# Excess Reserves and Monetary Policy Tightening*

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**Abstract**

We show that large excess reserves affect monetary policy transmission. Specifically, the net worth of reserve-rich banks may increase when the interest rate paid on excess reserves increases strongly. Focusing on the European Central Bank's 2022 rate hiking cycle, we show that banks with larger excess reserves display a relative increase in their credit supply following the rate hike. The effect is stronger for smaller banks and for banks with lower ex-ante equity ratios and mainly directed towards smaller firms and firms with higher credit quality.

**JEL Classification**: E43, E44, E52, G21

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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 and increased their policy rates. While it is well understood that monetary policy tightening induces a contraction in credit supply (Bernanke and Blinder 1992; Jiménez, Ongena, Peydró, and Saurina 2012), this rate hiking cycle may be different. This is due to the various quantitative easing (QE) policies that were implemented since the global financial crisis of 2008/09, which led to an expansion of central bank balance sheets and to the adoption of abundant reserve regimes.[1] In this paper we show that monetary policy transmission can be affected when central bank reserves are ample and their remuneration rate is the (implicit) key policy rate.

The idea is simple: When central banks increase their key policy rate materially (e.g., in the presence of an inflation shock), the net worth of reserve-rich banks can increase. This is because, when banks do not pass on the rate hike to their depositors, an increase in the remuneration of reserve holdings leads to an increase in interest rate margins. Therefore, reserve-rich banks may not have to contract their credit supply as strongly as other banks, at least in the short-term.[2] Hence, as expressed by the governor of the Banque de France, large (excess) reserves could weaken the transmission of monetary policy.

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 become less effective. As shown in Figure 1, the second half of 2022 was unique in that both conditions were met simultaneously in the euro area. Specifically, at the end of 2022, total reserves held by euro area banks amounted to an

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

[2] The 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.

unprecedented value of EUR 4.6 trillion - or 12% of their total assets.[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] This rapid interest rate hike in the euro area serves as the perfect laboratory to study the role of excess reserves in monetary policy transmission.

Our empirical framework compares lending by euro area banks with different ex-ante reserve ratios before and after the start of the interest rate hiking cycle in July 2022. Our identifying assumption is that, absent the rate hike, lending of banks with a lower reserve ratio provides a good counterfactual for lending of banks with a higher reserve ratio. 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 mainly 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 as banks choose their borrowers and vice versa, we also include bank-firm fixed effects in our regressions.

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.[5] 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.

[3]For the sake of reference, total reserves stood at EUR 0.12 trillion in early 2008 - or 0.75% of their total assets - and consisted almost exclusively of required reserves.

[4]Under the conservative assumption that the interest rate is not further increased and that the level of reserves is reduced by the maturing TLTRO-III credit operations, this amounts to total interest payments of approximately EUR 114 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).

[5]This is noteworthy since the existing literature on monetary policy and bank lending typically relied on credit registers for single (euro area) countries, which made it more challenging to assess the external validity of the empirical findings.

Our main finding is that there are statistically and economically significant differences in credit supply for banks with higher reserve ratios. On average, increasing the reserve ratio by one standard deviation increases banks' credit supply to non-financial firms by 0.84% after Juny 2022. Based on the total outstanding pre-period credit volume of banks in the upper quartile of the reserve ratios, this credit supply effect corresponds to 0.31% of euro area GDP in 2022. The effect on credit supply is stronger for smaller banks and for banks with lower equity ratios, which is reasonable given that these 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 smaller firms, consistent with small firms being more opaque than large firms, relying more on bank funding and, consequently, being more affected by shocks propagated 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. We also show that the rate hike, which eventually led to the positive remuneration of excess reserves, differentially affected banks' stock market performance. In particular, banks with higher reserve ratios displayed significantly higher (risk-adjusted) stock returns in the period after the first rate hike. This pattern is in line with more affected banks displaying an increase in net worth, both in relative and absolute terms. Lastly, we document that the rate hike was only partially passed on to bank deposit rates and 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, that is 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, we show that our main coefficient estimates are likely biased downwards. This is because these estimates tend to be *smaller* when we exclude our (time-varying) control variables.

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 reduction 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 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.

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 (where income gap is defined as 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 an increasingly important asset, namely 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 the zero lower bond, 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 our focus on monetary policy transmission in abundant reserve systems, whereas Gomez et al. (2021) focus on a sample period that captures a period of scarce reserves.

In principle, the positive income effect could be offset via the deposit channel of monetary policy. In particular, in the setup of Drechsler, Savov, and Schnabl (2017), banks widen the spreads they charge on deposits 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. So far, however, the empirical evidence does not suggest that euro area banks faced large deposit outflows due to the rate hike (see ECB).[6] Rather, depositors substituted from overnight deposits to time deposits for which the passthrough was substantially stronger.

Bank-based monetary policy transmission also 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' assets (e.g., a negative effect on bond prices) more strongly than their liabilities, thus reducing banks' net worth and leading to a contraction of credit supply. As such, our setting could in principle also be viewed as an analysis of the balance sheet channel in a (de facto) floor system with ample reserves.[7] When banks target a specific leverage ratio (Adrian and Shin 2010), this increase in net worth can, at least in relative terms, affect banks' credit supply and risk-taking when banks want to restore their *optimal* balance sheet composition.

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 an 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.

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 in a system with

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

[7]Our paper is also linked to the theoretical banking literature that studies monetary policy transmission in a model with central bank reserves or risk-free bonds (Koenig and Schliephake 2023; Martin, McAndrews, and Skeie 2016).

ample central bank reserves. Overall, we find a dampening effect on monetary policy transmission, which is ultimately related to the preceding large expansion of reserves during QE. As such, our paper documents side effects of unconventional monetary policy.

Lastly, our paper also contributes to the literature that studies the recent tightening of monetary policy. Acharya, Chauhan, Rajan, and Steffen (2023) and Lopez-Salido and Vissing-Jorgensen (2023) analyze the effects of quantitative tightening (QT) by the Federal Reserve. Both papers 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 the increase on the interest rate on reserves 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. When policy transmission is weakened due to the remuneration of large excess reserve holdings, this 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).

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. 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).[8] 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 set by the Eurosystem and depends crucially on its refinancing and open market operations. Put differently, individual

[8] Besides 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 withdrawable and therefore matter for banks' liquidity coverage ratios (LCR).

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 with demand for 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 shock on 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 ECB (green line). Over the last decade, the vast majority of these reserves were in excess of banks' minimum reserve requirements at the ECB (blue line).[9] 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. The reason for these increases were multiple 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 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 EUR 2 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 EUR 4.7 trillion in June 2022.[10]

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. This creates an interest

[9]Note 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.

[10]The 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 EUR 15 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.

rate corridor for money markets. Due to the large amounts of 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.[11]

In combination with the various QE measures described above, the DFR was gradually lowered to -0.5% by September 2019.[12] To contain the high inflation rates in the euro area due to skyrocketing energy prices, supply shortages, and the reopening of the economy after the pandemic lockdown, 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 2 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.

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 test for the effect of large excess reserves on the transmission of monetary policy.

[11] Prior to the currency union, European central banks generally did not remunerate reserve holdings. The Fed started remunerating reserves only in 2008.

[12] To 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.

## 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) increase their lending to non-financial firms more strongly compared to banks with lower RRs in the period after the hike of the interest on reserves.*

***Hypothesis 2:*** *The effect should be stronger for more constrained banks.*

These constraints could, for example, be related to bank size and banks capital ratios.

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

$$log(credit_{b,f,t}) = \beta \times (\mathrm{RR}_b) \times (\mathrm{DFR}_t \geq 0) + \mathbf{X}'_{b,t}\gamma + \alpha_{f,t} + \alpha_{b,f} + \alpha_{c,t} + u_{b,f,t}, \quad (1)$$

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 $\beta$, the interaction term between banks' average pre-period reserve ratios ($\mathrm{RR}_b$) and ($\mathrm{DFR}_t \geq 0$), a dummy that equals 1 from July 2022 onwards when the ECB's started the rate hike. Hence, $\beta$ gauges the differential lending effect due to the ECB's monetary policy tightening as a function of banks' reserve ratios. 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 $\mathrm{RR}_b$ dummy, which takes the value of 1 for banks above the 75th percentile of the pre-period RR, and zero otherwise.[13]

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), retail 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 impor-

[13] We should highlight that, while High RR banks display slightly larger minimum reserve requirements compared to other banks (0.6% versus 0.4% of total assets in June 2022), the difference is much more pronounced for the total reserve ratios that we use in the calculation of the High RR dummy (22.2% versus 6.7%). Hence, in line with Figure 1, the High RR classification is exclusively due to banks' holdings of excess reserves.

tant 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 retail 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 data sets 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 euro area, including their foreign branches, are required to report loan-by-loan data. Banks report loans to corporations and other legal entities (thus, 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).[14]

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.[15] To ensure that our results are not driven by very small credit institutions, we only keep banks with total assets of at least 5 billion EUR.

[14]More information is provided in the AnaCredit manual.

[15]For more information please refer to EU Regulation 2021/379.

We also obtain data on deposit rates from the individual interest rate statistics (iMIR), which are available for a subsample of 103 sample banks.[16] Lastly, for the subsample of 38 listed banks, we obtain daily stock prices from Refinitive-Eikon.[17]

Our final sample consists of a panel of 483 banks and 3,315,611 borrowing firms (494,749 in the multiple bank sample) 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. 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 therefore end our sample in February 2023.

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 (25.7% versus 6.2%). Moreover, they are larger compared to control banks (log(total assets) of 10.32 versus 9.69, respectively). They have a somewhat lower equity ratio (7.1% versus 8.6%), hold less household deposits (26% versus 38.4%) and hold slightly less fixed income securities on their balance sheet (7.6% versus 8.6%). High RR banks have fewer loans with a fixed loan rate as opposed to a variable loan rate (42.7% versus 57.8%). Focusing on cross-sectional differences during the pre-period (DFR $< 0$), Table 2 shows that banks with larger reserve ratios tend to be larger, display fewer retail deposits and fewer fixed rate loans.[18]

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.[19] Our identification strategy could be impaired, however, 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; Grosse-Rueschkamp, Steffen, and Streitz 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

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

[17] The subsample of listed banks covers roughly 36% of our sample banks' total assets.

[18] We also analyzed a matched sample of High RR and control banks. See Tables IA.1 and IA.2 in the Internet Appendix for details.

[19] Note that the included bank-firm fixed effects absorb any time-invariant differences between banks.

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). Lastly, in section 4 we 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. We start by establishing that banks only pass on higher policy rates to depositors to a very limited extend. Such a hampered deposit passthrough is a crucial prerequiste for increased reserve remuneration to affect net worth in the first place. In a second step, we examine the stock market reactions of reserve-rich banks relative to other banks around the start of the tightening cycle. To the extend 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. Finally, we move to the analysis of banks' credit supply. Our key result is that reserve-rich banks increase their lending relative to other banks once the ECB started to increase its policy rate. We view this finding as evidence for a weakening of the monetary transmission process when an increase in reserve remuneration comes along a regime of abundant reserves.

## 4.1 Deposit Passthrough and Net Worth

Before turning to our results on credit supply, we first analyze 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. An important ingredient for reserve remuneration to have a meaningful effect on net worth is that the rate hike is not completely passed on to bank depositors.

We therefore begin with an analysis of the deposit rate passthrough across banks. For this purpose, we draw on bank-level deposit rates for a subsample of 103 banks reporting to iMIR.

Focusing on the different deposit rates displayed in Figure 2, now at the bank-time level, we compute:

$$\text{Deposit } \beta_b = 100 \times \frac{\Delta DepositRate_b}{\Delta DFR}, \quad (2)$$

where $\Delta$ denotes the total change between June 2022 and February 2023.[20] The deposit $\beta$ in Eq. (2) 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 3 shows the results from a simple cross-sectional regression of Deposit $\beta_b$ 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. In line with the aggregate statistics in Figure 2, we find that the passthrough is stronger (i) for time deposits compared to overnight deposits[21] and (ii) for deposits of non-financials compared to households. Regarding our main variable of interest, however, we find little evidence that the passthrough is a function of banks' reserve ratios, since all coefficients on RR are insignificant in Panel A. Only for High RR banks we find a moderately stronger passthrough for non-financial overnight deposits. While this stronger passthrough could potentially *weaken* the overall effect, 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.

We now turn to an analysis of banks' net worth, focusing on the subsample of listed banks' stock prices. To set the stage, Figure 3 shows the value-weighted stock price indices for the subsample of listed High RR banks (blue) and for listed control banks (black). Prior to the rate hike (vertical line) both groups' stock prices evolved very similarly, whereas High RR banks' stocks substantially outperformed during the period after the first rate hike.[22] Given that these

[20] The results are robust to using shorter windows, e.g., up until December 2022 or January 2023.

[21] As 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.

[22] One could argue that the rate hikes themselves have not been large enough surprises to explain the outperformance of reserve-rich banks over time. However, a gradual resolution of uncertainty regarding the remuneration of excess reserves might have been an important contributing factor to the outperformance. After all, adaptions 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 scheme has remained unchanged.

differences could potentially be driven by differential exposure to common risk factors and/or by bank characteristics, we now turn to a more formal analysis.

Following Altavilla et al. (2022), we first estimate daily risk-adjusted abnormal returns after the onset of monetary policy tightening for each bank:

$$
\begin{aligned}
(R_{b,t} - r_t^F) = & \alpha_b + \beta_b^{MKT} \times \text{MKT}_t + \beta_b^{HML} \times \text{HML}_t + \beta_b^{SMB} \times \text{SMB}_t \\
& + \beta_b^{RMW} \times \text{RMW}_t + \beta_b^{CMA} \times \text{CMA}_t + \lambda_b \times (DFR_t \geq 0) + \varepsilon_{b,t},
\end{aligned} \tag{3}
$$

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 $\lambda_b$ on the DFR dummy. In the second step, we run a cross-sectional regression to explain the estimated $\lambda_b$ coefficients:

$$
\lambda_b = \alpha + \beta \times RR_b + X_b' \gamma + u_b. \tag{4}
$$

Our coefficient of interest is $\beta$, 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, retail deposit ratio, equity ratio, and the ratio of fixed rate loans).

Table 4 reports the estimation results for both the three- and five-factor model using heteroscedasticity robust standard errors.[23] In line with the visual evidence in Figure 3, 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 in the reserve ratio increases banks' average daily abnormal returns by around 12 basis points, corresponding to a monthly difference of around 2 percentage points. Hence, interpreting the stock market

[23] We confirm that the results are robust to using bootstrapped standard errors.

valuation as a proxy for banks' net worth suggests that the rate hiking cycle indeed increased reserve-rich banks' net worth, both in absolute and relative terms.

### 4.2 Main Results

We now turn to our analysis of banks' credit supply and Table 5 reports the main estimation results. It shows coefficient estimates 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 banks and borrowers (and vice versa). 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 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 % significance level. Our preferred specification in column (4), given that it is the most stringent one, suggests that, after the beginning of the rate hike, increasing the reserve ratio by one standard deviation increases banks' credit supply to non-financial firms by 0.84%. The effect is also economically large: Based on the total outstanding pre-period credit volume of banks above the median of the reserve ratio an increase of 0.84% corresponds to a magnitude of 0.31% of euro area GDP in 2022. Overall, the evidence suggests a less effective monetary policy transmission for reserve-rich banks (*Hypothesis 1*).

**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):

$$log(credit_{b,t}) = \mathrm{RR}_b \cdot \sum_{k=0}^{T} \beta_k \cdot D_t + X_{b,t}^{'}\gamma + \alpha_b + u_{b,t}, \quad (5)$$

where $D_t$ is an indicator variable that equals one in quarter $t$, and zero otherwise, with the first quarter in 2022 serving as the baseline effect. We cluster standard errors at the bank level to allow for serial correlation across time. Figure 4 shows the results. Most importantly, prior to the first interest rate hike in July 2022, the interaction term is relatively small and not statistically significant. Afterwards the estimate increases and remains statistically significant throughout the remaining sample period. Hence, our results are robust to variations in the DFR dummy.

**Robustness.** A concern with our identification strategy could be that time-varying differences of bank characteristics could introduce a bias in our coefficient estimates. The possible 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 specification. Therefore, in columns (1) and (2) of Table 6 we show two specifications that are identical to or baseline 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, column (3) of Table 6 shows that our results remain robust to an alternative definition of the treatment effect, where *High RR* is a dummy variable equal to one for banks with a reserve ratio above the 75th percentile in the pre-period. In column (4) we show robustness to a further definition of the treatment variable, where *Rank RR* is a variable that gives the rank of the continuous bank-level reserve ratio standardized by the total number of banks. In both cases the coefficient estimates remains both statistically and economically significant. Lastly, column (5) shows that the effect is also robust to including the raw DFR instead of the DFR dummy.

Finally, as another robustness check we focus on a matched sample based on 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.1 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.2 in the Internet Appendix we report our main regressions on credit volumes from Table 5, but focusing on the matched sample. The results remain highly statistically and economically significant in the matched sample.

## 4.3 Bank Heterogeneity

*Hypothesis 2* is concerned with heterogeneity of the credit supply differential along certain bank characteristics. Table 7 shows the results. For the sake of reference, column (1) reports the main specification from Table 5. In column (2) we test whether the effect is stronger for small banks. As described above, small banks' lending is more dependent on monetary policy because it it harder for them to raise additional funding. We incorporate the indicator variable *Large bank*$_b$, 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 $\text{RR}_b$ in regression (1). As expected, the interaction term is negative and statistically significant at the 1% significance level. This means that the effect is smaller for large banks (and larger for small banks), in line with *Hypothesis 2*.

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

Column (4) shows that the effect does not differ for banks with high retail deposits. Lastly, column (5) shows that the effect is stronger for banks with 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.

## 4.4 Borrower Characteristics

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.[24] 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.[25] Panel A of Table 8 reports the results. The effect is positive and significant across all size categories, but is largest for small firms and smallest for large 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 8 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.

Lastly, another dimension of interest is borrower quality, where 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).[26] Panel C of Table 8 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. These results could be related to skin-in-the-game effects, similar to Heider et al. (2019).

# 5 Policy Implications

Our findings have important policy implications. The aim of contractionary monetary policy is to contain inflation and traditional bank-based channels of monetary policy work through a reduction of bank lending. We show that when reserves are ample, the transmission of contractionary monetary policy can be weakened for reserve-rich banks via the remuneration of reserves. This might countervail the aim to reduce inflation and results in a need for action by policymakers. Importantly, given that we find only minor differences in the minimum reserve

[24] See e.g. Gertler and Gilchrist (1994), Chodorow-Reich (2014), Khwaja and Mian (2008), Iyer et al. (2014).

[25] The classification follows the EU recommendation 2003/361/EC, where a micro/small/medium enterprise has less then 10/50/250 employees and the annual turnover and/or annual balance sheet total does not exceed EUR 2/10/50 million, respectively.

[26] 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.

requirements for banks with higher reserve ratios, banks' total reserve holdings indeed consist mainly of excess reserves.

Therefore, it may be worthwhile considering not paying the same interest on all central bank reserves to contain some of the documented side effects. This could be done in various ways, for example by way of increasing unremunerated minimum reserve requirements. Such two-tier systems for minimum reserve requirements were proposed by e.g. De Grauwe and Ji (2023). An 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. It should be noted that the Norges Bank introduced its quota system in October 2021 and the Swiss National Bank implemented its reverse tiering approach in September 2022.[27]

# 6 Conclusion

This paper documents that monetary policy transmission is affected by large (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 there are statistically and economically significant effects on credit supply for reserve-rich banks. In line with the basic idea that banks with large reserve holdings should display an increase in their net worth, we provide evidence that banks with higher reserve ratios also displayed higher abnormal stock returns after the onset of the rate hiking cycle. 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. We aim to tackle these questions in the future.

[27]See Norges Bank (2021) and Swiss National Bank (2022) for details. The SNB complemented its reverse tiering with a reserve absorption by way of open market operations.

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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.

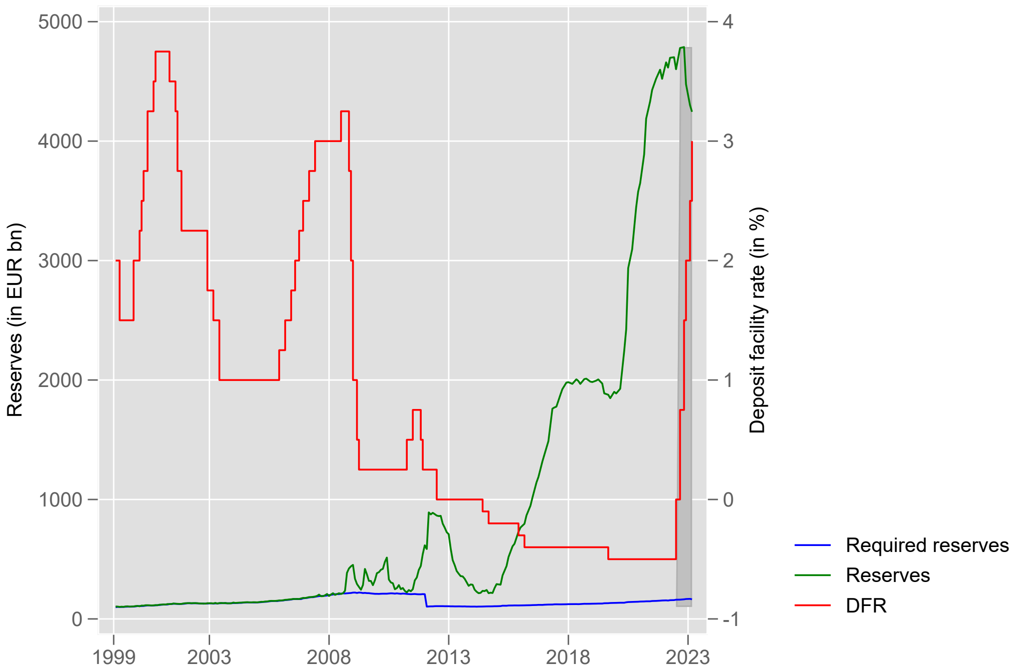


**Figure 2:** Deposit Rates in the Euro Area

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).

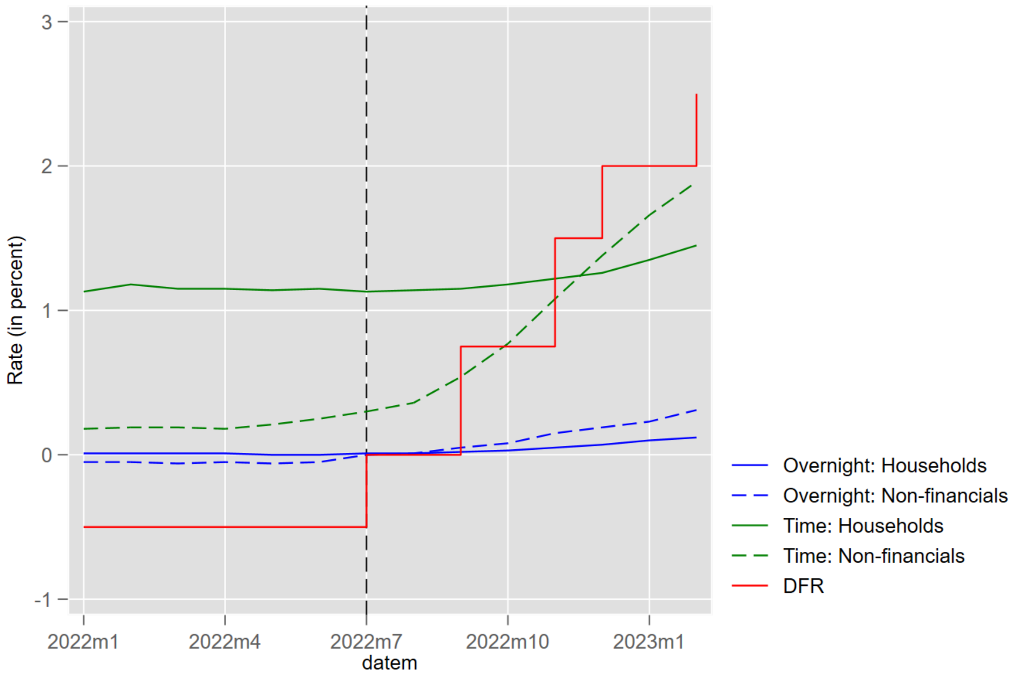


**Figure 3: Stock Price Dynamics**

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

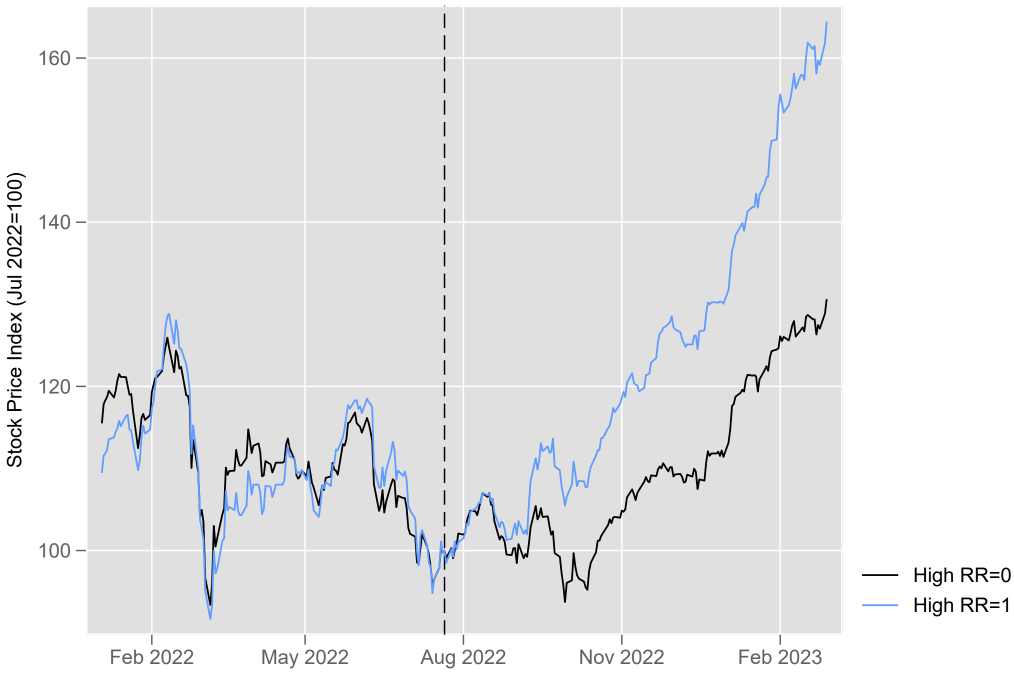
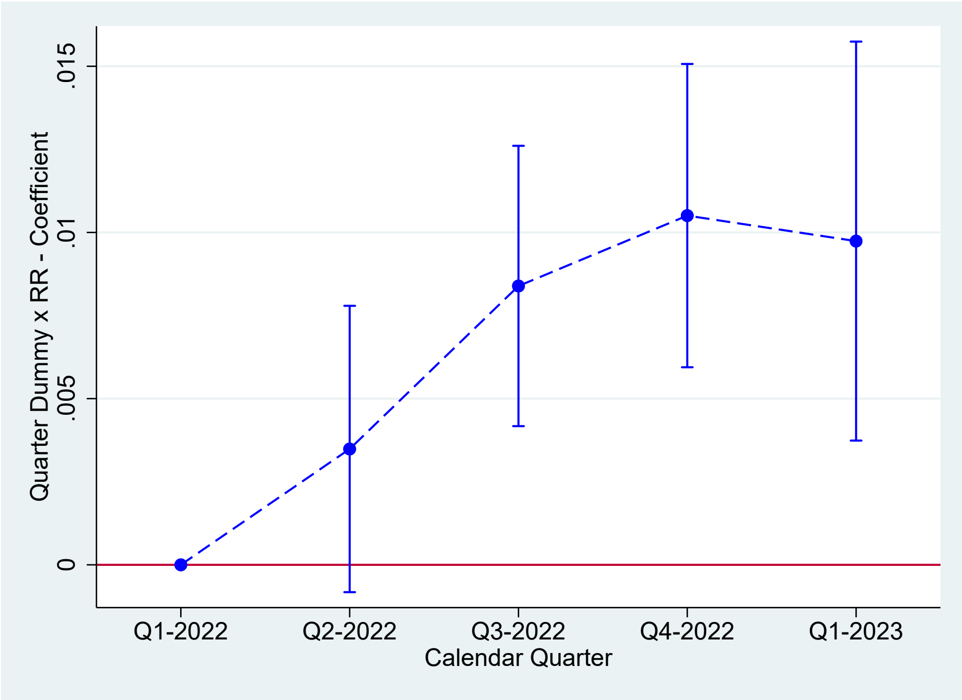


**Figure 4:** Timing of the Effect

Figure 4 shows the results for estimating equation (5) but where we replace the ($DFR_t \geq 0$) dummy with separate dummies for each sample quarter. We plot the differential effects relative to 2022-Q1 together with 90% confidence bands based on bank-level clustered standard errors.



## Table 1: Summary Statistics

Table 1 shows summary statistics or 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 (above the 75th percentile of the pre-period RR) and for low RR banks (below the 75th percentile of the pre-period RR).

**Panel A:** Summary Statistics (Full Sample)

| | Mean | Std. Dev. | p25 | p50 | p75 | Obs. |
|---|---|---|---|---|---|---|
| Bank-level Variables | | | | | | |
| log(total assets) | 9.847 | 1.234 | 8.856 | 9.552 | 10.502 | 6,568 |
| Equity Ratio | 0.082 | 0.043 | 0.053 | 0.082 | 0.103 | 6,568 |
| Retail Deposit Ratio | 0.353 | 0.239 | 0.112 | 0.385 | 0.558 | 6,568 |
| Reserve Ratio | 0.111 | 0.111 | 0.044 | 0.086 | 0.151 | 6,568 |
| Bonds held Ratio | 0.083 | 0.087 | 0.016 | 0.065 | 0.114 | 6,568 |
| Fixed to total loans Ratio | 0.541 | 0.320 | 0.241 | 0.616 | 0.809 | 6,568 |
| $DFR_t \geq 0$ | 0.570 | 0.495 | 0.000 | 1.000 | 1.000 | 6,568 |
| High RR | 0.250 | 0.433 | 0.000 | 0.000 | 1.000 | 6,568 |
| Large Bank | 0.053 | 0.223 | 0.000 | 0.000 | 0.000 | 6,568 |
| Low Equity Ratio | 0.245 | 0.430 | 0.000 | 0.000 | 0.000 | 6,568 |
| High Retail Deposit Ratio | 0.253 | 0.435 | 0.000 | 0.000 | 1.000 | 6,568 |
| Bank-firm-level Variables | | | | | | |
| log(credit) | 11.840 | 1.474 | 10.735 | 11.654 | 12.693 | 43,527,514 |

**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. |
| Bank-level Variables | | | | | | | | |
| log(Total Assets) | 9.688 | 1.170 | 9.288 | 4,924 | 10.324 | 1.294 | 10.078 | 1,644 |
| Equity Ratio | 0.086 | 0.040 | 0.087 | 4,924 | 0.071 | 0.049 | 0.061 | 1,644 |
| Retail Deposit Ratio | 0.384 | 0.240 | 0.442 | 4,924 | 0.260 | 0.211 | 0.242 | 1,644 |
| Reserve Ratio | 0.062 | 0.045 | 0.061 | 4,924 | 0.257 | 0.121 | 0.208 | 1,644 |
| Bonds held Ratio | 0.086 | 0.088 | 0.068 | 4,924 | 0.076 | 0.084 | 0.058 | 1,644 |
| Fixed to total loans Ratio | 0.578 | 0.312 | 0.664 | 4,924 | 0.427 | 0.316 | 0.376 | 1,644 |
| $DFR_t \geq 0$ | 0.570 | 0.495 | 1.000 | 4,924 | 0.571 | 0.495 | 1.000 | 1,644 |
| Large Bank | 0.042 | 0.201 | 0.000 | 4,924 | 0.085 | 0.278 | 0.000 | 1,644 |
| Low Equity Ratio | 0.194 | 0.395 | 0.000 | 4,924 | 0.400 | 0.490 | 0.000 | 1,644 |
| High Retail Deposit Ratio | 0.309 | 0.462 | 0.000 | 4,924 | 0.084 | 0.277 | 0.000 | 1,644 |
| Bank-firm-level Variables | | | | | | | | |
| 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.

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Dep. var.: | $RR_b$ | | High $RR_b$ | |
| | OLS | LPM | Logit | Probit |
| log(Total Assets) | 0.0764* | 0.0685*** | 0.3656*** | 0.2182*** |
| | (1.67) | (2.97) | (3.19) | (3.27) |
| Equity Ratio | -0.1140** | -0.0360 | -0.2103 | -0.1201 |
| | (-2.29) | (-1.51) | (-1.44) | (-1.57) |
| Retail Deposit Ratio | -0.0928* | -0.0557*** | -0.3359*** | -0.1978*** |
| | (-1.82) | (-2.65) | (-2.74) | (-2.75) |
| Bonds Held Ratio | -0.0176 | 0.0007 | -0.0033 | -0.0162 |
| | (-0.45) | (0.04) | (-0.03) | (-0.25) |
| Fixed to total loans Ratio | -0.2263*** | -0.0670*** | -0.3893*** | -0.2343*** |
| | (-4.37) | (-3.28) | (-3.47) | (-3.59) |
| adj. R2 | .09709 | .0982 | | |
| $\chi^2$ | | | 47.6 | 52.79 |
| p-value | | | <0.001 | <0.001 |
| N | 483 | 483 | 483 | 483 |

## Table 3: Deposit Passthrough Regressions

Table 3 shows the results of a simple cross-sectional regression of the deposit $\beta$ in Eq. (2) 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 size of the coefficient denotes a one-standard deviation increase. The deposit $\beta$ quantifies how much of the change in the DFR is reflected in changes in different deposit rates, where the $\Delta$ 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) |
|---|---|---|---|---|
| | Overnight deposit | | Time deposit | |
| | Non-Financials | Households | Non-Financials | Households |
| RR | 2.1617 | 0.1252 | -3.0610 | 1.8435 |
| | (0.86) | (0.13) | (-1.02) | (0.74) |
| Constant | 9.5612*** | 5.0722*** | 48.9675*** | 21.6519*** |
| | (7.44) | (5.35) | (18.32) | (9.39) |
| adj. R2 | .0149 | .0001 | .0076 | .0042 |
| N | 103 | 103 | 103 | 103 |

| **Panel B:** High RR | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Overnight deposit | | Time deposit | |
| | Non-Financials | Households | Non-Financials | Households |
| High RR | 6.3175** | 1.6388 | 2.9961 | 6.9493 |
| | (2.10) | (0.81) | (0.51) | (1.60) |
| Constant | 7.7593*** | 4.4859*** | 46.9974*** | 19.5238*** |
| | (5.98) | (4.18) | (16.02) | (7.21) |
| adj. R2 | .0515 | .0071 | .0029 | .0244 |
| N | 103 | 103 | 103 | 103 |

## Table 4: Average Daily Abnormal Returns

Table 4 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 size of the coefficient denotes a one-standard deviation increase. The estimation period ranges from January 2021 until February 2023. Bank controls include log total assets, bonds held ratio, retail 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 | 0.1282*** | 0.1180*** | 0.1276*** | 0.1176*** |
| | (3.07) | (2.90) | (3.09) | (2.92) |
| adj. R2 | .2174 | .4536 | .2137 | .4567 |
| N | 38 | 38 | 38 | 38 |
| Bank controls | No | Yes | No | Yes |

| **Panel B**: High RR | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | FF3 | | FF5 | |
| High RR | 0.1386*** | 0.0975* | 0.1397*** | 0.0985** |
| | (2.95) | (2.04) | (2.97) | (2.07) |
| adj. R2 | .1753 | .3382 | .1773 | .3452 |
| N | 38 | 38 | 38 | 38 |
| Bank controls | No | Yes | No | Yes |

**Table 5: Baseline Regressions - Credit Volume**

Table 5 shows the result for the fixed-effects panel regression described 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 size of the coefficient denotes a one-standard deviation increase. 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 | |
| ($DFR_t \geq 0$) x RR | 0.0049*** | 0.0050*** | 0.0079*** | 0.0084*** |
| | (5.01) | (5.29) | (5.05) | (5.67) |
| adj. R2 | .9772 | .9773 | .9744 | .9744 |
| N | 43,527,514 | 43,527,514 | 14,690,692 | 14,690,692 |
| 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 described 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) report results for the sample of firms that borrow from more than one bank. 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 size of the coefficient denotes a one-standard deviation increase. In column (3) the variable *High RR* is a dummy variable equal to one for banks with a reserve ratio above the 75th percentile in the pre-period. In column (4) *Rank RR* is a variable that gives the rank of the continuous bank-level reserve ratio standardized by the total number of banks. Column (5) 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.

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| | Excluding Controls | | Alternative RR definition | | Raw DFR |
| ($DFR_t \geq 0$) x RR | 0.0038** | 0.0049*** | | | |
| | (2.48) | (3.31) | | | |
| ($DFR_t \geq 0$) x High RR | | | 0.0139*** | | |
| | | | (4.32) | | |
| ($DFR_t \geq 0$) x Rank RR | | | | 0.0189*** | |
| | | | | (3.73) | |
| $DFR_t$ x RR | | | | | 0.0029*** |
| | | | | | (3.64) |
| adj. R2 | .974 | .9744 | .9744 | .9744 | .9744 |
| N | 14,690,692 | 14,690,692 | 14,690,692 | 14,690,692 | 14,690,692 |
| Controls | No | No | Yes | Yes | Yes |
| Country (bank)-Time FE | Yes | Yes | Yes | Yes | Yes |
| Country (firm)-Time FE | Yes | - | - | - | - |
| Bank-Firm Fixed Effects | Yes | Yes | Yes | Yes | Yes |
| Firm-Time Fixed Effects | No | Yes | Yes | Yes | Yes |

## Table 7: Bank Heterogeneity - Credit Volume

Table 7 shows the result for the fixed-effects panel regression described 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 (5) we add additional bank-level variables to examine differential effects for large banks (top 5th percentile), banks with low equity ratios (bottom quartile), banks with high retail deposit ratios (top quartile), 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 size of the coefficient denotes a one-standard deviation increase. 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) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| ($DFR_t \geq 0$) x RR | 0.0084*** | 0.0132*** | 0.0068** | 0.0073*** | 0.0068*** |
| | (5.67) | (9.60) | (2.44) | (4.67) | (3.74) |
| ($DFR_t \geq 0$) x Large bank | | 0.0400*** | | | |
| | | (7.54) | | | |
| ($DFR_t \geq 0$) x RR x Large bank | | -0.0317*** | | | |
| | | (-4.26) | | | |
| ($DFR_t \geq 0$) x Low Equity | | | -0.0179*** | | |
| | | | (-4.34) | | |
| ($DFR_t \geq 0$) x RR x Low Equity | | | 0.0062* | | |
| | | | (1.72) | | |
| ($DFR_t \geq 0$) x High Retail Deposit | | | | -0.0126*** | |
| | | | | (-2.72) | |
| ($DFR_t \geq 0$) x High RR x High Retail Deposit | | | | -0.0043 | |
| | | | | (-0.84) | |
| ($DFR_t \geq 0$) x Low Fixed-to-total Loans | | | | | 0.0001 |
| | | | | | (0.02) |
| ($DFR_t \geq 0$) x RR x Low Fixed-to-total Loans | | | | | 0.0108*** |
| | | | | | (3.38) |
| adj. R2 | .9744 | .9745 | .9744 | .9744 | .9744 |
| N | 14,690,692 | 14,690,692 | 14,690,692 | 14,690,692 | 14,690,692 |
| Controls | Yes | Yes | Yes | Yes | Yes |
| Country-Time Fixed Effects | Yes | Yes | Yes | Yes | Yes |
| Bank-Firm Fixed Effects | Yes | Yes | Yes | Yes | Yes |
| Firm-Time Fixed Effects | Yes | Yes | Yes | Yes | Yes |

## Table 8: Borrower Characteristics - Credit Volume

Table 8 shows the result for the fixed-effects panel regression described 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 size of the coefficient denotes a one-standard deviation increase.. 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 |
| ($DFR_t \geq 0$) x RR | 0.0069*** | 0.0135*** | 0.0092*** | 0.0051*** |
| | (3.88) | (6.00) | (4.48) | (3.74) |
| adj. R2 | .9733 | .9568 | .9602 | .9745 |
| N | 1,286,892 | 2,099,177 | 4,737,797 | 5,521,891 |
| Controls | Yes | Yes | Yes | Yes |
| Country-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 |
| ($DFR_t \geq 0$) x RR | 0.0135*** | 0.0114*** | 0.0048** | 0.0020* |
| | (5.80) | (4.81) | (2.00) | (1.79) |
| adj. R2 | .9656 | .9625 | .9712 | .987 |
| N | 3,227,300 | 3,516,479 | 1,577,246 | 2,133,114 |
| 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 |

| **Panel C**: Borrower Quality | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Probability of Default (PD) | | Arrears | |
| | High | Low | Yes | No |
| ($DFR_t \geq 0$) x RR | 0.0045** | 0.0099*** | 0.0060*** | 0.0100*** |
| | (2.38) | (6.72) | (2.71) | (7.15) |
| adj. R2 | .9767 | .9735 | .9766 | .9732 |
| N | 1,382,086 | 13,062,496 | 2,810,622 | 11,633,960 |
| 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 |

# Internet Appendix

# A Additional Figures and Tables

### Table IA.1: Cross-Sectional Characteristics - Matched Sample (High RR)

Table IA.1 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.

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Dep. var.: | $RR_b$ | | High $RR_b$ | |
| | OLS | LPM | Logit | Probit |
| log(Total Assets) | 0.0012 | -0.0012 | -0.0050 | -0.0030 |
| | (0.14) | (-0.03) | (-0.03) | (-0.03) |
| Equity Ratio | -0.0037 | -0.0093 | -0.0373 | -0.0233 |
| | (-0.50) | (-0.26) | (-0.26) | (-0.26) |
| Retail Deposit Ratio | -0.0107 | -0.0232 | -0.0930 | -0.0584 |
| | (-0.98) | (-0.54) | (-0.55) | (-0.55) |
| Bonds Held Ratio | 0.0025 | -0.0120 | -0.0482 | -0.0305 |
| | (0.26) | (-0.29) | (-0.29) | (-0.29) |
| Fixed to total loans Ratio | -0.0171 | 0.0079 | 0.0319 | 0.0201 |
| | (-1.42) | (0.19) | (0.20) | (0.20) |
| adj. R2 | -.00003 | -.02794 | | |
| $\chi^2$ | | | .5779 | .5748 |
| p-value | | | >0.95 | >0.95 |
| N | 483 | 483 | 483 | 483 |

## Table IA.2: Matched Sample (High RR) - Credit Volume

Table IA.2 shows the result for the fixed-effects panel regression described in equation (1) and reported column (3) in Table 6, but using the matched bank sample from Table IA.1. 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) |
|---|---|---|
| ($DFR_t \geq 0$) x High RR | 0.0176*** | 0.0216*** |
| | (4.29) | (5.23) |
| adj. R2 | .9735 | .9745 |
| N | 3,710,036 | 3,710,036 |
| 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 |

## 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. The dotted vertical line shows the cutoff for our High RR dummy.