **Impulse responses for savings banks**

Notes: Responses of NFC loans to a positive, 1-std.-dev. PMP shock (left) and CBI shock (right), identified as in Jarociński and Karádi (2020). Top panel: Average effects for banks that belong to the savings bank sector. Bottom panel: Effects for the 25% smallest banks with the 25% lowest ratio of liquid assets to total assets (blue) and 25% smallest banks with the 25% highest liquidity ratio (red). Loan growth is winsorized at the 1^{st} and 99^{th} percentile. 68% (dark shaded) and 90% (light shaded) confidence intervals based on Driscoll-Kraay standard errors.

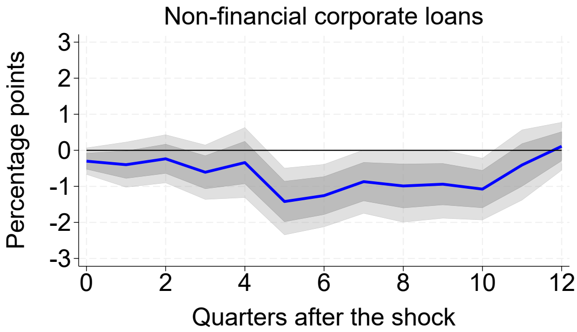


PMP shock – average effects **CBI shock – average effects**

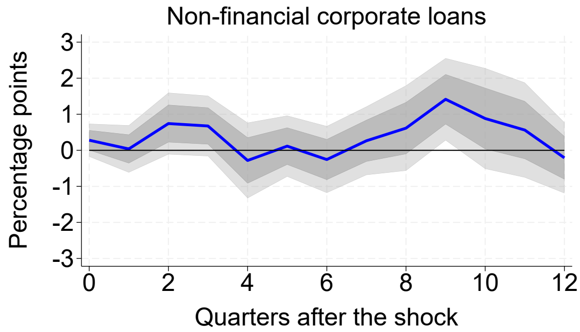
PMP shock – smaller banks split by liquidity **CBI shock – smaller banks split by liquidity**

Figure A.6: **Impulse responses for cooperative banks**

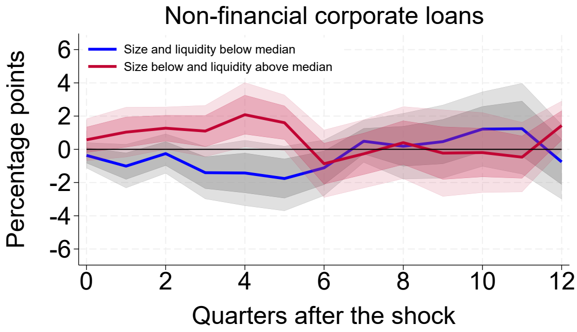
Notes: Responses of NFC loans to a positive, 1-std.-dev. PMP shock (left) and CBI shock (right), identified as in Jarociński and Karádi (2020). Top panel: Average effects for banks that belong to the cooperative bank sector. Bottom panel: Effects for the 25% smallest banks with the 25% lowest ratio of liquid assets to total assets (blue) and 25% smallest banks with the 25% highest liquidity ratio (red). The sample excludes the DZ Bank. Loan growth is winsorized at the 1$^{\text{st}}$ and 99$^{\text{th}}$ percentile. 68% (dark shaded) and 90% (light shaded) confidence intervals based on Driscoll-Kraay standard errors.



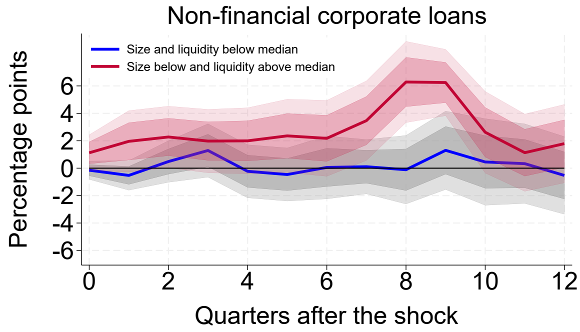
PMP shock – average effects



CBI shock – average effects



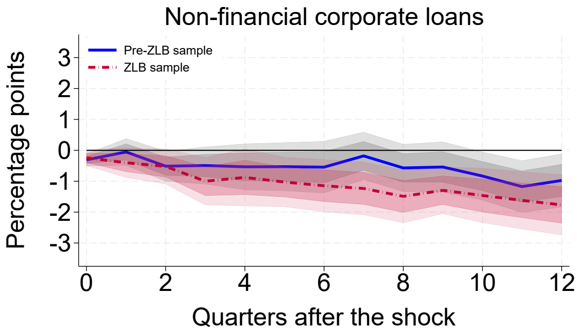
PMP shock – smaller banks split by liquidity



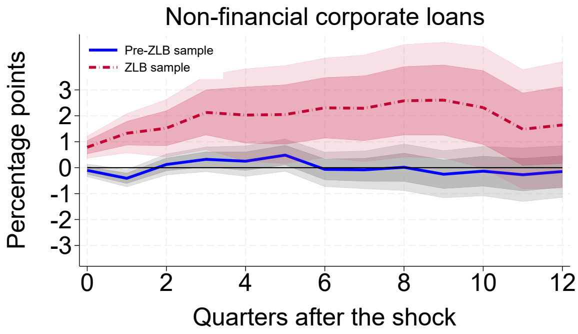
CBI shock – smaller banks split by liquidity

Figure A.7: **Impulse responses for commercial banks**

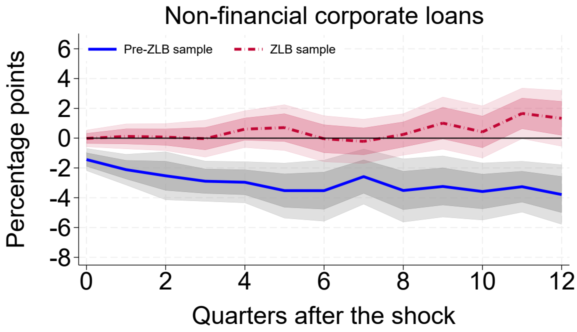
Notes: Responses of NFC loans to a positive, 1-std.-dev. PMP shock (left) and CBI shock (right), identified as in Jarociński and Karádi (2020). Top panel: Average effects for banks that belong to the commercial bank sector. Bottom panel: Effects for the 50% smallest banks with the 50% lowest ratio of liquid assets to total assets (blue) and 50% smallest banks with the 50% highest liquidity ratio (red). Median splits due to the relatively small cross-sectional sample size. The sample excludes three big banks (Deutsche Bank, Commerzbank, and UniCredit Bank). Loan growth is winsorized at the 1^{st} and 99^{th} percentile. 68% (dark shaded) and 90% (light shaded) confidence intervals based on Driscoll-Kraay standard errors.



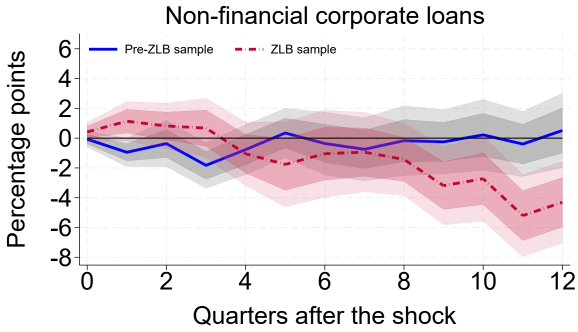
PMP shock – average effects



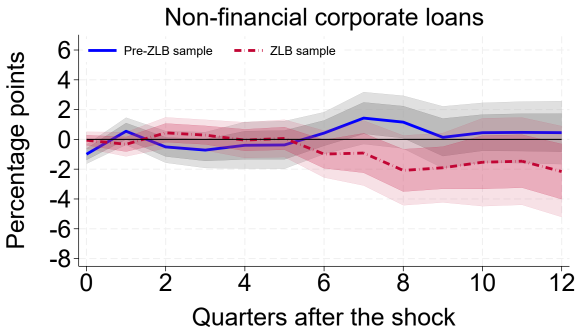
CBI shock – average effects



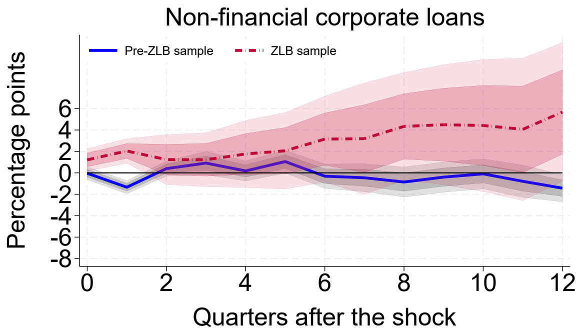
PMP shock – smaller and less liquid banks



CBI shock – smaller and less liquid banks



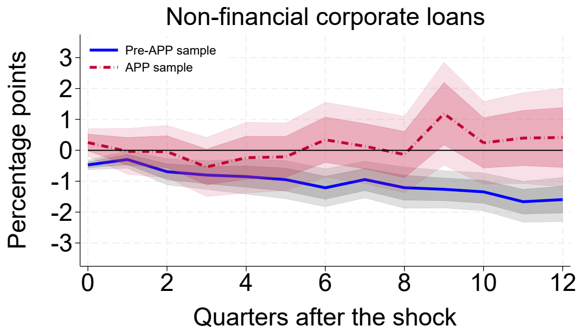
PMP shock – smaller and more liquid banks



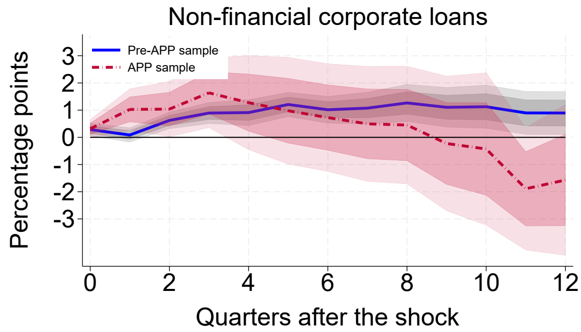
CBI shock – smaller and more liquid banks

Figure A.8: **Impulse responses with sample period split in 2012:Q3 (ZLB)**

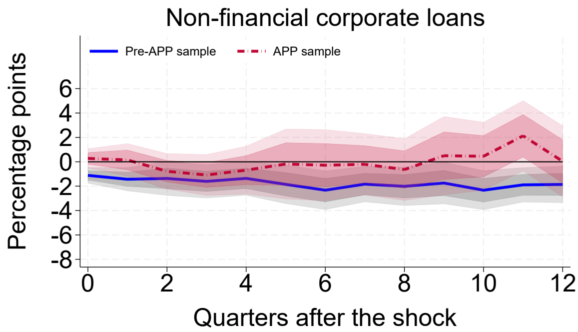
Notes: Responses of NFC loans to a positive, 1-std.-dev. PMP shock (left) and CBI shock (right), identified as in Jarociński and Karádi (2020). Top panel: Average effects for all banks. Middle panel: Effects for the 25% smallest banks with the 25% lowest ratio of liquid assets to total assets for the sample period 2002:Q2-2012:Q3 (blue) and 2012:Q4-2018:Q4 (red). Bottom panel: Effects for the 25% smallest banks with the 25% highest liquidity ratio for the sample period 2002:Q2-2012:Q3 (blue) and 2012:Q4-2018:Q4 (red). Loan growth is winsorized at the 1$^{\text{st}}$ and 99$^{\text{th}}$ percentile. 68% (dark shaded) and 90% (light shaded) confidence intervals based on Driscoll-Kraay standard errors.



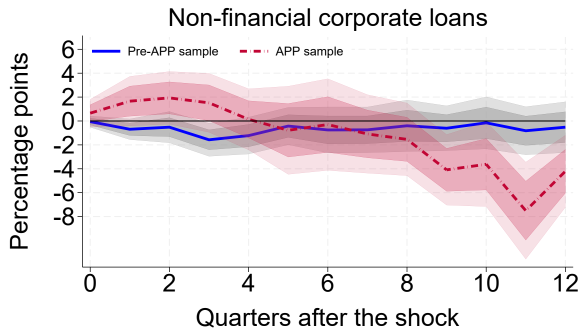
PMP shock – average effects



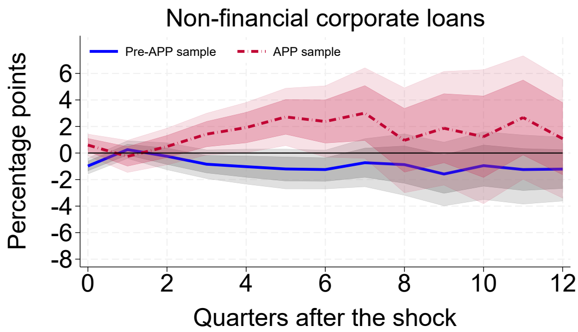
CBI shock – average effects



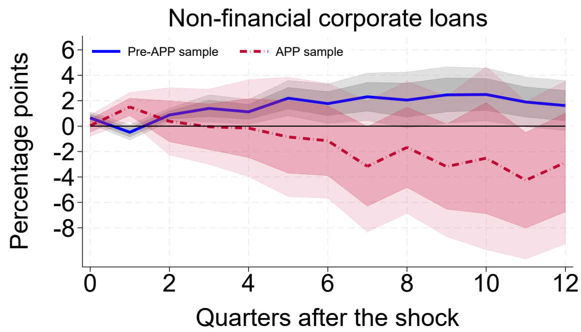
PMP shock – smaller and less liquid banks



CBI shock – smaller and less liquid banks



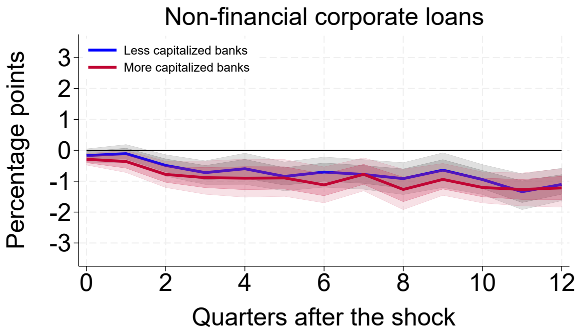
PMP shock – smaller and more liquid banks



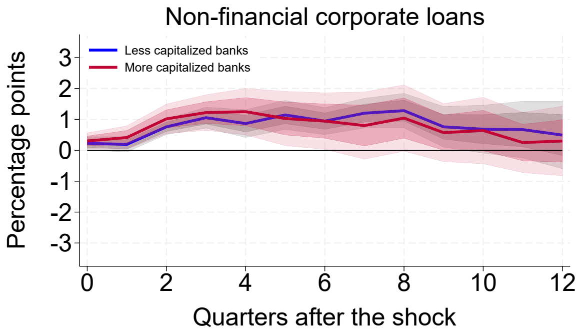
CBI shock – smaller and more liquid banks

Figure A.9: **Impulse responses with sample period split in 2014:Q3 (APP)**

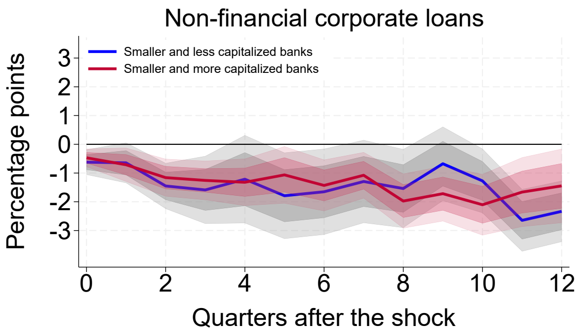
Notes: Responses of NFC loans to a positive, 1-std.-dev. PMP shock (left) and CBI shock (right), identified as in Jarociński and Karádi (2020). Top panel: Average effects for all banks. Middle panel: Effects for the 25% smallest banks with the 25% lowest ratio of liquid assets to total assets for the sample period 2002:Q2-2014:Q3 (blue) and 2014:Q4-2018:Q4 (red). Bottom panel: Effects for the 25% smallest banks with the 25% highest liquidity ratio for the sample period 2002:Q2-2014:Q3 (blue) and 2014:Q4-2018:Q4 (red). Loan growth is winsorized at the 1st and 99th percentile. 68% (dark shaded) and 90% (light shaded) confidence intervals based on Driscoll-Kraay standard errors.



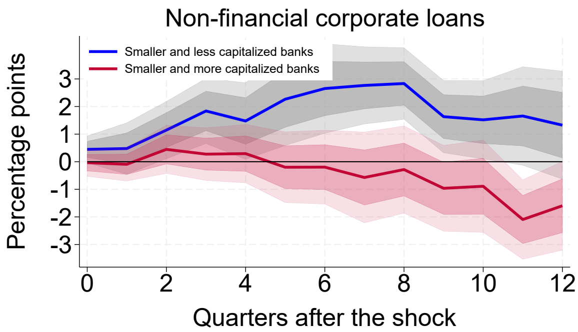
PMP shock – Banks split by capital



CBI shock – Banks split by capital



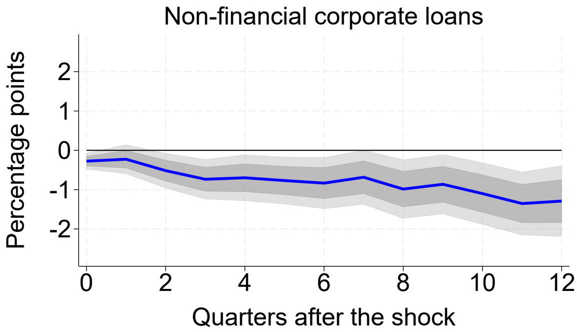
PMP shock – Smaller banks split by capital

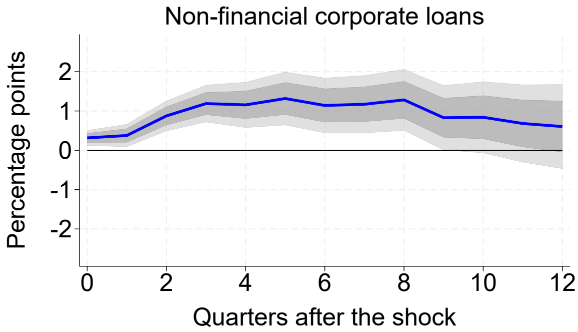


CBI shock – Smaller banks split by capital

Figure A.10: **Impulse responses for banks grouped by capitalization**

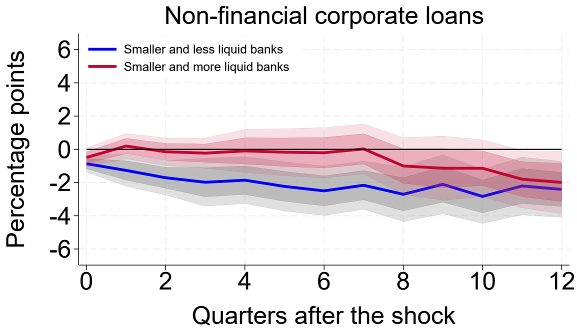
Notes: Responses of NFC loans to a positive, 1-std.-dev. PMP shock (left) and CBI shock (right), identified as in Jarociński and Karádi (2020). Top panel: Effects for banks with the 25% lowest ratio of capital to total assets (blue) and the 25% highest ratio of capital to total assets (red). Bottom panel: Effects for the 25% smallest banks with the 25% lowest ratio of capital to total assets (blue) and 25% smallest banks with the 25% highest capital ratio (red). Loan growth is winsorized at the 1$^{\text{st}}$ and 99$^{\text{th}}$ percentile. 68% (dark shaded) and 90% (light shaded) confidence intervals based on Driscoll-Kraay standard errors.

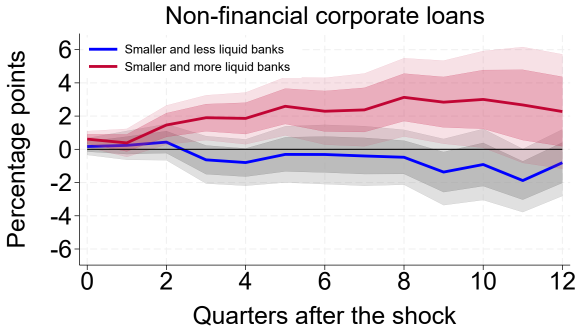




PMP shock – average effects

CBI shock – average effects



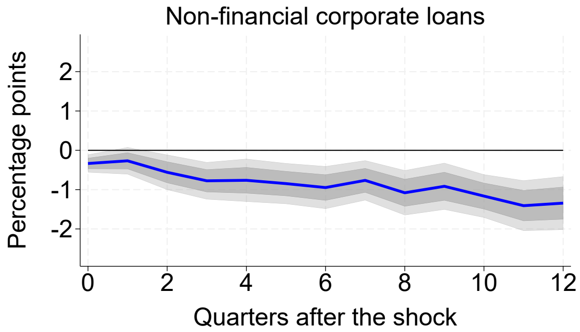


PMP shock – smaller banks split by liquidity

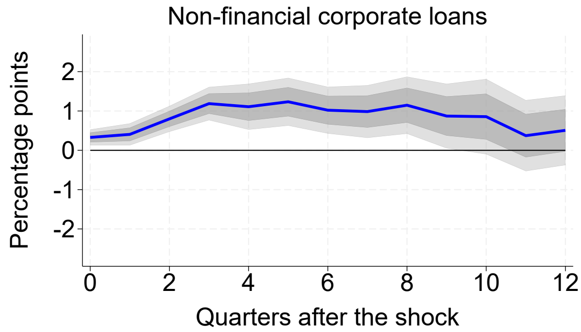
CBI shock – smaller banks split by liquidity

Figure A.11: **Impulse responses using two-way clustered standard errors**

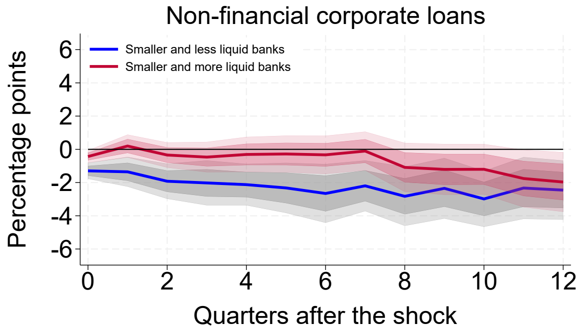
Notes: Responses of NFC loans to a positive, 1-std.-dev. PMP shock (left) and CBI shock (right), identified as in Jarociński and Karádi (2020). Top panel: Average effects for all banks. Bottom panel: Effects for the 25% smallest banks with the 25% lowest ratio of liquid assets to total assets (blue) and 25% smallest banks with the 25% highest liquidity ratio (red). Loan growth is winsorized at the 1$^{\text{st}}$ and 99$^{\text{th}}$ percentile. 68% (dark shaded) and 90% (light shaded) confidence intervals based on two-way clustered standard errors.



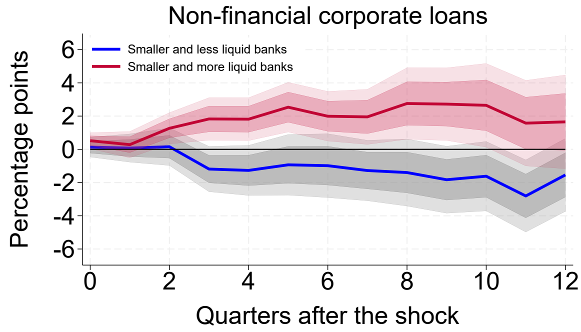
PMP shock – average effects



CBI shock – average effects



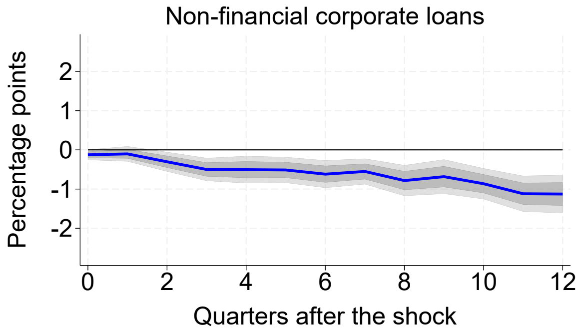
PMP shock – smaller banks split by liquidity



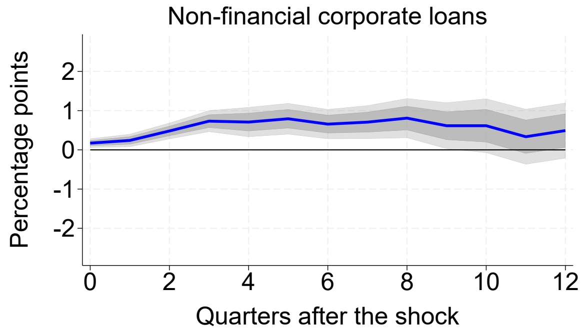
CBI shock – smaller banks split by liquidity

Figure A.12: **Impulse responses with non-winsorized loan growth data**

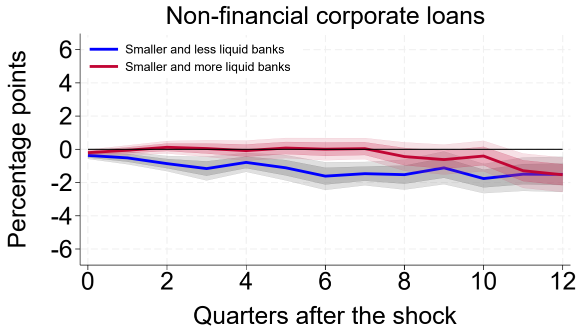
Notes: Responses of NFC loans to a positive, 1-std.-dev. PMP shock (left) and CBI shock (right), identified as in Jarociński and Karádi (2020). Top panel: Average effects for all banks. Bottom panel: Effects for the 25% smallest banks with the 25% lowest ratio of liquid assets to total assets (blue) and 25% smallest banks with the 25% highest liquidity ratio (red). Loan growth is not winsorized. 68% (dark shaded) and 90% (light shaded) confidence intervals based on Driscoll-Kraay standard errors.



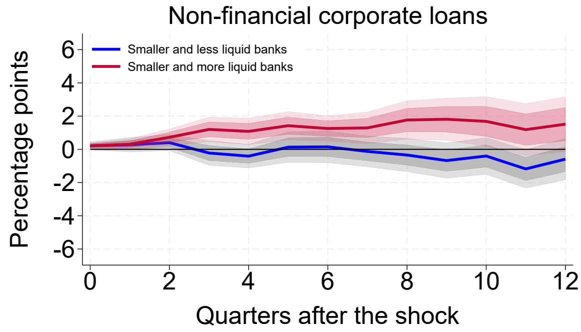
PMP shock – average effects



CBI shock – average effects



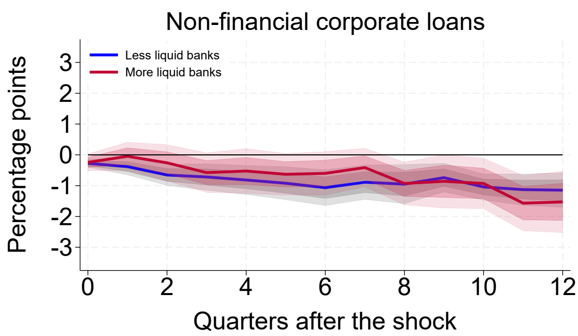
PMP shock – smaller banks split by liquidity



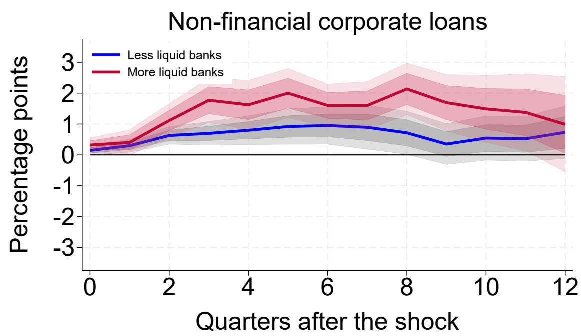
CBI shock – smaller banks split by liquidity

Figure A.13: **Impulse responses with strongly winsorized loan growth data**

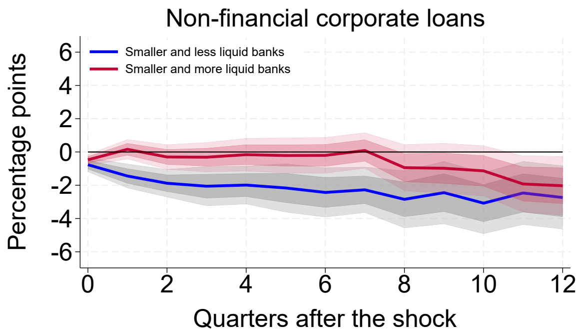
Notes: Responses of NFC loans to a positive, 1-std.-dev. PMP shock (left) and CBI shock (right), identified as in Jarociński and Karádi (2020). Top panel: Average effects for all banks. Bottom panel: Effects for the 25% smallest banks with the 25% lowest ratio of liquid assets to total assets (blue) and 25% smallest banks with the 25% highest liquidity ratio (red). Loan growth is winsorized at the 10^{th} and 90^{th} percentile. 68% (dark shaded) and 90% (light shaded) confidence intervals based on Driscoll-Kraay standard errors.



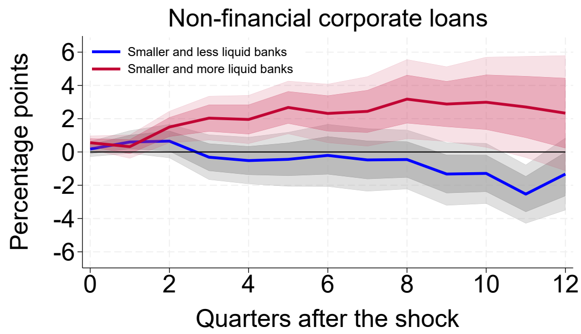
PMP shock – Banks split by liquidity



CBI shock – Banks split by liquidity



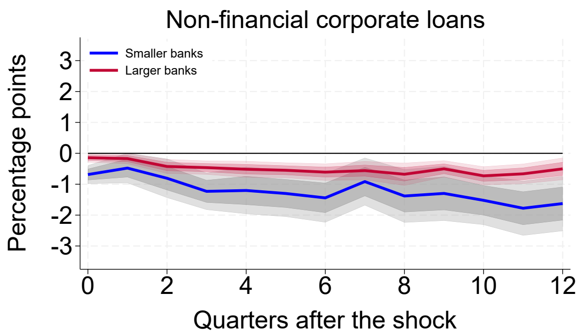
PMP shock – Smaller banks split by liquidity



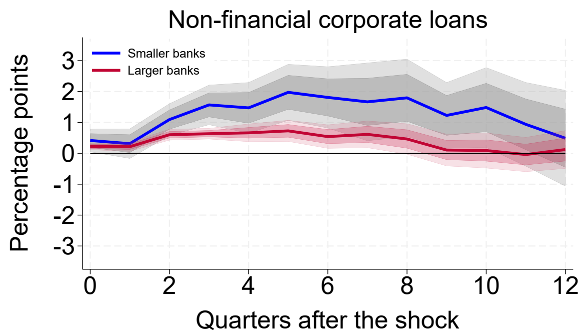
CBI shock – Smaller banks split by liquidity

Figure A.14: **Impulse responses for banks grouped by liquidity (bonds-to-assets ratio)**

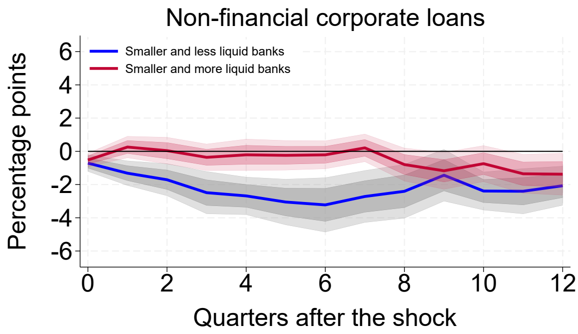
Notes: Responses of NFC loans to a positive, 1-std.-dev. PMP shock (left) and CBI shock (right), identified as in Jarociński and Karádi (2020). Top panel: Effects for banks with the 25% lowest ratio of liquid assets (bonds) to total assets (blue) and the 25% highest ratio of liquid assets (bonds) to total assets (red). Bottom panel: Effects for the 25% smallest banks with the 25% lowest ratio of liquid assets (bonds) to total assets (blue) and 25% smallest banks (by loans) with the 25% highest ratio of liquid assets (bonds) to total assets (red). Loan growth is winsorized at the 1^{st} and 99^{th} percentile. 68% (dark shaded) and 90% (light shaded) confidence intervals based on Driscoll-Kraay standard errors.



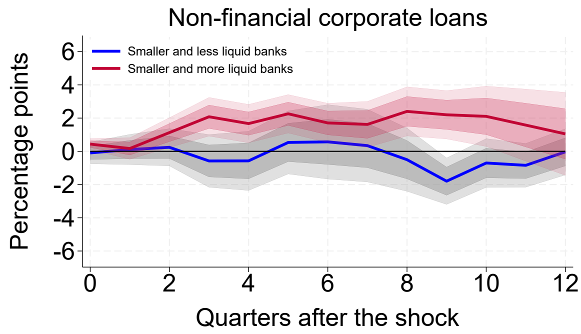
PMP shock – Banks split by lending volume



CBI shock – Banks split by lending volume



PMP shock – Smaller lenders split by liquidity



CBI shock – Smaller lenders split by liquidity

Figure A.15: **Impulse responses for banks grouped by loan volume**

Notes: Responses of NFC loans to a positive, 1-std.-dev. PMP shock (left) and CBI shock (right), identified as in Jarociński and Karádi (2020). Top panel: Effects for banks with the 25% lowest lending volume (blue) and the 25% highest lending volume (red). Bottom panel: Effects for the 25% smallest banks (by loans) with the 25% lowest ratio of liquid assets to total assets (blue) and 25% smallest banks (by loans) with the 25% highest liquidity ratio (red). Loan growth is winsorized at the 1^{st} and 99^{th} percentile. 68% (dark shaded) and 90% (light shaded) confidence intervals based on Driscoll-Kraay standard errors.