Differential Effects of Unconventional Monetary Policy†

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June 19, 2023

Did the Eurosystem's quantitative easing from 2015 to 2018 have differential effects regarding the bank lending volume to different institutional sectors, industry sectors, or types of loans? To investigate this question, this paper employs linked microdata of the German banking system. These allow for computing the volume of bond redemptions at bank level as a measure of banks' exposure to QE. Because when a bond matures, the bank is faced with the decision of whether to reinvest the proceeds into bonds or whether to rebalance into another asset such as loans. When the central bank squeezes bond yields through large-scale purchases, banks with more redemptions have a stronger incentive to rebalance. However, a fixed effects model reveals no significant difference between banks with a high exposure compared to the control group regarding their overall loan growth. Neither can any of the mentioned differential effects be observed. While these findings are at odds with some of the previous empirical literature, they are in line with theories that argue that lending is purely demand-led and any central bank action geared towards the supply side of the loan market merely constitutes "pushing the string".

Keywords: Unconventional monetary policy, portfolio rebalance, differential effects, panel regression.
JEL classification: C23, E51, E52, G11, G21.

†I undertook the analyses of the micro data sets employed in this paper at the premises of the German Bundesbank Research Data and Service Center (RDSC) via on-site access under project number 2021/0045. I thank the team at the RDSC for their support.
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1. Introduction

Did the Eurosystem's quantitative easing (QE) from 2015 to 2018 have differential effects regarding the bank lending volume to different institutional sectors, industry sectors, or types of loans? This question deserves an answer for at least two reasons. First, so-called unconventional monetary policy (UMP)[1] measures like QE have become part of the normal monetary policy toolkit over the last decade and this demands a profound understanding of their effects. Second, it is already a well-established empirical phenomenon that *conventional* monetary policy can have differential – i.e. heterogeneous – effects across various industry sectors (Dominguez-Torres and Hierro 2019). Research on differential effects of *unconventional* monetary policy, however, is still very scarce.

This paper strives to reduce that scarcity, employing linked microdata of the German banking system. Specifically, I adress the following set of research questions. First, does QE incentivize banks to increase their lending to non-banks? Second, if yes, are there any noteworthy differences across institutional sectors (government, corporations, households, foreign sector), industry sectors (secondary vs. tertiary), or types of loans (mortgage vs. non-mortgage)?

These questions are motivated as follows. The differentiation across institutional sectors serves as a check of whether German banks simply substituted government bonds through government loans. The differentiation across industry sectors is the main research interest of this paper. Previous research has found manufacturing to be much more sensitive to monetary policy innovations than services. This is important because there are cross-regional distributional effects behind this as the economic structure differs across geographic regions. The South of Germany, for instance, has a much higher share of manufacturing than the North. If manufacturing is more sensitive to UMP, then the German South has profited more from QE than the North. From the differentiation across types of loans we can learn whether the APP has contributed to financial instability. Past empirical research has found that unconventional monetary policy pushes house prices (Huber and Punzi 2020; Hülsewig and Rottmann 2021) and financial crises are often centered around credit-driven house price booms.[2] In the wake of the global financial crisis (GFC), financial stability has been made an explicit goal of the ECB, so it needs to know if its own monetary policies run contrary to that goal.[3]

[1]Unconventional monetary policy is usually referred to as all actions by the central bank that increase its balance sheet size at a given central bank interest rate. In the context of this paper it refers to the asset purchase program (APP) the Eurosystem ran between 2015 and 2018.

[2]Sufi and Taylor (2021) provide an overview over the financial crises literature.

[3]Borio et al. (2021) present a formal model on how monetary policy might counteract to financial stability.

I use a rich set of microdata provided by the German Bundesbank. The centerpiece is the monthly balance sheet statistics, which collects detailed data on balance sheet items of all German banks. It can be linked with the securities holding statistics, in which all German banks report their securities holdings by ISIN. The centralized securities database contributes further details on individual ISIN positions. Finally, the quarterly borrower statistic adds in-depth information on the industry structure of banks' loan portfolio. My final dataset is a balanced panel of almost 1,400 banks representing more than 90% of aggregate total assets of the German banking system. It covers the years 2011 to 2018 at quarterly frequency and 2013 to 2018 at monthly frequency.

To the best of my knowledge, this paper is the first to exploit microdata to analyze differential effects of unconventional monetary policy. Most of the previous literature on unconventional monetary policy makes use of macroeconomic (aggregate) data, and none of those studies examining microdata, like Paludkiewicz (2021) or Tischer (2018), investigate differential effects. The use of aggregate data, however, might be problematic in at least two interrelated ways. First, it might be rather difficult to clearly identify the treatment shock. Second, the short observation periods and low data frequency might make it difficult to properly estimate the multivariate time-series models that are usually applied. Microdata arguably allow for a better identification as the exposure to monetary policy measures can be observed and potential confounding factors be controlled for at the level of individual banks. The limited length of the observation period, in turn, can be compensated by the massively increased number of observations: rather than a two-digit number of countries or regions the data set contains thousands of banks.

Central bank measures affect the economy through a multitude of channels. Cecchetti (1995) and Mishkin (1996) provide overviews over the "traditional" or "conventional" channels of monetary policy transmission under the money view and the credit (or lending) view. Of importance for unconventional policies analyzed in this paper is the so-called portfolio rebalancing channel (Vayanos and Vila 2021). It states that if the central bank increases the prices and hence squeezes the returns of bonds via large-scale purchases, banks holding those bonds will then re-balance into other assets – like corporate loans – in an effort to maintain the overall yield of their asset portfolio (*search for yield*). If this channel does indeed work, one would expect to observe a positive correlation between the amount of reinvestment decisions a bank faces through maturing securities (called redemptions) and the size of its loan growth and this correlation should increase in periods where QE squeezes long-term assets' returns. The advantage of using maturing bonds as a proxy for QE exposure is that they were pre-determined – unlike bond sales which the bank can always undertake.

In order to evaluate my research questions, I run fixed effects regressions inspired by Tischer (2018). The dependent variable is loan growth, the main explanatory variable are redemptions, i.e. the volume of maturing bonds. Control variables include the securities trade position, deposits, wholesale funding, equity, interbank claims, and central bank liquidity, as well as the growth of total assets. Time dummies control for time-fixed effects.

Following Tischer (2018), I first check whether there is a relationship between redemptions and loan growth during the QE period (2015 to 2018) at all. Then I move on to investigate whether this relationship has changed as compared to the pre-QE period (2011 to 2014) by adding an interaction term between redemptions and a QE-period dummy. Finally, I take a broader approach by cumulating redemptions over 2015 to 2018 for each bank and then computing a variable which indicates in which quartile of the cumulated redemption a bank is. I then regress loan growth on an interaction term between this indicator variable and time dummies and the controls mentioned above. The idea behind this third specification is twofold. On the one hand, it provides a robustness check against the possibility that banks simply shift the granting of loans they would have granted anyway to months in which they have sufficient liquidity through maturing bonds in order to be able to conduct the payouts. On the other hand, this approach reveals time dynamics more clearly.

I also undertake two robustness checks. First, I use redemptions of only those assets which already were in banks' portfolio in January 2014, long before QE was launched, to further ensure exogeneity. Second, assuming that loan demand varies more across rather than within industry sectors, I use bank-industry sector pairs as panels rather than banks to control for demand.

Which results would we expect? As mentioned above, previous research finds that manufacturing industries are usually more sensitive to monetary policy changes. This is explained by the higher capital-intensity of their production function resulting in a higher need for external finance. This is, by itself, a demand-side effect. However, banks facing a higher exposure to QE through maturing bonds can be expected to be more aggressive in their supply of loans and the actual granting of a loan happens where lender supply and borrower demand coincide. If the portfolio rebalancing channel described above works as expected, we should be able to observe a strong shift in lending towards non-financial corporations and households after 2014 and this shift should be the stronger the more redemptions a bank has. If there are differential effects like those already known for conventional monetary policy, the bulk of this additional loan growth should be directed to manufacturing industries.

Which results do we observe? I find a mediocre relationship between redemptions and loan growth during the QE period: one additional Euro in redemptions is associated with eleven cents of additional loan growth. This pattern, however, almost completely disappears once controls for securities trade enter the regression: then, one Euro in redemptions is only associated with three cents of loan growth and the conventional levels of statistical significance are no longer reached. My monthly panel regression with the interaction term between redemptions and the QE-period dummy shows no effect of QE on loan growth. This is confirmed by the third specification: there is no economically or statistically significant change in the relationship between redemptions and loan growth after the start of QE. Also, I find no noteworthy differential effects across any of the dimensions stated above.

Which conclusions can we draw from these observations? While I fail to unveil evidence for the functioning of the portfolio rebalancing channel in the German banking system, this is merely one of multiple channels through which monetary policy can affect the economy. So my results should not be interpreted as proof for a non-effect of quantitative easing. In fact, failing to find supply side mechanism like portfolio rebalancing to be at work is perfectly in line with theories that stress the demand side of the loan market, like Post-Keynesian theorists do: Lavoie (2015), ch. 3, esp. pp. 226-230, and Lavoie and Fiebiger (2018).

The paper is structured as follows. Section 2 elaborates on the theoretical foundations. Section 3 reviews the literature on differential effects of monetary policy. Section 4 explains the econometric strategy applied to answer the research question and section 5 presents the microdata used to conduct this analysis. Section 6 contains the results. Section 8 concludes.

2. The Portfolio Rebalancing Channel of Monetary Policy

The theoretical foundation of the effectiveness of quantitative easing goes back at least to two papers: Modigliani and Sutch (1966) and Tobin (1969). Eggertsson and Woodford (2003) and Vayanos and Vila (2021) provide newer and more formal representations of earlier works. In Tobin's (1969) analytical framework, the private sectors hold a portfolio of various assets. The specific composition of this portfolio depends on the vector of interest rates of assets, which are imperfect substitutes. Usually, the increase in supply of an asset is accompanied by an increase in the interest rate of that asset to make sure that market demand shows a corresponding increase to absorb that supply. In other words, the demand for a particular asset is a function of that asset's own interest rate. Arbitrage will then make sure that the interest rates of other assets will also increase, though probably not as strongly as those of the initially affected asset. Put together, a change in supply of a particular asset will lead to a rate hike both in absolute terms and relative to other assets. An exception is money for which the interest rate is fixed (at zero). Hence, money's own interest rate in absolute terms cannot adapt if there is a supply increase. So an increase in private sector holdings of that additional supply of money via an increase in its *relative* interest rate can only happen through a *decrease* in the *absolute* rates of other assets. Tobin's (1969) model provides the theoretical grounding for why QE can be expected to have an effect on interest rates at all.

Modigliani and Sutch (1966) introduce what they call the Preferred Habitat Model of the yield structure. Key to this is the assumption that individual borrowers and lenders have strong preferences for specific maturities of their assets and liabilities. If those individuals are risk-averse, then holding instruments with diverging maturities will be unfavorable due to uncertainty regarding the yield that can be acquired over the investment horizon. Investing into assets with maturities shorter than the investment horizon will expose the investor to interest rate risk when they have to roll over. Maturities longer than the investment horizon require selling the asset before maturity which might have to be done at unfavorable prices. One real-world example might be German mortgage lenders: The average house buyer in Germany is around 40 years old and assuming that he/she wants to pay down their debt until they retire in the mid- to end-sixties results in a preferred habitat of 25 to 30 years for their mortgage loan.

Vayanos and Vila (2021) present a much more elaborate and formalized version of the Preferred Habitat Model of the term structure. This theory provides an explanation for why banks can be expected to increase their lending towards the non-bank sector under quantitative easing: As the central bank squeezes the yields of long-term bonds, banks which want to maintain their maturity structure (and overall yield) of their asset portfolio have an incentive to rebalance into other assets with comparable maturities, like corporate or mortgage loans. Boermans and Vermeulen (2018) empirically estimate Euro Area investors' bond demand function, particularly their demand for PSPP-eligible bonds. They find that it has not changed after the program was launched, providing empirical backing for the preferred habitat model.

Famously, Eggertsson and Woodford (2003) derive an irrelevance result of central bank asset purchases on long-term interest rates. This is because in their New-Keynesian model, long-term rates are determined by agents' saving and investment decisions. The only way through which QE can influence long-term rates is by changing agents' expectations on future short-term rates. So while Eggertsson and Woodford's (2003) model rejects the idea of a portfolio rebalancing channel, it stresses the role of the signaling or expectations channel of quantitative easing. Since I do not test the latter two, I do not delve into details on their functioning.

The usual explanation for the differential effects of monetary policy often observed empirically is that manufacturing industries are more capital-intense and hence need a higher share of external finance (see section 3). This results in a higher interest rate elasticity of their borrowing demand. This is the classic interest rate channel of monetary policy. Now what I investigate in this paper is the supply side of the loan market: Do banks which are exposed more strongly to quantitative easing increase their lending compared to banks which are exposed not so strongly? What allows me to observe differential effects – if they materialize – anyhow is the peculiarity of the loan market as opposed to the goods market: Output cannot be bigger than demand. A car manufacturer can actually produce cars for which there eventually is no demand. However, a bank cannot grant a loan for which there is no demand. Every credited loan was necessarily also demanded by the borrower. If a bank wants to increase its lending it must convince future debtors to increase their borrowing and the most simple way to do so is to offer lower interest rates on loans. Consequently, if a stronger exposure to QE triggers additional lending that additional lending also reflects increased loan demand and if there are differential effects we must observe a shift in QE-exposed banks' loan portfolio towards certain industry sectors or certain types of loans.

3. Related Literature

There is a broad literature on the differential effects of *conventional* monetary policies. Empirical research on this topic goes back at least to the 1990s when it gained attention in lieu of the formation of the Economic and Monetary Union (EMU) in Europe. Dominguez-Torres and Hierro (2019) provide a recent survey. Details on individual studies can be found in appendix A. The takeaway from that literature important for this paper is that regional differences in economic structure are often identified as cause of differential effects and that manufacturing is generally found to be more sensitive to monetary policy innovations than services sectors.

In comparison, research on the differential effects of *unconventional* monetary policy is still rather scarce. Gambacorta et al. (2014) and Peersman (2011), for instance, have taken the euro area as aggregate as the object of study. Boeckx et al. (2017), Burriel and Galesi (2016), Grandi (2019), and Lewis and Roth (2022) zoom in on the country level, but not on the industry level. Boeckx et al. (2017) investigate country-specific effects of the Eurosystem's UMP measures between 2007 and 2014, finding that prices react very similarly across EA economies, whereas output reactions are very heterogeneous and positively correlated with the degree of capitalization of the banking sector. Burriel and Galesi (2016)'s investigation ranges from 2007 to 2015 and goes beyond the scope of Boeckx et al. (2017) by explicitly taking spillover-effects between individual EA members into consideration which they find to be of significant size. Besides that, they again confirm a generally beneficial effect of UMP on output and prices (as well as on equity prices and credit). The cross-country heterogeneity in output reaction to UMP shocks which they find, is primarily explained through to differences in economic structure and bank capitalization. In line with these results, Grandi (2019) identifies differences in banks' exposure to critical government bonds as a source of non-uniform effects of both conventional and unconventional monetary policies. Euro Area banks holding more bonds from countries under macroeconomic stress are more reluctant to increase their lending in case of a monetary policy relaxation.

Lewis and Roth (2022) specifically compare the euro area aggregate and the German economy in their reaction to the APP. Importantly, they fail to find any evidence for the portfolio rebalancing channel to be at work in Germany. Asset purchases neither impact bank lending rates nor lending growth. This is at odds with the finding of Paludkiewicz (2021) and Tischer (2018) (see below).

The only study available so far, to the best of my knowledge, that looks at the output effects of UMP at the industry level is Goto (2020). This paper compares the differential effect of unconventional monetary policies to different industry sectors in Japan, the US, and the UK. The author observes differences not only across industries within the same economy, but also within the same industry across economies. The main explanatory factor for those differences is working capital: the higher it is, the weaker is a particular industry's reaction to the UMP stimulus.

There are two papers which address my first research question for part of the duration of the APP. Both use the same German microdata than I do. Paludkiewicz (2021) takes individual banks' securities portfolio from January 2014 and then computes the evolution of the portfolio yield from January 2014 to June 2015 under the assumption that the portfolio composition remains unchanged. He then uses this portfolio yield evolution as a proxy for how strong a bank is exposed to the monetary policy shock, finding a positive correlation between yield decline on the one hand and loan growth to the real sector and reduction in securities holdings on the other hand. Additionally, there is a positive interaction effect between the yield decline and the share of maturing assets in the benchmark portfolio. This is not surprising as the bank is exposed to the yield decline only when an asset matures and the proceeds need to be reinvested. What Paludkiewicz (2021) does *not* discover is a rebalancing into other securities or any robust evidence that bank capital has any influence on the described effects. This is likely because the German yield curve was already very depressed during the observation period and German banks were overall well capitalized. Those results are in line with those of Albertazzi et al. (2018).

An alternative approach is undertaken by Tischer (2018). This author uses the amount of maturing bonds in individual banks' bond portfolio in a particular month as proxy for the banks' exposure to the UMP shock in that month; see section 4 for details. Indeed, his regressions show that the loan growth of banks with higher redemptions increased after the APP was launched compared to banks with lower redemptions. The effect is stronger for higher spreads between bond yields and loan interest rates and also particularly pronounced for banks with low equity. The latter finding is contrary to that of Paludkiewicz (2021).

What I intend to add to these findings is an insight into whether the portfolio rebalancing which has been found by Paludkiewicz (2021) and Tischer (2018) in the German banking system also contained any of the differential effects outlined in section 1. Like Tischer (2018) I use redemptions as a proxy for an individual bank's exposure to QE, though I extend his approach in order to account for time dynamics. The details on methodology are presented in the next section.

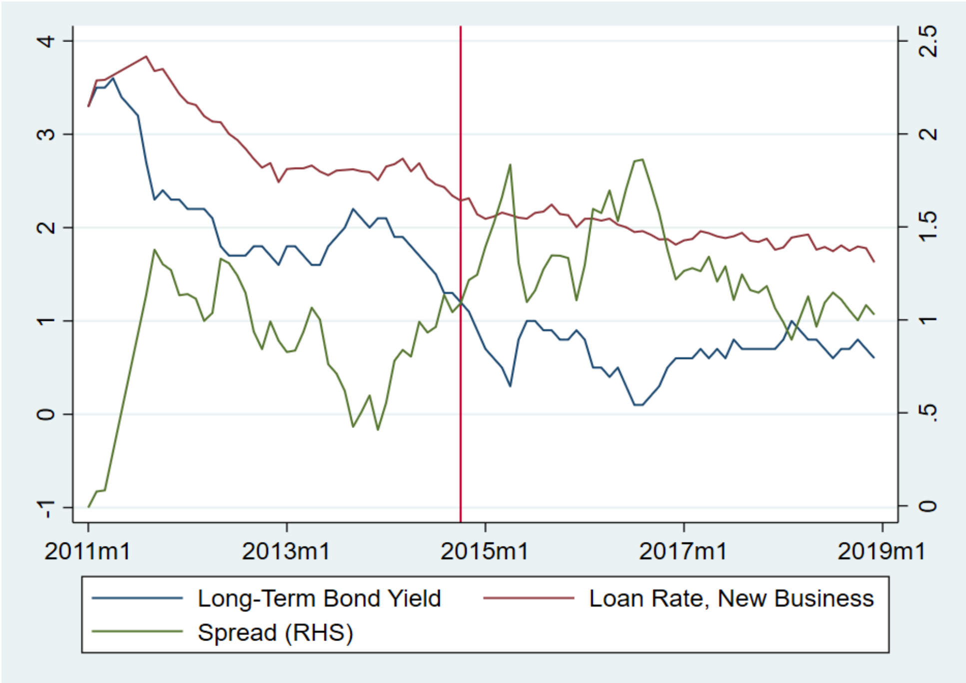
A possible problem with the approaches of Paludkiewicz (2021) and Tischer (2018) is that most of the decline in German bond yields during the observation period happened *before* the APP was announced and implemented, see figure 1. Paludkiewicz (2021) himself provides evidence that media reports about an imminent QE program started to show up from the end of March 2014 and argues that investors might have moved into bonds, driving up prices and anticipating the effect. The decline in bond yields, however, already began in late 2013 and then yields entered a sideways movement after the PSPP implementation in March 2015. In fact, the study by Boeckx et al. (2017) cited above does not find any impact of the APP on German bond yields.

4. Econometric Strategy

The econometric strategy will follow a two-step approach. First, I investigate the effect of asset purchases on the overall lending behavior of German banks. Second, I investigate whether this change shows any differences across institutional sectors, industry sectors, or types of loans.

To measure banks' exposure to quantitative easing, I follow the approach of Tischer (2018) and compute the level of maturing bonds at the bank level. Figure 2 provides

Figure 1: Bond Yields and Interest Rates in Germany



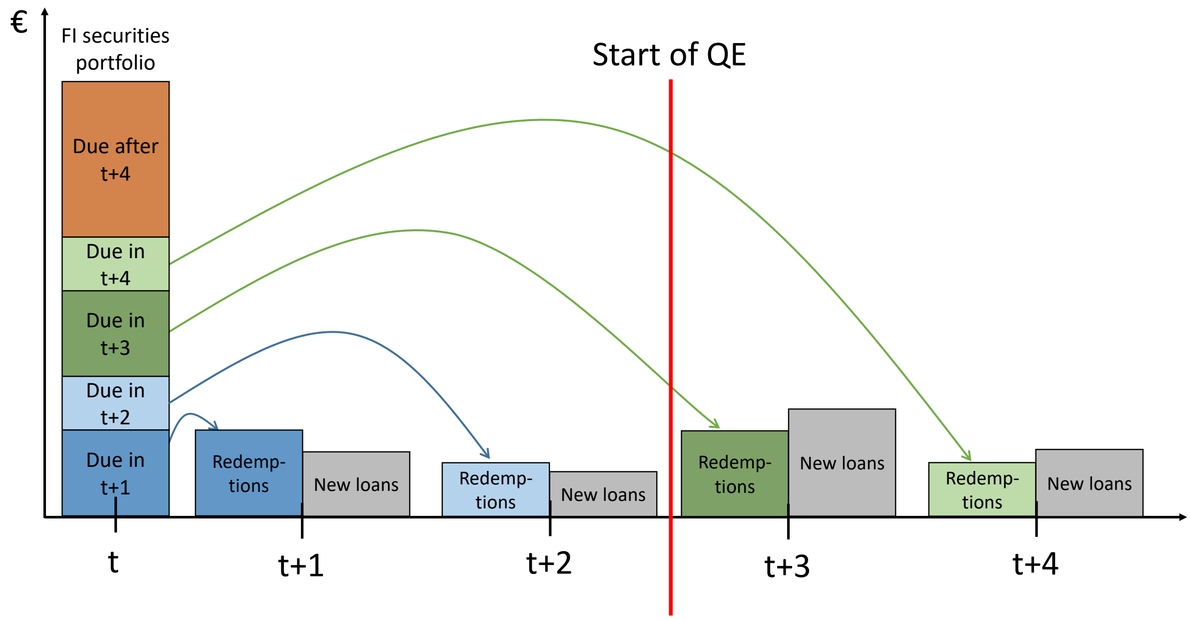
The figure shows the yield of German domestic bonds with a residual maturity of at least seven years and the interest rate on newly issued loans by German banks, retrieved from the Bundesbank's public database. The vertical line indicates the start of the APP. Source: Deutsche Bundesbank.

a schematic depiction. The reasoning is as follows. If a bond matures, the bank faces the decision of whether to re-invest the liquidity in bonds or to re-balance into other long-running assets like corporate loans; this is called the portfolio rebalancing channel of monetary policy described in section 2.[4] If this channel is at work, one should observe a stronger loan growth for banks with a higher level of redemptions compared to banks with a lower volume of maturing bonds, all else equal. The advantage of this measure as opposed to using bond sales is that redemptions can be considered exogenous because they are predetermined. Particularly in a liquid market like government bonds, banks can always sell their assets to obtain reserves if they have lending opportunities coming up and this is even more true under a monetary policy regime in which the central bank is undertaking large-scale asset purchases. This makes it difficult to tell whether sales drive lending or vice versa. Now it is certainly possible that banks try to gauge the maturity structure of their securities portfolio so that it matches their liquidity needs from loan payouts. This, though, seems feasible only in the shorter run, but not over longer periods

[4]Technically, banks can increase their book loans by simply extending their balance sheet (Bundesbank 2017; McLeay et al. 2014). However, central bank liquidity is probably the least profitable asset class, so having more of it in their balance sheet presents a strong incentive to acquire further yield-generating assets. Additionally, more loans will tend to be followed by increased payouts which constitute an outflow of central bank money.

of time because it seems unlikely that a bank has exact knowledge about its liquidity needs several years ahead. I will later conduct robustness checks by using only redemptions of bonds that banks held before QE, but for the start I simply use redemptions over all bonds, irrespective of when they entered a bank's books.

Figure 2: Redemptions and loan growth



The maturity structure of the fixed-income securities portfolio held in t determines the volume of redemptions in periods $t+1$ through $t+4$. If the central bank squeezes bond yields under quantitative easing, banks should increase the loan growth rather than reinvesting the proceeds of maturing bonds into new bonds.

My basic approach to the first part of my empirical inquiry is to adopt the method of Tischer (2018) and extend the sample period to the entire duration of the APP.[5] The first step is to unveil the relationship between redemptions and loan growth during the APP period. Hence, my first regression equation is as follows:

$$\text{LoanGrowth}_{\text{it}} = \alpha_i + \alpha_t + \beta_1 * \text{Redemptions}_{it} + \boldsymbol{\gamma'} * \mathbf{A}_{\boldsymbol{it}} + \boldsymbol{\delta'} * \mathbf{B}_{\boldsymbol{i,t-1}} + u_{it} \qquad (1)$$

In words, I regress the change in lending of bank i to non-banks between period t and $t-1$ on bank and time fixed effects (α_i, α_t) and redemptions. All variables are normalized

[5]Tischer's (2018) sample ends in September 2016.

by total assets in the previous period, i.e. the dependent variables is defined as:

$$\text{LoanGrowth}_{\text{it}} = \frac{\Delta\text{Lending}_{it}}{\text{TA}_{i,t-1}} \tag{2}$$

Redemptions are the sum of all individual bonds j held by bank i maturing in t, again as a share of total assets in the previous period:

$$\text{Redemptions}_{it} = \sum_{j \in maturing\ in\ t} \frac{\text{Holding amount}_{jit}}{\text{TA}_{i,t-1}} \tag{3}$$

Vector **A** captures net purchases and net sales of non-maturing assets:

$$\text{Net purchases}_{it} = \begin{cases} \dfrac{\text{purchases}_{it} - \text{sales}_{it}}{\text{TA}_{i,t-1}} & \text{if} \quad \text{purchases}_{it} > \text{sales}_{it} \\ 0 & \text{otherwise} \end{cases} \tag{4}$$

$$\text{Net sales}_{it} = \begin{cases} \dfrac{\text{sales}_{it} - \text{purchases}_{it}}{\text{TA}_{i,t-1}} & \text{if} \quad \text{sales}_{it} > \text{purchases}_{it} \\ 0 & \text{otherwise} \end{cases} \tag{5}$$

Both sales and purchases are measured in nominal values, not market values, for two reasons. First, all other variables are also in nominal terms. Second, only changes in nominal values capture actual purchases and sales as changes in the market value could also stem from price movements. Vector **B** includes the following set of control variables, predetermined in period $t-1$:

$$\frac{\text{deposits}_{i,t-1}}{\text{TA}_{i,t-1}}, \qquad \frac{\text{wholesale funding}_{i,t-1}}{\text{TA}_{i,t-1}}, \qquad \frac{\text{equity}_{i,t-1}}{\text{TA}_{i,t-1}}$$

$$\frac{\text{interbank claims}_{i,t-1}}{\text{TA}_{i,t-1}}, \qquad \frac{\text{central bank liquidity}_{i,t-1}}{\text{TA}_{i,t-1}}$$

$$\frac{\Delta\text{TA}_{\text{it}}}{\text{TA}_{i,t-1}}$$

While the variables in the first line control for the bank's capital position and financing structure and those in the second line for its liquidity position, the one in the third line (change in total assets since the previous period) is necessary to filter out possible secular trends in overall asset growth because $\text{TA}_{i,t-1}$ appears on both sides of the regression equation. The decisive question here is whether the coefficient β_1 in equation 1 is of meaningful size.

The next step is to investigate whether QE has influenced the behavior of banks. This can be tested by the following dummy regression:

$$\begin{aligned} \mathrm{LoanGrowth_{it}} =& \alpha_i + \alpha_t + \beta_1 * \mathrm{Redemptions}_{it} + \beta_2 * \mathrm{Redemptions}_{it} * \mathrm{QE_t} \\ & + \beta_3 * \mathrm{Redemptions}_{it} * \mathrm{LowEquity}_{i,t-1} \\ & + \beta_4 * \mathrm{Redemptions}_{it} * \mathrm{LowEquity}_{i,t-1} * \mathrm{QE_t} \\ & + \mathrm{QE_t} + \boldsymbol{\gamma'} * \mathbf{A_{it}} + \boldsymbol{\delta'} * \mathbf{B_{i,t-1}} + u_{it} \end{aligned} \tag{6}$$

QE_t and $\mathrm{LowEquity}_{i,t-1}$ are dummy variables. The former is equal to 1 from October 2014 on, the latter is 1 if the bank's equity ratio is below its within-bank sample mean. In this specification, the coefficients of interest are β_2 and β_4 as they show whether the relationship between redemptions and loan growth changed after 2014.

At first glance, it might be thorny to put both redemptions and net purchases in the regression as they must be considered to be highly correlated: A bank purchases many new bonds when it has many redemptions (roll-over). To test this, I computed the Pearson correlation coefficient ρ between to two variables for each bank in the sample. The average across all banks in the monthly dataset is 0.13 and 0.21 in the quarterly dataset. When only considering bonds from the ECB's Eligible Assets Database (EADB), the average ρ is 0.10 and 0.17, respectively. While these values should be unproblematic in the monthly specification, the quarterly specification should be taken with a little grain of salt. Two variables which are highly correlated are deposits and wholesale borrowing with $\rho = -0.75$ on average. Dropping either variable does not change the results in any noteworthy way which is why I keep them both as it is economically reasonable to control for them simultaneously.

Finally, I also take a more aggregate approach and run a dummy regression specified as in equation 7.

$$\begin{aligned} \mathrm{LoanGrowth}_{it}^{cum} &= \alpha_i + \beta_1 * \mathrm{Redemptions_i^{quantile}} * \alpha_t \\ & + \boldsymbol{\zeta'} * \mathbf{C_i} * \alpha_t + \boldsymbol{\delta'} * \mathbf{B_{i,t-1}} + u_{it} \end{aligned} \tag{7}$$

$\mathrm{LoanGrowth}_{it}^{cum}$ is defined as follows:

$$\mathrm{LoanGrowth}_{it}^{cum} = \sum_{k=2011m2}^{t} \frac{\Delta \mathrm{Lending}_{ik}}{\mathrm{TA}_{i,k-1}} \tag{8}$$

That is, my dependent variable is now the cumulated loan growth over total assets between the start of the sample and period t. There are two reasons why I use this measure instead of simply taking the stock of loans over total assets. First, the variable in equation 7 is more robust against changes in total assets: while the stock of loans over total assets could even grow when loans actually shrink (namely when total assets shrink faster), the cumulated loan growth can only go down if loan growth in the observed period is actually negative. Second, it is conceptually equivalent to the redemptions which are also *changes* in the stock of securities. The explanatory variable is an interaction term between an indicator variable $\text{Redemptions}_{\text{i}}^{\text{quantile}}$ and a time dummy α_t. This indicator variable is a dummy equal to 1 for banks whose redemptions cumulated over the entire treatment period (October 2014 to December 2018) are in a specified quantile q (quartiles and medians):

$$\text{Redemptions}_i^{quantile} = \text{Redemptions}_{\text{i}}^{\text{cum}} \in q \tag{9}$$

$$\text{Redemptions}_i^{cum} = \sum_{k=2014m10}^{2018m12} \text{Redemptions}_{ik} \tag{10}$$

Note how vector **A** from equations 1 and 6 is now replaced by vector **C** which contains equivalent interaction terms for cumulated sales and purchases:

$$\text{Sales}_i^{quantile} = \text{Sales}_{\text{i}}^{\text{cum}} \in q \tag{11}$$

$$\text{Sales}_i^{cum} = \sum_{k=2014m10}^{2018m12} \frac{\text{Sales}_{ik}}{\text{TA}_{i,t-1}} \tag{12}$$

$$\text{Purchases}_i^{quantile} = \text{Purchases}_{\text{i}}^{\text{cum}} \in q \tag{13}$$

$$\text{Purchases}_i^{cum} = \sum_{k=2014m10}^{2018m12} \frac{\text{Purchases}_{ik}}{\text{TA}_{i,t-1}} \tag{14}$$

I successively run the regression for two different types of quantiles: quartiles and medians in order to step-wise zoom out to more aggregate levels. The motivation for this is threefold. First, it constitutes another robustness control against endogeneity: any positive relationship between redemptions and loan growth measured by equations 1 and 6 might be because banks simply shift the granting of loans they would have granted anyway to months in which they have sufficient liquidity through maturing securities in order to be able to conduct the payouts. Tischer (2018) uses a difference-in-difference regression by collapsing his dataset into two periods (before and during QE) and two groups of banks (above and below the median of cumulated redemptions). I chose this different approach because, second, it allows me to have a more thorough look at time dynamics. This might be important because any cross-sectional effect of redemptions on loan growth might wash out over time as competition also forces banks with less redemptions to reduce their lending requirements. Put differently, the difference between treatment group and control group regarding the strength of the treatment effect might disappear. If such an effect is present in the data, the setup in equation 7 will unveil it. Third, it is better suited to present possible differential effects. The results of all regressions will be presented in section 6.

5. Data

To conduct my analysis I use microdata provided by the Research Data and Service Center (RDSC) of the German Bundesbank. I construct two datasets: A monthly one starting in January 2013, and a quarterly one starting in January 2011. Both end in December 2018. The centerpiece is the monthly balance sheet statistics (BISTA – Bilanzstatistik)[6] which contains detailed data on balance sheet positions of all banks resident in Germany; Gomolka et al. (2022) provide an overview. The BISTA can be linked with the SHS (Securities Holding Statistics)[7] in which banks report their monthly holdings of securities by ISIN (Blaschke et al. 2022). Further details on individual ISINs like the maturity date can be taken from the CSDB (Centralized Securities Database)[8] (Yalcin et al. 2021). Importantly, the CSDB also contains an indicator whether a security is in the ECB's Eligible Assets Database (EADB), i.e. whether it is eligible to be pledged as collateral for Eurosystem credit operations. All three databases are complete surveys and available on a monthly basis from January 2013 on; before that, the SHS is only available on a quarterly basis. Further detail on the industry structure of banks' lending portfolio is provided by the Quarterly Borrower Statistics (VJKRE - Viertljährliche Kreditnehmerstatistik)[9]. Here, banks have to report their lending volume to 22 different industry sectors at the end of each quarter. A list of the exact sector division can be found in Krodel et al. (2022). The VJKRE is aligned with the BISTA to ensure that the sum of loans over all sectors equals the total loan volume reported in the BISTA. Finally, I use data on bond yields and loan interest rates in Germany from the Bundesbank's public database.

Before running the regression, I undertake a number of adjustments to the data. In order to gain a balanced panel, I drop all banks that do not report to all datasets throughout the entire observation period. This reduces the number of banks to 1,384 in the monthly dataset (starting in January 2013) and to 1,377 in the quarterly dataset (starting in January 2011). For the third specification, I additionally drop all banks within the top 2% of cumulated redemptions as they constitute outliers, resulting in a sample of 1,350

[6]DOI = 10.12757/BBk.BISTA.99Q1-21Q4.01.01
[7]DOI = 10.12757/Bbk.SHSBaseplus.05122112
[8]DOI = 10.12757/BBk.CSDB.200903-202012.02.01
[9]DOI = 10.12757/BBk.VJKRE.99Q1-21Q4.01.01

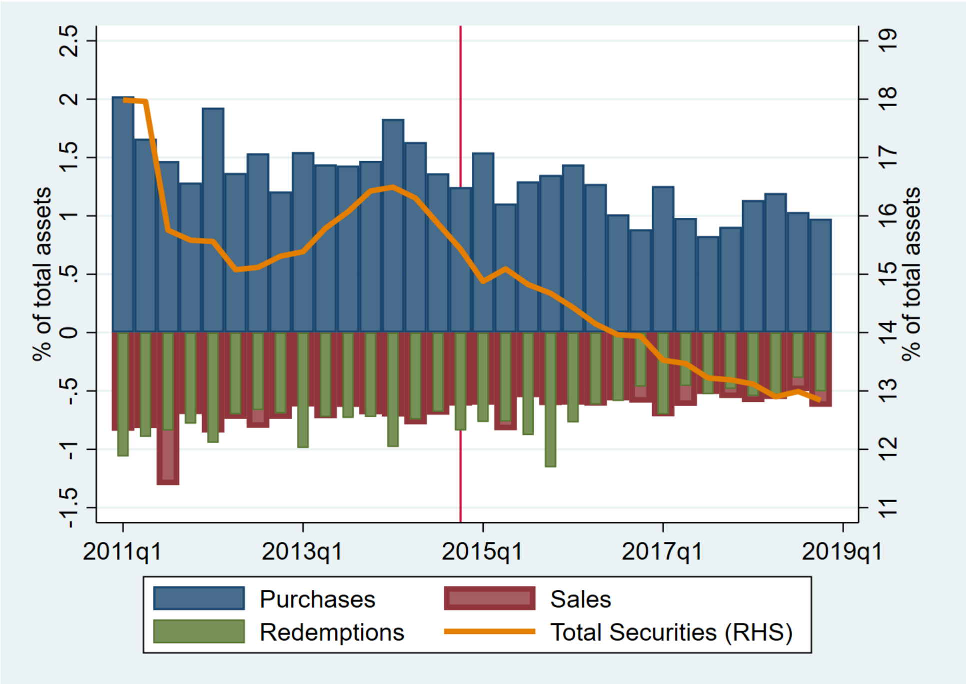
banks. Overall, my sample covers over 90% of total assets of the German banking system throughout 2011 to 2018. My merged CSDB/SHS dataset contains about 11.3 million bank-period-ISIN combinations. Here I drop all securities for which no maturity date is available (roughly 138,000 positions) or which are quoted in numbers rather than nominal values. In a few instances, banks report negative holding values to the SHS which indicate short positions. This is true for a little less than 200,000 positions. I drop these at the ISIN level before doing any calculations. I then compute the volume of maturing assets as well as sales and purchases of bonds at the bank level in every quarter from 2011 and every month from 2013 to end-2018, when the Eurosystem initially terminated its APP.

What I do not control for is merger and acquisition dynamics. This is unproblematic in my estimate as I configure all variables as percent of total assets and the bulk of M&A activities in the German banking system take place within the same bank types and at regional level. Hence, no huge change in the balance sheet structure are to be expected and even if, the time dummies should capture the effect. In the BISTA, the bank ID of the absorbing bank is kept after the merger.

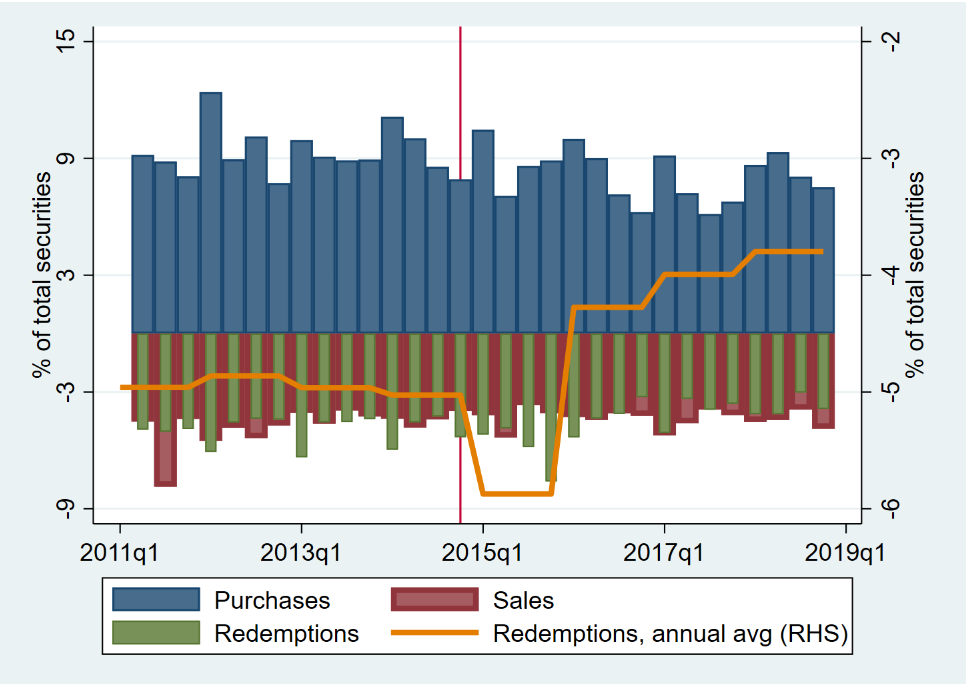
Figure 3 provides a breakdown of the changes of the German banking sector's aggregate securities portfolio. One can clearly see that, as a share of total assets, banks' holdings of bonds was pretty stable between 15 and 17.5 percent in the four years preceding QE and then entered a lasting downward trend: by end-2018, bonds made up only 13 percent of total assets. Another observation is that purchases, sales, and redemptions shrink after 2014. Regarding redemptions this does not come as a surprise as it simply reflects the decline in asset holdings. The decline in sales and purchases, however, is insofar interesting as it shows that, by and large, German banks did not increase their trading activity after the Eurosystem had started large-scale asset purchases. One might expect that under such an environment banks try and exploit valuation gains by increasing their sales. As Tischer (2018) shows, German banks are persistent buy-and-hold investors and they seem not to have changed their behavior during the prolonged period of QE.

At the same time, banks with a higher share of redemptions over the APP period increased the volume of loans to non-banks relative to their total assets more strongly compared to banks with fewer redemptions as can be seen from figure 4. Here I compute the sum of redemptions (as a share of total assets) over all months from October 2014 to December 2018 according to equation 10 and divided the sample along the median of that variable. As can be seen from panel (a) in figure 4, the total volume of outstanding loans is lower for banks with above-median cumulated redemptions and both groups already enter a clear upward trend in early-2013. However, for below-median banks this trend slackens off again after 2014 while it maintains its momentum for the above-median group. This

Figure 3: Fixed-Income Securities Portfolio Changes at Nominal Value



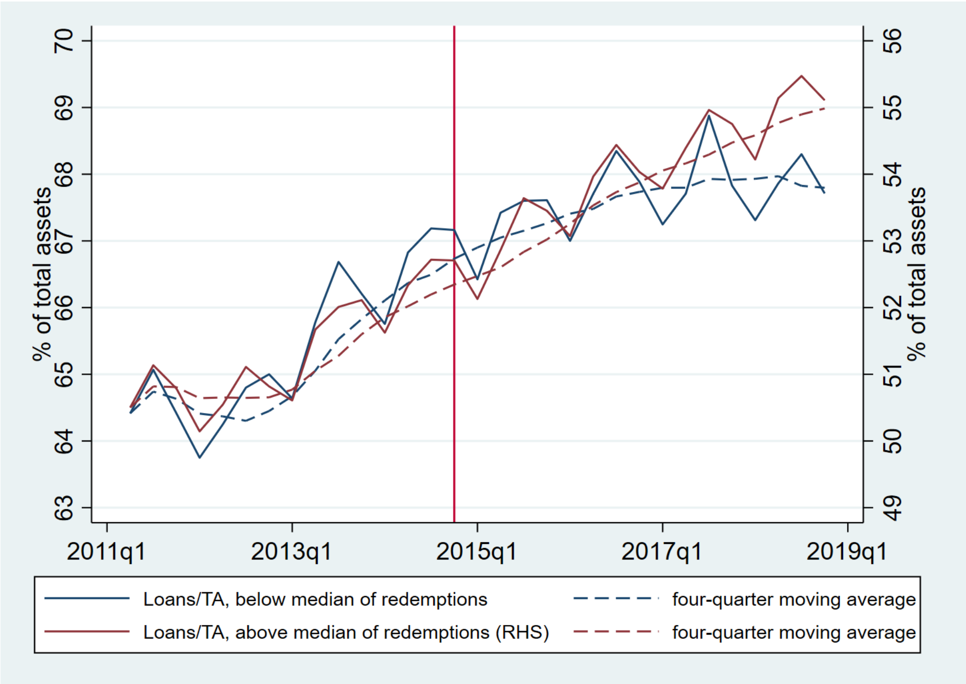
(a) share of total assets



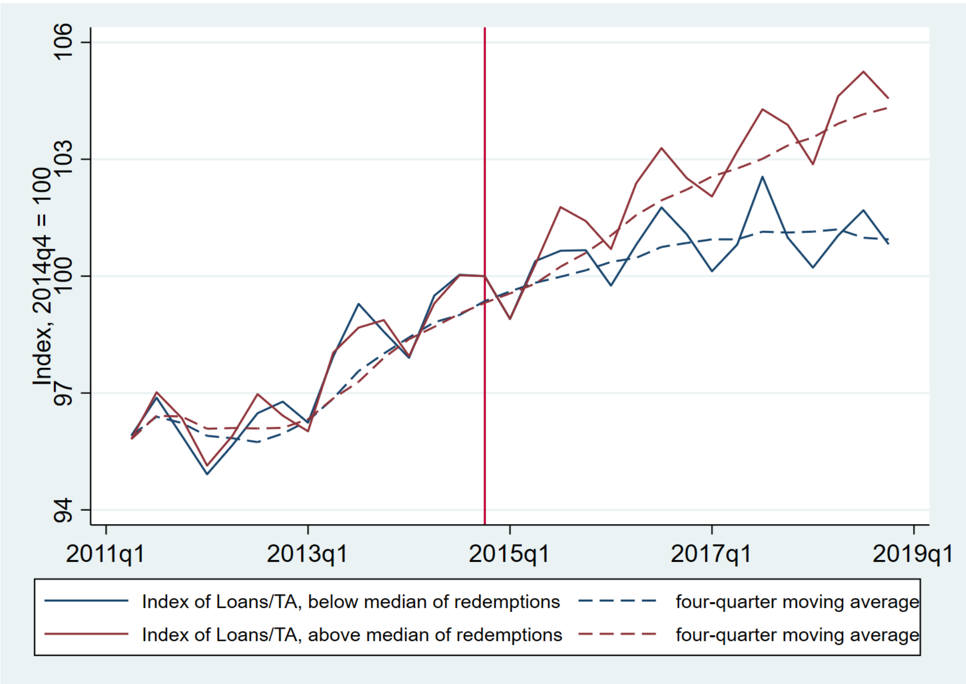
(b) share of securities portfolio

Both subfigures show the aggregate purchases, sales, and redemptions of all 1,377 banks in the quarterly sample, as a percentage of total bank assets (a) and as percentage of the previous quarters total bond holdings (b). The orange line shows the total FI securities portfolio (a) respectively the annual average of redemptions (b). The horizontal line in 2014q4 marks the beginning of the APP. Sources: Research Data and Service Centre (RDSC) of the Deutsche Bundesbank, BISTA, SHS, and CSDB, 2011-2018, own calculations.

Figure 4: Outstanding Loans to Non-Banks



(a) share of total assets



(b) share of total assets, indexed at reference quarter 2014q4

Both subfigures show the aggregate volume of outstanding loans to non-banks of all 1,377 banks in the quarterly sample, as a percentage of total bank assets (a) and this share indexed at reference quarter 2014q4 (b). In both cases the sample has been divided at the median of the sum of redemptions (as share of total assets) over the QE period (October 2014 to December 2018). The horizontal line in 2014q4 marks the beginning of the APP. Sources: Research Data and Service Centre (RDSC) of the Deutsche Bundesbank, BISTA, SHS, and CSDB, 2011-2018, own calculations.

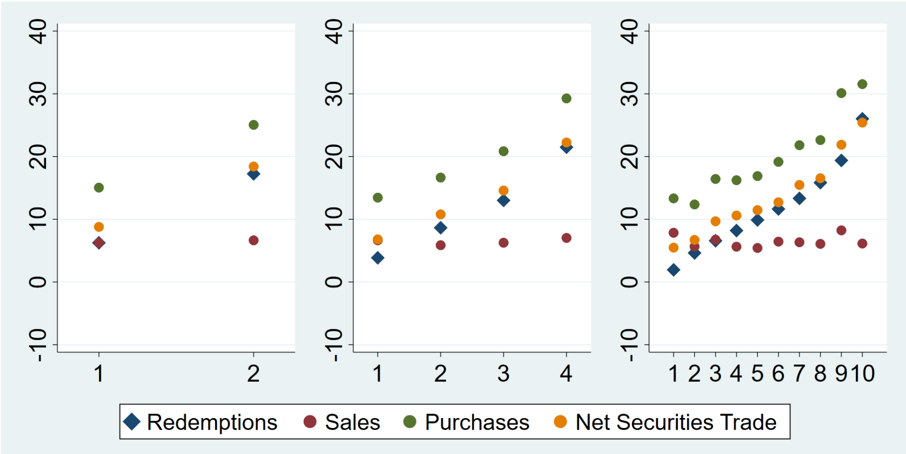
is further emphasized by panel (b) where the respective shares are indexed with reference quarter 2014q4 set to 100.

As I already mentioned in section 4, a problem with this depiction is that the share of outstanding loans in total assets can grow not only because loans grow, but also because other assets shrink. Computing the cumulated loan growth as in equation 8 produces a variable which is robust against this effect. The result is shown in figure 5. Here, I again compute cumulated redemptions according to equation 10 and split the dataset at the median (left-hand graphs), the quartiles (middle graphs), and deciles of cumulated redemptions. Before computing those quantiles, I drop the two percent banks with the topmost cumulated redemptions as they constitute outliers.[10] Each plot shows the within-quantile mean of each depicted variable. Panel (a) shows the various variables that contribute to changes in the securities portfolio. Panel (b) compares cumulated loan growth as defined in equation 8 to the change in the shares of outstanding loans and the stock of securities holdings in total assets between October 2014 and December 2018. Panel (c) shows the change in total assets between October 2014 and December 2018 as percentage of total assets in October 2014 as well as the change of the share of central bank liquidity in total assets. All three graphs in each panel show cumulated redemptions (blue diamonds). Table B.1 in the appendix also shows the within-decile means plus the standard deviations.

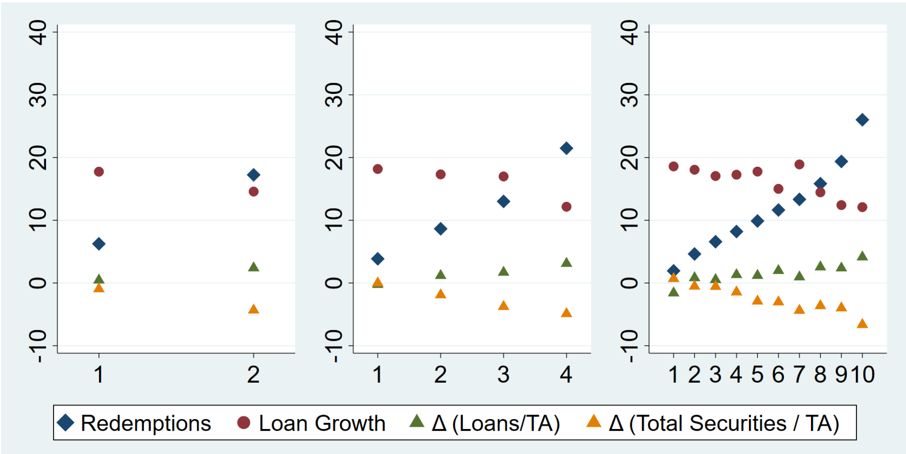
Two things can be seen from figure 5. First, there is a considerable variance in redemptions across all quantiles, i.e. the variance in the main explanatory variable is not driven by a few banks with very high redemptions. Second, while there is a mild positive correlation between cumulated redemptions and the change in outstanding loans over total assets, this is not the case for cumulated redemptions and cumulated loan growth (panel (b)). This indicates that banks with many redemptions have not so much increased their lending, but rather reduced the size of their balance sheets compared to banks with fewer redemptions. The latter is confirmed by panel (c) which additionally shows that the steep increase in central bank liquidity in the entire banking system after 2014 (see figure B.2 in appendix B) is evenly distributed across all quantiles. In fact, banks with the highest redemptions actually had *lower* loan growth. Now the figure does not tell us how loan growth within quantiles has changed compared to before October 2014. This question is answered by the regression analysis the results of which are presented in the following section. Appendix B shows some more descriptive information on the German banking system based on aggregate data available from the Bundesbank's public database.

[10]Unfortunately, variables for individual banks cannot be shown due to confidentiality issues.

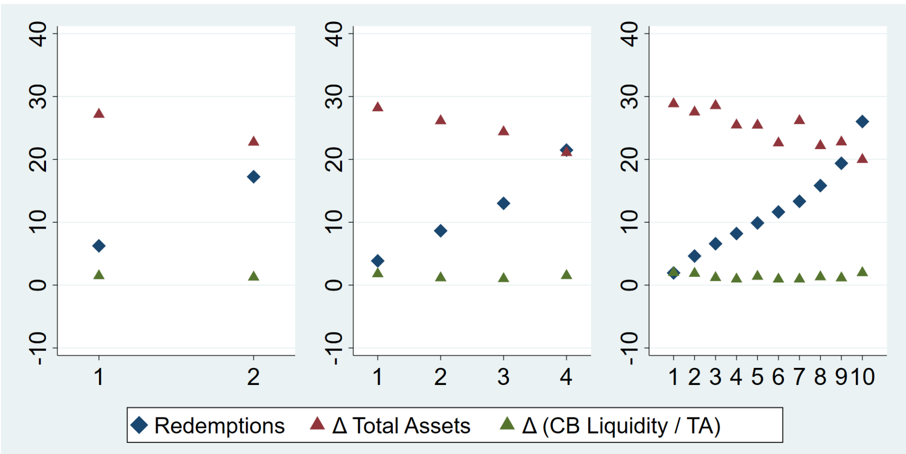
Figure 5: Within-Quantile Means



(a) security trade



(b) loan growth



(c) total assets and central bank liquidity

To construct this graph, I computed cumulated redemptions according to equation 10 and split the dataset at the median (left-hand graphs), the quartiles (middle graphs), and deciles of cumulated redemptions. Before computing those quantiles, I drop the two percent banks with the topmost cumulated redemptions as they constitute outliers. Each plot shows the within-quantile mean of each depicted variable. Blue diamonds indicate cumulated redemptions. Circles also depict cumulated changes over the QE period. Triangles show the change of the share of the respective variable in total assets between October 2014 and December 2018, except the change in total assets which is the change compared to October 2014 assets. Sources: Research Data and Service Centre (RDSC) of the Deutsche Bundesbank, BISTA, SHS, and CSDB, 2014-2018, own calculations.

6. Results

6.1. Panel Regressions

Table 1 shows the results of regression equation 1 on monthly basis, running from September 2014 to December 2018. As can be seen from column (1), I do confirm Tischer's (2018) result[11] that there is a statistically significant general connection between redemptions and loan growth during QE, though the effect is weaker: One Euro in additional redemptions comes along additional 11.6 cents of loan growth, in Tischer (2018) it is 17.3 cents. Another difference is that redemptions of securities which are not in the ECB's Eligible Assets Database have, by themselves, a little stronger effect on loan growth, but not much influence on the effect of total redemptions[12] (columns (2) and (3)). Controlling for net sales and net purchases of securities strongly changes the picture as the effect of redemptions is muted considerably both statistically and economically: Increasing redemptions by one Euro results in an increase in loan growth by a mere two cents if net sales and net purchases enter the regression (columns (4) and (5)).[13]

Columns (6) and (7) show additional specifications with sales split up into QE-eligible and non-QE-eligible assets and adding the change in central bank borrowing as a proxy for TLTRO. In contrast to Tischer (2018), I find that the sales of securities eligible for being purchased under the ECB's asset purchase programs have a *lower* impact on loan growth: the coefficient is only 0.09 (p-values are 0.46) as opposed to 0.161 ($p = 0.00$) for net sales of non-QE-eligible bonds. This is against expectation as bonds purchased by the central bank should show a stronger price increase. Hence, for a given amount of loan growth we should observe lower net sales in nominal terms for targeted bonds as opposed to non-targeted bonds. Regarding the impact of central bank borrowing, I too find a negative relationship, i.e. banks which borrowed more from the central bank rather decreased their lending compared to their peers. A possible explanation for this is that it might be mostly banks with stressed balance sheets that need to borrow from the central bank.

[11] The results of my (failed) 1:1 replication of Tischer (2018) can be found in tables C.1 to C.4 in appendix C.

[12] Roughly 90% of all securities in the CSDB are in the EADB.

[13] Considering the American Statistical Association's statement on p-values (Wasserstein and Lazar 2016), I also interpret the coefficients which lack the conventional levels of statistical significance. While I do not report p-values in line with established reporting standards, they are available upon request.

Table 1: Results of OLS regression of equation 1 on monthly basis

Dependent Variable:	$\text{LoanGrowth}_{\text{it}}$							
Time Period:	Monthly September 2014 to December 2018							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Redemptions	0.116***			0.015				
	(0.03)			(0.06)				
Redemptions Non-EADB		0.125**				-0.020		
		(0.06)				(0.10)		
Redemptions EADB		0.114***	0.113***		0.024	0.021	0.022	-0.052
		(0.03)	(0.03)		(0.05)	(0.05)	(0.05)	(0.05)
Net sales				0.157***	0.157***			0.132***
				(0.04)	(0.04)			(0.04)
Net sales Non-QE						0.161***	0.161***	
						(0.03)	(0.03)	
Net sales QE						0.090	0.090	
						(0.12)	(0.12)	
Net purchases				0.446***	0.446***	0.447***	0.447***	0.425**
				(0.16)	(0.16)	(0.16)	(0.16)	(0.17)
Change in CB borrowing						-0.102*	-0.102*	
						(0.06)	(0.06)	
RedemptionsEADB*LowEquity								0.160***
								(0.05)
NetSales*LowEquity								0.060
								(0.10)
NetPurchases*LowEquity								0.037
								(0.09)
Controls	yes	yes	yes	yes	yes	yes	yes	yes
Time FE	yes	yes	yes	yes	yes	yes	yes	yes
Bank FE	yes	yes	yes	yes	yes	yes	yes	yes
N	70,584	70,584	70,584	70,584	70,584	70,584	70,584	70,584
Number of banks	1,384	1,384	1,384	1,384	1,384	1,384	1,384	1,384
r2	0.4920	0.4920	0.4918	0.5177	0.5177	0.5181	0.5181	0.5205
corr(u_i, Xb)	-0.5047	-0.5047	-0.5035	-0.4191	-0.4193	-0.4138	-0.4142	-0.4571

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors (in parentheses) are clustered at the bank level. Sources: Research Data and Service Centre (RDSC) of the Deutsche Bundesbank, BISTA, SHS, and CSDB, 2014-2018, own calculations.

The final column (8) adds a dummy for low equity. This dummy takes the value of 1 in each month in which an individual bank's equity is below its within-bank sample mean. Low equity is a possible supply-side constraint to loan growth through regulatory and liquidity constraints (Bundesbank 2017; McLeay et al. 2014). Consequently, the positive relationships between redemptions and loan growth respectively net sales and loan growth should be stronger for banks with low equity. This is clearly the case. While the effect of redemptions on loan growth for banks with above-average equity is even *negative*, the coefficient of the interaction term RedemptionsEADB*LowEquity is strongly positive. For net sales, the result is less clear-cut: While the effect strength increases by 50% for banks with low equity, the interaction term is subject to strong data noise with $p = 0.53$. The relationship between net purchases and loan growth does not significantly change for low equity banks, neither economically nor statistically.

Table D.1 in appendix D repeats the previous exercise on a quarterly basis to check whether the frequency of the data has any impact on the results. Put briefly, the impact of redemptions is a bit stronger but the results generally follow the same pattern than in the monthly data. For a more thorough evaluation, see appendix D.

Table 2 then depicts the results of regression equation 6 at a monthly frequency. The aim here is to investigate whether the relationship between redemptions and loan growth changed during the QE period compared to the pre-QE period. Columns (1) and (2) add interaction terms which measure the change of the impact of redemptions, sales, and purchases on loan growth during the QE period, starting in October 2014. Column (1) in table 2 corresponds to column (5) in table 1. As can be seen, the effect of redemptions on loan growth is even *lower* after the start of QE.

Moving to column (2), you can see that for months in which equity is low, there is a mediocre effect as the coefficient increases from 0.083 to 0.104[14] though it lacks the general levels of statistical significance. The impact of net sales on loan growth shrinks during QE, though the interaction term is subject to strong data noise ($p = 0.58$). This is at odds with expectations, because remember net sales and net purchases are in nominal terms and if the market value of bonds is increasing during QE, a bank has to sell *less* bonds in nominal terms to finance a given amount of lending-induced payouts and this should result in a *larger* coefficient because vice versa this means that loan growth for a given euro of net sales is larger. For low equity banks, the effect is more positive before QE and decreases more strongly under QE which is also contrary to supply-side

[14]To get the coefficient of redemptions for months with low equity before QE, one has to sum up the coefficients of Redemptions EADB ($p = 0.88$) and RedemptionsEADB*LowEquity ($p = 0.44$). To get the coefficient during QE, one has to also add the coefficients of RedemptionsEADB, RedemptionsEADB*QE ($p = 0.31$) and Redemptions*QE*LowEquity ($p = 0.38$).

theories of lending: if low equity indicates a generally low balance sheet capacity, weak banks would have to sell more assets to finance their lending operations which should result in a negative coefficient for NetSales*LowEquity. And the coefficient for the triple interaction term NetSales*QE*LowEquity should be positive because supply-constrained banks should profit more from QE than others as QE-induced asset price increases ease that supply constraint.

Table 2: Results of OLS regression of equation 6 on monthly basis

Dependent Variable:	$\text{LoanGrowth}_{\text{it}}$			
Time Period:	Monthly January 2013 to December 2018			
	(1)	(2)	(3)	(4)
Redemptions EADB	0.057	0.010	0.012	-0.063
	(0.05)	(0.07)	(0.10)	(0.16)
RedemptionsEADB*LowEquity		0.073		0.125
		(0.10)		(0.20)
RedemptionsEADB*QE	-0.043	-0.076		
	(0.04)	(0.08)		
Redemptions*QE*LowEquity		0.097		
		(0.11)		
Redemptions*Spread5			0.013	0.018
			(0.06)	(0.10)
Redemptions*Spread5*LowEquity				0.006
				(0.14)
Net sales	0.183***	0.105**	0.278***	0.214**
	(0.05)	(0.05)	(0.08)	(0.09)
NetSales*LowEquity		0.181**		0.094
		(0.09)		(0.08)
NetSales*QE	-0.031	0.022		
	(0.06)	(0.07)		
NetSales*QE*LowEquity		-0.119		
		(0.09)		
NetSales*Spread5			-0.091	-0.071
			(0.06)	(0.07)
NetSales*Spread5*LowEquity				0.000
				(.)
Net purchases	0.161	0.105	0.138	0.159
	(0.13)	(0.16)	(0.23)	(0.33)
NetPurchases*LowEquity		0.143		-0.069
		(0.17)		(0.35)
NetPurchases*QE	0.289**	0.325**		
	(0.11)	(0.16)		
NetPurchases*QE*LowEquity		-0.109		
		(0.19)		

NetPurchases*Spread5			0.159	0.112
			(0.16)	(0.22)
NetPurchases*Spread5*LowEquity				0.122
				(0.24)
LowEquity		-0.003***		-0.003***
		(0.00)		(0.00)
QE	-0.003***	-0.002***		
	(0.00)	(0.00)		
Spread5			-0.007***	-0.006***
			(0.00)	(0.00)
Controls	yes	yes	yes	yes
Time FE	yes	yes	yes	yes
Bank FE	yes	yes	yes	yes
N	98,264	98,264	98,264	98,264
Number of banks	1,384	1,384	1,384	1,384
r2-within	0.4949	0.4978	0.4914	0.4945
corr(u_i, Xb)	-0.3814	-0.4132	-0.3869	-0.4189

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors (in parentheses) are clustered at the bank level. Sources: Research Data and Service Centre (RDSC) of the Deutsche Bundesbank, BISTA, SHS, and CSDB, 2013-2018, own calculations.

As for the observed effects of net purchases, I can only imagine one potential economic interpretation which is that net purchases serve as an indicator for excess liquidity. If a bank in a given period holds more reserves than it desires it can increase both its securities holdings and its lending to get rid of the undesired central bank money. If under QE the bank shifts its investments more towards lending, the within-estimator shows an increase in the coefficient between net purchases and loan growth. But even if this is a valid interpretation of the true economic mechanism at work between net purchases and lending, it is at odds with the lack of any effect of net sales and redemptions because in all three cases the centerpiece is a desire of the bank to reduce its liquidity holdings. Without further investigation, though, which goes beyond the scope of this paper, it is safer to take this lack of a coherent pattern as an indicator that QE did not trigger a stark portfolio rebalancing from securities to loans in the German banking system.

Columns (3) and (4) of table 2 take spreads between securities and loans into the picture. *Spread5* is a variable which shows the difference between the yield of securities with a residual maturity of at least five years issued in Germany and the average interest rate on new loans granted by German banks. This is an important indicator for the functioning of QE as QE primarily impacts the yields of long-term securities and hence should increase the spread of loan rates over bond yields. However, as already mentioned, there is no obvious relationship between the evolution of the spread and the start of QE, see figure 1. In fact, bond yields only decreased *before* QE and then entered a sideways movement while loan rates decline throughout the entire observation period. A possible explanation for the observed evolution of bond yields might be that the APP reduced risk premia on Southern European bonds and hence stopped the capital flight from those countries to Germany. In other words, the additional demand for German securities by the Eurosystem might have been overcompensated by a decrease in demand from private investors. In fact, a recent paper by Hudepohl (2022) provides empirical evidence for just that. Since the effect of spreads on loan growth does not depend on the presence of a central bank purchase program, however, we should still be able to observe a positive impact of spreads on the relationship between redemptions and loan growth.

My regressions indeed show a tiny positive impact of the spread of loan rates over bond yields on redemptions. The effect strength, however, is miniscule: an increase in the spread by one full percentage point - which is a massive effect - increases loan growth by a mere 1.3 cents (column (3)). Also, data noise behind Redemptions*Spread5 is huge with $p = 0.83$. Column (4) shows that the effect is a little stronger for low equity banks, but again we observe coefficients of negligible economic size against a highly noisy background. Taken together, these results constitute no convincing evidence that the spread of loan rates over bond yields is a trigger for portfolio rebalancing from bonds to loans.

Again, table D.2 in appendix D shows the same specifications for quarterly frequency in order to check for robustness against differing data frequencies. Again, the patterns are rather similar.

Taken together, I do find some mild interrelation between redemptions and loan growth at best and, what's more important, I fail to find a strong and robust impact of QE on this interrelation. In the following subsection I present the results of a broader approach which is also suitable to reveal dynamics over time and differential effects.

6.2. Time Dynamics and Differential Effects

Figure 6 shows the coefficient β_1 from regression equation 7 for each quarter throughout the observation period. 2014Q4 is the reference quarter where the time dummy α_t is zero. The lowest quantile is the reference quantile where $\text{Redemptions}_{\text{i}}^{\text{quantile}}$ is zero. Panel (a) shows the result of the regression in which $\text{Redemptions}_{\text{i}}^{\text{quantile}}$ indicates in which quartile of cumulated redemptions a bank is. Confidence intervals are not shown for clarity. Panel (b) shows the result of the regression in which $\text{Redemptions}_{\text{i}}^{\text{quantile}}$ indicates whether a bank is above or below the median of cumulated redemptions. The quartile regressions show that there is no noteworthy impact of QE, measured through a bank's exposure to redemptions. Banks in the second and third quartiles of cumulated redemptions stop decreasing their cumulated loan growth compared to the first quartile, but they already do so from early 2013 on, long before QE was launched. Plus, both groups of banks show virtually the same reaction which does not imply any impact of redemptions. Banks in the fourth quartile continuously *decrease* their lending compared to banks with the fewest redemptions and show no change in behavior from 2015 onward. Hence, it is of little surprise the regression in which the sample was split in two at the median of cumulated redemptions also reveals a zero effect of large-scale asset purchases by the Eurosystem on the lending behavior of German banks.

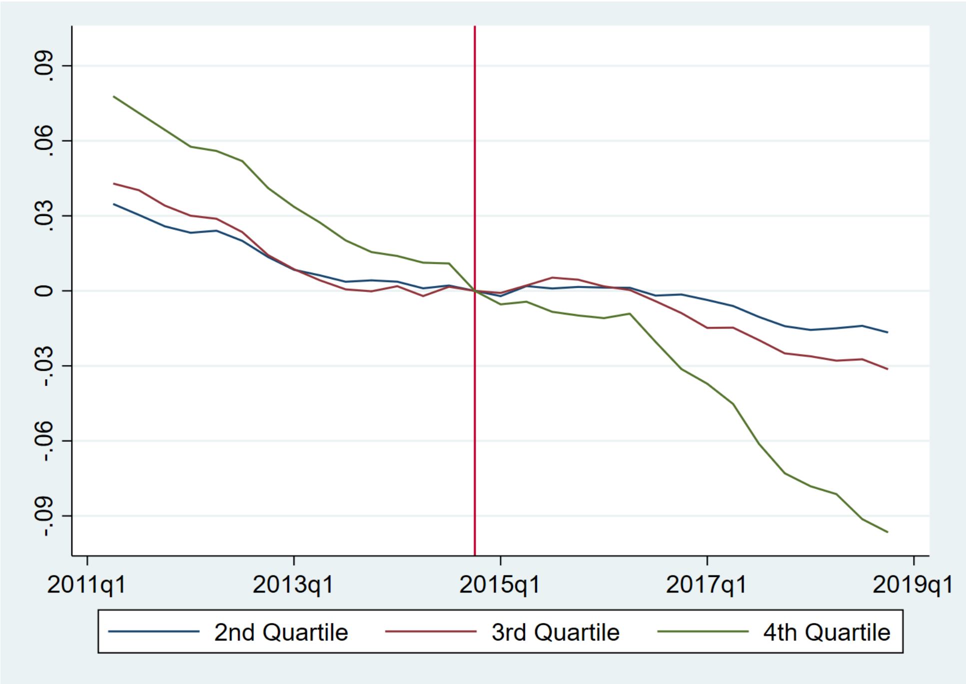
Even though there is no reason to expect to observe any differential effects in the rebalancing channel since the rebalancing channel itself does not seem to be at work, I still proceeded to check for differential effects, simply because this was the initial motivation for this paper. The results are shown in figure 7. Unsurprisingly, there are no differential effects to be observed across any dimension investigated. Banks with above-median cumulated redemptions over the QE period do not switch their loan portfolio towards any particular type of borrower or loan compared to banks with below-median redemptions. At first glance, one might think that there is a differential effect in lending to non-financial corporations as the coefficient line looks quite different compared to the others (figure 7, panel (a)). What the graph shows is that banks with above-median redemptions decrease their lending to non-financial corporations throughout the entire observation period compared to banks with below-median redemptions, whereas their lending to the domestic government, the euro area, and the rest of the world remains constant compared to the control group. For a differential effect to be there, one of the lines would need to change their slope after the start of QE relative to the slope of other lines. This is nowhere the case.

7. Robustness Checks

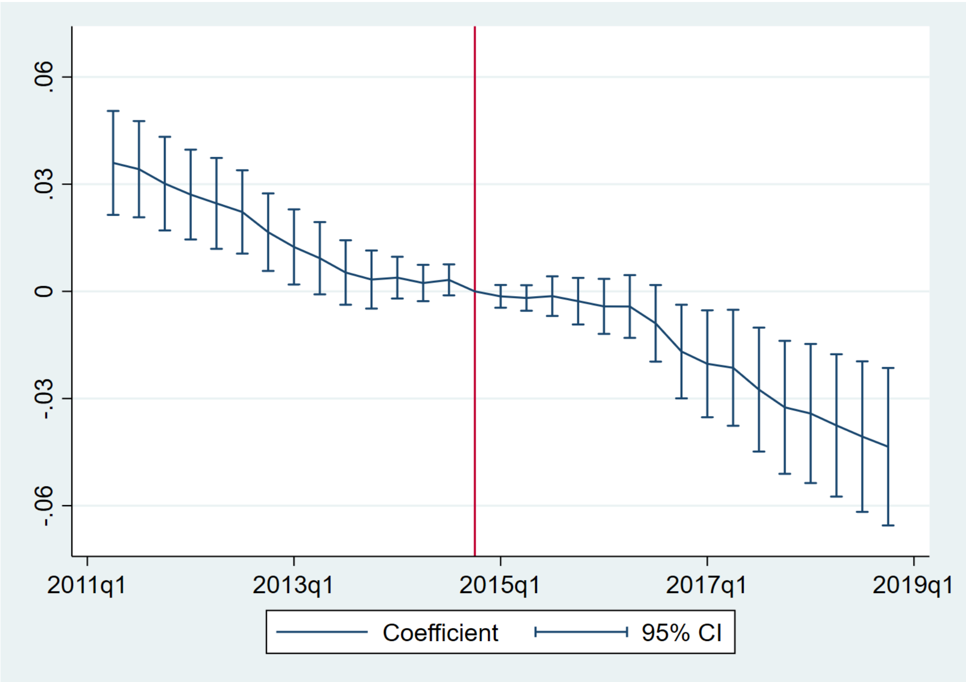
This section presents some robustness checks. Figure 8 and figure 9 correspond to figure 6. In the specification in figure 8 I only used the redemptions of securities that where in banks' portfolios in January 2014, well before the start of QE. The idea here is to add a further control for endogeneity because banks might have started adapting the maturity structure of their securities portfolio as a reaction to QE. Using redemptions exclusively from the January 2014 portfolio ensures that the model only captures the exposure of banks to redemptions which were already determined before QE.[15] This specification confirms the result from figure 6: The higher redemptions, the more *negative* is loan growth

[15]To be 100% precise one would have to use redemptions of bonds held in January 2014 which the bank has not traded since then. However, since German banks are robust by-and-hold investors as already mentioned in section 5, I skip this additional step.

Figure 6: Effect of cumulated redemptions on total lending to non-banks



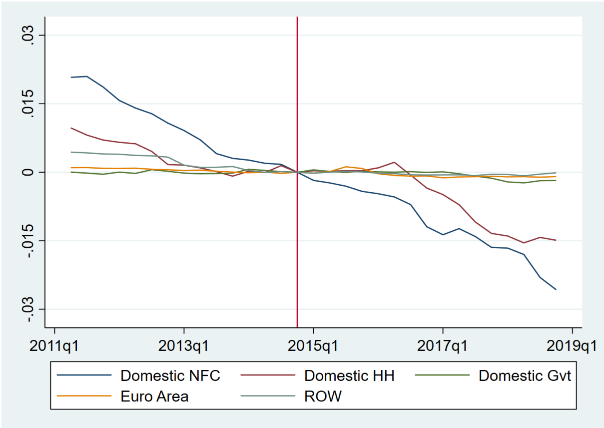
(a) by quartiles of cumulated redemptions



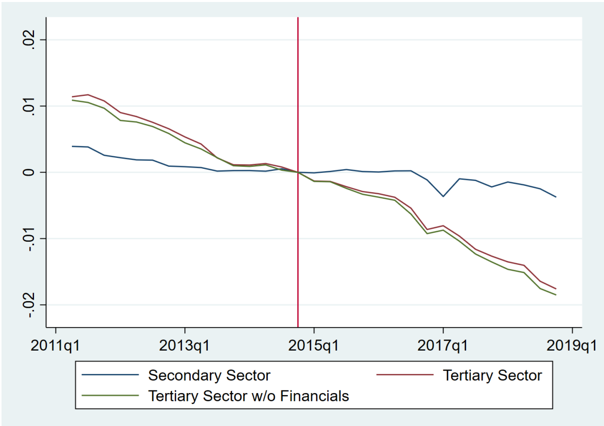
(b) above vs. below median of cumulated redemptions

Both subfigures show the coefficient β_1 from regression equation 7 for each quarter throughout the observation period. 2014Q4 is the reference quarter where the time dummy α_t is zero. The lowest quantile is the reference quantile where $\text{Redemptions}_i^{\text{quantile}}$ is zero. Before computing the respective quantiles, banks with the top 2% of cumulated redemptions were dropped to control for outliers; hence, 1,350 banks remain in the sample. Panel (a) shows the result of the regression in which $\text{Redemptions}_i^{\text{quantile}}$ indicates in which quartile of cumulated redemptions a bank is. Confidence intervals are not shown for clarity. Panel (b) shows the result of the regression in which $\text{Redemptions}_i^{\text{quantile}}$ indicates whether a bank is above or below the median of cumulated redemptions. Sources: Research Data and Service Centre (RDSC) of the Deutsche Bundesbank, BISTA, SHS, and CSDB, 2011-2018, own calculations.

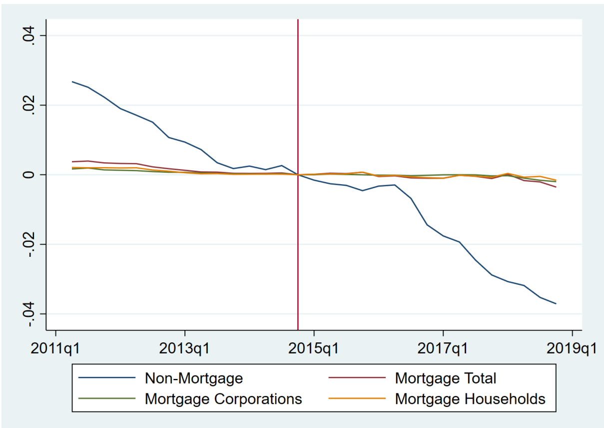
Figure 7: Effect of cumulated redemptions on lending to non-banks, differential effects



(a) lending by institutional sectors



(b) lending by industrial sectors



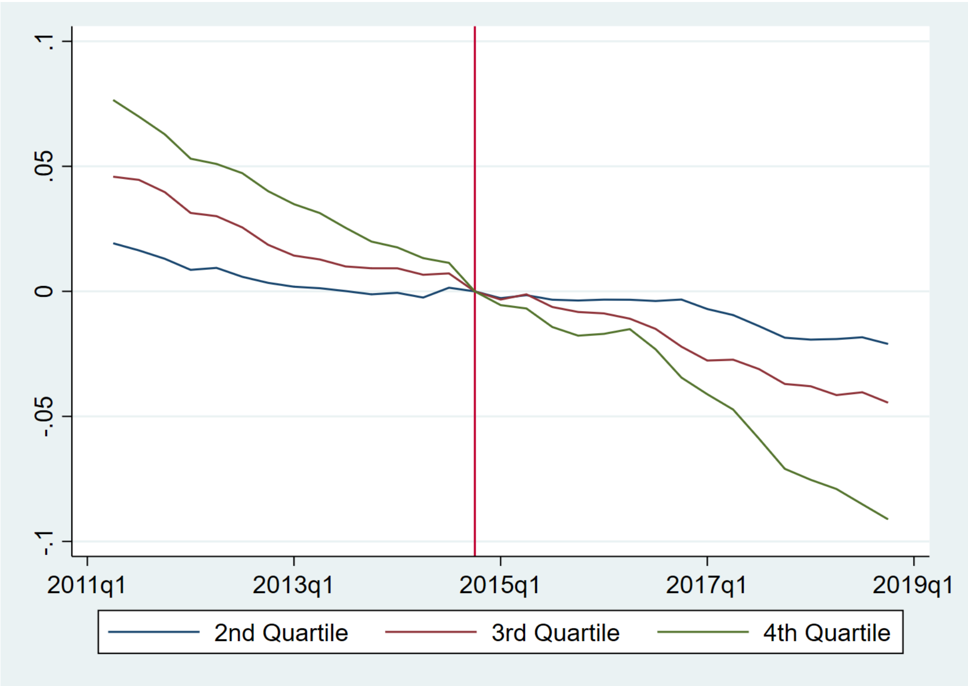
(c) lending by type of loans

Both subfigures show the coefficient β_1 from regression equation 7 for each quarter throughout the observation period with the quantile being the median. 2014Q4 is the reference quarter where the time dummy α_t is zero. Panel (a) shows the result for total lending to various institutional sectors as dependent variable. Panel (b) shows the results for total lending to various industry sectors as dependent variable. Panel (c) shows the results for different types of loans as dependent variable. Sources: Research Data and Service Centre (RDSC) of the Deutsche Bundesbank, BISTA, VJKRE, SHS, and CSDB, 2011-2018, own calculations.

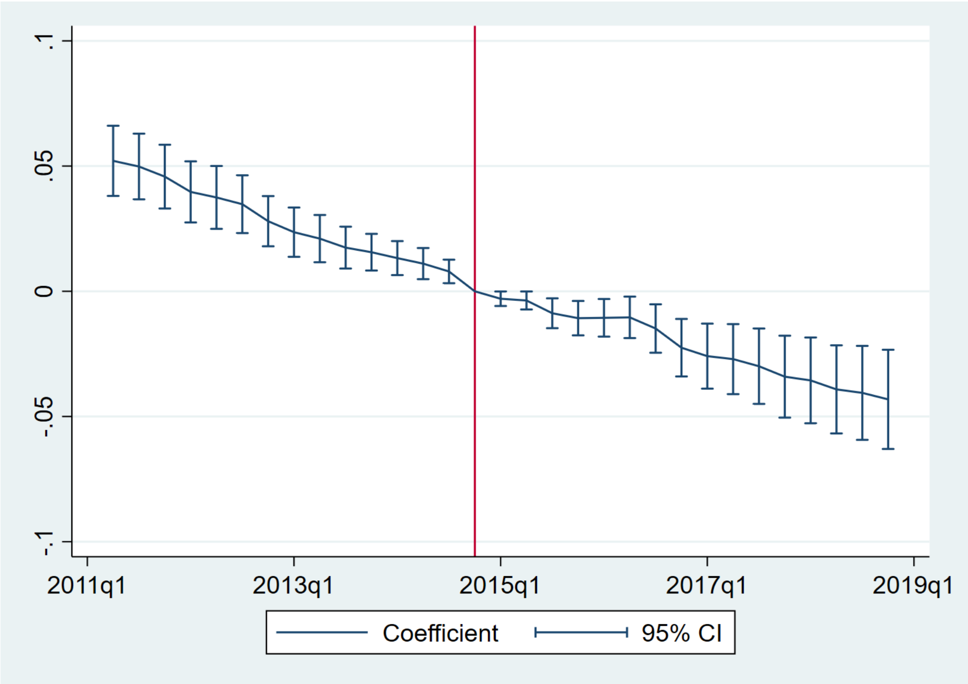
compared to the bottom quartile and there is absolutely no change in the time trend after the start of QE.

Figure 9 shows the result for running regression equation 7 with the panels not being banks but bank-industry sector pairs instead. Assuming that loan demand varies more across industry sectors than across firms within an individual sector, this approach allows to control for demand. The results are largely the same than in the other specifications which means that the previous outcomes are not driven by loan demand.

Figure 8: Robustness checks: effect of cumulated initial redemptions on total lending to non-banks



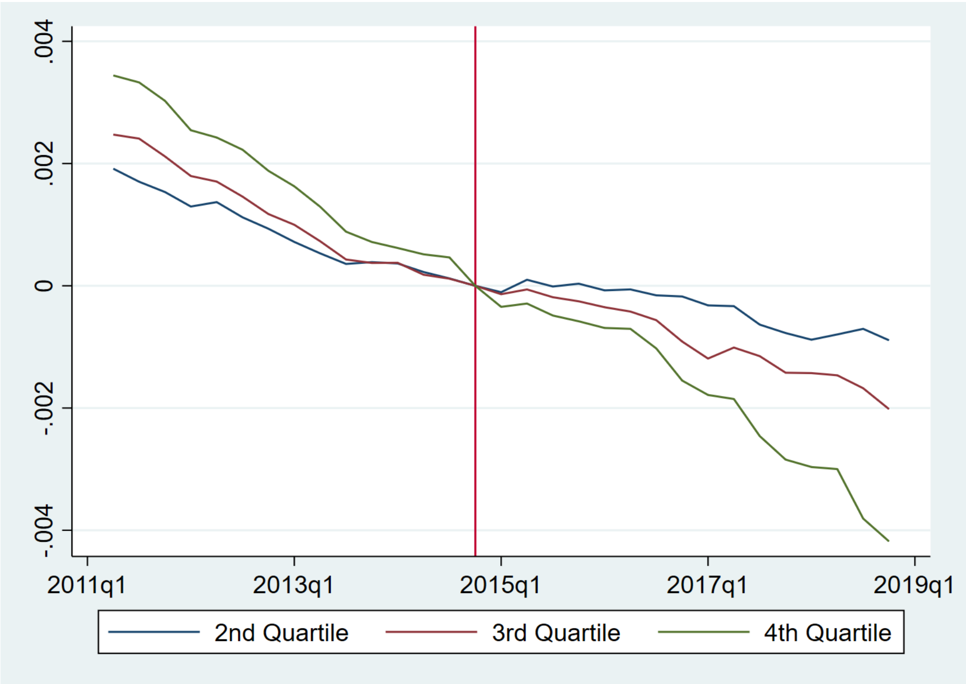
(a) by quartiles of cumulated redemptions



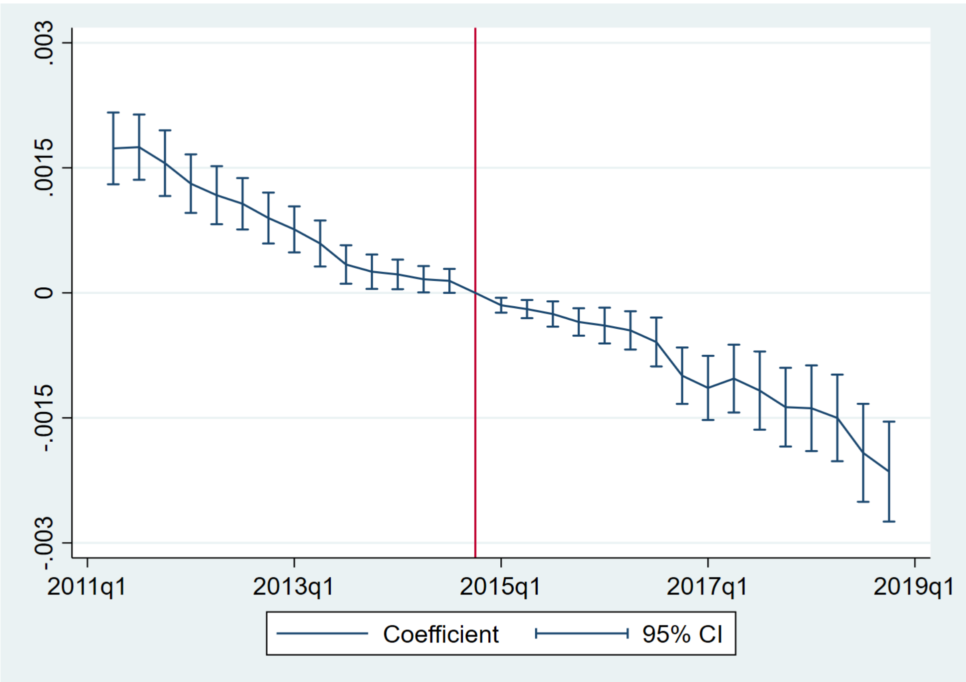
(b) above vs. below median of cumulated redemptions

Both subfigures show the coefficient β_1 from regression equation 7 like in figure 6. The difference is that in this specification redemptions of only those securities which were in banks' portfolio in January 2014 are used as main explanatory variable. Panel (a) shows the split by quartiles. Panel (b) shows the split by the median. Sources: Research Data and Service Centre (RDSC) of the Deutsche Bundesbank, BISTA, SHS, and CSDB, 2011-2018, own calculations.

Figure 9: Robustness checks: effect of cumulated redemptions on total lending to non-banks with control for loan demand



(a) by quartiles of cumulated redemptions



(b) above vs. below median of cumulated redemptions

Both subfigures show the coefficient β_1 from regression equation 7 like in figure 6. The difference is that in this specification the panel variable has been changed from banks to bank-industry sector pairs in order to control for loan demand which is assumed to vary across industry sectors but not so much within. Panel (a) shows the split by quartiles. Panel (b) shows the split by the median. Sources: Research Data and Service Centre (RDSC) of the Deutsche Bundesbank, BISTA, VJKRE, SHS, and CSDB, 2011-2018, own calculations.

8. Conclusion

In this paper, I investigated the impact of the Eurosystem's Asset Purchase Program (APP) on German banks' lending behavior from 2015 to 2018. The research questions I addressed are: First, does QE stimulate bank lending? Second, do banks which are more exposed to QE shift their lending portfolio towards particular institutional sectors, industry sectors, or types of loans? In order to answer the question, I used microdata from the German Bundesbank on German banks' balance sheets, their securities portfolio, and their lending structure. As the main indicator for banks' exposure towards QE, I used the volume of maturing securities because whenever an asset matures, the bank needs to decide whether to reinvest the proceeds into bonds or whether to shift to other assets like corporate loans. This is the portfolio rebalancing channel of monetary policy. The advantage of using redemptions rather than sales of assets is that they can be assumed to be more exogenous as banks have full control over their sales in each month or quarter whereas the maturity structure is predetermined by past investment decisions. Various specifications of fixed-effects panel regressions reveal, if at all, only a very loose connection between banks' exposure to QE and their lending growth, though. Consequently, no differential effects materialize, either. The results also hold when only using redemptions of securities which were already held by banks long before QE started and when controlling for loan demand through using bank-industry sector pairs as panels rather than banks.

The question is what to make of these results. They are peculiar insofar as they contradict two previous papers which have used the same datasets and similar methods to answer the same research question: Paludkiewicz (2021) and Tischer (2018). In that sense, this paper adds to the "replicability crisis" literature (see, e.g., Chang and Li (2015) and Duvendack et al. (2017)). Independently of that, my findings do *not* provide proof that quantitative easing does not have the desired effects on lending, economic activity, and, eventually, prices. They simply fail to provide evidence for one out of multiple channels through which QE is argued to work: the portfolio rebalancing channel. Depending on which theory one argues this is not necessarily a surprising result. For instance, it is perfectly in line with a Post-Keynesian line of reasoning in which it is purely loan demand that determines actual loan growth (Lavoie 2015, ch. 3, esp. pp. 226-230, and Lavoie and Fiebiger 2018), while the portfolio rebalancing channel stresses the loan supply side. Empirically, Caldentey (2017) also makes this point for unconventional monetary policy and Arnold et al. (2006) for conventional monetary policy in the German banking system. In that sense, finding no effect of asset purchases on loan supply in a healthy banking system is simply a manifestation of the famous parable of "pushing the string".

An empirical explanation for these results relates to the peculiar situation that prevailed in the Euro Area during the 2010s. Remember that the portfolio rebalancing channel is meant to work through increasing the spread between yields of securities purchased by the central bank and other assets. Contrary to theoretical expectation, though, there is no obvious relationship between the evolution of the bond-loan spread and the start of QE. This can be seen from publicly available data in figure 1. It shows the yields of all outstanding long-term securities issued in Germany and the average interest rates of long-term loans newly issued by German banks. In fact, bond yields only decreased *before* QE and then entered a sideways movement while loan rates decline throughout the entire observation period. A possible explanation for the observed evolution of bond yields might be that the APP reduced risk premia on Southern European bonds and hence stopped the capital flight from those countries to Germany. In other words, the additional demand for German securities by the Eurosystem might have been overcompensated by a decrease in demand from private investors. In fact, a recent paper by Hudepohl (2022) provides empirical evidence for just that.

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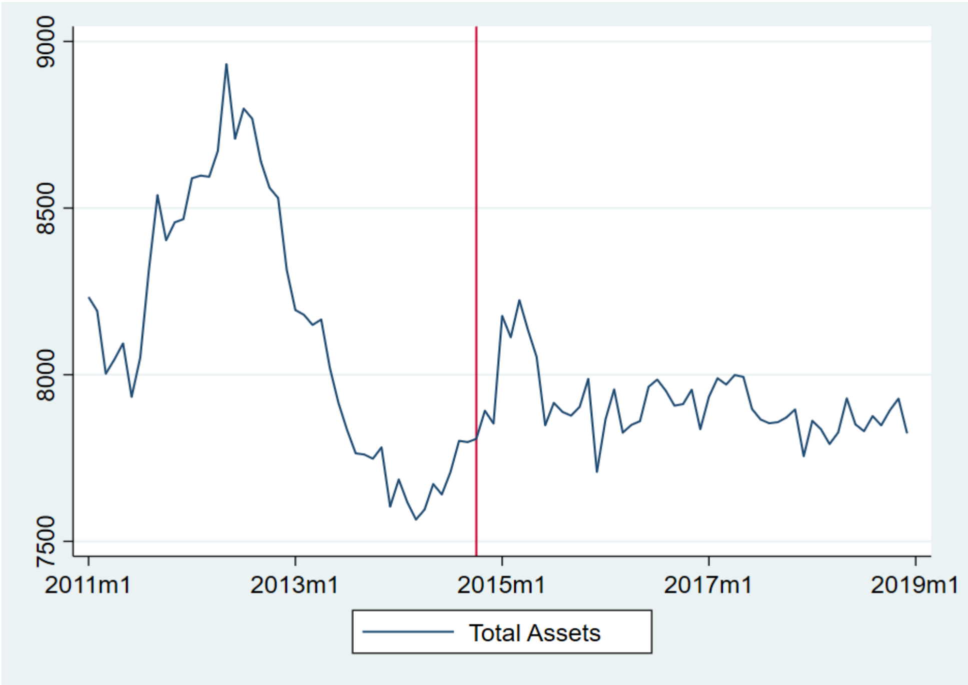
Appendix

A. Literature on Conventional MP Differential Effects

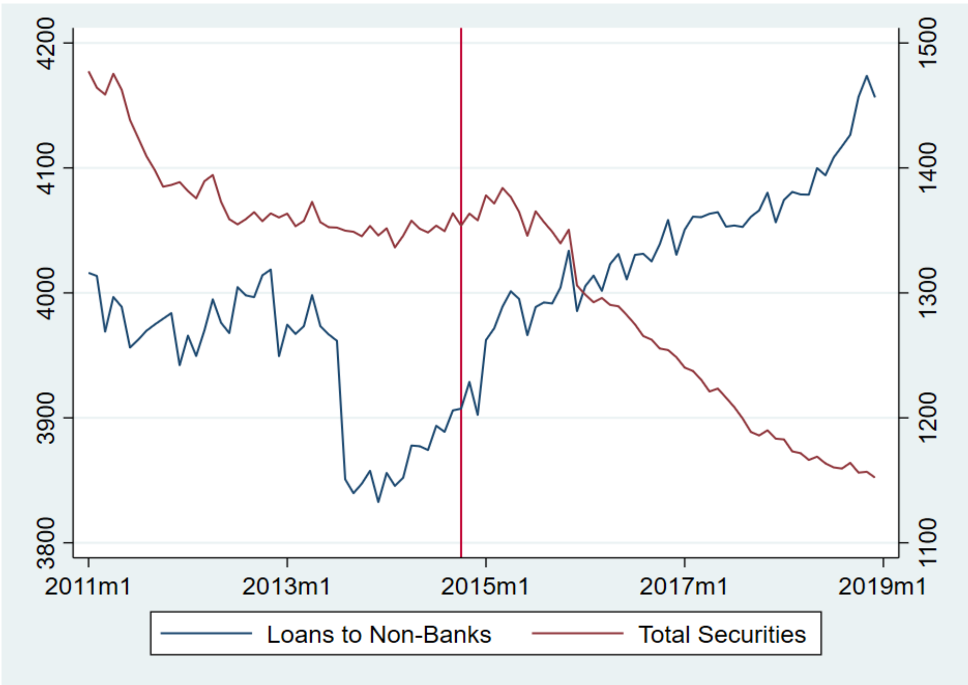
This appendix gives a quick overview on the literature on the differential effects of *conventional* monetary policy. According to Carlino and DeFina (1998b, 1999) the responsiveness of the economic activity of regions and states in the US to interest rate changes is strongly positively related to the share of manufacturing output in overall output, but only weakly – if at all – positively related to the share of employment accounted for by small firms; to the share of small banks it is even negatively related. Furceri et al. (2019), however, find that both the share of employment in small firms and the share of loans made by small banks are positively related to stronger output responses to expansive monetary policy shocks. Regarding the Euro Area, Carlino and DeFina (1998a) take their earlier findings from the US to draw conclusions on the sensitivity of European economies on the ECB's common monetary policy, ranking EMU members by their expected sensitivity. Georgiadis (2015) finds that a higher share of industries producing interest-rate sensitive demand (durable manufacturing and construction) and weaker labor market rigidities are both associated with a stronger reaction to interest rate innovations. Zooming in on the sub-national level, Arnold (2001) finds a positive relationship between the interest rate sensitivity of GDP and the share of the labor force that is employed in manufacturing in 58 European regions from eight countries. Anagnostou and Papadamou (2014) investigate the impact of interest rate shocks on regional GDP in 58 Southern European regions. They find a positive relationship between both wage flexibility and labor mobility and the responsiveness of regional GDP to interest rate shocks. They further find that a higher share of manufacturing output in regional output is associated with a lower responsiveness to monetary policy changes which is at odds with the rest of the literature. Nevertheless, their findings confirm that also in Europe, differences in economic structure are an important explanatory factor for differential effects of monetary policy. According to Barigozzi et al. (2014), national economies reacted more uniformly to monetary policy shocks after the introduction of the Euro than before, but measurable differences persist. Further evidence for differential effects within national economies have been provided for numerous countries: Germany (Arnold and Vrugt 2004), Spain (Lucio and Izquierdo 2002; Rodriguez-Fuentes 2005), the Netherlands (Arnold and Vrugt 2002), Greece (Anagnostou and Papadamou 2015), Sweden (Svensson 2012), the UK (Dow and Montagnoli 2007), Canada (Georgopoulos 2009; Georgopoulos and Hejazi 2009), China (Cortes and Kong 2007; Guo and Masron 2017), and Indonesia (Ridhwan et al. 2014). Again, the literature identifies structural differences as source of differential effects of a common monetary policy.

B. Descriptive Data

Figure B.1: Aggregate Values of Balance Sheet Data in Billion Euros



(a) total assets

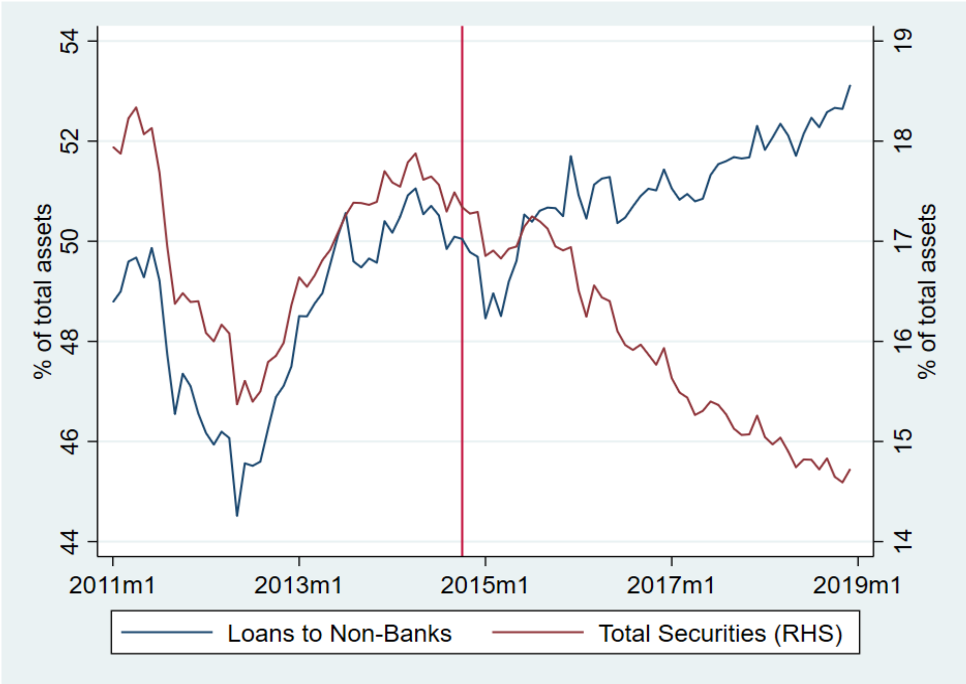


(b) loans to non-banks and securities

The drop in loans to non-banks in August 2013 is due to the re-classification of a large borrower.

Source: Deutsche Bundesbank.

Figure B.2: Aggregate Values as Shares of Total Assets



(a) loans to non-banks and securities

(b) reserves and excess reserves

Source: Deutsche Bundesbank.

Table B.1: Within-Decile Means and Standard Deviations

	1	2	3	4	5	6	7	8	9	10
Redemptions	.0194	.0463	.0659	.0821	.0989	.1164	.1333	.1583	.1938	.2602
	.0099	.0062	.0052	.0046	.0053	.005	.0056	.0086	.0113	.0322
Net Securities Trade	.0548	.0671	.0968	.106	.1146	.1272	.1547	.1655	.2188	.2541
	.074	.0538	.0661	.0631	.0696	.075	.0887	.0881	.11	.1017
Sales	.0785	.0565	.0675	.0563	.0542	.0644	.0633	.0608	.0823	.0614
	.106	.1242	.071	.0824	.0646	.0746	.0585	.0749	.1952	.064
Purchases	.1333	.1236	.1642	.1623	.1688	.1915	.2181	.2263	.3011	.3155
	.1388	.1277	.0926	.106	.0983	.1032	.0988	.1166	.1981	.1185
Loan Growth	.1859	.1806	.1706	.1726	.1776	.1501	.189	.1445	.1242	.1209
	.1935	.212	.1948	.1482	.2198	.1478	.2115	.1812	.1336	.1196
Δ (Loans/TA)	-.0159	.0083	.0053	.0131	.0119	.0197	.0095	.0255	.0237	.0414
	.1084	.0809	.0566	.0536	.0985	.0597	.1058	.1069	.06	.0751
Δ (Total Securities / TA)	.0069	-.0052	-.0058	-.0145	-.029	-.0302	-.0437	-.0363	-.0398	-.0663
	.0635	.0379	.0497	.052	.0641	.0562	.0696	.074	.0683	.0752
Δ Total Assets	.2884	.2751	.2854	.2545	.2543	.226	.2614	.2217	.2275	.1997
	.2999	.4002	.4081	.2465	.375	.2443	.3042	.2648	.2745	.2363
Δ (CB Liquidity / TA)	.0199	.0186	.0117	.0095	.0138	.0094	.0094	.013	.0114	.0197
	.0693	.0658	.0231	.0187	.0372	.0269	.0264	.0376	.0279	.0465

This table corresponds to the right column of figure 5. To construct it, I computed cumulated redemptions according to equation 10 and split the dataset at the deciles of cumulated redemptions. Before computing those quantiles, I drop the two percent banks with the topmost cumulated redemptions as they constitute outliers. The table shows the means (first row) and standard deviations (second row) of each variable named in the first column. Sources: Research Data and Service Centre (RDSC) of the Deutsche Bundesbank, BISTA, SHS, and CSDB, 2014-2018, own calculations.

C. Replication of Tischer (2018)

This appendix shows the outcome of my attempt to replicate the results of Tischer (2018) using his exact observation period and regression specification. Beware that I defined net sales so that the sign is opposite to Tischer's specification. This should not affect the coefficient size, though. Also, Tischer uses the spread between loan rates and yields of bonds with seven years of residual maturity rather than bonds of five years of residual maturity.

Table C.1 shows the result of an OLS regression of equation 1. I attempted to reconstruct the dataset of Tischer (2018) 1:1. The only obvious difference is that my dataset contains 1,558 banks while that of Tischer contains 1,565 – a difference which seems negligible. The coefficient of redemptions in column (1) of 0.112 is statistically highly significant and not at all economically negligible. Yet still it is already quite far away from Tischer's 0.173. The specifications in column (2), (3), and (5)[16] result in coefficients which have, at best, roughly half the size.

Table C.2 shows the result for running the same regression for the same time period (October 2014 to September 2016), but only for the 1,384 banks which constitute my own monthly dataset described in the main text. I have fewer banks in my dataset because my observation period is longer which results in a smaller balanced panel. Here, the coefficients are generally a bit closer to those of Tischer (2018) but differences are still striking. That there is not a huge difference between my results for Tischer's dataset and my dataset (for the same time period) at least shows that the results are not starkly influenced by those banks which are in Tischer's panel but not in mine.

Table C.3 reports the result of running equation 6 for Tischer's dataset. Here, I completely fail to reproduce his results. While for the specification in column (1) Tischer (2018) reports a coefficient of 0.069 for Redemptions EADB and 0.111 for the interaction term with the QE-period dummy which implies a massive effect of QE on loan growth, I find absolutely no effect whatsoever. Column (2), however, confirms that the expected effects are there in low equity banks. Columns (3) and (4) reveal the same pattern for using the spread of loan rates over bond yields: while I basically find a *negative* impact of the spread on loan growth, which is the opposite of what we would expect, this negative effect is purely driven by banks with equity above their within-sample average. Table C.4 again runs the same regression for the 1,384 panels in my dataset and again the results are, by and large, the same than in table C.3.

[16] I did not reproduce Tischer's column (4), though maintained the column numbering for the sake of easy comparison. Columns (1a), (1b), (2a), and (3a) are slight altercations which I added.

Table C.1: Replication of Tischer's (2018) Table 2

Dependent Variable:	LoanGrowth_{it}							
Time Period:	Monthly October 2014 to September 2016							
	(1)	(1a)	(1b)	(2)	(2a)	(3)	(3a)	(5)
Redemptions	0.112***			0.059*				
	(0.02)			(0.03)				
Redemptions Non-EADB		0.037				-0.022		
		(0.12)				(0.10)		
Redemptions EADB		0.123***	0.123***		0.071**	0.069*	0.069*	0.018
		(0.03)	(0.03)		(0.04)	(0.04)	(0.04)	(0.04)
Net sales				0.183***	0.183***			0.106
				(0.06)	(0.06)			(0.08)
Net sales Non-QE						0.174***	0.174***	
						(0.06)	(0.06)	
Net sales QE						0.161***	0.162***	
						(0.06)	(0.06)	
Net purchases				0.277***	0.277***	0.278***	0.277***	0.276***
				(0.09)	(0.09)	(0.09)	(0.09)	(0.09)
Change in CB borrowing						-0.102***	-0.103***	
						(0.03)	(0.03)	
Redemptions*LowEquity								0.100**
								(0.04)
NetSales*LowEquity								0.144
								(0.09)
Controls	yes	yes	yes	yes	yes	yes	yes	yes
Time FE	yes	yes	yes	yes	yes	yes	yes	yes
Bank FE	yes	yes	yes	yes	yes	yes	yes	yes
N	37,392	37,392	37,392	37,392	37,392	37,392	37,392	37,392
Number of banks	1,558	1,558	1,558	1,558	1,558	1,558	1,558	1,558
r2-within	0.4305	0.4305	0.4305	0.4440	0.4440	0.4448	0.4448	0.4445

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors (in parentheses) are clustered at the bank level. Sources: Research Data and Service Centre (RDSC) of the Deutsche Bundesbank, BISTA, SHS, and CSDB, 2014-2018, own calculations.

Table C.2: Replication of Tischer's (2018) Table 2 with banks in my dataset

Dependent Variable:	LoanGrowth_{it}							
Time Period:	Monthly October 2014 to September 2016							
	(1)	(1a)	(1b)	(2)	(2a)	(3)	(3a)	(5)
Redemptions	0.139***			0.084*				
	(0.03)			(0.04)				
Redemptions Non-EADB		0.162**				0.076		
		(0.08)				(0.10)		
Redemptions EADB		0.136***	0.136***		0.085**	0.083**	0.082**	0.045
		(0.03)	(0.03)		(0.04)	(0.04)	(0.04)	(0.04)
Net sales				0.184***	0.184***			0.087
				(0.06)	(0.06)			(0.09)
Net sales Non-QE						0.164***	0.164***	
						(0.06)	(0.06)	
Net sales QE						0.304***	0.304***	
						(0.10)	(0.10)	
Net purchases				0.250**	0.251**	0.252**	0.253**	0.251**
				(0.11)	(0.10)	(0.11)	(0.10)	(0.10)
Change in CB borrowing						-0.095***	-0.095***	
						(0.03)	(0.03)	
Redemptions*LowEquity								0.075*
								(0.04)
NetSales*LowEquity								0.215***
								(0.08)
Controls	yes	yes	yes	yes	yes	yes	yes	yes
Time FE	yes	yes	yes	yes	yes	yes	yes	yes
Bank FE	yes	yes	yes	yes	yes	yes	yes	yes
N	33,216	33,216	33,216	33,216	33,216	33,216	33,216	33,216
Number of banks	1,384	1,384	1,384	1,384	1,384	1,384	1,384	1,384
r2-within	0.4536	0.4536	0.4534	0.4648	0.4648	0.4655	0.4655	0.4653

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors (in parentheses) are clustered at the bank level. Sources: Research Data and Service Centre (RDSC) of the Deutsche Bundesbank, BISTA, SHS, and CSDB, 2014-2018, own calculations.

Table C.3: Replication of Tischer's (2018) Table 3

Dependent Variable:	$\text{LoanGrowth}_{\text{it}}$			
Time Period:	Monthly January 2014 to September 2016			
	(1)	(2)	(3)	(4)
Redemptions EADB	0.119***	0.118***	0.156***	0.207**
	(0.02)	(0.03)	(0.06)	(0.08)
Redemptions*LowEquity		0.001		-0.068
		(0.04)		(0.09)
RedemptionsEADB*QE	0.002	-0.065		
	(0.03)	(0.04)		
Redemptions*QE*LowEquity		0.127**		
		(0.05)		
Redemptions*Spread7			-0.029	-0.113
			(0.05)	(0.07)
Redemptions*Spread7*LowEquity				0.134*
				(0.07)
Net sales	0.106*	0.105*	0.098***	0.099***
	(0.06)	(0.06)	(0.03)	(0.03)
NetSales*QE	0.012	0.011		
	(0.08)	(0.08)		
NetSales*Spread7			0.029	0.026
			(0.07)	(0.07)
Controls	yes	yes	yes	yes
Time FE	yes	yes	yes	yes
Bank FE	yes	yes	yes	yes
N	49,856	49,856	49,856	49,856
Number of banks	1,558	1,558	1,558	1,558
r2-within	0.4165	0.4168	0.4166	0.4168

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors (in parentheses) are clustered at the bank level. Sources: Research Data and Service Centre (RDSC) of the Deutsche Bundesbank, BISTA, SHS, and CSDB, 2014-2018, own calculations.

Table C.4: Replication of Tischer's (2018) Table 3 with banks in my dataset

Dependent Variable:	$\text{LoanGrowth}_{\text{it}}$			
Time Period:	Monthly January 2014 to September 2016			
	(1)	(2)	(3)	(4)
Redemptions EADB	0.144***	0.136***	0.173***	0.196***
	(0.03)	(0.03)	(0.05)	(0.07)
Redemptions*LowEquity		0.014		-0.022
		(0.04)		(0.08)
RedemptionsEADB*QE	-0.014	-0.064*		
	(0.03)	(0.04)		
Redemptions*QE*LowEquity		0.096*		
		(0.05)		
Redemptions*Spread7			-0.033	-0.090*
			(0.04)	(0.05)
Redemptions*Spread7*LowEquity				0.088
				(0.06)
Net sales	0.108*	0.108*	0.100**	0.101**
	(0.06)	(0.06)	(0.04)	(0.04)
NetSales*QE	0.004	0.004		
	(0.09)	(0.09)		
NetSales*Spread7			0.024	0.022
			(0.11)	(0.11)
Controls	yes	yes	yes	yes
Time FE	yes	yes	yes	yes
Bank FE	yes	yes	yes	yes
N	44,288	44,288	44,288	44,288
Number of banks	1,384	1,384	1,384	1,384
r2-within	0.4457	0.4458	0.4457	0.4458

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors (in parentheses) are clustered at the bank level. Sources: Research Data and Service Centre (RDSC) of the Deutsche Bundesbank, BISTA, SHS, and CSDB, 2014-2018, own calculations.

D. Main Specification on Quarterly Basis

This appendix shows the same regression results as in subsection 6.1, just on a quarterly frequency rather than monthly frequency. Table D.1 reveals by and large the same results than table 1, just that the coefficients of redemptions and net sales are bigger and those of net purchases are smaller. Table D.2 corresponds to table 2. A direct comparison reveals a grossly similar pattern.

Table D.1: Results of OLS regression of equation 1 on quarterly basis

Dependent Variable:	$\text{LoanGrowth}_{\text{it}}$							
Time Period:	Quarterly 2013q1 to 2014q4							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Redemptions	0.146***			0.025				
	(0.03)			(0.10)				
Redemptions Non-EADB		0.082*				-0.093		
		(0.05)				(0.15)		
Redemptions EADB		0.166***	0.165***		0.063	0.057	0.059	0.001
		(0.03)	(0.03)		(0.08)	(0.09)	(0.08)	(0.08)
Net sales				0.349***	0.349***			0.251***
				(0.07)	(0.07)			(0.08)
Net sales Non-QE						0.391***	0.391***	
						(0.08)	(0.08)	
Net sales QE						0.048	0.052	
						(0.14)	(0.14)	
Net purchases				0.316	0.314*	0.322*	0.318*	0.284
				(0.19)	(0.19)	(0.19)	(0.19)	(0.20)
Change in CB borrowing						-0.093**	-0.092*	
						(0.05)	(0.05)	
RedemptionsEADB*LowEquity								0.113*
								(0.07)
NetSales*LowEquity								0.272**
								(0.12)
NetPurchases*LowEquity								0.068
								(0.08)
Controls	yes	yes	yes	yes	yes	yes	yes	yes
Time FE	yes	yes	yes	yes	yes	yes	yes	yes
Bank FE	yes	yes	yes	yes	yes	yes	yes	yes
N	23,528	23,528	23,528	23,528	23,528	23,528	23,528	23,528
Number of banks	1,384	1,384	1,384	1,384	1,384	1,384	1,384	1,384
r2-within	0.5138	0.5139	0.5138	0.5274	0.5275	0.5281	0.5281	0.5309
corr(u_i, Xb)	-0.5229	-0.5234	-0.5225	-0.4719	-0.4742	-0.4695	-0.4720	-0.4816

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors (in parentheses) are clustered at the bank level. Sources: Research Data and Service Centre (RDSC) of the Deutsche Bundesbank, BISTA, SHS, and CSDB, 2013-2018, own calculations.

Table D.2: Results of OLS regression of equation 6 on quarterly basis

Dependent Variable:	$\text{LoanGrowth}_{\text{it}}$			
Time Period:	Quarterly 2013q1 to 2014q4			
	(1)	(2)	(3)	(4)
Redemptions EADB	0.094	0.014	0.028	-0.163
	(0.09)	(0.12)	(0.16)	(0.21)
RedemptionsEADB*LowEquity		0.142		0.354
		(0.14)		(0.23)
RedemptionsEADB*QE	-0.026	-0.010		
	(0.06)	(0.11)		
Redemptions*QE*LowEquity		-0.017		
		(0.15)		
Redemptions*Spread5			0.036	0.127
			(0.09)	(0.13)
Redemptions*Spread5*LowEquity				-0.172
				(0.16)
Net sales	0.289**	0.195	0.365***	0.264**
	(0.12)	(0.13)	(0.13)	(0.13)
NetSales*LowEquity		0.243		0.244**
		(0.15)		(0.10)
NetSales*QE	0.045	0.051		
	(0.13)	(0.14)		
NetSales*QE*LowEquity		-0.000		
		(0.17)		
NetSales*Spread5			-0.033	-0.023
			(0.09)	(0.09)
NetSales*Spread5*LowEquity				0.000
				(.)
Net purchases	0.111	0.105	0.238	0.271
	(0.15)	(0.18)	(0.20)	(0.25)
NetPurchases*LowEquity		0.016		-0.105
		(0.15)		(0.24)
NetPurchases*QE	0.173*	0.147		
	(0.10)	(0.15)		
NetPurchases*QE*LowEquity		0.055		
		(0.17)		
NetPurchases*Spread5			-0.009	-0.055
			(0.10)	(0.13)
NetPurchases*Spread5*LowEquity				0.131
				(0.16)
LowEquity		-0.004***		-0.004***
		(0.00)		(0.00)
QE	-0.004***	-0.003**		
	(0.00)	(0.00)		
Spread5			-0.004*	-0.002
			(0.00)	(0.00)

Controls	yes	yes	yes	yes
Time FE	yes	yes	yes	yes
Bank FE	yes	yes	yes	yes
N	31,832	31,832	31,832	31,832
Number of banks	1,384	1,384	1,384	1,384
r2-within	0.5217	0.5247	0.5204	0.5235
corr(u_i, Xb)	-0.4460	-0.4540	-0.4484	-0.4565

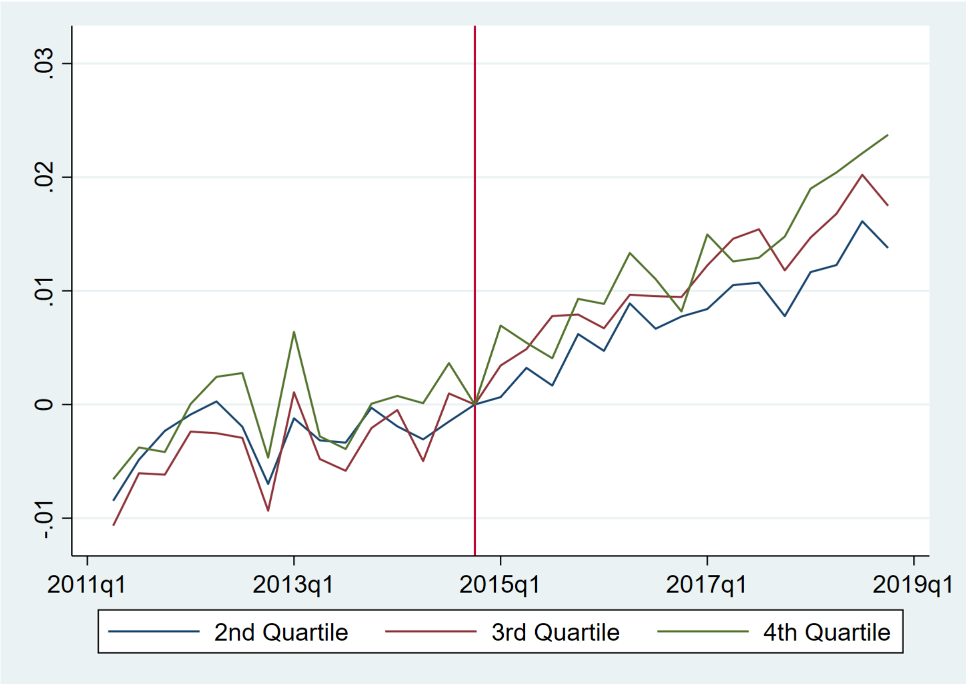
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors (in parentheses) are clustered at the bank level. Sources: Research Data and Service Centre (RDSC) of the Deutsche Bundesbank, BISTA, SHS, and CSDB, 2013-2018, own calculations.

E. Evolution of Loan Volume

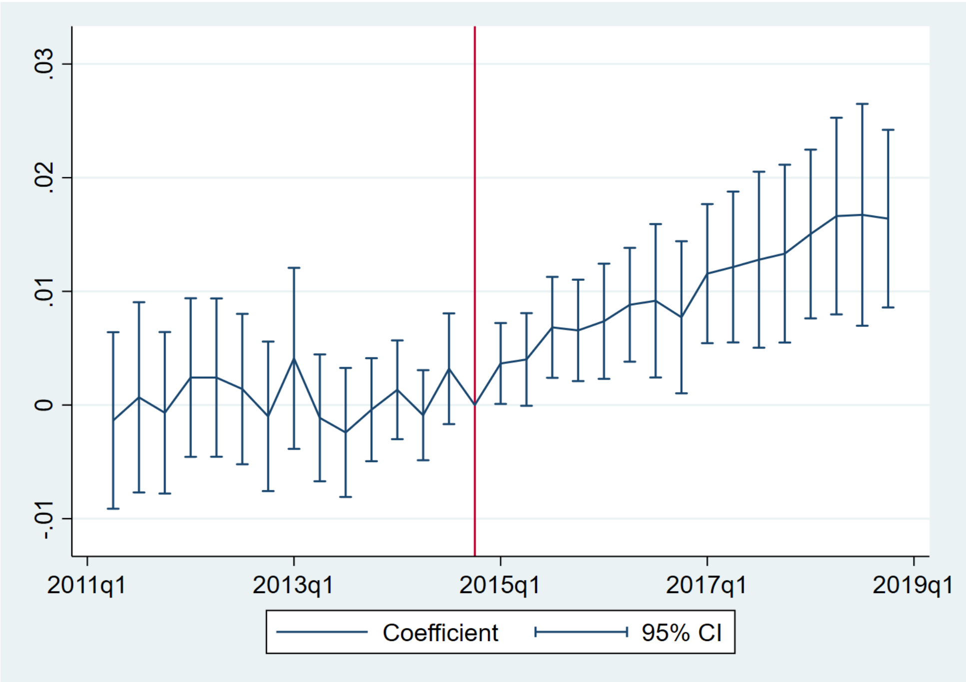
This appendix shows the results of running regression equation 7 with the volume of outstanding loans over total assets as dependent variable rather than cumulated loan growth. Figure E.1 corresponds to figure 6. It clearly shows that banks did indeed slightly increase the share of total loans in their total assets after 2014, but the fact that banks in the second through fourth quartile of cumulated redemptions show almost the same development in the dependent variable already casts doubt on whether this can be tracked back to redemptions. Figure E.2 corresponds to figure 7 and shows differential effects – or rather their absence. Only the split by type of loans might reveal a slight shift towards mortgage loans, though even if any of the coefficients had an statistical significance (which they don't) then the effect strength would be negligible.

Figure E.3 repeats the robustness check with using bank-industry pairs as panels to control for loan demand. Here, we actually see a nice pattern which by itself could be interpreted as a positive causal effect of redemptions on loan growth: banks in all quartiles of cumulated redemptions have the same share of loans in total assets before QE and then banks in higher quartiles start increasing this share compared to banks in lower quartiles. The comparison with figure E.1 shows that demand might be an important factor: banks with higher redemptions seem to experience lower loan demand. The effect strength, however, es very low: between end-2014 and end-2018, the average bank in the fourth quartile of cumulated redemptions increased its stock of loans by a mere 0.3 percent of total assets compared to the average bank in the first quartile. Plus, remember: a problem with looking at the stock of outstanding loans over total assets is that it can also grow because assets shrink and in my main specification where I used actual loan growth, I found no effect, be it with (figure 9) or without (figure 6) control for loan demand.

Figure E.1: Effect of cumulated redemptions on outstanding loan volume to non-banks



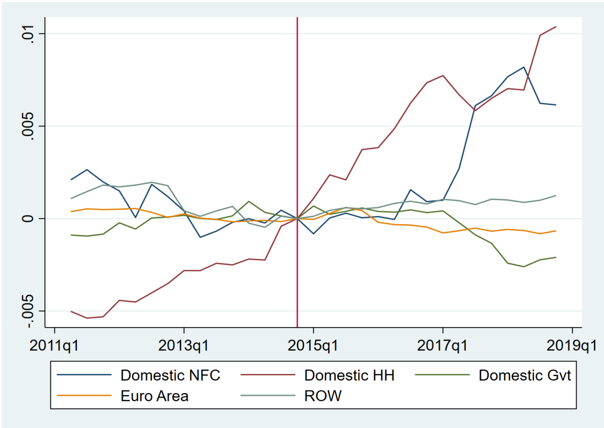
(a) by quartiles of cumulated redemptions



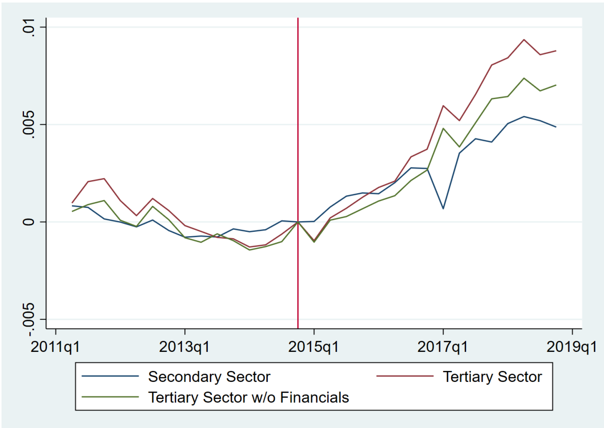
(b) above-median vs. below-median of cumulated redemptions

Both subfigures show the coefficient β_1 from regression equation 7 as in figure 6. The difference is that in this specification the dependent variable is the outstanding volume of loans over total assets: $\text{Loans}_{it}/\text{TA}_{it}$. Sources: Research Data and Service Centre (RDSC) of the Deutsche Bundesbank, BISTA, SHS, and CSDB, 2011-2018, own calculations.

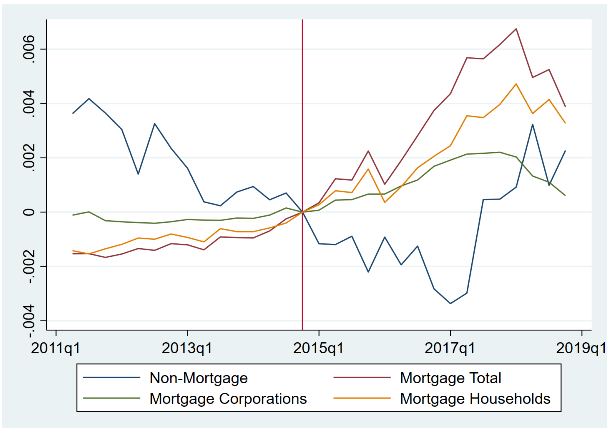
Figure E.2: Effect of cumulated redemptions on outstanding loan volume to non-banks, differential effects



(a) lending by institutional sectors



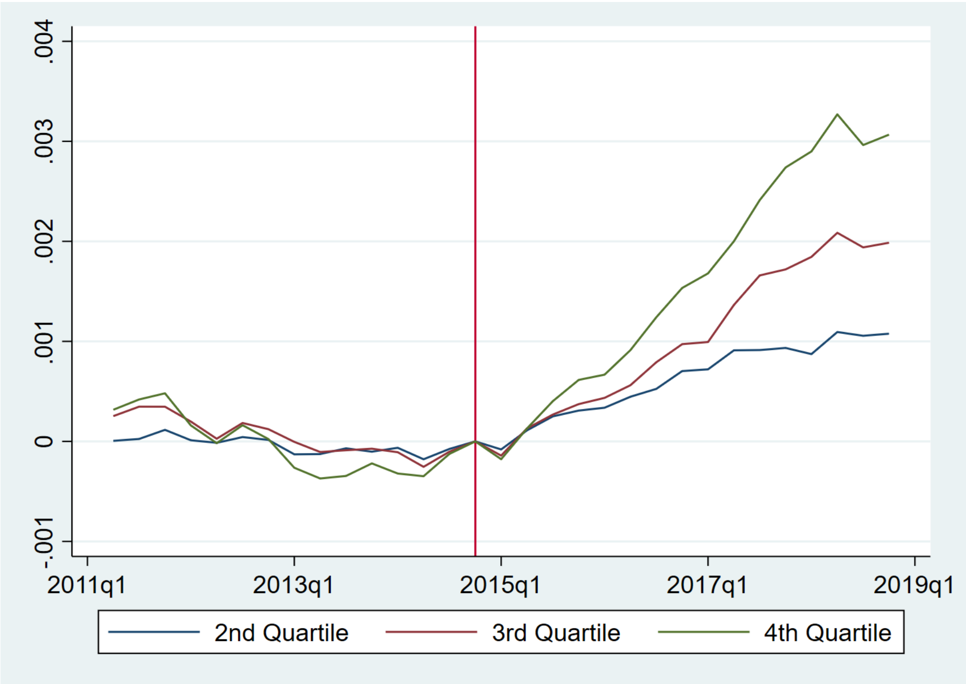
(b) lending by industrial sectors



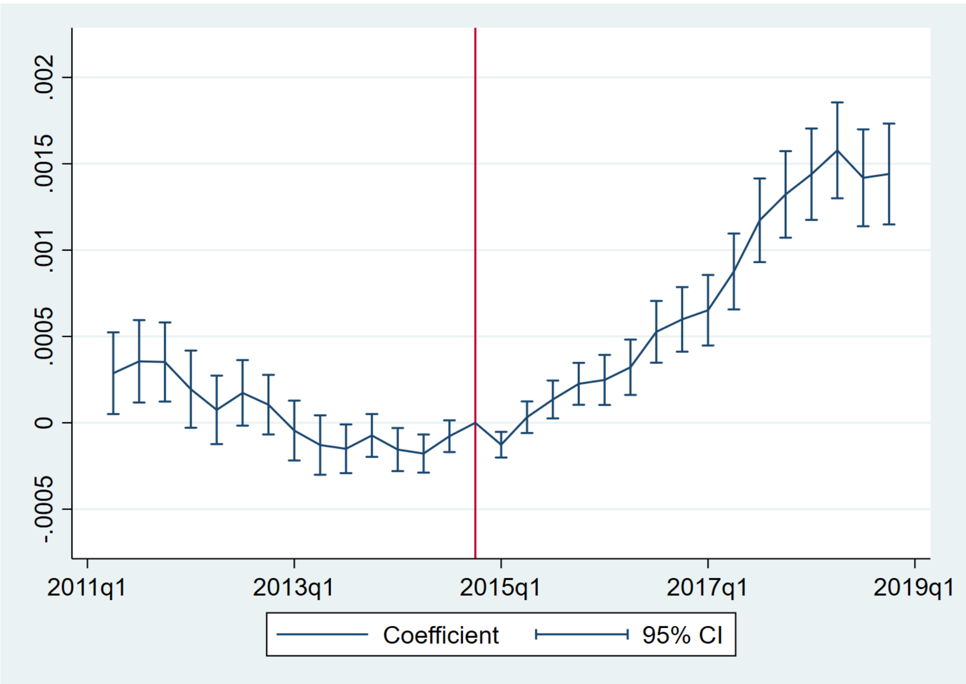
(c) lending by type of loans

All three subfigures show the coefficient β_1 from regression equation 7 as in figure 7. The difference is that in this specification the dependent variable is the outstanding volume of loans over total assets: $\text{Loans}_{it}/\text{TA}_{it}$. Sources: Research Data and Service Centre (RDSC) of the Deutsche Bundesbank, BISTA, VJKRE, SHS, and CSDB, 2011-2018, own calculations.

Figure E.3: Effect of cumulated redemptions on outstanding loan volume to non-banks with control for loan demand



(a) by quartiles of cumulated redemptions



(b) above-median vs. below-median of cumulated redemptions

Both subfigures show the coefficient β_1 from regression equation 7 as in figure E.1. The difference is that in this specification the panel variable has been changed from banks to bank-industry sector pairs in order to control for loan demand which is assumed to vary across industry sectors but not so much within. Sources: Research Data and Service Centre (RDSC) of the Deutsche Bundesbank, BISTA, VJKRE, SHS, and CSDB, 2011-2018, own calculations.