

Excess Reserves and Monetary Policy Tightening*

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Abstract

We show that the transmission of the European Central Bank's (ECB) recent monetary policy tightening differs across banks depending on their level of excess reserves. Specifically, the net worth of reserve-rich banks may display a boost when the interest rate paid on reserves increases strongly. Focusing on the ECB's 2022 rate hiking cycle, we show that reserve-rich banks' credit supply is less sensitive to the monetary policy tightening compared to other banks. The effect varies in the cross-section of both banks and firms. The results are binding at the firm level, indicating the presence of real effects.

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“The return of policy rates to positive territory would this time provide a sizeable risk free income to the banking system, and a similar loss for the Eurosystem. [...] The effect on banks’ net interest income nevertheless, if opposite in sign to the one under negative rates, could also distort the transmission of our monetary policy.”

François Villeroy de Galhau (Banque de France), August 2022, Jackson Hole

1 Introduction

Facing inflationary pressure, many central banks recently conducted monetary policy tightening by increasing their policy rates. It is well understood that such monetary policy tightening induces a contraction in credit supply (Bernanke and Blinder 1992; Jiménez, Ongena, Peydró, and Saurina 2012). However, this rate hiking cycle may be different due to the various quantitative easing (QE) policies that were implemented since the global financial crisis of 2008/09. These policies led to an expansion of central bank balance sheets and to the adoption of abundant reserve regimes.¹ In this paper we show that, when central bank reserves are ample and their remuneration rate is the (implicit) key policy rate, monetary policy transmission varies across banks’ level of excess reserves.

The idea is simple: When central banks increase rates materially, the net worth of reserve-rich banks may be positively affected because an increase in the reserve remuneration will boost net interest income. Therefore, reserve-rich banks may not have to contract their credit supply as strongly as other banks, at least in the short-term.² In other words, monetary policy transmission could differ in the cross-section. Focusing on the ECB’s 2022 rate hiking cycle, we show that reserve-rich banks’ credit supply is less sensitive to the monetary policy tightening compared to other banks.

Given that many central banks historically maintained a system with scarce reserves, the setup we describe would not have been particularly relevant until relatively recently. However, when (i) the aggregate level of reserves is large and (ii) the interest on reserves increases materially, monetary policy transmission can vary across banks’ level of excess reserves. As shown in Figure 1, the second half of 2022 was unique in that both conditions were met simultaneously in the euro area. Specifically, in June 2022, that is before the onset of the tightening cycle,

¹For example, in 2022 the size of the Eurosystem’s balance sheet peaked at 56% of euro area GDP (see [ECB Statistical Data Warehouse](#)).

²The effect should be transitory in that the interest margin differential should disappear as soon as the rate hike(s) are passed through to banks’ other assets (e.g., bonds and loans) and deposit liabilities.

total reserves held by euro area banks amounted to an unprecedented 4.7 EUR trillion - or 12% of their total assets - and consisted almost exclusively of reserves in excess of reserve requirements. For the sake of reference, these numbers stood at 0.12 EUR trillion in early 2008 - or 0.75% of total assets - and consisted almost exclusively of required reserves.³ Moreover, after an extended period of ultra-low rates, the ECB successively raised the interest rate on reserves –the so-called deposit facility rate (DFR)– from -0.5% to 3% between June 2022 and March 2023. Hence, a bank that had to *pay* 50 basis points on its reserves in June 2022, would *earn* 300 basis points on the same deposit in March 2023.⁴ Of course, it is also important to take into account that the total reserve holdings in Figure 1 are not equally distributed among banks: As shown in Figure 2, there is substantial cross-sectional variation in banks’ reserve-to-total asset ratios. Hence, we take a cross-sectional perspective and use the rapid interest rate hike in the euro area as a unique laboratory to study the role of excess reserves in monetary policy transmission.

Our empirical framework focuses on euro area banks’ credit supply to non-financial companies. In particular, we compare banks with different ex-ante reserve ratios before and after the start of the hiking cycle in July 2022. Our identification strategy uses lending of banks with lower reserve ratios as the counterfactual for lending of banks with higher reserve ratios. This approach addresses the empirical challenge that monetary policy is endogenous: Since all euro area banks face the same broad economic conditions, anything related to these economic conditions (which induced the ECB to increase rates in the first place) will cancel out when studying *differential lending* effects. Since we are interested in banks’ credit supply, a separate empirical challenge is that we need to disentangle banks’ credit supply from firms’ credit demand. We therefore follow the workhorse model in the empirical banking literature and control for credit demand factors via firm-time fixed effects (Khwaja and Mian 2008). Furthermore, given that the bank-firm matching in the credit market is not exogenous (banks choose their borrowers and vice versa), we also include bank-firm fixed effects.

³The numbers are broadly comparable to those in the U.S. (see [Federal Reserve Board](#)): total reserves stood at 3 USD tn in late 2022 - or 13% of commercial banks’ total assets, compared with only 0.1% in early 2008. Hence, a similar effect should have been at work in the US. Given that we are not aware of comparable granular datasets for the US, we focus on the euro area in this paper.

⁴If the rate were to remain at that level and taking into account that the level of reserves decreases by maturing TLTRO-III credit operations, this amounts to total interest payments of approximately 114 EUR billion in 2023 – roughly 3.3% of euro area GDP and 4.3% of total (book) equity of euro area banks. These interest payments were also picked up by the media as a relevant loss factor for the ECB, see [Financial Times \(February 23, 2023\)](#) and [Reuters \(February 23, 2023\)](#).

We use the novel and extremely rich AnaCredit dataset, a harmonised credit register for the entire euro area. Thus, we are among the first papers that are able to study the transmission of monetary policy in a dataset that covers the *entire* euro area. This is noteworthy since the existing literature on monetary policy and bank lending typically relied on credit registers for single (euro area) countries. The granular structure of the dataset allows for the inclusion of the aforementioned fixed effects. Additionally, given that AnaCredit contains detailed information on several loan- and borrower-specific characteristics (e.g., loan volume, borrower size), we shed light on credit supply along multiple dimensions.

Our main finding is that reserve-rich banks' credit supply is less sensitive to the monetary policy tightening compared to other banks. On average, increasing the reserve ratio by one standard deviation from the mean increases banks' credit supply to non-financial firms by 1.28% after July 2022. Based on the total outstanding pre-period credit volume of banks with reserve ratios above one standard deviation from the mean, this credit supply effect corresponds to between 0.16% and 0.28% of euro area GDP in 2022. Notably, while our empirical approach is cross-sectional by nature, we also find indicative evidence of aggregate effects. In particular, we quantify that –if high reserve banks would have behaved exactly as other banks– aggregate credit volumes would have been 0.5% lower in February 2023.

Turning to heterogeneity, we find that the credit supply effect is more pronounced for more financially constrained banks. For example, we find a stronger effect for smaller banks and for banks with lower equity ratios. This is in line with the idea that such banks face more severe agency problems (Holmstrom and Tirole 1997; Kashyap and Stein 1995). We also analyze which firms are at the receiving end and find that the effect is stronger for small and medium firms, consistent with such firms being more opaque, relying more on bank funding and, consequently, being more affected by shocks through the bank lending channel (Gertler and Gilchrist 1994; Chodorow-Reich 2014; Khwaja and Mian 2008; Iyer, Peydró, da Rocha-Lopes, and Schoar 2014). Moreover, the credit supply effect is particularly visible for borrowers with higher credit quality, suggesting that reserve-rich banks tend to reduce their risk-taking.

Given that the balance sheet channel of monetary policy works via banks' net worth, we provide evidence that reserve-rich banks indeed displayed a differential increase in their (net) interest income and, ultimately, their net worth. For example, the rate hike, which eventually led to the positive remuneration of excess reserves, differentially affected banks' stock market performance (an indirect measure of net worth). In particular, banks with higher reserve ratios displayed significantly higher (risk-adjusted) stock returns after the onset of the tightening cy-

cle. This pattern is in line with more affected banks displaying an increase in net worth, both in relative and absolute terms. Focusing on the broader sample of listed and non-listed banks, we also document that the rate hike had measurable effects on net interest income, return on assets, and book equity. In supplementary analyses, we document that the rate hikes were only partially passed on to bank deposit rates, but that the deposit passthrough does not appear to be a function of banks' reserve ratios. We complement our main results with a large number of additional analyses/robustness checks. Importantly, we show that our main effect on banks' credit supply is robust to alternative timing definitions and particularly visible in the upper tail of the reserve ratio distribution.

We should note that the main variable of interest—a bank's average reserve ratio prior to the first rate hike—is not randomly assigned. Our identification strategy could therefore be influenced by *time-varying* differences in bank characteristics which drive both lending decisions and reserve holdings during the monetary tightening period under consideration. We address this aspect in several ways, most importantly via the inclusion of time-varying bank characteristics in our regressions. In addition, we show that banks do not strategically respond to the rate hike by adjusting their reserve holdings. Lastly, our main coefficient estimates are likely biased downwards. This is because these estimates tend to be *smaller* when we exclude our time-varying bank control variables (as in [Grosse-Rueschkamp, Steffen, and Streit \(2019\)](#)).

It is important to note that, while possible in theory, it seems unlikely that any (other) short-term floating instrument would produce the same effect. This is because central bank reserves are special in that, besides being extremely safe, they (i) can only be held by banks and (ii) are in abundant supply. Hence, banks do not compete with non-bank investors over this abundant short-term asset. To put things in perspective, it is useful to compare the peak value of total euro area reserves of 4.7 EUR tn in 2022 with the size of the euro area short-term government bond market, which stood at 0.7 EUR tn (of which 0.15 EUR tn are German bonds, which are among the safest ones). Hence, it is difficult to construct a scenario where the same effect could arise due to short-term bonds given they are in relatively short supply. Of course, the same would be true for other money market securities (e.g., commercial paper or certificates of deposits), which are in fact predominantly issued by banks themselves.

The idea that central bank reserves have an effect on bank lending is not new. As described by [Woodford \(2010\)](#), according to the traditional bank lending channel, deposits are an indispensable funding source of commercial banks. These deposits are subject to minimum reserve requirements and, given that these requirements are binding in a scarce reserve system, a re-

duction in the reserve supply by the central bank would go along with a reduction of bank deposits. Consequently, banks would have to cut their lending (Bernanke and Blinder 1988; Kashyap and Stein 1994). This channel has been called into question due to its dependence on minimum reserve requirements that have been too small (or even absent) to exert a meaningful effect on banks' balance sheets (Romer, Romer, Goldfeld, and Friedman 1990; Bernanke and Gertler 1995, Woodford 2010). Our setup is novel in that, while the traditional bank lending channel works through *required* reserves, we study a period with ample reserves. Hence, we analyse whether large excess reserves affect monetary policy transmission in the cross-section of banks.

Higher excess reserve holdings have a positive effect on interest income when monetary policy tightens. Gomez, Landier, Sraer, and Thesmar (2021) show that a similar effect on earnings is induced through a bank's income gap, which is the difference between assets and liabilities maturing or being repriced within one year. As a consequence, banks with a large income gap lend relatively more when monetary policy tightens. While the effect of reserve holdings on the transmission of monetary policy is similar to the income gap effect, a major novelty of our setting is that we focus on one specific and increasingly important short-term asset: central bank reserves. This type of asset is distinct from other assets because (a) it is the most liquid and risk-free asset available, (b) central banks created it in order to stimulate monetary transmission at/below the zero lower bound, and (c) both the relative value and the remuneration of this asset increases during a tightening monetary policy. In particular, the rate hike *immediately* affects the remuneration of reserves, whereas it would be slower for other securities (such as existing bonds and loans which predominantly determine the income gap), where banks would need to actively shift towards higher-yielding products. One final peculiarity of our setting is the focus on monetary policy transmission in abundant reserve systems, whereas Gomez et al. (2021) analyse a period of scarce reserves.

In principle, the positive interest income effect could (at least partially) be offset via the deposit channel of monetary policy. In particular, in the setup of Drechsler, Savov, and Schnabl (2017), banks widen their deposit spreads after a rate hike, which induces households to shift deposits to alternative money-like instruments (e.g., short-term bonds or money market funds). As a consequence, banks would have to cut their lending even in the absence of changes in net worth. However, the empirical evidence does not suggest that euro area banks faced large

aggregate deposit outflows due to the rate hike (see [ECB](#)).⁵ Rather, depositors substituted their overnight deposits with time deposits for which the passthrough was substantially stronger. Importantly, for our specific dataset, we also do not find that differential deposit flows could serve as a viable explanation for the documented credit supply effect.

Bank-based monetary policy transmission mainly works through the balance sheet channel ([Bernanke and Gertler 1989](#); [Kiyotaki and Moore 1997](#); [Gertler and Kiyotaki 2010](#); [He and Krishnamurthy 2013](#); [Brunnermeier and Sannikov 2014](#); [Abadi, Brunnermeier, and Koby 2023](#)). The idea is that higher interest rates can affect the market value of banks' (longer-term) assets more strongly than their (short-term) liabilities, thus reducing banks' net worth and leading to a contraction of credit supply. As such, our setting can also be interpreted as an analysis of the balance sheet channel in a (de facto) floor system with ample reserves.⁶ In particular, given our cross-sectional focus, the main idea is that positive effect on banks' net interest income works at least partly against the negative effect on net worth. Hence, reserve-richer banks would not have to cut their credit supply as strongly as other banks.

Previous work also suggests that the effect of monetary policy on net worth should be larger in the presence of frictions, in particular for banks that are subject to more severe agency problems. One example of such frictions would be bank size (see e.g. [Kashyap and Stein 1995](#); [Kashyap and Stein 2000](#); [Campello 2002](#); [Rodnyansky and Darmouni 2017](#)). Since raising additional funding should be more difficult for smaller banks, their lending is more dependent on the stance of monetary policy. Hence, the effects on net worth should be stronger for smaller banks. Another example would be the capital-to-assets ratio, a measure of balance sheet strength (see e.g. [Holmstrom and Tirole 1997](#); [Jiménez, Ongena, Peydró, and Saurina 2014](#); [Jiménez et al. 2012](#); [Peydró, Polo, and Sette 2021](#)). Again, the effect on net worth should be stronger for weakly capitalized banks. We find evidence in line with such frictions.

More recently the balance sheet channel has mainly been analyzed empirically in the context of quantitative easing (QE) and, therefore, primarily focused on securities that were subject to central bank asset purchases (see e.g. [Rodnyansky and Darmouni 2017](#); [Chakraborty, Goldstein, and MacKinlay 2020](#); [Koetter 2020](#)). To the best of our knowledge, our paper is the first to empirically analyse the transmission of contractionary monetary policy via credit supply in

⁵In principle, money market funds could serve as a viable alternative to bank deposits for certain investor clienteles. And while euro area money market funds indeed received sizeable inflows, they remain economically small. For example, MMFs' total assets under management stood at 1.5 EUR trillion in 2023Q1, compared with 38 EUR trillion for commercial banks (of which 23.2 EUR trillion are deposit liabilities). Source: [ECB SDW](#).

⁶A related theoretical banking literature studies monetary policy transmission in a model with central bank reserves or risk-free bonds (e.g., [Koenig and Schliephake 2023](#); [Martin, McAndrews, and Skeie 2016](#)).

a system with ample central bank reserves. Overall, we find that monetary policy transmission varies across banks' level of excess reserves, which is ultimately related to the preceding large expansion of reserves during QE. As such, our paper contributes to the discussion on potential side effects of unconventional monetary policy.

Lastly, our paper also contributes to the literature that studies the recent tightening of monetary policy. In particular, a lot of research focused on potential negative side effects of ultra-loose monetary policy (e.g., excessive risk-taking as in [Jiménez et al. \(2014\)](#)) and the vulnerabilities that would arise with the eventual monetary policy normalisation. Focusing on the Federal Reserve's recent quantitative tightening (QT), [Acharya, Chauhan, Rajan, and Steffen \(2023\)](#) and [Lopez-Salido and Vissing-Jorgensen \(2023\)](#) conclude that QT is unlikely to be a simple reversal of QE. In contrast to these papers we do not study QT, but rather analyze tightening conventional monetary policy in the context of large excess reserves. We reach a similar conclusion in that the recent monetary policy tightening is not a benign process because earlier QE measures transformed a system with scarce reserves into a system with ample reserves.

Our findings have important policy implications. Contractionary monetary policy has the aim to contain inflation. We document that the transmission of contractionary monetary policy differs across banks depending on their level of excess reserves. In addition, we provide tentative evidence that the remuneration of large excess reserves tends to weaken overall monetary policy transmission. Hence, our findings might call for action by policymakers. One example to contain the side effects in abundant reserve systems could be to not pay the same interest rate on all reserves (e.g., [De Grauwe and Ji 2023](#)). Our findings are also important from a financial stability perspective. The fact that the negative net worth effect from the rate hikes is at least partially offset for high reserve banks indicates a positive interaction between central bank reserves and contractionary (conventional) monetary policy. In addition, the credit supply results indicate a more stable funding base for firms that borrow from high reserve banks. Given that this financing is targeted towards less risky firms, the overall financial stability effects are therefore likely positive.

The remainder of this paper is organized as follows. Section 2 describes the key stylized facts that motivate our study and provides the necessary institutional details. Section 3 describes the empirical strategy and the data used. Section 4 presents the results. Section 5 discusses the policy implications and Section 6 concludes.

2 Reserves and their Remuneration in the Euro Area

Banks domiciled in the euro area hold accounts at their corresponding national central bank where they keep overnight cash balances – central bank reserves (reserves for short). These reserve holdings are driven by a variety of factors, such as payment settlement but also regulatory requirements (Åberg, Corsi, Grossmann-Wirth, Hudepohl, Mudde, Rosolin, and Schobert 2021).⁷ Their pivotal role in settling payments make central bank reserves the most liquid and risk-free asset available in the financial system.

The supply of reserves is ultimately determined by the Eurosystem and crucially depends on its refinancing and open market operations. In general, individual banks cannot simply reduce/increase aggregate reserves when interacting with each other, they can only redistribute them – reserves leaving one bank's balance sheet (e.g., by lending in the interbank market) will show up on another bank's balance sheet. Importantly, obtaining additional reserves always comes at a cost: a bank demanding additional reserves can, for example, borrow liquidity in refinancing operations (paying the rate for main refinancing operations which is above the deposit facility rate) or in the money market (paying a rate which currently stands slightly below the deposit facility rate but which would adjust upwards when demand increases). The main focus of our paper is on the conjunction of large reserve holdings and a sizeable increase in the remuneration of these reserves.

To set the stage, Figure 1 shows the evolution of the ECB's deposit facility rate (DFR, red line), which is the interest rate paid on banks' reserve holdings at the deposit facility, along with the total reserves held by commercial banks at the Eurosystem (green line). Over the last decade, the vast majority of these reserves were in excess of banks' minimum reserve requirements (blue line).⁸ Total reserves in the euro area displayed a first strong increase following the Global Financial Crisis (GFC) in 2008-09 and the European sovereign debt crisis in 2011-12 due to several QE measures taken by the ECB (e.g., smaller-scale asset purchase programmes, full allotment of credit operations, and long-term credit operations). The second strong increase in total reserves was driven by the larger-scale asset purchases that started in 2015 and

⁷Besides minimum reserve requirements, banks may hold liquidity buffers to meet unexpected deposit outflows. In this regard, it is worth noting that excess central bank reserves are treated as a high-quality liquid asset (HQLA) to the extent that they are redeemable and therefore matter for banks' liquidity coverage ratios (LCR).

⁸Note that the minimum reserve ratio was lowered from 2% to 1% in January 2012. This explains the drop in the required reserves in early 2012. Prior to October 2022, minimum reserves were remunerated at the (higher) main refinancing rate, rather than at the deposit facility rate. As of July 2023, minimum reserves are remunerated at 0%. See ECB for details.

by several funding-for-lending schemes (so-called targeted longer-term refinancing operations, TLTROs). These measures had a major impact on total reserves, which reached 2 EUR trillion in 2018. The final increase in 2020 was due to the extension of asset purchases and credit operations in light of the COVID-19 pandemic. Consequently, total reserves reached a record level of 4.7 EUR trillion in June 2022.⁹

The DFR is the rate on the deposit facility, which banks can use to make overnight deposits with the Eurosystem. Besides the DFR, the ECB also sets the main refinancing rate for the refinancing operations with banks, and the rate on the marginal lending facility, which offers overnight credit to banks. The DFR and the marginal lending facility rate define a floor and a ceiling for the overnight interest rate at which banks lend to each other, creating a corridor for money markets. Due to the large excess reserves, following the GFC and the European sovereign debt crisis, the Eurosystem operated in a de facto floor system, where the DFR is the key policy rate.

In combination with the various QE measures described above, the DFR was gradually lowered to -0.5% by September 2019.¹⁰ To contain the high inflation rates in the euro area due to skyrocketing energy prices, supply shortages, and the post-pandemic reopening of the economy, the ECB started increasing policy rates in the second half of 2022. In particular, between July 2022 and March 2023, the ECB increased policy rates by 3.5 percentage points, which is the fastest and steepest rate hike in the ECB's history. This culminated in the unprecedented situation of (i) large excess reserves, and (ii) a large rate increase on these reserves. Importantly, aggregate data provided by the ECB Statistical Data Warehouse in Figure 3 illustrate that the rate hike was far from perfectly passed on to bank deposits, particularly so for overnight deposits which are by far the biggest part of banks' deposit liabilities. This leaves room for reserve remuneration having a sizeable effect on reserve-rich banks' net worth.

⁹The drop in total reserves at the end of 2022 was mainly driven by early repayments of TLTRO funds. The ECB discontinued purchases under its asset purchase programme (APP) in July 2022 and will no longer reinvest 15 EUR bn principal payments from maturing securities per month starting in March 2023. Moreover, further TLTRO repayments are expected over the course of 2023. Although all of these factors are likely to lead to a reduction of excess reserves, the aggregate amount is expected to remain large.

¹⁰To support the bank-based transmission of monetary policy, while preserving the positive contribution of negative rates to the accommodative stance of monetary policy, the ECB introduced a two-tier system for remunerating excess reserve holdings in September 2019. This policy exempted a certain share of excess reserves from a negative remuneration, see [Altavilla, Boucinha, Burlon, Giannetti, and Schumacher \(2022\)](#) for details. Following the raising of the DFR to above zero, the two-tier system for the remuneration of excess reserves was suspended in September 2022.

These empirical observations set the stage for our main analysis. We should highlight that the fact that it is costly to obtain additional reserves (see the first paragraph of this section) implies that banks cannot simply benefit from the higher remuneration by scaling up their reserve holdings. It is the level of reserves prior to the rate hike that primarily determines banks' additional gains.

3 Empirical Strategy and Data

In the following, we develop the main hypotheses, explain our empirical strategy, and describe the dataset that we employ to study cross-sectional differences in the transmission of monetary policy.

3.1 Hypotheses and Empirical Strategy

Based on the theoretical considerations described in the introduction we develop the following hypotheses:

***Hypothesis 1:** Banks with higher reserves-to-asset ratios (RR) should be less sensitive in their credit supply to non-financial firms after the onset of the rate hiking cycle.*

***Hypothesis 2:** The effect on credit supply should be stronger for more financially constrained banks.* These constraints could, for example, be related to bank size and capital ratios, since such banks face more severe agency problems ([Holmstrom and Tirole 1997](#); [Kashyap and Stein 1995](#)).

We test these hypotheses on the basis of loan-level data using the following setup:

$$\log(Credit_{b,f,t}) = \beta \times (RR_b) \times (DFR_t \geq 0) + \mathbf{X}'_{b,t} \gamma + \alpha_{f,t} + \alpha_{b,f} + \alpha_{c,t} + u_{b,f,t}, \quad (1)$$

where the dependent variable $\log(Credit_{b,f,t})$ is the natural logarithm of the total credit volume granted by bank b to firm f in month t . The coefficient of interest is β , the interaction term between banks' average pre-period reserve ratios (RR_b) and $(DFR_t \geq 0)$, a dummy that equals 1 from July 2022 onwards when the ECB's initiated the rate hiking cycle. Hence, β gauges the differential lending effect due to the ECB's monetary policy tightening as a function of banks' reserve ratios. Note that regression (1) takes a cross-sectional perspective on banks' sensitivity

to the tightening cycle, which is motivated by the fact that banks' total reserve holdings in Figure 3 are not equally distributed across banks. Rather, Figure 2 shows that there is substantial cross-sectional variation in banks' pre-period RRs. To take a closer look at the upper tail of the reserve distribution, we also conduct several of our analyses by replacing the continuous reserve ratio with a High RR_b dummy, which takes the value of 1 for banks with reserve ratios above one standard deviation from the mean during the pre-period, and zero otherwise.¹¹

The vector $X_{b,f}$ includes several bank-level control variables (which are separately also interacted with the *DFR* dummy and the *RR* variable), namely the natural logarithm of total assets, equity ratio (book equity to total assets), deposit ratio (household deposits to total assets), bonds held ratio (bond holdings to total assets), and a variable capturing the loan fixation terms (fixed rate credit volumes to total credit). We control for the bonds held ratio because banks with a large security portfolio may face larger (mark-to-market) losses on their bond portfolio after the rate hike, which could offset the positive net worth effect stemming from the remuneration of reserves. Relatedly, controlling for the loan fixation terms is important since these can be viewed as a proxy for a bank's interest rate risk exposure (Ampudia and Van den Heuvel 2022; Gomez et al. 2021): a bank with more fixed rate loans would suffer a relative decline in its interest income when rates increase. The deposit ratio could play a role in that the deposit passthrough tends to be lower for household deposits, such that a widening interest spread could, in and of itself, positively affect bank profitability.

Crucially, we include bank-firm fixed effects and conduct a within-firm comparison via the inclusion of firm-time fixed effects (Khwaja and Mian 2008). Hence, our comparison focuses on credit volumes between banks with different reserve ratios within the same firm - as such, firms with a single banking relationship drop out from the main analysis. We also include bank-firm fixed effects in the regression to capture the endogenous selection of bank-firm relationships. Lastly, we include country-time fixed effects. Standard errors are clustered at the bank-time level.

3.2 Data

We use several administrative datasets covering the entire euro area. To identify credit supply, our main dataset is AnaCredit (*Analytical Credit Database*), a harmonized proprietary credit register for all euro area member states. In principle, all credit institutions domiciled in the

¹¹ We confirm that our results are robust to alternative High RR dummies that focus further on the tail of the distribution.

euro area, including their foreign branches, are required to report loan-by-loan data. Banks report loans to corporations and other legal entities (excluding private households) on a monthly basis. At the borrower level, all individual loans from a credit institution are reported as soon as a borrower exceeds an aggregate loan amount of €25,000 with this credit institution. In total AnaCredit covers various loan attributes (loan amount, interest rate, maturity, amount in arrears etc.), the borrowing firm (size, PD, sector etc.) and the guarantor (if any). More information can be found in the [AnaCredit manual](#).

AnaCredit covers a broad range of loan types including, for example, term loans, credit lines, revolving credit or financial leases. In this paper, we focus on term loans and credit lines as the most common types of loans.¹² We complement the AnaCredit data with bank balance sheet information from the Individual Balance Sheet Indicators (IBSI), a proprietary dataset maintained at the ECB. This dataset covers the main asset and liability items for a sample of credit institutions. The sample is chosen across business models and jurisdictions to provide a representative coverage (see [EU Regulation 2021/379](#)). To ensure that our results are not driven by smaller institutions, we only keep banks with total assets of at least 5 EUR billion. For the subsample of 38 listed banks, we obtain daily stock prices from Refinitive-Eikon.¹³ Lastly, we use the ECB's financial reporting (FINREP) data on banks' profit/loss accounts which are available for the subsample of significant institutions that are directly supervised by the ECB.¹⁴

Our final sample consists of a panel of 472 banks and 3,315,611 borrowing firms (494,749 in the multiple bank sample, which make up around 57% of the total credit volume) from January 2022 to February 2023. The sample is representative in that our sample banks cover 71% of the total assets in the euro area banking sector (see [Table IA.1](#) in the Internet Appendix for details on the composition of our sample banks). Using this relatively short window minimizes the influence of potentially confounding factors, e.g., the disruptions due to the collapse of Silicon Valley Bank in the U.S. and the takeover of Credit Suisse in Europe. We should also note that the ECB announced on July 27th 2023, that it would remunerate minimum reserve require-

¹²To be more specific, we include loans with instrument types 1001, 1002, and 1004. We do not differentiate further between these types of loans in our analysis as the distinction between term loans and credit lines is not necessarily clear-cut. Non-revolving credit lines can be very similar to loans with the only difference being whether the loan is paid out in pre-established tranches or all at once. In terms of additional filters, we drop loans for which (1) information on the loan rate or loan rate type is incomplete; (2) the loan rate is non-positive; (3) the loan maturity exceeds thirty years. Moreover, we exclude loans with multiple borrowers, loans to non-euro area borrowers as well as borrowers which have defaulted on any of their loans across banks.

¹³The subsample of listed banks covers roughly 36% of our sample banks' total assets.

¹⁴More information on significant banks is available in the ECB's [list of supervised banks](#). The subsample of significant banks covers 84% of our sample banks' total assets.

ments at 0%, i.e., it will not pay the DFR on these required reserves (see [ECB](#) for details). This potentially confounding event is therefore not covered by our sample.

Panel A of [Table 1](#) reports summary statistics across the full sample. Panel B reports differences in observables across the full sample on the basis of the High RR dummy. By construction, High RR banks have a larger reserve ratio (44.1% versus 9.0%). Moreover, they are larger compared to control banks (log(total assets) of 9.89 versus 9.61, respectively). They have a somewhat lower equity ratio (6.3% versus 8.4%), have fewer household deposits (17.6% versus 37.3%) and hold less fixed income securities on their balance sheet (4.7% versus 8.7%). High RR banks have fewer loans with a fixed loan rate as opposed to a variable loan rate (33.0% versus 54.7%). Focusing on the pre-period ($DFR < 0$), [Table 2](#) shows that banks with larger reserve ratios indeed appear to differ across these characteristics. (We therefore also analyzed a matched sample of High RR and control banks, see [Tables IA.3](#) and [IA.4](#) in the Internet Appendix for details.)

Note that such cross-sectional differences of banks with higher reserve ratios do not impact our identification strategy in that they are differenced out in our estimation approach. (The included bank-firm fixed effects absorb any time-invariant differences between banks.) However, our identification strategy could be impaired by *time-varying* differences between banks which simultaneously affect lending and reserve holdings. Following previous work that assessed heterogeneous effects of monetary policy on the basis of cross-sectional variation along certain bank balance sheet characteristics (e.g., [Heider, Saidi, and Schepens 2019](#); [?](#); [Rodnyansky and Darmouni 2017](#)), we address this aspect in several ways. Most importantly, we include (time-varying) bank characteristics as control variables in our regressions. In addition, we check whether banks strategically respond to the rate hike by adjusting their reserve holdings over time. In this regard, [Figure IA.1](#) in the Internet Appendix shows a simple binscatter-plot of our sample banks' average reserve ratios before and after the first rate hike. While the level of reserves has shifted (in line with the dynamics in [Figure 1](#)), the relative composition is very stable indeed, ensuring that banks with lower reserve ratios indeed serve as a viable counterfactual for banks with higher reserve ratios (e.g., [Heider et al. 2019](#)). We also explore the sensitivity of our estimates to the inclusion of time-varying controls as another robustness check and as an exercise to assess the direction of a potential bias in our estimates.

4 Results

We now turn to the description of our main empirical results. In line with the standard balance sheet channel of monetary policy, our starting point will be a differential effect on banks' net worth. We start with the stock price dynamics of reserve-rich banks relative to other banks around the start of the tightening cycle. To the extent that market equity serves as a proxy for net worth, we document that the recent monetary tightening indeed had a positive effect on the net worth of banks that is *conditional* on its reserve holdings. We then confirm this result by analyzing directly whether the interest on reserves of banks with higher reserve ratios translates into higher interest income and consequently into higher profits. Finally, we establish our key result that reserve-rich banks' credit supply is less sensitive to the monetary policy tightening compared to other banks.

4.1 Net Worth

We begin with an analysis of how the change in the remuneration of reserves affected banks' net worth. This is important given that our setup presupposes a positive effect of reserve remuneration on the (relative) net worth of banks with higher reserve ratios.

To set the stage, Figure 4 shows the value-weighted stock price indices for the subsample of listed High RR banks (red) and for listed control banks (blue). Prior to the rate hike (vertical line) both groups' stock prices evolved similarly, whereas High RR banks' stocks substantially outperformed during the period after the first rate hike.¹⁵

Given that these differences could potentially be driven by differential exposure to common risk factors and/or by bank characteristics, we conduct a more formal analysis as in [Altavilla et al. \(2022\)](#). We first estimate daily risk-adjusted abnormal returns after the onset of monetary policy tightening for each bank:

$$(R_{b,t} - r_t^F) = \alpha_b + \beta_b^{MKT} \times MKT_t + \beta_b^{HML} \times HML_t + \beta_b^{SMB} \times SMB_t + \beta_b^{RMW} \times RMW_t + \beta_b^{CMA} \times CMA_t + \lambda_b \times (DFR_t \geq 0) + \varepsilon_{b,t}, \quad (2)$$

¹⁵While the rate hiking cycle itself may not have been a surprise, its scale and the speed almost certainly was. While it is possible that the rate hikes themselves may not fully explain the outperformance of reserve-rich banks over time, a gradual resolution of uncertainty regarding the remuneration of excess reserves might have been an important contributing factor to the outperformance. After all, adaptations to the reserve remuneration system have been discussed since the start of the tightening period. See, for example, [Reuters \(August 27, 2022\)](#), but to date, the remuneration of excess reserves remains unchanged.

where $R_{b,t}$ is the daily stock return of bank b on day t . The Fama-French three factor model (FF3) includes the market factor (MKT), the value factor (HML; high versus low market-to-book), and the size factor (SMB; small versus large). The Fama-French five factor model (FF5) further includes the profitability factor (RMW; robust versus weak operating profitability), and the investment factor (CMA; conservative versus aggressive). We obtain daily risk factors for Europe from Ken French's website.

To obtain more precise estimates of the corresponding factor loadings, we include data since 2021 (the results are unaffected by extending the sample further back in time). Abnormal returns are simply the estimated coefficients λ_b on the DFR dummy. In the second step, we run a cross-sectional regression to explain the estimated λ_b coefficients:

$$\lambda_b = \alpha + \beta \times RR_b + X_b' \gamma + u_b. \quad (3)$$

Our coefficient of interest is β , which measures whether stock returns during the post-period are a function of banks' reserve ratios. For the sake of completeness, we also report results for the High RR dummy. The most stringent specification further controls for a variety of bank characteristics (namely log total assets, bonds held ratio, deposit ratio, equity ratio, and the ratio of fixed rate loans).

Table 3 reports the estimation results for both the three- and five-factor model using heteroscedasticity robust standard errors. (We confirm that the results are robust to using bootstrapped standard errors.) In line with the visual evidence in Figure 4, we find that banks with higher reserve ratios displayed significantly higher (risk-adjusted) stock returns in the period after the first rate hike. The differential is also economically sizeable. For example, the results in panel A suggest that a one-standard deviation increase from the mean in the reserve ratio increases banks' average daily abnormal returns by around 15 basis points, corresponding to a monthly difference of more than 3 percentage points. Hence, interpreting the stock market valuation as a proxy for banks' net worth, the rate hiking cycle indeed improved reserve-rich banks' net worth.

As a next step, we study more directly whether the interest on reserves of banks with higher reserve ratios translates into higher interest income and consequently into higher profits. For this purpose, we use (i) FINREP data on significant banks' profit/loss accounts (see Section 3.2) and (ii) data on banks' book equity for the full IBSI sample. Note that the FINREP data

are only available at the quarterly frequency, whereas our main dataset is at the monthly level. We are interested in the following relationship:

$$y_{b,t} = \beta \times (\text{RR}_b) \times (\text{DFR}_t \geq 0) + \mathbf{X}'_{b,t} \gamma + \alpha_t + \alpha_b + u_{b,t}, \quad (4)$$

where $y_{b,t}$ are different outcome variables (interest income/expenses, profits, and log(book equity)) and α_t and α_b are time and bank fixed effects, respectively. We include the same time-varying controls as in regression (1) and cluster standard errors at the bank-level to allow for serial correlation across time.

Table 4 reports the results: column (1) shows that banks with higher reserve ratios displayed a significant relative increase in their interest income (relative to total assets) compared to other banks. For example, increasing the reserve ratio by one standard deviation from the mean increases banks' interest income ratio by approximately 9 basis points, which is sizeable given a mean interest income ratio of 1.46% in our sample. In column (2) we find no significant differential effect on banks' interest expenses ratio, which is broadly in line with the observation in Table IA.8 in Internet Appendix B that the deposit passthrough does not seem to be a function of banks' reserve ratios. Crucially, column (3) shows the coefficient estimates for the net interest ratio, i.e. the difference between interest income and interest expenses. We obtain a highly statistically and economically significant coefficient estimate: increasing the reserve ratio by one standard deviation from the mean increases banks' net interest ratio by 5 basis points. This is economically relevant given a mean net interest ratio of 0.87% in our sample. Column (4) shows that these patterns also matter for bank profits: we obtain a positive and significant coefficient estimate for the return on assets. Increasing the reserve ratio by one standard deviation from the mean increases banks' return on assets by 8 basis points, which is again sizeable given a sample mean of ROA of 1.48%. Lastly, we analyze banks' (log) book equity for the full IBSI sample and the effects are again statistically and economically significant. For example, an increase in the reserve ratio by one standard deviation from the mean, implies an increase in book equity by 1.4 percent. Overall, this evidence suggests that reserve-rich banks indeed experienced a measurable boost in their net worth, which could make these banks' credit supply less sensitive to the rate hikes. Hence, the net worth results set the stage for our main analysis on banks' credit supply.

4.2 Credit Supply

We now turn to our analysis of banks' credit supply. Table 5 reports the main estimation results of the loan-level regression (1). In all regressions we include country-time fixed effects (both for the location country of the bank and for the location country of the firm) to control for time-varying country-wide characteristics. We also include bank-firm fixed effects to control for the non-random matching between lenders and borrowers. In columns (1) and (2) we report the coefficient estimates for the full sample, i.e. including also firms that borrow from a single bank. In columns (3) and (4) we then report results for the sample of firms that borrow from more than one bank. Columns (1) and (3) do not control for credit demand, whereas columns (2) and (4) do. In particular, in column (2) we include industry-country-size-time fixed effects as demand controls similar to Degryse, De Jonghe, Jakovljević, Mulier, and Schepens (2019). Both coefficient estimates in column (1) and (2) are positive and statistically significant at the 1% level. For the multi-bank sample we find that the inclusion of demand controls in column (4), as in Khwaja and Mian (2008), increases the economic significance of the estimated coefficient compared to column (3), which suggests that it is indeed important to include demand controls. Both coefficient estimates in columns (3) and (4) are statistically significant at the 1% level. Our preferred specification is the one in column (4), given that it is the most stringent one. The corresponding coefficient indicates that, after the beginning of the rate hike, increasing the reserve ratio by one standard deviation from the mean increases banks' credit supply to non-financial firms by 1.28%.¹⁶ The effect is also economically large: Based on the total outstanding pre-period credit volume of banks with reserve ratios above one standard deviation from the mean, this credit supply effect corresponds to between 0.16% and 0.28% of euro area GDP in 2022. Overall, the evidence suggests that reserve-rich banks' credit supply is less sensitive to the monetary policy tightening compared to other banks (*Hypothesis 1*).

Aggregate credit volumes. Given that our empirical approach is cross-sectional by nature, an important question is whether our estimates also imply aggregate effects. To get at this, Figure 5 shows the evolution of banks' aggregate credit volumes of high reserve banks (red) and all other banks (blue). For the sake of reference, we also show the aggregate time series across all banks (black). The figure clearly shows that, while aggregate credit volumes ultimately

¹⁶As noted above, we report t-statistics based on standard errors clustered at the bank-time level. Table IA.2 in the Internet Appendix shows that the main coefficient of interest remains statistically significant at the 1% level when using alternative clustering approaches.

indeed went down, this effect is due to banks with relatively low reserves. In fact, if reserve-rich banks would have behaved exactly as lower reserve banks, we estimate that total credit volumes would have been 0.5% lower by February 2023 (the difference between the black and the blue line in Figure 5). One important caveat in this analysis is that, contrary to our credit supply regressions in Table 5, these aggregate volumes contain both credit supply and credit demand effects - where the strong credit demand effects around the onset of the hiking cycle potentially overlay some of the credit supply effects.¹⁷ We view this as indicative evidence that overall monetary policy transmission was affected.

Timing of the effect. Our DFR dummy takes the value of 1 from July 2022 onwards, i.e., the month when the ECB initiated the rate hiking cycle. Hence, our main coefficient of interest measures the difference in credit supply during the Post-period as a function of banks' reserve ratios. To investigate the timing of the effect in more detail, we also run the following dynamic version of regression (1):

$$\log(\text{Credit}_{b,t}) = \text{RR}_b \cdot \sum_{k=0}^T \beta_k \cdot D_t + X'_{b,t} \gamma + \alpha_{f,t} + \alpha_{b,f} + \alpha_{c,t} + u_{b,t}, \quad (5)$$

where D_t is an indicator variable that equals one in month t , and zero otherwise, with January 2022 serving as the baseline effect. Standard errors are clustered at the bank-time level. Figure 6 shows that, prior to the first interest rate hike in July 2022, the interaction terms are small and not statistically significant. The only exception is the coefficient for June 2022. Afterwards the estimate increases and remains statistically significant for most of the remaining sample period. This is a first indication that our results are robust to variations in the DFR dummy.

Robustness. A potential concern with our identification strategy might be that time-varying differences of bank characteristics could bias our coefficient estimates. The direction of the bias depends on the covariance of the unobservable factor with our coefficient estimate. Following Grosse-Rueschkamp et al. (2019), the direction of this covariance might be possibly inferred by the comparison of the coefficient estimate across different specifications. Therefore, in columns (1) and (2) of Table 6 we show two specifications that are identical to or baseline

¹⁷As a robustness check, Figure IA.2 in the Internet Appendix repeats the same analysis as in Figure 5 for banks' total credit volumes reported in IBSI. In this case, we find a very similar pattern, suggesting that our results also hold when going beyond non-financial companies (which are not covered in AnaCredit).

results in columns (3) and (4) of Table 5, but where we do not include the (time-varying) bank-level characteristics as controls. In this case the coefficient estimates remain highly statistically significant, however, the magnitude of the effect is approximately halved. This suggests that the covariance is negative and that our estimates are likely biased downward.

As another robustness check, columns (3) and (4) of Table 6 report the baseline estimation results when adding further time-varying bank level controls. In particular, column (3) includes banks' sectoral loan concentration (based on the standard Hirschmann-Herfindahl Index) as a proxy for specialized credit demand from specific industries as in Paravisini, Rappoport, and Schnabl (2023). In this case, we find that the effect remains very similar to our baseline estimate. In column (4) we add banks' value-weighted credit duration as an additional control. In this case, the coefficient is very similar to our baseline estimate, suggesting that differences in loan duration do not drive our results.¹⁸

We also test whether our results are robust to alternative definitions of the effective treatment variable. In particular, column (5) of Table 6 shows that the effect is also visible when replacing the continuous RR with *High RR*, a dummy variable equal to one for banks with a reserve ratio at least one standard deviation above the mean in the pre-period. The fact that the effect is also visible in the upper tail of the RR distribution suggests that the differential is not strongly driven by banks in the lower tail of the RR distribution since these make up only a small part of the control group in this setting. In column (6) we report the robustness to a further definition of the treatment variable, where *Rank RR* the rank of the continuous bank-level reserve ratio standardized by the total number of banks. The coefficient estimates remains both statistically and economically significant. Column (7) shows a simple placebo test based on banks' minimum reserve requirements. Similar to the definition of our main variable of interest, the continuous bank-level minimum reserve requirements (MRR) are standardized such that the coefficient captures a one-standard deviation increase from the mean. Importantly, we find no effect when using this alternative treatment variable, suggesting that the main effect is indeed driven by banks' excess reserves. In other words, our main credit supply effect is not mechanically driven by differences in minimum reserve requirements. Lastly, column (7) shows that the effect for the baseline RR is robust to including the raw DFR instead of the DFR dummy. This is in line with our dynamic estimates in Figure 6. The point estimate implies that

¹⁸In additional analyses (unreported), we find that banks' value-weighted loan duration is not (linearly) related to the RR. Hence, there is no simple mechanical correlation between these measures. Details are available upon request from the authors.

a rate hike of 100 basis points increases banks' credit supply to non-financial firms by 0.4% when increasing the reserve ratio by one standard deviation from the mean.

We also conduct additional analyses based on a matched sample using the High RR dummy. Specifically, we use a standard propensity score matching approach of High RR banks with banks in the control group (e.g., [Rodnyansky and Darmouni 2017](#)). In this regard, Table IA.3 in the Internet Appendix shows that the cross-sectional differences from Table 2 indeed disappear after using a standard propensity score matching approach (based on the Probit model in column (3) of Table 2). Crucially, in Table IA.4 in the Internet Appendix we report our baseline credit supply regressions for the substantially smaller matched sample. The coefficient on the RR remains highly statistically significant in this case, showing a broadly similar magnitude of the effect as our baseline estimate.

Lastly, our credit supply result could be partly driven by differential deposit flows. In particular, in the setup of [Drechsler et al. \(2017\)](#), banks widen their deposit spreads after a rate hike, which induces households to shift deposits to alternative money-like instruments (e.g., short-term bonds or money market funds). As a consequence, banks would have to cut their lending. Therefore, if our effect was driven by the deposit channel, we would expect that reserve-rich banks should have received larger deposit inflows. However, as documented in Table IA.5 in the Internet Appendix, we do not find any differences in the deposit flows of banks as a function of banks' reserve ratios. Hence, differential deposit flows do not appear to serve as a viable explanation for the documented credit supply results.

Survey-based evidence. We presented various pieces of evidence that are in line with the main mechanism we laid out in the paper. Nevertheless, it is useful to look to further data sources for external validity. In this regard, Figure 7 –which is taken from [Hueneke \(2023\)](#) and reproduced thanks to the kind permission of the author– shows the development of credit standards based on the Eurosystem's confidential bank lending survey (iBLS). As noted by [Altavilla, Boucinha, Holton, and Ongena \(2021\)](#), iBLS is a survey containing self-reported information on banks' credit supply and demand developments, which are collected for a representative subsample of institutions. Figure 7 shows three distinct measures that capture banks' credit supply conditions, namely credit standards, liquidity positions, and risk tolerance. In line with our main findings, the results indicate that banks with higher reserve ratios tend to report more favourable credit supply conditions along all three measures.

Collapsed Regressions. Our results are also robust to using a collapsed specifications at the (i) bank-firm level and (ii) at the firm-level. The latter result is particularly important, since a potential concern might be that firms that borrowed more from high-reserve banks could reduce their credit volume by the same proportion from banks with a low reserve ratio - corresponding to a zero-sum outcome.

First, we focus on the bank-firm level and show additional regression results for a collapsed version of our sample. In particular, we estimate the following relationship:

$$\Delta \log(\text{Credit}_{b,f}) = \beta \times (\text{RR}_b) + \mathbf{X}'_b \gamma + \alpha_f + u_{b,f}, \quad (6)$$

where the dependent variable is the log-difference of the average credit volume granted by a bank b to firm f during the pre-period (Jan. 2022 - Jun. 2022) and the post-period (Jul. 2022 - Feb. 2023). All control variables are the pre-period averages. The coefficient estimate in column (1) of Table 7 is statistically significant and similar to the coefficient estimates in Table 5 in terms of their magnitude.

As a second check, we study whether the loan-level results are binding at the firm- level:

$$\Delta \log(\text{Credit}_f) = \delta \times (\overline{\text{RR}}_f) + \alpha_1 \times \overline{B}_f + \alpha_2 \times F_f + u_f, \quad (7)$$

where the dependent variable is the log-difference between the pre- and post-period average credit volume of firm f . $\overline{\text{RR}}_f$ is the pre-period value-weighted average reserve ratio of banks that firm f had credit relationships with:

$$\overline{\text{RR}}_f = \frac{\sum_b (\text{RR}_b \times \text{Credit}_{b,f,t=pre})}{\sum_b (\text{Credit}_{b,f,t=pre})}. \quad (8)$$

The same procedure is used to compute the indirect bank control variables denoted by \overline{B}_f . We further include firm-size buckets and industry-country fixed effects. The coefficient estimate of δ in column (2) of Table 7 is positive and statistically significant. Hence, firms that borrowed relatively more from banks with higher reserve ratios displayed a relative increase in their borrowing during the post-period. We should also note that the coefficient estimate is comparable but slightly smaller in magnitude to the bank-firm collapse estimate in column (1). Lastly, we also report the bias-corrected coefficient as in Jiménez, Mian, Peydró, and Saurina (2020). The correction addresses that Eq. (7) does not include firm fixed effects and thus is potentially

biased via firm-specific shocks. The corrected coefficient is slightly smaller compared to $\hat{\delta}$, suggesting that the effect is indeed relevant at the firm level.

Our results indicate that firms that borrowed more from high-reserve banks do not reduce their credit volume by the same proportion from banks with a low reserve ratio. Hence, our loan-level results are binding at the firm-level, which means that the documented effects of banks' excess reserves indicate the presence of real effects. While it would be interesting to study these firm-level implications in more detail, the corresponding firm-level financial reports for the year 2023 were not yet available at the time of writing. We aim to investigate this in future research.

4.3 Bank Heterogeneity

Hypothesis 2 is concerned with whether the credit supply effect is more pronounced for more financially constrained banks. To assess such heterogeneity, Table 8 shows the results for three proxies of such financial constraints, namely bank size, bank equity, and fixed to total loans.

For the sake of reference, column (1) reports our baseline specification from Table 5. In column (2) we test whether the effect is weaker for the very largest banks. As described above, small banks' lending is more dependent on monetary policy because they find it more difficult to raise additional funding. We incorporate the *Large Bank* indicator variable, which takes the value of 1 if a bank is above the 95 percentile of the pre-period natural logarithm of total assets, along with the interaction term between $(DFR_t \geq 0$ and RR_b in regression (1). As expected, the interaction term is negative and statistically significant at the 1% significance level. Hence, the effect is smaller for large banks (and larger for small banks), in line with *Hypothesis 2*.¹⁹

In column (3) we include an indicator variable *Low Equity* in the regression that takes the value of 1 if a bank's pre-period equity ratio is in the bottom decile. The results indeed indicate that the effect is stronger for banks with lower equity ratios, which are more financially constrained. We find a positive and significant coefficient estimate of the triple interaction term.

A final dimension of financial constraints is the fraction of fixed versus variable rate loans, since a larger share of fixed rate loans means that these will display relatively unfavourable loan terms for some time. In this regard, column (4) shows that the effect is stronger for banks with

¹⁹Regarding bank size, it is worth mentioning that all of our loan-level regressions are weighted in the sense that larger banks have a larger loan portfolios and therefore contribute more observations to our sample. In unreported analyses we also conducted weighted least squares (WLS) regressions, where we use as weights either banks' (pre-period) log total assets or log total credit. The main coefficient of interest, $(DFR_t \geq 0) \times RR$, remains highly statistically significant and of similar magnitude as the baseline in column (4) of Table 5.

more variable-rate, rather than fixed-rate, loans. These patterns are in line with [Ampudia and Van den Heuvel \(2022\)](#) in that the net worth effect of large excess reserve holdings should be even stronger for banks that are more likely to adjust their loan rates after the rate hike. Overall, the results in Table 8 are in line with Hypothesis 2 and suggest that the credit supply effect is indeed more pronounced for more financially constrained banks.

4.4 Borrower Heterogeneity

We now turn to the question whether the credit supply effect is concentrated on borrowers with specific characteristics. According to the bank lending channel literature, small firms are more dependent on bank funding and should be more affected by variations in credit supply (e.g. [Gertler and Gilchrist \(1994\)](#), [Chodorow-Reich \(2014\)](#), [Khwaja and Mian \(2008\)](#), [Iyer et al. \(2014\)](#)). Following this literature, we split the sample according to the size of the borrowing firms and re-run our baseline specification for different subsamples. For this purpose, we divide our sample firms into four size categories, namely micro, small, medium, and large enterprises. This classification follows the EU recommendation 2003/361/EC, where a micro/small/medium enterprise has less than 10/50/250 employees and the annual turnover and/or annual balance sheet total does not exceed 2/10/50 EUR million, respectively. Panel A of Table 9 reports the results. The effect is positive and significant across all size categories, but is largest for small (and medium) firms and smaller for the largest firms. This could be due to the fact that larger firms have better access to market-based financing opportunities which banks might take into account in their credit supply decisions.

Panel B of Table 9 differentiates between borrowers from different industries, based on broad NACE sectoral affiliations. Here we focus on the major industries in terms of overall credit volumes, namely Manufacturing (NACE code K), Construction (NACE F), Trade (NACE G) and Information (NACE J). The results indicate that the effect indeed varies across borrower industries and is strongest for manufacturing firms, which are relatively bank-dependent.

Lastly, another dimension of interest is borrower quality and we conduct sample splits using either (i) banks' reported probabilities of default (PD) or (ii) information on whether firms had at least one exposure in arrears prior to the first rate hike ([Altavilla, Boucinha, Peydró, and Smets 2020](#)). The definition of arrears is homogeneous across countries and refers to the delayed principal amount and/or the delayed interest payments that are past due more than 90 days. Panel C of Table 9 shows that the effect tends to be stronger for *higher* quality

firms, suggesting that banks with higher reserve ratios tend to reduce their risk-taking. (For the sake of completeness, Table IA.6 in the Internet Appendix shows that the difference in the point estimates for the two sample splits is also statistically significant.) These results could be related to skin-in-the-game effects, similar to Heider et al. (2019). In addition, the results suggest that banks take into account the risk profile of their counterparties in their credit supply decisions. As such, it seems natural to expect that riskier firms would find it more difficult to service their bank financing at the higher level of interest rates. These results are particularly relevant from a financial stability perspective, as they suggest that the funding base of lower-risk firms was more stable.

In Table IA.7 in the Internet Appendix we present further results when using the value-weighted loan rates as the dependent variable. In column (1) we find a significantly positive coefficient estimate for our baseline specification indicating that, for the average firm, there is a positive pricing differential as a function of banks' reserve ratios. The remaining columns show that this pricing differential is particularly pronounced for High PD firms, which seems reasonable from a risk-management perspective. In particular, column (4) shows that the difference for the subsamples based on High PD is also significant. Overall, this indicates that the loan pricing was also differentially affected for low versus high PD firms.

5 Policy Implications

We show that when reserves are ample, the transmission of contractionary monetary policy is weaker for reserve-rich banks. These findings have important policy implications. The aim of contractionary monetary policy is to contain inflation. While our analysis is cross-sectional by nature, we provided indicative evidence that the lower sensitivity of reserve-rich banks' credit supply could, at least partly, work against the aim to reduce inflation and may therefore require action by policymakers.

One might consider different options that would alter banks' interest income from reserve remuneration. We should stress that an in-depth evaluation of the different alternatives is beyond the scope of this paper and we therefore only provide an overview of current discussions on the matter. The transition to an abundant reserves regime was ultimately driven by the various QE programs in the past. One option could therefore be to reduce reserves via a more active

QT policy, as for example implemented by the Bank of England.²⁰ While such an approach could be feasible in the euro area, a number of additional aspects should be taken into account: first, the pace at which such an active QT policy could be implemented is limited, such that the reduction in excess reserves would be unlikely to have immediate effects. Second, even a moderate QT policy could have an effect on market liquidity, market functioning and, ultimately, financial stability. Lastly, active bond sales would lead to the actual materialization of the rate hike-induced paper losses by the ECB.

Another option would be to not pay the same interest on all central bank reserves. This could be done in various ways, for example [Angeloni \(2023\)](#) proposes an alternative approach via reverse long-term refinancing operations, where the ECB would swap long-term securities against reserves on a long-term basis. To ensure that banks would engage in these operations, the (bank-specific) deposit rate would be negatively affected if the bank does not participate. Another alternative would be reverse tiering (or quota systems), where total reserves are remunerated up to a certain threshold (which could be a multiple of minimum reserve requirements) and at a lower rate for reserves exceeding the threshold. This would reduce some of the interest earnings of banks with higher reserve holdings.²¹ Another approach would be to increase (unremunerated) minimum reserve requirements. Such two-tier systems for minimum reserve requirements were proposed by e.g. [De Grauwe and Ji \(2023\)](#). Importantly, the ECB announced on July 27th 2023, that it would remunerate minimum reserve requirements at 0%, i.e., it will not pay the DFR on these required reserves (see [ECB](#) for details). Given that the vast majority of banks' total reserves consist of excess reserves, however, this policy adjustment is unlikely to contain (or even reverse) the documented side effects.²²

Finally, we should also highlight that our findings are important from a financial stability perspective. In particular, a lot of research focused on potential negative side effects of ultra-loose monetary policy (e.g., excessive risk-taking as in [Jiménez et al. \(2014\)](#)) and the vulnerabilities that would arise with the eventual monetary policy normalisation. The fact that the negative net worth effect from the rate hikes is at least partially offset for high reserve banks

²⁰As noted by the [Bank of England](#): "We stopped buying bonds at the end of 2021. We stopped reinvesting the proceeds from maturing bonds in February 2022. And we began actively selling bonds in November 2022. As a result the amount of bonds we hold has started to fall."

²¹The Norges Bank introduced its quota system in October 2021 and the Swiss National Bank implemented its reverse tiering approach in September 2022. See [Norges Bank \(2021\)](#) and [Swiss National Bank \(2022\)](#) for details. The SNB complemented its policy with a reserve absorption via open market operations.

²²As of July 2023, minimum reserve requirements stood at 165 EUR bn compared with excess reserves of 3.6 EUR tn. Under the assumption that the DFR would remain at its latest value of 4% (November 2023), the ECB's policy adjustment reduces banks' annual interest income by 6.6 EUR bn.

indicates a positive interaction between central bank reserves and contractionary (conventional) monetary policy. In addition, the credit supply results indicates a more stable funding base for firms that borrow from high reserve banks. Given that this financing is focused on less risky firms, the overall financial stability effects are likely positive.

6 Conclusion

This paper documents that monetary policy transmission varies in the cross-section of banks' level of excess reserves. Focusing on the unique situation in the euro area from mid-2022 onwards when (i) the aggregate level of reserves was historically large and (ii) the interest on reserves increased materially, our main finding is that reserve-rich banks' credit supply is less sensitive to the monetary policy tightening compared to other banks. Notably, while our empirical setup is cross-sectional by nature, we find indicative evidence of aggregate effects.

In line with the basic idea that banks with large reserve holdings should benefit from a (partly offsetting) net worth effect, we provide evidence that banks with higher reserve ratios also displayed higher abnormal stock returns after the onset of the rate hiking cycle. This effect is also visible in banks' net interest income, profits, and book equity.

An open question is whether banks' increase in net worth was also accompanied by higher dividend payments to shareholders and/or excessive executive compensation. Similarly, while our focus was on credit supply, banks' could also adjust other balance sheet positions (e.g., securities) following the rate hike. Lastly, while our analysis focused on the euro area, there is reason to believe that the basic mechanism uncovered in this paper should matter in other currency areas that operate in an ample reserves framework (such as the U.S. or the UK). We leave these aspects for future research.

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Figures and Tables

Figure 1: Reserves and Deposit Facility Rate

The figure displays total reserves held by banks in the Eurosystem (green line) along with the required reserves (blue line) and the deposit facility rate (red line). The shaded area marks the main period of interest, i.e. when both reserves are large and the deposit facility rate is high.

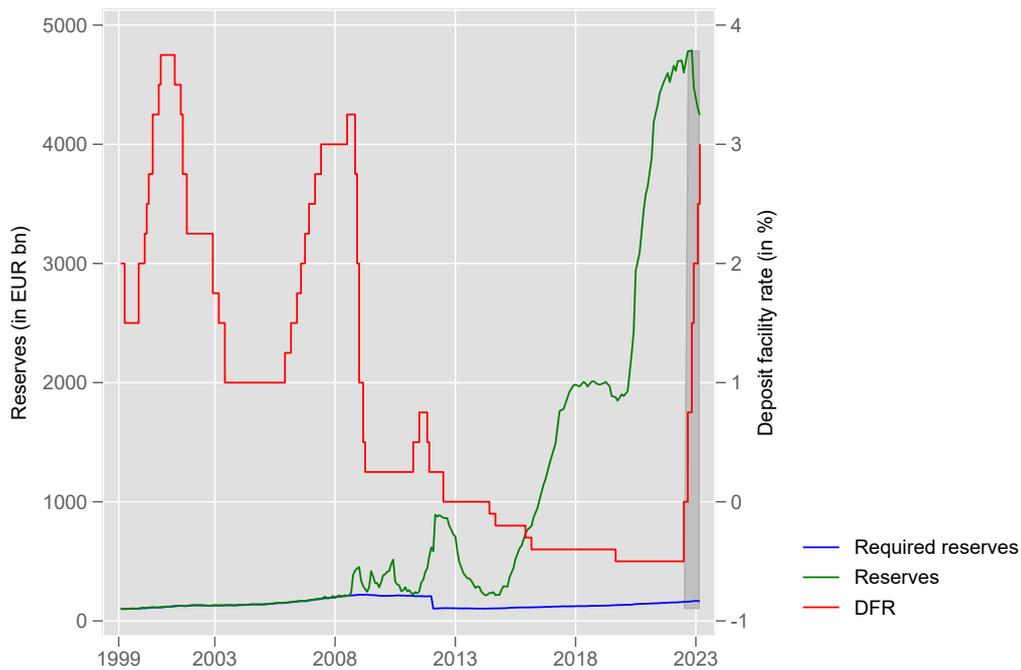


Figure 2: Cross-Sectional Variation in Reserves/Total Assets

The figure shows the Kernel density distribution of our sample banks' average reserves-to-total assets ratios, prior to the onset of the rate hiking cycle.

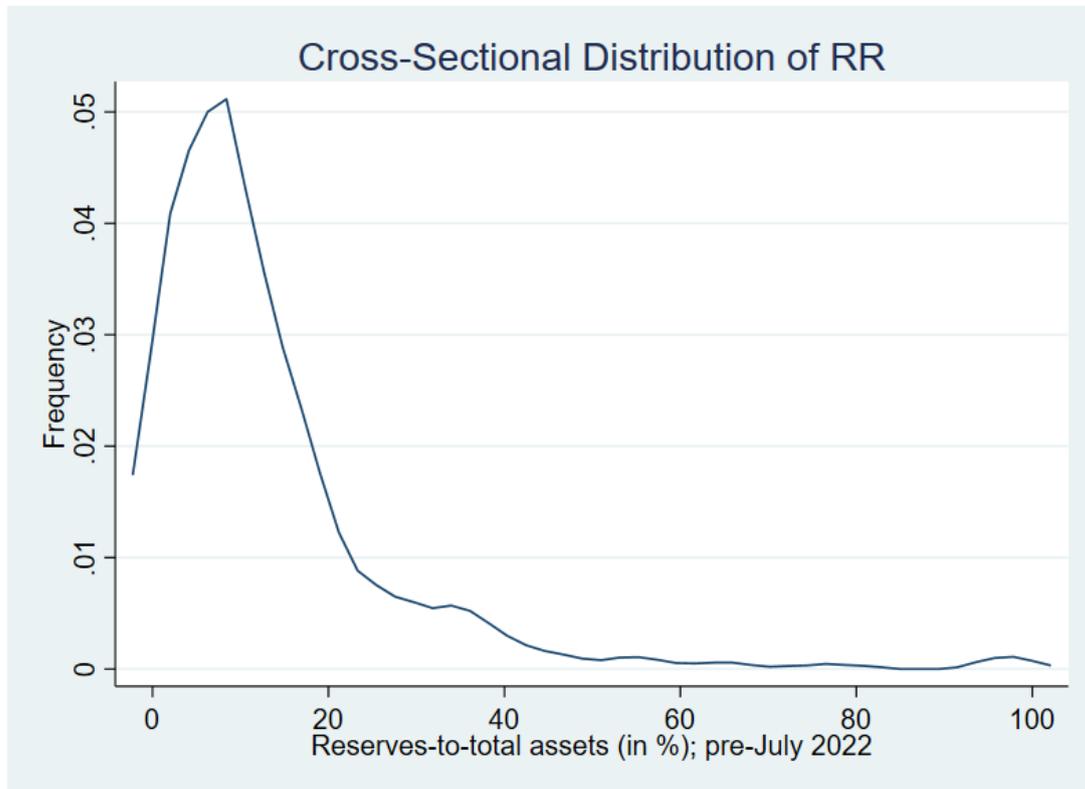


Figure 3: Deposit Rates in the Euro Area

The figure displays different deposit rates of Euro area banks, as reported in the ECB Statistical Data Warehouse, alongside the deposit facility rate (DFR). The blue lines show overnight deposit rates (in percent, per annum) and the green lines time deposit rates (that is, deposits with agreed maturity).

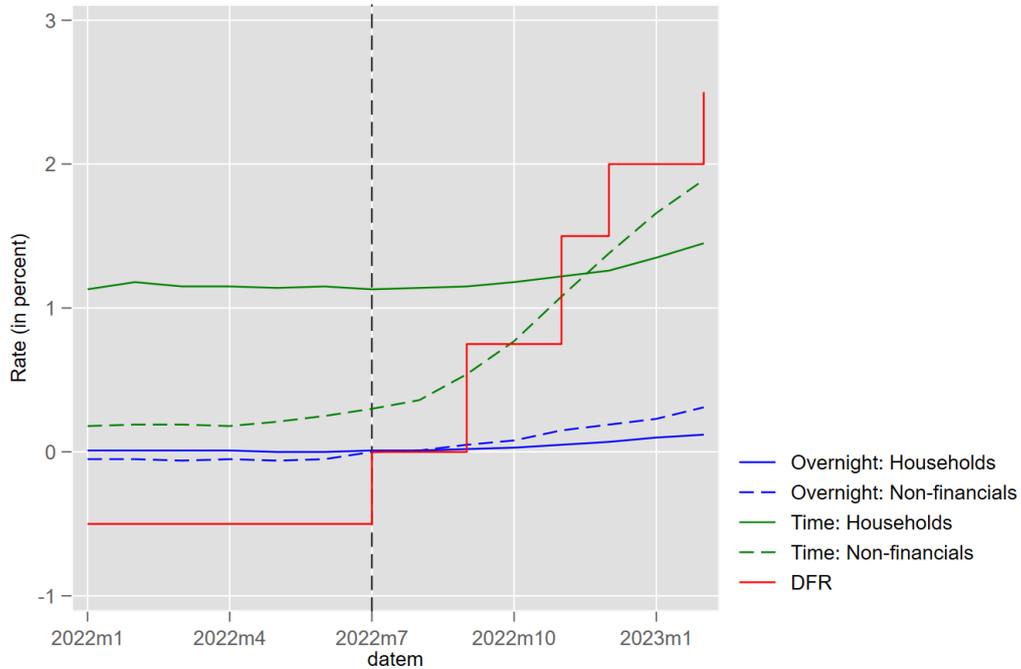


Figure 4: Stock Price Dynamics

This figure shows the evolution of the value-weighted stock price indices (July 2022=100) for High RR banks (red line) and for the control group (blue line). Stock market data are from Refinitive-Eikon. By construction, this analysis is restricted to the subsample of listed euro area banks.



Figure 5: Aggregate Credit Volumes

Figure 5 shows the evolution of the aggregate credit volumes (indexed, May 2022 = 100) from AnaCredit for banks with reserve ratios above one standard deviation from the mean (red) and for all other banks (blue). For the sake of reference, we also show the aggregate time series across all banks (black).

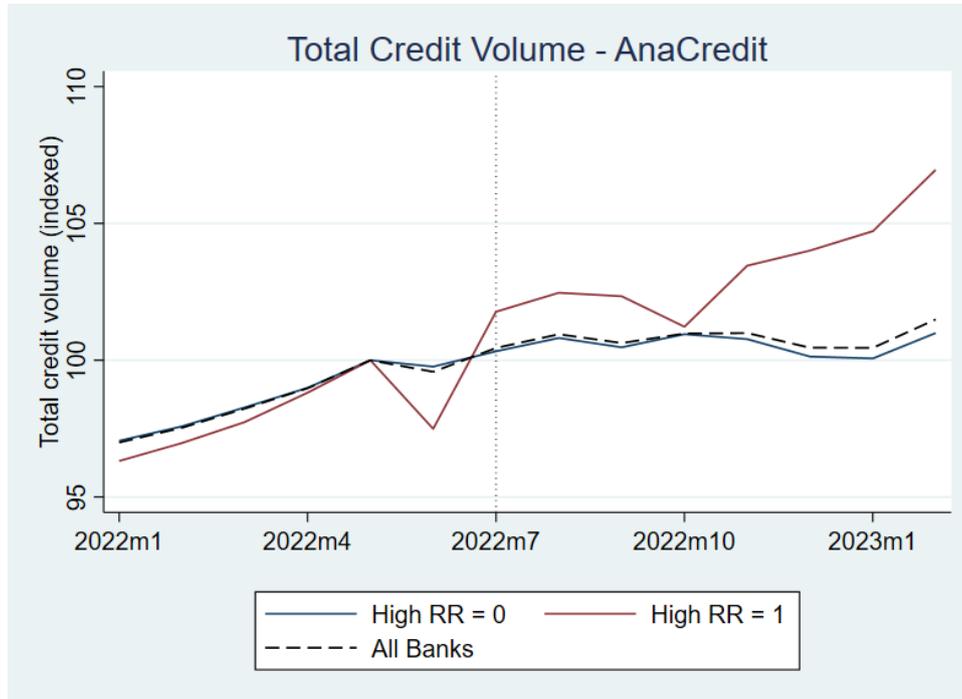


Figure 6: Timing of the Effect

Figure 6 shows the results for estimating the dynamic credit supply regression in equation (5), where January 2022 serves as the baseline effect. We plot the dynamic coefficient on the continuous RR together with 90% confidence bands.

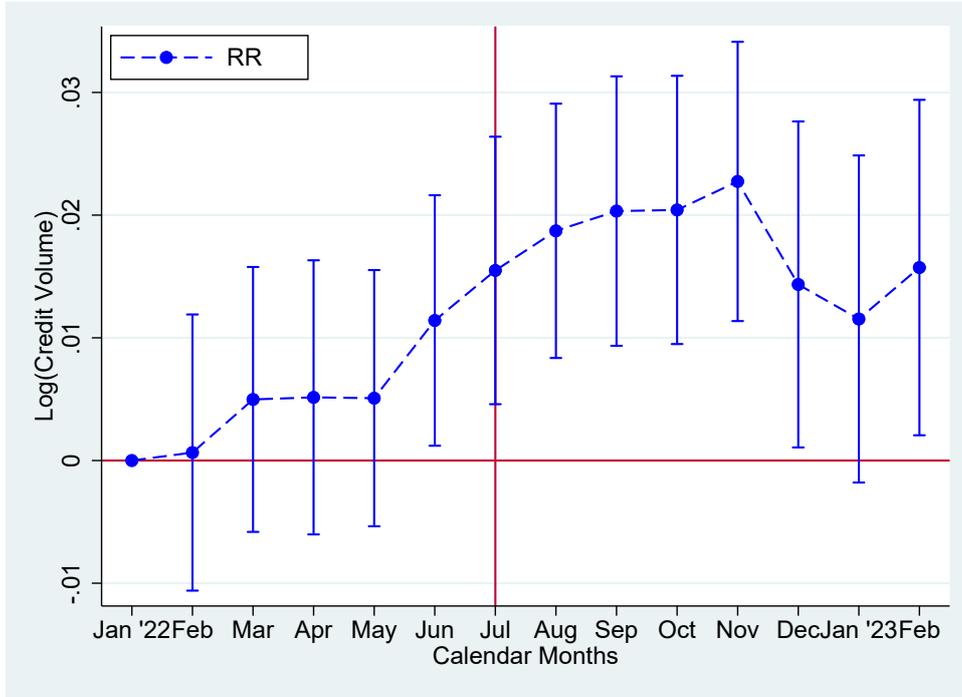


Figure 7: Survey-Based Evidence

Figure 7 is reproduced from [Huenekeles \(2023\)](#) and shows the relationship between excess liquidity and credit standards based on the Eurosystem's bank lending survey.

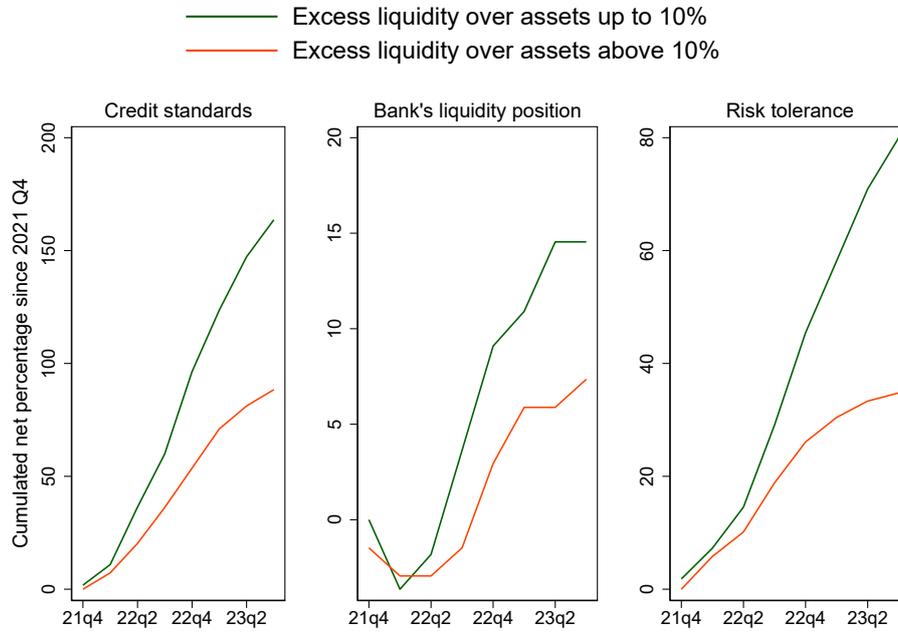


Table 1: Summary Statistics

Table 1 shows summary statistics of the variables used in the analysis. The sample period is January 2022 to February 2023. Panel A shows descriptive statistics for the full sample. Panel B shows descriptive statistics for High RR banks (for banks with a reserve ratio at least one standard deviation above the mean) and for low RR banks (the remaining banks).

Panel A: Summary Statistics (Full Sample)						
	Mean	Std. Dev.	p25	p50	p75	Obs.
<u>Bank-level Variables</u>						
log(Total Assets)	9.860	1.246	8.866	9.585	10.532	6,584
Equity Ratio	0.082	0.044	0.054	0.080	0.101	6,584
Deposit Ratio	0.352	0.254	0.077	0.383	0.564	6,584
Reserve Ratio	0.128	0.139	0.048	0.091	0.163	6,584
Bonds held Ratio	0.082	0.085	0.018	0.065	0.112	6,584
Fixed to total loans Ratio	0.524	0.329	0.202	0.608	0.801	6,584
$DFR_t \geq 0$	0.572	0.495	0.000	1.000	1.000	6,584
High RR	0.107	0.309	0.000	0.000	0.000	6,584
Large Bank	0.051	0.220	0.000	0.000	0.000	6,584
Low Equity Ratio	0.101	0.301	0.000	0.000	0.000	6,584
<u>Bank-firm-level Variables</u>						
log(credit)	11.864	1.480	10.761	11.688	12.722	42,696,834

Panel B: Summary Statistics - Split based on High RR Dummy								
	High RR=0				High RR=1			
	Mean	Std. Dev.	p50	Obs.	Mean	Std. Dev.	p50	Obs.
<u>Bank-level Variables</u>								
log(Total Assets)	9.889	1.268	9.594	5,879	9.613	1.022	9.452	705
Equity Ratio	0.084	0.040	0.084	5,879	0.063	0.063	0.050	705
Deposit Ratio	0.373	0.251	0.413	5,879	0.176	0.200	0.108	705
Reserve Ratio	0.090	0.067	0.084	5,879	0.441	0.186	0.373	705
Bonds held Ratio	0.087	0.085	0.070	5,879	0.047	0.078	0.010	705
Fixed to total loans Ratio	0.547	0.321	0.646	5,879	0.330	0.332	0.202	705
$DFR_t \geq 0$	0.572	0.495	1.000	5,879	0.573	0.495	1.000	705
Large Bank	0.057	0.232	0.000	5,879	0.000	0.000	0.000	705
Low Equity Ratio	0.078	0.268	0.000	5,879	0.288	0.453	0.000	705
<u>Bank-firm-level Variables</u>								
log(Credit)	11.886	1.451	11.703	26,395,024	11.770	1.507	11.564	17,132,490

Table 2: Cross-Sectional Characteristics

Table 2 shows the results of a cross-sectional regression of the continuous reserve ratio (column (1)) and the High RR dummy (columns (2)-(4)) on several normalized bank characteristics. The bank-level characteristics are calculated as averages during the pre-period and then normalized to have zero mean and unit standard deviation. Column (2) shows the results from a linear probability model (LPM). Columns (3) and (4) show results from Logit/Probit regressions, respectively. We report t-statistics based on robust standard errors in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level respectively.

Dep. var.:	(1)	(2)	(3)	(4)
	RR _b	High RR _b		
	OLS	LPM	Logit	Probit
log(Total Assets)	-0.0771 (-1.49)	-0.0539*** (-3.69)	-0.4336*** (-2.61)	-0.2222** (-2.55)
Equity Ratio	-0.1305** (-2.18)	-0.0456* (-1.74)	-0.4030 (-1.15)	-0.1828 (-1.38)
Deposit Ratio	-0.2333*** (-4.28)	-0.0644*** (-3.96)	-0.6640*** (-3.38)	-0.3591*** (-3.72)
Bonds Held Ratio	-0.0864** (-2.25)	-0.0327** (-2.57)	-0.3798 (-1.61)	-0.2138* (-1.90)
Fixed to total loans Ratio	-0.1683*** (-3.35)	-0.0385** (-2.38)	-0.3734* (-1.95)	-0.2195** (-2.35)
adj. R2	.1389	.1167		
χ^2			54.2	55.5
p-value			<0.001	<0.001
N	472	472	472	472

Table 3: Average Daily Abnormal Returns

Table 3 shows the results of a two-step procedure as in Altavilla et al. (2022) that estimates daily abnormal percentage returns based on a Fama-French three factor (columns (1)-(2)) and five factor model (columns (3)-(4)). Panel A shows the results for the continuous reserve ratio and Panel B for the High RR dummy. *RR* is the continuous bank-level reserve ratio during the pre-period, which is standardized such that the coefficient captures a one-standard deviation increase from the mean. The estimation period ranges from January 2021 until February 2023. Bank controls include log total assets, bonds held ratio, deposit ratio, equity ratio, and the ratio of fixed rate loans. We report t-statistics based on robust standard errors in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level respectively.

Panel A: RR	(1)	(2)	(3)	(4)
	FF3		FF5	
RR	0.1639*** (3.06)	0.1510*** (2.86)	0.1631*** (3.08)	0.1506*** (2.88)
adj. R2	.2158	.4476	.2122	.4509
N	38	38	38	38
Bank controls	No	Yes	No	Yes
Panel B: High RR	(1)	(2)	(3)	(4)
	FF3		FF5	
High RR	0.2549* (1.83)	0.2772*** (2.82)	0.2526* (1.84)	0.2744*** (2.82)
adj. R2	.1244	.4265	.1208	.427
N	38	38	38	38
Bank controls	No	Yes	No	Yes

Table 4: Interest Income, Profits, and Equity

Table 4 shows the result for the fixed-effects panel regression executed on the bank-level panel dataset. We use the following outcome variables of bank b in month t : the interest income (column 1), interest expenses (column 2), net interest income (column 3), return on assets (EBITDA) (column 4) all normalized by total assets in $t - 1$, and the logarithm of the book equity (column 5). $DFR_t \geq 0$ is a dummy variable for the period from the first rate hike. RR is the continuous bank-level reserve ratio during the pre-period and standardized such that the coefficient captures a one-standard deviation increase from the mean. All regressions include bank-level control variables interacted with the DFR dummy, country-time fixed effects and bank fixed effects. We report t-statistics based on standard errors clustered at the bank level in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level respectively.

	(1)	(2)	(3)	(4)	(5)
	%Interest Income Ratio	%Interest Expenses Ratio	%Net Interest Inc. Ratio	%ROA	log(Book Equity)
$(DFR_t \geq 0) \times RR$	0.0877* (1.78)	0.0276 (1.07)	0.0506* (1.74)	0.0801* (1.96)	0.0138* (1.70)
	.8536 736	.8801 736	.8393 736	.8275 736	.9962 6388
Controls	Yes	Yes	Yes	Yes	Yes
Country-Time FE	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes

Table 5: Baseline Regressions - Credit Volume

Table 5 shows the result for the fixed-effects panel regression in equation (1) executed on the bank-firm-level. We use the logarithm of credit volume to non-financial corporations f by bank b in month t as outcome variable. Columns (1) and (2) show results for the full sample, i.e. including also firms that borrow from a single bank. Columns (3) and (4) report results for the sample of firms that borrow from more than one bank. $DFR_t \geq 0$ is a dummy variable for the period from the first rate hike and RR is the continuous bank-level reserve ratio during the pre-period, which is standardized such that the coefficient captures a one-standard deviation increase from the mean. All regressions include bank-level control variables interacted with the DFR dummy and country-time (both location of the bank and firm), and bank-firm fixed effects. Industry-country-size-time and firm-time fixed effects are included (Yes) not included (No) or absorbed by other fixed effects (-). The sample period is January 2022 to February 2023. We report t-statistics based on standard errors clustered at the bank-time level in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level respectively.

	(1)	(2)	(3)	(4)
	All firms		Multiple bank firms	
$(DFR_t \geq 0) \times RR$	0.0071*** (6.78)	0.0074*** (7.36)	0.0106*** (6.25)	0.0128*** (7.57)
adj. R2	.9782	.9784	.9749	.9753
N	42,580,697	42,580,697	14,062,930	14,062,930
Controls	Yes	Yes	Yes	Yes
Country (bank)-Time FE	Yes	Yes	Yes	Yes
Country (firm)-Time FE	Yes	-	Yes	-
Bank-Firm Fixed Effects	Yes	Yes	Yes	Yes
Industry-Country (firm)-Size-Time FE	No	Yes	No	-
Firm-Time Fixed Effects	No	No	No	Yes

Table 6: Robustness - Credit Volume

Table 6 shows the result for the fixed-effects panel regression in equation (1) executed on the bank-firm-level. We use the logarithm of credit volume to non-financial corporations f by bank b in month t as outcome variable. All specifications are based on the multi-bank sample in columns (3) and (4) from Table 5. Bank-specific control variables are either included (Yes) or not included (No). $DFR_t \geq 0$ is a dummy variable for the period from the first rate hike and RR is the continuous bank-level reserve ratio during the pre-period, which is standardized such that the coefficient captures a one-standard deviation increase from the mean. Columns (1) and (2) show the results from our baseline regressions but excluding all control variables. Columns (3) and (4) add further time-varying control variables to our baseline specification, namely banks' sectoral loan concentration (HHI) as a proxy for specialized demand, and banks' value-weighted loan duration, respectively. In column (5) *High RR* is a dummy variable equal to one for banks with a reserve ratio at least one standard deviation above the mean in the pre-period. In column (6) *Rank RR* is a variable that gives the rank of the continuous bank-level reserve ratio standardized by the total number of banks. Column (7) shows the results when defining the treatment variable based on the continuous bank-level minimum reserve requirements (MRR), which is standardized such that the coefficient captures a one-standard deviation increase from the mean. Column (8) includes a specification with the time-varying DFR instead of a dummy. All regressions include country-time (both location of the bank and firm), and bank-firm fixed effects. Firm-time fixed effects are included (Yes) not included (No) or absorbed by other fixed effects (-). The sample period is January 2022 to February 2023. We report t-statistics based on standard errors clustered at the bank-time level in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level respectively.

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	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Excluding Controls		Additional Bank Controls Spec. Demand Loan Duration		Alternative RR definition		Minimum Reserves	Raw DFR
$(DFR_t \geq 0) \times RR$	0.0080*** (4.20)	0.0103*** (5.36)	0.0133*** (7.61)	0.0152*** (8.29)				
$(DFR_t \geq 0) \times \text{High RR}$					0.0217*** (8.22)			
$(DFR_t \geq 0) \times \text{Rank RR}$						0.0277*** (6.14)		
$(DFR_t \geq 0) \times \text{MRR}$							0.0002 (0.16)	
$DFR_t \times RR$								0.0042*** (3.94)
adj. R2	.9749	.9753	.9753	.9753	.9753	.9753	.9753	.9753
N	14,062,930	14,062,930	14,062,930	14,062,930	14,062,930	14,062,930	14,062,930	14,062,930
Controls	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Country (bank)-Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank-Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Time Fixed Effects	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 7: Collapse - Credit Volume

Column (1) of Table 7 shows the result for the bank-firm level regression (Eq. (6)), where the dependent variable is the first differences in logs of the pre-period (Jan. 2022 - Jun. 2022) and post-period (Jul. 2022 - Feb. 2023) mean of the credit volume granted by a bank b to a firm f . All control variables are the pre-period averages. Column (2) of Table 7 shows the results of the firm-level regressions (Eq. (7)), where the dependent variable is the first differences in logs of the pre-period and post-period mean of the credit volume of firm f . \overline{RR}_f is the reserve ratio at the firm level, which we calculate as the weighted average of the pre-period reserve ratio of each bank (which has a credit relationship to the firm). The weights are based on the pre-period credit of the firm with the corresponding bank (see Eq. (8)). We report t-statistics based on standard errors clustered at the bank and firm level (in column 1) and clustered at the industry-country level (in column 2) in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level respectively.

	(1)	(2)
	Bank-firm-level	Firm-level
RR	0.0109** (2.91)	
\overline{RR}		0.0068*** (2.92)
Bias corrected \overline{RR}		0.0042
adj. R2	.04256	.01962
N	1,015,495	373,845
Controls	Yes	Yes
Firm Fixed Effects	Yes	-
Industry-Country Fixed Effects	-	Yes

Table 8: Bank Heterogeneity - Credit Volume

Table 8 shows the result for the fixed-effects panel regression in equation (1) executed on the bank-firm-level. We use the logarithm of credit volume to non-financial corporations f by bank b in month t as outcome variable. Column (1) displays the baseline effect from Table 5. In Columns (2) to (4) we add additional bank-level variables to examine differential effects for large banks (top 5th percentile), banks with low equity ratios (bottom decile), and banks with low fixed to variable loan ratios (bottom quartile), respectively. $DFR_t \geq 0$ is a dummy variable for the period from the first rate hike and RR is the continuous bank-level reserve ratio during the pre-period, which is standardized such that the coefficient captures a one-standard deviation increase from the mean. All regressions include bank-level control variables interacted with the DFR dummy and country-time, bank-firm as well as firm-time fixed effects. The sample period is January 2022 to February 2023. We report t-statistics based on standard errors clustered at the bank-time level in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level respectively.

	(1) Baseline	(2) Bank Size	(3) Equity	(4) Fixed-to-total
$(DFR_t \geq 0) \times RR$	0.0128*** (7.57)	0.0185*** (11.19)	0.0135*** (5.52)	0.0095*** (4.69)
$(DFR_t \geq 0) \times$ Large bank		-0.2250*** (-3.02)		
$(DFR_t \geq 0) \times RR \times$ Large bank		-0.0578*** (-5.10)		
$(DFR_t \geq 0) \times$ Low Equity			-0.0050 (-0.20)	
$(DFR_t \geq 0) \times RR \times$ Low Equity			0.0111** (2.55)	
$(DFR_t \geq 0) \times$ Low Fixed-to-total Loans				-0.0196 (-0.70)
$(DFR_t \geq 0) \times RR \times$ Low Fixed-to-total Loans				0.0175*** (4.55)
adj. R2	.9753	.9753	.9753	.9753
N	14,062,930	14,062,930	14,062,930	14,062,930
Controls	Yes	Yes	Yes	Yes
Country (bank)-Time Fixed Effects	Yes	Yes	Yes	Yes
Bank-Firm Fixed Effects	Yes	Yes	Yes	Yes
Firm-Time Fixed Effects	Yes	Yes	Yes	Yes

Table 9: Borrower Characteristics - Credit Volume

Table 9 shows the result for the fixed-effects panel regression in equation (1) executed on the bank-firm-level. We use the logarithm of credit volume to non-financial corporations f by bank b in month t as outcome variable. Panel A differentiates by firm size: in Column (1) we examine micro enterprises, in column (2) small enterprises, in column (3) medium enterprises, and in column (4) large enterprises. Panel B differentiates by industry, focusing on the major industries, namely Manufacturing (NACE code K), Construction (NACE F), Trade (NACE G), and Information (NACE J). Lastly, panel C uses a credit risk proxy based on whether (i) a firm has a PD in the top decile of the distribution or (ii) whether the firm had any credit volume in arrears during the pre-period. $DFR_t \geq 0$ is a dummy variable for the period from the first rate hike and RR is the continuous bank-level reserve ratio during the pre-period, which is standardized such that the coefficient captures a one-standard deviation increase from the mean. All regressions include bank-level control variables interacted with the DFR dummy and country-time, bank-firm as well as firm-time fixed effects. The sample period is January 2022 to February 2023. We report t-statistics based on standard errors clustered at the bank-time level in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level respectively.

Panel A: Borrower Size				
	(1)	(2)	(3)	(4)
	Micro	Small	Medium	Large
$(DFR_t \geq 0) \times RR$	0.0073*** (3.23)	0.0206*** (8.18)	0.0186*** (7.57)	0.0099*** (6.68)
adj. R2	.973	.9567	.9607	.9756
N	1,298,483	2,063,478	4,744,448	5,412,478
Controls	Yes	Yes	Yes	Yes
Country (bank)-Time Fixed Effects	Yes	Yes	Yes	Yes
Bank-Firm Fixed Effects	Yes	Yes	Yes	Yes
Firm-Fixed Effects	Yes	Yes	Yes	Yes

Panel B: Borrower Industry				
	(1)	(2)	(3)	(4)
	Manufacturing	Construction	Trade	Information
$(DFR_t \geq 0) \times RR$	0.0211*** (7.34)	0.0170*** (5.99)	0.0158*** (6.04)	0.0023 (1.60)
adj. R2	.9656	.9634	.9728	.9875
N	3,148,100	3,321,470	1,494,115	2,091,341
Controls	Yes	Yes	Yes	Yes
Country (bank)-Time Fixed Effects	Yes	Yes	Yes	Yes
Bank-Firm Fixed Effects	Yes	Yes	Yes	Yes
Firm-Time Fixed Effects	Yes	Yes	Yes	Yes

Panel C: Borrower Quality				
	(1)	(2)	(3)	(4)
	Probability of Default (PD)		Arrears	
	High	Low	Yes	No
$(DFR_t \geq 0) \times RR$	0.0025 (1.12)	0.0141*** (7.98)	0.0081*** (3.22)	0.0136*** (8.15)
adj. R2	.9782	.9743	.9801	.9742
N	1,218,148	12,844,782	2,043,266	12,019,664
Controls	Yes	Yes	Yes	Yes
Country (bank)-Time Fixed Effects	Yes	Yes	Yes	Yes
Bank-Firm Fixed Effects	Yes	Yes	Yes	Yes
Firm-Time Fixed Effects	Yes	Yes	Yes	Yes

Internet Appendix

A Additional Figures and Tables

Figure IA.1: Reserve Ratio - ($DFR_t < 0$) vs. ($DFR_t \geq 0$)

Figure IA.1 shows the average bank-level reserve ratios before and after the first rate hike. Due to data confidentiality requirements, we are unable to present statistics for individual banks and therefore produced a binscatter-plot with 20 bins. The x-axis (y-axis) shows the average reserve ratio during the pre-(post-)period.

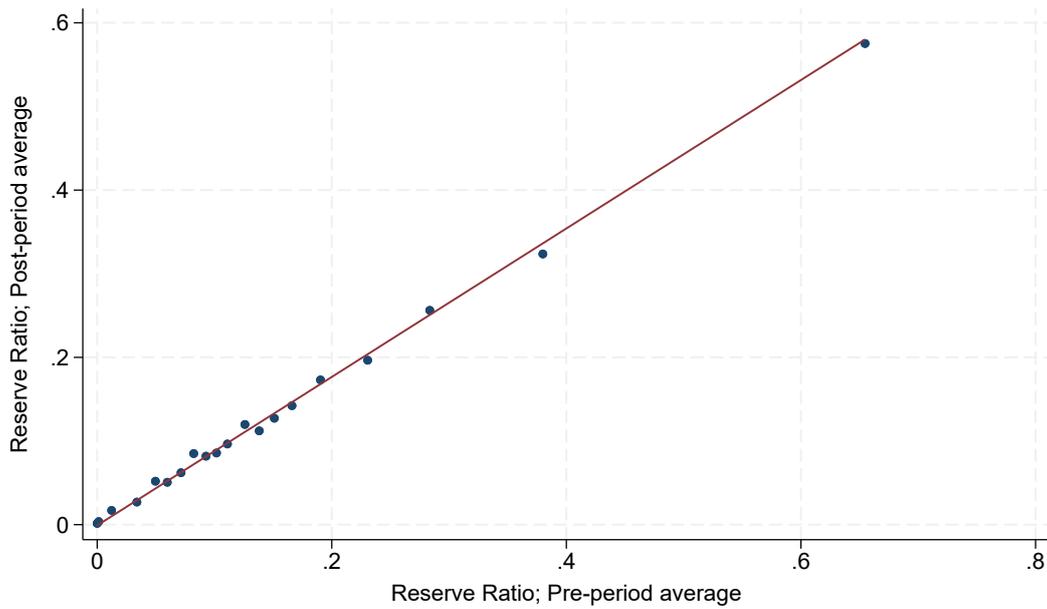


Figure IA.2: Robustness: Aggregate Credit Volumes from IBSI

Figure IA.2 shows the evolution of the aggregate credit volumes (indexed, May 2022 = 100) from IBSI for banks with reserve ratios above one standard deviation from the mean (red) and for all other banks (blue). For the sake of reference, we also show the aggregate time series across all banks (black). Note: the IBSI credit volumes include lending to private households, whereas Figure 5 in the main text is based on AnaCredit data, which only includes lending to non-financials.

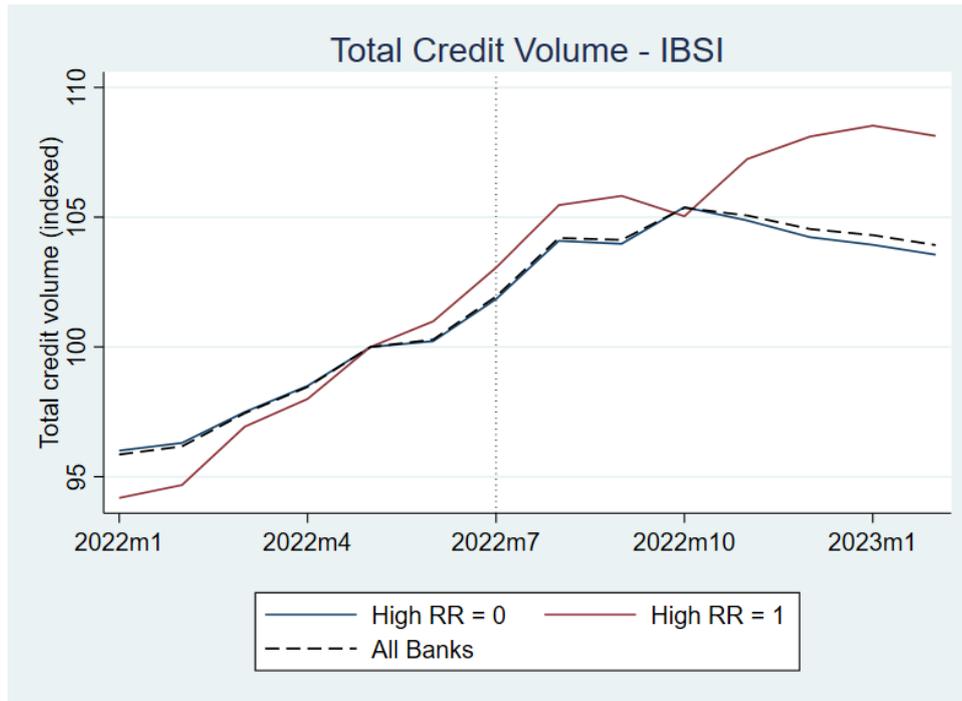


Table IA.1: Sample Composition

Table IA.1 shows details on the composition of the sample banks by country.

Country		High RR	
		= 0	= 1
AT	27	24	3
BE	12	12	0
CY	3	0	3
DE	208	188	20
EE	4	3	1
ES	21	21	0
FI	11	8	3
FR	66	53	13
GR	4	4	0
IE	12	9	3
IT	52	51	1
LT	3	2	1
LU	23	20	3
NL	11	11	0
PT	8	8	0
SK	7	7	0
Total	472	421	51

Table IA.2: Robustness: Baseline Regressions - Credit Volume (Clustering)

Table IA.2 shows the result for the fixed-effects panel regression in equation (1) executed on the bank-firm-level. We use the logarithm of credit volume to non-financial corporations f by bank b in month t as outcome variable. We focus on our main specification from Table 5, namely column (4), for the multi-bank sample. Our baseline setup is based on t-statistics for standard errors clustered at the bank-time level. Here we report results for alternative clustering approaches. $DFR_t \geq 0$ is a dummy variable for the period from the first rate hike and RR is the continuous bank-level reserve ratio during the pre-period, which is standardized such that the coefficient captures a one-standard deviation increase from the mean. All regressions include bank-level control variables interacted with the DFR dummy and country-time (both location of the bank and firm), and bank-firm fixed effects. The sample period is January 2022 to February 2023. *, **, and *** indicate significance at the 10%, 5%, and 1% level respectively.

	(1)	(2)	(3)	(4)
S.e. clustering	Bank-time	Bank	Time	Bank, time
$(DFR_t \geq 0) \times RR$	0.0128*** (7.57)	0.0128*** (3.47)	0.0128*** (5.83)	0.0128*** (3.74)
adj. R2	.9753	.9738	.9738	.9738
N	14,062,930	14,062,930	14,062,930	14,062,930
Controls	Yes	Yes	Yes	Yes
Country (bank)-Time FE	Yes	Yes	Yes	Yes
Bank-Firm Fixed Effects	Yes	Yes	Yes	Yes
Firm-Time Fixed Effects	Yes	Yes	Yes	Yes

Table IA.3: Cross-Sectional Characteristics - Matched Sample (High RR)

Table IA.3 shows the results of a cross-sectional regression of the continuous reserve ratio (column (1)) and the High RR dummy (columns (2)-(4)) on several normalized bank characteristics for a matched sample. The bank-level characteristics are calculated as averages during the pre-period and then normalized to have zero mean and unit standard deviation. Column (2) shows the results from a linear probability model (LPM). Columns (3) and (4) show results from Logit/Probit regressions, respectively. We report t-statistics based on robust standard errors in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level respectively.

Dep. var.:	(1)	(2)	(3)	(4)
	RR _b OLS	LPM	High RR _b Logit	Probit
log(Total Assets)	-0.1149 (-0.83)	-0.0458 (-0.75)	-0.1862 (-0.76)	-0.1163 (-0.75)
Equity Ratio	-0.0353 (-0.38)	0.0086 (0.21)	0.0345 (0.21)	0.0215 (0.21)
Deposit Ratio	-0.0250 (-0.14)	0.0690 (0.84)	0.2816 (0.84)	0.1721 (0.86)
Bonds Held Ratio	-0.1137 (-0.60)	-0.0542 (-0.62)	-0.2208 (-0.63)	-0.1348 (-0.63)
Fixed to total loans Ratio	-0.1089 (-0.61)	0.0024 (0.04)	0.0090 (0.04)	0.0069 (0.05)
adj. R2	-.04465		-.04597	
χ^2			1.253	1.301
p-value			>.90	>.90
N	84	84	84	84

Table IA.4: Matched Sample (High RR) - Credit Volume

Table IA.4 shows the result for the fixed-effects panel regression in equation (1), but using the much smaller matched bank sample from Table IA.3. All regressions include bank-level control variables interacted with the *DFR* dummy and country-time (both location of the bank and firm), and bank-firm fixed effects. The sample period is January 2022 to February 2023. We report t-statistics based on standard errors clustered at the bank-time level in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level respectively.

	(1)	(2)
(DFR _t ≥ 0) x RR	0.0131*** (5.69)	0.0172*** (6.94)
adj. R2	.9808	.9826
N	616,994	616,994
Controls	Yes	Yes
Country (bank)-Time FE	Yes	Yes
Country (firm)-Time FE	Yes	-
Bank-Firm Fixed Effects	Yes	Yes
Firm-Time Fixed Effects	No	Yes

Table IA.5: Deposits

Table IA.5 shows the result for the fixed-effects panel regression executed on the bank-level panel dataset. We use the total deposits (in logs) of bank b in month t as the outcome variable. RR is the continuous bank-level reserve ratio during the pre-period and standardized such that the coefficient captures a one-standard deviation increase from the mean. All regressions include bank-level control variables interacted with the DFR dummy, country-time fixed effects and bank fixed effects. The sample period is January 2022 to February 2023. We report t-statistics based on standard errors clustered at the bank level in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level respectively.

	(1)	(2)
	log(Total Deposits)	
$(DFR_t \geq 0) \times RR$	0.0047 (0.46)	
$(DFR_t \geq 0) \times \text{High } RR$		0.0567 (1.21)
adj. R2	.9953	.9953
N	5,179	5,179
Controls	Yes	Yes
Country-Time FE	Yes	Yes
Bank FE	Yes	Yes

Table IA.6: Borrower Quality - Triple Interaction

Table IA.6 shows the result for the fixed-effects panel regression executed on the bank-firm-level. We use the logarithm of credit volume to non-financial corporations f by bank b in month t as outcome variable. RR is the continuous bank-level reserve ratio during the pre-period and standardized such that the coefficient captures a one-standard deviation increase from the mean. The reported regressions correspond to Panel C of Table 9 and include triple interaction terms for High PD firms (column 1) and firms with credit in arrears (column 2, respectively). All regressions include bank-level control variables interacted with the DFR dummy, country-time, bank-firm fixed effects, and firm-time fixed effects. The sample period is January 2022 to February 2023. We report t-statistics based on standard errors clustered at the bank-time level in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level respectively.

	(1) PD	(2) Arrears
$(DFR_t \geq 0) \times RR$	0.0141*** (7.98)	0.0136*** (8.19)
$(DFR_t \geq 0) \times RR \times \text{High PD}$	-0.0116*** (-6.19)	
$(DFR_t \geq 0) \times RR \times \text{Arrears}$		-0.0055*** (-2.68)
adj. R2	.9747	.9752
N	14,062,930	14,062,930
Controls	Yes	Yes
Country-Time Fixed Effects	Yes	Yes
Bank-Firm Fixed Effects	Yes	Yes
Firm-Time Fixed Effects	Yes	Yes

Table IA.7: Loan Rates

Table IA.7 shows the result for the fixed-effects panel regression executed on the bank-firm-level, using the value-weighted loan rates of bank b with firm f in month t as the outcome variable. RR is the continuous bank-level reserve ratio during the pre-period and standardized such that the coefficient captures a one-standard deviation increase from the mean. Column (1) shows the results for the full sample, columns (2) and (3) differentiate between firms with High and Low PDs (as in Table 9), respectively. Column (4) is based on the full sample and includes a triple interaction term with the High PD dummy. All regressions include bank-level control variables interacted with the DFR dummy, country-time, bank-firm fixed effects, and firm-time fixed effects. The sample period is January 2022 to February 2023. We report t-statistics based on standard errors clustered at the bank-time level in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level respectively.

	(1)	(2)	(3)	(4)
	Baseline	Loan rate (in percent)		Interaction
		High PD	Low PD	
$(DFR_t \geq 0) \times RR$	0.0337* (1.84)	0.0636*** (2.88)	0.0328* (1.80)	0.0342* (1.87)
$(DFR_t \geq 0) \times RR \times \text{High PD}$				0.0119* (1.93)
adj. R2	.8976	.9087	.8875	.8919
N	14,062,930	1,218,148	12,844,782	14,062,930
Controls	Yes	Yes	Yes	Yes
Country-Time Fixed Effects	Yes	Yes	Yes	Yes
Bank-Firm Fixed Effects	Yes	Yes	Yes	Yes
Firm-Time Fixed Effects	Yes	Yes	Yes	Yes

B Deposit Passthrough in the Cross-Section

Figure 3 in the main text indicates that euro area banks did not fully pass on the rate hikes to their depositors. Here we present supplementary evidence that the deposit passthrough does not appear to be a function of banks' reserve ratios.

To analyse the deposit rate passthrough in the cross-section of banks, we draw on bank-level deposit rates for the subsample of banks reporting to iMIR.¹ Focusing on the different deposit rates from Figure 3, now at the bank-time level, we compute:

$$\text{Deposit } \beta_b = 100 \times \frac{\Delta \text{DepositRate}_b}{\Delta \text{DFR}}, \quad (\text{IA.1})$$

where Δ denotes the total change between June 2022 and February 2023. (The results are robust to using shorter windows, e.g., up until December 2022 or January 2023.) The deposit β in Eq. (IA.1) quantifies how much of the change in the DFR is reflected in changes in different deposit rates. A complete passthrough would correspond to a value of 100%.

Table IA.8 shows the results from a simple cross-sectional regression of Deposit β_b on the continuous reserve ratio (Panel A) and on the High RR dummy (Panel B), with t-statistics based on heteroscedasticity robust standard errors in parentheses. In this setup, the intercept shows the average passthrough across the different deposit rates for banks with a reserve ratio equal to the sample mean and the coefficients on the RR or the High RR dummy display the differential in the passthrough across banks with different reserve ratios. Column (1) shows that, when we look at banks' aggregate (overnight and time) deposits from both households and non-financials, there is no significant difference in the deposit β along banks' reserve ratios. Columns (2) to (4) further separate between the different categories and, in line with the aggregate statistics in Figure 3, we find that the passthrough is stronger (i) for time deposits compared to overnight deposits² and (ii) for deposits of non-financials compared to households. Regarding our main variable of interest, however, we find no evidence that the passthrough is a function of banks' reserve ratios, since all coefficients on RR are insignificant in Panel A. Only

¹More information is available in [guideline \(EU\) 2017/148](#). The iMIR-subsample covers roughly 82% of our sample banks' total assets.

²As noted in the Introduction, the positive income effect could be offset via the deposit channel of monetary policy. In this case, we would expect that the weak deposit passthrough would induce depositors to switch to alternative money-like instruments (e.g., short-term bonds or money market funds). The empirical evidence, however, does not suggest that euro area banks faced large deposit outflows due to the rate hike ([ECB SDW](#)). Rather, in line with their stronger passthrough, there was a shift from overnight to time deposits.

for High RR banks we find a weaker passthrough for non-financial time deposits, but this effect is not large enough to significantly affect the total deposit β in the cross-section. Overall, the fact that deposit betas are generally far from 100 percent leaves room for the increased reserve remuneration being a relevant feature for reserve-rich banks' net worth.

Table IA.8: Deposit Passthrough

Table IA.8 shows the results of a simple cross-sectional regression of the deposit β in Eq. (IA.1) on the continuous reserve ratio (Panel A) and on the High RR dummy (Panel B). *RR* is the continuous bank-level reserve ratio during the pre-period, which is standardized such that the coefficient captures a one-standard deviation increase from the mean. The High RR dummy takes a value of 1 for banks with reserve ratios above one standard deviation from the mean during the pre-period. The deposit β quantifies how much of the change in the DFR is reflected in changes in different deposit rates, where the Δ is the total change between June 2022 and February 2023. A complete passthrough would correspond to a value of 100%. We report t-statistics based on robust standard errors in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level respectively.

Panel A: RR	(1)	(2)	(3)	(4)	(5)
	Total deposits	Overnight deposits		Time deposits	
		Non-Financials	Households	Non-Financials	Households
RR	2.0125 (0.97)	2.8987 (1.26)	1.0190 (0.67)	-4.9080 (-1.33)	1.8435 (0.61)
Constant	14.5521*** (10.12)	11.0227*** (8.00)	6.5829*** (6.08)	45.6957*** (18.97)	20.6141*** (10.73)
adj. R2	.0057	.01235	.0026	.01267	.00293
N	138	138	138	138	138

Panel B: High RR	(1)	(2)	(3)	(4)	(5)
	Total deposits	Overnight deposits		Time deposits	
		Non-Financials	Households	Non-Financials	Households
High RR	-3.1058 (-0.84)	0.0257 (0.01)	-0.5841 (-0.16)	-19.2561** (-2.41)	-2.7311 (-0.46)
Constant	15.1056*** (9.44)	11.3636*** (7.45)	6.7629*** (5.75)	47.0677*** (18.82)	21.1096*** (10.50)
adj. R2	.0029	0.000	.0001	.04217	.00139
N	138	138	138	138	138