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The Post-2015 German Lending Surge - What Role for QE?[†]

Sebastian Eiblmeier[*]

August 29, 2025

This paper uses German microdata to test whether the ECB's quantitative easing (QE) spurred bank lending to non-financial firms. Bank-firm loan data allow me to control for loan demand at firm level. The share of bonds in banks' total assets before QE serves as treatment proxy. While the effects are positive and statistically significant, they are small: Increasing the bond/asset share in a firm's lender bank by one standard deviation increases the de-trended outstanding bilateral loan volume by 3-5% of its within-sample mean. At firm level, no unambiguous effect can be observed.

Keywords: Unconventional monetary policy, Germany, bank lending, portfolio rebalancing, panel regression.
JEL classification: C23, E51, E52, G11, G21.

[†]I undertook the analyses of the micro data sets employed in this paper at the premises of the German Bundesbank Research Data and Service Center (RDSC) via on-site access under project number 2023/0042. I thank the team at the RDSC for their support.
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1 Introduction

As of yet, empirical research has not unveiled unanimous results on whether quantitative easing (QE) is effective in stimulating bank lending. While some papers find a strong impact (e.g. Paludkiewicz 2021; Rodnyansky and Darmouni 2017; Tischer 2018), others find only mixed effects (e.g. Acharya et al. 2019; Chakraborty et al. 2020). These differences in the results might stem from differences in the countries under observation, the time period, and definitions of outcome and explanatory variables that were used (Dell'Ariccia et al. 2018). With the question unanswered, further research is necessary.

This paper investigates whether QE stimulated bank lending in the German economy between 2015 and 2018. This question continues to be important because QE evolved from an unconventional monetary policy to a standard component of central banks' toolbox. For the Eurosystem, it is particularly relevant as it oversees a very heterogeneous currency area comprised of 20 national economies which, most of the time, take different positions in both the business and financial cycle (Mandler and Scharnagl 2022). The Eurosystem's monetary policy, however, is carried out on equal terms throughout the euro area, and QE was no exception.[1] Hence, it is important to analyze the effects of QE at the national level. For instance, the German banking system was not under any stress in 2015, unlike those of Southern European countries like Spain or Italy that were still suffering from the preceding financial crises.

My contribution is that I use high-quality microdata on individual German banks and their loans to individual German firms. This allows me to control for firm-level loan demand by using firm fixed effects. While I find that banks which are more exposed to QE increase their lending compared to less exposed banks that lend to the same firm, this is not associated with an increase in the overall debt of the borrowing firm. Instead, firms seem to substitute their borrowing between banks. These results tell us that a central bank's ability to stimulate the loan market via the supply side has limits.

The specific channel I test is the portfolio rebalancing channel: when the central bank purchases large quantities of government bonds and other fixed income assets, this increases the prices of those assets and hence squeezes the yield. Assuming search for yield by bond-holding banks, this should trigger portfolio rebalancing: in order to keep their overall return on assets stable, banks should switch into other assets that might be riskier

[1] To be precise, the Public Sector Purchase Program (PSPP) launched in 2015 was no exception as the amount of government bonds the ECB purchased from each member state was determined by the state's share in the ECB's capital. Under the Pandemic Emergency Purchase Program (PEPP) launched in 2020, purchases deviated from the shares indicated by the capital key. PEPP, however, is not part of my investigation.

but generate a higher yield, for instance corporate loans. In this way QE is assumed to increase the supply of corporate loans and decrease their interest rate. The following increase in corporate borrowing and investment should increase inflation via increased demand in the goods market (Hammermann et al. 2019). Conceptually, portfolio rebalancing hinges on preferred habitat investors: see Tobin (1969) and Vayanos and Vila (2009, 2021) for details and formalization. In a wider sense, the portfolio rebalancing channel can be interpreted as a manifestation of the bank lending channel which states that monetary policy affects loan supply via affecting banks' balance sheets (Bernanke and Gertler 1995).

In my research design, I follow a two-step approach as is common in this line of literature. First, I run a loan-level regression. Using a subsample of firms with more than one bank connection allows me to control for loan demand at the firm level, following Khwaja and Mian (2008). The results of this regression, however, only show me whether banks in the treatment group increase their *relative* loan volume compared to banks in the control group *within* the same firm. For this reason, second, I run a firm-level regression to see whether the receiving firm actually increases its total loan volume or merely substitutes loans from control group banks with loans from treatment group banks.

My proxy to measure the cross-sectional exposure of banks towards QE is a bank's ratio of fixed-income bonds over total assets before the start of QE in 2015, as in Bittner et al. (2024), Chakraborty et al. (2020), and Rodnyansky and Darmouni (2017). To measure the exposure of a firm to QE, I take the share of bonds in total assets of all banks lending to that firm and compute the weighted firm-level average across all banks, with the weights being the share of each bank's loan volume in all banks' loan volumes. This approach is similar to that in Jiménez et al. (2020).

My dependent variable is the detrended outstanding loan volume of an individual bank to an individual firm. I expect to observe a positive relationship: the higher the pre-QE share of bonds in a bank's total assets, the more should this bank's loan volume deviate from its pre-QE trend compared to other banks lending to the same firm.

What are my main findings? At the loan level, I find a small positive effect of QE (section 5.1). When the bank's bond-to-asset ratio is increased by one standard deviation (roughly 12%-points), the de-trended outstanding loan volume from a bank to a firm increases by 3-5% of the mean outstanding loan volume over the observation period (2011-2018). At the firm level, my results do not reveal a clear picture: depending on the control variables included, some specifications show a weak negative effect, others show a weak positive effect, sometimes statistically significant, sometimes not (section 5.2).

All my results are robust across sub-samples of: (1) all firms in the dataset, (2) non-financial firms for which balance sheet data are available in the firm dataset, (3) firms that issue no market debt, (4) and firms where the sum of bilateral loans in the credit register makes up at least 75% of total bank loans reported by the same firm in the firm dataset[2]. Each sub-sample is a strict subset of the previous one. Also, the inclusion of the extensive margin, i.e. bank-firm connections that are newly established or terminated during the observation period, does not change the overall picture, although the coefficients tend to be smaller and less statistically significant (section 6.1). The results are also robust to using different proxies for QE (section 6.2): only bonds that eventually become eligible for being purchased by the Eurosystem, only bonds that mature during QE, only government bonds from GIIPS countries, and the volume of bond redemptions during QE. As a third robustness check I test different weights for the firm-level shock, finding little differences (section 6.3). Finally, the results are also very similar in bank-industry-level and bank-level regressions (section 6.4).

Related Literature. The three papers that, to the best of my knowledge, are closest to the present study are Bittner et al. (2024), Rodnyansky and Darmouni (2017) and Chakraborty et al. (2020). Bittner et al. (2024) use German credit register and bank microdata to investigate interactions between quantitative easing and negative interest rate policy (NIRP). They measure banks' exposure to QE through banks' share of bonds in total assets and banks' exposure to negative interest rates through banks' share of household deposits in total assets. Their main finding is that there is a strong negative interaction effect between the two: banks with high exposure to QE lend relatively less when they are also strongly exposed to NIRP. My paper differs from Bittner et al. (2024) in several important aspects. First and foremost, I investigate the pure effect of QE rather than the interaction between QE and NIRP; this makes our papers complements rather than substitutes because their regression does not unveil the direct effect of QE. Second, I test various alternative QE proxies. Third, I also take the extensive margin into account. Fourth, in my firm-level regressions I use data on bank debt from the Bundesbank's firm dataset rather than the sum over all bilateral loan volumes from the credit register. The latter is important because it gives me a more complete gauge of a firm's bank debt as the credit register has a reporting threshold.

Rodnyansky and Darmouni (2017) investigate the effect of the Federal Reserve System's three rounds of QE on US bank lending. Using the securities-to-asset ratio as proxy for a bank's exposure to QE, in their bank-level regression they find that banks in the top

[2]Due to a reporting threshold of 1 million EUR (1.5 million before 2015) in the credit register, the sum of individual loans is usually below the total bank debt reported by the same firm in the firm dataset, see section 3.

quartile of that measure increase their loan volume by more than 3% compared to banks in the bottom quartile. Controlling for loan demand in a loan-level (bank-firm) regression cuts the effect in half. These results, however, only hold for the first and third round of US QE during which MBS were purchased. For the second round, which focused on the purchase of Treasury securities, the authors do not find any positive effects on lending. Building on Rodnyansky and Darmouni (2017), Chakraborty et al. (2020) find that mortgage-backed securities purchases by the Federal Reserve induced affected banks to increase mortgage lending at the expense of commercial lending; firms negatively affected by this crowding-out effect decreased their total borrowing and investment. For treasury purchases, the authors find only a small positive impact on lending.

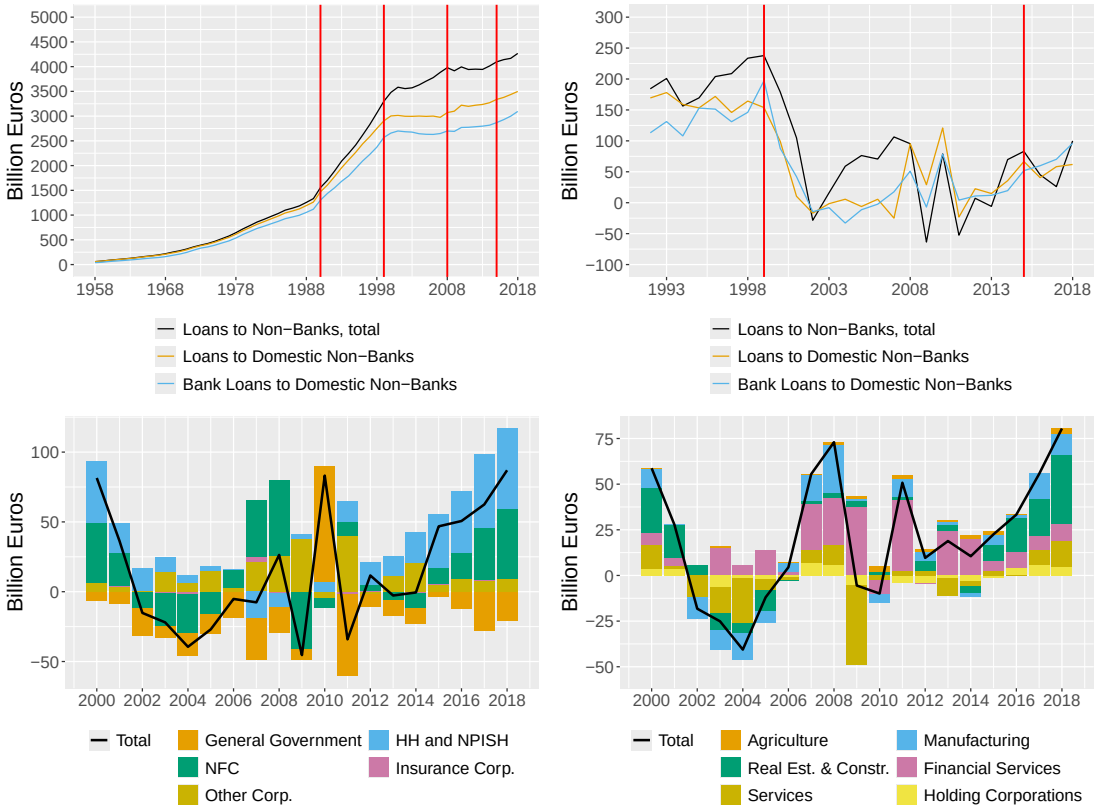
Paludkiewicz (2021) and Tischer (2018) also use German bank data to investigate whether the APP triggered additional firm lending, both finding a sizeable effect. Both papers' level of analysis is the bank level, however, i.e. neither of them uses loan-level data. Paludkiewicz (2021) uses the volume of new loans at bank level as a dependent variable rather than the volume of total outstanding loans. Two further papers that employ bank-level data to investigate the effect of QE on bank lending are Bowman et al. (2015) and Joyce and Spaltro (2014). The former investigate the effects of the Bank of Japan's QE (2001-2006), finding a statistically significant positive but economically negligible effect in the early stages and no effect in the later stages of QE. The latter investigate the effects of the Bank of England's QE (2009-2010) and their findings mirror those of Bowman et al. (2015): positive and statistically significant, but of little economic relevance. More literature using similar data than the present study can be found in online appendix A.

This paper adds to the existing literature on QE in that it employs matched bank-firm microdata to investigate the effect of the Eurosystem's QE in a large euro zone country. To the best of my knowledge, this has not yet been done. In a wider sense, it adds to the literature using such loan-level data by investigating a *positive* shock to the banking system while the bulk of the literature, to the best of my knowledge, investigates *negative* lending shocks. This is important because previous literature has found monetary policy to have asymmetric effects (Jordà et al. 2020).

The rest of the paper is structured as follows. Section 2 provides some more detail on the evolution of private sector debt in Germany over time, using data from public sources. Section 3 describes the data. Section 4 outlines the empirical strategy. In sections 5 and 6 I present the results of the main specification and robustness checks, respectively, and then move on to discuss those results in section 7. Section 8 concludes.

2 Private debt and bank lending in Germany

Figure 1: Loan Volume of German Banks



Outstanding loans (top left) and y-o-y change of outstanding loans (top right) from German banks in Billion Euros. The black and orange lines show total lending (bank loans and securities) to all non-banks and domestic non-banks respectively, the blue line shows only bank loans to domestic non-banks. The bottom left panel shows the y-o-y change of outstanding bank loans by institutional sectors. The bottom right panel shows the y-o-y change of outstanding bank loans by industry. Source: Deutsche Bundesbank public database.

Stylized facts seem to suggest that QE in Germany worked as intended. The Eurosystem launched its asset purchase program in 2015 with the intention to bring inflation back to its 2% target by stimulating the real economy via spurring bank lending. At the same time, the German economy experienced a surge in private debt that was strongly driven by bank lending. This can be seen in figure 1 which shows the lending of German banks, based on publicly available Bundesbank data. The top left panel shows the outstanding stock of loans in the long run. The top right panel depicts year-on-year changes and zooms in on the period between German Reunification, which posed a major macroeconomic shock, and the end of QE in 2018. The data show a surge after 1990 which ended after 2000 and a return to growth at a much lower level after 2014 – and this rebound is particularly pronounced when zooming in on bank loans (blue line). The bottom left

panel decomposes the growth of bank loans to domestic non-banks into the growth by various institutional sectors. Here we can see that the post-2015 increase was strongly driven by a rebound in the growth of loans to non-financial corporations (NFC). The other major contributor, loans to households, started to increase in 2010 already, although their grow rate also gained momentum after 2015. The bottom right panel further decomposes growth of lending to the firm sector into various industry sectors. Here we can see that the post-2015 surge was strongly driven by loans to the real estate and construction sectors.

These data clearly show that the German private non-financial sector stepped up its borrowing after 2014, that the vast majority of that debt seems to have been sourced from the domestic banking system, and that a significant and increasing share of the new debt went to the non-financial corporate sector. By explaining lending from German banks to German non-financial firms one can hence explain a non-trivial share of this post-2014 debt surge. That the surge in loan growth coincides with the launch of QE in the euro zone makes QE the prime suspect in explaining it.

3 Data

To conduct the analysis, I merge multiple micro datasets. The centerpiece is the bank balance sheet statistics (BISTA – Bilanzstatistik)[3] of all banks resident in Germany. I then link the BISTA to the SHS (Securities Holding Statistics)[4] in which banks report their holdings of securities by ISIN. Further details on individual ISINs can be taken from the CSDB (Centralized Securities Database)[5]. All three databases cover the complete universe of German banks and are available on a monthly basis from January 2013 on; before that, the SHS is only available on a quarterly basis. Further detail on the industry structure of banks' lending portfolio is provided by the Quarterly Borrower Statistics (VJKRE - Viertljährliche Kreditnehmerstatistik)[6]. Here, banks report their end-of-quarter lending volume to 24 different industry sectors. The VJKRE is aligned with the BISTA to ensure that the sum of loans over all sectors equals the total loan volume reported in the BISTA. The final bank dataset I use is the selected master data for MFI (MaMFI)[7]. This dataset allows me to identify and drop banks that leave the dataset due to bankruptcy or mergers.

To this I add data from the German credit register of loans of 1 million EUR or more (MIO - Millionenkreditevidenz)[8] and from the individual financial statements of

[3]DOI = 10.12757/BBk.BISTA.99Q1-21Q4.01.01; dataset description in Gomolka et al. (2022)
[4]DOI = 10.12757/Bbk.SHSBaseplus.05122112; dataset description in Blaschke et al. (2022)
[5]DOI = 10.12757/BBk.CSDB.200903-202012.02.01; dataset description in Yalcin et al. (2021)
[6]DOI = 10.12757/BBk.VJKRE.99Q1-21Q4.01.01; dataset description in Krodel et al. (2022)
[7]DOI = 10.12757/Bbk.MaMFI.199901-202106.01.01; dataset description in Stahl (2021)
[8]The reporting threshold was lowered from 1.5 million EUR at the beginning of 2015.

non-financial firms (JANIS - Jahresabschlüsse-nichtfinanzieller-Unternehmen-Statistik)[9] in order to create bank-firm links. While linking the credit register to the BISTA is comparatively straightforward as both are reported by banks, linking the credit register to the JANIS is not a trivial exercise; details can be found in online appendix B. Two things are important here. First, the credit register does not contain individual loans, but the total outstanding credit of the reporting bank vis-à-vis individual borrowers, whereas total credit is defined as the sum of debt and equity instruments. So if a bank reports credit of one million Euros it cannot be determined whether the bank granted a loan or bought a bond or a share of that borrower or any combination thereof. I used cross-referencing with the CSDB to ensure that the bank-firm pairs I keep for my analysis are connected through debt and not through equity – again, see online appendix C.[10] Second, in the credit register banks have to report their credit vis-à-vis an individual borrower at the end of a quarter if the credit to the borrower *unit* to which that individual borrower belongs exceeded a threshold[11] at any point during that quarter; a borrower unit is defined as a combination of connected borrowers. Hence, the outstanding credit reported in the dataset can be well below the reporting threshold and even be zero. Still, the data have the important limitation that we cannot know whether a lender-borrower relationship that shows up for the first time in the data at any particular point in time is genuinely new or simply an old one that previously was just below the reporting threshold. For this reason, my analysis in the main specification focuses on a balanced panel and hence on the intensive margin. Details on the credit register can be found in Bundesbank (2021).

The JANIS contains annual financial statements of non-financial corporations. It covers a plethora of items of the balance sheet, income statements, and, in some cases, statement of changes in tangible fixed assets. Additionally, it contains information on the industry and the legal form of each firm.

Table 1 provides descriptive statistics for loan-level, bank-level, and firm-level variables, each for two different sub-sets of the data: one with all non-financial firms that have at least two bank connections and for which firm data are available in the JANIS (dataset 2), and one in which all firms have been dropped that issued no bonds before QE and for which the sum of the bilateral lending relationships from the credit register is less than 75% of the total bank loans reported by the firm in the JANIS (dataset 4).[12] The

[9] DOI = 10.12757/Bbk.JANIS.9722.11.11; dataset description in Becker et al. (2023)

[10] Besides, it's probably save to assume that banks generally do not own equity of non-financial firms at a large scale.

[11] 1.5 million Euros until 2014 Q4, 1 million thereafter.

[12] Dataset (1) contains all borrowers with at least two bank connections, irrespective of whether there are firm balance sheet data available or not. Dataset (3) is dataset (2) minus those firms that issued market debt before 2015. Both datasets are excluded from the descriptive statistics in the interest of clarity.

descriptive statistics of the two datasets are remarkably similar with one exception: firms in dataset (4) are a lot smaller on average. Table 2 provides variable labels.

Coverage of the BISTA is very good: bank total assets make up around 85% of the full dataset. Since the BISTA is a census, this is also 85% of the German banking systems aggregate total assets. Coverage of the JANIS is a lot lower: while dataset (2) covers around 30% of total assets of the full dataset, dataset (4) covers 10%. This is mostly due to the credit register's reporting threshold. Looking at the JANIS alone, the firms in the balanced panel cover around 60% of total assets of all firms in the JANIS. Additional descriptive data can be found in online appendices A.1 and A.2.

4 Empirical Strategy

The key appeal of matched bank-firm data is that both the bank lending channel and the balance sheet channel can be thoroughly tested by controlling for credit demand at the firm level and by controlling for credit supply at the bank level. In this paper, the focus is on the bank lending channel. Instrumental for the use of firm dummies to control for demand is that there are firms with multiple bank connections. Unfortunately, this is only true for a sub-sample because particularly smaller firms often only have one bank from which they borrow. Plus, the reporting threshold must be expected to cut off secondary lending relationships, again most likely for smaller firms. (Harhoff and Körting 1998)

The economic mechanism I test is called the portfolio rebalancing channel. According to it, banks with a larger bond portfolio should be particularly sensitive to quantitative easing. This is because a reduction in bond yields through central bank purchases creates an incentive for banks to reduce their bond holdings and instead increase their lending to firms and households (portfolio rebalancing) in order to retain their overall income (search for yield motive).

In order to estimate the portfolio rebalancing channel, I follow a two-stage procedure well established in the literature following Khwaja and Mian (2008). First, I use loan-level data to see whether banks with strong exposure to QE – as measured by their bond-to-asset ratio – increased their loans compared to banks with weak exposure to QE lending to the same firm. Second, I test whether receiving firms actually increased their total borrowing or merely used loans from treatment group banks to replace loans from control group banks.

Table 1: Descriptive Statistics

	Model (2)			Model (4)		
	Mean	SD	N	Mean	SD	N
	Loan-Level Variables					
LOANS_DT_norm_post	-.044	.872	15,578	-.044	.804	7,806
	Bank-Level Variables					
Total Assets (Mn. EUR)	7,923	59,507	911	9,396	65,485	750
BONDS_bank	.194	.119	911	.190	.115	750
BONDS_bank_eligible	.014	.021	911	.015	.021	750
BONDS_bank_maturing	.090	.059	911	.087	.057	750
BONDS_bank_giips	.002	.007	911	.002	.008	750
RDPTNS_bank	.026	.023	911	.026	.021	750
INIT_RDPTNS_bank	.021	.015	911	.020	.015	750
b1	.685	.157	911	.684	.158	750
b2	.159	.133	911	.159	.132	750
b2cb	.008	.023	911	.008	.014	750
b3	.057	.024	911	.057	.025	750
b4	.102	.104	911	.101	.101	750
b5	.016	.041	911	.015	.036	750
b6	.036	.091	911	.035	.089	750
b7	14.306	1.27	911	14.502	1.256	750
	Firm-Level Variables					
Total Assets (Mn. EUR)	339	2,792	4,551	133	1328	2,528
BANKDEBT_DT_norm_post	-.020	.706	4,551	-.022	.666	2,528
BONDS_bank_f_sc	.039	.037	4,551	.049	.041	2,528
BONDS_bank_f_pre_sc	.042	.04	4,551	.053	.044	2,528
BONDS_bank_f_post_sc	.038	.038	4,551	.049	.042	2,528
BONDS_bank_f_unw_sc	.052	.042	4,551	.056	.043	2,528
BONDS_bank_f	.115	.074	4,551	.143	.074	2,528
BANKDEBT_RESTATE	1.556	1.84	3,910	1.483	1.787	2,224
RESTATE_TA	.391	.334	3,910	.431	.339	2,224
f1	.055	.076	4,551	.055	.075	2,528
f2	.087	.081	4,551	.088	.081	2,528
f3	-.017	.012	4,551	-.017	.012	2,528
f4	.052	.104	4,551	.045	.095	2,528
f5	.076	.329	4,551	.066	.253	2,528
f6	11.015	1.433	4,551	10.722	1.232	2,528

Descriptive statistics of loan-level, bank-level, and firm-level variables. Variable names are labeled in table 2. Source: Research Data and Service Centre (RDSC) of the Deutsche Bundesbank, BISTA, SHS, CSDB, JANIS, Credit register of loans of 1 Mn. EUR or more, 2011-2018, own calculations.

Table 2: Variable Labels

LOANS_DT_norm_post	De-trended bilateral loan volume, as defined in equation 1
BONDS_bank	Bond-to-asset ratio, as defined in equation 4
BONDS_bank_eligible	... only bonds eligible for QE
BONDS_bank_maturing	... only bonds maturing during QE
BONDS_bank_giips	... only GIIPS government bonds
RDPTNS_bank	Volume of redemptions during QE, mean over 2015-2018
INIT_RDPTNS_bank	... only from bonds held before QE, mean over 2015-2018
b1	Deposits over total assets
b2	Wholesale borrowing over total assets
b2cb	Central bank borrowing over total assets
b3	Equity over total assets
b4	Interbank claims over total assets
b5	Central bank liquidity over total assets
b6	Change in total assets, y-o-y
b7	ln(total assets)
BANKDEBT_DT_norm_post	De-trended firm debt volume
BONDS_bank_f_sc	Firm-level shock, as defined in equation 7
BONDS_bank_f_pre_sc	... with only using 2011-2014 loan volumes to compute weights
BONDS_bank_f_post_sc	... with only using 2015-2018 loan volumes to compute weights
BONDS_bank_f_unw_sc	... with using equal weights
BONDS_bank_f	... with using equal weights and no scaling by firm bank debt
BANKDEBT_RESTATE	Bank-debt-real-estate ratio
RESTATE_TA	Real-estate-over-total-asset ratio
f1	Cash holdings over total assets
f2	Cash flow over total assets
f3	Net interest income over total assets
f4	Change in total firm assets, y-o-y
f5	Sales growth, y-o-y
f6	ln(total assets)

Labels of variables in table 1. Unless stated otherwise, all variables are means over 2011-2014.

4.1 Estimating loan-level effects

The basic equation for estimating the bilateral loan volume between bank and firm is as follows:

$$y_{bf} = \beta_1 * \gamma_b + \boldsymbol{\beta_2'} * \mathbf{A_b} + \delta_f + \epsilon_{bf} \tag{1}$$

The dependent variable y_{bf} is the mean difference between the bilateral loan volume from bank b to firm f and its pre-QE trend during 2015 and 2018, divided by the mean outstanding loan volume over the observation period:

$$y_{bf} = \frac{mean_{15-18}\left[\text{DetrendedLoans}_{bf,t}\right]}{mean_{11-18}\left[\text{Loans}_{bf,t}\right]} \tag{2}$$

The variable in the numerator is defined as:

$$\text{DetrendedLoans}_{bf,t} = \text{Loans}_{bf,t} - \text{LoansLinearTrend}_{bf,11-14} \tag{3}$$

In words, starting with equation 3: I take the loan volume of bank b to firm f in year t and subtract the linear trend of that bilateral loan volume of the years 2011 to 2014, i.e. before QE started. By this I control for possible violations in the common trends assumption.[13] Then I compute the mean of that detrended loan volume during QE (2015 to 2018) and normalize it by the mean of the loan volume of bank b to firm f over the entire observation period[14]. This is my dependent variable (equation 2). Importantly, I censor the linear trend to be non-negative as the actual lending volume can never be negative and this would bias the results: against a negative trend a zero outstanding loan volume would be interpreted by the model as a positive effect of QE.

On the right-hand side of equation 1, γ_b is a bank-level shock. In my case, γ_b is the exposure of a bank b to quantitative easing via the mean share of fixed-income assets (bonds) over total assets over the years 2011 to 2014:

$$\gamma_b = mean_{11-14}\left[\frac{\text{bonds}_{\text{b,t}}}{\text{TA}_{\text{b,t}}}\right] \tag{4}$$

Vector $\mathbf{A_b}$ contains the following set of bank control variables:

$$\text{b1} = mean_{11-14}\left[\frac{\text{deposits}_{b,t}}{\text{TA}_{b,t}}\right], \qquad \text{b2} = mean_{11-14}\left[\frac{\text{wholesale funding}_{b,t}}{\text{TA}_{b,t}}\right]$$

$$\text{b2cb} = mean_{11-14}\left[\frac{\text{central bank borrowing}_{b,t}}{\text{TA}_{b,t}}\right], \qquad \text{b3} = mean_{11-14}\left[\frac{\text{equity}_{b,t}}{\text{TA}_{b,t}}\right]$$

$$\text{b4} = mean_{11-14}\left[\frac{\text{interbank claims}_{b,t}}{\text{TA}_{b,t}}\right], \qquad \text{b5} = mean_{11-14}\left[\frac{\text{central bank liquidity}_{b,t}}{\text{TA}_{b,t}}\right]$$

$$\text{b6} = mean_{11-14}\left[\frac{\Delta\text{TA}_{\text{b,t}}}{\text{TA}_{b,t-1}}\right], \quad \text{b7} = ln(\text{TA}_{2014})$$

ϵ_{bf} is the error term and δ_f a firm-level loan demand shock. A simple OLS estimation of β_1 produces biased results if γ_b and δ_f are correlated: $\hat{\beta}_1^{OLS} = \beta + \frac{Cov(\gamma_b, \delta_f)}{Var(\gamma_b)}$. This problem can be remedied with data in which there are multiple bank connections per firm. Then, a (within-firm) fixed effects regression delivers unbiased results. The size and sign of the correlation can easily be shown by running both FE and OLS regressions on the same sub-sample and comparing the coefficients: $\hat{\beta}_1^{OLS} > \hat{\beta}_1^{FE}$ implies a positive correlation. See Jiménez et al. (2020) who also provide proof from simulations that this method is viable.

[13] I also tested a specification in which I take the non-detrended loan volume. The unreported results are very different.

[14] Using the pre-QE mean is unfeasible because if the loan volume is zero before 2015, I cannot compute y_{bf}. This is particularly relevant when including the extensive margin (section 6.1)

I will also test an adaption of equation 1 in which I substitute the firm fixed effect δ_f with a number of firm-level control variables $\mathbf{B_{f,T}}$ in order to test how they perform in controlling for firm-level loan demand:

$$y_{bf} = \beta_1 * \gamma_b + \boldsymbol{\beta_2'} * \mathbf{A_b} + \boldsymbol{\beta_3'} * \mathbf{B_f} + \epsilon_{bf} \tag{5}$$

Vector $\mathbf{B_f}$ contains the following set of firm control variables:

$$\text{f1} = mean_{11-14}\left[\frac{\text{cash holdings}_{f,t}}{\text{TA}_{f,t}}\right], \qquad \text{f2} = mean_{11-14}\left[\frac{\text{cash flow}_{f,t}}{\text{TA}_{f,t}}\right],$$

$$\text{f3} = mean_{11-14}\left[\frac{\text{net interest income}_{f,t}}{\text{TA}_{f,t}}\right], \qquad \text{f4} = mean_{11-14}\left[\frac{\Delta\text{TA}_{f,t}}{\text{TA}_{f,t-1}}\right]$$

$$\text{f5} = mean_{11-14}\left[\frac{\Delta\text{sales}_{f,t}}{\text{sales}_{f,t-1}}\right], \qquad \text{f6} = ln(\text{TA}_{2014})$$

Higher cash holdings and a higher cash flow over total assets should both reduce the requirement for external finance. The net interest income is a proxy for the debt burden the firm is facing. The growth rates of total assets and sales are included as controls for firm growth: strongly growing firms can be expected to have a higher demand for finance. Finally, the logarithm of total assets proxies firm size.

4.2 Estimating firm-level effects

Looking at bilateral lender-borrower relations does not reveal the full picture of the firm-level borrowing. This is because a loan-level regression as described by equations 1 and 5 tells us how loans from banks in the treatment group evolve *relative* to loans from banks in the control group *within* the same firm. Any positive (or negative) effect might simply represent substitution of a given firm between different banks rather than an increase (or decrease) in overall borrowing by that very firm. From a theoretical point of view it sounds reasonable for a firm to exploit more favorable loan conditions from one bank to replace loans from another bank. To test whether firms increase their overall borrowing following a bank-specific supply shock, we need to look at the firm level:

$$\bar{y}_f = \bar{\beta}_1 * \bar{\gamma}_f + \delta_f + \bar{\epsilon}_f \tag{6}$$

Here, $\bar{y}_f$ is computed the same way as y_{bf} from equation 1, but this time with the total volume of bank loans of the firm from all banks, as reported in the JANIS, rather than the bilateral loan volume. Since this variable also includes lender-borrower relationships that are below the credit register's reporting threshold, it is not necessarily identical to

the sum of all bilateral relationships that enter equation 1. We will come back to this point later. Again, $\bar{\epsilon}_f$ is the error term. δ_f is the same firm-level demand shock as in equation 1. $\bar{\gamma}_f$ is the weighted average exposure of the firm to the bank supply shocks:

$$\bar{\gamma}_f = \left[\sum_{b \in N_f} (W_{\gamma_b} * \gamma_b) \right] * \frac{\text{BankLoans}_f}{\text{TA}_f} \tag{7}$$

N_f is the set of banks lending to firm f. W_{γ_b} is the weight of bank b in firm f's total borrowing over the observation period, defined as follows:

$$W_{\gamma_b} = \frac{\sum_{11-18} \text{Loans}_{bf}}{\sum_{b \in N_f} \sum_{11-18} \text{Loans}_{bf}} \tag{8}$$

I.e. I take the sum of the end-of-year loan volumes from bank b to bank firm f over the years 2011 to 2018 and divide it by the sum of the end-of-year loans to that firm from all banks over the years 2011 to 2018. In section 6.3 I will discuss alternative weights. The final term in equation 7 additionally considers the firm's bank loan leverage. If the firm does not substitute between its various sources of loans at all, then $\bar{\beta}_1 = \beta_1$. In the other extreme case, in which the firm undertakes perfect substitution, $\bar{\beta}_1 = 0$.

A problem with the firm-level regression is that it suffers from the same potential correlation between supply shock $\bar{\gamma}_f$ and demand shock δ_f as the loan-level regression, but this time it cannot be controlled for through firm-level fixed effects because both shocks are now invariant at firm level. Previous literature provided different solutions for this issue. Khwaja and Mian (2008), for instance, luckily escape these troubles because in their case the shocks are actually negatively correlated which means that their firm-level OLS results are even underestimates. Bentolila et al. (2018) and Bottero et al. (2020) saturate their firm-level regressions with firm controls and industry-location dummies. Cingano et al. (2016) include the estimates of δ_f from their loan-level equation in their firm-level equation. Jiménez et al. (2020) derive a mathematical solution to compute an unbiased coefficient at firm level, starting with the fact that the coefficient computed with a firm-level OLS regression is biased:

$$\hat{\bar{\beta}}_1^{OLS} = \beta_1 + \frac{Cov(\gamma_b, \delta_f)}{Var(\bar{\gamma}_f)} \tag{9}$$

While $Cov(\gamma_b, \delta_f)$ is not observable, the fact that a loan-level fixed effects estimation in the vein of equation 1 delivers an unbiased estimate of β_1, namely $\hat{\beta}^{FE}$, allows us to re-arrange the previous equation to express the covariance as follows:

$$Cov(\gamma_b, \delta_f) = \left(\hat{\beta}_1^{OLS} - \hat{\beta}_1^{FE} \right) * Var(\bar{\gamma}_f) \tag{10}$$

Plugging equation 10 into equation 9 then gives us the following formula with which we can compute an unbiased estimate of β at firm level:

$$\hat{\tilde{\beta}}_1 = \hat{\tilde{\beta}}_1^{OLS} - \left(\hat{\beta}_1^{OLS} - \hat{\beta}_1^{FE}\right) * \frac{Var(\gamma_b)}{Var(\bar{\gamma}_f)} \tag{11}$$

$\hat{\tilde{\beta}}_1^{OLS}$ is from equation 6, $\hat{\beta}_1^{OLS}$ is from equation 1 without firm fixed effects, and $\hat{\beta}_1^{FE}$ is from equation 1 with firm fixed effects.

5 Results

5.1 Loan-level effects

Table 3 shows the results of the loan-level regression as defined by equation 1. I run the regression on four different sub-sets of the dataset and with three different specifications. Within each dataset, in panel (a) I run a OLS regression of the dependent variable as defined by equation 2 on the share of bonds in banks' balance sheets as defined by equation 4. Panel (b) adds firm fixed effects and panel (c) further adds the bank control variables.

Dataset (1) contains all firms with at least two bank connections. Including firm FEs increases the coefficient by around one half, indicating that there is indeed a positive correlation between supply and demand effects. Further saturating the model with bank controls increases the coefficient by another half. This pattern holds throughout all datasets. The reason why I run all regressions both with and without bank controls is that in the firm-level regression I undertake later I cannot include bank control variables, so I need specification (b) to maintain comparability of the coefficients of the QE shock. Yet still, bank characteristics other than the share of bonds in total assets must be expected to play a role in banks' loan supply.

In dataset (2), I only use non-financial corporations for which firm balance sheet data are available in the JANIS. In dataset (3), I additionally drop all firms which have issued bond debt before 2015 to keep the analysis focused on firms which are arguably dependent on bank loans. In dataset (4), I further drop those firms for which the sum of bilateral loans to that firm reported in the credit register accounts for less than 75% of total bank loans reported by the same firm in the JANIS. The effect strength of γ_b is remarkably stable throughout all datasets and stays within conventional boundaries of statistical significance (p-values are shown in brackets).

What do the results of table 3 mean in terms of economic relevance? Remember, the dependent variable is the mean difference between the loan volume of bank b to firm f

Table 3: Results of the Loan-Level Regression with Firm Fixed Effects (equation 1)

Dataset	(1)			(2)			(3)			(4)		
Model	(a)	(b)	(c)	(a)	(b)	(c)	(a)	(b)	(c)	(a)	(b)	(c)
γ_b	0.148*	0.228**	0.328***	0.162**	0.293***	0.395***	0.200**	0.332***	0.426***	0.098	0.234**	0.285**
	(0.09)	(0.10)	(0.11)	(0.08)	(0.09)	(0.10)	(0.09)	(0.10)	(0.11)	(0.11)	(0.11)	(0.13)
	[0.083]	[0.023]	[0.003]	[0.048]	[0.002]	[0.000]	[0.022]	[0.001]	[0.000]	[0.366]	[0.029]	[0.023]
Constant	-0.064***	-0.077***	-0.552***	-0.065***	-0.086***	-0.664***	-0.065***	-0.086***	-0.680***	-0.056**	-0.078***	-0.387
	(0.02)	(0.02)	(0.18)	(0.02)	(0.02)	(0.20)	(0.02)	(0.02)	(0.20)	(0.03)	(0.02)	(0.25)
	[0.005]	[0.001]	[0.002]	[0.002]	[0.000]	[0.001]	[0.001]	[0.000]	[0.001]	[0.031]	[0.001]	[0.118]
Firm FE		Y	Y		Y	Y		Y	Y		Y	Y
Bank controls			Y			Y			Y			Y
N Banks	1,067	1,067	1,067	911	911	911	874	874	874	750	750	750
N Firms	9,050	9,050	9,050	4,551	4,551	4,551	4,313	4,313	4,313	2,528	2,528	2,528
N Pairs	28,242	28,242	28,242	15,578	15,578	15,578	13,906	13,906	13,906	7,806	7,806	7,806
R^2	0.0003	0.3906	0.3912	0.0004	0.3703	0.3710	0.0006	0.3859	0.3866	0.0001	0.3853	0.3861

Dataset (1) contains all firms with at least two bank connections. Dataset (2) contains only non-financial corporations for which balance sheet data are available. Dataset (3) contains only firms that never issued bonds before 2015. Dataset (4) contains only firms where bilateral lending in the credit register sums up to at least 75% of total bank loans reported in the JANIS. γ_b is the share of bonds in bank total assets as defined in equation 4. Standard errors (in parentheses) are clustered at the bank level. p-values are shown in square brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Source: Research Data and Service Centre (RDSC) of the Deutsche Bundesbank, BISTA, SHS, CSDB, Credit register of loans of 1 Mn. EUR or more, 2011-2018, own calculations.

and its pre-QE trend, divided by its own mean over the observation period. Hence, the coefficient of 0.148 in model (1a) means that an increase in the fraction of bonds over bank total assets by the value of 1 (i.e. by 100 percentage points) implies that the de-trended bilateral loan volume increases by 14.8% of its own within-sample mean. At first glance, this appears to be a sizable effect, but a variation in the explanatory variable by the value of 1 would imply comparing a bank with no bonds at all to a bank whose assets are comprised solely of bonds. A more reasonable gauge would be to check the impact of a change by one standard deviation. Additionally, how does the change in the dependent variable implied by the model compare to its variance we observe in the data? Table 4 shows the coefficient of each regression (column (2)), the standard deviation of the bank-level shock γ_b (column (3)), the product of the two (column (4)), the standard deviation of the dependent variable y_{bf} (column (5)) and the ratio of the latter two (column (6)).

Table 4: Effect strengths in regression equation 1

(1)	(2)	(3)	(4)	(5)	(6)
Model	Coefficient (table 3)	SD(γ_b) (table 1)	(2)*(3)	SD(y_{bf}) (table 1)	(4)/(5)
1a	0.148	0.12	0.018	0.87	0.020
1b	0.228	0.12	0.027	0.87	0.031
1c	0.328	0.12	0.039	0.87	0.045
2a	0.162	0.12	0.019	0.87	0.022
2b	0.293	0.12	0.035	0.87	0.040
2c	0.395	0.12	0.047	0.87	0.054
3a	0.200	0.12	0.024	0.87	0.028
3b	0.332	0.12	0.040	0.87	0.046
3c	0.426	0.12	0.051	0.87	0.059
4a	0.098	0.12	0.012	0.87	0.014
4b	0.234	0.12	0.028	0.87	0.032
4c	0.285	0.12	0.034	0.87	0.039

Column (4) shows how y_{bf} in regression model 1 changes as a reaction to a change of γ_b by one standard deviation. Column (5) shows the standard deviation of y_{bf} as observed in the data. Column (6) sets the two in relation.

In words: in model (1a), a change in bonds over bank total assets by one standard deviation leads to a change in the de-trended loan volume by 1.8% of its own within-sample mean. This is not a large number by itself and it is also small compared to the standard deviation of the dependent variable, which is 0.87. Taken together, a typical change in the independent variable (bonds over bank total assets) triggers a change in the dependent variable (difference between outstanding loans and their pre-QE trend as fraction over outstanding loans) that is at best 4-5% of the standard deviation of the

dependent variable. However, remember that this is not a final assessment because at this point we can only say that banks increase their loans relative to other banks when they are arguably more exposed to QE. From this regression we cannot say whether the receiving firm actually increases its total volume of bank loans or whether it is merely substituting between banks.

Another issue that should be mentioned in this context is that the effects shown in table 3 show the evolution of bilateral loan volumes normalized by their own within-sample mean. This could be another source of bias, both upward or downward. Just because the loan volume of one bank to a given firm grows strongly compared to the loan volume of another bank does not mean that it is important in aggregate terms. In table 10, I repeat all specifications from table 3 but normalized the bilateral loan volumes not by their own within-sample mean but by the within-sample mean of the total bank loans of the receiving firm. The coefficients in those regressions are much smaller than those in table 3, though still statistically significant in many cases. Hence, the results shown in table 3 should be considered an upper limit of the effects of QE.

In table 5, I test whether specific firm variables can sufficiently replace firm fixed effects as controls for firm-level loan demand. This is important because in the firm-level regression, demand must be controlled for by other means than a firm dummy. Model (2a) repeats model (2b) from table 3 to serve as benchmark. In model (2b) I drop the firm FE in favor of the firm controls (vector $\mathbf{B_f}$ from equation 5); additionally, I add the fraction of bank debt reported by the firm in the JANIS over its real estate before QE (model 2b) and the share of real estate in firm total assets before QE (model 2c). My motivation here is that loan supply does not only depend on the lending bank's characteristics but also on the borrowing firm's characteristics. Real estate assets are often used as collateral in loan contracts, so the higher the ratio between bank loans and real estate already is, the less inclined should a bank be to extend further loans to that firm. For this reason, I drop all firms from the datasets where the ratio of bank debt and real estate before QE exceeds the factor of 10 to ensure I only keep firms in the dataset that actually have a noteworthy amount of real estate in their balance sheet. QE has been known to push tangible asset prices[15] and hence those firms which are arguably supply-restricted via their bank loan / real estate ratio should receive additional lending. The coefficient of this variable is practically zero, though, and technically even negative. The coefficient of real estate over total assets is also close to zero in all specifications.[16] The coefficient of γ_b

[15] see, e.g., Berg et al. (2023), Huber and Punzi (2020), and Rahal (2016). In fact, property price growth in Germany gained momentum after 2015 (Federal Statistical Office of Germany 2020-12-28).

[16] The is a sizeable literature on this collateral channel of monetary policy which finds conflicting results on the effect of real estate prices on firm borrowing and investment. Bednarek et al. (2021) find a positive impact of real estate prices in German firm activity. Chaney et al. (2012) do so for the US.

Table 5: Results of the Loan-Level Regression with Firm Control Variables (equation 5)

Dataset	(2)				(4)			
Model	(a)	(b)	(c)	(d)	(a)	(b)	(c)	(d)
γ_b	0.404***	0.142	0.146*	0.160*	0.270**	0.026	0.010	0.018
	(0.10)	(0.09)	(0.09)	(0.09)	(0.11)	(0.11)	(0.10)	(0.10)
	[0.000]	[0.100]	[0.094]	[0.083]	[0.018]	[0.810]	[0.922]	[0.859]
BANKDEBT_RESTATE		-0.021***		-0.027***		-0.021***		-0.019***
		(0.00)		(0.00)		(0.01)		(0.01)
		[0.000]		[0.000]		[0.001]		[0.010]
RESTATE_TA			0.032	-0.058			0.081***	0.020
			(0.03)	(0.04)			(0.03)	(0.04)
			[0.309]	[0.123]			[0.010]	[0.593]
Constant	-0.629***	-0.046	-0.092	0.009	-0.136	0.108	0.017	0.094
	(0.19)	(0.08)	(0.09)	(0.09)	(0.11)	(0.13)	(0.13)	(0.13)
	[0.001]	[0.586]	[0.334]	[0.926]	[0.200]	[0.393]	[0.894]	[0.479]
Firm FE	Y				Y			
Bank controls	Y	Y	Y	Y	Y	Y	Y	Y
Firm controls		Y	Y	Y		Y	Y	Y
N Banks	882	882	882	882	721	721	721	721
N Firms	3,910	3,910	3,910	3,910	2,224	2,224	2,224	2,224
N Pairs	13,209	13,209	13,209	13,209	6,924	6,924	6,924	6,924
R^2	0.3742	0.0095	0.0075	0.0098	0.3780	0.0160	0.0148	0.0160

Datasets (2) and (4) are as defined in table 3 minus those firms where BANKDEBT_RESTATE > 10. γ_b is the share of bonds in bank total assets as defined in equation 4. BANKDEBT_RESTATE is the ratio of bank loans of a firm over firm real estate assets. RESTATE_TA is the ratio of firm real estate assets over firm total assets. Standard errors (in parentheses) are clustered at the bank level. p-values are shown in square brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Source: Research Data and Service Centre (RDSC) of the Deutsche Bundesbank, BISTA, SHS, CSDB, JANIS, Credit register of loans of 1 Mn. EUR or more, 2011-2018, own calculations.

is larger in the benchmark specification than in the main specification, but its size drops strongly and it loses statistical significance. This means that replacing the firm dummy with firm control variables leads to an underestimation of the loan-level effect of QE. In other words, the firm characteristics used here are not very good at capturing firms' loan demand. In model (4) the picture is generally the same.

5.2 Firm-level effects

Table 6 shows the results of the firm-level regression (equation 6). This time, I restrict the analysis to model 4 in which the sum of bilateral loans from the credit register makes up at least 75% of the total bank loans from the firm dataset because this condition ensures that the weighted firm-level shocks (equation 7) are actually meaningful. The reason why I do not use a 100% threshold is that I would lose too many firms, then. Testing different thresholds revealed that the coefficients tend to increase in size and statistical significance when lowering the threshold. Panel (a) shows the base model without additional controls. The coefficient of $\bar{\gamma}_f$ is now even negative and below, though close to ($p = 0.14$), conventional levels of statistical significance.

As has been outlined in section 4.2, firm fixed effects cannot be used to control for loan demand in the firm-level regression. In the loan-level regressions, the supply and demand shocks (γ_b and δ_f) appear to be correlated. This must not necessarily be true at the firm level, though, as the firm-level shock $\bar{\gamma}_f$ is not identical to the bank-level shocks γ_b. One option to tackle this issue is to extract the firm fixed effects from the loan-level regression and include them in the firm-level regression, as has been done by Cingano et al. (2016). I mimic this approach in panel (b) of table 6. This leaves the coefficient and p-value of the firm-level shock largely unchanged. As in the loan-level regression, the effect strength is negligible: the standard deviation of $\bar{\gamma}_f$ is 0.04, meaning that increasing the explanatory variable by one SD decreases the difference between outstanding bank loans of a firm and its pre-QE trend, but by a mere 1.5% of its within-sample mean.

A second way to control for loan demand in the firm-level regression is to include firm control variables, as has been done by Bentolila et al. (2018) and Bottero et al. (2020). I mimic this approach in panels (c) through (e) of table 6, where I include vector $\boldsymbol{B_f}$ as well as bank loans over real estate and real estate over total assets. Including the latter two separately does not much affect the coefficient of $\bar{\gamma}_f$. Including them simultaneously, though, turns the coefficient positive but also drives up its p-value (panel (e)): Increasing $\bar{\gamma}_f$ by one SD results in an increase of the dependent variable by $0.320 * 0.04 = 0.013 \approx 1\%$ of its within-sample mean. This is a little less than 2% of the standard deviation of the dependent variable (0.67).

In China, in contrast, the collateral channel seems hardly at work and displaced by other real estate

Table 6: Results of the Firm-Level Regression (equation 6)

Dataset	(4)				
Model	(a)	(b)	(c)	(d)	(e)
$\bar{\gamma}_f$	-0.467	-0.384	-0.188	-0.190	0.320
	(0.31)	(0.25)	(0.31)	(0.28)	(0.25)
	[0.136]	[0.131]	[0.545]	[0.500]	[0.209]
$\delta_f^{model4b}$		0.759***			
		(0.03)			
		[0.000]			
BANKDEBT_RESTATE			-0.037***		-0.049***
			(0.01)		(0.01)
			[0.000]		[0.000]
RESTATE_TA				0.032	-0.152**
				(0.05)	(0.06)
				[0.480]	[0.015]
Constant	0.021	0.008	0.209	0.079	0.272*
	(0.03)	(0.02)	(0.17)	(0.17)	(0.16)
	[0.432]	[0.732]	[0.209]	[0.638]	[0.099]
Firm controls			Y	Y	Y
N	2,224	2,224	2,224	2,224	2,224
R^2	0.0010	0.3752	0.0570	0.0472	0.0596

Dataset (4) is as defined in table 3, minus those firms where BANKDEBT_RESTATE > 10. $\bar{\gamma}_f$ is the firm-level shock as defined in equation 7. BANKDEBT_RESTATE is the ratio of bank loans of a firm over firm real estate assets. RESTATE_TA is the ratio of firm real estate assets over firm total assets. Standard errors (in parentheses) are clustered at the bank level. p-values are shown in square brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Source: Research Data and Service Centre (RDSC) of the Deutsche Bundesbank, BISTA, SHS, CSDB, JANIS, Credit register of loans of 1 Mn. EUR or more, 2011-2018, own calculations.

A third way to compute an unbiased coefficient in the firm-level regression is via equation 11, as has been done by Jiménez et al. (2020). Table 7 shows the results. The unbiased coefficient in table 7 is positive and more than twice the size of its loan-level correspondent. Remember, the case of perfect substitution between banks would result in $\hat{\tilde{\beta}}_1 = 0$, while no substitution implies $\hat{\tilde{\beta}}_1 = \hat{\beta}_1^{FE}$. These results mean, then, that firms use what they newly borrow from banks strongly exposed to QE mostly to increase their overall borrowing. The total effect, however, is still weak: multiplying the 0.573 we get in the final column with the standard deviation of $\bar{\gamma}_f$ results in 0.024 which is 3.6% of the standard deviation of the dependent variable. Taken together, there is no conclusive evidence that QE has an economically noteworthy impact on the volume of bank loans to non-financial firms.[17]

related channels (Wu et al. 2024).

[17] Also interesting to note is that the fixed effects implanted from the loan-level regression have a much stronger effect on the dependent variable than any other regressor. Also, their inclusion drastically increases R^2. This indicates that firm-level loan demand effects are much more important than any supply effects.

Table 7: Unbiased $\hat{\bar{\beta}}_1$ from Equation 6 Using the Equation 11 Formula

$\hat{\bar{\beta}}_1^{OLS}$	$\hat{\beta}_1^{OLS}$	$\hat{\beta}_1^{FE}$	$Var(\gamma_b)$	$Var(\bar{\gamma}_f)$	$\hat{\bar{\beta}}_1$
-0.467	0.098	0.234	0.013	0.0017	0.573

The table shows the values that are plugged into equation 11 to compute an unbiased coefficient from the firm-level regression (equation 6). $\bar{\beta}_1^{OLS}$ is the coefficient from the firm-level regressions (table 6, model (4a)). β_1^{OLS} is the coefficient from the loan-level regression without firm fixed effects (table 3, model (4a)). β_1^{FE} is the coefficient from the loan-level regression with firm fixed effects (table 3, model (4b)). $Var(\gamma_b)$ and $Var(\bar{\gamma}_f)$ are the variance of γ_b and $\bar{\gamma}_f$ (see table 1).

6 Robustness checks

6.1 Including the extensive margin

The results in section 5 are drawn from regressions that only take pre-existing bank-firm relationships into consideration. Put technically: they are limited to the intensive margin. In reality, though, banks and firms are free to establish new relationships or terminate existing ones. As I show in online appendix A.3, new and terminated bank-firm pairs make up a third of the aggregate loan volume in the credit register. Because of the reporting threshold in the credit register[18] a lender-borrower relationship that newly pops up after the beginning of the observation period is not automatically genuinely new; it might as well just be an existing relationship that simply did not exceed the reporting threshold before. For this reason, I flag a relationship as being new when it fulfills the following four criteria. First, it has not been in the dataset between 2008 and 2010, i.e. in the three years preceding the beginning of the observation period. Second, it exceeds 3 million euros – i.e. twice the threshold – at its first appearance. These criteria ensure that even if the relationship was simply lingering below the reporting threshold, it has not exceeded it for a prolonged period of time and then increased significantly. Third, it remains the dataset for at least three consecutive years; this keeps the analysis focused on longer-term financing relationships and drop bridging loans or cases in which a bank purchases a firm bond in the secondary market and sells it on shortly after. Fourth, it stays in the dataset at least until 2016q4 or has also flagged as a terminal pair (see below); this ensures that the time series covers both the control and treatment period.

Regarding lender-borrower relationships that are terminated during the observation period, the same problem with the reporting threshold holds: was the relationship really terminated or did it simply drop below the threshold? And in this case, the problem is worse than with new relationships because typically borrowers take in a loan at one

[18] 1.5 million euros until end-2014, 1 million thereafter.

point in time and the gradually pay it down.[19] So when we observe the volume of outstanding loans, we observe a steep increase at the beginning and then a gradual decline. This means that we can be certain that a relationship that lies well above the reporting threshold at its first appearance, at least shows a significant increase even if it was not a genuinely new relationship but merely crossed the threshold. With relationships *exiting* the dataset, however, we do not have this certainty. They could still linger below the threshold for a long time. The only exception are loans that are zero in their final, and only their final, entry. Because remember, in the German credit register a bank must report its outstanding loan volume to a borrower at the end of the quarter when it exceeds the reporting threshold at any point during that quarter. Hence, a sole zero final entry indicates payback during the final reporting quarter. Besides those loans, I also keep all loans which closely follow a negatively sloped quadratic time trend (R^2 must be above 0.8) which I use to extend the time series after its final appearance in the dataset until the end of the observation period. As with the new pairs, I again only keep pairs for which the reported or extrapolated values are above zero for at least three consecutive years.

The results of the loan-level regression including the extensive margin are shown in table 11. The number of borrowing firms and firm-bank pairs is drastically increased throughout all datasets. The coefficients tend to be smaller and less statistically significant. The results of the firm-level regression including the extensive margin are shown in table 12. Here, the coefficient of $\bar{\gamma}_f$ tends to be more negative and more significant than in the main specification, with one exception: in column (4b) in which the coefficient of the firm fixed effect from the loan-level regression has been implanted as a control for loan demand, the coefficient is almost exactly the same size. Also the coefficients of the bank loans/real estate ratio and the real estate/total asset ratio are almost identical. Table 8 repeats the exercise of table 7. This time, the unbiased firm-level coefficient $\hat{\bar{\beta}}_1$ remains negative and its size is even smaller. Taken together, these results indicate that including the extensive margin into the regression does not change the overall result that there is a slight positive effect of QE in the loan-level regression but no conclusive evidence for an effect at firm level.

6.2 Different QE proxies

Identifying an individual bank's exposure to QE is not straightforward. In my main specification I used the bond-to-asset ratio which is the broadest possible measure because even if the central bank is targeting only specific types of assets, there can be spillover effects to non-targeted assets (Gnewuch 2022; Selgrad 2023). Spillover effects must be expected to be non-perfect, however, and hence it seems prudent to check the effect of

[19] This might not be the case with consumer or, above all, student loans which might also show a gradual increase. In this study, however, we only observe corporate loans.

Table 8: Unbiased $\hat{\bar{\beta}}_1$ from Equation 6 Using the Equation 11 Formula

$\hat{\bar{\beta}}_1^{OLS}$	$\hat{\beta}_1^{OLS}$	$\hat{\beta}_1^{FE}$	$Var(\gamma_b)$	$Var(\bar{\gamma}_f)$	$\hat{\bar{\beta}}_1$
-0.787	0.124	0.168	0.013	0.0017	-0.435

The table shows the values that are plugged into equation 11 to compute an unbiased coefficient from the firm-level regression (equation 6). $\bar{\beta}_1^{OLS}$ is the coefficient from the firm-level regressions (table 12, model (4a)). β_1^{OLS} is the coefficient from the loan-level regression without firm fixed effects (table 11, model (4a)). β_1^{FE} is the coefficient from the loan-level regression with firm fixed effects (table 11, model (4b)). $Var(\gamma_b)$ and $Var(\bar{\gamma}_f)$ are the variance of γ_b and $\bar{\gamma}_f$ (see table 1).

different sub-classes of bonds that might proxy a bank's exposure to QE more effectively than the top aggregate. Tables 13 through 17 repeat the regression analyses of table 3 with different explanatory variables.

In table 13, I use the pre-QE share of bonds in bank total assets that become eligible to be purchased under the Eurosystem's APP at some point during the observation period. This is arguably the narrowest measure of QE exposure. The pattern from table 3 with the coefficient increasing when introducing firm fixed effects and bank control variables remains.

In table 14, I use the pre-QE share of bonds in bank total assets that mature during QE. The motivation here is that it is only at maturity of a bond that a bank is actually exposed to the yield-squeezing effect that central bank purchases exercise on the bond. This is because then the bank gets paid the nominal value of the maturing bond and has to make a decision: does it want to re-invest into bonds or rather rebalance into other assets? Again, the pattern from table 3 is upheld, though coefficients stay slightly below conventional levels of statistical significance in some specifications.

In table 15, I use the pre-QE share of bonds in bank total assets that where issued by GIIPS governments. The motivation here is that those bonds might have experienced the largest increase in prices – and hence the largest drop in yields – during QE. Once more the known pattern regarding coefficients prevails, but p-values are much higher than in the other specifications.

In table 16, I use the mean share of bond redemptions over bank total assets during QE (2015-2018) as explanatory variable. Bond redemptions are the volume of maturing bonds that a bank holds in a specific time period. With German banks being strong buy-and-hold investors this measure is similar to the one in table 14, but not identical because even German banks sell some of their bonds before maturity (Paludkiewicz 2021; Tischer 2018). In table 17, I again use redemptions but this time only of bonds that banks

already held before QE to control for any adaptions that banks might have undertaken in their bond portfolio in response to QE.

What do these results mean economically? The coefficients are not directly comparable because the explanatory variables have different levels and hence different variances across banks. Hence, we repeat the exercise from table 4 and multiply the coefficient of each specification with the standard deviation of the respective regressor and express the result as share of the dependent variable's standard deviation. Table 9 shows the results. Column (2) repeats column (6) from table 4 for easy comparison. With the exception of bonds eligible for QE and GIIPS government bonds which both show much weaker effects, these values confirm that the main specification's results are extremely robust against the use of different proxies for banks' exposure towards QE.

Table 9: Effect strength of robustness checks

(1)	(2)	(3)	(4)	(5)	(6)	(7)
Model	Bonds	Bonds eligible	Bonds maturing	Bonds GIIPS	Redemptions	Initial Redemptions
1a	0.020	0.013	0.020	0.004	0.007	0.014
1b	0.031	0.011	0.030	0.001	0.015	0.024
1c	0.045	0.015	0.043	0.005	0.024	0.033
2a	0.022	0.012	0.026	0.004	0.018	0.023
2b	0.040	0.014	0.043	0.002	0.025	0.038
2c	0.054	0.017	0.055	0.007	0.031	0.047
3a	0.028	0.011	0.033	0.001	0.021	0.029
3b	0.046	0.014	0.051	-0.001	0.031	0.045
3c	0.059	0.019	0.062	0.004	0.040	0.053
4a	0.014	0.011	0.017	0.003	0.001	0.015
4b	0.032	0.014	0.032	0.004	0.017	0.031
4c	0.039	0.020	0.036	0.010	0.017	0.031

This table repeats the calculation from table 4, using the coefficients from tables 13 through 17. Column (2) repeats column (6) from table 4 for easy comparison.

6.3 Different weights for firm-level shocks

In the main specification I used the share of a particular bank's loans in all loans to a firm over the entire observation period as a weight to compute the firm-level exposure to QE. It is not entirely straightforward, however, which is the ideal way to compute the QE-induced supply shock at firm level. For instance, one might argue that one should compute the firm-level exposure to QE by using only lending before QE as weight. At first

glance this sounds reasonable: A firm is flagged as exposed if it has strong ties to treated banks before QE because when a bank has an incentive to increase its lending its main loan customers will be the first ones it might turn to. Alternatively, it should be firms that have strong ties to treated banks during QE that should be flagged as exposed. Imagine a firm starts borrowing more from a treated bank because the treated bank offers more favorable loan conditions compared to other banks due to its exposure to QE. Then the firm would not be strongly exposed to QE when it had strong ties to treated banks *before* QE, but when it develops strong ties *during* QE. Since it is not per se clear which weight gives the best measure of firm-level QE exposure, I will undertake robustness checks in this section using different weights: From only the pre-QE period and from only the QE period. Additionally, I also compute an unweighted firm-level shock where I simply take the mean of bonds-to-bank asset ratios across all banks that lend to a firm. The results are shown in tables 18 to 20.

In table 18 I used the weighted mean with only loan volumes before QE (2011-2014) to compute the weights. In table 19 I used the weighted mean with only loan volumes during QE (2015-2018). In table 20 I used the unweighted mean of banks' bond-to-asset ratio across all banks lending to a firm as the firm-level shock. At first glance, the coefficients of $\bar{\gamma}_f$ seem to be starkly different across the different tables, but remember they have to be multiplied with the standard deviation of $\bar{\gamma}_f$, which is around 0.04 in all three cases. Still, it is clear that firms with strong ties to exposed banks during the control period (table 18) reduced their borrowing compared to firms with strong ties to exposed banks during the treatment period (table 19). This fits the picture, though, as the main specification has shown that there seems to have been some slight shift of firms' borrowing from less exposed to more exposed banks. Hence it is no surprise that firms that started to borrow more from exposed banks and thus become more exposed themselves during the treatment period, show a growth in borrowing compared to their peers. Again, in column (4b) which includes the firm dummy from the loan-level regression, the coefficient of $\bar{\gamma}_f$ is very similar to the one in the main specification and for all versions of $\bar{\gamma}_f$.

6.4 Industry-bank- and bank-level regressions

As a final robustness check, I investigated whether the results from the loan-level regressions also hold at a more aggregate level. To do so, I used data from the quarterly borrower statistics in which all German banks report their outstanding loan volume to 24 different industry sectors. Table 21 shows the results. The effect strength of γ_b is roughly the same size as firm-bank-level regression (table 3). E.g., in model (4c), increasing the bonds-to-asset ratio of a bank by one standard deviation increases the de-trended loan volume by 2.5% ($= 0.21 * 0.12$) of its within-sample mean; this is roughly 5% of the

dependent variable's standard deviation. More importantly, adding industry fixed effects does not impact the coefficients in any noteworthy manner. This indicates that if there is an industry-level loan demand effect, it is uncorrelated with the bank-level shock.

In tables 22 and 23 I go even one step further and run bank-level regressions. Here, the dependent variable is a bank's total outstanding loan volume to all industries (table 22) respectively real-estate industries only (table 23). The coefficients of γ_b are generally larger than in the bank-industry-level regressions. Implementing the bank-level fixed-effects from the industry-bank-level regression (model c) reduces the effect strength somewhat, but not dramatically. This underscores that industry-level effects play only a minor role in determining bank lending. Finally, comparing tables 22 and 23 tells us that the effect of γ_b on real estate lending is larger than on overall lending. This is in line with previous literate that finds QE to stimulate the housing market.

7 Discussion

How do these results relate to the remaining literature on QE? As mentioned in the introduction, papers employing bank-firm level data (Bittner et al. 2024; Chakraborty et al. 2020; Rodnyansky and Darmouni 2017) generally do not find a strong effect of QE on lending. With papers employing bank-level data (Bowman et al. 2015; Joyce and Spaltro 2014; Paludkiewicz 2021; Tischer 2018) the picture is mixed. Importantly, the two papers that use German data (Paludkiewicz 2021; Tischer 2018) find a positive effect which seems to contradict some of my findings at first glance. It does not, though, as both my loan-level, industry-bank-level, and bank-level regressions do indeed reveal a positive effect, albeit small. The firm-level is not addressed by either paper, i.e. neither author's data allow investigating substitution effect between exposed and non-exposed banks.

Taken together, the literature employing micro data (be it at bank, loan, or firm level) to find out whether QE stimulated lending to the real economy finds mild effects at best. Assuming the portfolio rebalancing channel is at work, we would expect to see banks which are more exposed to QE to increase their lending compared to less exposed banks after controlling for demand. Evidently, though, this channel is only weak in most cases. The question is: is that surprising? From the perspective of the loanable funds hypothesis and the money multiplier model, the answer would be yes. This is because those two concepts postulate a mechanical relationship between reserves and bank deposits with the causality running from the former to the latter. If the central bank injects additional reserves into the bank system, banks would increase deposits via additional lending. In this line of thinking, lending is supply-led. On the other end of the spectrum would be the Post-Keynesian theory which argues that lending is purely demand-led. Accord-

ing to this reasoning, the banking system as a whole can only increase the outstanding amount of loans if aggregate loan demand increases accordingly. Any attempt to push lending via supply stimulus would, at best, lead of a shift of lending between banks. The empirical observations presented in this paper are in line with the second line of reasoning.

On a quick side note, these empirical patterns are also true in a wider sense, not only regarding quantitative easing. There is a sizable literature employing loan-level data to investigate the impact of various types of bank-level shocks on firm debt, e.g. Altavilla et al. (2022), Amador and Nagengast (2016), Amiti and Weinstein (2018), Banerjee et al. (2021), Bentolila et al. (2018), Bottero et al. (2020), Cingano et al. (2016), Jiménez et al. (2020, 2012, 2014), Khwaja and Mian (2008), and Schivardi et al. (2021). The general pattern is that negative bank shocks also transmit to firm-level, while positive bank shocks do not. This again confirms that the financial system can deny financing to the economy, but its capacity to push lending is very limited. Firms do not borrow simply because they can do so at favorable terms.[20]

Does all this mean that QE is generally ineffective? The answer is no. First, as we have seen, supply shocks can indeed have negative effects on loan volumes. This typically happens in the aftermath of financial crises when damage to their balance sheets inhibits banks' lending capacity. In such a situation, QE can have positive effects on loan volumes via releasing bank balance sheets from stressed assets. In fact, the results of Rodnyansky and Darmouni (2017) are in line with this as they find that the purchase of stressed assets (MBS) exercises a positive stimulus on bank lending while the purchases of non-stressed assets (Treasuries) does not. The German banking system, however, was under no financial stress when QE was launched in 2015. If at all, one would expect to observe positive effects on bank lending in countries like Greece, Spain, or Italy whose banking systems took severe damage during the preceding financial crises. Applying the method presented in this paper to data from those countries might be a worthwhile future research endeavor. Indeed, results from the survey on the access to finance of enterprises (SAFE) show that financial conditions in Spain, France, and Italy improved a lot whereas the data from Germany do not show much of a reaction and the turning point in all time series (interest expenses, access to finance, availability of external finance) was not 2015, but 2012, indicating that Mario Draghi's 'whatever it takes' was the more important and effective measure while QE might simply have come too late (European Central Bank 2019). This indicates that central banks should take the economic circumstances under careful consideration when the implement QE.

[20] Another piece that fits the puzzle here is the observation that investment is very insensitive to investment: see, for instance, Best et al. (2024), Gennaioli et al. (2015), and Sharpe and Suarez (2021). This is important because financing investment is one of the key reasons for why firms take in debt (European Central Bank 2019).

Second, the present study and the literature cited investigate the portfolio rebalancing channel. However, there might well be other channels through which QE might affect lending volumes and, in a wider sense, economic activity. Krishnamurthy and Vissing-Jorgensen (2011) investigate multiple channels for QE in the US and find the signaling channel to be important, as do Urbschat and Watzka (2020) for Europe. The latter also find the effect to be particularly strong during times of financial market stress – again, 'whatever it takes' is a superb example. Taken together, these results clearly show that a central bank's ability to directly stimulate the economy has limits and is likely confined to periods of acute financial stress.

On a final note, in online appendix A.4, I undertake quick reverse analysis. Because so far we have seen that there is no apparent difference between banks (firms) regarding their lending (borrowing) behavior conditional on their exposure to QE. But maybe there are any apparent differences between banks (firms) conditional on their lending (borrowing) behavior? As can be seen in online appendix A.4, though, this seems not to be the case. The balance sheet structures of banks and firms show no systematic relationship to the evolution of their loans during QE. Obviously, however, this is only a very superficial take on an approach that might deserve a more thorough consideration in future research: if the factors highlighted by theory cannot explain bank lending, then what does?

8 Conclusion

In this paper I assess the impact of quantitative easing on bank lending. To do so, I use loan-level data from the German credit register in combination with balance sheet data on both lenders and borrowers. Theoretically, large-scale asset purchases by the Eurosystem increase those bonds' prices and squeeze their yields, hence setting an incentive for bond-holding banks to rebalance into other assets like corporate loans. Therefore, I use the bond-to-asset ratio to measure the cross-sectional exposure of individual banks to QE. Using a subset of firms with multiple bank connections allows me to control for loan demand at borrower level via firm fixed effects. I find that exposed banks slightly increase their lending towards the same firm compared to less exposed banks. Though statistically significant in most specifications, the effect is economically small. At the firm level, the evidence is even weaker: there is no consistent evidence in the data that firms that are more exposed to QE via their bank linkages increase their total volume of bank loans compared to their less exposed peers. These findings are in line with the empirical literature. While they do not necessarily imply that QE is generally ineffective, they clearly show that a central bank's ability to directly stimulate the economy via incentivizing additional lending has limits.

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Further Results

This section contains all the regression tables from the robustness checks to maintain the readability of the main text.

Table 10: Robustness Check of table 3: Bilateral Loan Volume Normalized by Firm-Level Debt

Dataset	(1)			(2)			(3)			(4)		
Model	(a)	(b)	(c)	(a)	(b)	(c)	(a)	(b)	(c)	(a)	(b)	(c)
γ_b	0.043	0.068*	0.076**	0.020	0.055**	0.050**	0.013	0.055*	0.049*	-0.009	0.037	0.027
	(0.04)	(0.04)	(0.04)	(0.04)	(0.03)	(0.02)	(0.04)	(0.03)	(0.03)	(0.06)	(0.04)	(0.04)
	[0.285]	[0.077]	[0.031]	[0.595]	[0.046]	[0.024]	[0.753]	[0.066]	[0.061]	[0.871]	[0.300]	[0.504]
Constant	-0.023**	-0.027***	-0.073	-0.016	-0.022***	-0.079	-0.016	-0.022***	-0.075	-0.017	-0.024***	-0.020
	(0.01)	(0.01)	(0.05)	(0.01)	(0.01)	(0.05)	(0.01)	(0.01)	(0.05)	(0.01)	(0.01)	(0.06)
	[0.035]	[0.003]	[0.149]	[0.101]	[0.002]	[0.110]	[0.122]	[0.002]	[0.172]	[0.226]	[0.003]	[0.740]
Firm FE		Y	Y		Y	Y		Y	Y		Y	Y
Bank controls			Y			Y			Y			Y
N Banks	1,067	1,067	1,067	911	911	911	874	874	874	750	750	750
N Firms	9,050	9,050	9,050	4,551	4,551	4,551	4,313	4,313	4,313	2,528	2,528	2,528
N Pairs	28,242	28,242	28,242	15,578	15,578	15,578	13,906	13,906	13,906	7,806	7,806	7,806
R^2	0.0002	0.4671	0.4679	0.0001	0.4494	0.4510	0.0000	0.4493	0.4510	0.0000	0.4493	0.4506

Datasets (1) through (4) are as defined in table 3. The depdent variable is the bilateral bank-firm loan volume as defined by equation 2, but normalized by the within-sample mean of the firm-level debt rather than the within-sample mean of the bilateral loan volume. γ_b is the share of bonds in bank total assets as defined in equation 4. Standard errors (in parentheses) are clustered at the bank level. p-values are shown in square brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Source: Research Data and Service Centre (RDSC) of the Deutsche Bundesbank, BISTA, SHS, CSDB, Credit register of loans of 1 Mn. EUR or more, 2011-2018, own calculations.

Table 11: Robustness Check of table 3: Including the Extensive Margin

Dataset	(1)			(2)			(3)			(4)		
Model	(a)	(b)	(c)	(a)	(b)	(c)	(a)	(b)	(c)	(a)	(b)	(c)
γ_b	0.240*	0.215	0.262**	0.215	0.257*	0.311**	0.197	0.249*	0.256*	0.124	0.168	0.148
	(0.13)	(0.13)	(0.13)	(0.13)	(0.14)	(0.15)	(0.13)	(0.14)	(0.15)	(0.13)	(0.15)	(0.15)
	[0.074]	[0.109]	[0.049]	[0.110]	[0.076]	[0.039]	[0.121]	[0.084]	[0.088]	[0.324]	[0.275]	[0.333]
Constant	-0.027	-0.023	-0.394	-0.023	-0.030	-0.367	-0.023	-0.031	-0.333	-0.030	-0.037	-0.314
	(0.03)	(0.03)	(0.38)	(0.03)	(0.03)	(0.41)	(0.03)	(0.03)	(0.38)	(0.03)	(0.03)	(0.38)
	[0.357]	[0.404]	[0.303]	[0.408]	[0.290]	[0.375]	[0.372]	[0.251]	[0.381]	[0.248]	[0.186]	[0.407]
Firm FE		Y	Y		Y	Y		Y	Y		Y	Y
Bank controls			Y			Y			Y			Y
N Banks	1,157	1,157	1,157	1,012	1,012	1,012	969	969	969	868	868	868
N Firms	13,969	13,969	13,969	5,957	5,957	5,957	5,670	5,670	5,670	3,609	3,609	3,609
N Pairs	51,229	51,229	51,229	25,369	25,369	25,369	21,707	21,707	21,707	13,766	13,766	13,766
R^2	0.0005	0.4050	0.4069	0.0004	0.3329	0.3354	0.0004	0.3511	0.3538	0.0002	0.3304	0.3324

Datasets (1) through (4) are as defined in table 3, but include new and terminated bank-firm relationships. γ_b is the share of bonds in bank total assets as defined in equation 4. Standard errors (in parentheses) are clustered at the bank level. p-values are shown in square brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Source: Research Data and Service Centre (RDSC) of the Deutsche Bundesbank, BISTA, SHS, CSDB, Credit register of loans of 1 Mn. EUR or more, 2011-2018, own calculations.

Table 12: Robustness Check of table 6: Including the Extensive Margin

Dataset	(4)				
Model	(a)	(b)	(c)	(d)	(e)
$\bar{\gamma}_f$	-0.787***	-0.360	-0.391	-0.451	0.215
	(0.28)	(0.24)	(0.30)	(0.29)	(0.27)
	[0.004]	[0.127]	[0.187]	[0.116]	[0.418]
$\delta_f^{model4b}$		0.745***			
		(0.02)			
		[0.000]			
BANKDEBT_RESTATE			-0.043***		-0.058***
			(0.01)		(0.01)
			[0.000]		[0.000]
RESTATE_TA				0.038	-0.179***
				(0.04)	(0.06)
				[0.359]	[0.003]
Constant	0.042*	0.023	0.272*	0.143	0.352**
	(0.02)	(0.02)	(0.14)	(0.14)	(0.14)
	[0.086]	[0.252]	[0.057]	[0.317]	[0.013]
Firm controls			Y	Y	Y
N	3,176	3,176	3,176	3,176	3,176
R^2	0.0023	0.3737	0.0428	0.0313	0.0459

Dataset (4) is as defined in table 3, minus those firms where BANKDEBT_RESTATE > 10, but include new and terminated bank-firm relationships. $\bar{\gamma}_f$ is the firm-level shock as defined in equation 7. BANKDEBT_RESTATE is the ratio of bank loans of a firm over firm real estate assets. RESTATE_TA is the ratio of firm real estate assets over firm total assets. Standard errors (in parentheses) are clustered at the bank level. p-values are shown in square brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Source: Research Data and Service Centre (RDSC) of the Deutsche Bundesbank, BISTA, SHS, CSDB, JANIS, Credit register of loans of 1 Mn. EUR or more, , own calculations.

Table 13: Robustness Check of table 3: Using Only Bonds Eligible for QE as Proxy for Bank Exposure

Dataset	(1)			(2)			(3)			(4)		
Model	(a)	(b)	(c)	(a)	(b)	(c)	(a)	(b)	(c)	(a)	(b)	(c)
γ_b	0.558**	0.495*	0.667**	0.519**	0.604**	0.751***	0.480*	0.621**	0.817***	0.495*	0.604**	0.866**
	(0.25)	(0.28)	(0.28)	(0.25)	(0.26)	(0.27)	(0.26)	(0.25)	(0.27)	(0.30)	(0.30)	(0.36)
	[0.023]	[0.075]	[0.019]	[0.041]	[0.020]	[0.005]	[0.068]	[0.015]	[0.003]	[0.096]	[0.043]	[0.017]
Constant	-0.052***	-0.051***	-0.344**	-0.050***	-0.052***	-0.406**	-0.044***	-0.048***	-0.418**	-0.052***	-0.055***	-0.278
	(0.02)	(0.02)	(0.17)	(0.02)	(0.01)	(0.18)	(0.01)	(0.01)	(0.17)	(0.02)	(0.01)	(0.20)
	[0.001]	[0.001]	[0.039]	[0.001]	[0.000]	[0.022]	[0.002]	[0.000]	[0.017]	[0.001]	[0.000]	[0.172]
Firm FE		Y	Y		Y	Y		Y	Y		Y	Y
Bank controls			Y			Y			Y			Y
N Banks	1,067	1,067	1,067	911	911	911	874	874	874	750	750	750
N Firms	9,050	9,050	9,050	4,551	4,551	4,551	4,313	4,313	4,313	2,528	2,528	2,528
N Pairs	28,242	28,242	28,242	15,578	15,578	15,578	13,906	13,906	13,906	7,806	7,806	7,806
R^2	0.0002	0.3903	0.3907	0.0002	0.3697	0.3701	0.0002	0.3852	0.3857	0.0003	0.3851	0.3860

Datasets (1) through (4) are as defined in table 3. γ_b is the share of bonds in bank total assets as defined in equation 4, but only bonds that become eligible to be purchased by the Eurosystem at some point during 2011-2018. Standard errors (in parentheses) are clustered at the bank level. p-values are shown in square brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Source: Research Data and Service Centre (RDSC) of the Deutsche Bundesbank, BISTA, SHS, CSDB, Credit register of loans of 1 Mn. EUR or more, 2011-2018, own calculations.

Table 14: Robustness Check of table 3: Using Only Bonds Maturing During 2015-2018 as Proxy for Bank Exposure

Dataset	(1)			(2)			(3)			(4)		
Model	(a)	(b)	(c)	(a)	(b)	(c)	(a)	(b)	(c)	(a)	(b)	(c)
γ_b	0.290	0.439**	0.622***	0.373**	0.617***	0.798***	0.483***	0.734***	0.898***	0.250	0.463**	0.525*
	(0.18)	(0.21)	(0.23)	(0.18)	(0.22)	(0.23)	(0.18)	(0.21)	(0.23)	(0.23)	(0.23)	(0.27)
	[0.114]	[0.040]	[0.007]	[0.033]	[0.005]	[0.001]	[0.007]	[0.000]	[0.000]	[0.277]	[0.044]	[0.052]
Constant	-0.061***	-0.072***	-0.507***	-0.066***	-0.083***	-0.614***	-0.068***	-0.085***	-0.636***	-0.058**	-0.074***	-0.322
	(0.02)	(0.02)	(0.18)	(0.02)	(0.02)	(0.21)	(0.02)	(0.02)	(0.21)	(0.03)	(0.02)	(0.25)
	[0.006]	[0.002]	[0.005]	[0.001]	[0.000]	[0.003]	[0.000]	[0.000]	[0.002]	[0.021]	[0.001]	[0.195]
Firm FE		Y	Y		Y	Y		Y	Y		Y	Y
Bank controls			Y			Y			Y			Y
N Banks	1,067	1,067	1,067	911	911	911	874	874	874	750	750	750
N Firms	9,050	9,050	9,050	4,551	4,551	4,551	4,313	4,313	4,313	2,528	2,528	2,528
N Pairs	28,242	28,242	28,242	15,578	15,578	15,578	13,906	13,906	13,906	7,806	7,806	7,806
R^2	0.0002	0.3906	0.3911	0.0004	0.3702	0.3709	0.0007	0.3860	0.3866	0.0002	0.3852	0.3860

Datasets (1) through (4) are as defined in table 3. γ_b is the share of bonds in bank total assets as defined in equation 4, but only bonds that mature during 2015-2018. Standard errors (in parentheses) are clustered at the bank level. p-values are shown in square brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Source: Research Data and Service Centre (RDSC) of the Deutsche Bundesbank, BISTA, SHS, CSDB, Credit register of loans of 1 Mn. EUR or more, 2011-2018, own calculations.

Table 15: Robustness Check of table 3: Using Only GIIPS Government Bonds as Proxy for Bank Exposure

Dataset	(1)			(2)			(3)			(4)		
Model	(a)	(b)	(c)	(a)	(b)	(c)	(a)	(b)	(c)	(a)	(b)	(c)
γ_b	0.341	0.045	0.410	0.311	0.208	0.593	0.106	-0.070	0.326	0.253	0.379	0.846
	(0.48)	(0.43)	(0.52)	(0.50)	(0.39)	(0.51)	(0.55)	(0.46)	(0.57)	(0.73)	(0.61)	(0.72)
	[0.481]	[0.916]	[0.430]	[0.531]	[0.599]	[0.246]	[0.846]	[0.879]	[0.565]	[0.729]	[0.537]	[0.239]
Constant	-0.042***	-0.041***	-0.298*	-0.040***	-0.040***	-0.352*	-0.034***	-0.033***	-0.325*	-0.042***	-0.043***	-0.205
	(0.01)	(0.01)	(0.17)	(0.01)	(0.01)	(0.18)	(0.01)	(0.01)	(0.19)	(0.01)	(0.01)	(0.20)
	[0.003]	[0.004]	[0.080]	[0.002]	[0.002]	[0.052]	[0.007]	[0.008]	[0.084]	[0.002]	[0.000]	[0.300]
Firm FE		Y	Y		Y	Y		Y	Y		Y	Y
Bank controls			Y			Y			Y			Y
N Banks	1,067	1,067	1,067	911	911	911	874	874	874	750	750	750
N Firms	9,050	9,050	9,050	4,551	4,551	4,551	4,313	4,313	4,313	2,528	2,528	2,528
N Pairs	28,242	28,242	28,242	15,578	15,578	15,578	13,906	13,906	13,906	7,806	7,806	7,806
R^2	0.0000	0.3902	0.3906	0.0000	0.3695	0.3699	0.0000	0.3850	0.3853	0.0000	0.3848	0.3856

Datasets (1) through (4) are as defined in table 3. γ_b is the share of bonds in bank total assets as defined in equation 4, but only GIIPS government bonds. Standard errors (in parentheses) are clustered at the bank level. p-values are shown in square brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Source: Research Data and Service Centre (RDSC) of the Deutsche Bundesbank, BISTA, SHS, CSDB, Credit register of loans of 1 Mn. EUR or more, 2011-2018, own calculations.

Table 16: Robustness Check of table 3: Using Volume of Redemptions as Proxy for Bank Exposure

Dataset	(1)			(2)			(3)			(4)		
Model	(a)	(b)	(c)	(a)	(b)	(c)	(a)	(b)	(c)	(a)	(b)	(c)
γ_b	0.315	0.678	1.034*	0.788*	1.087*	1.343**	0.902**	1.340**	1.736**	0.062	0.738*	0.756
	(0.40)	(0.46)	(0.61)	(0.41)	(0.56)	(0.66)	(0.45)	(0.58)	(0.70)	(0.44)	(0.43)	(0.58)
	[0.430]	[0.139]	[0.088]	[0.057]	[0.054]	[0.042]	[0.044]	[0.020]	[0.013]	[0.887]	[0.090]	[0.196]
Constant	-0.049***	-0.058***	-0.374**	-0.059***	-0.067***	-0.430**	-0.056***	-0.068***	-0.448**	-0.042**	-0.060***	-0.181
	(0.02)	(0.02)	(0.18)	(0.02)	(0.02)	(0.20)	(0.02)	(0.02)	(0.21)	(0.02)	(0.02)	(0.22)
	[0.004]	[0.000]	[0.038]	[0.000]	[0.000]	[0.032]	[0.002]	[0.000]	[0.033]	[0.038]	[0.000]	[0.412]
Firm FE		Y	Y		Y	Y		Y	Y		Y	Y
Bank controls			Y			Y			Y			Y
N Banks	1,067	1,067	1,067	911	911	911	874	874	874	750	750	750
N Firms	9,050	9,050	9,050	4,551	4,551	4,551	4,313	4,313	4,313	2,528	2,528	2,528
N Pairs	28,242	28,242	28,242	15,578	15,578	15,578	13,906	13,906	13,906	7,806	7,806	7,806
R^2	0.0000	0.3904	0.3908	0.0003	0.3699	0.3703	0.0004	0.3856	0.3861	0.0000	0.3850	0.3856

Datasets (1) through (4) are as defined in table 3. γ_b is the mean over 2015-2018 of the ratio of the volume of bond redemptions over total bank assets. Standard errors (in parentheses) are clustered at the bank level. p-values are shown in square brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Source: Research Data and Service Centre (RDSC) of the Deutsche Bundesbank, BISTA, SHS, CSDB, Credit register of loans of 1 Mn. EUR or more, 2011-2018, own calculations.

Table 17: Robustness Check of table 3: Using Volume of Redemptions of Bonds Held Before 2015 as Proxy for Bank Exposure

Dataset	(1)			(2)			(3)			(4)		
Model	(a)	(b)	(c)	(a)	(b)	(c)	(a)	(b)	(c)	(a)	(b)	(c)
γ_b	0.796	1.365*	1.929**	1.333**	2.186***	2.713***	1.702**	2.607***	3.062***	0.859	1.808**	1.812*
	(0.68)	(0.72)	(0.78)	(0.67)	(0.81)	(0.85)	(0.67)	(0.76)	(0.85)	(0.86)	(0.81)	(0.98)
	[0.242]	[0.058]	[0.013]	[0.047]	[0.007]	[0.002]	[0.011]	[0.001]	[0.000]	[0.320]	[0.026]	[0.065]
Constant	-0.054**	-0.064***	-0.421**	-0.061***	-0.076***	-0.509**	-0.062***	-0.077***	-0.519**	-0.055**	-0.071***	-0.247
	(0.02)	(0.02)	(0.18)	(0.02)	(0.02)	(0.20)	(0.02)	(0.02)	(0.21)	(0.02)	(0.02)	(0.24)
	[0.015]	[0.003]	[0.017]	[0.002]	[0.000]	[0.012]	[0.001]	[0.000]	[0.015]	[0.021]	[0.000]	[0.300]
Firm FE		Y	Y		Y	Y		Y	Y		Y	Y
Bank controls			Y			Y			Y			Y
N Banks	1,067	1,067	1,067	911	911	911	874	874	874	750	750	750
N Firms	9,050	9,050	9,050	4,551	4,551	4,551	4,313	4,313	4,313	2,528	2,528	2,528
N Pairs	28,242	28,242	28,242	15,578	15,578	15,578	13,906	13,906	13,906	7,806	7,806	7,806
R^2	0.0001	0.3905	0.3909	0.0004	0.3702	0.3707	0.0006	0.3859	0.3864	0.0002	0.3853	0.3859

Datasets (1) through (4) are as defined in table 3. γ_b is the mean over 2015-2018 of the ratio of the volume of bond redemptions over total bank assets, only using bonds that were held before 2015. Standard errors (in parentheses) are clustered at the bank level. p-values are shown in square brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Source: Research Data and Service Centre (RDSC) of the Deutsche Bundesbank, BISTA, SHS, CSDB, Credit register of loans of 1 Mn. EUR or more, 2011-2018, own calculations.

Table 18: Robustness Check of table 6: Using firm-level shocks with weights computed from 2011-2014 loan volumes.

Dataset	(4)				
Model	(a)	(b)	(c)	(d)	(e)
$\bar{\gamma}_f$	-0.850***	-0.440*	-0.726**	-0.858***	-0.439*
	(0.31)	(0.25)	(0.30)	(0.29)	(0.25)
	[0.006]	[0.084]	[0.015]	[0.003]	[0.083]
$\delta_f^{model4b}$		0.757***			
		(0.03)			
		[0.000]			
BANKDEBT_RESTATE			-0.037***		-0.045***
			(0.01)		(0.01)
			[0.000]		[0.000]
RESTATE_TA				0.071	-0.095
				(0.05)	(0.06)
				[0.128]	[0.131]
Constant	0.044	0.012	0.256	0.119	0.295*
	(0.03)	(0.02)	(0.17)	(0.17)	(0.17)
	[0.110]	[0.585]	[0.126]	[0.475]	[0.074]
Firm controls			Y	Y	Y
N	2,224	2,224	2,224	2,224	2,224
R^2	0.0036	0.3755	0.0589	0.0494	0.0599

Dataset (4) is as defined in table 3, minus those firms where BANKDEBT_RESTATE > 10. $\bar{\gamma}_f$ is the firm-level shock as defined in equation 7, using only loan volumes from 2011 to 2014 to compute weights W_{γ_b}. BANKDEBT_RESTATE is the ratio of bank loans of a firm over firm real estate assets. RESTATE_TA is the ratio of firm real estate assets over firm total assets. Standard errors (in parentheses) are clustered at the bank level. p-values are shown in square brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Source: Research Data and Service Centre (RDSC) of the Deutsche Bundesbank, BISTA, SHS, CSDB, JANIS, Credit register of loans of 1 Mn. EUR or more, 2011-2018, own calculations.

Table 19: Robustness Check of table 6: Using firm-level shocks with weights computed from 2015-2018 loan volumes.

Dataset	(4)				
Model	(a)	(b)	(c)	(d)	(e)
$\bar{\gamma}_f$	-0.165	-0.313	0.252	0.342	0.793***
	(0.30)	(0.24)	(0.30)	(0.28)	(0.26)
	[0.587]	[0.201]	[0.394]	[0.214]	[0.002]
$\delta_f^{model4b}$		0.760***			
		(0.03)			
		[0.000]			
BANKDEBT_RESTATE			-0.036***		-0.051***
			(0.01)		(0.01)
			[0.000]		[0.000]
RESTATE_TA				0.002	-0.184***
				(0.05)	(0.06)
				[0.964]	[0.004]
Constant	0.006	0.004	0.175	0.050	0.252
	(0.03)	(0.02)	(0.17)	(0.17)	(0.16)
	[0.815]	[0.855]	[0.294]	[0.765]	[0.126]
Firm controls			Y	Y	Y
N	2,224	2,224	2,224	2,224	2,224
r2	0.0001	0.3750	0.0571	0.0475	0.0612

Dataset (4) is as defined in table 3, minus those firms where BANKDEBT_RESTATE > 10. $\bar{\gamma}_f$ is the firm-level shock as defined in equation 7, using only loan volumes from 2015 to 2018 to compute weights W_{γ_b}. BANKDEBT_RESTATE is the ratio of bank loans of a firm over firm real estate assets. RESTATE_TA is the ratio of firm real estate assets over firm total assets. Standard errors (in parentheses) are clustered at the bank level. p-values are shown in square brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Source: Research Data and Service Centre (RDSC) of the Deutsche Bundesbank, BISTA, SHS, CSDB, JANIS, Credit register of loans of 1 Mn. EUR or more, 2011-2018, own calculations.

Table 20: Robustness Check of table 6: Using firm-level shocks with equal weights for each lending bank.

Dataset	(4)				
Model	(a)	(b)	(c)	(d)	(e)
$\bar{\gamma}_f$	-0.421	-0.335	-0.062	-0.093	0.597**
	(0.31)	(0.25)	(0.33)	(0.30)	(0.28)
	[0.178]	[0.187]	[0.849]	[0.758]	[0.031]
$\delta_f^{model4b}$		0.759***			
		(0.03)			
		[0.000]			
BANKDEBT_RESTATE			-0.036***		-0.051***
			(0.01)		(0.01)
			[0.000]		[0.000]
RESTATE_TA				0.027	-0.179***
				(0.04)	(0.06)
				[0.545]	[0.005]
Constant	0.022	0.007	0.200	0.073	0.271*
	(0.03)	(0.02)	(0.17)	(0.17)	(0.16)
	[0.460]	[0.763]	[0.228]	[0.659]	[0.099]
Firm controls			Y	Y	Y
N	2,224	2,224	2,224	2,224	2,224
r2	0.0009	0.3751	0.0569	0.0472	0.0602

Dataset (4) is as defined in table 3, minus those firms where BANKDEBT_RESTATE > 10. $\bar{\gamma}_f$ is the firm-level shock as defined in equation 7, but with equal weights for all banks b lending to firm f. BANKDEBT_RESTATE is the ratio of bank loans of a firm over firm real estate assets. RESTATE_TA is the ratio of firm real estate assets over firm total assets. Standard errors (in parentheses) are clustered at the bank level. p-values are shown in square brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Source: Research Data and Service Centre (RDSC) of the Deutsche Bundesbank, BISTA, SHS, CSDB, JANIS, Credit register of loans of 1 Mn. EUR or more, 2011-2018, own calculations.

Table 21: Robustness Check of table 3: Using Banks' Loan Volume to Industry Sectors as Dependent Variable.

Dataset	(0)			(1)			(2)			(3)			(4)		
Model	(a)	(b)	(c)	(a)	(b)	(c)	(a)	(b)	(c)	(a)	(b)	(c)	(a)	(b)	(c)
γ_b	0.132**	0.132**	0.160**	0.199***	0.200***	0.224***	0.178***	0.178***	0.201***	0.151**	0.152**	0.183**	0.175***	0.176***	0.207***
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.06)	(0.06)	(0.06)
	[0.023]	[0.023]	[0.011]	[0.002]	[0.001]	[0.001]	[0.008]	[0.008]	[0.005]	[0.024]	[0.024]	[0.011]	[0.007]	[0.007]	[0.001]
Constant	0.076***	0.076***	0.042	0.062***	0.062***	0.257	0.064***	0.064***	0.317	0.070***	0.070***	0.364	0.060***	0.060***	0.127
	(0.01)	(0.01)	(0.13)	(0.02)	(0.02)	(0.29)	(0.02)	(0.02)	(0.34)	(0.02)	(0.02)	(0.35)	(0.02)	(0.02)	(0.22)
	[0.000]	[0.000]	[0.743]	[0.000]	[0.000]	[0.381]	[0.000]	[0.000]	[0.346]	[0.000]	[0.000]	[0.294]	[0.000]	[0.000]	[0.568]
Industry FE		Y	Y		Y	Y		Y	Y		Y	Y		Y	Y
Bank controls			Y			Y			Y			Y			Y
N Banks	1,604	1,604	1,604	1,064	1,064	1,064	908	908	908	871	871	871	749	749	749
N Industries	24	24	24	24	24	24	24	24	24	24	24	24	24	24	24
N Pairs	38,277	38,277	38,277	25,441	25,441	25,441	21,731	21,731	21,731	20,850	20,850	20,850	17,928	17,928	17,928
r2	0.0005	0.0117	0.0151	0.0012	0.0154	0.0206	0.0011	0.0165	0.0228	0.0008	0.0167	0.0230	0.0010	0.0171	0.0231

Regressions in this table use the outstanding loan volume of individual banks to 24 industry sectors as reported in the quarterly borrower statistics (VJKRE) as dependent variable. The dependent variable is transformed as in equation 2. Dataset (0) contains all banks in the BISTA/VJKRE. Datasets (1) through (4) are as defined in table 3. γ_b is the mean over 2015-2018 of the ratio of the volume of bond redemptions over total bank assets, only using bonds that were held before 2015. Standard errors (in parentheses) are clustered at the bank level. p-values are shown in square brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Source: Research Data and Service Centre (RDSC) of the Deutsche Bundesbank, BISTA, SHS, CSDB, VJKRE, 2011-2018, own calculations.

Table 22: Robustness Check: Bank-Level Regression Using Banks' Total Firm Loan Volume as Dependent Variable.

Dataset	(0)		(1)		(2)		(3)		(4)	
Model	(b)	(c)	(b)	(c)	(b)	(c)	(b)	(c)	(b)	(c)
γ_b	0.152**	0.152**	0.199***	0.200***	0.205***	0.200***	0.239***	0.230***	0.265***	0.253***
	(0.06)	(0.06)	(0.07)	(0.07)	(0.07)	(0.07)	(0.06)	(0.06)	(0.06)	(0.06)
	[0.019]	[0.019]	[0.004]	[0.004]	[0.003]	[0.003]	[0.000]	[0.000]	[0.000]	[0.000]
FE_bank		0.876**		1.239***		1.209***		1.474***		1.704***
		(0.34)		(0.47)		(0.35)		(0.31)		(0.33)
		[0.011]		[0.008]		[0.000]		[0.000]		[0.000]
Constant	-0.218	-0.162	-0.239	-0.168	-0.296	-0.216	-0.333	-0.240	-0.408*	-0.315
	(0.17)	(0.17)	(0.21)	(0.21)	(0.22)	(0.23)	(0.22)	(0.22)	(0.23)	(0.24)
	[0.198]	[0.336]	[0.244]	[0.434]	[0.189]	[0.351]	[0.132]	[0.286]	[0.082]	[0.186]
Bank controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
N	1,587	1,587	1,063	1,063	907	907	870	870	748	748
r2	0.0302	0.0395	0.1391	0.1589	0.1975	0.2192	0.2139	0.2483	0.2567	0.2974

Regressions in this table use the outstanding loan volume of individual banks to 24 industry sectors as reported in the quarterly borrower statistics (VJKRE) as dependent variable. The dependent variable is transformed as in equation 2. Dataset (0) contains all banks in the BISTA/VJKRE. Datasets (1) through (4) are as defined in table 3. γ_b is the mean over 2015-2018 of the ratio of the volume of bond redemptions over total bank assets, only using bonds that were held before 2015. Standard errors (in parentheses) are clustered at the bank level. p-values are shown in square brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Source: Research Data and Service Centre (RDSC) of the Deutsche Bundesbank, BISTA, SHS, CSDB, VJKRE, 2011-2018, own calculations.

Table 23: Robustness Check: Bank-Level Regression Using Banks' Total Loan Volume to Real-Estate Sectors as Dependent Variable.

Dataset	(0)		(1)		(2)		(3)		(4)	
Model	(b)	(c)	(b)	(c)	(b)	(c)	(b)	(c)	(b)	(c)
γ_b	0.305**	0.263*	0.262*	0.230*	0.344**	0.296**	0.278*	0.241*	0.359**	0.327**
	(0.14)	(0.14)	(0.14)	(0.14)	(0.15)	(0.15)	(0.14)	(0.14)	(0.16)	(0.16)
	[0.025]	[0.054]	[0.060]	[0.095]	[0.018]	[0.042]	[0.053]	[0.096]	[0.021]	[0.039]
FE_bank		1.292***		1.167**		1.285**		1.039*		1.013
		(0.37)		(0.46)		(0.54)		(0.55)		(0.62)
		[0.000]		[0.012]		[0.018]		[0.061]		[0.105]
Constant	0.501*	0.408	0.535	0.448	0.464	0.387	0.394	0.338	0.124	0.056
	(0.28)	(0.28)	(0.44)	(0.45)	(0.51)	(0.53)	(0.52)	(0.54)	(0.46)	(0.46)
	[0.075]	[0.138]	[0.221]	[0.321]	[0.364]	[0.464]	[0.450]	[0.529]	[0.786]	[0.904]
Bank controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
N	1,594	1,594	1,062	1,062	908	908	871	871	749	749
r2	0.0275	0.0394	0.0470	0.0576	0.0478	0.0597	0.0500	0.0577	0.0536	0.0606

Regressions in this table use the outstanding loan volume of individual banks to 24 industry sectors as reported in the quarterly borrower statistics (VJKRE) as dependent variable. The dependent variable is transformed as in equation 2. Dataset (0) contains all banks in the BISTA/VJKRE. Datasets (1) through (4) are as defined in table 3. γ_b is the mean over 2015-2018 of the ratio of the volume of bond redemptions over total bank assets, only using bonds that were held before 2015. Standard errors (in parentheses) are clustered at the bank level. p-values are shown in square brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Source: Research Data and Service Centre (RDSC) of the Deutsche Bundesbank, BISTA, SHS, CSDB, VJKRE, 2011-2018, own calculations.

The Post-2015 German Lending Surge - What Role for QE?

– online appendix –

The web appendix to 'The Post-2015 German Lending Surge - What Role for QE?' is divided into two sections. In section A I show additional descriptive statistics for the data used in the regression analysis. Section B provides a detailed description of how I linked the German credit register with the firm dataset.

Online Appendix

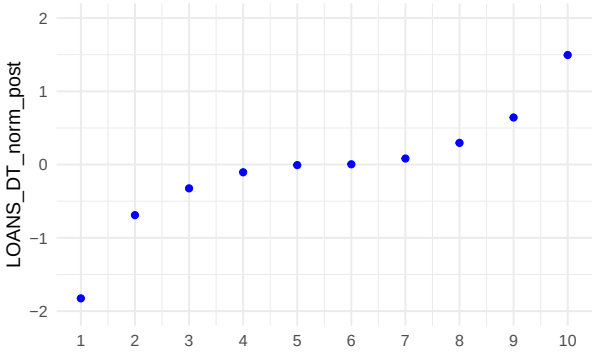
A. Descriptive Appendix

In the section A.1 I provide further descriptive statistics for the variables used in the regression. In section A.2 I provide additional details on the structure of the firm dataset. In section A.3 I show that new and terminal pairs make up a sizeable chunk of the total loan volume. In section A.4 I reverse the analysis and show that there are no apparent differences between banks respectively firms with a strong increase in loan growth during QE and their peers with weak growth.

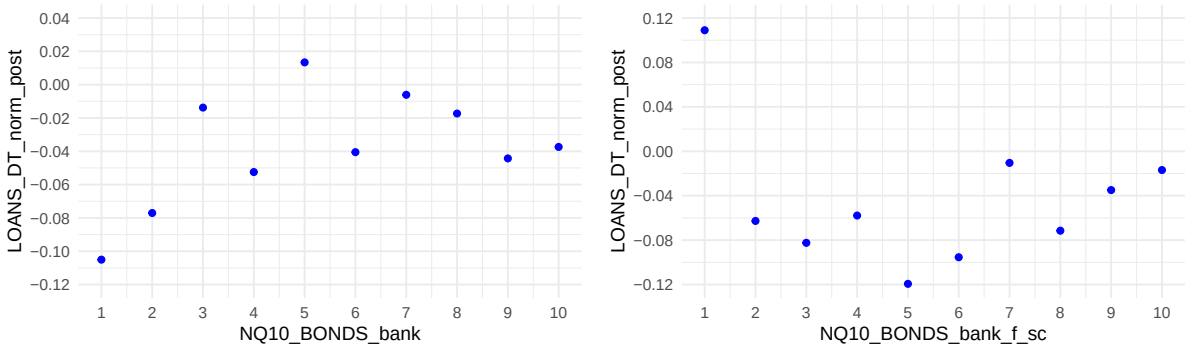
A.1. Distribution of Variables

Figure A.1: Distribution of Loan-Level Variable.

(a) means within its own deciles



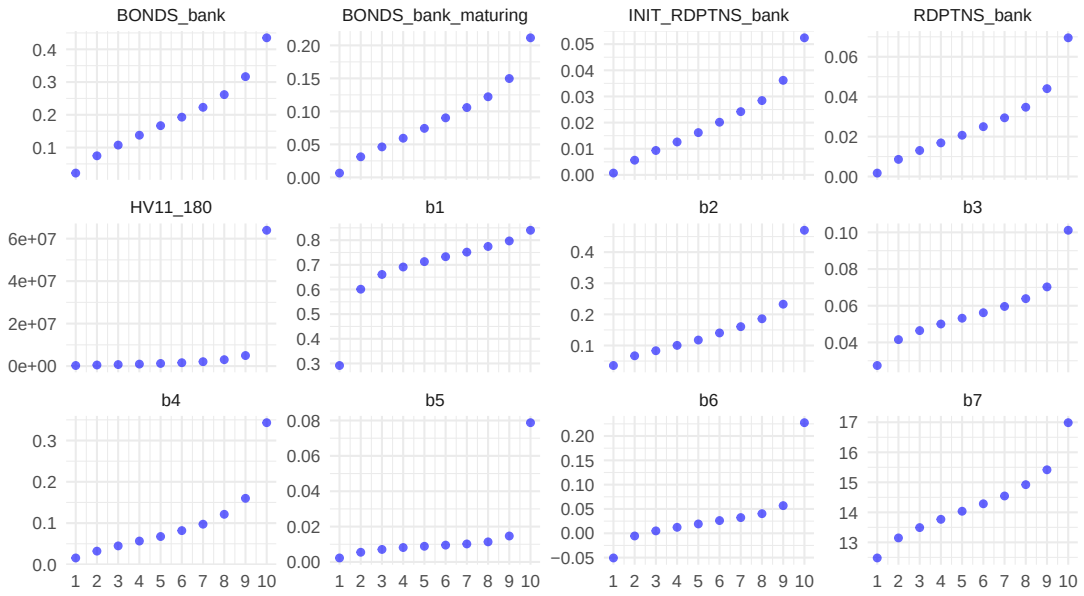
(b) means within deciles of bank and firm shock variables



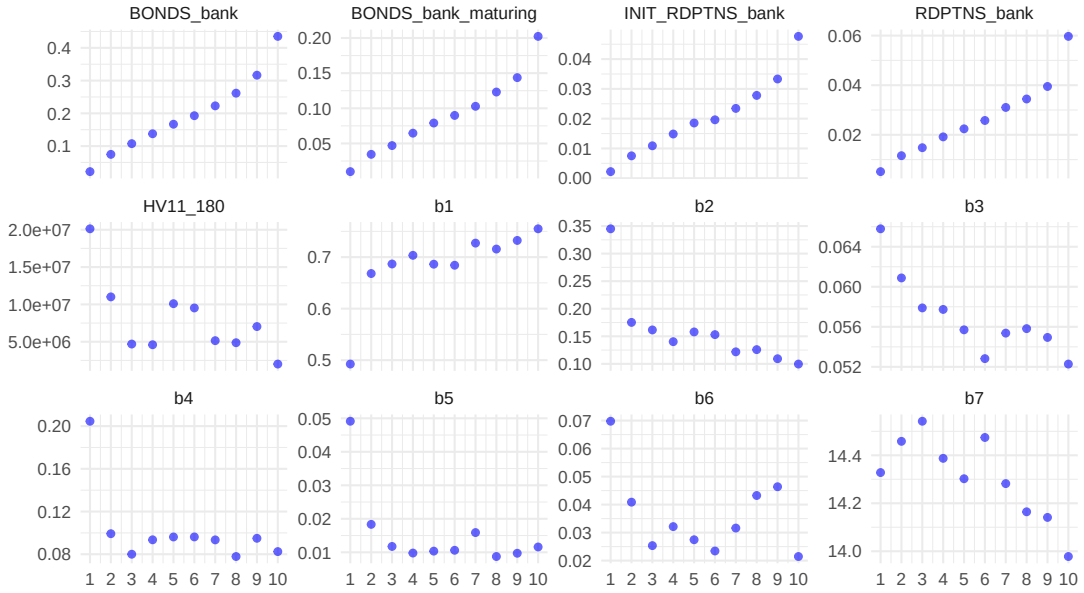
Mean of LOANS_DT_norm_post within its own deciles (panel (a)), the deciles of BONDS_bank (panel (b), left) and BONDS_bank_f_sc (panel (b), right). Variable labels are explained in table 2 of the main text. Source: Research Data and Service Centre (RDSC) of the Deutsche Bundesbank, BISTA, SHS, CSDB, credit register, 2011-2018, own calculations.

Figure A.2: Distribution of Bank-Level Variables.

(a) means within its own deciles



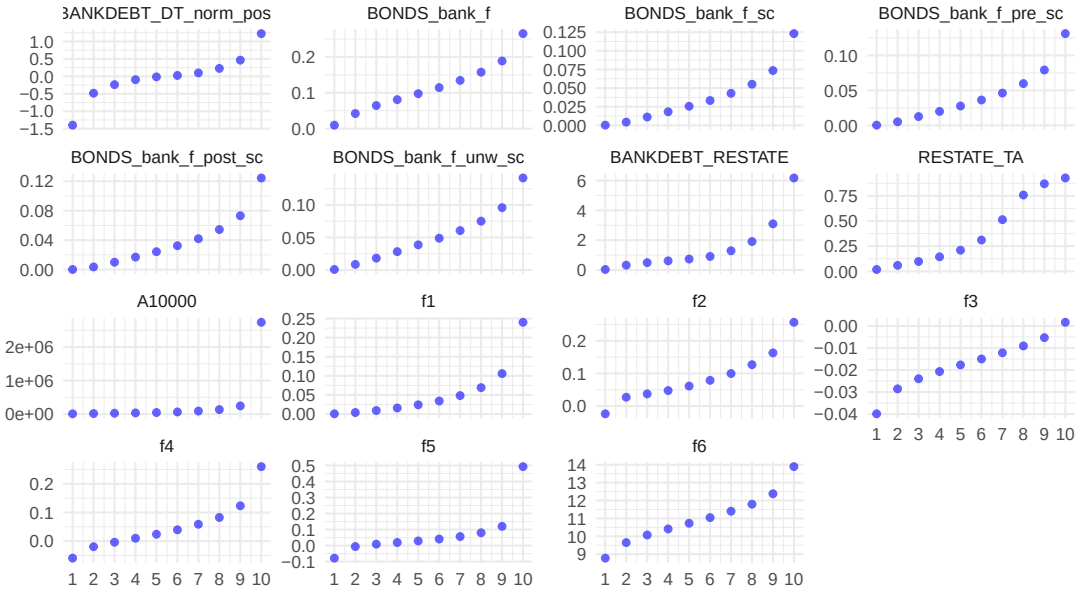
(b) means within deciles of the bank shock variable



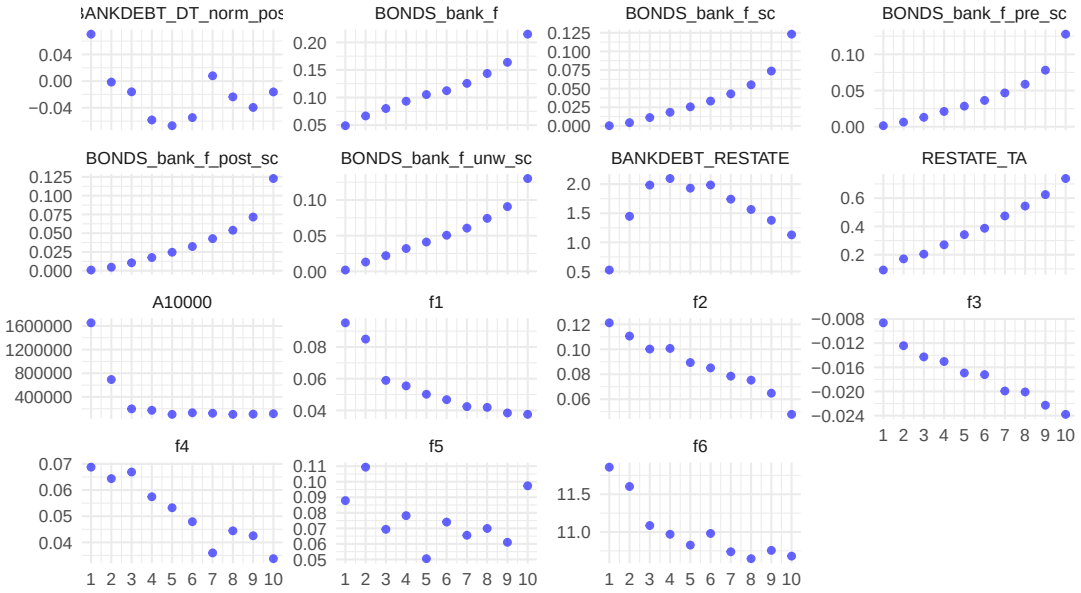
Means of bank-level variables within their own deciles (panel (a)) and the deciles of BONDS_bank (panel (b)). Variable labels are explained in table 2 of the main text. In panel (a) some of the variables cannot be shown due to the Bundesbank's disclosure rules. Source: Research Data and Service Centre (RDSC) of the Deutsche Bundesbank, BISTA, SHS, CSDB, 2011-2018, own calculations.

Figure A.3: Distribution of Firm-Level and Firm-Level variables.

(a) means within its own deciles



(b) means within deciles of the firm shock variable

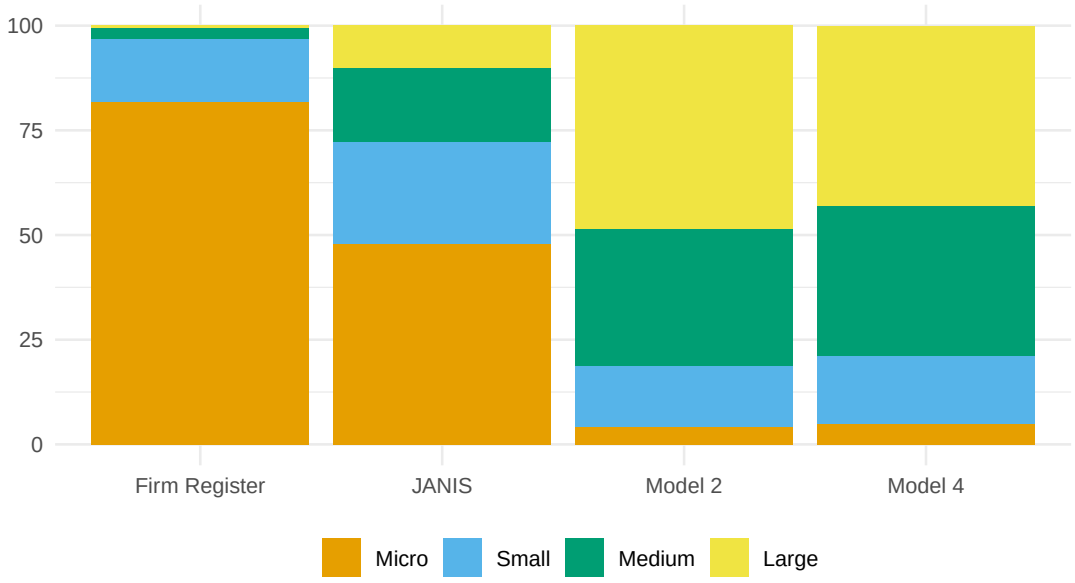


Means of firm-level variables within their own deciles (panel (a)) and the deciles of BONDS_bank_f_sc (panel (b)). Variable labels are explained in table 2 of the main text. Source: Research Data and Service Centre (RDSC) of the Deutsche Bundesbank, BISTA, SHS, CSDB, JANIS, 2011-2018, own calculations.

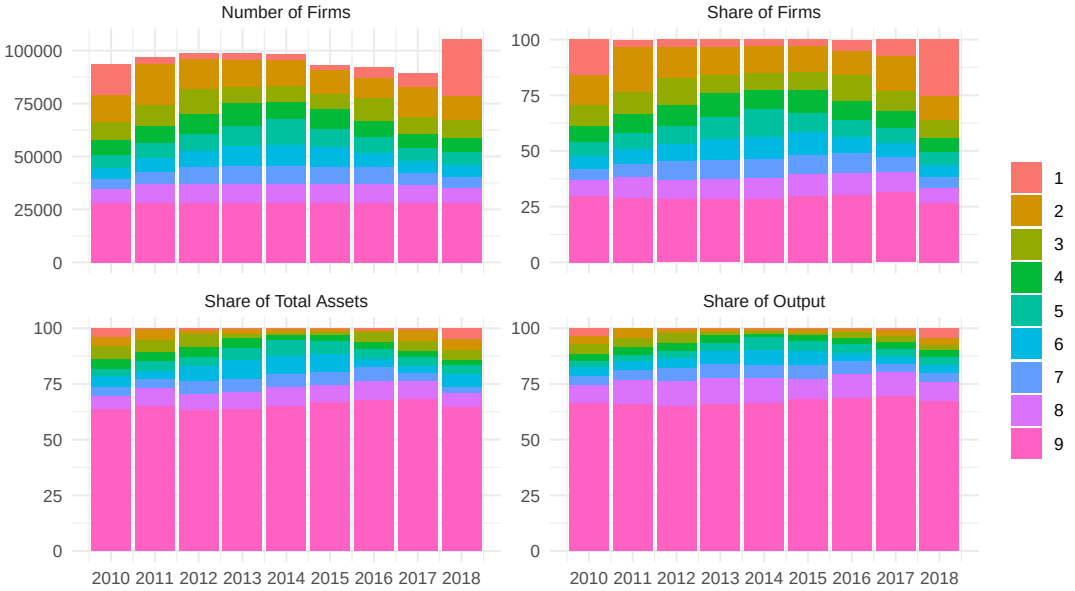
A.2. Firm Structure

Figure A.4: Firm Structure.

(a) Share of Firms by Size Class.



(b) Number and Share of Firms by Time in JANIS.



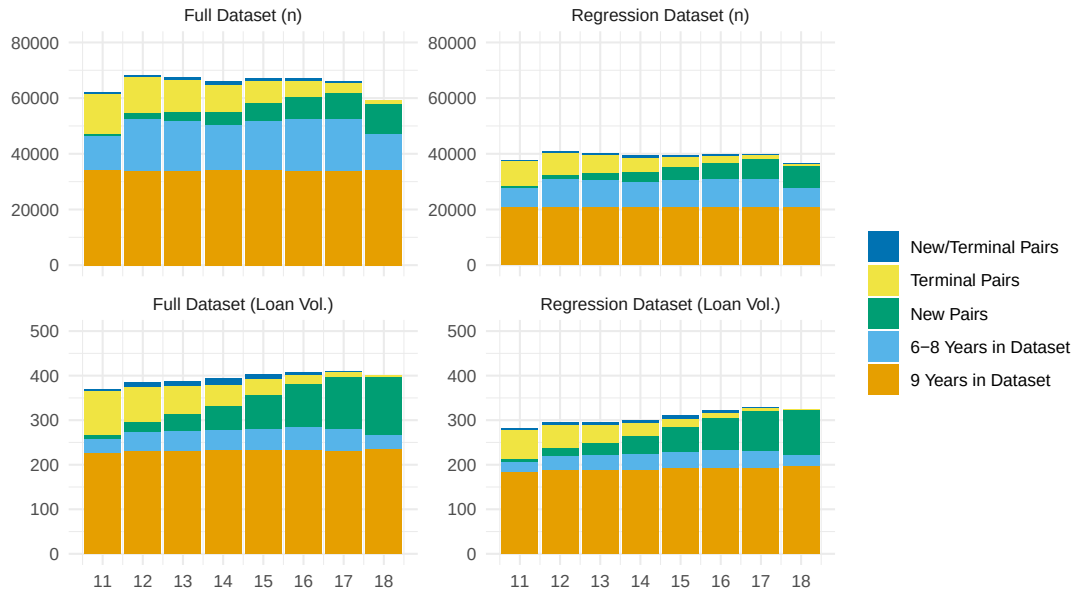
Share of firms of different size classes according to EU definition (panel (a)) and number and share of firms of different duration in JANIS dataset, by their number, by total assets, and by output (panel (b)). Sources: Research Data and Service Centre (RDSC) of the Deutsche Bundesbank, JANIS, 2011-2018, own calculations; German Federal Statistical Office (Destatis).

Figure A.4a shows the share of firms of different size classes in the total number of firms in the German firm register, the JANIS dataset and the two regression datasets. As can be seen, large and medium firms are massively over-represented in my regression. It is probably save to assume, though, that micro and small firms only account for a very small part of aggregate corporate debt, anyway.

Figure A.4b shows the number of firms by the respective number of years in the JANIS dataset (upper left panel), the share of firms (upper right), the share of total assets over all firms in each category (lower left), and the share of output over all firms in each category (lower right). There are around 30,000 firms which are in the JANIS for the entirety of the observation period (nine years) which is around 30% of all firms in the dataset in each year. These firms account for over 60% the total assets and 60% of the output of all firms. This shows that keeping firms that are observable for at least six years, like in the regressions in the main text, maintains a wide coverage of the overall dataset.

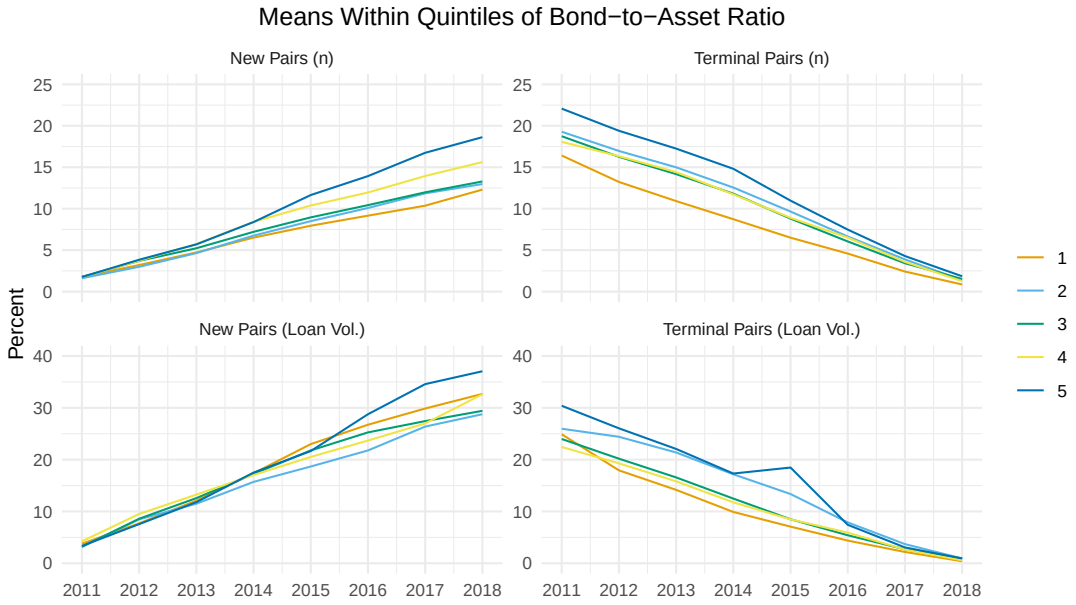
A.3. Pair Structure

Figure A.5: Structure of Bank/Firm Pairs (1).



Number of bank/firm pairs by category (top row) and loan volume in Bn. EUR over all pairs in each category (bottom row), full dataset (left column) and regression dataset (right column). Sources: Research Data and Service Centre (RDSC) of the Deutsche Bundesbank, credit register, 2011-2018, own calculations.

Figure A.6: Structure of Bank/Firm Pairs (2).



Share of new and terminal borrower connections in all borrower connections of a lending bank, means within quantiles of bond-to-asset ratio. Upper row shows the share of the number of pairs, lower row shows the share of loan volume. Sources: Research Data and Service Centre (RDSC) of the Deutsche Bundesbank, credit register, 2011-2018, own calculations.

The top row of figure A.5 shows the number of bank/firm pairs in the full credit register dataset (left) and the dataset on which the regressions run (right) by different categories: pairs which are in the dataset for the full nine years between 2010 and 2018 and for 6 to 8 years, respectively; pairs which are newly established and terminated during the observation period; and pairs which are both newly established and terminated again during the observation period.

Figure A.6 shows the mean share of new and terminal pairs in all borrower pairs of banks within the quantiles of the bond-to-asset ratio (top row) and the mean share in total loan volume of new and terminal pairs (bottom row). Banks with a higher bond-to-asset ratio tend to establish more new borrower connections, but at the same time they also terminate a larger share: in 2018, newly established borrower connections account for 12% of all borrower connections in a mean bank in the bottom quintile of the bond-to-asset ratio, as opposed to 19% in the top quintile; in 2011, borrower connections that get terminated account for 16% of all borrower connections in a mean bank in the bottom quintile of the bond-to-asset ratio, as opposed to 22% in the top quintile. The share in the loan volume (bottom row of figures) shows a similar pattern.

A.4. Bank and Firm Characteristics by Loan Growth

In this section, I reverse the analysis from the main text to investigate in how far banks and firms with a strong increase in lending respectively borrowing during QE compared to before QE are different to their respective peers with weak growth. As can be seen from the following tables, there is no apparent difference regarding their balance sheet structure or size.

Table A.1: Firm Balance Sheet Structures

Quintile	BANKDEBT_DT_norm	BONDS_bank_f_sc	BANKDEBT_RESTATE	RESTATE_TA	TANGIBLE_TA	BONDDEBT_TA	BANKDEBT_TA	BONDDEBT_LIAB	BANKDEBT_LIAB	f1	f2	f3	f4	f5
1	-.864	.031	2.078	.256	.429	.004	.283	.008	.501	.055	.095	-.016	.085	.092
2	-.143	.05	1.689	.486	.637	.002	.401	.003	.675	.045	.071	-.018	.046	.052
3	.004	.045	.93	.494	.596	.001	.352	.002	.558	.062	.074	-.018	.027	.051
4	.153	.048	1.501	.482	.609	.003	.376	.005	.629	.053	.078	-.018	.026	.071
5	.843	.027	1.583	.236	.379	.007	.211	.013	.39	.066	.114	-.015	.044	.081

Quintile indicates the Qintile of BANKDEBT_DT_norm. All other values are means within that quintile. Variable labels are explained in table 2 of the main text. Source: Research Data and Service Centre (RDSC) of the Deutsche Bundesbank, JANIS, 2011-2018, own calculations

Table A.2: Bank Balance Sheet Structures

Quintile	LA_VJKRE_DT_norm	BONDS_bank	b1	b2	b2cb	b3	b4	b5	b6	b7	b8	b9	b9nfc	b9hh	b9gg
1	-.128	.179	.685	.152	.009	.063	.09	.021	.007	14.298	9399.182	.604	.15	.386	.025
2	-.001	.19	.71	.139	.011	.056	.064	.021	.01	14.375	8031.594	.618	.15	.416	.027
3	.052	.197	.716	.127	.01	.06	.064	.015	.011	14.48	10638.39	.602	.141	.411	.027
4	.125	.197	.716	.136	.011	.057	.081	.015	.014	14.228	3010.434	.588	.136	.403	.026
5	.331	.226	.704	.141	.012	.06	.09	.024	.029	14.099	5343.819	.54	.122	.365	.019

Quintile indicates the Qintile of LA_VJKRE_DT_norm. All other values are means within that quintile. LA_VJKRE_DT_norm is detrended volume of outstanding loans of a bank to the German business sector, computed by equation (2) of the main text. b8 are total bank assets in billion euros. b9, b9nfc, b9hh, and b9gg are the share of bank loans in total bank assets to all bank customers, non-financial corporations, households, and the government, respectively. All other variable labels are explained in table 2 of the main text. Source: Research Data and Service Centre (RDSC) of the Deutsche Bundesbank, BISTA, VJKRE, 2011-2018, own calculations

B. Technical Appendix

This appendix provides an in-depth description of how I linked the German Credit Register (credit register) with the balance sheet statistics (BISTA; appendix B.1) and with the non-financial firm dataset (JANIS; appendix B.2). It is primarily directed at readers interested in replicating my results or conduct similar research and probably of limited interest for others.

B.1. Link credit register and BISTA

The German Credit Register (MIO – *Millionenkreditevidenz*) is a dataset raised for regulatory purposes, particularly to identify cluster risks.[1] Hence, the focus is not to identify the type of asset held by the bank but rather the risk to the bank stemming from its total credit towards an individual borrower, whereas total credit is defined as the sum of all debt and equity instruments. The only type of asset that is specifically raised in the Credit Register before Q1/2019 are mortgage loans. Besides that, the credit register only differentiates between on-balance sheet items, off-balance sheet items, and derivatives. A further differentiation (e.g. fixed-income securities or shares) is only available from Q1/2019 on, which is right after the end of my observation period.[2] Before that, the best approximation to what I want to observe (bilateral lender-borrower connections) is the on-balance sheet claims (variable `pos_110`) which is the sum of loans, fixed-interest rate securities, shares, participations, interests in companies, and claims from repo businesses (both as creditor and debtor).

To seek out outliers at the level of the reporting bank, I first compute a reference item with data from the BISTA and the SHS and CSDB. Details on these datasets including full lists of all variables can be found in Gomolka et al. (2022) for the BISTA and Blaschke et al. (2022) and Yalcin et al. (2021) for the SHS respectively CSDB.[3] The BISTA is comprised of a main form (*HV - Hauptvordruck*) which contains key categories of assets (HV1) and liabilities (HV2) like loans and advances to non-banks (variable `HV11_070`), debt instruments (`HV11_080`), and multiple forms of equity claims (`HV11_090`, `HV11_100`, `HV11_110`) as well as various annexes which contain detailed breakdowns of these positions. A breakdown by maturity, type of loan, and borrower sector can be found in Annex B

[1] The historical roots of the dataset go back to the collapse of the Danat bank (*Darmstädter und Nationalbank*) in 1931 which was mainly due to the bankruptcy of one if its main borrowers, the *Nordwolle AG*, a wool processing corporation.

[2] A full list of variables covered by the dataset (from Q1/2019 on) can be found in Bundesbank (2021, p. 97). Before Q1/2019, only the following variables are available (besides master data on lenders and borrowers): `pos_090`, `pos_091`, `pos_092`, `pos_100`, `pos_101`, `pos_102`, `pos_107`, `pos_108`, `pos_110`, `pos_120`, `pos_121`, `pos_130`, `pos_140`, `pos_150`, `pos_160`

[3] The reader may also be referred to the Research and Data Center's homepage at which further information on all available datasets is provided: `https://www.bundesbank.de/en/bundesbank/research/rdsc/research-data/research-data-617996`.

for loans and advances to non-banks and in Annex E for securities. Specifically, for each bank I compute reference variables as follows:

$$\texttt{BISTA_REF_LOANS}_{t,i} = \texttt{B1_114_04}_{t,i} + \texttt{B1_114_05}_{t,i} + \texttt{B1_114_06}_{t,i} + \texttt{B1_114_07}_{t,i} \quad \text{(A.1)}$$

$$\texttt{BISTA_REF_BONDS}_{t,i} = \texttt{E1_123_02}_{t,i} + \texttt{E1_123_05}_{t,i} \quad \text{(A.2)}$$

BISTA_REF_LOANS is the sum of all loans and advances to domestic non-financial corporations and BISTA_REF_BONDS is the sum of all holdings of debt securities issued by domestic non-financial corporations, each for bank i at the end of period t. Unfortunately, the equity holdings of banks are not reported in further detail in the BISTA. I have to turn to the SHS and CSDB for that. In the SHS, banks report their holdings of securities by ISIN, and the CSDB contains details on each ISIN, including instrument class (ESA_INS_2010, ESA_INS_1995), issuer sector (ESA_ISSUER_2010, ESA_ISSUER_1995), and issuer country (ISSUER_COUNTRY). This information can be used to compute the total holdings of all variable-yield assets (F5, without F52) j for bank i at the end of period t issued by non-financial firms (S_11 respectively S.11) in Germany:

$$\begin{aligned}\texttt{BISTA_REF_EQUITY}_{t,i} = \sum_j \left\{\texttt{STOCK_NOMINAL_VALUE}_{t,i,j}\right\}, \text{if} \quad \text{(A.3)}\\ \texttt{ESA_INS_2010} = \texttt{F_5} \;\&\; \texttt{ESA_INS_2010} \neq \texttt{F_52}\\ \&\; \texttt{ESA_INS_1995} = \texttt{F.5} \;\&\; \texttt{ESA_INS_1995} \neq \texttt{F.52}\\ \&\; \texttt{ESA_ISSUER_2010} = \texttt{S_11} \;\&\; \texttt{ESA_ISSUER_1995} = \texttt{S.11}\\ \&\; \texttt{ISSUER_COUNTRY} = \texttt{DE}\end{aligned}$$

Finally, I can aggregate these three reference variables to a total at bank level:

$$\texttt{BISTA_REF_TOTAL}_{t,i} = \texttt{BISTA_REF_LOANS}_{t,i} + \texttt{BISTA_REF_BONDS}_{t,i} + \texttt{BISTA_REF_EQUITY}_{t,i} \quad \text{(A.4)}$$

This can then be compared to the total of on-balance sheet loans of bank i at the end of period t vis-à-vis borrowers k from the credit register:

$$\texttt{LOANS_TOTAL}_{t,i} = \sum_k \left\{\texttt{pos_110}_{t,i,k}\right\} \quad \text{(A.5)}$$

To the best of my estimate, $\texttt{BISTA_REF_TOTAL}_{t,i}$ is the best possible approximation of banks' reports in the credit register that can be computed from the BISTA/SHS/CSDB. It must be stressed, though, that it is only an approximation and an exact match cannot be computed for three main reasons. First, remember there is a reporting threshold of 1 million Euros (1.5 million before Q1/2015) in the credit register. Second, the sectoral and

geographical breakdown of equity instruments is only possible for shares (HV11_090), not for participating interest and amounts paid up on cooperative society shares (HV11_100) or shares in affiliated enterprises (HV11_110). Third, the SHS is only available for domestic banks and domestic parts of multi-office banks whereas the credit register also includes foreign parts of multi-office banks.

All banks where the sum of reports in the credit register is lower than or equal to the reference variable from the BISTA/SHS ($\texttt{LOANS_TOTAL}_{t,i} <= \texttt{BISTA_REF_TOTAL}_{t,i}$) are kept in the dataset. Those (roughly 100) banks where $\texttt{LOANS_TOTAL}_{t,i} > \texttt{BISTA_REF_TOTAL}_{t,i}$, I manually checked by graphically analyzing the within-bank time series of $\texttt{LOANS_TOTAL}_{t,i}$ and of $\texttt{pos_110}_{t,i,k}$ for each k and then decided that it is save to keep all of those banks as well. This is because even though there are cases in which $\texttt{LOANS_TOTAL}_{t,i}$ is absurdly large compared to $\texttt{BISTA_REF_TOTAL}_{t,i}$, compared to bank total assets there is nothing unusual. Checking banks individually might be more time-consuming than simply dropping all banks above a clearly specified threshold. However, since dropping a single bank creates collateral damage in possibly hundreds of borrower connections, I deem the additional effort worthwhile.

B.2. Linking the Credit Register and JANIS

Linking the credit register to the JANIS is not a straightforward task and can be a major exercise depending on the level of detail one is interested in. Neither dataset is raised for research purposes or with the intention in mind of linking them with each other. The Bundesbank itself is already putting a lot of effort into resolving issues that arise when linking different datasets with company data (Doll et al. 2021; Gábor-Tóth and Schild 2021a,b). The first – and, as a matter of fact, main – problem is that in both datasets the borrowing entities have different IDs. The Bundesbank provides a mapping table which links the firm ID in the JANIS (BBK_HM_CO_ID1) to the borrower ID in the credit register (anehmernr). I renamed these into JANIS_ID and BORID to have more intuitive variable names. The problem now is that in the Bundesbank-provided mapping table, there are not only 1:1 relations between the two, but also 1:m, m:1, and even m:n relations; i.e. there are cases where more than one BORID refer to one and the same JANIS_ID, or vice versa, or multiple JANIS_ID and multiple BORID constitute a common entity. There are manifold reasons for this, e.g. an entity might receive a new ID in one of the datasets at one point in time, or the ID in one dataset refers to a different kind of borrowing unit than the ID in the other dataset (branches vs. corporations); for further details on this please refer to Gábor-Tóth and Schild (2021b). These non-1:1 relations make up only a limited number of entries in the mapping table, but since the validity of my method rests on having as much within-borrower variance as possible, I wanted to reduce data losses as much as

possible. To solve those non-1:1 relations in the mapping table, I first merge the mapping table with the JANIS and the credit register because I need information from both in the process. The first piece of information is whether an ID can actually be matched with the corresponding dataset as this might shape the type of relationship we are facing: if, for instance, a 1:m relationship between the JANIS and the credit register can only be linked with one ID from the credit register, then it turns into a 1:1 relationship.

B.2.1. m:1 relations

Table B.1: Structure of m:1 relations between `JANIS_ID` and `BORID`

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
_n	JANIS (using)	_merge	MAPPING (master)		_merge	MIO (using)	
	JANIS_ID		JANIS_ID	BORID		BORID	BAID
1	I	3	I	A	3	A	α
2	II	3	II	A	3	A	α
3	II	3	II	A	3	A	β
4		1	III	A	3	A	β
5		1	IV	C	3	C	α
6					2	D	α

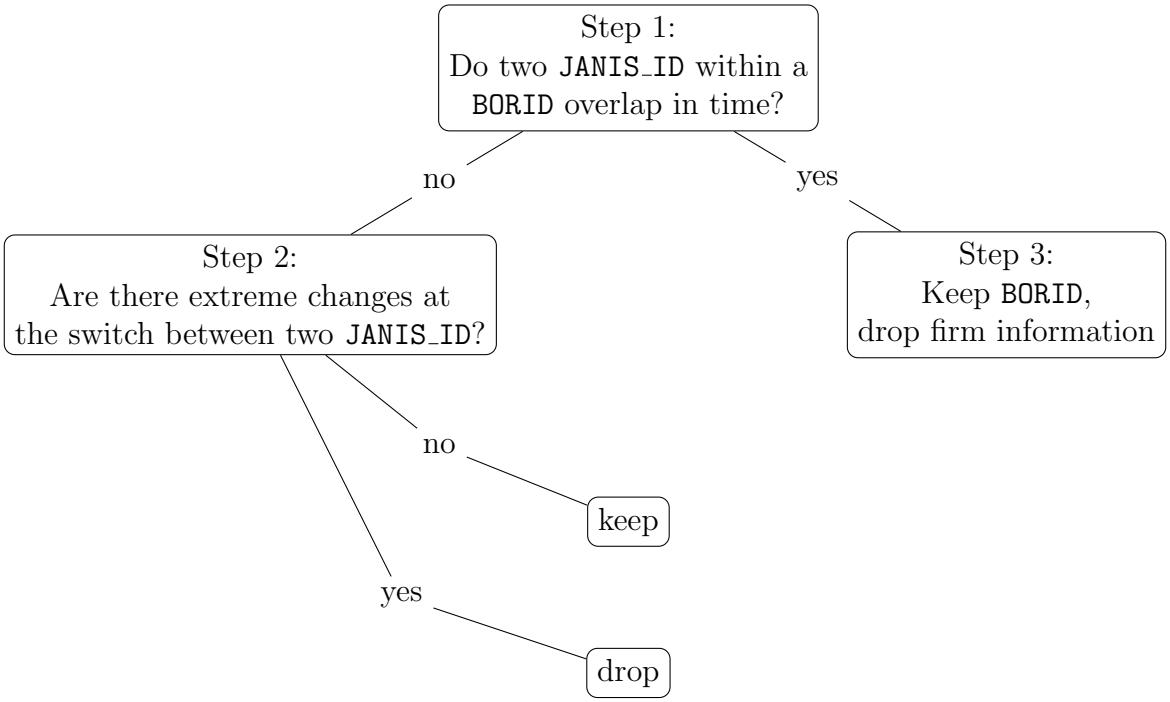
Sketch of the mapping table between JANIS and credit register (MIO) provided by the Bundesbank (columns (4) and (5)), merged with the JANIS (column (2)) and the credit register (columns (7) and (8)), whereas the mapping table is considered the master file in both matching processes. _merge shows the status of merging between the mapping table and the JANIS (3) respectively credit register (6): 1 = master only, 2 = using only, 3 = match.

Table B.1 shows a simplified version of the m:1 relations. Lines 1 through 4 constitute one borrower entity, whereas `BORID` A refers to three `JANIS_ID`: I, II, and III, for the last of which there is no balance sheet data available in the JANIS. In this case, I do not drop line 4 because it still contains information on the bilateral lending between the bank and the borrowing entity. Lines 5 and 6, however, can be dropped because neither C nor D can be linked to a `JANIS_ID` for which any balance sheet data is available.

Figure B.1 shows the analytical steps in solving the m:1 relations. Here, I start with testing whether two (or more) `JANIS_ID` that refer to the same `BORID` ever appear in the same time period (step 1). If that is not the case, step 2 could then be to check whether there are extreme changes in the total firm assets where a `BORID` switches from one `JANIS_ID` to another. I decided to keep all of these units, however, because extreme changes in total assets could also appear within the same `JANIS_ID` and outliers in total asset growth can still be sorted out in the final dataset before doing the analysis.

In cases where two or more JANIS_ID within a BORID appear at the same time period (step 3) I delete all firm information and only keep the BORID. This is because these units can still be used to control for loan demand at borrower level in the supply side regression (see main text). The reason why I do not use firm information here is because I shy away from aggregating non-financial corporate balance sheets because if they have claims on each other – and two JANIS_ID which refer to the same BORID must be expected to have mutual claims with a high probability as they obviously have some close connection – then aggregating creates a double-counting problem.

Figure B.1: Resolution scheme for m:1 relations between JANIS_ID and BORID



B.2.2. 1:m relations

Table B.2 shows the structure of 1:m relations between JANIS_ID and BORID. The BAID is the bank identifier. The table abstracts from the time dimension for simplicity.

Table B.2: Structure of 1:m relations between JANIS_ID and BORID

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
_n	JANIS (using)	_merge	MAPPING (master)		_merge	MIO (using)	
	JANIS_ID		JANIS_ID	BORID		BORID	BAID
1	I	3	I	A	3	A	α
2	I	3	I	B	3	B	α
3	I	3	I	B	3	B	β
4	I	3	I	B	3	B	γ
5	II	3	II	C	3	C	β
6	II	3	II	D	1		

Sketch of the mapping table between JANIS and credit register (MIO) provided by the Bundesbank (columns (4) and (5)), merged with the JANIS (column (2)) and the credit register (columns (7) and (8)), whereas the mapping table is considered the master file in both matching processes. _merge shows the status of merging between the mapping table and the JANIS (3) respectively credit register (6): 1 = master only, 2 = using only, 3 = match.

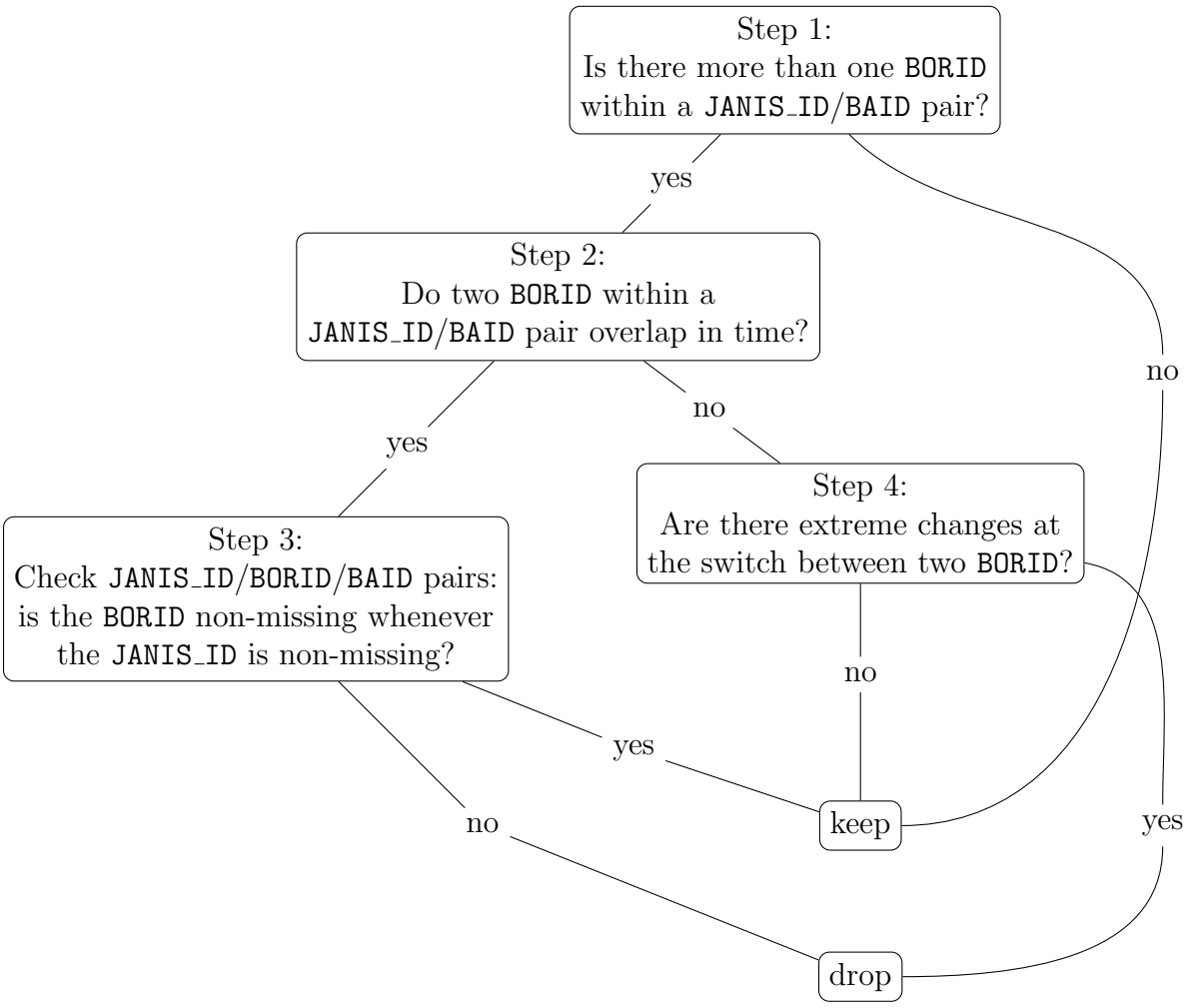
Lines 1 through 4 show JANIS_ID I which links to two BORID: A and B. While A receives loans from bank α, B receives loans from banks α, β, and γ. Line 5 and 6 show JANIS_ID II which also links to two BORID: C and D. However, in this case only C can be matched with the credit register while for D there is no match. A possible explanation for why this happens is that no bank reported any loans to D during my observation period but did so at some other point in time.[4] Important to me is that dropping line 6 turns II/C into a 1:1 connection which does not warrant any further analysis and can be kept in any case.

What I am ultimately interested in is firm-bank connections, or in technical terms: JANIS_ID/BAID pairs. So when solving the 1:m relations between JANIS_ID and BORID, my first step was to single out all JANIS_ID/BAID pairs which materialize through only one BORID – see figure B.2. In table B.2 this would be lines 3 and 4: β and γ both lend out to I exclusively through B. In the remaining cases, I then check whether two BORID within the same JANIS_ID/BAID pair ever appear at the same point in time (step 2). If that is indeed the case, the level of analysis switches to JANIS_ID/BORID/BAID pairs (step 3). Of these, I keep only those in which the BORID is a non-missing in every period in which also

[4]The JANIS is available for researchers from 1997 on, the credit register from 2002 on. My data cover 2010 to 2018.

the JANIS_ID is non-missing. The case that two BORID within a JANIS_ID/BAID pair do not overlap in time (step 4) does not actually show up in my data. If that did, in fact, happen, one could test whether the switch from one BORID to another coincides with unusually large changes in pos_110 because if that is not the case it could be justified to assume that the borrower entity simply received a new BORID in the credit register at that point in time for whatever reason.

Figure B.2: Resolution scheme for 1:m relations between JANIS_ID and BORID



B.2.3. m:n relations

Table B.3 shows a network of m:n relations between JANIS_ID and BORID: I links to A and D; A also links to II which also links to B and C; D also links to III. The first challenge is to correctly attribute a common ID to each network. To this end, the original mapping table has to be reshaped to the wide format twice; see table B.4. Once the BORID are reshaped to wide so that in each line there is one JANIS_ID and all BORID that refer to it – this is shown in panel b) of table B.4. And once the JANIS_ID are reshaped to wide so that in each line there is one BORID and all JANIS_ID that refer to it – this is shown in panel c). Now these two tables iteratively have to be merged to each other via JANIS_ID respectively BORID until there are all JANIS_ID and BORID that belong to each other are in one row. That is, in the first step, table c) is merged to table b) three times via all three BORID – the outcome of this is shown in panel d). To this outcome table then table b) is merged again via all JANIS_ID. This process is repeated until all three lines contain all three JANIS_ID and all four BORID that make up this network. Finally, duplicate rows are dropped so that each row then represents one m:n network to which a network ID (NETWID) can be attributed.

Table B.3: Structure of m:n relations between JANIS_ID and BORID

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
_n	JANIS (using)	_merge	MAPPING (master)		_merge	MIO (using)	
	JANIS_ID		JANIS_ID	BORID		BORID	BAID
1	I	3	I	A	3	A	α
2	II	3	II	A	3	A	α
3	II	3	II	A	3	A	β
4	II	3	II	B	3	B	α
5	II	3	II	C	1	C	α
6	I	3	I	D	3	D	α
7	III	3	III	D	3	D	α

Sketch of the mapping table between JANIS and credit register (MIO) provided by the Bundesbank (columns (4) and (5)), merged with the JANIS (column (2)) and the credit register (columns (7) and (8)), whereas the mapping table is considered the master file in both matching processes. _merge shows the status of merging between the mapping table and the JANIS (3) respectively credit register (6): 1 = master only, 2 = using only, 3 = match.

The decision on which networks to keep is then made by means of the following steps (figure B.3). The first three steps are akin to solving the m:1 relations. All networks that are left at the beginning of step 4 are now akin to 1:m relations and can hence dissolved by the same pattern. All borrower-bank connections (NETWID/BAID connections in technical terms) which materialize through only one BORID are kept anyway (step 4).

Table B.4: Identification of m:n relations between JANIS_ID and BORID

a) Original mapping

JANIS_ID	BORID
I	A
I	D
II	A
II	B
II	C
III	D

b) BORID reshaped to wide

JANIS_ID	BORID1	BORID2	BORID3
I	A	D	
II	A	B	C
III	D		

c) JANIS_ID reshaped to wide

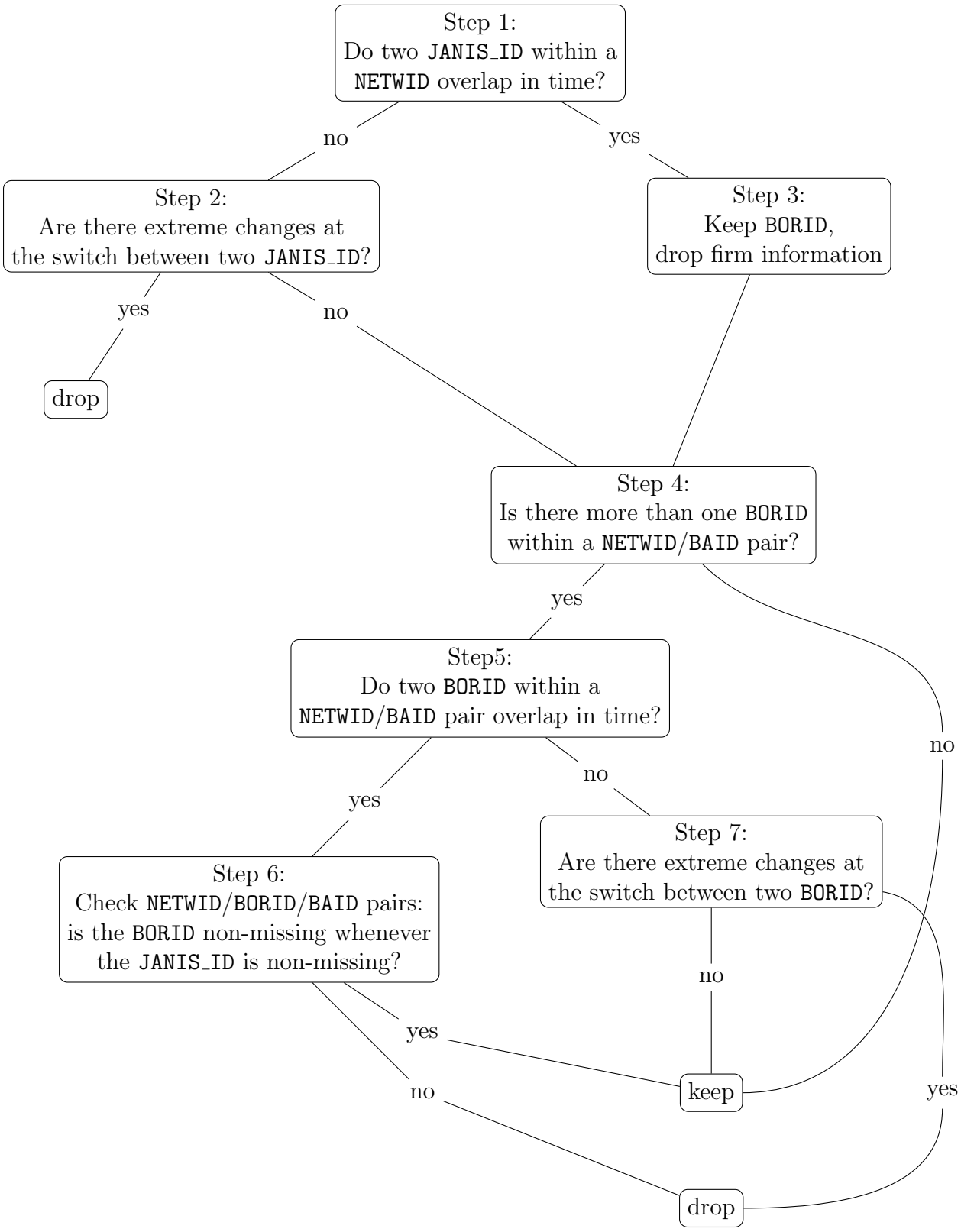
BORID	JANIS_ID1	JANIS_ID2
A	I	II
B	II	
C	II	
D	I	III

d) table c) merged to table b) via each BORID

JANIS_ID	BORID1	JANIS_ID1	JANIS_ID2	BORID2	JANIS_ID1	JANIS_ID2	BORID3	JANIS_ID1	JANIS_ID2
I	A	I	II	D	I	III			
II	A	I	II	B	II		C	II	
III	D	I	III						

Where multiple BORID form the link between a NETWID and a BAID, I differentiate between overlapping and non-overlapping BORID (step 5). As with the 1:m relations, there are no cases where there is no temporal overlap between two BORID within a borrower-bank pair, so step 7 is void. Where multiple BORID within a NETWID/BAID pair do appear simultaneously, I switch the level of analysis to NETWID/BORID/BAID pairs and keep only those where there is a bilateral loans in all time periods where there are total assets available for the JANIS_ID.

Figure B.3: Resolution scheme for m:n relations between JANIS_ID and BORID



B.2.4. Cross-referencing borrowing/lending volumes in credit register and JANIS

Finally, I cross-reference the borrowing a firm reports in the JANIS with the lending to that firm reported by banks in the credit register to filter implausible differences. Due to the vast number of firms a manual check is not feasible here. After checking the distribution of the share of lending reported in the credit register over borrowing reported in the JANIS and the distribution of the share of lending reported in the credit register over total assets reported in the JANIS, I decided to keep all firms where the lending from credit register does not exceed 120% of total assets from JANIS. This may sound counter-intuitive as lending/borrowing can logically never the larger than total assets, however, what is relevant for my analysis is not the absolute levels of any variable reported in either dataset but their evolution over time, and correlation analyses reveal that the evolution of credit register lending is a good representative of the evolution of JANIS borrowing even in cases where the absolute level is higher.

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