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Quantitative easing, portfolio rebalancing and credit growth: micro evidence from Germany

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④# Non-technical summary

Research Question

How does quantitative easing (QE) affect bank lending? Since the financial crisis that started in 2008, central banks around the world engaged in various types of unconventional monetary policy. Most prominently, central banks employed quantitative easing measures, which aimed at stimulating growth and inflation via reductions in long term yields. One transmission channel of QE is the stimulation of bank lending supply. Using micro data on German banks, this paper asks whether and how quantitative easing by the ECB did increase banks' lending supply.

Contribution

Broadly speaking, quantitative easing can affect bank lending via three channels. First, QE can increase banks' equity through higher asset prices, which stimulates lending. Second, increases in central bank reserve holdings incentivize banks to rebalance their portfolio towards longer-term assets like loans, because they want to restore the amount of duration risk of their asset holdings. Third, QE is designed to change the relative prices of assets by increasing prices of bonds. This change in the relative prices of bonds and loans makes loans relatively more attractive. Hence, banks have the incentive to rebalance their portfolio from bonds to loans. This paper develops a new identification strategy based on the maturity structure of banks' bond portfolio to identify the effect of QE on banks' lending supply.

Results

Banks increase their lending growth when the amount of bond redemptions in their portfolio is higher. This relationship is stronger during QE and depends strongly on the yield spread between loans and bonds. The higher loan yields are relative to bond yields, the stronger is the response of lending growth to an increase in redemptions. Difference-in-Differences estimates show that banks with more maturing bonds during the QE period increase their lending growth during to QE compared to banks with less redemptions. The growth differential between the two bank groups depends positively on the yield spread between loans and bonds as well. Hence, the yield spread between loans and bonds, which is likely influenced by QE, seems to influence the lending supply decision of banks. The result is likely not driven by unobserved bank characteristics as the same correlation between redemptions and credit growth and its dependence on the yield spread is not only visible between bank groups, but also within each bank over time.

Nichttechnische Zusammenfassung

Fragestellung

In diesem Papier untersuchen wir die Frage, wie unkonventionelle Geldpolitikmaßnahmen die Kreditvergabe der Banken beeinflussen. Seit der Finanzkrise von 2008/9 haben Zentralbanken auf unkonventionelle Maßnahmen der Geldpolitik zurückgegriffen, wobei eine wichtige Maßnahme im Aufkaufen von langlaufenden Anleihen besteht, das sogenannte Quantitative Easing (QE). Ein Ziel dieser Maßnahme besteht darin, die Kreditvergabe der Banken anzuregen, wenn konventionelle Maßnahmen der Geldpolitik ausgeschöpft sind. Wir verwenden Mikrodaten für deutsche Banken, um zu untersuchen, ob und wie das QE-Programm der Europäischen Zentralbank (EZB) die Kreditvergabe der deutschen Banken beeinflusst hat.

Beitrag

Drei Kanäle sind denkbar, wie das QE-Programm die Kreditvergabe beeinflussen kann. Erstens machen die Banken zusätzliche Gewinne, wenn der Wert ihres Anleiheportfolios steigt, so dass ihr Eigenkapital und damit ihre Fähigkeit, Kreditrisiken zu tragen, zunehmen. Zweitens können durch das zusätzliche Zentralbankgeld Anreize für die Banken entstehen, in langfristige Anlagen wie Kredite zu investieren, um das Fälligkeitsprofil auf der Aktivseite wiederherzustellen. Drittens soll das QE-Programm die relativen Preise von Vermögensgegenständen verändern, zum Beispiel gewinnen die Anleihen, die die EZB kauft, stärker an Wert als Kredite, was letztere aus Sicht einer Bank im Vergleich zu Anleihen attraktiver werden lässt. Dieses Papier macht sich die unterschiedliche Fälligkeitsstruktur der Anleiheportfolien der Banken zunutze, um den Effekt des QE-Programms auf die Kreditvergabe zu messen.

Ergebnisse

In unserer Studie finden wir, dass Banken ihre Kreditvergabe verstärkt ausweiten, wenn überdurchschnittlich viele Anleihen in ihrem Portfolio getilgt werden. Dieser Zusammenhang ist stärker ausgeprägt während des QE-Programms und hängt stark von der Renditedifferenz zwischen Krediten und Anleihen ab: Umso einträglicher Kredite im Vergleich zu Anleihen sind, desto stärker reagiert das Kreditwachstum auf Tilgungen. Dieses Resultat ist wohl nicht durch unbeobachtete Bankeigenschaften getrieben, da der gleiche Zusammenhang zwischen Tilgungen und Kreditwachstum nicht nur zwischen den Banken, sondern auch innerhalb einer Bank über die Zeit beobachtet werden kann.

Bundesbank Discussion Paper No 20/2018

Quantitative Easing, Portfolio Rebalancing and Credit Growth: Micro Evidence from Germany *

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Abstract

This paper sheds light on the effect of quantitative easing (QE) on bank lending. Using data on German banks for 2014–2016, I show that QE encourages banks to rebalance from securities to loans. For identification, I use bond redemptions as exogenous variation in banks' need to rebalance their portfolio and hence their exposure to QE. I find that more exposed banks increase their loan growth during QE relative to other banks. The growth differential is larger when bond market yields decrease stronger than loan market yields and for banks with equity constraints. These results imply that QE can affect bank lending even if banks do not hold assets purchased under the QE program, by increasing incentives to invest in higher-yield assets.

Keywords: Quantitative easing, bank lending, proprietary trading, monetary transmission

JEL classification: E51, E58, G11, G21.

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1 Introduction

Many central banks around the world engaged in quantitative easing (QE) policies after the recent financial and sovereign debt crises with the goal of stimulating economic activity and inflation. This revived interest in the transmission channels and effects of such unconventional monetary policies. One possible transmission channel of QE is to stimulate bank lending. Hence, an important question in the policy debate is whether and how asset purchases by the central bank affect bank lending. Therefore, this paper empirically tests whether banks increase their loan supply and rebalance their portfolio towards loans in response to the European version of QE using a sample period ranging from 2014 to 2016.

As laid out in Bernanke and Reinhart (2004), QE policies usually imply that the central bank purchases longer term bonds and pays with newly created central bank reserves. Under certain assumptions such as segmented markets, "preferred habitat" preferences or the existence of a money premium on short-term safe assets, relative asset prices will change (Andres, Lopez-Salido, and Nelson, 2004; Vayanos and Vila, 2009; Woodford, 2016).

The effects of QE on bank lending follow directly from these basic features. While an increase in reserve holdings might induce banks to hold more longer-term assets like loans to restore the desired level of duration risk (Christensen and Krogstrup, 2016)[1], changes in relative prices may affect lending for two reasons. First, higher asset valuations might boost bank equity, thereby fostering credit supply (Brunnermeier and Sannikov, 2016). Second, the new yield structure implies a new optimal portfolio allocation with a higher proportion of higher-yielding long-term assets (Andres et al., 2004; Gertler and Karadi, 2013), which induces portfolio rebalancing.

For empirical evaluations of these QE effects, the obvious identification challenge is to isolate the supply response of banks from the demand response of borrowers. Previous papers tried to solve this problem by comparing the lending behavior of banks with different exposure to the change in the monetary policy environment.[2] However, since they identified banks' QE exposure with time-invariant characteristics, it is difficult to rule out any bias due to correlation of the identification variable with other time-invariant and unobservable bank characteristics.

To make sure that time-invariant bank characteristics are not driving the results, one would ideally want to show the effect not only between bank groups, but also for each bank. However, this requires an identification variable that varies both between and within banks.

My identification strategy achieves this by exploiting heterogeneity in the maturity structure of banks' bond portfolios. By using data on German banks for 2014–2016, I can extract monthly information on security-specific redemption volumes in banks' portfolios from the German security register. This approach allows me to generate exogenous *and* time varying heterogeneity in the exposure to QE. Further, by fixing the security portfolio before the start of QE, I can extract information on redemptions that is determined before

[1] See Butt, Churm, McMahon, Morotz, and Schanz, 2014; Christensen and Krogstrup, 2017; Kandrac and Schlusche, 2017 for evidence on the effects of increases in central bank reserves.

[2] Albertazzi, Becker, and Boucinha (2018); Chakraborty, Goldstein, and MacKinlay (2017); Darmouni and Rodnyansky (2017); Kurtzman, Luck, and Zimmermann (2017); Paludkiewicz (2017).

banks could anticipate the change in policy. Still, due to the staggered occurrence of redemptions, the heterogeneity varies between and within banks over time. This allows us to show the same mechanism in panel regressions with bank fixed effects, exploiting variation within each bank over time, and in difference-in-differences regressions, which compare the change in behavior of specific bank groups.

An example might illustrate why this identification approach is desirable. Chakraborty et al. (2017) and Darmouni and Rodnyansky (2017) both use the balance sheet share of QE-eligible mortgage backed securities (MBS) to identify US banks that are more and less exposed to QE. In the former paper, this share is supposed to sort banks according to their ability to originate MBS. Banks with an MBS-related business model should increase loan growth during QE because the Federal Reserve bought these assets, possibly at favorable prices. Taking a different stance, the latter paper argues that banks holding more QE-eligible assets should experience higher increases in equity, because these assets should show the strongest change in prices. Hence, it remains unclear which of the channels drives the result. Using time varying exposure to the underlying transmission channel would make the distinction clear, since time varying measures of banks' willingness to originate MBS and of QE-induced changes in equity should not be found in the same variable.

So which transmission channel can be identified by using bond redemptions? Redemptions induce exogenous changes in banks' need and ability to rebalance the portfolio. First, whenever an asset matures, the bank faces a reinvestment decision.[3] It can choose between investing in bonds and granting loans. Given that a rebalancing motive exists, it will at the margin grant more loans. Second, redemptions, which result in an exchange of risky bonds and riskless cash, increase the bank's risk-bearing capacity. Hence, to the extent that banks' rebalancing is hampered by capital constraints, higher redemptions will lead to more rebalancing. This means that a higher volume of redemptions implies a higher loan growth, both within each bank over time and between banks. Theory predicts that this effect should increase in the rebalancing motive, which can be expressed as the yield differential between loans and bonds.

To theoretically understand how QE can induce rebalancing from bonds to loans, it is instructive to look at models with different asset classes, as is the case in, e.g., Dai, Dufourt, and Zhang (2013) and Jouvanceau (2016). They extend the standard models on QE (see, e.g., Andres et al., 2004; Chen, Cúrdia, and Ferrero, 2012; Harrison, 2012; Gertler and Karadi, 2013; Falagiarda, 2014), which only distinguish long- and short-term assets, by a second long-term asset. One implication of these models is that QE primarily decreases yields of the purchased assets when asset market are to some extent segmented (see, e.g., Krishnamurthy and Vissing-Jorgensen, 2011; D'Amico and King, 2013; Weale and Wieladek, 2016; Arrata, Nguyen, Rahmouni-Rousseau, and Vari, 2017 for empirical evidence) and the resulting yield differential spurs investments in the asset class with higher yields. In sum, portfolio rebalancing should not only take place between different maturities, but also between different asset classes when the yield differential between the asset classes increases.

[3]This can also be interpreted in the spirit of Christensen and Krogstrup (2016): Redemptions change banks' portfolio structure since the bond is replaced by cash when the principal is repaid. To make up for the additional cash holdings, banks have to rebalance their portfolio towards higher-yielding, less liquid and longer-term assets such as loans.

In principle, rebalancing could also be achieved by selling bonds without the need for redemptions. To rule out the possibility of banks increasing the importance of loans on their balance sheet simply by selling securities, thereby reducing the relevance of redemptions, I use the German banking sector as an ideal laboratory. The vast majority of the over 1500 German banks are buy-and-hold investors (see also Hildebrand, Rocholl, and Schulz, 2012). Only 5% of banks have a trading book and most assets in the banking books are recognized at historical cost. This results in the tendency to hold security investments until maturity: In the sample period spanning from 2014 to September 2016, which includes the European Central Bank's (ECB) quantitative easing program, the average bank keeps 85% of its positions unchanged until the end of the sample. This portfolio inertia is common across banks: 90% of banks keep more than 70% of their positions unchanged until maturity. Hence, most banks are actually buy-and-hold investors, rendering asset sales less important for German banks. Instead, redemptions have a significant role in changing banks' portfolio allocation (the importance of redemptions can also be seen in Figure 1).[4]

The results confirm the postulated relation between redemptions and credit growth: Credit growth is higher when a bank has a higher volume of maturing assets. This effect is robust to the inclusion of various controls, monthly ZIP-code fixed effects to control for local demand and is neither driven by specific characteristics of the maturing assets nor by an endogenous alignment of the maturity structure of asset portfolios with upcoming loan investment opportunities. Consistent with the idea that maturing assets increase the risk-bearing capacity of banks, the effect is stronger for banks with low equity.

In line with the theoretical predictions, the effect of redemptions on credit growth is much stronger in the period after the start of the ECB's QE program in October 2014 and its massive expansion in March 2015. This is because the effect increases with the interest rate spread between loans and bonds, which widened as a result of QE. Hence, banks rebalanced their portfolio more towards credit when loans were relatively more attractive from a yield perspective. To show that higher reserves increase the need to rebalance the portfolio as argued by Christensen and Krogstrup (2016), I use the volume of maturing assets as an instrument for changes in banks' reserve holdings and show that exogenous variation in bank reserves increases credit growth. This result is in line with existing research on the effect of reserves on bank lending, see e.g. Butt et al. (2014); Christensen and Krogstrup (2017); Kandrac and Schlusche (2017).

This rebalancing results in considerable loan growth: In a difference- in-differences framework I show that banks with higher redemption volumes increase their monthly credit growth during QE by 0.1–0.2 p.p. of total assets compared to other banks. This effect is robust to using a collapsed pre/post sample with only two periods, using a matched sample based on banks' propensity scores and using variation in banks' redemption volumes based on their portfolio in January 2014, 8 months before the first QE purchases. Importantly, the influence of maturing volumes is also robust to the inclusion of variables used in related work like the volume of banks' initial holdings of QE-eligible assets, as used in Darmouni and Rodnyansky (2017), and the yield change of the initial portfolio from Albertazzi et al. (2018).

[4]Besides the institutional argument, banks are unlikely to reduce the size of their balance sheet in such a situation, since this would result in capital being unused. Also, liquidity regulations require banks to hold a certain amount of relatively liquid bonds on their balance sheet.

These results have important implications for our understanding of QE policies. First, they provide evidence that changes in relative prices impact on credit growth. Second, the results show that QE can also be effective in banking systems where most banks are buy-and-hold investors and where most assets are recognized on the balance sheet at historical cost. What matters is not security trading and changes in fair values, but the price incentives and the ability of banks to adjust their balance sheet accordingly. Since the share of securities held to maturity increases drastically in other countries, these results have important implications for the way unconventional monetary policy measures affect real future outcomes.[5] For example, in the US the share of held-to-maturity securities has risen from around 10% after the financial crisis to 28% in 2017. This implies that an increasing portion of securities is recognized at historical cost and cannot easily be traded.[6] In such an environment, effects on bank lending via changes in equity are much less likely, whereas transmission via changes in relative prices and maturing securities should become more important.

The remainder of the paper is structured as follows. Section 2 describes the related literature, lists the key points of the ECB's QE program and summarizes the data. Section 3 contains the main steps of the empirical analysis and Section 4 shows further results and robustness tests. Section 5 concludes.

2 Literature, Institutional Setting and Data

2.1 Related Literature

Quantitative easing is generally understood as an increase in central bank reserves. In recent years, most central banks have achieved this increase by using new reserves to purchase long-term government debt or other long-term securities. In a standard new-Keynesian general equilibrium model, this policy should have no effect on market prices since the pricing of assets does not depend on the relative supply of these assets, but on the future path of consumption (Eggertsson and Woodford, 2003). However, by assuming certain market imperfections, the relative supply of assets starts to matter for asset prices. These mechanisms are called portfolio rebalancing theories and date back to Tobin (1969). Modern versions assume that long- and short-term assets are imperfect substitutes like in Andres et al. (2004), that investors have a "preferred habitat" for assets of different maturities (Vayanos and Vila, 2009) or that some securities offer money-like services as in Krishnamurthy and Vissing-Jorgensen (2012). Then investors cannot simply hold more short-term bonds if QE increases the supply of money and decreases the supply of long-term bonds. Instead, prices of long-term bonds have to adjust to incentivize investors to hold the additional supply of money.

Empirical papers studying these theories generally find that QE flattened the yield curve and decreased the level of market rates (see, e.g. Gagnon, Raskin, Remache, and Sack (2011), D'Amico and King, 2013 for the US, Joyce, Lasaosa, Stevens, and Tong

[5] Contributing factors to this effect could be regulatory changes that make it more costly to hold mark-to-market assets and the desire of banks to hedge their bond portfolios against rising interest rates.

[6] Data are from "Assets and Liabilities of FDIC-Insured Commercial Banks and Savings Institutions", https://www.fdic.gov/bank/analytical/qbp/, last accessed on September 27, 2017.

(2011) for the UK and Altavilla, Carboni, and Motto (2015) for the euro area).[7] Importantly, though, the effects differ between assets, with the highest price changes for assets that are purchased under QE (Krishnamurthy and Vissing-Jorgensen, 2011; D'Amico and King, 2013). One prominent example of these local effects is the recurring scarcity of QE-eligible assets as collateral in repo markets (Arrata et al., 2017). Since the costs of borrowing the collateral have to be approximately equal to the costs of buying it, elevated repo rates determine higher security prices.

The aforementioned characteristics of QE suggest that banks might be directly affected through at least three channels: changes in relative prices, higher asset valuations, and a higher aggregate level of reserves.

Changes in relative prices imply new optimal portfolio allocations, thereby inducing changes in investors' portfolios; investors then adjust their asset holdings to the new relative prices and yields. This can be a rebalancing from short- to long-term assets as in Andres et al. (2004); Gertler and Karadi (2013); Stein (2012); Woodford (2016), or also imply a rebalancing between different asset classes, if those asset classes are differently affected by QE (Dai et al., 2013; Jouvanceau, 2016). Evidence for rebalancing towards other securities can be found in Domanski, Shin, and Sushkoi (2017), Joyce, Liu, and Tonks (2017) and Koijen, Koulischer, Nguyen, and Yogo (2017), among others.

If the change in relative prices coincides with price increases, an additional effect can operate through bank equity: if the bank recognizes the price increase on the balance sheet (i.e. if it recognizes the assets at fair value), its equity will increase, which releases risk-bearing capacity and fosters investment in long-term, illiquid assets like loans (Brunnermeier and Sannikov, 2016).[8] However, this effect relies on the assumption that changes in security prices directly affect bank equity. This is not the case if securities are recognized at historical cost and are unlikely to be traded, as is the case with assets classified as held-to-maturity under IFRS.[9] Hence, in the setting in this paper equity changes are unlikely to play a substantial role since banks have the majority of their assets recognized at historical cost and are largely buy-and-hold investors that hold most of their assets until maturity.

Apart from price changes, changes in reserve holdings can also play a role in the transmission of QE. In Christensen and Krogstrup (2016), banks' holdings of central bank reserves change as a result of QE, for example if bank customers sell assets to the central bank and receive deposits in return. This disturbs the optimal portfolio allocation of the bank since the portfolio is now tilted towards safe, short-term assets. Hence, banks rebalance their portfolio and invest in riskier, long-term securities. In a similar vein, Bianchi and Bigio (2014) point out that increases in holdings of central bank reserves decrease the liquidity risk on banks' asset side. To restore the equilibrium liquidity risk, banks increase their holdings of illiquid assets, which mostly are long-term bonds or loans.[10] The same logic applies when (parts of) banks' security portfolios become more

[7] Borio and Zabai (2016) review the literature on QE effects.

[8] Similarly, by impacting their leverage ratio, banks could be inclined to increase lending if they target a fixed leverage ratio as in Adrian and Shin (2010, 2014).

[9] Also, if banks hedge the interest rate risk of their exposures, price increases will be offset by negative derivative valuations.

[10] The effects are related to the literature on the bank lending channel following Kashyap and Stein (1995) and Disyatat (2011): higher reserve holdings and higher equity lessen banks' need for, and cost of, expensive external financing, which should increase bank lending. However, it is unclear whether this

liquid due to the high demand for assets on the part of the central bank. Bowman, Cai, Davies, and Kamin (2015), Butt et al. (2014), Joyce and Spaltro (2014) and Kandrac and Schlusche (2017) provide empirical evidence for a positive effect of higher reserve holdings on bank lending.

The papers closest to this one are Albertazzi et al. (2018), Chakraborty et al. (2017), Darmouni and Rodnyansky (2017) and Paludkiewicz (2017). All study the impact of QE on bank-level lending behavior using slightly different approaches. Chakraborty et al. (2017) and Darmouni and Rodnyansky (2017) measure banks' QE exposure by their holdings of QE-eligible assets, finding higher mortgage lending growth for banks with higher QE exposure.[11] However, they differ in the interpretation of their results: while Chakraborty et al. (2017) base their finding on the argument that banks with different business models reacted differently to the price incentives set by QE, Darmouni and Rodnyansky (2017) explain their result by different changes in equity due to the differences in asset holdings.[12]

Albertazzi et al. (2018) and Paludkiewicz (2017) measure banks' QE exposure by the aggregate yield change in the security portfolio before and during the start of QE in Europe, finding that banks experiencing a higher reduction in yields increase their loan growth by more. However, the exact interpretation of this result is unclear since the yield decline in the security portfolio is not directly linked to a theoretical transmission channel. Still, Paludkiewicz (2017) finds that the relationship between loan growth and security yield decline is stronger for banks with more maturing assets and that these banks do not experience overproportional changes in equity. This supports the interpretation that banks' rebalancing decisions are driven by relative yield levels and that bond redemptions are linked to credit growth, both being consistent with the findings in this paper.

In order to effectively design unconventional monetary policy measures, it is crucial to understand their transmission mechanisms. The empirical research so far has often used identification mechanisms that are not directly linked to a specific channel and are prone to bias by bank-specific characteristics. This paper adds to the literature by proposing a new identification strategy for QE effects based on the maturity structure in banks' security portfolios. This allows us to complement difference-in-differences estimates, where the differential behavior of certain bank groups is tested, with panel regressions, which use variation within each bank over time.

The results imply that higher bond redemptions increase credit supply, indicating a rebalancing by banks from bonds to loans. This effect is stronger during QE and when the spread between yield on loans and bonds is higher. This lends support to theories that emphasize the role of changes in relative asset prices in the transmission of QE like Andres et al. (2004); Dai et al. (2013); Gertler and Karadi (2013); Jouvanceau (2016) and those that link portfolio rebalancing to changes in bank's portfolio allocation due to inflows of reserves (Christensen and Krogstrup, 2016). The important policy implication of this finding is that QE matters, even for banks that do not hold QE-eligible assets.

channel plays an important role in an environment with ample surplus liquidity.

[11] Kurtzman et al. (2017) also use this identification approach to show that banks with higher holdings of QE-eligible assets decrease their lending standards during QE, leading to higher risk-taking on the asset side of the balance sheet.

[12] The business model interpretation is in line with the finding by DiMaggio, Kermani, and Palmer (2016) that purchases of mortgage-backed securities increased, first and foremost, originations of QE-eligible mortgages.

2.2 Data & Setting

In this paper, I use data on the German banking sector from January 2014 to September 2016, which includes the first 2 years of large-scale asset purchases by the ECB, whose quantitative easing (QE) program is described in more detail in the appendix A.1.

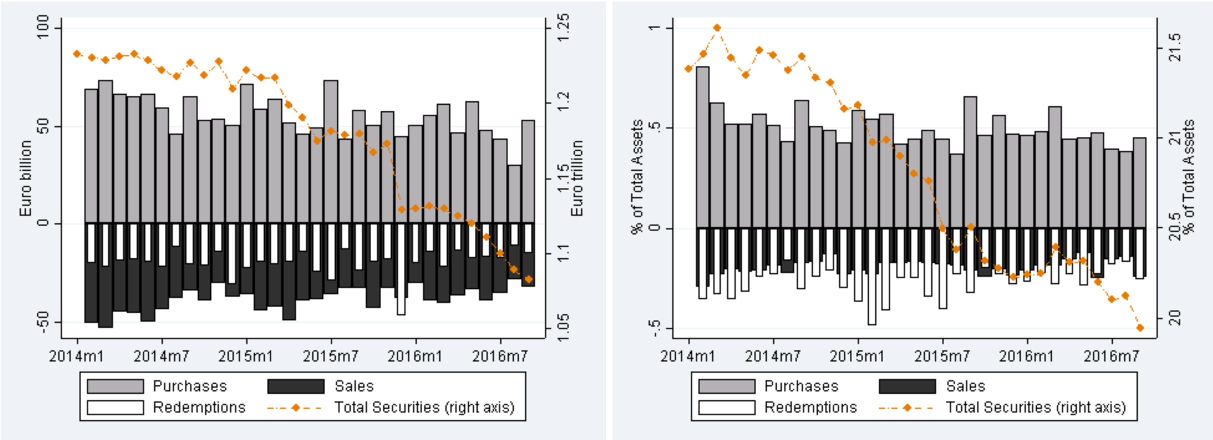
The German banking system has several features that are highly conducive to the identification approach. First, the majority of German banks are buy-and-hold investors. Of all securities banks held in January 2014, 82% were held until maturity or until the end of the sample in September 2016. 82% of these positions that were held to maturity saw no change in amount during the entire holding period. The picture is even stronger across banks: 70% of banks hold more than 70% of their positions unchanged until maturity or the end of the sample. The average bank even holds 85% of its positions unchanged. This is also true for maturing assets: of assets maturing during the sample period, 89% are held unchanged until maturity. And across banks, 90% of banks hold more than 70% of their maturing assets unchanged until maturity. This tendency to hold on to assets decreases during QE only for assets held in the trading book. Assets in the banking book are not more likely to be sold during QE as compared to the pre-QE period. All in all, most German banks sell assets seldom, especially when it comes to assets in the banking book.

This tendency to hold assets until maturity is also expressed in the usage of trading books. Only 115 out of 1565 banks in the sample ever hold assets in their trading book. Even for those banks, assets in the banking book are, on average, five times larger. It is important to note, though, that banking book assets are not automatically recognized at historical cost. Also within the banking book, banks can hold assets for trading purposes, which are recognized at current market prices. For most banks, however, this share is small.[13] Taken together, banks in Germany hold most assets until maturity, recognize a large share of their assets at historical cost and seldom trade assets. This implies that effects via bank equity are less likely to play a role: market prices are not reflected directly on banks' balance sheets, nor do most banks resort to asset sales to realize gains from increased asset valuations.

In this favorable setting where sales and equity effects are less likely to play a huge role, much of the changes in banks' security portfolios occur via maturing assets. To identify the monthly volume of redemptions, I use data from the Deutsche Bundesbank's Securities Holdings Statistics (SHS) (for an introduction to this dataset see Amann, Baltzer, and Schrape, 2012). This register contains monthly information on the security holdings of German banks at ISIN level. I match the information on monthly holding amounts with data from the ECB's Centralised Securities Database for the maturity date. I further use the ECB's Eligible Assets Database (EADB) and information on QE-eligibility provided by the Deutsche Bundesbank to identify assets eligible for ECB open market operations and ECB asset purchases under the QE program. In addition, I obtain the following bank-level information from the Bundesbank's monthly bank balance sheet statistics (BISTA): total assets, equity, wholesale borrowing, deposits, central bank borrowing, central bank

[13] Holding assets in the banking book with the intent of holding them until maturity can also entail trading restrictions: under IFRS, selling assets classified as held-to-maturity can imply that the entire portfolio has to be recognized at market prices instead of historical cost, because the sale questions the bank's ability to hold the assets until maturity.

Figure 1: Breakdown of Security Portfolio Changes: Redemptions, Sales, Purchases



(a) Aggregate security holdings **(b) Average share of security holdings**

Notes: Subfigure (a) shows the evolution of aggregate security holdings on the right axis and the aggregate portfolio changes by purchases, sales and redemptions on the left axis. Subfigure (b) shows the evolution of the average balance sheet share of security holdings, together with the average balance sheet share of purchases, sales and redemptions. Securities comprise only of debt security holdings of the 1565 banks in the final sample. Sources: SHS, BISTA, CSDB.

reserves and interbank lending as well as lending to non-banks, governments, corporations and households.

I adjust the data in the following way: I only use information on percent-denominated securities where the maturity date is known (98% of the total security volume). I further drop all banks that are not observed in all datasets over the entire sample period. This leaves 1565 out of 1711 banks in the sample.

For a better understanding of the changes in the security portfolios, Figure 1 breaks down the changes in security portfolios by sales, purchases and redemptions. We can see in subfigure (a) that aggregate holdings of debt securities started declining in late 2014/early 2015, around the start of QE. The €100 billion decrease in security holdings is considerable, even when compared to previous periods analyzed in Hildebrand et al. (2012).[14] The breakdown of portfolio changes shows that purchases almost balance out the sum of sales and redemptions. Purchases, sales and redemptions show a slight downward trend, which likely reflects the decrease in security holdings. The average shares across banks in subfigure (b) reveal the same pattern for security holdings, but show that in the cross section of banks, redemptions are more important than sales.

The aggregate numbers already show that redemption volumes change over time. But, the variance at the bank level is even larger. The average bank has redemptions only every 2.5 months, which translates into a transition probability to having a redemption of 33%. And the redemption volumes are sizable, averaging 3% of total securities. Moreover, even for banks that have redemptions in almost every month, the standard deviation of redemption volumes only shrinks to 80% of the overall standard deviation.

Regarding other key balance sheet variables, Table 1 provides summary statistics for

[14]This speaks to the results in Podlich, Schnabel, and Tischer (2017) who show that unconventional monetary policies are an important determinant of banks' security investments.

Table 1: Descriptive Statistics Before vs. During QE

All 1565 Banks			
	2014m9	2016m9	%
Securities/TA	0.216	0.202	-6.5
Lending/TA	0.588	0.599	1.9
Reserves/TA	0.016	0.025	59.4
Equity/TA	0.063	0.063	0.2
Total Assets	4.69E+09	4.81E+09	2.6

Notes: This table shows the evolution of the average balance sheet composition from September 2014, the last month before the start of QE, to September 2016, the end of the sample. Securities are all debt securities, TA stands for total assets. Lending is the lending volume to non-banks. Sources: SHS, BISTA.

the portfolio share before the start of QE and at the end of the sample.[15] We see that banks on average held 21.6% of their total assets in debt securities before the start of QE. During QE, the share of securities dropped by 6.5%. The opposite happened for loans: The share of loans increased during QE, from 59% to 60% of total assets. Taken together, banks on average rebalanced from securities to credit.[16] At the same time, banks' holdings of central bank reserves increased by 60%, as a result of QE, which increased aggregate reserves dramatically. Interestingly, we do not see a disproportionate change in equity. Instead, the equity share stayed roughly constant, suggesting that either monetary policy transmission via equity plays a minor role or banks economized on their equity. During QE, average total assets increased by 2.6% to €4.8 billion. This implies that banks reduced their security holdings in absolute terms as well, while aggregate lending rose.[17]

3 Results

The results section consists of three parts. First, I will establish the link between redemptions and credit growth during the QE period from October 2014 to September 2016. This relationship and its robustness to multiple alternative hypotheses serve as the basis for the second part, which will deal with the impact of QE on this relationship. The question will be whether QE encouraged banks to increase loan supply when bonds mature. While the first two parts will use the variation of credit growth and redemptions within banks, the third part will focus on differential behavior between bank groups. This analysis will reveal whether banks with a higher aggregate volume of redemptions during QE increased

[15] See Table A1 in the appendix for full descriptive statistics.

[16] Section A.3 in the appendix shows that this rebalancing took place within banks: banks with a higher reduction in the share of assets also had a significantly higher increase in the share of lending. The same holds for banks with higher cumulated net sales and higher cumulated redemptions between September 2014 and September 2016.

[17] These results remain unchanged when the numbers are weighted by the volume of banks' credit portfolio in the respective year.

their lending growth in a difference- in-differences framework, consistent with a positive effect of QE on credit growth.

3.1 Redemptions and Credit Growth during QE

In this section, I establish a link between redemptions in the security portfolio and credit growth during QE. I use the full panel of 1565 banks observed at monthly frequency for the October 2014 to September 2016 period. This time frame matches the time when the ECB purchased assets under its QE program. The main explanatory variable is the volume of bond redemptions in month t for bank i. Formally, if j counts individual securities, the maturing volume is calculated as follows[18]:

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

where TA stands for total assets. Obviously, changes in the security portfolio can also occur through asset sales. Since sales might also be important for the transmission of QE, it is necessary to control for the trading behavior of banks. I do so by calculating the net purchasing volume of bank i at time t and split the variable for observations where the bank is a net buyer and those where it is a net seller:

$$\text{Net trade}_{it} = \sum_{j \in not\ maturing\ in\ t} \frac{\Delta\text{Holding amount}_{ijt}}{\text{TA}_{i,t-1}} \tag{2}$$

$$\text{Net purchases}_{it} = \text{Net trade}_{it} * \text{I}[\text{Net trade}_{it} > 0] \tag{3}$$

$$\text{Net sales}_{it} = \text{Net trade}_{it} * \text{I}[\text{Net trade}_{it} < 0] \tag{4}$$

The regression looks as follows:

$$\frac{\Delta\text{Lending}_{it}}{\text{TA}_{i,t-1}} = \alpha_i + \alpha_t + \beta_1 * \text{Redemptions}_{it} + \boldsymbol{\gamma}' * \mathbf{A}_{it} + \boldsymbol{\delta}' * \mathbf{B}_{i,t-1} + u_{it} \tag{5}$$

The dependent variable is the change in the volume of lending to non-banks by bank i between t and t–1, normalized by total assets in t–1. α_i, α_t are bank and time fixed effects, while Redemptions_{it} is the volume of maturing assets in bank i's portfolio at time t, as defined in Equation 1. $\mathbf{A}_{it}$ is a vector containing the net purchases and net sales at time t, as defined in Equations 3 and 4. Note that the variable $\text{Net purchases}_{it}$ is *higher* if the bank purchases more assets, while the variable Net sales_{it} is *lower* if the bank sells more assets. $\mathbf{B}_{i,t-1}$ contains important determinants of credit growth which are often used in the bank lending literature (e.g., Gambacorta and Marques-Ibanez, 2011; Kashyap and Stein, 2000; Darmouni and Rodnyansky, 2017): the lagged balance sheet shares of deposits, wholesale funding and equity to control for the capital position and the funding structure as well as the lagged shares of interbank claims and central bank

[18] In the complete sample, there are very few (197) short positions in the redemption month. I exclude these observations from the calculation of redemptions, as it is unclear whether they initiate liquidity (out-)flows.

liquidity to control for the liquidity position of the bank. As lagged total assets occur on the left and right hand side of the equation, results might be biased by secular trend in total assets. To guard against this effect, $\mathbf{B}_{i,t-1}$ also includes the lagged natural logarithm of total assets and the growth rate of total assets between t and t–1 to control for trends in bank size and asset growth.[19] The results can be found in Table 2.

Column (1) of Table 2 shows that credit growth of a bank in a given month is higher if the volume of redemptions in its security portfolio increases. This result shows that banks use redemptions to rebalance from securities to credit during QE. It is robust to the inclusion of bank and time fixed effects to capture time-invariant bank-specific factors such as bank business models and aggregate effects that affect all banks in the same way, like changes in the monetary policy environment. Further, it is robust to controlling for important determinants of bank credit supply identified in the literature, like bank size, its equity ratio and funding structure as well as its liquidity position. The effect is quite sizeable: For each euro of maturing assets, credit growth increases by €0.17.

To make sure that redemptions do not coincidentally capture other variations in banks' security portfolio that are related to credit growth, I further control for the aggregate net sales and purchases of securities in column (2), which does not affect the result. Interestingly, the coefficient on Net sales is negative and highly significant, implying higher credit growth when banks sell more assets. One possible interpretation is that asset sales lead to realized gains, which increase banks' equity cushion and foster new lending. However, sales are not predetermined like redemptions. Hence, the coefficient might be driven endogenously by the decision of banks to cross-finance new credit by selling securities. I will tackle this endogeneity issue further in Section 3.3.[20] A first step to rule out that asset sales interfere with the measurement of the effect of redemptions is to estimate the specification in column (2) only for banks that do never (net) sell any assets during the entire sample period. Unreported results show that the coefficient of redemptions remains significant and of comparable size when only banks that never sell or never net sell are included in the regression.

In column (3), I explore whether heterogeneity across securities matters for the results. To this end, I split the redemption volumes between assets eligible for ECB open market operations at time t (Redemptions ECB$_{it}$) and those assets that are ineligible at time t (Redemptions Non-ECB$_{it}$).[21] The results suggest that primarily redemptions of assets that are ECB-eligible increase credit growth, while ineligible assets do not. But the null result for the ineligible assets could also stem from the fact that they occur much less often since, on average, 90% of the portfolio volume of banks consists of ECB-eligible assets.[22]

[19]Dividing by total assets ensures that the resulting growth rate of credit and volume of redemptions are comparable in size. Hence, ths specification is more suited than, e.g., a specification in logs. Column (5) of Table A5 shows that the result also holds when credit growth is calculated as log growth rate and redemptions are in logs, when an interaction term of redemptions with the lagged volume of credit is added to account for the variation in the log growth rate depending on the size of the credit portfolio.

[20]Note that net sales occur in roughly 10% of the sample observations, while redemptions occur in more than 50%, demonstrating that redemptions are a more important factor for rebalancing.

[21]Note that assets that mature during the sample period, including maturing assets eligible for ECB open market operations, were generally not eligible for QE purchases, as the ECB did not buy assets with a remaining maturity of less than two years at that time.

[22]For expositional brevity, I will from now on skip the redemption volumes of ineligible assets. None of the results depends on this differentiation.

Regarding sales, I differentiate between assets eligible for purchases under QE and other assets. If there are local effects on asset prices, as found for the US by Krishnamurthy and Vissing-Jorgensen (2011), the prices of QE-eligible assets should increase more. Then, sales of these assets could result in higher realized gains and larger effects on equity. The coefficient on QE-eligible asset sales is indeed higher than the coefficient for the remaining assets, but both remain significant. A test of equality of coefficients reveals that the effect of QE-eligible assets is significantly higher, but only at the 10% level. So there is mild indirect evidence for the existence of local price effects.

Table 2: Redemptions and Credit Growth

Dependent Variable:	ΔLending$_{it}$/TA$_{i,t-1}$				
Time Period:	Monthly October 2014 to September 2016				
	(1)	(2)	(3)	(4)	(5)
Redemptions$_{it}$	0.173***	0.151***			
	(0.031)	(0.041)			
Redemptions Non-ECB$_{it}$			0.027		
			(0.148)		
Redemptions ECB$_{it}$			0.173***	0.158***	0.109**
			(0.039)	(0.050)	(0.050)
Net sales$_{it}$		-0.243***		-0.218***	-0.190***
		(0.037)		(0.083)	(0.052)
Net sales Non-QE$_{it}$			-0.182***		
			(0.038)		
Net sales QE$_{it}$			-0.322***		
			(0.096)		
Net purchases$_{it}$		0.102	0.073	0.141*	0.065
		(0.070)	(0.070)	(0.073)	(0.069)
ΔCB Borrowing$_{it}$/TA$_{i,t-1}$			-0.104***		
			(0.028)		
Redemptions ECB$_{it}$*I[Low equity]$_{i,t-1}$					0.122***
					(0.043)
Net sales $_{it}$*I[Low equity]$_{i,t-1}$					-0.083
					(0.073)
Controls	yes	yes	yes	yes	yes
Month*ZIP FE	no	no	no	yes	no
Month FE	yes	yes	yes	-	yes
Bank FE	yes	yes	yes	yes	yes
Observations	37,560	37,560	37,560	13,608	37,560
R^2	0.514	0.518	0.545	0.487	0.549

Notes: This table shows results from OLS regressions of Equation 5. Dependent Variable is the change in lending to non-banks between t and t–1, divided by total assets in t–1 on a monthly basis from October 2014 to September 2016 for the 1565 banks in the sample. Redemptions ECB are the maturing volumes of ECB-eligible assets. Net sales QE measures the volume of net sales of QE-eligible assets. ΔCB Borrowing is the change in total borrowing from the central bank between t and t–1. Control variables are the lagged balance sheet share of deposits, wholesale deposits, equity, interbank lending and central bank reserves, the lagged logarithm of total assets as well as the growth rate of total assets between t and t–1. I[Low equity]$_{i,t-1}$ is a dummy for banks whose lagged equity share is below its sample mean, i.e. banks that are below their target equity ratio. The dummy is also included individually in column (5). ZIP FE are fixed effects based on the zip code of a bank's headquarters. Standard errors (in parentheses) are clustered at the bank level. ***, **, * denote significance at $p < 0.01$, $p < 0.05$, $p < 0.1$. For further information, please refer to Tables 1 and A1. Sources: SHS, BISTA, CSDB.

While the time fixed effects capture changes in the macro environment that affect banks homogeneously, there have been policy instruments that might affect banks differently. The most important central bank policy in this respect was the targeted longer-term refinancing operations (TLTROs), that supplied unlimited central bank liquidity with a maturity of up to three years. TLTROs were explicitly designed to increase credit supply: the interest rate charged for these loans decreased if the bank hit a pre-specified target for credit growth during the term of the TLTROs (Deutsche Bundesbank, 2016). Obviously, TLTRO uptake might be an important omitted variable if it is correlated with bond redemptions.

To control for TLTROs, I include the change in central bank refinancing (ΔCB Borrowing$_{it}$/TA$_{i,t-1}$) as a control in column (3). The main result remains unaffected. Interestingly, the coefficient on central bank refinancing is negative. This implies that banks that *increased* their central bank refinancing *decreased* their credit growth. The most compelling explanation for this finding is that troubled banks with lower credit growth increase their dependence on central bank refinancing.

One obvious problem has not been explicitly addressed: Banks' credit growth can differ because of differences in credit demand. While this should be less of a concern for redemptions, which are to a large extent predetermined, we can still try to capture this in a better way. To explicitly control for the demand each bank is facing, I include time varying fixed effects at the ZIP code level in column (4). These fixed effects capture differences in local demand under the assumption that all banks residing in the same ZIP code area are equally affected by it. The coefficient on redemptions decreases slightly, but is generally not affected by local demand differences. Since many banks drop out of the sample, the question remains whether the remaining banks are to some extent special. To rule out that either very small banks (which might be special as regards their balance sheet management behavior) or very large banks (for whom local demand should not be decisive) dominate the remaining sample; I repeat the estimation of column (4) using only banks between the 25th and 75th percentile of the total assets distribution in January 2014. The results (unreported) remain unchanged also in the restricted sample.

While we now know that a relationship between redemptions and credit exists, we do not know why it exists. Banks can create new loans by simply extending their balance sheet without needing maturing assets in that process. However, they will do so only as long as they can bear the additional risk. Hence, banks whose risk-bearing capacity is constrained might need to wait for maturing assets, which decreases the credit and liquidity risk on their asset side. Hence, the relationship between redemptions and credit should be stronger for banks with a low risk-bearing capacity. Measuring this capacity by the book equity ratio might be misleading since different banks target different equity ratios, e.g., depending on the overall riskiness of their operations (Gropp and Heider, 2010).

To control for the target equity ratio of banks, I correct the lagged equity ratio of each bank by its within-bank sample mean, which serves as an estimate of a bank's target equity ratio. To test whether the relationship between redemptions and credit is driven by banks with limited risk-bearing capacity, I interact the redemption volume with a dummy variable that takes the value of 1 for banks that are below their target equity ratio (the individual dummy is included as well). The results in column (5) show that the effect of redemptions is primarily driven by banks with equity constraints: the coefficient for constrained banks is more than twice as large and the difference between the coefficients highly significant. So banks that have free risk-bearing capacity because their equity ratio is above target can deliberately increase their lending, while constrained banks increase their lending whenever they have maturing assets.

This chapter established that a relationship between redemptions and credit growth exists during the QE period, indicative of a portfolio rebalancing from securities to credit. This relations proves robust to controlling for demand and other credit related variables. Consistent with the idea that redemptions increase the risk-bearing capacity of banks, the relationship between redemptions and credit growth is much stronger for banks with low equity.

3.2 Did QE initiate Portfolio Rebalancing?

The question that has to be answered now is why banks want to expand their credit supply and reduce the importance of securities in their portfolio.

In general, the optimal portfolio composition should be determined by the risk-return characteristics of different asset classes (Chakroun and Abid, 2016).[23] If the risk-return characteristics change, banks should seek to adjust their portfolio. This is exactly what happened as a result of QE: as many papers have shown, QE decreased bond yields to a significant extent (see, e.g., Gagnon et al., 2011; Joyce et al., 2011; Altavilla et al., 2015), with the largest effects on the assets that were targeted (Krishnamurthy and Vissing-Jorgensen, 2011; D'Amico and King, 2013; Weale and Wieladek, 2016; Arrata et al., 2017). Hence, since QE primarily affects bond yields, it increases the spread between the yields on new loans and bonds. In line with this, I find that the spread between the interest rate on new loans and the current yield on long-term bonds is 56 bps higher during QE. So since QE makes loans relatively more attractive, it becomes optimal to hold a higher proportion of loans on the balance sheet.

In order to test whether QE influenced the tendency of banks to rebalance towards loans, I now include the period before the start of QE. This allows me to test whether the behavior of banks changed as a result of QE. Hence, I estimate the following regression:

$$\begin{aligned}\frac{\Delta\text{Lending}_{it}}{\text{TA}_{i,t-1}} =&\alpha_i + \alpha_t + \beta_1 * \text{Redemptions}_{it} + \beta_2 * \text{Redemptions}_{it} * \text{I}[\text{QE}_t] \\ &+ \beta_3 * \text{Redemptions}_{it} * \text{I}[\text{Low equity}_{i,t-1}] + \beta_4 * \text{I}[\text{QE}_t] * \text{I}[\text{Low equity}_{i,t-1}] \\ &+ \beta_5 * \text{Redemptions}_{it} * \text{I}[\text{Low equity}_{i,t-1}] * \text{I}[\text{QE}_t] + \boldsymbol{\gamma}' * \mathbf{A}_{it} + \boldsymbol{\delta}' * \mathbf{B}_{i,t-1} + u_{it}\end{aligned} \tag{6}$$

Regression 6 features a full set of interaction terms between redemptions, $\text{I}[\text{Low equity}_{i,t-1}]$, a dummy for banks with equity below the target ratio, and $\text{I}[\text{QE}_t]$, a time dummy that is one during the QE period from October 2014 until the end of the sample (dummies are are included individually in $\mathbf{B}$).

The focus in these regressions will be on the interaction of redemptions and the QE time dummy as well as the triple interaction of redemptions, the time dummy and the low equity dummy. The former coefficient shows whether the rebalancing from securities to

[23] In a general sense, returns can also include non-monetary returns like improved access to liquidity if the asset is repoable. Obviously, regulation can also play a role, e.g. by asking banks to hold a specific portion of their assets in highly liquid assets such as government bonds.

credit increases with the introduction of QE, which would lend support to the interpretation that QE is responsible for the rebalancing. The latter coefficient shows whether this change in behavior is especially pronounced for banks that are likely capital-constrained.

Table 3: QE and Portfolio Rebalancing to Credit

Dependent Variable:	ΔLending$_{it}$/TA$_{i,t-1}$			
Time Period:	Monthly February 2014 to Sep 2016			
	(1)	(2)	(3)	(4)
Redemptions ECB$_{it}$	0.069**	0.088**	-0.077	0.030
	(0.030)	(0.040)	(0.074)	(0.110)
Redemptions ECB$_{it}$*I[Low Equity$_{i,t-1}$]		-0.030		-0.147
		(0.047)		(0.150)
Redemptions ECB$_{it}$*I[QE$_t$]	0.111***	0.018		
	(0.031)	(0.041)		
Redemptions ECB$_{it}$*I[QE$_t$]*I[Low Equity$_{i,t-1}$]		0.172***		
		(0.050)		
Redemptions ECB$_{it}$*Spread$_t$			0.178***	0.056
			(0.059)	(0.077)
Redemptions ECB$_{it}$*Spread$_t$*I[Low Equity$_{i,t-1}$]				0.184*
				(0.106)
Net sales$_{it}$	-0.101*	-0.103**	-0.067	-0.068
	(0.052)	(0.052)	(0.114)	(0.113)
Net sales$_{it}$*I[QE$_t$]	-0.114**	-0.113**		
	(0.056)	(0.056)		
Net sales$_{it}$*Spread$_t$			-0.088	-0.088
			(0.077)	(0.077)
Controls	yes	yes	yes	yes
Month FE	yes	yes	yes	yes
Bank FE	yes	yes	yes	yes
Observations	50,080	50,080	50,080	50,080
R^2	0.513	0.517	0.513	0.517

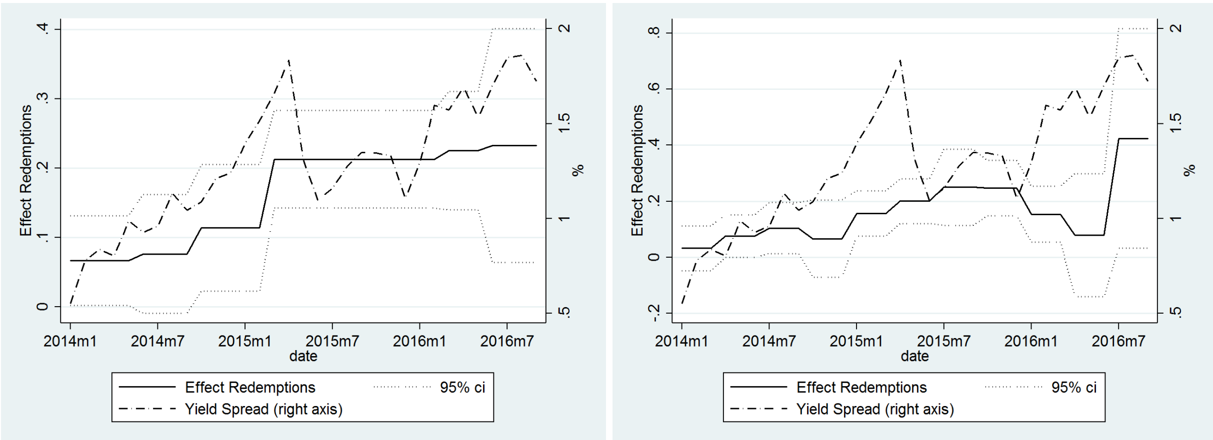
Notes: This table shows results from OLS regressions of Equation 6. Dependent Variable is the change in lending to non-banks between t and t–1, divided by total assets in t–1 on a monthly basis from February 2014 to September 2016 for the 1565 banks in the sample. Redemptions ECB are the maturing volumes of ECB-eligible assets. Control variables are the lagged balance sheet share of deposits, wholesale deposits, equity, interbank lending and central bank reserves as well as the lagged logarithm of total assets and the growth rate of total assets between t and t–1. I[Low equity]$_{i,t-1}$ is a dummy for banks that are below their target equity ratio, which is also included individually in columns (3) and (5), and I[QE$_t$] is a time dummy for the QE period, starting October 2014. Spread$_t$ is the monthly spread between average interest rates on new loans with a maturity of more than 5 years and the current yield on bonds issued in Germany with a residual maturity of more than 7 years. Standard errors (in parentheses) are clustered at the bank level. ***, **, * denote significance at $p < 0.01$, $p < 0.05$, $p < 0.1$. Sources: SHS, BISTA, CSDB, ZIS.

One would expect the effect to be stronger for capital-constrained banks as they have two incentives to rebalance towards loans. First, they should rebalance their portfolio towards higher-yielding, longer-term assets since the bank has too much cash on its balance sheet following the redemption. At least partly, the rebalancing can be in form of new loans (see Christensen and Krogstrup (2016) for a related model). Second, if QE creates incentives to extend new loans by increasing the yield spread between bonds and loans, banks with capital constraints might not be able to extend as many new loans as they desire. But redemptions release risk-bearing capacity, thereby allowing the bank to increase its loan growth. Dai et al. (2013) and Jouvanceau (2016) feature models where QE changes relative yields which encourages banks to rebalance their portfolio.

Interestingly, there is already evidence for the reverse situation: Abbassi, Iyer, Peydró, and Tous (2016) show that banks with expertise in security trading increased their security holdings and reduced their loan supply after the Lehman Brothers default in September 2008, which they explain with the relatively high returns on securities, whose prices had suffered more during the crisis than loans.

Turning to the results, we see in column (1) of Table 3 that the effect of redemptions on credit is higher during QE as compared to the February 2014 to September 2014 period.[24] This implies that banks rebalanced more towards loans after the introduction of QE. In column (2), we see that this change in behavior was driven by capital-constrained banks, which is in line with our predictions.

Figure 2: The Effect of Redemptions over Time



(a) Important QE periods **(b) Quarterly effects**

Notes: Subfigure (a) shows the monthly spread between the yields on new loans in Germany and long-term bond yields (time to maturity at least 7 years, issued in Germany) alongside the effect (coefficient) of redemptions on credit growth from estimating Equation 5 with interactions for different economically meaningful periods: two pre-QE periods until September 2014, the period of the first purchases until March 2015, the first period of large-scale asset purchases until February 2016, the period from March 2016 onwards, when purchases amounted to €80 bn and the period following June 2016, when the CSPP started. Subfigure (b) shows the quarterly effect of redemptions on credit together with the monthly yield spread between loans and bonds. Sources: SHS, BISTA, CSDB, ZIS.

We argued earlier that QE increased the yield spread between loans and bonds, which might be a driver of the rebalancing towards loans. To formally test whether the increase in the effect reflects changes in the yield spread between bonds and loans, I calculate the difference between the average interest rate on new loans extended in a given month and the monthly current yield of all long-term bonds issued in Germany. This spread captures the average yields on long-term bonds and loans in the German market for a given month. Thus, it is representative for the current relative attractiveness of loans and bonds. Column (3) shows that the effect of redemptions on credit is significantly

[24]I define October 2014 as the start of QE because this is the time when the ECB started to purchase assets, albeit on a smaller scale. However, the results in this paper also hold if I use March 2015 as the start of QE instead.

stronger when bonds become unattractive relative to loans. In fact, the average level of the yield spread during QE explains almost the entire effect of redemptions on credit.[25] It is also interesting to note that with a yield spread of zero, the effect of redemptions is insignificant, as represented by its base coefficient in column (3).

Again, the question is whether the rebalancing from bonds to loans was driven by banks with capital constraints. Indeed, column (4) shows that the triple interaction term is significant, implying that banks with capital constraints want to increase their loan growth when loans are attractive and do so especially when they have maturing securities. This result extends the literature on the interplay of monetary policy and bank capital as in Jiménez, Ongena, Peydró, and Saurina (2012). They show that the reduction in lending supply following an interest rate raise is stronger for weakly capitalized banks. Turning the results around, weakly capitalized banks show a stronger increase in lending supply following an interest rate cut. The results here suggest that the increase in loan growth might come at the expense of security holdings, especially when capital is tight and yield incentives favor loans over securities.

Figure 2 plots the evolution of the coefficient over time. In subfigure (a), the coefficient is estimated for economically meaningful subperiods[26], while subfigure (b) estimates the coefficient quarterly.[27] In both graphs, it can be nicely seen that the effect of redemptions on credit growth increases slightly when the purchases start and jumps to a high level with the start of large-scale purchases in March 2015. This is also the time when the yield spread between loans and bonds reaches its first local maximum. Hence, the response of the effect to QE is clearly visible. Also the correlation of the yield spread with the time series of effects is very high at 0.75 for the effect in subfigure (a) and 0.53 in subfigure (b). This high correlation strengthens the evidence that the effect responds to changes in the yield spread between loans and bonds.

The results in this section have established that the relationship between redemptions and credit growth is stronger during QE since it varies with the yield spread of loans to bonds.[28] This result can be explained by the need to rebalance the portfolio after assets mature and taking into account the relative attractiveness of loans compared to bonds *for reinvestment*. A complementary interpretation is that *all* banks want to change their portfolio structure in favor of loans since a change in yields implies a new optimal portfolio composition. This is consistent with the finding that the effect of redemptions on credit is stronger for banks whose equity ratio is below target; these banks can reach the new optimal level of loans only by replacing maturing bonds with loans.

[25] A 56 bps increase in the yield spread implies an average yield spread of 140 bps during QE. This predicts an effect in column (6) of $-0.077 + 0.178 * 1.40 = 0.1722$. This is almost equal to the effect of 0.173 in column (2), which was measured during QE.

[26] The periods are two pre-QE periods until September 2014, the period of the first purchases until March 2015, the first period of large-scale asset purchases until February 2016, the period from March 2016 onwards, when purchases amounted to €80 bn and the period following June 2016, when the CSPP started.

[27] The effects on both subfigures can differ, because quarterly estimates come at the cost of restricting the within bank correlation that can be used to estimate the effect.

[28] That the yield spread between loans and bonds is indeed driven by the impact of unconventional monetary policy on bond yields and not by changes in banks' risk attitudes is shown in Section 4.2.2.

3.3 Average Credit Growth Effects of QE

In this section, I establish that the amount of maturing assets has a positive effect on credit growth during QE. So far, we know that credit growth is higher in months with higher redemption volumes and that the response of credit growth to redemptions was stronger during QE. However, it is not clear whether this has aggregate positive effects on credit supply. It might be, for example, that banks adjust their security portfolio such that its maturity structure matches the arrival of new investment opportunities for loans. Or, banks hold back new loans until they have maturing assets in the portfolio to economize on equity or liquidity. In these cases, the results from Section 3.2 are endogenously driven and do not represent actual effects on credit growth. While Section 4.2.1 shows that the results from the previous sections are not driven by the endogenous adjustment of the bond portfolio such that bond redemptions meet loan investment opportunities, it still cannot be ruled out that banks shift the *timing of loans* to correspond to the maturity structure in the bond portfolio.

In general, it is unclear why an endogenously driven effect should change during QE. But there is also an empirical way to rule out an endogenous relationship. The idea is to show that higher redemptions lead to higher average credit growth *over a relatively long time period*. The reason is that endogenous adjustments of credit extension and bond redemptions would lead to a higher correlation within banks over time without altering aggregate credit supply: banks would merely shift the same loan or redemption quantities over time such that high loan and redemption volumes fall on the same month instead of increasing their credit supply when assets in the bond portfolio mature. But wherever redemptions have a positive effect on average credit growth over a relatively long period, it is very unlikely that this is driven by endogenous adjustments: If the results were driven endogenously, the average level of credit growth over time should be independent of the volume of redemptions because banks would only shift the same quantities of credit growth between months, regardless of the volume of redemptions.

To measure whether higher aggregate redemptions increase average credit growth over a longer time period, I employ a difference-in-differences design, comparable to Darmouni and Rodnyansky (2017). A huge advantage of this approach is that it also serves to test the effect of QE on credit growth. By comparing the response of credit growth for banks with more and less redemptions to the implementation of QE, we can test whether banks that are more exposed to QE respond differently compared to other banks: Banks with more redemptions during QE can overcome equity constraints more easily and are more exposed to reinvestment decisions to rebalance their portfolio. Thus, these banks should increase their credit growth by more as a result of QE. To identify these banks, I aggregate the monthly volume of redemptions of ECB-eligible assets for each bank over the entire QE period in the sample as shown in Equation 7:

$$\text{Redemptions}_i^{cum} = \sum_{t \in [2014m10-2016m9]} \sum_{j \in maturing\ in\ t} \frac{\text{Holding amount}_{ijt}}{\text{TA}_{i,t-1}} \tag{7}$$

Then, I split the banks according to the median of the cumulated redemptions.[29] Banks

[29]Splitting the sample at the median is a more conservative approach compared to other papers which compare the lowest and highest quartile, e.g. Darmouni and Rodnyansky (2017). The results in this

with redemptions above the median are the "affected" banks:[30]

$$\text{I}[\text{Redemptions}^{high}]_i = \text{I}[\text{Redemptions}_i^{cum} > p(50)]_i \tag{8}$$

I repeat this approach for the trading position of banks: I aggregate Net trade$_{it}$ from Equation 2 over the period from October 2014 to September 2016 and split the sample at the median of this variable. The resulting dummy I[Net trade^{low}]$_i$ equals 1 for banks with low (and mostly negative) values of net trade, which resembles net selling.

Before we look at the regression results, we can already see the aggregate effect of redemptions in Figure 3. It shows the evolution of lending aggregated within the "affected" and "unaffected" group. In subfigure (a), we see that the average balance sheet share of lending shows a parallel trend for both groups before the start of QE. But after the start QE and, more pronouncedly, after the start of large-scale purchases in March 2015, the two series start to diverge: Banks with more redemptions increase the balance sheet share of lending by more. Hence, the behavior of the two groups changed during QE. The evidence in subfigure (b) complements this picture: the change in the growth of total lending is much more pronounced for the group of banks with high redemptions. Also, subfigure (b) shows that the total volume of lending indeed increased in both groups. This makes it much more likely that positive difference-in-differences estimates represent increases in credit growth, not smaller credit reductions.

To estimate the difference-in-differences effect, I use the following regression design:

$$\frac{\Delta\text{Lending}_{it}}{\text{TA}_{i,t-1}} = \alpha_i + \alpha_t + \beta_1 * \text{I}[\text{Redemptions}^{high}]_i * \text{I}[\text{QE}]_t + \boldsymbol{\delta}' * \mathbf{B}_{i,t-1} + \boldsymbol{\kappa}' * \mathbf{B}_{i,t-1} * \text{I}[\text{QE}]_t + u_{it} \tag{9}$$

In this regression, I[QE]$_t$ is a time dummy that equals 1 after the start of the first asset purchases in October 2014.[31] Hence, the coefficient β_1 captures the change in the growth rate of lending during QE for banks with high redemptions as compared to the change in the growth rate of lending during QE for the banks with low redemptions. If β_1 is positive, the banks with high redemptions during QE increased their lending growth by more. The control variables in $\mathbf{B}_{i,t-1}$ are the same as in Table 2 and are also interacted with the QE dummy. Hence, all determinants of lending are allowed to change their effect as a result of QE. Standard errors are clustered both at the bank and time level.[32] The results can be found in Table 4.

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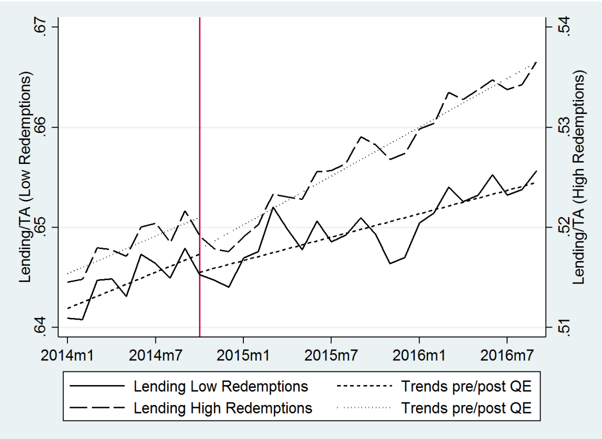
chapter are even robust to using the raw cumulated maturity shares Redemptions$_i^{cum}$.

[30] Another theoretical interpretation of the split between banks with high and low redemptions comes from Andres et al. (2004). They model the term structure by assuming two types of agents: restricted agents who can only invest in cash and long-term assets and unrestricted agents who invest in cash, long- and short-term assets. Unrestricted agents view long-term bonds and cash as imperfect substitutes. Banks with more redemptions are c.p. banks with a lower duration of their asset portfolio, so they hold more short-term assets. Hence, the "affected" banks resemble the unrestricted agents in their model. One prediction of their model is that when the central bank increases the level of reserves and decreases the supply of long-term assets (as does QE), unrestricted agents want to rebalance their portfolio more heavily towards long-term securities than restricted agents.

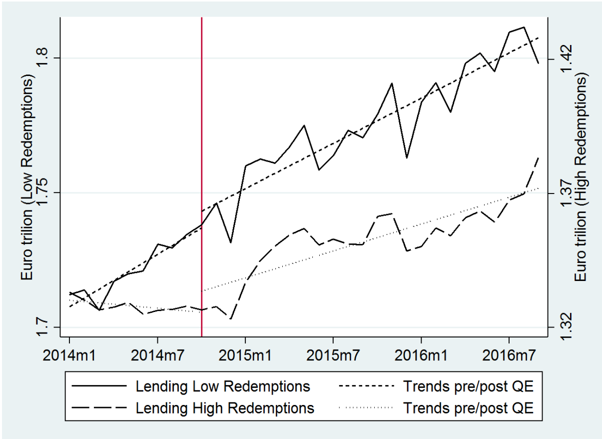
[31] As in Tables 2 and 3, the results do not hinge on the definition of the QE dummy. The results still hold if I use March 2015 as the start of QE instead.

[32] Since there are only 33 observations over time, there are just enough observations to justify clustering at both dimensions. The results also all hold with clustering at the bank level only.

Figure 3: The Evolution of Lending Volumes



(a) Average share of lending



(b) Aggregate volume of lending

Notes: Subfigure (a) shows the evolution of the average balance sheet share of lending for the banks with high and those with low redemptions during QE, as defined in Equation 8. Subfigure (b) shows for the same groups the evolution of the aggregate volume of lending. The vertical line depicts the start of QE in October 2014. Trends are calculated as linear fit for the pre-QE and post-QE period, respectively. Source: BISTA.

Column (1) of Table 4 shows that $\hat{\beta}_1$, the difference-in-differences effect, is positive and significant. Banks with high redemptions during QE increase their lending growth during QE by 0.2% of their total assets in each month relative to banks with fewer redemptions. Hence, higher redemptions lead to *persistently* higher growth rates of credit during QE. This strongly supports the notion that the correlation of redemptions and credit growth found in Tables 2 and 3 is not driven by endogenous relationships, but instead by an underlying economic mechanism. Regarding the trading behavior of banks, the results show that banks that are strong net sellers of assets also increase their lending growth during QE by a comparable magnitude. This result indicates that some banks try to rebalance their portfolios more aggressively towards credit. However, it might also be driven endogenously if banks sell assets to use the risk-bearing capacity/liquidity to meet increases in credit demand. I try to address the problem of endogeneity of sales in column (6).

Earlier, we established that banks primarily rebalance from maturing securities to credit when they are below their target equity ratio. So if equity is indeed important for credit growth, we should find that redemptions are of particular importance when equity is low. If this is true, credit growth should be higher for those banks that have many maturing assets when their equity is low. To test this, I calculate the total redemption volume of assets during QE by only using months where a bank is below its equity target. Banks above the median of this variable are the affected banks whose credit growth should increase most during QE ($\mathrm{I}[\text{Redemptions low Equity}^{high}]_i$). Column (2) shows the results: The coefficient for the affected banks is of comparable size to column (1) and highly significant. So redemptions matter when equity is low.

As with the results in the previous section, we might face the problem that banks adjust their maturity structure endogenously to the arrival of new lending opportunities.

If banks anticipated that QE would result in higher economic activity and higher credit growth, they might have adjusted their security portfolio so that many redemptions fall into a period of high lending growth. To rule out the possibility of this driving the results, I use the maturity information contained in banks' security portfolios in January 2014 in column (3). This means I add up the holding amounts in banks' portfolios of January 2014 for those bonds that mature between October 2014 and September 2016. Then I create the dummy I[Initial Redemptions^{high}]$_i$, which equals one for those banks that are above the median of the aggregated holding amounts.

Table 4: Difference-in-Differences Estimation

Dependent Variable:	ΔLending$_{it}$/TA$_{i,t-1}$					
Time Period:	Monthly February 2014 to September 2016					
	(1)	(2)	(3)	(4)	(5)	(6)
I[Redemptions^{high}]$_i$*I[QE]$_t$	0.002***					
	(0.000)					
I[Redemptions Low equity^{high}]$_i$*I[QE]$_t$		0.002***				
		(0.000)				
I[Initial Redemptions^{high}]$_i$*I[QE]$_t$			0.002**	0.002***		0.001***
			(0.001)	(0.000)		(0.000)
I[Net trade^{low}]$_i$*I[QE]$_t$	0.002***	0.002***	0.003***	0.002***		
	(0.000)	(0.000)	(0.001)	(0.000)		
I[Initial Exposure^{high}]$_i$*I[QE]$_t$				0.000		
				(0.000)		
I[Yield Change^{high}]$_i$*I[QE]$_t$				0.000		
				(0.000)		
I[Init Redemptions^{high}]$_i$*Yield Spread$_t$					0.003***	
					(0.001)	
I[Net trade^{low}]$_i$*Yield Spread$_t$					0.003***	
					(0.001)	
I[QE sales^{high}]$_i$*I[QE]$_t$						0.002
						(0.004)
Controls	yes	yes	yes	yes	yes	yes
Controls*I[QE]$_t$	yes	yes	yes	yes	yes	yes
Month*ZIP FE	no	no	yes	no	no	no
Month FE	yes	yes	-	yes	yes	yes
Bank FE	yes	yes	yes	yes	yes	yes
rk LM p-value	-		-	-	-	0.00
Observations	50,080	50,080	18,144	50,080	50,080	50,080
R^2	0.511	0.511	0.444	0.511	0.511	0.510

Notes: This table shows regressions of Equation 9. The dependent variable is the change in total lending over lagged total assets. Control variables are the lagged balance sheet share of deposits, wholesale deposits, equity, interbank lending and central bank reserves as well as the lagged logarithm of total assets and the growth rate of total assets between t and $t-1$. rk LM p-value is the p-value for the test of underidentification of the IV regression following Kleibergen and Paap (2006) (H_0: Underidentification). ZIP FE are fixed effects based on the ZIP code of a bank's headquarters. Standard errors (in parentheses) are double-clustered at the bank and time level. ***, **, * denote significance at $p < 0.01$, $p < 0.05$, $p < 0.1$. Sources: SHS, BISTA, CSDB.

The result remains unchanged: the difference-in-differences effect is just as high as in columns (1) and (2). Since the results from Tables 2, 3 and 4 are all robust to using initial redemptions, it is highly likely that redemptions indeed have an exogenous effect on lending. It seems improbable that banks had already adjusted the maturity structure of their security portfolios in January 2014 to the arrival of lending opportunities during QE on a monthly basis.

Still, the demand facing individual banks might have changed as a result of QE, leading to changes in their credit growth. While there is generally no reason why demand should be related to redemptions that are predetermined, I still try to rule out the possibility of changes in demand driving the results. As in Table 2, I control for the local demand facing individual banks by including monthly varying ZIP-code fixed effects. However, as the results in column (3) suggest, local demand does not seem to drive the results.

Redemptions have not been used to identify QE effects so far. Yet other papers claim that QE-eligibility and the price sensitivity of assets are important for the transmission of QE (Albertazzi et al., 2018; Chakraborty et al., 2017; Darmouni and Rodnyansky, 2017; Paludkiewicz, 2017). It is thus possible that the result for redemptions simply captures the effects of QE eligibility or the security portfolio's price sensitivity. This would be the case if banks with higher redemptions also hold more eligible assets or assets whose price is more sensitive to speculations over the introduction of QE.

To test whether redemptions are biased by alternative identification procedures, I replicate the identification strategies based on QE-eligibility and price sensitivity. I assign banks with above-median holdings of QE-eligible assets in January 2014 (relative to their total assets) to the group with high initial exposure, which resembles the more affected banks in Darmouni and Rodnyansky (2017).[33] In the spirit of Albertazzi et al. (2018) and Paludkiewicz (2017), I calculate the volume weighted average yield decline of the security portfolio in January 2014 by multiplying the yield change between January 2014 and March 2015 by the holding volume in January 2014 for each ISIN. Then I add the results within banks and normalize with total assets as of January 2014. Banks above the median of this variable are then assigned to the group of banks with a high yield change ($\mathrm{I}[\text{Yield Change}^{high}]_i$).

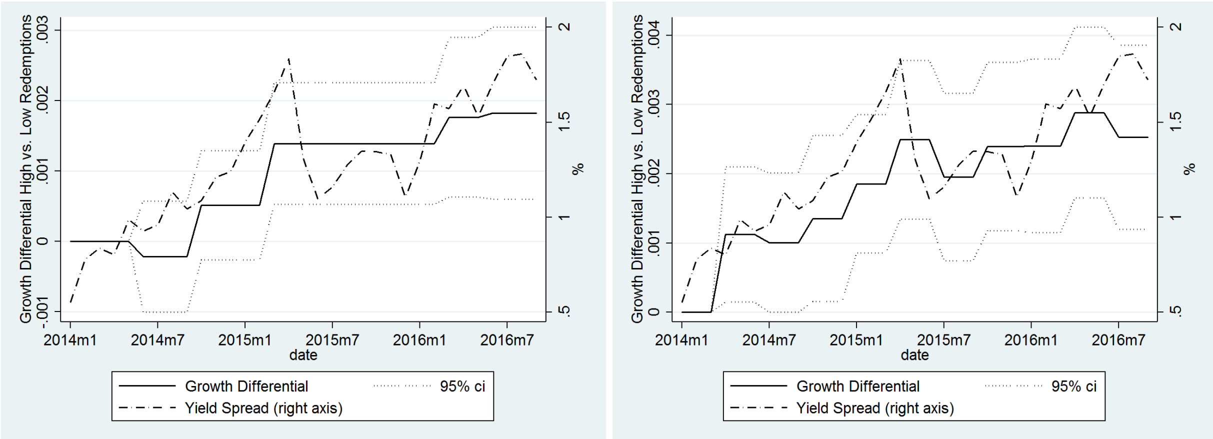
As can be seen in columns (1) and (2) of Table A4 in the appendix, banks with a higher initial exposure to QE-eligible assets and banks with a higher yield decline in the portfolio are more likely to be in the group of banks with higher redemptions. So if redemptions indeed just pick up information about the eligibility structure and the price sensitivity of the security portfolio, the coefficient on high redemption banks should decrease once I add the other identification variables to the regression.

Column (4) of Table 4 shows that the opposite is true: while the coefficient on banks with high redemptions remains unaltered, the other two factors are insignificant and their coefficients close to zero. These results imply that if omitted variables play a role, it is the maturity structure of banks' security portfolios that should not be omitted. To put the results into perspective, I have to note that redemptions should play a larger role in banking systems where more banks act as buy-and-hold investors and where a large share of assets are recognized at historical costs. Since Albertazzi et al. (2018) look at large banks, which have usually more assets marked-to-market, and Darmouni and Rodnyansky (2017) look at US banks, where the share of assets held-to-maturity was around 10% on aggregate at the time of QE, the role of redemptions might not be as prominent as for German banks.

So far, all we have seen is that the growth rate differential between banks with high and

[33]For this exercise, I define all assets that become QE-eligible during the sample period as QE-eligible.

Figure 4: Growth Differential Banks with High vs. Low Redemptions



(a) Important QE periods **(b) Quarterly effects**

Notes: Subfigure (a) shows the monthly spread between the yields on new loans in Germany and long-term bond yields (time to maturity at least 7 years, issued in Germany) alongside the growth differential between banks with high and low redemptions according to Equation 8 for different economically meaningful periods: two pre-QE periods until September 2014, the period of the first purchases until March 2015, the first period of large-scale asset purchases until February 2016, the period from March 2016 onwards, when purchases amounted to €80 bn and the period following June 2016, when the CSPP started. The growth differential is the coefficient on I[Initial Redemptions^{high}]$_i$ when interacted with time dummies for the aforementioned subperiods in an estimation of Equation 9. Subfigure (b) shows the growth differential between banks with high and low redemptions on a quarterly basis together with the monthly yield spread between loans and bonds. Sources: SHS, BISTA, CSDB, ZIS.

low redemptions changed in a binary way during QE. This corresponds to the evidence in Table 2, column (4), where the maturing volume is interacted with the time dummy for QE. But, the time dummy could pick up different events or changes in the environment that are not related to QE. To overcome this problem, columns (3) and (4) of Table 3 show that the effect of redemptions on credit growth varies with the yield spread between loans and bonds, which is more closely linked to the unconventional monetary policy measures. The growth differential in the current setting should behave similarly: if the yield spread is indeed the driver of credit growth, we would expect to also see that the growth differential between the two groups of banks rises when the yield spread increases. Column (5) of Table 4 shows that this is the case: banks with more redemptions grow more strongly than other banks, the higher the yield spread between loans and bonds is. To visualize this result, Figure 4 shows the growth differential between banks with high and low initial redemptions ($\hat{\beta}_1$) for different subperiods alongside the yield spread. Clearly, the growth differential between banks with high and low redemptions rises alongside the yield spread between loans and bonds and is high during the term of QE.

Lastly, I try to address the issue of endogenous sales. Column (4) of Table A4 shows that the initial exposure to QE-eligible assets has strong explanatory power for banks with higher cumulated sales of QE-eligible assets. Hence, the initial holdings of QE-eligible assets could serve as a valid IV for higher sales of those assets. It seems plausible to assume that the exclusion restriction holds, because the structure of the security portfolio in January 2014 should not be directly related to credit growth more than one year later.

But, as many assets are recognized at historical cost, sales of those assets that have risen in price more due to QE lead to higher realized gains, which might affect bank lending through effects on equity. Thus, initial holdings of QE-eligible assets can have an effect on lending through asset sales.

Comparable to the effect of higher sales of all assets in columns (1) - (4), higher sales of QE-eligible assets ($\text{I}[\text{QE sales}^{high}]_i$) have a significant and positive effect of 0.001 (not reported), which is possibly biased by endogeneity. Column (6) presents the corresponding IV estimate, where the dummy for high sales is instrumented by the dummy for high initial holdings of QE-eligible assets. Although the instrument passes the tests for underidentification (p-value 0.00) and weak instruments (rk Wald F-statistic 26.7) as advocated by Kleibergen and Paap (2006), the resulting coefficient for QE sales is higher than the OLS estimate, but insignificant.

One concern could be that the instrument combines holdings in the banking and trading book, so that mark-to-market holdings in the trading book are included as well. Since price changes in the trading book affect equity directly, one could argue that this allows for a direct effect of initial QE-eligible asset holdings that is not related to sales. Yet the results remain unchanged even if I include the share of QE-eligible assets in the trading book as a control or calculate the initial exposure dummy based on the holdings of QE-eligible assets in the banking book. So there is only limited evidence for an exogenous effect of asset sales on credit growth. Importantly though, the effect of redemptions is still significant in the IV specification, which implies that the effect of redemptions is not driven by a misspecified regression with endogenous regressors.

3.4 Transmission Channels: Reserves and Equity

We saw in the previous sections that banks' equity constraints are an important driver of the effect of redemptions. However, this does not explain why redemptions increase credit growth when banks are less equity-constrained (see the significant positive coefficient of the base effect of redemptions in column (5) of Table 2). The theoretical literature suggests that redemptions could also have an effect on lending by increasing banks' central bank reserves, which requires them to rebalance the portfolio towards longer-term, illiquid assets (Bianchi and Bigio, 2014; Christensen and Krogstrup, 2016).

While it is difficult to truly separate the two effects, it is at least possible to gather some suggestive evidence. In particular, when redemptions affect credit growth via increases in reserves, shocks to redemptions should change reserves, which in turn should change loan growth. In order to test whether such a correlation exists, I employ a design inspired by instrumental variables estimation. I regress changes in central bank reserves on the volume of redemptions (including the control variables). This isolates the relationship between redemptions and reserve holdings and allows me to test the resulting impact on lending growth. More formally, I estimate the following equation:

$$\frac{\Delta\text{Lending}_{it}}{\text{TA}_{i,t-1}} = \alpha_i + \alpha_t + \beta_1 * [\Delta\text{CB Reserves}_{it} = \text{Redemptions}_{it}] + \boldsymbol{\delta}' * \mathbf{B}_{i,t-1} + u_{it} \quad (10)$$

Similar to the effect of redemptions, I study whether we find hints that higher sales affect lending through changes in equity. The idea is again that if sales affect lending through changes in equity, shocks to sales should trigger changes in equity, which should go along with increases in lending growth. Note that the results are not supposed to identify a causal effect of reserves or capital on lending. Rather, the results suggest whether a correlation between the variables exists that is consistent with the view that changes in redemptions or sales trigger changes in reserves or equity, which correlate with lending growth. The results can be found in Table 5.

Column (1) shows that changes in central bank reserves, triggered by higher volumes of maturing assets, go along with increases in credit growth. The result suggests that increases in central bank reserves incentivize banks to rebalance their portfolio towards credit, as suggested by economic theory. Note that the raw correlation of reserve and lending changes is negative, which is probably driven by reverse causality: new lending coincides with transactions of the new borrowers which deplete reserve holdings. Using redemptions as an instrument helps isolate changes in central bank reserves unrelated to lending.

Table 5: Evidence on the Theoretical Channels

Dependent Variable:	$\Delta\text{Lending}_{it}/\text{TA}_{i,t-1}$			
Time Period:	Monthly October 2014 to September 2016			
Bank Sample:	All banks			$\text{I[Low equity]}_{i,t-1} = 0$
	(1)	(2)	(3)	(4)
Instrumented				
Δ CB $\text{Liquidity}_{i,t}/\text{TA}_{i,t-1}$	2.122*		0.642**	2.662**
	(1.158)		(0.322)	(1.280)
Δ $\text{Equity}_{i,t}/\text{TA}_{i,t-1}$		3.409*	7.445***	8.379***
		(1.788)	(1.163)	(3.146)
Controls	yes	yes	yes	yes
Month FE	yes	yes	yes	yes
Bank FE	yes	yes	yes	yes
Observations	37,560	37,560	37,560	18,820
rk Wald Stat	5.83	17.04	16.21	3.69
rk LM p-value	0.02	0.00	0.00	0.00
Instruments	Redemptions ECB_{it}	Net sales_{it}	Net sales_{it} + Redemptions ECB_{it}	

Notes: This table shows regressions of Equation 10. The dependent variable is the change in total lending over lagged total assets. Column (4) restricts the sample to observations where banks are below their target equity ratio. Control variables are the lagged balance sheet share of deposits, wholesale deposits, equity (except in column (3)), interbank lending and central bank reserves, as well as the lagged logarithm of total assets and the growth rate of total assets between t and t–1. rk Wald Stat and rk LM p-value are the test statistic for the test of weak instruments and the p-value for the test of underidentification (H_0: IV underidentified) following Kleibergen and Paap (2006). Standard errors (in parentheses) are clustered at the bank level. ***, **, * denote significance at $p < 0.01$, $p < 0.05$, $p < 0.1$. Sources: SHS, BISTA, CSDB.

The effect of net sales might operate through changes in equity (besides operating by "freeing up" equity). As shown in column (2), higher net sales are indeed positively correlated to changes in equity, which is related to lending growth. Column (3) estimates the two channels simultaneously. The results are now significant at the 5% and 1% level, respectively and the tests for weak instruments following Kleibergen and Paap (2006) indicate that the instruments are relevant (the p-value of the rk LM statistic rejects the null hypothesis of underidentification and the rk Wald statistic is fairly high).

While the reserve-induced rebalancing could, in principle, also affect those banks with equity below target, it should be the main effect for banks with equity above target, since these banks are less equity-constrained and do not need to free up capital to grant new loans. To test whether this argument is true, column (4) restricts the observations to those where banks are above their target equity ratio. The results show that the effect of reserves stems primarily from these banks. So we see some suggestive evidence that net sales are linked to credit growth through changes in equity, while redemptions can have an independent effect on lending through increases in central bank reserves. The positive effect of reserve changes on lending is in line with other IV estimates of this relationship; see Buchholz, Schmidt, and Tonzer (2017) or Kandrac and Schlusche (2017).

4 Further Results and Robustness

This section is devoted to a further exploration of the heterogeneity and the robustness of the results. In particular, it will deal with different borrower types, loan redemptions and the problem of security-specific effects.

4.1 Heterogeneity by Borrower Type and Maturity

While we have established that redemptions are related to lending growth, we do not know which loan types are actually affected. It might be, for example, that banks have many maturing government securities and in turn, they increase their lending to governments, without positive effects on lending to corporates. Or, one might expect to find something comparable to Chakraborty et al. (2017) and DiMaggio et al. (2016). They showed for US banks that the Federal Reserve purchases of mortgage-backed securities led to more origination of QE-eligible assets, but reduced lending to firms. In such a case, it is unclear whether the increase in lending entails positive real effects. To check whether such substitution took place for German banks, I differentiate lending volumes between different borrowing sectors. Since not all banks report volumes by borrower types, the number of observations is slightly smaller in this sample. Using growth of lending to different types of borrower as the dependent variable, I estimate equations 5 and 9. The results can be found in Table 6.

Column (1) shows results for equation 5 for the credit growth to non-financial corporations for the October 2014 to September 2016 period. The coefficient on redemptions is positive and highly significant and comparable in magnitude to the coefficients found in Table 2. In line with this, the difference-in-differences estimate in column (2) shows that banks with higher redemptions increase their lending to non-financial corporations by more. Hence, redemptions led banks to increase lending to corporations, which lays the groundwork for positive real effects. Columns (3) and (4) repeat the regressions for consumer credit: While the effects are slightly smaller, they are still highly significant. Lastly, in columns (5) and (6) one can see that that lending to governments did not increase due to redemptions, but did not decrease either. Hence, there is evidence neither for a substitution across borrower types nor for a replacement of government securities with loans to governments. Instead, non-financial corporations and consumers seem to have benefited most from QE.

In Table 6, it can be seen nicely that the panel and difference-in-differences regressions really seem to measure the same thing: the smaller the coefficient on lending in the panel

Table 6: Different Borrower Types

Dependent Variable:	$\Delta\text{Lending}_{it}/\text{TA}_{i,t-1}$					
Borrowing Sector:	NFC		Consumer		Government	
Estimation Method:	Panel	DiD	Panel	DiD	Panel	DiD
	(1)	(2)	(3)	(4)	(5)	(6)
Redemptions ECB_{it}	0.150***		0.056***		0.020**	
	(0.039)		(0.015)		(0.009)	
$\text{I[Initial Redemptions}^{high}]_i\text{*I[QE]}_t$		0.001**		0.001***		0.000
		(0.001)		(0.000)		(0.000)
Net sales_{it}	-0.102***		-0.113***		-0.013***	
	(0.028)		(0.017)		(0.005)	
Net purchases_{it}	-0.091		0.163***		-0.013**	
	(0.076)		(0.039)		(0.006)	
$\text{I[Net trade}^{low}]_i\text{*I[QE]}_t$		0.001**		0.001***		0.000***
		(0.001)		(0.000)		(0.000)
Controls	yes	yes	yes	yes	yes	yes
Controls*I[QE]_t	-	yes	-	yes	-	yes
Month FE	yes	yes	yes	yes	yes	yes
Bank FE	yes	yes	yes	yes	yes	yes
Observations	31,954	42,484	31,954	42,484	31,954	42,484
R^2	0.389	0.366	0.506	0.464	0.00409	0.00651

Notes: This table shows regressions of Equation 5 in the odd columns and Equation 9 in the even columns. Odd columns are for the QE period October 2014 to September 2016, even columns for February 2014 to September 2016. The dependent variable is the change in total lending to non-financial corporations, consumers or government over lagged total assets. Not all banks reported the dependent variables, which is why the number of observations is smaller. For further information, please refer to Tables 2 and 4. Standard errors (in parentheses) are clustered at the bank level. ***, **, * denote significance at $p < 0.01$, $p < 0.05$, $p < 0.1$. Sources: SHS, BISTA, CSDB.

regressions, the smaller the coefficient for banks with high redemptions in the difference-in-difference regression. This picture is neatly complemented if we look at credit to non-bank financial corporations, which I have left out for brevity: the coefficient in the panel regression is even smaller than for governments (0.001, insignificant) and the difference-in-differences estimate is close to zero (0.00001, insignificant).

Another interesting characteristic is the maturity structure of the new loans. If the increase in loan growth due to QE is concentrated in long maturities, banks increase their exposure to interest rate risk. To explore which loan maturities benefited most from QE, Table 7 repeats the estimation of Equations 5 and 9 for different borrower types and different maturities. I focus on credit to non-financial corporations and consumers, because these borrowers saw the greatest loan growth increase due to QE, as was shown in Table 6. Loans are split between those with time to maturity of 1 to 5 years and those with a maturity of more than 5 years. For both borrower types, the effect of redemptions can only be found for maturities of more than 5 years, which means that QE primarily affected the supply of long-term loans (see the significant effects in columns (3)-(4) and (7)-(8)).

Looking at the maturity structure of loan growth also allows us to further test the finding that the spread between bonds and loans informs banks' investment decision. In columns (3) and (4) of Table 3, redemptions are interacted with the spread between the

Table 7: Different Borrower Types and Maturities

Dependent Variable:	ΔLending$_{it}$/TA$_{i,t-1}$							
Borrowing Sector:	NFC				Consumer			
Maturity:	1y - 5y		> 5y		1y - 5y		> 5y	
Estimation Method:	Panel	DiD	Panel	DiD	Panel	DiD	Panel	DiD
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Redemptions ECB$_{it}$	0.062		0.061***		0.002		0.054***	
	(0.046)		(0.020)		(0.001)		(0.015)	
I[Initial Redemptions^{high}]$_i$*I[QE]$_t$		0.000		0.001***		0.000		0.001***
		(0.000)		(0.000)		(0.000)		(0.000)
Net sales$_{it}$	-0.032		-0.081***		-0.005***		-0.103***	
	(0.022)		(0.014)		(0.001)		(0.019)	
Net purchases$_{it}$	-0.100		0.037		0.010***		0.150***	
	(0.083)		(0.031)		(0.002)		(0.033)	
I[Net trade^{low}]$_i$*I[QE]$_t$		0.001**		0.001***		0.000**		0.001***
		(0.000)		(0.000)		(0.000)		(0.000)
Controls	yes	yes	yes	yes	yes	yes	yes	yes
Controls*I[QE]$_t$	-	yes	-	yes	-	yes	-	yes
Month FE	yes	yes	yes	yes	yes	yes	yes	yes
Bank FE	yes	yes	yes	yes	yes	yes	yes	yes
Observations	31,954	42,484	31,954	42,484	31,954	42,484	31,954	42,484
R^2	0.0816	0.0650	0.363	0.356	0.146	0.127	0.512	0.470

Notes: This table shows regressions of Equation 5 in the odd columns and Equation 9 in the even columns. Odd columns are for the QE period October 2014 to September 2016, even columns for February 2014 to September 2016. The dependent variable is the change in total lending to non-financial corporations or consumers, each split between maturities of 1-5 years and more than five years, normalized by lagged total assets. Not all banks reported the dependent variables, which is why the number of observations is smaller. For further information, please refer to Tables 2 and 4. Standard errors (in parentheses) are clustered at the bank level. ***, **, * denote significance at $p < 0.01$, $p < 0.05$, $p < 0.1$. Sources: SHS, BISTA, CSDB.

interest rate on new loans and the current yield on German bonds with a remaining time to maturity of at least 7 years. The choice of the bond yield is motivated by the fact that QE tries to affect long -term interest rates. Reassuringly, the relation also holds for the spread between the interest rate on new loans and the yield on bonds with 6 to 7 years or 5 to 6 years until maturity (results not reported). Interestingly enough, though, the interaction term becomes insignificant and smaller in size, when the spread to yields of bonds with less remaining maturity is used. Given that we now know that the growth of total lending is driven by loans with longer maturities, this fact is easy to rationalize: the growth of long-term loans should depend on the spread between the own interest rate and the yield on bonds that could serve as a substitute investment. Abstracting from risk, the most important characteristic of these substitute investments is their maturity. Hence, loan growth should react most strongly to the yield spread to bonds of comparable maturity.

4.2 Robustness

4.2.1 Endogenous Redemptions

One important problem for the analysis could be the endogenous adjustment of redemptions to the timing of lending opportunities or the switching of new loans to months where many assets mature. While this behavior cannot explain the aggregate increase in credit growth we saw in the difference-in-differences estimation, it could well explain the correlation between redemptions and credit growth in the panel regression. To guard against these endogenous adjustments, I use the same strategy as for the difference-in-differences estimation: I extract the information on redemptions and holdings contained in banks' portfolios in January 2014 to obtain variation in redemptions that is affected neither by QE (which was not expected at that time, see Paludkiewicz, 2017) nor by upcoming lending opportunities (which certainly are postponed for more than one year). I use this information to construct a variable with exogenous redemption volumes and use this as explanatory variable in the panel estimations of Equations 5 and 6.

The results can be found in the appendix, Tables A5 and A6. The coefficients are nearly identical to Tables 2 and 3, respectively.[34] Consequently, endogenous adjustments of redemptions or lending cannot drive the results. This is not very surprising, given the observed inertia in banks' portfolios. In fact, the actual and the initial redemptions are fairly highly correlated, with a correlation coefficient of 0.87.

4.2.2 Risk-adjusted Loan-Bond Spread

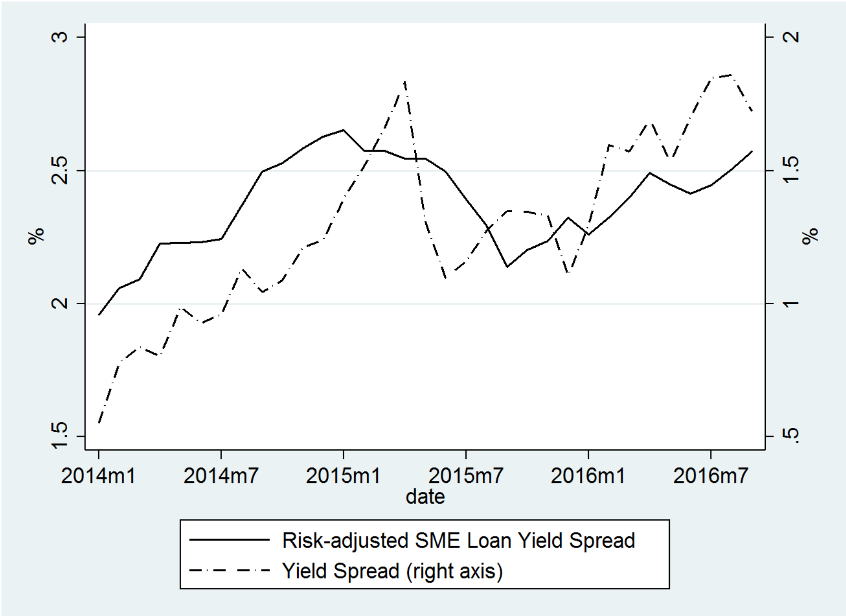
The analysis above used the plain spread of average interest rates on new longer term loans and the average interest rate prevailing in the longer term German bond market. One main criticism of using this spread is that it might reflect two different channels of monetary policy transmission. As argued above, an increase in the spread can reflect the impact of unconventional monetary policy on bond rates, which are depressed before loan rates react. However, it might also imply that banks react to unconventional monetary policy by taking on more risk in their loan portfolio, which is compensated by higher interest rates. To avoid drawing inference from a spread that might also be driven by banks' risk taking behavior, using a risk-adjusted spread would be desirable. However, this is complicated by the lack of combined data on riskiness and interest rates on individual loans. There is a workaround, though, that allows me to estimate the risk-adjusted level of loan rates at least from a subset of loans originated in Germany.

As part of the ECB's ABS Loan Level Initiative, the European Data Warehouse (EDWH) was founded in 2012 to improve transparency in the European market for Asset Backed Securities (ABS). This shall be achieved by providing information for each loan underlying each ABS that was issued in the European market. Hence, the data is representative at least for the loan market backing ABS, which comprises primarily of loans for cars, houses or small and medium-sized enterprises (SME). The information for each individual loan usually entails the interest rate and information on the credit risk of the borrower like the bank internal probability of default, primary income or loan-to-value ratios, depending on the loan type. This information allows me to adjust loan interest rates for borrower risk and the loan term. The result is an estimate of the general risk-adjusted level of loan interest rates than can be compared to a similar measure of bond interest rates.

More specifically, for almost 60000 SME loans, 180000 mortgage loans and 3.3 million auto loans, I estimate regressions of loan interest rates on borrower risk, loan maturity and time fixed effects. Borrower risk is captured by the bank-internal probability of default in case of SME loans and primary income of the borrower and loan-to-value ratios for mortgage and auto loans. Then for each loan type, the time fixed effects represent the

[34] Column (3) of Table 2 is left out for brevity in Table A5, but the robustness result also holds.

Figure 5: Risk-adjusted Loan-Bond Spread



Notes: The graph depicts the raw, unadjusted spread between the average interest rate on new longer term German loans and the average market yield in the longer term German bond market ("Yield Spread", dashed line), as well as the spread between risk-adjusted SME loan rates and risk-adjusted German bond yields ("Risk-adjusted SME Loan Yield Spread", or short "SME Spread"; moving average with 3 period window). Sources: EDWH, CSDB, ZIS.

risk-adjusted average loan interest rate level. A similar approach is taken for bond yields, where I use yield and rating data on bonds issued in Germany from the CSDB. The time fixed effects produce three risk-adjusted time series for loan rates (for SME loans, mortgages and auto loans) and one risk-adjusted time series for bond market rates. The differences between the risk-adjusted loan rates and the risk-adjusted bond rate can be used as risk-adjusted spreads between loan and bond yields.

Figure 5 depicts the spread between risk-adjusted SME loan rates and risk-adjusted bond yields ("SME spread") along with the raw spread used in the previous regressions. As can be seen, the behavior of the risk-adjusted spread for SME loans is relatively similar to the unadjusted spread for all loans, but on slightly a smaller scale. This shows that changes in risk attitudes might have contributed to a widening of the yield spread, but are far from being the only driver. Rather, it seems also that unconventional monetary policy was primarily depressing bond yields, which widened the spread to loan rates.

To ensure that banks' loan supply reacted to the risk-adjusted spreads, I include them in estimations of Equation 6, as in column (3) of Table 3. The results can be found in Table 8. They show that regardless of the spread measure, the effect of redemptions increases significantly when the spread is higher. This shows that the main result in Table 3 is not driven by changing risk-taking behavior of banks. Rather, it seems that the impact of unconventional monetary policy on the spread between loan and bond rates is driving banks' tendency to rebalance from securities to loans.[35]

[35]This result does not, however, rule out that banks' risk attitude changed as well as a result of QE, so that greater risk-taking in the loan portfolio might also have contributed to the increase in loan growth

Table 8: Risk-adjusted Loan–Bond Spreads and Credit Growth

Dependent Variable:	ΔLending$_{it}$/TA$_{i,t-1}$		
Time Period:	Monthly February 2014 to September 2016		
Risk-adjusted Spread Measure:	SME spread	Mortgage spread	Auto spread
	(1)	(2)	(3)
Redemptions ECB$_{it}$	0.129***	0.137***	0.136***
	(0.023)	(0.024)	(0.023)
Redemptions ECB$_{it}$*Risk-adjusted Spread$_t$	0.143**	0.184*	0.168***
	(0.059)	(0.096)	(0.059)
Controls	yes	yes	yes
Month FE	yes	yes	yes
Bank FE	yes	yes	yes
Observations	50,080	50,080	50,080
R^2	0.513	0.513	0.513

Notes: This table shows regressions of Equation 6, but leaves out the interaction with I[Low equity$_{i,t-1}$], comparable to column (3) of Table 3. The key difference is the choice of the loan–bond spread measure. Here, the spread is calculated from risk-adjusted loan rates for SME, mortgage or auto loans using data from German loans collateralizing ABS from European Data Warehouse combined with risk-adjusted yield data for German bonds from the CSDB. Interest rates are adjusted for risk by regressing them on loan-level borrower quality variables (bank-internal probability of default for SME loans, primary income of the borrower and loan-to-value ratios for mortgages and auto loans), loan maturity and time fixed effects, where the time fixed effects are used as risk-adjusted interest rate measure. For further information, please refer to Tables 2 and 3. Standard errors (in parentheses) are clustered at the bank level. ***, **, * denote significance at $p < 0.01$, $p < 0.05$, $p < 0.1$. Sources: SHS, BISTA, CSDB, EDWH.

4.2.3 Security Specific Effects

One question regarding the results is whether they are driven by security-specific effects. This could be risk characteristics such as the probability of default, or service characteristics such as central bank eligibility. For maturing assets, all these characteristics should not play a prominent role, since assets upon maturity are quite similar anyway: they have a low probability of default, a comparable yield and the same residual maturity. However, since we found out that equity constraints drive the effect of redemptions, regulatory characteristics such as the risk weight could play a role. Also, the assets that are sold can be quite different from each other. Therefore, I test whether security-specific effects drive the results in two ways: In this subsection, I analyze whether individual securities drive the results or whether the results apply to a broader set of securities. The next subsection tests whether the effects differ between specific groups of securities.

Regarding effects of individual securities, the problem is that ideally, one would want to control for security*time fixed effects to remove security-specific time-varying information. But since the left-hand side variable is credit growth at the bank level, this is not easily done. There are two ways to include security*time fixed effects in the regression models. One is to regress the redemption and trading information at the bank-ISIN-month level on security*time fixed effects and aggregate the residuals. While this allows the current data structure to be maintained, the aggregation blurs the identification through the

experienced after the start of QE.

fixed effects. The other possibility is to match the left-hand side variable to the security holdings at the bank-ISIN-month level. This allows us to include security*time fixed effects directly, but comes at the cost of explaining bank-specific variables with security-specific information. Since neither approach is optimal, I show results for both.

Table A7 shows results for the estimation of Equation 5 at the bank-date level. The main explanatory variable is replaced by the residuals from regressions of the security-specific redemptions at the bank-ISIN-date level on bank*security and security*time fixed effects. These residuals are then aggregated at the bank-date level. Purchases and sales are treated similarly. The approach is straightforward for redemptions and yields results in all three columns that are comparable to the baseline results in Table 2, albeit slightly smaller. This implies that security-specific effects only play a minor role for the effect of redemptions, as we expected.

Also for the trading behavior of banks, the results show a clear picture: Regardless of whether I include adjusted purchases and sales separately in column (1), use a net trade specification in column (2) or split net trade into net sales and net purchases in column (3), the result that higher sales are associated with higher credit growth remains. Here, however, the coefficients are quite a bit smaller compared to the baseline effects in Table 2. This suggests that the asset type matters for the effect of sales. This is consistent with the previous finding in Table 2, column (3) that the effect for net sales of QE-eligible assets is higher.

The results of the second approach are shown in Table A8. Here, I match the bank-month level credit growth data to the bank-ISIN-month level data of security holdings so that each bank-ISIN position explains the credit growth of the bank for the time for which the bank is holding the asset. This disaggregation allows us to directly control for security*time and bank*security fixed effects (bank*time fixed effects would eliminate all left-hand side variation). Hence, I estimate the following equation:

$$\begin{aligned}\frac{\Delta \text{Lending}_{i(j)t}}{\text{TA}_{i(j),t-1}} =& \alpha_{ij} + \alpha_{jt} + \beta_1 * \Delta\text{Holdings}_{ijt} + \beta_2 * \Delta\text{Holdings}_{ijt} * \text{I}[\text{Net sale}_{i(j)t} < 0] \\ & + \beta_2 * \Delta\text{Holdings}_{ijt} * \text{I}[\text{Asset matures}_{ijt}] + \boldsymbol{\delta}' * \mathbf{B}_{i(j),t-1} + u_{ijt} \qquad (11)\end{aligned}$$

Here, i counts banks, j securities and t the month. I put the security level j in parentheses whenever a variable is actually at the it level. $\Delta\text{Holdings}_{ijt}$ is the first difference of the holdings of security j by bank i between t and t–1 normalized by lagged total assets. Hence, it is comparable to the net trade variable used in Table A7. I interact this variable with a dummy that is 1 when the bank is a net seller of assets at time t to find differential effects for net buyers and net sellers. Then, I construct the redemption variable by interacting ΔHoldings with a dummy that indicates whether the asset matures at time t.[36]

The results can be read as follows. Column (1) includes bank*security fixed effects, hence the positive coefficient of ΔHoldings means that higher purchases for the same bank and the same asset are correlated with higher credit growth. However, this relation is reversed for banks that are aggregate net sellers at time t: Here, higher sales of the same asset by the same bank indicate higher credit growth. Similarly, higher redemptions

[36] In the maturity month, the holdings of the asset go to zero, meaning that the change from t–1 to t represents the maturing amount.

also indicate higher credit growth (higher redemptions imply more negative changes of holdings). Column (2) adds security*time fixed effects, which even strengthens the results. The results imply that if a bank has a higher maturing volume (relative to its lagged total assets) of the same security than another bank, its credit growth is higher. In column (3), I further test whether the effect of selling the asset is stronger for QE-eligible assets by interacting the trading variable with a dummy that indicates whether an asset is eligible for QE purchases at time t. Indeed, while the result does not change for net buyers, net sellers of assets have stronger increases in credit growth when they sell more QE-eligible assets than ineligible assets. [37]

4.2.4 Redemption Effects: Heterogeneity by Bond Risk

Although the previous subsection revealed the effect of redemptions is not entirely driven by individual securities, it might still be the case that the effect of redemptions differs in size depending on different asset characteristics. The most likely case relates to securities of different risk. We saw in Tables 2 and 3 that the effect of redemptions depends on equity constraints. If the bank exclusively targets a raw leverage ratio, all securities would count similarly towards this constraint. However, if risk-weighted capital ratios also play a role, the risk-weight of the maturing asset might matter: an asset of higher risk that carries a higher risk weight should set free more capital upon redemption than a less risky asset. Hence, for banks with equity constraints, redemptions of high-risk assets should enable more credit growth than redemptions of low-risk assets.

In order to test whether this is the case, I split assets according to different risk measures: the rating (derived from CSDB), the haircut when used as ECB collateral and the ECB's liquidity rating (both from the EADB). I calculate each bank's monthly redemption volume for bonds of higher and lower risk, splitting the rating at BBB+ and the haircut and the liquidity measures at the monthly median. The results can be found in Table 9.

Column (1) shows the results for the split according to the bond's rating. Interestingly, the effect is significantly stronger for equity constrained banks for both risk classes and the effect of high risk bond redemptions is higher for both constrained and unconstrained banks. However, the differences between high and low risk bonds are not statistically significant. Column (2) and (3) show the results for splits according to ECB haircut and liquidity class. Here, the results are even clearer: redemptions of high-risk bonds have a positive and significant effect on credit growth. Importantly, this effect is stronger for equity constrained banks. This supports the notion that redemptions relax equity constraints, which enables banks to increase their loan growth. Further, this result suggests that besides raw leverage constraints, risk-weighted constraints might play a role, too.[38]

[37] I do not test for higher effects of QE-eligible maturing assets because there are hardly any maturing assets in the sample that are also QE-eligible. Government bonds where only eligible when they had more than 2 years to maturity. Therefore, only a few eligible covered bonds matured during the sample period.

[38] This holds to the extent that risk-weighted and unweighted capital ratios are correlated. This is plausible given that banks' unweighted equity ratios are best explained by bank fixed effects (Gropp and Heider, 2010), suggesting that banks revert to unweighted capital ratios, and given that changes in weighted capital ratios are generally more driven by retained earnings than by changes in asset risk (Cohen and Scatigna, 2016). Comparable to Gropp and Heider (2010), the R^2 of bank fixed effects for

Table 9: Redemption Effects: Heterogeneity by Bond Risk

Dependent Variable:	$\Delta \text{Lending}_{it}/\text{TA}_{i,t-1}$		
Time Period:	Monthly October 2014 to September 2016		
Bond Risk Measure:	Rating	ECB Haircut	ECB Liquidity Class
	(1)	(2)	(3)
Redemptions Low Risk$_{it}$	0.140	0.093	0.083
	(0.151)	(0.114)	(0.105)
Redemptions High Risk$_{it}$	0.225	0.119***	0.128***
	(0.154)	(0.027)	(0.027)
Redemptions Low Risk$_{it}$*I[Low Equity$_{i,t-1}$]	0.598*	0.153	0.158
	(0.307)	(0.113)	(0.103)
Redemptions High Risk$_{it}$*I[Low Equity$_{i,t-1}$]	0.695*	0.102***	0.094***
	(0.373)	(0.031)	(0.031)
Controls	yes	yes	yes
Month FE	yes	yes	yes
Bank FE	yes	yes	yes
Observations	37,560	37,560	37,560
% R^2	0.546	0.546	0.546

Notes: This table shows regressions of Equation 5, comparable to Table 2. The key difference is that redemption volumes are split according to the riskiness of the bonds. Column (1) uses the Long-Term Issuer Rating and defines low risk bonds as A- or better. Columns (2) and (3) use the haircut in ECB open market operations or the liquidity class as provided by the ECB. Bond redemptions are split according to the monthly median of these variables. For further information, please refer to Table 2. Standard errors (in parentheses) are clustered at the bank level. ***, **, * denote significance at $p < 0.01$, $p < 0.05$, $p < 0.1$. Sources: SHS, BISTA, CSDB, EADB.

4.2.5 Sample Heterogeneity

The biggest concern with difference-in-differences estimates is that the classification into treated and untreated groups does not measure the intended transmission channel, but captures something else. For example, this might be caused by the comparison of very different subjects in the two groups. The approach presented in this paper alleviates these concerns, because it shows that the variable that is supposed to generate the differences in behavior between banks also generates this behavior within each bank over time.

Still, I test whether underlying differences between the affected and unaffected banks bias the results. To this end, I match banks according to their propensity scores and reestimate Equation 9 based on the matched sample of banks. First, I test whether any of the control variables as of January 2014 predicts membership in the group of affected banks. As can be seen in column (1) of Table A9, this is the case for deposits, equity and interbank lending. Column (2) estimates the propensity scores based on these three variables. I then apply a nearest neighbor matching without replacement based on the resulting propensity score. Column (3) confirms that the variables do not predict membership in the matched sample, which suggests that the matching was successful.

A further concern with difference-in-differences designs is autocorrelation, as mentioned in Bertrand, Duflo, and Mullainathan (2005). Although bank and time fixed

the unweighted capital ratio is beyond 95% in my sample.

effects, double clustered standard errors and time-varying controls should already diminish the importance of autocorrelated errors, I nevertheless follow the recommendation of Bertrand et al. (2005) and collapse the sample in two periods by averaging all variables before the start of QE in October 2014 and during QE. The results on the collapsed and matched sample can be found in Table A10. All results still hold even in the sample that is matched and collapsed at the same time.[39]

5 Conclusion

In this paper, I develop a new strategy to identify the effects of QE on bank lending by making use of the role of redemptions for portfolio rebalancing. This approach allows us to show not only that bank groups with different exposure to QE respond differently, but also possible that the same bank reacts to differing QE exposure over time. While difference-in-differences estimates find that banks with higher redemptions change their aggregate credit supply during QE and relative to other banks, the panel regressions ensure that the difference-in-differences effect can be traced back to correlation between redemptions and credit growth for each bank over time. This strategy reduces typical problems like the influence of other changes in the macro environment and concerns about a biased selection into the treatment group.

The underlying mechanism on which the identification strategy relies is based on typical portfolio rebalancing theories. QE policies change relative prices of assets, which implies a different optimal allocation of assets in investor portfolios. For bank lending, QE effects rely on changes in the relative price of loans and bonds. If banks want to switch to the new portfolio equilibrium, they have to increase the portfolio share of lending, which can be done either by selling assets and replacing them with loans or expanding the balance sheet. However, German banks are to a large extent buy-and-hold investors, who hold the majority of their assets in the banking book, recognized at historical cost. Hence, large asset sales only occur infrequently. Therefore, the largest variations in the size of the security portfolio occur through redemptions. When banks are equity-constrained, bond redemptions relax these constraints and allow for additional lending.

The findings of this paper imply that QE can impact on bank lending even in the absence of security trades by banks and without affecting bank equity through higher security prices. What matters is an incentive to rebalance, as indicated by the change in relative prices of different asset classes, and the ability of banks to adjust their balance sheet accordingly. Since the share of held-to-maturity securities increases drastically in other countries, e.g. in the US, security trading and effects on equity might become less important. Therefore, this paper conveys crucial information about the way unconventional monetary policy measures can affect real future outcomes.

[39] Note that the dummy indicating high yield changes in the portfolio before the start of QE is significant in the collapsed sample, hinting mildly at a possible effect of yield changes on lending. Interestingly, this regression approach resembles the one taken in Paludkiewicz (2017), who finds a similar effect.

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A Appendix

A.1 The QE program of the European Central Bank

The Asset Purchase Program (APP) of the ECB, which is the European version of quantitative easing, consists of several subprograms. The covered bond purchase program 3 (CBPP3) and the asset-backed securities purchase program (ABSPP), which started in October and November 2014 and mark the beginning of the APP, were initially designed to target and revive specific asset markets, namely the market for covered bonds and for asset-backed securities. With the decision to start large scale purchases in January 2015, these subprograms were prolonged and combined with the public sector purchase program (PSPP), under which the ECB and the national central banks of the European system of Central Banks started to buy government and supranational bonds starting in March 2015. This took place amidst fears of deflation in an environment where inflation expectations had become deanchored from the ECB's target (see, e.g., Deutsche Bundesbank, 2015 or Nautz, Pagenhardt, and Strohsal, 2017).

The combined monthly volume of the programs was €60 bn (probably €10 bn for ABSPP and CBPP3, while the PSPP was split between €6 bn for supranational debt and €44 bn for government debt; see Claeys, Leandro, and Mandra, 2015) and the purchases were to be conducted by the national central banks, with each central bank focusing on eligible assets issued in its jurisdiction.[40] To stick to the principle of applying a single monetary policy to all member states, the program does not specifically target countries with low inflation, but instead the purchasing volume is split among countries according to their share in the ECB's capital (hence, Bundesbank's monthly purchases should amount to roughly $44 * 0.25 =$€11 bn).[41] The assets are bought from the best offer among a panel of large investment banks. Hence, the majority of banks do not trade directly with the central banks.

A.2 Descriptive Statistics

[40] The monthly purchase volume was increased from €60 bn to €80 bn in March 2016. From June 2016 on, corporate bonds were purchased as well.

[41] To avoid holding a blocking minority in debt restructurings of collective actions clause bonds and to preserve the functioning of government bond markets, the purchases per ISIN and per issuer are not permitted to exceed, respectively, 25% and 33% of the outstanding volume (Claeys et al., 2015).

Table A1: Descriptive Statistics

	N	mean	sd	p5	p95
Assets					
$\text{Lending}_{it}/\text{TA}_{it}$	51,645	0.59	0.16	0.29	0.81
$\text{Lending Corporations}_{it}/\text{TA}_{it}$	44,406	0.27	0.12	0.05	0.48
$\text{Lending Consumers}_{it}/\text{TA}_{it}$	44,406	0.29	0.13	0.02	0.49
$\text{Lending Governments}_{it}/\text{TA}_{it}$	44,406	0.02	0.04	0.00	0.09
$\text{CB Liquidity}_{it}/\text{TA}_{it}$	51,645	0.02	0.04	0.00	0.03
$\text{Interbank Lending}_{it}/\text{TA}_{it}$	51,645	0.09	0.11	0.01	0.28
$\text{Securities}_{it}/\text{TA}_{it}$	51,645	0.21	0.12	0.05	0.44
$\log(\text{TA}_{it})$	51,645	20.41	1.53	18.12	23.02
TA_{it}	51,645	4.7E+09	3.4E+10	7.4E+07	1.0E+10
Liabilities					
$\text{Wholesale Deposits}_{it}/\text{TA}_{it}$	51,645	0.15	0.13	0.03	0.36
$\text{Deposits}_{it}/\text{TA}_{it}$	51,645	0.72	0.13	0.51	0.85
$\text{Equity}_{it}/\text{TA}_{it}$	51,645	0.06	0.03	0.04	0.09
Changes					
$\Delta\text{Lending}_{it}/\text{TA}_{i,t-1}$	50,080	0.0028	0.0187	-0.0063	0.0121
$\Delta\text{CB Liquidity}_{it}/\text{TA}_{i,t-1}$	50,080	0.0005	0.0192	-0.0072	0.0083
$\Delta\text{Equity}_{it}/\text{TA}_{i,t-1}$	50,080	0.0003	0.0025	0	0.0015
$\Delta\text{CB Borrowing}_{it}/\text{TA}_{i,t-1}$	50,080	0.0002	0.0059	0	0
$\text{TA}_{it}/\text{TA}_{i1}$	51,645	1.067	0.305	0.971	1.208
$\text{TA}_{it}/\text{TA}_{i,t-1}$	50,080	1.004	0.037	0.981	1.026
Security Portfolio					
Redemptions_{it}	51,645	0.003	0.005	0	0.012
$\text{Redemptions ECB}_{it}$	51,645	0.002	0.005	0	0.011
$\text{Initial Redemptions}_{it}$	50,080	0.003	0.005	0	0.012
$\text{Initial Redemptions ECB}_{it}$	50,080	0.003	0.005	0	0.012
Net sales_{it}	50,080	-0.001	0.005	-0.005	0
Net sales QE_{it}	37,560	0.000	0.002	0	0
$\text{Net purchases}_{it}$	50,080	0.004	0.010	0	0.017
$\text{Initial Exposure}_{i}$	1,565	0.049	0.055	0	0.154
Yield Change_{i}	1,565	0.222	0.252	-0.002	0.699
Interaction terms					
Yield Spread_{t}	51,645	1.30	0.34	0.78	1.85
I[QE]_{t}	51,645	0.73	0.45	0	1
$\text{I[Low equity]}_{i,t-1}$	50,080	0.50	0.50	0	1
Portfolio Characteristics					
Duration_{it}	51,390	3.75	2.02	1.90	5.85
Coupon_{it}	51,390	1.96	0.77	0.71	3.21
Yield_{it}	51,390	0.71	0.86	0.04	1.86
Illiquidity_{it}	51,390	7.50	3.39	2.31	12.13
Haircut_{it}	51,390	3.25	0.84	2.20	3.92

Notes: TA is the total assets of the bank. Ratios are displayed as decimals. "CB Liquidity" is the central bank money that banks hold on their accounts at the central bank. "CB Borrowing" is borrowing from the central bank. For lending split by borrowing sector, not all institutions reported the respective amounts, which leads to the smaller number of observations. The smaller number for portfolio characteristics is because of lacunae in the underlying CSDB data. The time period is January 2014 to September 2016. Sources: SHS, BISTA, CSDB, ZIS.

A.3 Portfolio Rebalancing: Security and Credit Portfolio

To add econometric structure to the suggestive evidence in the descriptive statistics in Table 1, I formally study the relationship between changes in the security portfolio and credit growth. More specifically, I examine whether the change in the portfolio share of credit between the start of QE and the end of the sample is related to the change in the share of securities during the same period for the same bank, as suggested by the descriptive statistics. I employ the following regression design, where t is restricted to the two periods shown in Table 1 (September 2014 and September 2016):

$$\frac{\text{Lending}_{it}}{\text{TA}_{it}} = \alpha_i + \alpha_t + \beta_1 * \frac{\text{Securities}_{it}}{\text{TA}_{it}} + \beta_2 * \frac{\text{TA}_{it}}{\text{TA}_{i1}} + u_{it} \tag{12}$$

where α_i, α_t are bank and time fixed effects, respectively. The dependent variable is the ratio of total lending to non-banks over total assets in September 2014 and September 2016, i.e. before the start of QE and at the end of the sample period. β_1 is the main coefficient of interest, which measures the correlation between the change in the balance sheet share of securities and the change in the share of lending. Due to the restriction to just two periods and the employment of bank fixed effects α_i, the estimate is (asymptotically) similar to an estimate of a first differenced equation.

Table A2: Portfolio Rebalancing: Securities vs. Credit

Dependent Variable:	$\text{Lending}_{it}/\text{TA}_{it}$			
Timer Period:	September 2014 & September 2016			
	(1)	(2)	(3)	(4)
$\text{Securities}_{it}/\text{TA}_{it}$	-0.413***	-0.429***		
	(0.036)	(0.037)		
Maturities ECB_{it}^{cum}			0.319***	0.314***
			(0.040)	(0.042)
Net trade_{it}^{cum}			-0.261***	-0.260***
			(0.031)	(0.031)
$\text{TA}_{it}/\text{TA}_{i1}$		-0.009***	0.003	0.003
		(0.002)	(0.006)	(0.006)
Initial Exposure_i*I[QE]_t				0.001
				(0.021)
Yield Change_i*I[QE]_t				0.009*
				(0.005)
Month FE	yes	yes	yes	yes
Bank FE	yes	yes	yes	yes
Observations	3,130	3,130	3,130	3,130
R^2	0.974	0.975	0.971	0.971

Notes: This table shows results from the OLS regression of Equation 12. The left-hand side variable is the balance sheet share of lending in September 2014 and September 2016 for each bank i. $\text{Securities}_{it}/\text{TA}_{it}$ is the balance sheet share of securities. Redemptions ECB_{it}^{cum} is defined in Equation 7 and Net trade_{it}^{cum} is from Equation 2, cumulated as in Equation 7. Initial Exposure_i*I[QE]_t and Yield Change_i*I[QE]_t are as defined in Table 4 but are not reduced to binary information. TA_t/TA_1 is the gross growth of total assets between January 2014 and t. Robust standard errors in parentheses. ***, **, * denote significance at $p < 0.01$, $p < 0.05$, $p < 0.1$. Sources: SHS, BISTA, CSDB.

Column (1) shows that indeed a rebalancing from securities to credit takes place within banks: for each bank, a higher reduction in the security portfolio coincides with a higher increase in lending. This effect, however, might be driven mechanically: If banks increase their lending and hence their total assets, the share of securities decreases even without changes in the security portfolio. A similar argument holds for a negative change in securities. To guard against this mechanical correlation, I include the gross growth rate of total assets in column (2), which should capture the direct effect of changes in securities or lending on total assets. The result remains unchanged. To further dismiss the influence of mechanical correlation, column (3) splits the change in securities into cumulated redemptions and the cumulated net trade of assets. This rules out mechanical changes in total assets due to increases in lending. Both net trade and redemptions are strongly related to changes in credit: Banks with higher cumulated redemptions and with higher cumulated net sales (negative net trade) experience larger increases in the share of lending. Column (4) adds the variables that other papers use for identification, as argued in Section 3.3: the initial holdings in January 2014 of QE-eligible assets and the volume-weighted yield change of the security portfolio in the pre-QE period. The results remain unchanged, suggesting that changes in the security portfolio are a stronger determinant of changes in lending than the variables used in other research.

Table A3: Portfolio Rebalancing: Security Portfolio Characteristics

Time Period:	September 2014 & September 2016					
Dependent Variable:	$\text{Securities}_{it}/\text{TA}_{it}$	Duration_{it}	Coupon_{it}	Yield_{it}	Haircut_{it}	Illiquidity_{it}
	(1)	(2)	(3)	(4)	(5)	(6)
$\text{I[Initial Redemptions}^{high}]_i\text{*I[QE]}_t$	-0.032***	-0.049	0.069***	0.072***	0.036**	0.514***
	(0.002)	(0.106)	(0.025)	(0.021)	(0.017)	(0.094)
$\text{I[Net trade}^{low}]_i\text{*I[QE]}_t$	-0.044***	-0.346***	0.134***	-0.006	-0.112***	-0.630***
	(0.002)	(0.128)	(0.026)	(0.022)	(0.017)	(0.091)
$\text{I[Initial Exposure}^{high}]_i\text{*I[QE]}_t$	-0.005**	-0.779***	0.016	-0.098***	0.210***	0.287***
	(0.002)	(0.109)	(0.026)	(0.024)	(0.018)	(0.101)
$\text{I[Yield Change}^{high}]_i\text{*I[QE]}_t$	-0.003	-0.371***	0.002	-0.021	-0.045**	0.068
	(0.003)	(0.101)	(0.026)	(0.023)	(0.018)	(0.107)
$\text{TA}_{it}/\text{TA}_{i1}$	-0.024*	-0.134**	0.010	-0.020*	0.033***	0.177
	(0.013)	(0.066)	(0.028)	(0.012)	(0.009)	(0.135)
Month FE	yes	yes	yes	yes	yes	yes
Bank FE	yes	yes	yes	yes	yes	yes
Observations	3,130	3,098	3,098	3,130	3,098	3,098
R^2	0.949	0.440	0.836	0.691	0.831	0.864

Notes: The dependent variables Duration, Coupon, Yield, Haircut and Illiquidity are volume-weighted average values in September 2014 and September 2016. The number of observations is smaller than in Table A2 as I restrict the sample to banks that have assets with all relevant information in both months of interest. Robust standard errors in parentheses. ***, **, * denote significance at $p < 0.01$, $p < 0.05$, $p < 0.1$. Sources: SHS, BISTA, CSDB.

To complement the evidence on the changes in banks' balance sheets, I provide further evidence on the evolution of the characteristics of the security portfolio. To this end, I use the empirical specification in Equation 12 and add the difference-in-differences dummies generated in Section 3.3. This shows us which group of banks saw which changes in the security portfolio.

Column (1) shows that banks with high redemptions, high net sales and a high initial QE-exposure show stronger declines in the balance sheet share of securities. Except for banks with higher redemptions, this resulted in a disproportionately strong reduction in the average duration. This is consistent with the notion that QE programs reduce the average duration in the market. Regarding the profitability of the securities in columns (3) and (4), banks with high redemptions show relative increases in the coupon and yield of their assets. This matches the fact that their security portfolios became relatively riskier in terms of haircut and illiquidity (see columns (5) and (6)). All in all the results suggest that the composition of the security portfolio changes and that banks more exposed to QE end up with smaller, but riskier security portfolios. These results complement the findings in Albertazzi et al. (2018), who only find that investors in European periphery countries with higher potential QE exposure have relative increases in their exposure to credit risk. In contrast, I show that there are significant differences in changes in the characteristics of security portfolios in relation to banks' QE exposure in core European countries as well.

A.4 Empirical Relationship Between Different Identification Approaches

Table A4: Relationship Between Identification Approaches

Dependent Variable:	$I[\text{Redemptions}^{high}]_i$	$I[\text{Initial Redemptions}^{high}]_i$	$I[\text{Net trade}^{low}]_i$	$I[\text{QE sales}^{high}]_i$
Time Period:	January 2014			
	(1)	(2)	(3)	(4)
$I[\text{Initial Exposure}^{high}]_i$	0.160***	0.175***	-0.094***	0.092***
	(0.028)	(0.028)	(0.028)	(0.018)
$I[\text{Yield Change}^{high}]_i$	0.267***	0.272***	-0.202***	-0.012
	(0.027)	(0.027)	(0.028)	(0.017)
Wholesale $\text{Deposits}_{i1}/\text{TA}_{i1}$	-0.269	-0.101	0.328	0.188
	(0.282)	(0.227)	(0.255)	(0.189)
$\text{Deposits}_{i1}/\text{TA}_{i1}$	0.055	0.211	-0.235	0.061
	(0.273)	(0.217)	(0.236)	(0.183)
$\text{Equity}_{i1}/\text{TA}_{i1}$	-0.765	-0.673	-0.655	0.697
	(0.555)	(0.410)	(0.530)	(0.446)
Interbank $\text{Lending}_{i1}/\text{TA}_{i1}$	-0.013	-0.201**	-0.415***	0.056
	(0.110)	(0.102)	(0.120)	(0.094)
CB $\text{Liquidity}_{i1}/\text{TA}_{i1}$	0.564**	0.043	-0.262	0.142
	(0.232)	(0.240)	(0.256)	(0.249)
$\text{Log}(\text{TA}_{i1})$	-0.024***	-0.027***	0.021**	0.007
	(0.008)	(0.008)	(0.009)	(0.007)
Constant	0.806**	0.742***	0.434	-0.201
	(0.334)	(0.283)	(0.311)	(0.224)
Observations	1,565	1,565	1,565	1,565
% R^2	0.152	0.175	0.0941	0.0215

Notes: This table shows how the grouping based on redemptions used for identification in this paper is related to groups based on identification approaches in other papers (the initial exposure as in Darmouni and Rodnyansky (2017) and the yield change of the initial portfolio as in Albertazzi et al. (2018)) conditional on control variables. The regression is based on data from January 2014. Robust standard errors in parentheses. ***, **, * denote significance at $p < 0.01$, $p < 0.05$, $p < 0.1$. Sources: SHS, BISTA, CSDB.

A.5 Robustness

Table A5: Redemptions and Credit Growth

Dependent Variable:	ΔLending$_{it}$/TA$_{i,t-1}$				ΔLog(Lending$_{it}$)
Time Period:	Monthly October 2014 to September 2016				
	(1)	(2)	(3)	(4)	(5)
Initial Redemptions$_{it}$	0.178***	0.160***			
	(0.023)	(0.028)			
Initial Redemptions ECB$_{it}$			0.112***	0.103***	
			(0.040)	(0.028)	
Net sales$_{it}$		-0.244***	-0.217***	-0.190***	
		(0.037)	(0.083)	(0.052)	
Net purchases$_{it}$		0.104	0.143**	0.066	
		(0.069)	(0.073)	(0.069)	
Init. Red. ECB$_{it}$*I[Low equity]$_{i,t-1}$				0.104***	
				(0.029)	
Net sales $_{it}$*I[Low equity]$_{i,t-1}$				-0.086	
				(0.072)	
Log(Redemptions ECB$_{it}$)					0.003**
					(0.001)
Log(Red. ECB$_{it}$)*Log(Lending$_{i,t-1}$)					-0.000*
					(0.000)
Controls	yes	yes	yes	yes	yes
Month*ZIP FE	no	no	yes	no	no
Month FE	yes	yes	-	yes	yes
Bank FE	yes	yes	yes	yes	yes
Observations	37,560	37,560	13,608	37,560	37,551
R^2	0.514	0.518	0.486	0.549	0.097

Notes: This table shows regressions of Equation 5 and repeats in the first four columns the specifications (1), (2), (4) and (5) of Table 2, but uses predetermined information on redemptions. The maturity information to build Initial Redemptions$_{it}$ and Initial Redemptions ECB$_{it}$ is taken from banks' balance sheets in January 2014. Column (5) of this table shows results when the dependent variable is calculated as log growth rate and the redemptions are in logs, whereas the other control variables are unchanged. For further information, refer to Table 2. Standard errors (in parentheses) are clustered at the bank level. ***, **, * denote significance at $p < 0.01$, $p < 0.05$, $p < 0.1$. Sources: SHS, BISTA, CSDB.

Table A6: QE, Redemptions and Credit Growth

Dependent Variable:	$\Delta\text{Lending}_{it}/\text{TA}_{i,t-1}$			
Time Period:	Monthly February 2014 - Sep 2016			
	(1)	(2)	(3)	(4)
Initial Redemptions ECB_{it}	0.069**	0.083**	-0.036	0.083
	(0.027)	(0.034)	(0.056)	(0.075)
Initial Redemptions ECB_{it}*I[QE_t]	0.088***	0.017		
	(0.027)	(0.036)		
Initial Redemptions ECB_{it}*I[Low $\text{Equity}_{i,t-1}$]		-0.025		-0.000
		(0.042)		(0.001)
Initial Redemptions ECB_{it}*I[QE_t]*I[Low $\text{Equity}_{i,t-1}$]		0.136***		
		(0.047)		
Initial Redemptions ECB_{it}*Spread_t			0.131***	0.009
			(0.043)	(0.056)
Initial Redemptions ECB_{it}*Spread_t*I[Low $\text{Equity}_{i,t-1}$]				0.216***
				(0.069)
Net sales_{it}	-0.099*	-0.101*	-0.067	-0.068
	(0.052)	(0.052)	(0.114)	(0.113)
Net sales_{it}*I[QE_t]	-0.116**	-0.116**		
	(0.056)	(0.056)		
Net sales_{it}*Spread_t			-0.093	-0.094
			(0.079)	(0.078)
Controls	yes	yes	yes	yes
Month FE	yes	yes	yes	yes
Bank FE	yes	yes	yes	yes
Observations	50,080	50,080	50,080	50,080
R^2	0.513	0.516	0.513	0.516

Notes: This table shows regressions of Equation 6 and repeats the specifications of Table 3, but uses predetermined information on redemptions. The maturity information to build Initial Redemptions ECB_{it} is taken from banks' balance sheets in January 2014. For further information, refer to Table 3. Standard errors (in parentheses) are clustered at the bank level. ***, **, * denote significance at $p < 0.01$, $p < 0.05$, $p < 0.1$. Sources: SHS, BISTA, CSDB, ZIS.

Table A7: Robustness: Fixed Effects Adjustment

Dependent Variable:	$\Delta\text{Lending}_{it}/\text{TA}_{i,t-1}$		
1. Stage Security*Month FE	yes	yes	yes
1. Stage Security*Bank FE	yes	yes	yes
	(1)	(2)	(3)
$\widehat{\text{Redemptions}}\ \text{ECB}_{it}$	0.126**	0.124**	0.170***
	(0.053)	(0.053)	(0.057)
$\widehat{\text{Sales}}_{it}$	-0.033***		
	(0.010)		
$\widehat{\text{Purchases}}_{it}$	-0.002		
	(0.006)		
$(\widehat{\text{Purchases-Sales}})_{it}$		-0.011***	
		(0.004)	
$\widehat{\text{Net sales}}_{it}$			-0.063***
			(0.022)
$\widehat{\text{Net purchases}}_{it}$			0.009
			(0.011)
Controls	yes	yes	yes
2. Stage Month FE	yes	yes	yes
2. Stage Bank FE	yes	yes	yes
Observations	37,560	37,560	37,560
R^2	0.542	0.542	0.546

Notes: This table shows regressions of Equation 5, where the main explanatory variables are adjusted for bank*security and security*time fixed effects at the bank-ISIN-month level before aggregation at the bank-month level. Redemption, purchase and sale variables are calculated from residuals of regressions of the monthly changes of security holdings at the bank-ISIN-month level on bank*security and security*time fixed effects, separately for redemptions and holding changes not on maturity dates. For further information, please refer to Table 2. Standard errors (in parentheses) are clustered at the bank level. ***, **, * denote significance at $p < 0.01$, $p < 0.05$, $p < 0.1$. Sources: SHS, BISTA, CSDB.

Table A8: Robustness: Bank-ISIN-Month level

Dependent Variable:	ΔLending$_{it}$/TA$_{i,t-1}$		
Time Period:	Monthly February 2014 to Sep 2016		
	(1)	(2)	(3)
ΔHoldings$_{ijt}$	0.208*	0.301***	0.316***
	(0.107)	(0.088)	(0.084)
ΔHoldings$_{ijt}$*I[Net sale$_{it}$ < 0]	-0.452***	-0.615***	-0.558***
	(0.091)	(0.079)	(0.066)
ΔHoldings$_{ijt}$*I[QE-eligible]$_{jt}$			-0.069
			(0.150)
ΔHoldings$_{ijt}$*I[QE-eligible]$_{jt}$*I[Net sale$_{it}$ < 0]			-0.710*
			(0.372)
ΔHoldings$_{ijt}$I[Asset matures$_{jt}$]	-0.304***	-0.453***	-0.474***
	(0.096)	(0.086)	(0.085)
Controls	yes	yes	yes
Security*Bank FE	yes	yes	yes
Security*Month FE	no	yes	yes
Observations	4,590,556	3,932,835	3,932,835
R^2	0.600	0.664	0.664

Notes: This table uses security holdings at the bank (i) - ISIN (j) - month (t) level for the February 2014 to September 2016 period. The dependent variable is still at the i,t level and is matched to the i,j,t level data. ΔHoldings is the change in holdings of security j of bank i between t and t–1. I[Net sale$_{it}$ < 0] is a dummy indicating banks that are net sellers of assets according to Equation 4 at time t. I[QE-eligible]$_{jt}$ is a dummy that indicates whether security j is QE-eligible at time t. I[Asset matures$_{jt}$] indicates whether asset j matures at time t. For further information, please refer to Table 2. Standard errors (in parentheses) are clustered at the bank level. ***, **, * denote significance at $p < 0.01$, $p < 0.05$, $p < 0.1$. Sources: SHS, BISTA, CSDB.

Table A9: Propensity Score Matching

Dependent Variable:	I[Initial Redemptions^{high}]$_i$		
Time Period:	January 2014		
Matching:	Pre-Matching		Post-Matching
	(1)	(2)	(3)
Wholesale Deposits$_{i1}$/TA$_{i1}$	0.594		
	(1.053)		
Deposits$_{i1}$/TA$_{i1}$	2.099**	1.543***	0.396
	(1.027)	(0.266)	(0.352)
Equity$_{i1}$/TA$_{i1}$	-3.474*	-3.676**	-0.297
	(1.964)	(1.499)	(1.582)
Interbank Lending$_{i1}$/TA$_{i1}$	-1.039***	-1.116***	-0.600
	(0.338)	(0.333)	(0.477)
CB Liquidity$_{i1}$/TA$_{i1}$	-0.278		
	(0.854)		
Log(TA$_{i1}$)	-0.032		
	(0.024)		
TA$_{i1}$/TA$_{i0}$	-2.266		
	(1.546)		
Constant	1.642	-0.780***	-0.232
	(1.335)	(0.218)	(0.291)
Observations	1,565	1,565	1,104
Pseudo-R^2	0.034	0.031	0.002
P-value Chi^2 Test	0	0	0.369

Notes: This table shows probit estimations for the preparation (columns (1) and (2)) and the result of the propensity score matching (column (3)). Column(1) identifies the control variables that predict belonging to the treated group with high redemptions in January 2014, whereas column (2) estimates the propensity scores based on the significant variables from column (1). Column (3) repeats the estimation in column (2) on the matched sample, showing that the variables do not predict the treatment status in the matched sample. Banks are matched to one nearest neighbor without replacement, reducing the number of banks in the sample from 1565 to 1104. P-value Chi^2 Test is the p-value of the Chi^2 test on joint significance of the regression coefficients with the null hypothesis that the coefficients are jointly insignificant. The regression is based on data from January 2014. Robust standard errors in parentheses. ***, **, * denote significance at $p < 0.01$, $p < 0.05$, $p < 0.1$. Sources: SHS, BISTA, CSDB.

Table A10: Robustness: Difference-in-Differences

Dependent Variable:	$\Delta\text{Lending}_{it}/\text{TA}_{i,t-1}$								
Bank Sample:	Alll 1565 Banks			Propensity Score Matched Sample					
Time Period:	Collapsed pre/post Oct 2014			Monthly Feb 2014 to Sep 2016			Collapsed pre/post Oct 2014		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
I[Redemptions^{high}]$_i$*I[QE]$_t$	0.001***			0.001**			0.001***		
	(0.000)			(0.000)			(0.000)		
I[Initial Redemptions^{high}]$_i$*I[QE]$_t$		0.001***	0.001**		0.002***	0.002***		0.001***	0.001**
		(0.000)	(0.000)		(0.000)	(0.000)		(0.000)	(0.000)
I[Net trade^{low}]$_i$*I[QE]$_t$	0.000*	0.000*	0.001**	0.002***	0.002***	0.002***	0.001**	0.001**	0.001**
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)
I[Initial Exposure^{high}]$_i$*I[QE]$_t$			0.000			-0.000			0.000
			(0.000)			(0.001)			(0.000)
I[Yield Change^{high}]$_i$*I[QE]$_t$			0.001**			0.000			0.000
			(0.000)			(0.001)			(0.000)
Controls	yes	yes	yes	yes	yes	yes	yes	yes	yes
Controls*QE	-	-	-	yes	yes	yes	-	-	-
Month FE	yes	yes	yes	yes	yes	yes	yes	yes	yes
Bank FE	yes	yes	yes	yes	yes	yes	yes	yes	yes
Observations	3,130	3,130	3,130	35,328	35,328	35,328	2,208	2,208	2,208
R^2	0.538	0.537	0.541	0.628	0.628	0.628	0.563	0.563	0.563

Notes: This table shows regressions of Equation 9, which repeat the specifications from Table 4, columns (1), (3) and (4) for different samples. Columns (1)-(3) and (7)-(9) collapse the sample to two periods containing average values of the variables for the pre-QE period, February 2014 to September 2014 and the post-QE period, October 2014 to September 2016. Columns (4)-(9) use a subsample of banks matched on their propensity scores. For the matching, see Table A9 in the Appendix. Standard errors (in parentheses) are clustered at the bank level in columns (4)-(6). Columns (1)-(3) and (7)-(9) show robust standard errors. ***, **, * denote significance at $p < 0.01$, $p < 0.05$, $p < 0.1$. Sources: SHS, BISTA, CSDB.