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Verfasser: Talina Sondershaus, M.Sc.

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Prof. Michael Koetter, PhD

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Unintended Side Effects of Financial Market Interventions on Banks and Firms

To Stephan and Thea.

Preface

The economy is a complex system because market participants do not act independently but adjust their behavior to other agents and to the outcome which emerges from their joint actions (Arthur, 2014). Dependencies among participants can impede policy makers capabilities to influence or steer the course of the economy. Kambhu et al. (2007) argue that to influence developments in financial markets, for instance to prevent crises from spreading, there are only “coarse or indirect options” available for policy makers. Similar to crises which propagate through a complex system, interventions might result in unintended side effects which can also disseminate through the system. Thus, in a complex system, unintended consequences of policy efforts may well be the rule.

Policy makers try to ward off or mitigate negative consequences for the economy and society during periods of crisis. For instance, during the Covid crisis large scale support programs for firms in Western economies were set up to avoid bankruptcies. Similarly, during the sovereign debt crisis in the Eurozone, the European Central Bank (ECB) set up large scale asset purchase programs as well as additionally longer-term refinancing operations (LTRO) which provided immediate support to financial market participants’ liquidity positions and thereby prevented a melt-down of the financial system. During these periods, immediate and abundant liquidity supply is of utmost importance. Meanwhile, crisis measures, due to their massive scale and non-specific target group, may entail unknown or unintended side effects for instance on competition among market participants, firms’ investment behavior, or changes in lending strategies and risk taking behavior of banks. Likewise, new regulatory frameworks such as the introduction of new markets can have consequences previously not thought of. For policy makers it is important to know direct effects of policy interventions but also to be aware of the possibility and impact of indirect or unexpected side effects in order to evaluate measures taken and to learn for future design of regulation or intervention.

This thesis sheds light on the unintended side effects that followed policy interventions such as the introduction of new markets by the regulator or unconventional monetary policy measures. More specifically, in Paper 1, together with my co-authors, I study how banks respond in terms of their lending as well as risk-taking behavior when the regulator allows a market for covered bonds. Covered bonds reduce refinancing costs of mortgage loans and therefore make mortgage lending more profitable. Surprisingly, we observe that banks exposed to the regulation do not increase mortgage lending. Instead, we find that covered bonds increase total balance sheet liquidity which enables banks to extend more risky and less liquid firm lending.

In Paper 2 and 3 I assess the unintended side effects of the first large asset purchase program of the ECB - the Securities Market Program (SMP). I show that asset purchases can cause spillover effects on investments across firms in Paper 2. In line with previous findings on peer effects between firms (e.g. Bustamante and Frésard, 2021; Dougal et al., 2015), I observe that firms adapt their investment decisions to affected peer firms. With this finding, I contribute to the understanding of a slowdown in economic recovery after large asset purchases as pointed out by Acharya et al. (2019). In Paper 3, together with my co-author, I provide an explanation for the phenomenon of a slowing down of business dynamics among very small firms which began in 2010 in Germany. We show that small and medium sized enterprises (SMEs) and their plants have lower market exit probabilities when they were exposed to asset purchases during the SMP.

In Paper 4, together with my co-authors, I demonstrate that banks which operate in many different regulatory regimes, i.e. which have a geographically complex organizational structure, show higher default risks and are more likely to receive state aid. The results indicate that a lack of international coordination in financial regulation might result in the unintended side effect that internationally operating banks increase their risk-taking behavior.

Interrelations and connections across market participants such as bank-firm links, supply chains, demand factors or peer behavior, form the economy into a complex system. This poses challenges to empirically assess unintended consequences of policies on banks and firms. The researcher is faced with a dilemma of more complex empirical modelling, which can take at least some parts of the relationships between market participants into account but which is difficult to comprehend, versus simple but very reductive models which might not be able to capture interconnections because they rely on assumptions such as independently drawn observations or isolated treatment and control groups. In this thesis, I accommodate these challenges by choosing empirical strategies which are very much related to a common framework, which is difference-in-differences analysis, but extend it to allow for a more comprehensive understanding.

The common difference-in-differences model is attractive and very popular due to its relative simplicity. The researcher compares a treatment group e.g. affected by a policy change, to a control group over time. However, there are strong assumptions underlying the difference-in-differences approach, for instance there must not be spillovers from one group to the other. To ease this assumption, in Paper 2, I extend the empirical model similar to Berg et al. (2021) and allow for spillover effects across firms which operate in the same region and industry. The extended version is comparable to previous difference-in-differences approaches but allows for somewhat more complex modelling to gain insights into potential biases due to spillovers. In Paper 1, we also adapt the common difference-in-differences framework to allow for time-varying differential effects to assess whether differential effects decay over time. This approach is in particular suitable for our empirical setting as we conjecture in this analysis that differences between treated and control group vanish over time. In Paper 4 we make the complexity of organizations the topic of research itself and can see that geographical complexity can lead to higher default risks.

In this thesis I emphasize the *causal* identification of effects of policy shocks on banks and firms. This approach might suffer from taking little account of external validity. The price of a stringent causal analysis can be that the finding only holds for a sub-sample of firms. In Paper 1, we focus on the Norwegian economy, which might be a special case with its prolonged house price growth and its dependency on the oil market, among others. We try to provide generalizable arguments by adding a theoretical model from which we derive predictions. For instance, we learn that banks extend firm lending only if firm risk is sufficiently low. It might well be that in other countries firm risk is higher, and therefore the impact of the covered bond market on bank lending is different. In Paper 2, I restrict the sample of firms to SMEs which only have one bank. On the one hand, this allows me to draw conclusions on the group of firms which are highly innovative and important for the German economy - SMEs. On the other hand, it limits the informative value when judging on the *whole* economy including also larger firms. However, the results on SMEs' behavior might be generalizable to other Western countries as long as the context in which firms operate is comparable. In Paper 4 we include almost all large European banks in the analysis which has the advantage that results apply to a wider setting. Nevertheless, in this set up we do not claim to find causal effects and restrict ourselves to a descriptive analysis.

Conclusions drawn from assessing side effects should also take into account the intended effects of policy measures and whether these succeeded. Concerning the introduction of covered bond markets in Norway, the intention was to create a market for safe assets, i.e. assets which are low in risk and money-like. As a consequence, balance sheet liquidity of banks increased and therefore liquidity risks were lowered. The side effect that banks extend lending to firms while still becoming more stable institutions seems to be a positive effect to the Norwegian economy. Concerning the main and side effects of asset purchases during the sovereign debt crisis, we must note that for instance the SMP was very successful in achieving its main goal of lowering government bond yields (e.g. Gibson et al., 2016; Eser and Schwaab, 2016; Ghysels et al., 2016) and therefore in preventing a collapse of the Eurozone. Detrimental side effects as this thesis finds, have to be weighed against the success of the program. Policy makers can learn from this thesis the nature of side effects, such that they can decide whether they want to accept these, pursue countervailing measures, or take them into account when considering to set up similar programs at other times.

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Paper 1:

Covered bonds and bank portfolio rebalancing

Covered bonds and bank portfolio rebalancing*

Jin Cao[†] Ragnar E. Juelsrud[‡] Talina Sondershaus[§]

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Abstract

We use administrative and supervisory data at the bank and loan level to investigate the impact of the introduction of covered bonds on the composition of bank balance sheets and bank risk. Covered bonds, despite being collateralized by mortgages, lead to a shift in bank lending from mortgages to corporate loans. Young and low-rated firms in particular receive more credit, suggesting that overall credit risk increases. At the same time, we find that total balance sheet liquidity increases. We identify the channel in a theoretical model and provide empirical evidence:Banks with low initial liquidity and banks with sufficiently high risk-adjusted return on firm lending drive the results.

JEL Classification: G21, G23, G28

Keywords: Asset encumbrance, covered bond, portfolio rebalancing, liquidity management

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[†]Norges Bank, Norway and CESifo, Germany. Address: Bankplassen 2 PB1179 Sentrum, N-0107 Oslo, Norway. E-mail: jin.cao@norges-bank.no.

[‡]Norges Bank, Norway. Address: Bankplassen 2 PB1179 Sentrum, N-0107 Oslo, Norway. E-mail: ragnar.juelsrud@norges-bank.no.

[§]Halle Institute for Economic Research (IWH), Germany. Address: Kleine Märkerstraße 8, 06108 Halle (Saale), Germany. E-mail: talina.sondershaus@iwh-halle.de.

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1 Introduction

Covered bonds are debt instruments with primarily mortgages as collateral. Although a covered bond shares some characteristics with an asset-backed security (ABS) in that they are both financial securities backed by bank assets (Jiménez et al., 2020), covered bonds differ along several dimensions. First, issuers keep the underlying collateral on their balance sheets instead of selling it to the market.[1] Second, while the credit standard associated with the underlying mortgages of an ABS can be poor (Mian and Sufi, 2009; Purnanandam, 2011), the underlying collateral of a covered bond is subject to strict quality requirements.

The covered bond market has shown substantial growth since the financial crisis of 2007-2008. Covered bond issuance relative to total bond issuance for banks grew from 26 % in 2007 to 42 % during the sovereign debt crisis of 2011 (Van Rixtel and Gasperini, 2013). By the end of 2019, the total volume of covered bonds outstanding worldwide corresponded to EUR 2.7 trillion (European Covered Bond Council, 2020), approximately 36 % of all debt securities issued by European banks.[2] Going forward, the harmonization of covered bond markets across Europe is one of the main goals of the European capital markets union. New rules aimed at expanding the market for covered bonds were introduced in the EU in November 2019, and should be implemented in all jurisdictions by the summer of 2021. Covered bonds are therefore expected to play an increasingly important role in the banking system going forward.

The increased reliance on covered bonds has raised a discussion about its implications for bank behavior and ultimately financial stability. Covered bonds — due to their strict requirements — are issued at a relatively low risk premium. Since their issuance is usually tied to mortgage origination, a common concern is that banks' ability to issue covered bonds induces banks to finance mortgage lending at the expense of firm lending (Nicolaisen, 2017). Another concern relates to how asset encumbrance via covered bond issuance affects banks' appetite for credit risk. International Monetary Fund (2013) highlights that asset encumbrance can lead to a concentration of risks in unencumbered assets and that this enables banks to shift risks to uninsured creditors and public guarantors such as deposit insurance schemes (Ahnert et al., 2018; Banal-Estañol et al., 2018; Garcia-Appendini et al., 2021). De-

[1] Issuing ABS is associated with a bank business model of "originate to distribute", so that after a mortgage is originated its risk is transferred to market investors while the issuing bank earns fee income. In contrast, the issuer of a covered bond expands its balance sheet. On the liability side the issuer raises secured long-term funding, while on the asset side the issuer raises cash, thereby increasing the share of liquid assets.

[2] Data extracted from European Covered Bond Council (2020) and European Central Bank Statistical Data Warehouse.

spite the importance of covered bonds for bank financing and these competing views, there is limited empirical evidence to show how reliance on covered bonds affects bank portfolios.

In this paper we analyze how covered bonds affect bank portfolio decisions and risk-taking and provide evidence on the explicit mechanism through which covered bond issuance affects bank behavior. We focus on the introduction of covered bond legislation in Norway in 2007, which marked the start of covered bond issuance in Norway. As we show, the introduction of this legislation led to a boom in the issuance of covered bonds by Norwegian banks, with significant and large effects on bank credit allocation. We combine data from three different sources: detailed supervisory bank-level data, loan-level data on the universe of firm loans and firm-level accounting data. This data-rich environment enables us to show the impact of covered bond issuance on bank portfolios at a granular level.

The analysis in this paper consists of four main steps. First, we exploit the fact that banks had different scope for issuing covered bonds due to different existing mortgage portfolios, implying that some banks were able to shift to covered bonds as a source of financing to a larger extent than others. Mortgages with LTVs below 75 % were eligible for use as the underlying asset of a covered bond, i.e. being included in the "cover pool". Our data contains a breakdown of mortgages according to their LTV, thereby allowing us to classify banks according to their ex ante scope for exploiting this new source of funds. We show that banks with an above-median fraction of mortgages with a low LTV ("high-exposure" banks) issued substantially more covered bonds after the legal change compared with other banks.

Second, we document in a dynamic difference-in-differences setup that the relative increase in covered bond issuance translates into substantial changes in bank-level portfolios. Specifically, the portfolio share of firm lending for high-exposure banks increases by up to 7.4 % compared with the pre-reform mean and compared with other banks following the introduction of covered bonds. This implies that, even though covered bonds are primarily collateralized by mortgages, covered bond issuance is accompanied by a *portfolio rebalancing* away from mortgages to firm loans. Using loan-level data on the universe of firm loans in Norway, we show that covered bond issuance increases lending volumes and leads to weakly lower interest rates, conditional on a large set of firm controls such as firm $\times$ year FEs (Khwaja and Mian, 2008) or high-dimensional FEs (Degryse et al., 2019). The increase in firm credit is not uniform across firms, but tailored towards young firms and firms with a low credit rating, suggesting an increase in overall credit risk.

The introduction of covered bonds also leads high-exposure banks to increase their holdings of liquid financial securities, thus enhancing banks' asset liquidity. In total, we find that balance sheet liquidity — asset *and* funding liquidity — increases for high-exposure banks.

Third, we investigate the implications for overall bank risk. We proxy overall bank risk by using the risk premium on unsecured debt funding. This is an important step in our analysis, as the impact of covered bond issuance on credit risk and liquidity risk moves in an opposite direction due to the portfolio rebalancing, i.e. banks increase the share of risky firm lending while also increasing their share of liquid financial assets. We document that the risk premium on unsecured debt funding declines for high-exposure banks, suggesting that any effects of increased credit risk on overall risk is offset by improved balance sheet liquidity.

Fourth and finally, we analyze our baseline bank-level findings through the lens of a simple theoretical framework to understand the conditions under which covered bond issuance induces bank portfolio rebalancing towards firm lending. In the model, we consider a bank that provides liquidity services and extends mortgages and risky firm loans. The bank is funded by uninsured depositors with a preference for liquidity. Firm loans are illiquid if an exogenously determined bad state of the economy materializes. Hence, banks that have a larger fraction of firm loans will in equilibrium be charged a higher risk premium by depositors. Issuance of covered bonds has two countervailing effects on the portfolio allocation of banks. On the one hand, covered bond issuance reduces mortgage funding costs, thereby making mortgages more profitable. On the other hand, covered bond issuance improves balance sheet liquidity, which enhances banks' ability to engage in risky firm lending. This latter substitution effect is more likely to dominate when depositors have limited risk aversion and when the level of credit risk in firm lending is not too high. Importantly, the magnitude of the substitution effect also varies with initial bank liquidity. Banks with low initial liquidity have stronger incentives to switch to firm loans when the mortgage portfolio becomes more liquid. We then return to the data and show support for our theoretical model: The observed portfolio rebalancing from mortgage loans to firm loans is indeed driven by banks with low initial liquidity as well as by banks with relatively low initial firm credit risk.

Our identification relies on ex ante differences in the LTV distribution within banks, but it does not require banks to choose the LTV of mortgages randomly or be identical in terms of the levels of various covariates. It only requires that high- and low-exposure banks would have behaved similarly in terms of the outcomes we consider in absence of the introduction of covered bonds. To verify the plausibility of this assumption, we adopt two approaches. First, we adopt a flexible difference-in-differences design where we explicitly test for differences in the outcomes considered before the introduction of covered bonds. The raw data and the estimated coefficients are consistent with parallel trends for all the outcomes considered prior to the introduction of covered bonds. Second, we show that bank-level changes after the introduction of covered bonds are unlikely to be driven by other confounding factors, such as differential exposure to the financial crisis across banks.[3] The Norwegian economy was fairly insulated from the direct effects of the financial crisis. Unemployment rates remained relatively low and GDP growth relatively high, compared with other comparable countries (NOU, 2011). Moreover, the Norwegian financial sector did not experience substantial losses (Kragh-Sørensen and Solheim, 2014). The financial crisis primarily affected Norwegian banks indirectly through lower returns on financial assets and a temporary increase in interbank liquidity premia. Importantly, we show that the fraction of low-LTV mortgages in 2006 on which our exposure measure is based is orthogonal to reliance on interbank funding or holdings of financial assets, as well as a wide of range of other pre-crisis bank characteristics such as ex ante funding costs and the volatility of the return on assets.[4]

Related literature Our paper relates to the literature on how asset encumbrance affects bank outcomes. By exploring the pre-crisis credit boom in Spain, Jiménez et al. (2020) show how market funding through covered bonds and ABS together provided liquidity relief for banks and allowed them to increase the credit supply to new borrowers, at the expense of existing borrowers, which were crowded out. They also show that during the credit boom, banks with higher exposure to the real estate sector increased their risk-taking. Similarly, Chakraborty et al. (2018) show that banks with higher exposure to the US real estate market increase mortgage lending and crowd out firm lending. They find similar results for banks that securitized compared to banks that did not securitize assets. Carbó-Valverde et al. (2017) provides a comprehensive overview and comparison of ABS and covered bonds.

Focusing on banks' encumbrance choice, Ahnert et al. (2018) show that asset encumbrance allows banks to raise cheaper funding through secured debt. At the same time, however, it reduces banks' scope for repaying unsecured creditors out of unencumbered assets in the event of market stress, increasing the likelihood of bank failure. Using cross-country data with more than 100 listed banks in Europe over 2004-2013, Garcia-Appendini et al. (2021) find that a bank's default risk is positively correlated with its covered bond issuance. They attribute such correlation to the fact that increasing encumbered assets for covered bond issuance leads to risk concentration in the unencumbered assets. Banal-Estañol et al. (2018)

[3] We also discuss and address other potential confounding factors in Section 3.3.

[4] We also show our results are robust to alternative treatment measures, following Callaway et al. (2021).

find that, after controlling for bank liquidity and capital ratios, a higher asset encumbrance ratio relates to lower spreads in banks' credit default swaps (CDS).

Our main contribution to the literature is to document how covered bond issuance affects bank portfolios, considering a wide set of outcomes and what the overall implications for bank risk are. Our results highlight an interesting tension between the effects of covered bond issuance on credit risk and liquidity risk: on the one hand credit risk increases in line with Ahnert et al. (2018) and International Monetary Fund (2013), whereas on the other hand liquidity risk decreases. As a result, the implications of covered bond issuance for overall bank risk are ambiguous. When focusing on the risk premium on unsecured bond funding, we show that overall risk declines despite an increase in credit risk. The empirical findings are therefore consistent with the seemingly different views in Ahnert et al. (2018) and Garcia-Appendini et al. (2021) versus Banal-Estañol et al. (2018).

Our paper proceeds as follows: in Section 2, we briefly present the institutional settings of the covered bond market. In Section 3, we outline the data sources we use and describe our empirical strategy. Then in Section 4 we present results. We demonstrate how covered bond issuance leads to rebalancing of banks' portfolios in Section 4.1, and how it impacts overall banks' balance sheet liquidity, bank risk and profitability in Section 4.2. In Section 4.3, we explore the mechanisms at work, guided by a simple, stylized model. We provide robustness checks to our identification strategy in Section 4.4. Section 5 concludes.

2 Institutional background

In this section we outline the institutional background of the covered bond market in Norway. A covered bond is a debt security issued by banks or mortgage companies that is collateralized by a pool of assets ("cover pool"). Mortgage companies are owned by banks and its sole purpose is the issuance of covered bonds. Specifically, when a bank initiates the issuance of a covered bond, the cover pool is sold from the bank to the mortgage company, which then issues the covered bond.[5] A covered bond and the underlying cover pool is subject to three important types of restrictions. First, the quality of the underlying collateral must be high. Mortgage loans that are included in the cover pool must have sufficiently low loan-to-value (LTV) ratios. The value of the assets in the cover pool must exceed the face value of the covered bond itself, i.e. covered bonds are over-collateralized. Second, the cover pool is dy-

[5]Importantly, any assets transferred to a mortgage company remains on-balance sheet for the bank on a consolidated basis, in contrast to for instance ABS before the financial crisis.

namic: if the quality of certain assets in the covered pool deteriorates and violates the quality requirements, the issuer must replace these assets by other eligible assets or cash. Third and finally, if the issuer goes bankrupt within the maturity of a covered bond, the covered bond holders take control of the cover pool.

After the 2007-2009 global financial crisis, covered bond issuance started to gain momentum across Europe, especially after the ECB accepted covered bonds as eligible collateral and included covered bond purchases in its unconventional monetary policy toolbox. As of 2019q4, covered bonds outstanding worldwide amount to EUR 2.705 trillion, about 90 % of which is issued by banks in European countries. The largest covered bond markets in terms of volume of total outstanding covered bonds as at the end of 2019 are Denmark, Germany, France and Spain, followed by Sweden and Norway (European Covered Bond Council, 2020).[6]

The context of our empirical analysis is Norway, where the necessary legislation for covered bond issuance was implemented on the 1st of June, 2007. Mortgages with an LTV below 75 % were eligible for the cover pool. Norwegian banks started issuing the first covered bonds in the second half of 2007 (Finance Norway, 2018). Covered bond issuance increased substantially thereafter. In the time period from the introduction of covered bond markets until 2012 – the time period we focus on in the empirical analysis – the fraction of mortgages transferred to cover pools increased from 0 to approximately 55 %, as highlighted in Figure 1.

– Insert Figure 1 around here –

In Figure 2 we show that the majority of Norwegian covered bonds are issued in foreign currencies. The birth of the covered bond market was associated with a swap agreement allowing banks to exchange covered bonds for Treasury bills that was launched by the Ministry of Finance in October 2008.

– Insert Figure 2 around here –

Although the swap arrangement only lasted until October 2009, covered bond issuance continued to increase substantially. As Figure 2 shows, the rapid growth in covered bond issuance after 2008 was largely driven by demand from foreign investors. After the end of

[6]Banks in countries such as Denmark, Germany or Spain have long histories of covered bond issuance, whereas there was a wave of covered bond market introductions starting in the 2000s in Finland (2000), Ireland (2001), Sweden (2004), Portugal (2006), Italy and Greece (2007) and in the UK and the Netherlands (2008) (ECB, 2008).

our sample period, covered bond issuance has continued to experience fast growth. As at 2020q3, covered bonds outstanding in Norway amount to 143 billion euros, equivalent to 43 % of Norwegian GDP.

3 Data and methodology

In this section, we outline the data sources we use and describe our empirical approach.

3.1 Data

Our sample period is 2003-2012. Our data is merged from three different data sources. The first data source is quarterly balance sheet data used for supervisory purposes for all Norwegian banks. We exclude foreign branches or subsidiaries in Norway and consider only banks issuing mortgages. We drop banks that only existed before the introduction of covered bonds and include new banks from their third quarter of existence onward.[7] The data source covers 133 banks and 5,150 bank-quarter observations. It provides us with the volume of mortgage transfers from banks to mortgage companies from 2008q4 onward.

There are 21 mortgage companies in our sample, 11 are owned by one bank and 10 are co-owned by several banks. In total, 11 banks are not linked to any mortgage company. We consolidate balance sheet items of mortgage companies and banks. If banks share a mortgage company, we consolidate on the basis of the share of mortgages stemming from bank i on the mortgage company's balance sheet. Between 2008-2012, banks transferred on average 15.17 % of mortgages to mortgage companies. In aggregate, 30.51 % of all mortgages issued were transferred (see Figure 1). We have information on the share of loans on the banks' balance sheets at loan-to-value ratios (LTV) above or below 80 % in 2006q4. This will be important for constructing our treatment indicator, as highlighted in Section 3.2. Table 1 reports summary statistics at the bank-time level.

– Insert Table 1 around here –

Our second data source is loan-level data obtained from the Norwegian Tax Administration. By the end of each year, all banks report all outstanding loan and deposit accounts to the tax administration for tax purposes. In total, we observe 3,885,845 firm-account-bank-year observations, based on 250,545 limited liability firms.[8] We aggregate loans and deposits to

[7] Nine banks enter the market during our sample period.

[8] Limited liability firms represent the vast majority of the Norwegian private sector. In most of the years in our sample, these firms employ roughly 90 % of the private sector labor force.

the firm-bank-year level, which results in 1,627,319 firm-bank-year observations. In our dynamic regression estimation we use 1,355,289 firm-bank-year observations for which we can estimate the symmetric growth rate of loans (see below) from 220,059 firms. On average, a firm maintains a relationship to 1.19 banks, and 83.74 % of firm-year observations are linked to one bank only. A firm has on average 1.57 loans with its bank conditional on the existence of a loan relationship. Table 2 reports summary statistics at the firm-bank-year level.

– Insert Table 2 around here –

In the loan-level regressions we use the symmetric growth rate of credit as dependent variable, defined as

$$\Delta L_{b,f,t} \equiv 2 \times \frac{D_{b,f,t} - D_{b,f,t-1}}{D_{b,f,t} + D_{b,f,t-1}}. \tag{1}$$

where $D_{b,f,t}$ is the outstanding credit volume between bank b and firm f in year t.

We use the fact that we observe both the outstanding debt volume and the interest paid to compute a proxy for the interest rate for every firm-bank-year combination. This interest rate proxy is defined as

$$i_{b,f,t} \equiv 2 \times \frac{\text{Interest paid}_{b,f,t}}{D_{b,f,t} + D_{b,f,t-1}}. \tag{2}$$

We only include interest payments if we also observe a loan in year $t - 1$. To limit the influence of outliers, we truncate $i_{b,f,t}$ at the 1$^{\text{st}}$ and the 99$^{\text{th}}$ percentile.

Our third and final data source is firm-level data from a major credit rating agency on all major balance sheet items and other information on the universe of Norwegian limited liability firms. We add information on firm age, rating and balance sheet variables to investigate the role of firm characteristics in explaining banks' potential change in credit allocation following the introduction of covered bonds. We exclude financial firms. Table 3 shows summary statistics.

– Insert Table 3 around here –

We merge 130,661 firms (933,746 firm-year observations). The median firm has total assets of approximately NOK 2,782,000[9], is 10 years old and has an A rating.[10] We define a

[9]Approximately USD 324,000. 1 USD = 8.58 on 5 March, 2021.
[10]AAA (coded as 1) is the top rating a firm can achieve, while C (coded as 5) is the worst rating.

binary variable $Rating(0/1)$ which is 0 for low-rated firms (A, B or C) and 1 for high-rated firms (AA or AAA).

3.2 Empirical strategy

3.2.1 Exposure to covered bonds and identifying assumptions

Our empirical strategy exploits the fact that only mortgages with an LTV below 75 % ("low LTVs") were eligible for being transferred to the cover pool. As a result, banks with different initial distributions of LTVs in their mortgage portfolios had different scope for issuing covered bonds. As described in Section 3.1 we observe the breakdown of the volume of mortgages with an LTV below and above 80 %. We use this information to approximate the fraction of loans for each bank below the regulatory threshold of 75 %. We construct a treatment indicator equal to 1 for banks that had a share of low LTV mortgages over total mortgages that is above the median of all banks in the quarter before the covered bond introduction (2006q4), i.e. $T_b = 1$. We set $T_b = 0$ for all other banks and refer to them as "low-exposure banks" or "other banks" throughout the text.[11] On average, 84.2 % of mortgages on banks' balance sheets have low LTVs. Banks that we define as high-exposure had on average 89.2 % low LTV mortgages, while other banks had on average 79.2 % low LTV mortgages in 2006q4. In line with Callaway et al. (2021), we also use the continuous ratio of low LTV mortgages over total mortgages as the treatment measure in a robustness exercise and show that the results remain qualitatively similar. Table 4 shows summary statistics on our treatment indicators.

– Insert Table 4 around here —

Note that our treatment definition does not exclude the possibility that low-exposure banks issue covered bonds. We merely capture the fact that high-exposure banks could more readily issue covered bonds due to the availability of eligible mortgages on their balance sheets. Hence, we capture the difference in the intensity of exposure to the introduction in covered bonds. To illustrate this difference, we show in Figure 3 the fraction of mortgages transferred to the cover pools for high-exposure banks and other banks, respectively. By 2011, the fraction of mortgages transferred by high-exposure banks was approximately 70% larger compared with other banks.

– Insert Figure 3 around here —

[11] Note that we slightly overestimate the share of eligible mortgages for *all* banks in our sample and hence introduce a slight measurement error in T_b.

Over time, other banks can shift the supply of credit towards low-LTV mortgages relative to high-exposure banks. However, this is likely to be a slow-moving process, as shown in Figure C.1 in Appendix C, as the cross-sectional differences in the average LTV in banks' mortgage portfolios not only reflect bank factors, but also relatively persistent regional factors such as house prices and borrower type heterogeneity more broadly. However, over time it is likely that banks can adjust the composition of mortgage credit to improve the scope for issuing covered bonds. Hence, our treatment measure T_b is meant to capture the short- and medium-run effects of exposure to the introduction of covered bonds. We therefore focus on the impact of covered bonds on bank outcomes only up until six years after the legal change was implemented.

At the bank-level, the fraction of low-LTV mortgages has strong predictive power on post-treatment mortgage transfers to cover pools. In Table 5, we report the results from a univariate regression of the fraction of mortgages transferred post-treatment against the pre-treatment fraction of low-LTV mortgages. There is a strong and statistically significant relationship, suggesting that a 1 percentage point increase in the ratio of low-LTV mortgages to total mortgages pre-treatment is associated with a 0.19 percentage point increase in the fraction of transferred mortgages post-treatment. Moreover, the fraction of low-LTV mortgages explains roughly half of the variation in the fraction of mortgages transferred. We thus conclude that our exposure measure captures banks' subsequent issuance of covered bonds well.

– Insert Table 5 around here –

In Table B.1 in Appendix B, we report summary statistics on a range of outcomes for banks defined as high-exposure and other banks in the pre-reform period. We also include the results from t-tests on the difference between the two groups. Importantly, our identification strategy outlined below does not rely on similarities in these measures across high- and low-exposure banks. High-exposure banks are slightly larger in size and issue slightly more mortgages and firm loans. The share of loans over total assets is slightly lower for the high-exposure banks, though the difference amounts to 0.007 percentage point only. The two groups do not differ in terms of mortgages and firm loans over total assets or over total loans. High-exposure banks hold less HTM (hold-to-maturity) financial assets over total assets, but more MM (marked-to-market) financial assets over total assets compared with other banks. The differences are also statistically significantly different from zero. We include bank fixed effects in our regression specification in order to control for level differences. In the robustness check in Section 4.4, we further show that banks do not differ in terms of ex ante risk-taking behavior.

In the next subsections, we outline our empirical strategy at the different levels of analysis.

3.2.2 Bank level

We estimate the following dynamic estimation equation at the bank level:

$$Y_{b,t} = \alpha_b + \sum_{\tau} \delta_\tau \mathbf{1}_{t=\tau} + \sum_{\tau=2003q1,\tau\neq 2006q4}^{2012q4} \gamma_\tau \ (\mathbf{1}_{t=\tau} \times T_b) + \epsilon_{b,t}. \tag{3}$$

Dependent variables $Y_{b,t}$ are balance sheet items of bank b in year-quarter t. We focus on outcomes in ratios, but also verify whether the differences we observe are due to changes in the numerator or denominator by focusing on the log level of the various variables. The regression includes bank fixed effects (α_b) and quarter-year fixed effects (δ_τ). Standard errors are clustered at the bank level.

We interact the treatment variable T_b with indicators for every quarter-year. We leave out 2006q4 as the base quarter-year before the introduction of covered bonds in 2007. With this dynamic approach, we can trace the effect of the issuance of covered bonds on a quarterly basis. Moreover, we can investigate whether outcomes differ pre-treatment by testing whether γ_τ is significantly different from zero for $\tau < 2006q4$.

3.2.3 Loan level

We estimate the following dynamic estimation equation at the firm-bank level:

$$Y_{f,b,t} = \alpha_{f,b} + \sum_{\tau} \delta_\tau \mathbf{1}_{t=\tau} + \sum_{\tau=2003,\tau\neq 2006}^{2012} \gamma_\tau \ (\mathbf{1}_{t=\tau} \times T_b) + \epsilon_{f,b,t}. \tag{4}$$

Dependent variables are symmetric growth of loans of firm f with bank b in year t defined as in equation (1), as well as the interest rate paid by firm f to bank b in year t, approximated as in equation (2). We interact the treatment variable T_b with indicators for every year. We leave out 2006 as the base year before the introduction of covered bonds in 2007. We include bank-firm fixed effects $\alpha_{f,b}$, as well as time fixed effects (δ_τ), and cluster standard errors at the bank level.

To control for firm-level demand shocks, we exploit the structure of our loan-level data to control for different firm characteristics to ensure that we compare outcomes from relatively similar firms. Specifically, we follow two different approaches. First, we follow Degryse et al. (2019) and introduce industry-location-size-time fixed effects, defined as the two-digit industry code, two-digit zip-code, deciles of total assets and year to control for local, industry- and size-specific demand effects. Their approach is especially suitable for data consisting of many small firms with single bank links, as in our case (83.74 % of firm-year observations are by firms linked to one bank only). Second, we follow Khwaja and Mian (2008) and introduce firm-time fixed effects in the sample of multi-bank firms.

3.3 Threats to identification

Our identifying assumption is that the outcomes we consider would be similar—conditional on a set of fixed effects depending on the level of analysis—for high- and low-exposure banks in the absence of the introduction of covered bonds. Conditional on this assumption being true, we can then interpret our estimates as the causal effect of covered bond issuance on bank outcomes. In this section, we discuss factors which may potentially invalidate this interpretation. It is useful to group the potential identification challenges into four: systematic differences, confounding credit demand shocks, confounding credit supply shocks, and anticipation effects.

Systematic differences The first threat to identification is that banks with different initial mortgage portfolios are structurally different in terms of outcomes. For instance, if banks with a high fraction of low LTV mortgages and thus a larger share of cover pool transfers increase their firm lending share throughout our sample period, we would estimate a positive and significant effect of low-LTV mortgages on firm lending that would not be due to the introduction of covered bonds.

An advantage in our dynamic difference-in-differences approach is that it allows us to directly test for systematic differences between banks according to the exposure measure, by estimating period-specific treatment effects also prior to the introduction of covered bonds. Specifically, we can explore if there were parallel trends among banks with different fractions of low-LTV mortgages prior to the transition by testing if $\gamma_\tau = 0 \; \forall \; \tau < 2006q4$ in equations (3) and (4).

Confounding credit demand shocks Even if banks with different exposures to the introduction of covered bonds are similar prior to 2007, they may experience different credit demand shocks in the subsequent years. This is a concern as the introduction of covered bonds coincided with the financial crisis, which could affect firms differently. Shocks to banks' firm clients could affect our results if firms and banks are systematically linked. For instance, banks that are less exposed to the introduction of covered bonds could lend more to export-oriented firms, or more generally to regions with relatively high exposure to the international downturn associated with the financial crisis. In that case, differences in credit growth between banks with different initial fractions of low-LTV mortgages could be a result of a reduction in credit demand from customers of low-exposed banks rather than an increase in credit supply by high-exposed banks.

In order to alleviate this concern, we control for firm demand shocks with an extensive set of fixed effects, that is industry-location-time-size fixed effects as well as firm-time fixed effects as described in Section 3.2.3. The latter approach holds firm factors fixed, provided that they are invariant at the firm $\times$ year level. Moreover, by observing both quantities and prices at the loan level, we can exploit the fact that demand and supply shocks move prices in opposite directions. For instance, an increase in the volume of credit and a decline in the interest rate on loans from high-exposure banks would only be consistent with a relative expansion in the supply of credit.

Confounding supply shocks A third threat to identification could arise if there are other factors affecting banks' supply of credit that are correlated with our exposure measure. One potential concern is that banks with a large fraction of low-LTV mortgages were less exposed to the financial crisis and as a result had higher risk-bearing capacity than other banks, which in turn could induce them to rebalance their portfolio.

In general, the Norwegian economy and financial system were relatively unaffected by the financial crisis. Norwegian banks were affected indirectly in primarily two ways. First, banks to varying degrees invested in financial assets that would potentially depreciate in value ex post due to the ongoing crisis. This would especially be a relevant concern for financial instruments that are marked-to-market. Second, a more indirect contagion happened in the form of short-term liquidity stress in Norwegian interbank markets. The interbank spread increased substantially in mid-September 2008. It was lowered to pre-crisis level towards the end of 2008, but in theory this short-term disruption in access to liquidity could confound at least some of our results.

In order to gauge the severity of these concerns, we investigate how our treatment measure correlates with (1) banks' holdings of financial instruments that are marked-to-market and (2) banks' reliance on interbank funding, both measured at the end of 2006. A negative correlation between our treatment measure and these measures would indicate that exposure to the crisis through either measure could pose an identification concern.

Further, changes in risk-taking behavior during the financial crisis conditional on our treatment measure might confound our results. If low-exposed banks had a larger risk appetite before the financial crisis and became more risk averse during the crisis as in Guiso et al. (2018), differential effects between high-exposure and other banks might be merely driven by relative changes in risk aversion over time. In order to address this concern, we investigate differences in ex ante risk-taking across high- and low-exposure banks.

A final potential confounding credit supply shock is the transition to Basel II. The transition to Basel II took place in 2007, and entailed for most banks a reduction in average risk-weights, applied to retail loans and mortgages with a low LTV. This could then imply that there was also a larger reduction in the effective capital requirement for banks that were high-exposure according to our measure and that this relative reduction in the capital requirement is driving our results. The largest absolute reduction in risk weights for banks computing risk weights under the standard method was for retail firm loans.[12] As a robustness check, we therefore use balance sheet information and actual changes in risk weights to compute—bank by bank—the actual reduction in the capital requirement due to the Basel II transition. We can then correlate the capital requirement reduction with our treatment measure to investigate whether banks that were more exposed to the Basel II transition were also more exposed to the introduction of covered bonds.

Anticipation effects A final concern is that high-exposure banks according to our measures adjusted prior to the introduction of covered bonds. This is a valid concern if the introduction of covered bonds were known well in advance. Note that such anticipation effects are likely to lead us to underestimate the effects of covered bond issuance. Judging from Figure C.1 in Appendix C, it seems unlikely that banks selected themselves into the group of high-exposed banks, as the share of eligible mortgages in the pre period is fairly stable over time. Moreover, the flexible difference-in-differences approach allows us to explicitly map out

[12]The risk weight on loans in the retail portfolio was lowered from 100 % to 75 %. The risk weight on mortgages with an LTV below 80 % was reduced from 50 % to 35 %.

when high-exposure banks adjust relative to the actual introduction of covered bonds and hence we can be somewhat agnostic about the exact timing of the treatment.

4 Results

In this section we assess the impact of covered bond issuance on banks' balance sheets. We also outline a theoretical model to explain how covered bond issuance affects bank portfolio allocation and test the model's predictions. We end the section by showing a series of robustness exercises.

4.1 Results on portfolio rebalancing

4.1.1 Credit at bank level

We start by comparing the evolution of credit at the bank level, and show the main results at this level of aggregation in Figure 4 and Figure 5. Accompanying statistics of the regression output are listed in Table 6.

First, consider how the introduction of covered bonds affected lending in general. In Figure 4a we plot the raw data of the share of lending over total assets from 2003-2012. The average lending share of high-exposure banks is depicted in red, while the average for other banks is in blue. Both groups decreased the share of lending to total assets, while the decline was largest for high-exposure banks. The coefficient plot from estimating equation (3) in Figure 4b highlights that the relative reduction is statistically significant: high-exposure banks show a statistically significantly lower ratio of total loans over total assets compared to other banks in the post period from 2011q4 onward, whereas there are no differences in the pre period. The relative reduction in loans over assets for high-exposed banks is not driven by a reduction in total lending; there is even a mild relative increase in total lending as we show in Figure B.1b in Appendix B. The reduction is rather due to a relative increase in total assets, as we highlight in Figure B.1a. By issuing covered bonds, high-exposure banks expand their balance sheets relative to other banks.

– Insert Figure 4 around here –

Figure 4c plots the raw data of the share of mortgage lending over total loans. There is a divergence in mortgage lending between the two groups from 2008 and onward. The difference is inconsistent with the view that covered bonds would lead to an expansion of mortgages as often discussed (Nicolaisen, 2017)—on the contrary, the high-exposure banks reduce the fraction of mortgages compared with other banks. Importantly, given that the data is consolidated at the bank-credit company level, this reduction in the fraction of mortgages is not mechanically related to mortgages being transferred to the mortgage company for the purpose of issuing covered bonds. In Figure 4d we plot the coefficients from estimating equation (3) with mortgages over total loans as dependent variable. Before the introduction of covered bonds, there are no statistically significant time-varying differences between the two groups. After the introduction, high-exposure banks lower their mortgages to total loans ratio compared with other banks. The differences are statistically significantly different from zero at the 5 % level from 2008q2 and at the 1 % level from 2008q4 onward. The relative reduction in the mortgage share is driven by a relative increase in total lending, whereas total mortgage lending does not differ between the two groups, as we show in Figure B.1c in Appendix B. The reduction in the mortgage share is quantitatively large. High-exposure banks lowered the mortgage share by up to 5.7 percentage points compared with other banks over the post period. This compares to a pre-period mortgage share for high-exposure banks of 64.8 %, suggesting that the relative reduction in the mortgage share in the post period is sizable and corresponds to almost 9 % of the average mortgage share of high-exposure banks in the pre period.

– Insert Figure 5 around here –

– Insert Table 6 around here –

Next, we assess the fraction of firm loans relative to total loans. In Figure 5a we illustrate that firm loans increase for high-exposure banks relative to other banks post-2007. In Figure 5b we show that there are no differences between the two groups in the pre period compared with 2006q4. Differences in the post period are statistically significantly different from zero at the 1 % level in 2007q2 and at the 5 % level thereafter until 2009q2, with varying significance levels afterwards. The firm lending share is up to 1.9 percentage points higher for high-exposure banks compared with other banks. This is an increase of 7.5 % relative to the average share of firm lending for high-exposure banks in the pre period (25.7 %). As total lending mildly increases for high-exposure banks relative to other banks, the increase in the firm share is driven by an even larger relative increase in firm lending, as highlighted in Figure B.1d in Appendix B.

A valid concern against our identification could be that it is not the high-exposed banks which adjust their lending portfolios, but low-exposed banks which actually increase their mortgage lending in order to be able to participate in covered bond markets and hence we see a negative differential effect between high and low exposed banks in terms of the share of mortgages in their lending portfolio. However, there are two stylized facts which speak against this hypothesis: First, as we show in Figure 5a there is a clear surge in the share of firm loans over total loans for high exposed banks after the introduction of covered bond markets. Second, there is actually *no difference* in mortgage lending between the two groups as we show in Figure B.1c in Appendix B where we compare log level mortgage issuance. The difference between the two groups is driven by increases in firm lending by high exposed banks compared to low exposed banks (see Figure B.1d) which also leads to higher total lending of high exposed banks compared to low exposed banks (see Figure B.1b).

4.1.2 Credit at loan level

Next, we turn to the loan level to further shed light on the increase in firm lending. Using loan-level data, we can tighten identification by adopting firm controls to address possible confounding firm-level demand shocks. We estimate the dynamic regression equation (4) with the symmetric growth rate of debt as defined in equation (1) and our interest proxy as defined in equation (2) as dependent variables. Further, we provide evidence for whether the increase in firm credit for high-exposure banks is uniform across all firms, or whether it is driven by a subset.

Loan growth and interest rates In Figure 6a we show the average of the symmetric growth rate of loans extended by high-exposure banks in red, and for loans extended by other banks in blue over time. After the introduction of covered bonds, loan growth for loans stemming from high-exposure banks increases, whereas loan growth decreases for loans from other banks. In Figure 6b we plot the coefficients from estimating equation (4) with symmetric growth of debt as the dependent variable. Estimation results and accompanying statistics are reported in Table B.3 in Appendix B. Loan growth does not differ in the pre-reform period between the two groups. From 2008 onward, loan growth from high-exposure banks is larger than from other banks compared with base year 2006. The difference is statistically significantly different from zero at the 1% level for most years. High-exposure firm-bank pairs have a symmetric growth rate which is on average up to 0.05 higher than for other firm-bank pairs. The relative change is substantial: it compares to an average symmetric growth rate for loans from high-exposure banks in the pre-reform period of -0.073. These results are consistent with the findings at the bank level.

To further sharpen identification, we apply the estimation strategy as proposed by Degryse et al. (2019) and introduce industry-location-size-time fixed effects to control for confounding loan demand shocks. In Figure 6c we show the corresponding coefficient plot. Again, we do not observe differences between the two groups in the pre-reform period. From 2008 onward, high-exposure firm-bank pairs have larger loan growth than loans from other banks. The difference is statistically significantly different from zero in 2010 at the 10 % level, in the years 2008, 2009 and 2011 at the 5 % level and in the year 2012 at the 1 % level. The symmetric growth rate for loans from high-exposure banks is up to 0.031 higher than the symmetric growth rate for loans from other banks. Given that the average symmetric growth rate for high-exposure firm-bank pairs in the pre-reform period is -0.048, we observe again a substantial relative increase.

– Insert Figure 6 around here –

Finally we follow Khwaja and Mian (2008) and introduce firm–year fixed effects for the sample of firms borrowing from multiple banks. In Figure 6d we show the corresponding coefficient plot. There are no differences between the two groups in the pre period. Although our estimates become more imprecise, we still observe a positive difference between the two groups for the post-treatment year 2008, which is statistically significantly different from zero at the 10 % level. In terms of economic magnitude, the effect becomes stronger compared with the estimates for the full sample. Specifically, loan growth increase by 0.052 for high-exposure firm-bank pairs compared with loan growth for other firm-bank pairs. Given that for high-exposure firm-bank pairs in this sub-sample the average symmetric growth rate in the pre-reform period is -0.059, we observe again a substantial relative increase of the loan growth rate.

To investigate whether banks changed their pricing behavior, we next examine the impact of being linked to a high-exposure bank on the proxied interest rate. In Figure 7a we show the development of interest rates for high-exposure firm-bank pairs and other firm-bank pairs over time. The raw data suggest that firms paid slightly lower interest rates after 2009 if the loan stemmed from a high-exposure bank. In Figure 7b we show the coefficient estimates from estimating equation (4) with our proxy for the interest rate as dependent variable. We can see a slight move towards lower interest rates for loans from high-exposure banks. The estimates, however, are somewhat imprecise, and we cannot reject the null hypothesis that the coefficients are zero. As before, we follow Degryse et al. (2019) and introduce industry-location-size-time fixed effects and plot the corresponding coefficients in Figure 7c. Again, we see a negative difference between the two groups in the post-reform period, but the difference is imprecisely measured. Finally, we proceed by introducing firm-time fixed effects as in Khwaja and Mian (2008). Figure 7d shows the corresponding coefficient plot. The results are in line with the previous findings.

– Insert Figure 7 around here –

Importantly, the results in Figure 7 suggest that interest rates do not *increase* for loans from high-exposure banks. This, combined with the fact that point estimates decline, provides support for our interpretation of the results above, namely, that the increase in firm credit comes from a credit supply expansion rather than an increase in credit demand.

Low-rated and young firms obtain more lending Next, we assess whether the increase in firm credit is uniform across all firms or driven by a subset of firms. Two important dimensions for understanding the heterogeneous impact of credit supply expansions in the existing literature are firm risk and firm age (Gertler and Gilchrist, 1994; Holmström and Tirole, 1997). We therefore group the firms in our sample according to firm rating and firm age in 2006. We define a firm as low-rated if it has a rating of A or below (A, B, or C), and a firm as high-rated if it has a rating of AA or AAA. We define a firm as young if it has an age below or equal to the median firm age (eight years), and a firm as old if it has an age above the median. We re-estimate equation (4) for the sample of low- and high-rated firms, as well as young and old firms separately, using the symmetric growth rate of loans as dependent variable. In Figure 8 we show coefficient plots and in Table B.4 in Appendix B regression results.

– Insert Figure 8 around here –

– Insert Table 7 around here –

In Figure 8a we show that for the sample of low-rated firms there is a positive differential effect between high-exposure and low-exposure banks from 2008 and onward, which lasts until the end of the sample period and amounts to up to 0.063. For ex ante high-rated firms, there is a significant difference in 2008, which levels off quickly. As we show in Table 7, the symmetric growth rate of debt on average increases by 0.05 for ex ante low-rated firms that borrow from high-exposure banks compared with other banks. Given that the average growth rate for all treated firm-bank pairs in the pre period is -0.073, the differential effect between high- and low-exposure banks of 0.05 is again substantial. For the sample of high-rated firms the average differential effect is close to zero.

In Figure 8b we show the results when grouping firms according to age. The relative increase in credit is larger for the sample of young firms, consistent with Gertler and Gilchrist (1994).

4.1.3 Asset liqudity at bank level

Next, we assess whether there are changes in banks' investments in financial assets. As in Section 4.1.1, the unit of analysis is now bank $\times$ year-quarter, and we estimate equation (3) with financial asset holdings as dependent variables.

In Figure 9 we plot the raw data in the left column, and coefficients from a dynamic regressions in the right column. In Table 8 we report the corresponding regression statistics. In the first row in Figure 9 we show the evolution of hold-to-maturity (HTM) financial assets, while we show the evolution of marked-to-market (MM) financial assets in the second row. According to Figure 9a, high-exposure banks change their investment behavior after the introduction of covered bonds. Specifically, the share of HTM assets over total assets increases relative to other banks.

– Insert Figure 9 around here –

– Insert Table 8 around here –

In Figure 9b we show that there are no statistically significant differences between the different bank types before the introduction of covered bonds. In the post period, the difference increases and high-exposure banks have a higher share of HTM securities over total assets compared to other banks. The difference is statistically significantly different from zero at varying levels up to 2010q1 and at the 1 % level thereafter. Up to 2011q4, high-exposure banks increase the share of HTM assets by two percentage points. Given that the share of HTM securities over total assets for high-exposure banks in the pre-reform period is 2.2 %, the relative increase corresponds to more than 90 % of the average share of HTM assets to total assets for high exposed banks in the pre period. As highlighted in Figure B.1e in the Appendix B, this increase is driven by an increase in the volume of HTM assets.

In the second row we show the impact of covered bond issuance on holdings of marked-to-market financial instruments. After the introduction of covered bonds, there is a relative increase for high-exposure banks. The difference varies around 2 percentage points. Given that high-exposure banks had approximately 5 % of their pre-period assets in MM financial assets, the relative increase in MM asset holdings corresponds to 40 % of the latter. We discuss potential explanations for the differential evolution of HTM and MM financial asset holdings in Section 4.3.

Overall, the results in Figure 9 show that the introduction of covered bonds leads to a substantial increase in bank holdings of financial instruments. Especially the increase in HTM financial instruments entailed an increase in the overall liquidity position of the high-exposure banks, relative to other banks.

4.2 Results on bank balance sheet liquidity, risk and profitability

In the previous section, we documented an increase in lending to risky firms as well as an increase in the holdings of liquid assets. An important question is whether the balance sheet adjustments lead to overall riskier banks due to increased credit risk, or whether the increased holdings of liquid financial assets offset credit risk, or even outweigh it. In this section, we therefore investigate how covered bonds impact overall bank risk, taking into account overall balance sheet liquidity, credit risk and bank profitability.

– Insert Figure 10 around here –

– Insert Table 9 around here –

Liquidity versus credit risk Covered bonds can increase banks' funding liquidity as covered bonds are a source of long-term funding, as well as market liquidity as they allow banks to raise cash. To get a comprehensive view of the overall liquidity position of the banks in our sample, we use Berger and Bouwman (2009)'s definition of liquidity creation, which encompasses both the liquidity of assets and liabilities. We take the negative of this index as a measure of banks' overall balance sheet liquidity. In Figure 10a we plot the average balance sheet liquidity for high-exposure banks in red and other banks in blue. Both groups of banks increase their balance sheet liquidity after the introduction of covered bonds. In Figure 10b we show the coefficient plot from estimating equation (3) with balance sheet liquidity as dependent variable and we report regression statistics in Table 9. Though both groups increase balance sheet liquidity, there is a relative increase for high-exposure banks especially after 2009.[13]

[13] High-exposure banks increase balance sheet liquidity compared with low-exposure banks by up to 0.03 percentage points. Given that mean balance sheet liquidity for high exposed banks in the pre period is -0.34, the relative increase corresponds to 8.8 % of the latter.

While balance sheet liquidity improves, we also document that covered bond issuance increases credit risk. It is therefore not clear how *overall* bank risk evolves. The risk premia asked by unsecured creditors provides us with an indication of the market's perception of overall bank risk. In Figure 11a we plot the average interest rate paid by banks for subordinated debt.[14] After the introduction of covered bonds in 2007, we see a wedge building up between the two groups, with high-exposure banks showing on average lower funding costs on subordinated debt. In Figure 11b we show results from estimating equation (3) with interest paid on subordinated debt as dependent variable and we report the regression output in Table B.5 in Appendix B. High-exposure banks pay lower funding costs on subordinated debt compared with other banks and the difference is statistically significantly different from zero at the 5 % level in 2008 and 2009.[15] We conclude that covered bond issuance reduces bank risk, suggesting that any positive effects from increased balance sheet liquidity offset any potential increase in credit risk due to more firm lending.

– Insert Figure 11 around here –

Bank profitability Finally, covered bonds have sizable effects on bank profitability. In Figure 11c we show the evolution of average total funding costs over time and in Figure 11d the coefficient plot from estimating equation (3) with interest paid on total funding as dependent variable. Covered bonds lower funding costs on secured debt, and as we have shown in the previous paragraph also on subordinated debt. This is reflected in the evolution of total funding costs: High-exposure banks pay lower total funding costs compared with other banks. The negative differential effect is statistically significantly different up to the 1 % level in 2011.[16]

In Figure 11e we assess net interest margins defined as net interest income over total assets as a measure of banks' profitability. Net interest margins decrease for both groups,

[14] Note that yearly data such as the banks' income statements that we use to construct the funding cost measures are reported in annual frequency and that not all banks use subordinated debt in every period, hence the number of observations is reduced.

[15] High-exposure banks reduce funding costs on subordinated debt compared with other banks by up to 4.79 percentage points. Given that mean funding costs in the pre period for high-exposure banks is 5.70 %, the relative decrease corresponds to 84 % of the latter.

[16] High-exposure banks reduce their total funding costs in the post period compared with other banks by up to 21 basis points. Given that average funding costs in the pre-period for high-exposure banks is 2.38 %, the relative reduction corresponds to 8.8 % of the latter.

but less so for high-exposure banks. In fact, there is a mild positive differential effect as we show in Figure 11f.[17]

We conclude that issuing covered bonds not only reduces overall bank risk, but also reduces total funding costs by reducing interest paid by banks and therefore increases banks' profitability.

4.3 Inspecting the mechanism

In this section, we outline a simple model to theoretically analyze the mechanisms through which covered bond issuance can induce a reallocation of credit away from mortgages to corporate loans such as the one documented above. We then show support for some of the testable predictions of the model.

4.3.1 Summary of a stylized model of bank lending and covered bonds

In Appendix A, we present a stylized model to clarify how a risk-neutral bank adjusts its portfolio and risk-taking in response to an asset encumbrance technology such as covered bonds. The asset encumbrance technology improves the liquidity of the assets that are subject to potential encumbrance. The bank provides two products that meet creditors' different risk appetites: a safe demand deposit contract with non-state contingent return backed by encumbered safe assets (call it mortgage lending) and a risky financial security with state-contingent return backed by a risky project (call it firm lending). Ideally, the bank prefers to invest more funds in risky firm lending since it has a higher expected return, but this increases volatility in asset return, making it more uncertain whether the bank is able to meet depositors' demand for liquidity. As a response, depositors charge a higher risk premium when banks invest more in firm loans. In equilibrium, the optimal credit allocation of the bank equates the marginal gain from firm lending by the marginal increase in the risk premium.

Asset encumbrance technology, such as covered bonds, reduces the funding cost of mortgages while also increasing their liquidity. This generates two diverting effects on the optimal credit allocation: on the one hand, there is an *income effect* that encourages the bank to invest more in safer mortgages as the return from mortgage lending increases. However, there is also a *substitution effect* that encourages the bank to engage more in riskier firm lending due to the enhanced balance sheet liquidity. This liquidity effect occurs because a more

[17] High-exposure banks increase their net interest margin in the post period compared with low-exposure banks by up to 0.001. Given that mean interest margins in the pre-period for high-exposure banks is 0.022, the relative increase corresponds to 4.5 % of the latter.

liquid balance sheet reduces the risk premium that depositors charge banks when engaging in firm lending. If the risk aversion of depositors is very high and/or firm risk is high, the bank would choose to invest more in mortgage lending to reduce asset return volatility and the risk premium, i.e. the return effect dominates. If the risk aversion of depositors is very low and/or firm risk is sufficiently low, the bank would invest more in risky firm lending for higher profit. Such effect is particularly strong for banks with low initial liquidity. In the lens of our model, we would therefore expect to see a larger shift from mortgages to firm loans following the introduction of covered bonds for banks with low initial liquidity. We refer to this testable hypothesis as H1.

H1: Previously liquidity-constrained banks shift more to firm lending.

The bank in our model balances the trade-off between higher returns and higher funding costs when considering the optimal firm lending share. On the one hand, a higher firm lending share would increase bank profits due to higher yields. On the other hand, more firm lending would increase the risk premium the bank is charged by its depositors. If the existing firm lending is sufficiently safe, the former effect dominates the latter in our model and we would therefore expect that banks with initially safer borrowers would have stronger incentives to reallocate their portfolio towards firm lending. We refer to this testable hypothesis as H2.

H2: Banks facing lower firm risk shift more to firm lending.

We now turn to test these predictions.

4.3.2 Heterogeneous effects of the introduction of covered bonds

H1: Liquidity constraints We divide banks into two groups based on their 2006q4 ratio of net liquid assets to total assets as defined in Section 3.1 to test whether banks with low liquidity increase firm lending more than other banks. *Net* liquid assets jointly captures banks' market liquidity *and* funding liquidity and the risks emerging from the discrepancy between the two. We then re-estimate equation (3) for the sample of low- and high-liquidity banks respectively, using different bank-level portfolio shares as dependent variables.

In Figure 12 we show the result from this exercise, using the share of mortgages (left panel) and firm loans (right panel). Starting with the left panel, the fraction of mortgages declines for high-exposure banks irrespective of whether we consider the low- or high-liquidity sample. In terms of magnitudes, however, the drop is roughly three times the size for banks in the low-liquidity sample. In Table 10 we summarize the average treatment effect over the post-2007q6 period within the low- and high-liquidity samples respectively. In the sample of high-liquidity banks, the mortgage share decreases by approximately -2.0 percentage points on average. In the low-liquidity sample, however, the drop in the mortgage share is approximately -6.5 percentage points on average.

– Insert Figure 12 around here –

In the right panel, we show the results focusing on firm lending. In this case, the results are starker - while there is no treatment effect in the high-liquidity sample, high-exposure banks in the low-liquidity sample increase the firm lending share by approximately 3.3 percentage points on average. Generally speaking, the larger treatment effects on firm lending are consistent with the model outlined above. Our results are in line with previous findings that liquidity is a constraint on firm lending (Webb, 2000). Once liquidity improves, it is optimal for banks to provide more firm credit.

Next, we consider other assets. Starting with the left panel in Figure 13, we show that high-exposure banks in the low-liquid sample increase HTM financial assets, while there is no treatment effect in the high-liquidity sample. We report corresponding regression statistics in Table 10. This qualitative difference is completely switched when focusing on financial assets that are marked-to-market. In this case, there is no treatment effect for low-liquidity banks, while high-liquidity banks expand their relative holdings of financial instruments marked-to-market.

– Insert Figure 13 around here –

– Insert Table 10 around here –

What can explain the differences in financial asset holdings? One plausible explanation is that the introduction of covered bonds implies a new financial asset that is attractive to invest in, and that initial bank liquidity needs determine whether banks invest in them primarily to pledge to lenders to obtain further liquidity or whether they treat it as a pure financial investment. In the former case, financial assets need to be defined as held-to-maturity, whereas in the latter case they can be marked-to-market.

H2: Credit risk A second testable prediction of our model is that banks are more likely to switch to firm lending when the returns from doing so are high. In our model, the bank is risk-neutral, so a higher marginal return on firm credit would incentivize banks to engage more in firm lending. In fact, for most banks and in most time periods, firm lending is more profitable than mortgage lending. In 92 % of bank-year observations the approximated interest rate on firm lending is higher than on other lending.[18] Further, according to SSB (Statistics Norway) the average interest rate margin on loans to non-financial corporations between 2014q1 and 2021q1 was 2.22 % and while it was 1.60 % on mortgages, which also reflects higher yields on firm lending on average. However, according to our model, banks have to balance higher yields from firm lending with higher funding costs due to higher risk premia. We examine prediction *H2* from our model that banks rather turn to firm lending if credit risk is relatively low. We measure credit risk according to interest yield on firm lending and divide our sample at the median.

– Insert Figure 14 around here –

– Insert Table 11 around here –

We show in blue in Figure 14a that banks with low firm yields decrease the share of mortgages over total lending quicker than banks with high firm yields. However, when taking averages over the whole post period, banks with high firm yields reduce mortgage lending by -1.3 percentage points more than banks with low firm yields, as can be seen in Table 11. Nevertheless, we show in Figure 14b that the increase in firm lending following the introduction of covered bonds is driven by banks with initially lower yields on firm loans. On average, these banks increase the share of firm lending by 3.9 percentage points as reported in Table 11, whereas banks with high-yield firm loans do not increase firm lending. We conclude that banks with lower initial credit risk have more credit risk capacity and hence increase firm lending to more risky borrowers as a response to the introduction of covered bonds.

4.4 Robustness

We address the concern of confounding demand shocks in our baseline approach at the loan level in Section 4.1.2 by including an extensive sets of fixed effects in our regression estimations to control for firm loan demand. Also, we control for systemic differences between banks with bank fixed effects in estimations at the bank level. Further, we observe whether differences between high-exposure and other banks change in the pre period, and can confirm

[18]We approximate the average interest rate on firm lending per bank from our loan-level data set as in equation (2) and average over all firm-bank observations per bank in 2006. We derive interest on all other lending by subtracting total interest paid by firms per bank from total interest income from loans in banks' income statements and divide it by total lending minus total firm lending.

that for most of our specifications the empirical evidence is consistent with parallel trends in the pre period. However, the analysis above cannot exclude the possibility that there are potentially other confounding *supply-side* (e.g. bank) shocks that affect our results. In Section 3.3 we discussed three potential concerns: exposure to the ongoing financial crisis, changes in relative risk aversion due to the financial crisis, and exposure to the capital requirement reduction due to the transition to Basel II. Below, we show the robustness of our results to these potentially confounding factors. Finally, we also present results with a continuous treatment measure in line with Callaway et al. (2021).

Exposure to the financial crisis To investigate the correlation between our treatment measure and the exposure to the financial crisis, we compute a bank's ratio of marked-to-market financial instruments to total assets and the ratio of interbank borrowing to total assets in 2006q4. These measures are aimed at capturing the two main channels of exposure to the financial crisis, as discussed in Section 3.3. In panels (a) and (b) of Figure B.2 in Appendix B, we plot these variables against our treatment measure, the share of eligible mortgages over total mortgages in 2006q4. For interpretation, we also include the regression coefficient from a univariate cross-sectional regression of the different variables on our treatment measure. In both cases, there is a weak and positive relationship between the exposure variable and our treatment measure. In both cases, we fail to reject the null hypothesis of no significant relationship.

Differences in changes in risk-taking behavior Further, we want to rule out that our results are driven by differences in risk-taking behavior, which might change with the onset of the financial crisis as in Guiso et al. (2018). In Figure B.3 and Figure B.4 in Appendix B we show the correlation of our treatment measure and risk indicators in 2006q4. In particular, in Figure B.3a we show the correlation of our treatment measure with total funding costs, in Figure B.3b with the changes in funding costs from 2006-2008 and in Figure B.3c with funding costs on unsecured debt. Less risk-averse banks should have higher funding costs and hence if high-exposure banks were more risk averse ex ante there should be a negative correlation with funding costs and our treatment measure. However, we find a very mild positive correlation with total funding costs. Moreover, there is no correlation with the change of funding costs at the onset of the financial crisis and with funding costs on subordinate debt.

As further indicators of risk-taking behavior, we show the correlation of our treatment measure with the standard deviation of return on assets over four quarters and over eight quarters in Figures B.3d and B.3e, respectively. If high-exposure banks were more prudent, we would expect them to have a lower standard deviation of return on assets. The correlations are close to zero. Further we show correlations with the share of liquid assets and the share of net liquid assets in Figures B.4a and B.4b, respectively. If high-exposure banks were more prudent before, we would expect to see a positive correlation with the share of liquid assets. There is only a mild negative correlation with net liquid assets.

Finally, we present three further measures to gauge the correlation between our treatment measure and bank risk. Banks with a larger share of eligible mortgage loans show lower equity ratios in 2006q4 in Figure B.4c. This in fact goes hand-in-hand with the definition of our treatment measure: banks that hold more high-quality loans do need to hold less equity. Meanwhile these banks also have lower non-performing loan (NPL) ratios in Figure B.4d, which also reflects the fact that they have more high-quality mortgage loans on their balance sheets. According to these two indicators, banks seem on the one hand less risk-averse due to lower equity ratios, but on the other hand more risk-averse due to lower NPL ratios. There is only one indicator that might indicate higher risk aversion for high-exposure banks: banks with a higher share of eligible assets supply on average higher-rated firms, as can be seen in Figure B.4e.

Transition to Basel II As discussed in Section 3.3, a further potential confounding factor could be the transition to Basel II. In panel (c) of Figure B.2 in Appendix B, we investigate the correlation with the capital requirement change due to the Basel II transition and our treatment measure. Specifically, the Basel II transition reduced capital requirements due to a reduction in average risk weights. The reduction in average risk weights was a function of banks' initial portfolios. We therefore follow Juelsrud and Arbatli-Saxegaard (2020) and compute the reduction in average risk weights due to the Basel II transition for each bank, and multiply that with the headline capital requirement of 8% to get a measure of the actual capital requirement reduction for each bank. We then plot this measure against our treatment variable. There is a very weak and statistically insignificant relationship between the capital requirement reduction due to Basel II and the fraction of low LTV mortgages, supporting our identifying assumptions.

Continuous treatment measure Throughout our analyses we use a binary indicator to measure banks' exposure to the introduction of covered bonds. For robustness, we use our actual continuous treatment measure, the share of eligible mortgages 2006q4, and re-estimate equation (3) in line with Callaway et al. (2021). We show the results in Figure B.5 and in Table B.6 in Appendix B. The results are consistent with the results in the preceding paragraphs.

5 Conclusion

How do banks rebalance their portfolios in response to the possibility of issuing covered bonds? Evidence on that question is rare so far. We aimed to fill this gap by analyzing the consequences of the introduction of covered bond issuance in Norway in June 2007. While some initial concerns were that covered bonds would lead to an expansion of mortgage credit, our main result shows that the opposite took place: banks reallocated funds *from* mortgages and *to* firm loans. However not all corporations benefit from the increases in loan supply. In particular, banks tailor new loan supply to ex ante younger and low-rated firms, thereby increasing credit risk. We further find that banks increase holdings of liquid assets and increase total balance sheet liquidity. We assess risk premia asked by unsecured creditors and find that total bank risk decreases: lower liquidity risky outweighs higher credit risk.

We can reconcile previous contradictory findings in the literature on whether covered bonds increase or decrease banks' risk taking by carving out conditions under which banks shift to more firm lending. We sketch out a model that predicts that banks with low initial liquidity would use the possibility of covered bonds to raise liquidity to extend more risky lending such as firm lending. Further, in the model credit risk needs to be sufficiently low. We find empirical evidence consistent with the predictions of the model.

Our paper raises related issues for future research. One is whether the impact of covered bond issuance on bank lending differs under different institutional and market setups. As our theoretical model predicts, our finding that banks rebalance portfolios from mortgages to firm loans is context-specific and depends on several deep parameters, such as default risk in the firm sector. Our paper thus encourages cross-country studies for a better understanding of how covered bonds influence market outcomes.

Figures and Tables

Figure 1: Share of total mortgages transferred

This figure shows the share of mortgages transferred over total mortgages from 2008q4 until 2017. Note that although banks started to transfer mortgages from 2007q3 onward, ORBOF provides data on transfers from 2008q4 onward only. Source: ORBOF, with authors' own calculations.

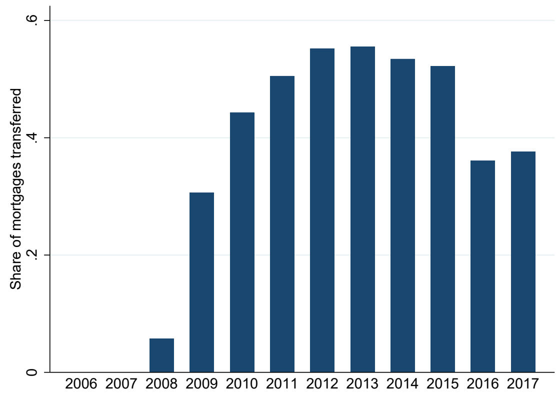


Figure 2: Outstanding debt and currency decomposition of Norwegian covered bonds

This figure shows the outstanding debt (in billion NOK) and currency decomposition (in NOK, denoted by the blue area, or other currencies, denoted by the orange area) of covered bonds issued in Norway from 2007 until 2019. Source: Norwegian covered bonds statistics, Finance Norway.

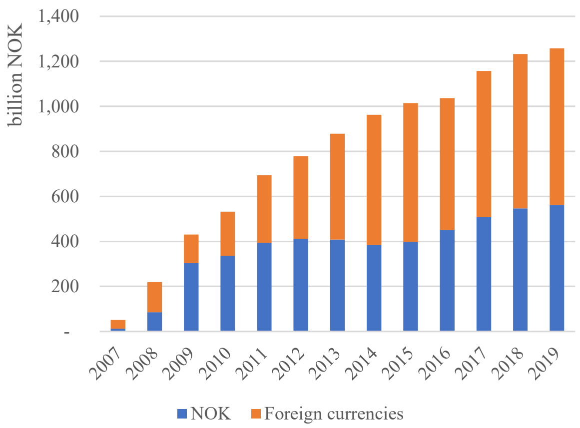


Table 1: Summary statistics at the bank-time level

This table reports summary statistics for 133 banks, or 5,150 bank-quarter-year observations. HTM are hold-to-maturity securities, and MM are marked-to-market securities. We follow Deep and Schaefer (2004) and define net liquidity over total assets as the share of net liquid assets over total assets as (marked-to-market (MM) assets + central bank reserves - interbank borrowings - certificates) / total assets. We define balance sheet liquidity over total assets as the negative of Berger and Bouwman (2009)'s definition of liquidity creation. We use Berger and Bouwman (2009)'s definition and adapt it to the availability of our balance sheet data. Illiquid assets encompass firm loans, intangible HTM assets, HTM owner assets and other assets. Liquid assets are assets at the central bank, HTM bonds, other HTM assets, and MM assets. Illiquid liabilites are subordinated debt and equity. Liquid liabilities are deposits and deposits from the central bank. We add the sum of illiquid assets and the sum of liquid liabilities with weights of 0.5 and subtract the sum of liquid assets and illiquid liabilities with weights of 0.5. We divide by total consolidated assets and multiply the index by -1. We estimate the interest on total funding costs in % as the share of interest costs over total liabilities, and the interest on subordinated funding in % as interest costs on subordinated funding over total subordinated debt. We truncate interest paid on subordinated debt at the 1st and the 99th percentile per year due to outliers and set negative values to missings.

	N	Mean	Sd	Min	Median	Max
Logs						
Total assets	5,150	14.957	1.409	11.934	14.674	21.519
Total loans	5,150	14.781	1.340	11.436	14.508	20.820
Mortgage loans total	5,150	14.506	6.226	10.087	14.302	20.283
Mortgage loans transferred to credit company, 2008-2012	2,122	10.347	5.578	0.000	12.447	20.114
Firm loans	5,150	13.327	1.341	0.000	13.014	19.667
HTM	5,150	10.831	4.510	0.000	10.554	18.803
MM	5,140	11.447	3.061	0.000	11.838	19.815
Ratios						
Total loans over total assets[19]	5,148	0.843	0.081	0.301	0.861	0.997
Mortgage loans over total assets	5,150	0.654	0.123	0.044	0.676	0.954
Mortgage loans over total loans	5,150	0.773	0.128	0.051	0.793	1.000
Firm loans over total assets	5,150	0.218	0.084	0.000	0.209	0.810
Firm loans over total loans	5,150	0.260	0.102	0.000	0.251	0.935
HTM over total assets	5,150	0.026	0.037	0.000	0.014	0.329
MM over total assets	5,150	0.063	0.027	-0.005	0.059	0.314
Net liquidity over total assets	5,135	0.053	0.078	-0.553	0.056	0.386
Balance sheet liquidity over total assets	5,150	-0.324	0.074	-0.648	-0.324	-0.046
Interest income						
Mean interest on firm lending in %, yearly	1,006	5.890	0.699	3.140	5.909	7.720
Ratio interest firm over interest other lending, yearly	1,006	1.269	0.221	0.545	1.250	2.130
Funding costs						
Interest paid on total funding in %, yearly	1,251	2.723	1.049	0.57	2.399	6.307
Interest paid on subordinated funding in %, yearly	421	8.178	5.149	0.398	6.947	46.057
Profitability						
Net interest margin, yearly	1,251	0.020	0.006	0.001	0.020	0.040

[19] We consolidate balance sheet positions from banks with their mortgage companies on the basis of the share of mortgage transfers to the mortgage company. As this is only an approximation of the exact positions, it might be that the sum of average ratios exceeds 1. In two instances, total loans over total assets exceeded 1. We set these two observations to missing.

Table 2: Summary statistics at firm-bank-year level

This table reports summary statistics for 275,323 firm-bank relationships, or 220,059 firms.

	N	Mean	Sd	Min	Median	Max
Log(loans)	1,355,289	4.552	6.567	0.000	0.000	23.363
Number of loans per borrower$\|_{\text{loan}>0}$	457,962	1.566	1.950	1.000	1.000	310.000
Symmetric credit growth ($\Delta L_{b,f,t}$)	1,355,289	-0.067	0.710	-2.000	0.000	2.000
Interest rate ($i_{b,f,t}$, in %)	401,673	6.614	3.595	0.000	6.166	35.473

Table 3: Summary statistics at firm-year level

This table reports summary statistics for 130,661 firms.

	N	Mean	Sd	Min	Median	Max
Size and Age						
Assets (in 1000s of NOK)	933,746	42,270.250	1,563,833	0.000	2,782.000	$5.84\times e^8$
Age	933,738	13.71379	13.00164	0.000	10.000	169.000
Rating						
Rating (AAA:5 - C:1)	933,746	3.278	0.991	1.000	3.000	5.000
Rating(0/1)	933,746	0.425	0.494	0.000	0.000	1.000

Table 4: Summary statistics on treatment definitions

This table reports summary statistics on variables used for the treatment definition for 133 banks, or 5,150 bank-quarter-year and for 275,323 firm-bank links.

	N	Mean	Sd	Min	Median	Max
T_b (treatment indicator at *bank level*)	5,150	0.496	0.500	0.000	0.000	1.000
Share of mortgages transferred to mortgage companies, 2007-2012	3,048	0.106	0.140	0.000	0.038	0.869
Ratio of low LTV mortgages over total mortgages, 2006q4	133	0.842	0.064	0.662	0.850	1.000
Ratio of low LTV mortgages over total mortgages, 2006q4, $T_b = 1$	67	0.892	0.039	0.850	0.876	1.000
Ratio of low LTV mortgages over total mortgages, 2006q4, $T_b = 0$	66	0.792	0.039	0.662	0.799	0.844
T_b (treatment indicator at *loan level*)	1,355,289	0.880	0.325	0.000	1.000	1.000

Figure 3: Share of mortgages transferred for high-exposure and low-exposure banks

This figure shows the average share of mortgages transferred to credit companies over total mortgages issued by high-exposure banks in red, and other banks in blue. We define high exposed banks as having a share of low-LTV mortgages over total mortgages that is above the median of all banks before the covered bond introduction in 2006q4.

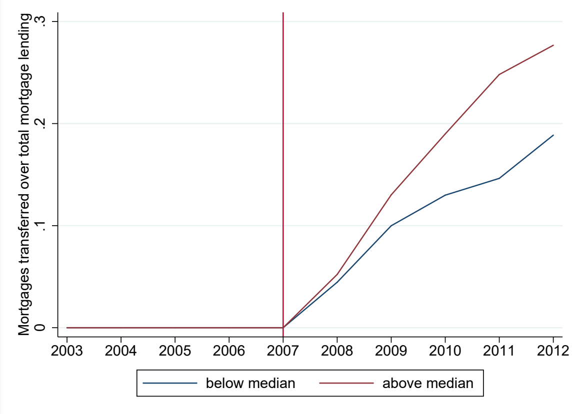


Table 5: Share of eligible mortgages predict mortgage transfers

This table shows the correlation of the share of eligible mortgages over total mortgages in 2006q4 and the actual share of mortgages transferred to mortgage companies over total mortgages issued. The regression includes quarter-year fixed effects. *, **, *** indicate significant coefficients at the 10%, 5%, and 1% level, respectively.

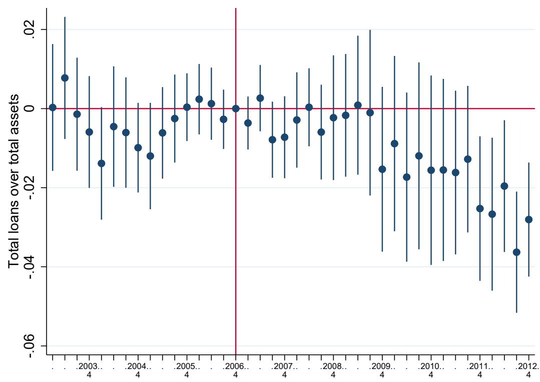
	Mortgage transfers over total mortgages
Eligible mortgages over total mortgages	0.190**
	(0.089)
Observations	5,150
Number of banks	133
R-squared	0.484

Figure 4: Bank portfolio re-balancing: total lending and mortgage lending

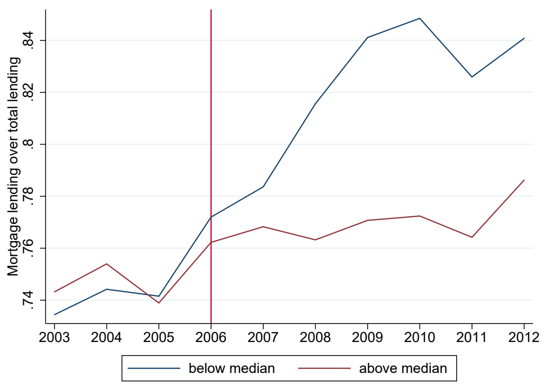
In this figure we show the average loan and the average mortgage share over time on the left hand side. On the right hand side, we show the coefficient plots with confidence intervals at 90% from estimating equation (3). Statistics from estimations can be found in Table 6.

(a) Total loans over total assets

(b) Total loans over total assets



(c) Mortgages over total loans



(d) Mortgages over total loans

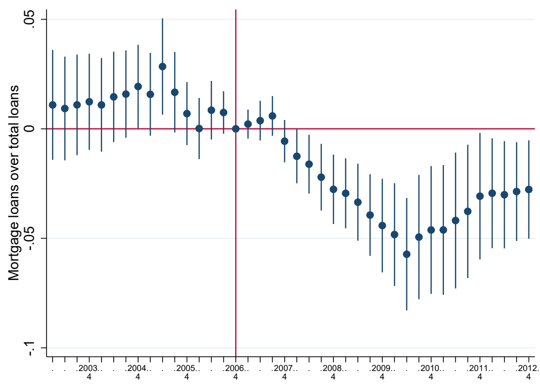


Figure 5: Bank lending portfolio re-balancing: firm lending

In this figure we show the average firm share over time on the left hand side. On the right hand side, we show the coefficient plots with confidence intervals at 90% from estimating equation (3). Statistics from estimations can be found in Table 6.

(a) Firm loans over total loans

(b) Firm loans over total loans

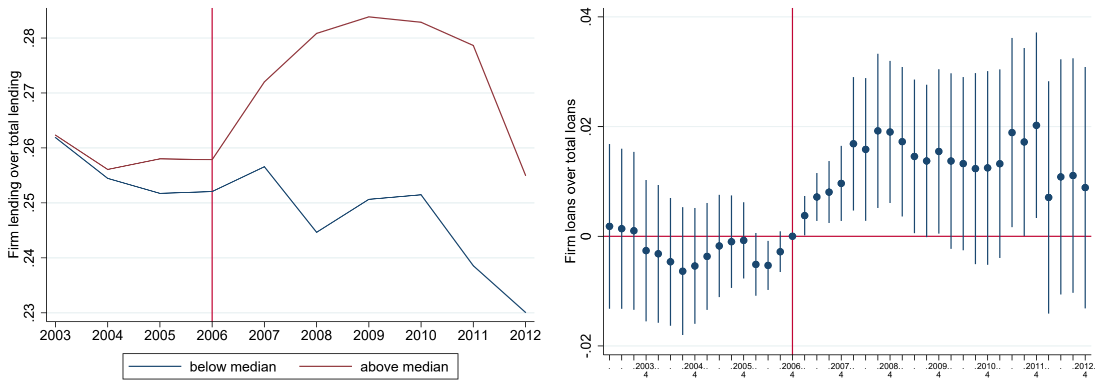


Table 6: Regression information corresponding to Figures 4 and 5

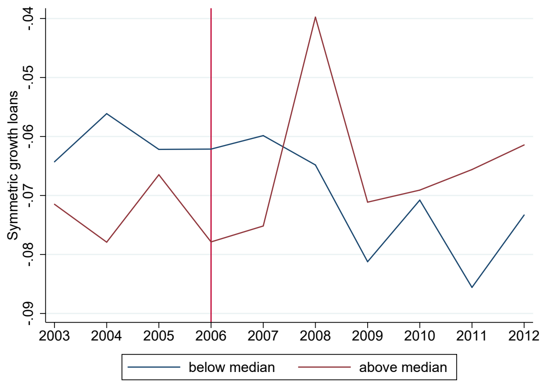
This table reports statistics from estimating equation (3). The second column ("Figure") refers to the corresponding coefficient plot.

Dependent variable	Figure	N	No. of banks	R2	Mean dependent	SD dependent
Total loans over total assets	4b	5,148	133	0.356	0.843	0.081
Mortgage loans over total loans	4d	5,150	133	0.260	0.773	0.128
Firm loans over total loans	5b	5,150	133	0.056	0.260	0.102

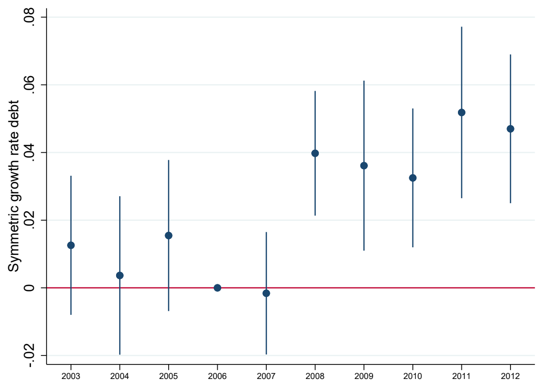
Figure 6: Changes on loan growth on the loan-level.

In Figure 6a we show mean symmetric loan growth for loans with high-exposure banks in red and loans with other banks in blue over time. In Figure 6b we show coefficient plots from estimating the dynamic regression equation (4) with confidence intervals at 90% with symmetric growth for loans as dependent variable. In Figure 6c we include industry-location-time fixed effects, and in Figure 6d firm-time fixed effects. In Table B.3 in Appendix B, columns I-III show the results.

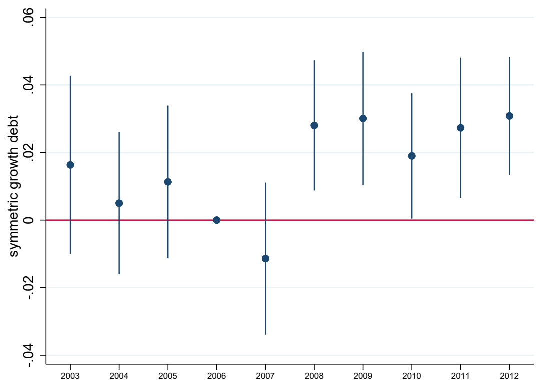
(a) Descriptive



(b) Baseline



(c) Industry-location-size-time fixed effects



(d) Firm-time fixed effects

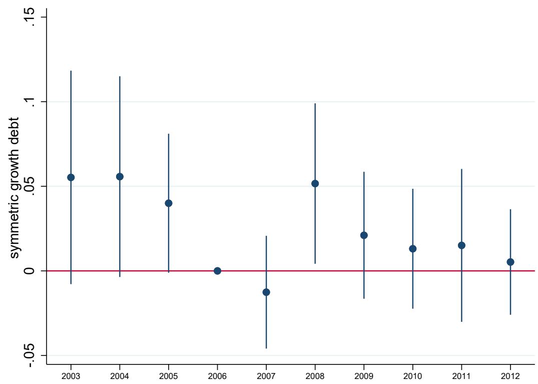
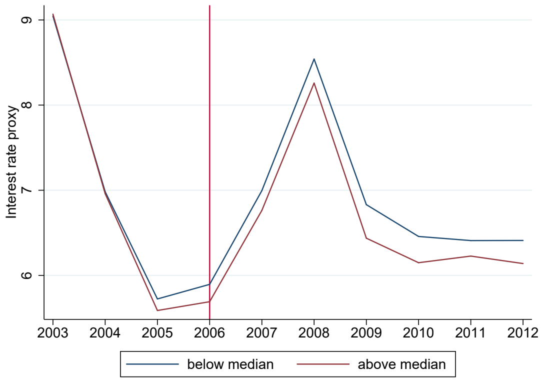


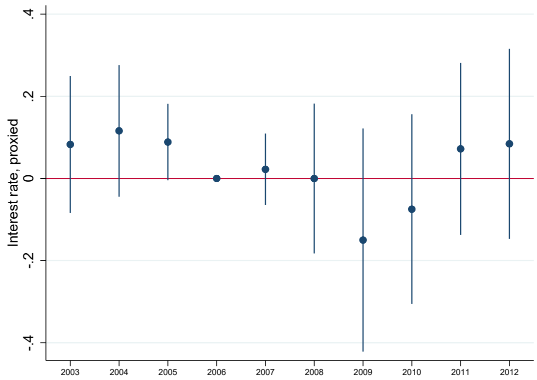
Figure 7: Changes in interest rate proxy at the loan-level.

In Figure 7a we show the mean interest rate paid for loans with high-exposure banks in red and loans with other banks in blue over time. In Figure 7b we show coefficient plots from estimating the dynamic regression equation (4) with confidence intervals at 90% with the interest rate proxy as dependent variable. In Figure 7c we include industry-location-time fixed effects, and in Figure 7d firm-time fixed effects. In Table B.3 in Appendix B, columns IV-VI show the results.

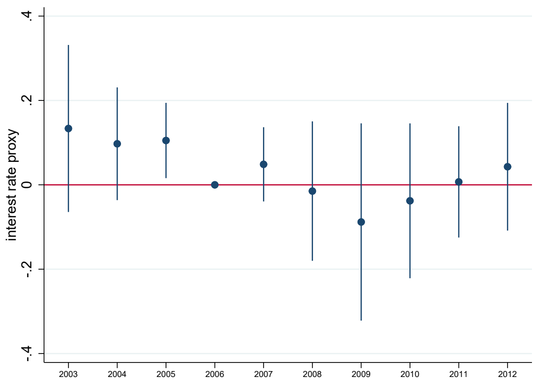
(a) Descriptive



(b) Baseline



(c) Industry-location-size-time fixed effects



(d) Firm-time fixed effects

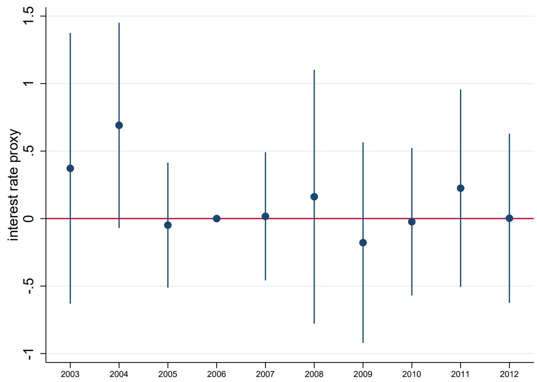


Figure 8: Changes in loan growth at the loan-level conditional on firm rating and age.

In this figure we show coefficient plots from estimating the dynamic regression equation (4) with confidence intervals at 90 % with symmetric growth for loans as dependent variable. We split the sample according to firm rating or the median firm age in 2006. Low-rated firms had a rating of A, B or C, and high-rated firms a rating of AA or AAA. Young firms are aged 8 years or below, old firms above 8 years. Table 7 shows the average differential effect in the post period for the two samples respectively. Table B.4 in Appendix B shows the complete regression output.

(a) Firm rating **(b)** Firm age

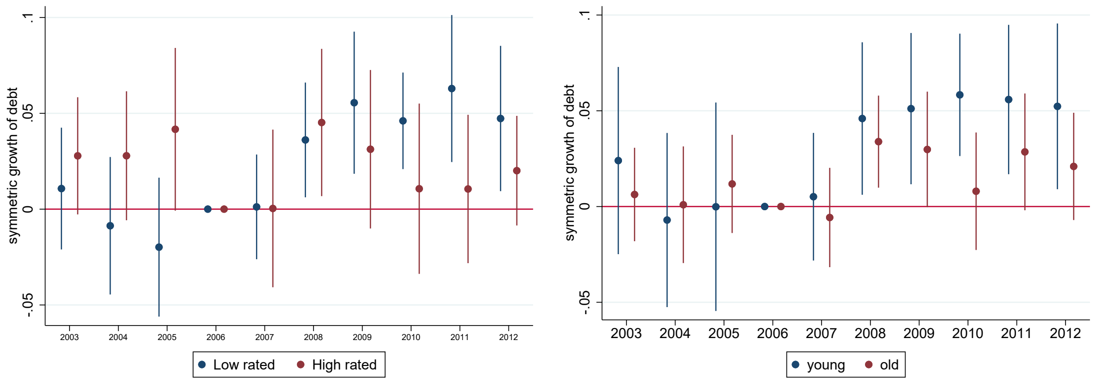


Table 7: Summarizing symmetric growth of debt across bank-firms

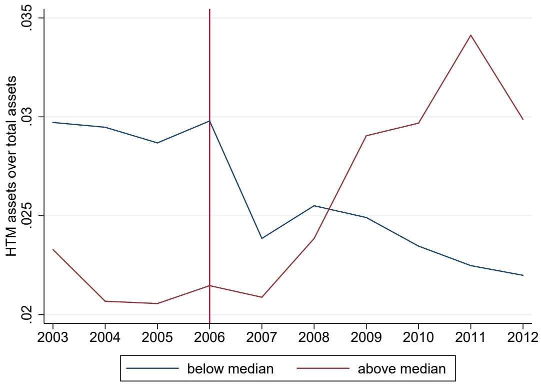
This table summarizes the estimated treatment effect from estimating equation (4) splitting the sample according to firm age or firm rating in 2006. Robust standard errors are clustered on the bank level and are depicted in parentheses. *, **, *** indicate significant coefficients at the 10 %, 5 %, and 1 % level, respectively.

Sample split by ...	low	high
rating	0.050*** (0.012)	0.000 (0.011)
age	0.049*** (0.012)	0.021** (0.008)

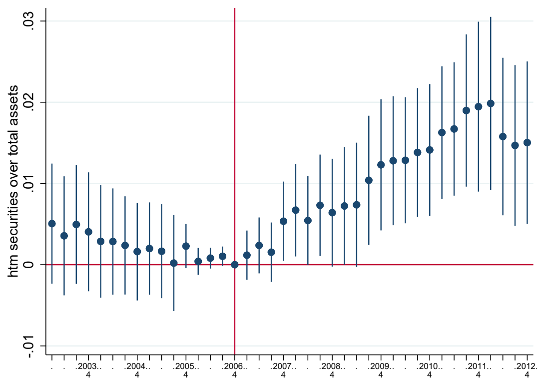
Figure 9: Bank portfolio re-balancing: Financial assets

In these figures we show mean dependent variables of the raw data over time in the left column. In the right column, we show coefficient plots with confidence intervals at 90% from estimating equation (3). Statistics from estimations can be found in Table 8.

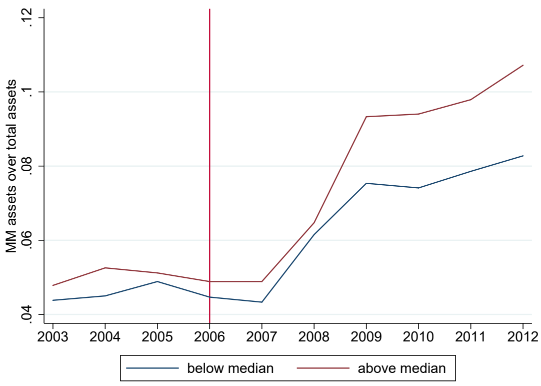
(a) HTM over total assets



(b) HTM over total assets



(c) MM over total assets



(d) MM over total assets

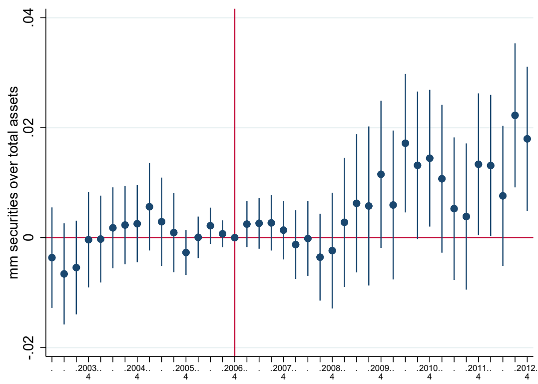


Table 8: Regression information corresponding to Figure 9.

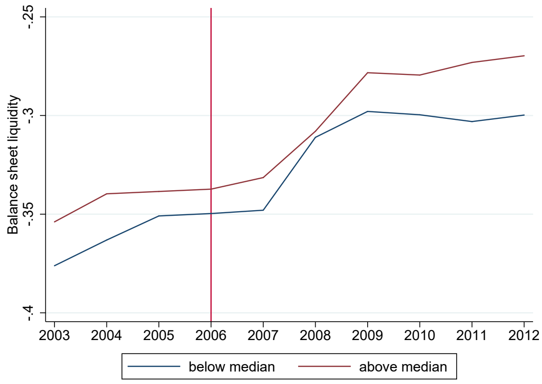
This table reports statistics from estimating equation (3). The second column ("Figure") refers to the corresponding coefficient plot.

Dependent variable	Figure	N	No. of banks	R2	Mean dependent	SD dependent.
HTM over total assets	9b	5,150	133	0.043	0.026	0.028
MM over total assets	9d	5,150	133	0.349	0.063	0.046

Figure 10: Bank-level: Balance sheet liquidity

In this figure we show mean dependent variables of raw data over time in the left column. In the right column we show a coefficient plot with confidence intervals at 90% from estimating equation (3) with quarterly data. Table 9 reports regression statistics for Figure 10b.

(a) Balance sheet liquidity



(b) Balance sheet liquidity

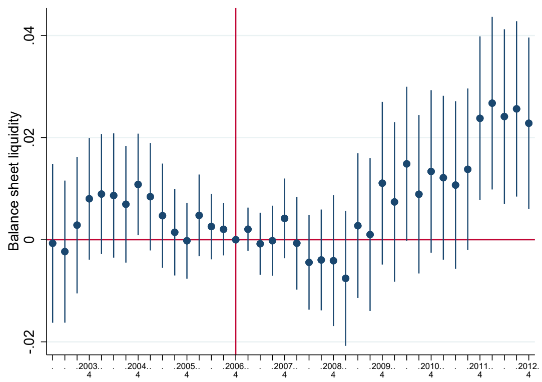


Table 9: Regression information corresponding to Figure 10.

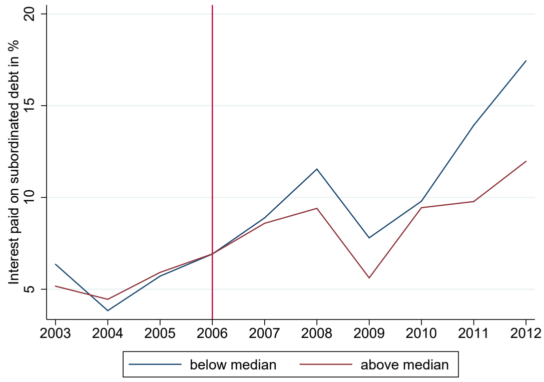
This table reports statistics from estimating equation (3) with balance sheet liquidity as dependent variable. The second column ("Figure") refers to the corresponding coefficient plot.

Dependent variable	Figure	Observations	N cluster	R2	Mean dependent	SD dependent
Balance sheet liquidity	10b	5,150	133	0.447	-0.324	0.074

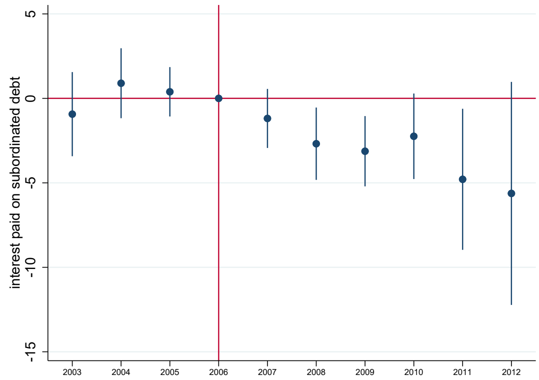
Figure 11: Bank-level: Funding costs and profitability

In this figure we show mean dependent variables of raw data over time in the left column. In the right column we show coefficient plots with confidence intervals at 90% from estimating equation (3) with annual data. Table B.5 reports the regression output for Figures 11b, 11d and 11f.

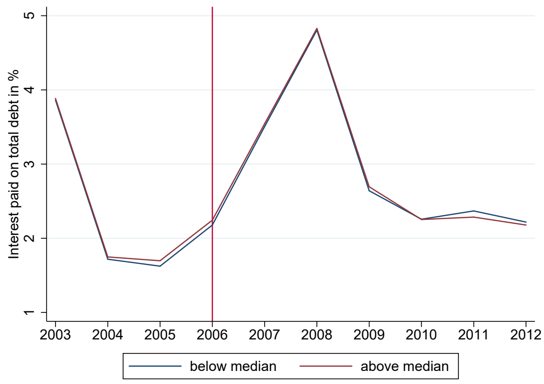
(a) Interest paid on subordinated funding



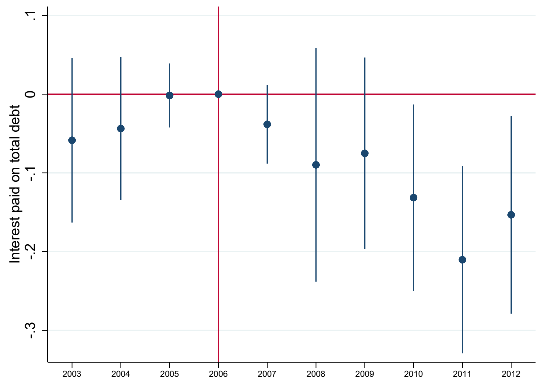
(b) Interest paid on subordinated funding



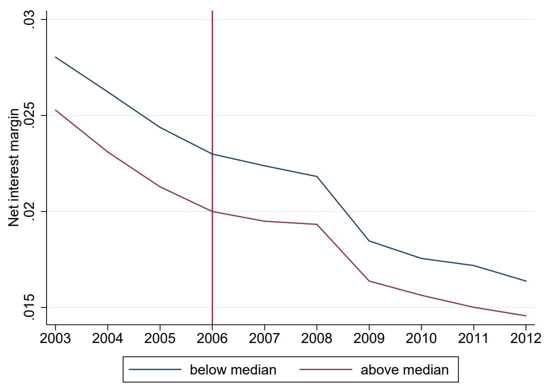
(c) Interest paid on total funding



(d) Interest paid on total funding



(e) Net interest margin



(f) Net interest margin

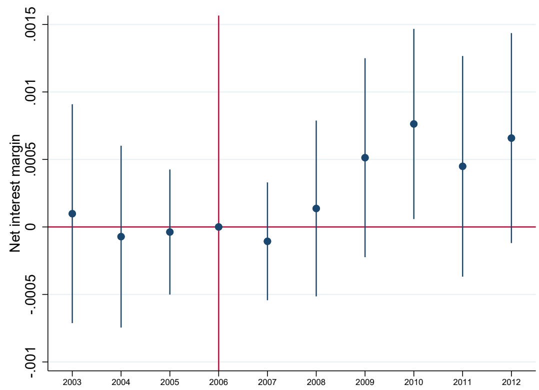


Figure 12: Bank portfolio re-balancing according to liquidity: Lending

In these graphs we show coefficient plots from re-estimating equation (3) for the sample of low- and high-liquidity banks respectively with confidence intervals at 90 %.

(a) Mortgages over total loans **(b)** Firm loans over total loans

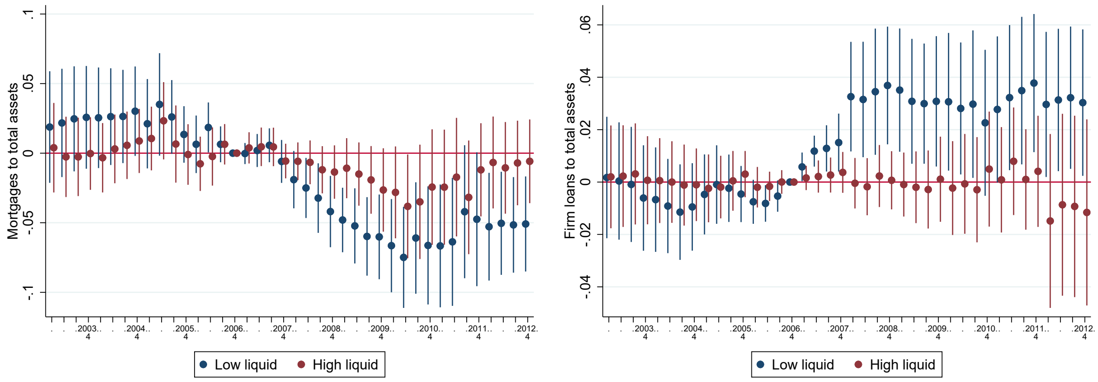


Figure 13: Bank portfolio re-balancing according to liquidity: Financial assets.

In these graphs we show coefficient plots from re-estimating equation (3) for the sample of low- and high-liquidity banks respectively with confidence intervals at 90%.

(a) HTM financial assets over total assets **(b)** MM financial assets over total assets

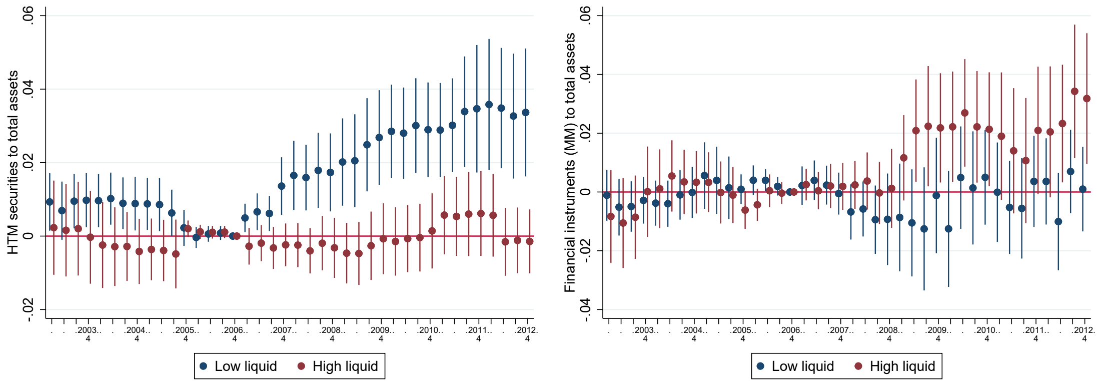


Table 10: Summarizing portfolio rebalancing across banks

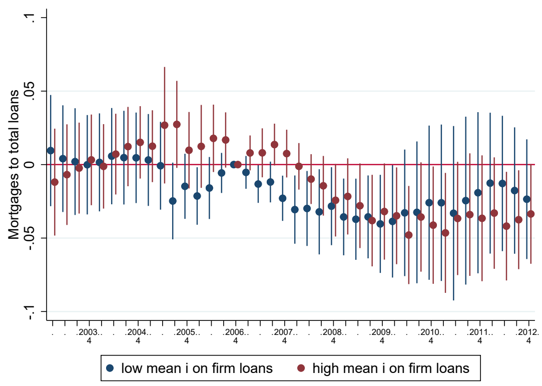
This table summarizes the estimated treatment effect from estimating equation (3) splitting the sample according to liquidity in the pre-reform period. Robust standard errors are clustered at the bank level and are depicted in parentheses. *, **, *** indicate significant coefficients at the 10 %, 5 %, and 1 % level, respectively.

Change in portfolio share in pp of ...	Low liquid banks	High liquid banks
Mortgages (relative to total loans)	-6.5*** (1.7)	-2.0 (1.3)
Firm loans (relative to total loans)	3.3** (1.6)	-0.1 (1.1)
HTM financial assets	1.9*** (0.6)	0 (0.5)
MM financial assets	-0.4 (0.9)	1.6* (0.9)

Figure 14: Bank portfolio re-balancing according to credit risk and profitability of firm lending

In these graphs we show coefficient plots from re-estimating equation (3) for the sample of banks with high and low interest on firm lending with confidence intervals at 90 %.

(a) Mortgages over total loans



(b) Firm loans over total loans

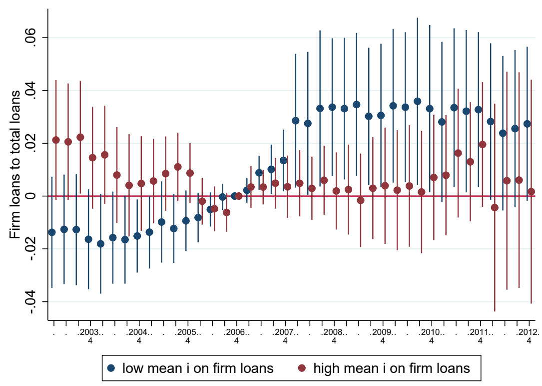


Table 11: Summarizing portfolio rebalancing across banks

This table summarizes the estimated treatment effect from estimating equation (3) splitting the sample according to firm loan risk measured according to firm loan yield in 2006. Robust standard errors are clustered at the bank level and are depicted in parentheses. *, **, *** indicate significant coefficients at the 10 %, 5 %, and 1 % level, respectively.

Change in portfolio share in pp of ...	Low firm risk	High firm risk
Mortgages (relative to total loans)	-2.4 (1.9)	-3.7** (1.4)
Firm loans (relative to total loans)	3.9** (1.7)	-0.2 (1.4)

Appendices

A Model

In this section, we present a stylized model to show how a bank adjusts its portfolio and risk-taking, in reaction to an asset encumbrance technology that improves the bank's balance sheet liquidity. The bank provides two products that meet creditors' different risk appetites: a safe demand deposit contract with non-state contingent return backed by encumbered safe assets (call it mortgage lending), and a risky financial security with state-contingent return backed by a risky project (call it firm lending). Ideally, the bank prefers to invest more funds in risky firm lending to achieve higher expected return, but this increases volatility in asset return as well as the risk premium required by investors; such a risk premium thus captures the punishment for bank's risk-taking. In equilibrium, the bank will invest so much in firm lending that its marginal gain from firm lending is only just offset by the marginal increase in risk premium.

Asset encumbrance technology, such as covered bonds, increases the liquidity of mortgage loans, generating two diverting effects on bank's balance sheet: the *income effect* that encourages the bank to invest more in mortgage lending, and *substitution effect* that encourages the bank to engage more in riskier firm lending. If investors' risk aversion were very high, the bank would choose to invest in mortgage lending, hoping to reduce asset return volatility as well as the costly risk premium it incurs, and it would adjust less in lending under tighter liquidity constraints; the income effect thus dominates. If investors' risk aversion were very low so that the cost of paying the risk premium were low, the bank would invest more in risky firm lending for higher profit, and it would tend to adjust more in lending under tighter liquidity constraints; the substitution effect thus dominates.

A.1 Agents, preferences, and technologies

The basic structure of the model is based on Dang et al. (2017). Consider an economy with one good that extends over three periods, $t = 0, 1, 2$. There are three types of agents in the economy:

- A bank living through all three periods that is operated by a banker. The bank does not have any initial wealth, but it has a risky investment technology—call it firm lending—that will return $f(i)$ in $t = 2$ with probability p (call it normal state), or 0, otherwise (call it crisis state), for any investment i that is made in $t = 0$. The actual return on firm lending is not known in $t = 0$, and it will only be revealed in $t = 1$. Firm lending is socially desirable, with Inada condition

$$\lim_{i \to 0} f'(i) \to +\infty.$$

In addition, a firm loan in progress cannot be liquidated prematurely in $t = 1$.

The bank also has a safe investment technology—call it mortgage lending: for one unit investment in $t = 0$, the gross return from mortgage lending is r, $r \geq 1$, but only a share of λ ($0 < \lambda < 1$) returns in $t = 1$, and the rest $1 - \lambda$ returns in $t = 2$. Liquidity creation by issuing mortgage loans is costly—for example, the bank has to exert effort in screening through loan applications—so that the bank incurs a convex cost of $\frac{1}{2}c\phi^2$, $c > 0$ being a constant, for mortgage loans with face value ϕ. c thus captures the bank's cost efficiency in liquidity management. For instance, in reality, banks with tighter liquidity constraints usually have higher c, as these banks rely more on costly funding from interbank markets, as Bianchi and Bigio (2022) show;

- One early consumer that is born in $t = 0$ with endowment e, and dies after $t = 2$;
- One late consumer that is born in $t = 1$ with endowment e, and dies after $t = 2$.

The banker derives utility, u_B, from her total consumption over time, c_{Bt}

$$u_B = c_{B0} + c_{B1} + c_{B2},$$

so that she has no preference on the timing of consumption.

In contrast, consumers have special liquidity preferences, or preferences in the timing of consumption: they prefer to consume in the period after their birth up to $\overline{k}$, that is, for the early consumer, her utility u_E from her consumption c_{Et}, $t = 0, 1, 2$, is characterized by

$$u_E = c_{E0} + c_{E1} + \alpha \min\left\{c_{E1}, \overline{k}\right\} + c_{E2} \text{ with } \alpha > 0$$

so that she gains extra utility from her consumption c_{E1} in $t = 1$, $\alpha \min\left\{c_{E1}, \overline{k}\right\}$, up to a level of $\overline{k}$. Assume that $\overline{k} < e$, so that $\overline{k}$ can be fulfilled in autarky. This also implies that, should there be no resource constraint, the early consumer prefers to consume at least $\overline{k}$ in $t = 1$.

Similarly, for the late consumer, her utility u_L from her consumption c_{Lt}, $t = 1, 2$, is characterized by

$$u_L = c_{L1} + c_{L2} + \alpha \min \left\{c_{L2}, \overline{k}\right\}.$$

Such utility function for consumers is *locally* linear so that we can solve the model analytically, and *globally* risk-averse so that we can properly capture the risk premium in security pricing.[20] More details are provided at the end of Section A.2.

Given that $\overline{k} < e$, consumers can live in autarky: if they do so, their utility is

$$u_E = u_L = \underline{u} = e + \alpha \overline{k}. \tag{A.1}$$

Consumers can also deposit in the bank, in order to access the high return from risky firm lending. The expertise in firm lending also justifies the role of the bank, in that it improves total output in the economy and makes consumers better off. The timing of the model goes as follows:

- In $t = 0$, the early consumer deposits her endowment in the bank, and the bank gives her a "take-it-or-leave-it" offer that includes a fixed, demand deposit contract and a risky financial security with state-contingent return. Here we should interpret the consumer of our economy rather as a *representative* consumer: she has a need for liquidity insurance provided by the demand deposit contract, but she also has a need for higher return from risky financial investment. To fulfill its agreement with the early consumer, in $t = 0$, the bank invests in a portfolio that consists of safe mortgage lending and risky firm lending. To guarantee the repayment of the demand deposit contract, the mortgage loan is encumbered to the early consumer; the risky financial security is backed by a risky firm loan. After collecting the funds, e, from the early consumer, the bank invests an amount of θ in mortgage lending, and $e - \theta$ in firm lending;
- In $t = 1$, the state of the world, or return on firm lending in $t = 2$, is revealed. The early consumer can withdraw funds from the bank for consumption, including both deposits and return on the risky security, and the bank meets her withdrawal demand by collecting the realized return on the mortgage loan, as well as selling the early consumer's other claims to the late consumer who enters the market: suppose the bank does so by giving the late consumer a "take-it-or-leave-it" offer.
- In $t = 2$, the late consumer is repaid by the bank using collected returns on all assets.

[20] See applications in, for example, Hirshleifer (1971).

A.2 Equilibrium Analysis

We solve the model by backward induction. Given the bank's portfolio that is fixed in $t = 0$, in $t = 1$, after the state of the world is revealed:

- In a crisis state, the bank can collect $\theta\lambda r$ return on the mortgage loan, and sell the claim on the remainder of the mortgage loan at price $\theta(1-\lambda)r$ to the late consumer. As the firm will return 0 in $t = 2$, the bank cannot sell it for any price higher than $s^B = 0$;
- In a normal state, the bank can collect $\theta\lambda r$ return on the mortgage loan, and sell the claim on the remainder of the mortgage loan at price $\theta(1-\lambda)r$ to the late consumer, and sell the claim on the firm loan at a price of s^G, which is to be determined.

The early consumer's expected return in $t = 0$, before she decides to accept the bank's, is

$$\theta r + \alpha\theta r + p\left[s^G + \alpha\left(\overline{k} - \theta r\right)\right] \tag{A.2}$$

and she will only accept the offer, instead of staying in autarky, if her expected return in (A.2) exceeds her utility under autarky, (A.1)

$$\theta r + \alpha\theta r + p\left[s^G + \alpha\left(\overline{k} - \theta r\right)\right] \geq \underline{u}. \tag{A.3}$$

Solve (A.3) for the security price

$$s^G \geq \frac{e - \theta r}{p} + \frac{\alpha(1-p)\left(\overline{k} - \theta r\right)}{p} = \underline{s}^G.$$

Since the bank is assumed to have full bargaining power in its "take-it-or-leave-it" offer and seizes all the rent, the equilibrium price must be

$$\underline{s}^G = \frac{e - \theta r}{p} + \frac{\alpha(1-p)\left(\overline{k} - \theta r\right)}{p}.$$

Given that the bank has full bargaining power in selling the claim on the firm loan to the late consumer in its "take-it-or-leave-it" offer, it will repay her $s^G = \underline{s}^G$ in $t = 2$ in the good state. The bank's expected return is thus

$$
\begin{aligned}
\Pi &= pf\left(e-\theta\right)-\frac{1}{2}c\left(\theta r\right)^{2}-p\underline{s}^{G} \\
&= pf\left(e-\theta\right)-\frac{1}{2}c\left(\theta r\right)^{2}-p\left(\frac{e-\theta r}{p}+\frac{\alpha\left(1-p\right)\left(\overline{k}-\theta r\right)}{p}\right)
\end{aligned}
\tag{A.4}
$$

and to maximize its expected return, its optimal choice in θ is given by the first-order condition of (A.4)

$$
\frac{\partial \Pi}{\partial \theta}=-pf'\left(e-\theta\right)-c\theta r^{2}+\left[r+\alpha r\left(1-p\right)\right]=0 \tag{A.5}
$$

under the assumption that our parameter values ensure the interior solution.

The intuition behind our model can be easily seen in Figure A.1, which illustrates the early consumer's utility as a function of her state-contingent consumption.[21] Liquidity preference gives her higher marginal utility on consumption from 0 to $\overline{k}$—the OA part in her utility curve with a slope of $\alpha > 1$, and her marginal utility is lower for consumption exceeding $\overline{k}$—the AH part with a slope of 1. Liquidity preference thus makes the early consumer locally risk-neutral, but globally risk-averse.

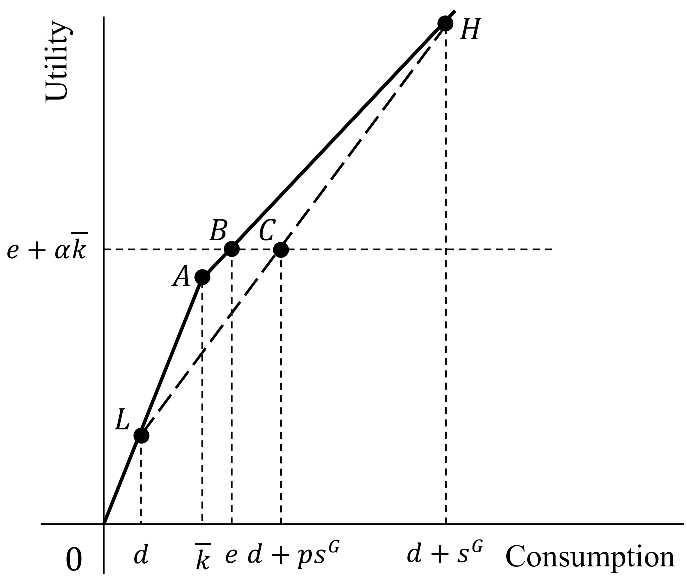


Figure A.1: Global risk aversion and risk premium

[21]It is easy to see that the late consumer is guaranteed with utility of $\underline{u}$ so that she will always be willing to accept the bank's offer that is characterized in the model.

With the bank's investments in mortgage and firm lending in $t = 0$, in $t = 1$, the early consumer receives a fixed return from deposit contract $d = \theta r$, plus $s^G > 0$ in good state (with total consumption as point H shows) or $s^B = 0$ in bad state (with total consumption as point L shows), and point C denotes her expected consumption, $d + ps^G$. In order to induce the consumer to provide funding, the bank must ensure her expected utility is as least as high as her utility under autarky, implying that a risk premium—the distance between B and C—must be incurred to compensate the consumer. As a result, although the bank is willing to invest in more risky firm lending for higher return, it will be punished by increasing risk premia arising from higher consumption volatility. In equilibrium, the bank's investment in firm lending should be made when the marginal return from firm lending is just offset by the marginal increase in risk premium.

A.3 Comparative statics

A.3.1 Portfolio Adjustments

Next we conduct a comparative analysis to see how the bank adjusts its balance sheet in response to the introduction of covered bond technology. Covered bonds are introduced as a technology to improve a bank's liquidity through a higher return r for the encumbered asset of a mortgage loan. This captures the fact that introducing covered bonds does not increase credit risk in the encumbered asset as long as the asset remains on balance sheet, as Gorton and Pennacchi (1995) demonstrate (however, introducing covered bonds may still increase credit risk in the *unencumbered* asset, as shown below), instead, it increases bank liquidity by reducing funding costs (as Ahnert et al. (2018) demonstrate, although we do not explicitly model the pricing of encumbered assets here), or, correspondingly, higher profit from mortgage loans.

The following proposition illustrates how the bank's adjustment in its balance sheet, with covered bond technology, depends on other settings in the model:

Proposition 1. *After introducing covered bond technology ($r \uparrow$),*

1. *Invest more in mortgages ($\theta \uparrow$) if consumers are more risk-averse (α is high), and/or credit risk in firm lending is high (p is low), and/or liquidity creation is not costly (c is low);*
2. *Invest less in mortgages ($\theta \downarrow$) when consumers are less risk-averse (α is low), and/or credit risk in firm lending is (p is high), and/or liquidity creation is costly (c is high).*

Proof. Apply the implicit function theorem on the first-order condition (A.5),

$$\frac{d\theta}{dr} = -\frac{1 + \alpha (1 - p) - 2c\theta r}{pf'' (e - \theta) - cr^2}. \tag{A.6}$$

Given that the denominator, $pf'' (e - \theta) - cr^2$, is strictly negative, (A.6) implies that

- If $1 + \alpha (1 - p) - 2c\theta r > 0$, $\frac{d\theta}{dr} > 0$. This happens when consumers are more globally risk-averse (high α), riskier firm lending (low p), or liquidity is less costly (low c). Covered bonds lead to more investments in mortgage lending, in order to reduce the risk premium that is needed to compensate for volatility in consumers' consumption;
- If $1 + \alpha (1 - p) - 2c\theta r < 0$, $\frac{d\theta}{dr} < 0$. This happens when consumers are less globally risk-averse (low α), safer firm lending (high p), or liquidity is more costly (high c). Covered bonds lead to more investments in firm lending, in order to benefit more from the high yields.

□

Intuitively, when r increases, mortgages become more efficient in terms of generating liquidity, and an increase in θ has a large impact on the risk premium. As a result, banks are incentivized to invest more in safer mortgage lending— we refer to this as an *income effect*. On the other hand, a higher r also increases the relative yield on firm lending – call it a *substitution effect*. If investors' risk aversion were very high, the bank would find it more profitable to invest in mortgage lending to reduce asset return volatility and the risk premium it incurs; the income effect dominates in this case. On the contrary, if investors' risk aversion were not high, the bank would find it more profitable to invest in high-yield firm lending, without incurring too high a risk premium; the substitution effect dominates in this case.

A.3.2 Sensitivity analysis

Given that covered bond technology improves the bank's balance sheet liquidity, to what extent the bank reacts to such a positive liquidity shock will be influenced by the efficiency of its liquidity management. Next, we show that how much the bank adjusts its portfolio in response to introducing the technology is indeed influenced by the cost efficiency of liquidity management, which is measured by c in our model.

Proposition 2. *After introducing covered bond technology,*

1. *When consumers are more risk-averse, and/or credit risk in firm lending is high, and/or liquidity creation is not costly, the more efficient the bank is in liquidity management, i.e., when c is lower, the larger the increase in the bank's investment in safe, liquid, mortgage lending will be;*
2. *When consumers are less risk-averse, and/or credit risk in firm lending is low, and/or liquidity creation is costly, and the elasticity of mortgage lending to liquidity shock is less than 2, the less efficient the bank is in liquidity management, i.e., when c is higher, the larger the increase in the bank's investment in risky, illiquid, firm lending will be.*

Proof. Differentiate equation (A.6) with c and yield

$$\frac{d^2\theta}{drdc} = \frac{2\theta r\left[pf''\left(e-\theta\right)-cr^2\right]-\left[1+\alpha\left(1-p\right)-2c\theta r\right]r^2}{\left[pf''\left(e-\theta\right)-cr^2\right]^2}.$$

Given that the denominator is positive and the first term in the numerator is negative, this implies that

- When $1+\alpha\left(1-p\right)-2c\theta r>0$ so that $\frac{d\theta}{dr}>0$, $\frac{d^2\theta}{drdc}<0$, so that θ is more sensitive to r if c is low;
- If $1+\alpha\left(1-p\right)-2c\theta r<0$ so that $\frac{d\theta}{dr}<0$, $\frac{d^2\theta}{drdc}<0$ only if

$$\begin{aligned}
2\theta r\left[pf''\left(e-\theta\right)-cr^2\right]-\left[1+\alpha\left(1-p\right)-2c\theta r\right]r^2 &< 0\\
\frac{1+\alpha\left(1-p\right)-2c\theta r}{pf''\left(e-\theta\right)-cr^2} &< \frac{2\theta}{r}\\
-\frac{d\theta}{dr} &< \frac{2\theta}{r}\\
\epsilon &< 2
\end{aligned}$$

by defining the elasticity of mortgage lending to liquidity shock ϵ as $\epsilon=-\frac{d\theta}{\theta}\frac{r}{dr}$. In this case, θ is more sensitive to r if c is high.

□

B Further results

Table B.1: Summary statistics of bank-level variables in the pre-reform period 2003-2006

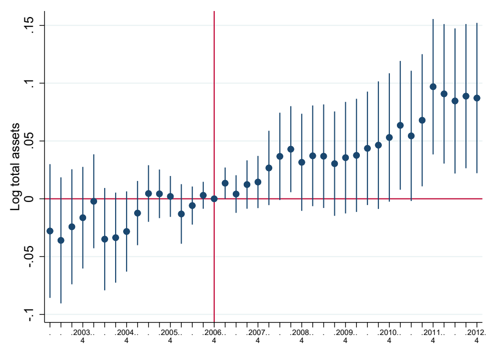
This table shows the mean of outcomes for low exposure ($T_b = 0$) and high exposure ($T_b = 1$) banks in the pre-reform period 2003-2006 and t-statistics of tests on the differences between the two groups.

	$T_b = 0$ (low exposure)		$T_b = 1$ (high exposure)					
	N	Average	N	Average	Difference	Std. error	t-statistic	p-value
Log(total assets)	1,056	14.033	1,046	15.163	-1.130	0.052	-21.747	0.000
Log(loans)	1,056	13.897	1,046	15.013	-1.116	0.052	-21.614	0.000
Log(mortgages)	1,056	13.570	1,046	14.697	-1.126	0.050	-22.327	0.000
Log(firm loans)	1,056	12.450	1,046	13.433	-0.982	0.075	-13.142	0.000
Log(HTM financial assets)	1,056	9.982	1,046	10.819	-0.837	0.062	-13.536	0.000
Log(MM financial assets)	1,054	10.058	1,046	11.132	-1.075	0.142	-7.550	0.000
Loans over total assets	1,056	0.874	1,046	0.867	0.007	0.003	2.288	0.022
Mortgages over total assets	1,056	0.649	1,046	0.648	0.001	0.006	0.213	0.831
Mortgages over total loans	1,056	0.741	1,046	0.745	-0.004	0.006	-0.685	0.493
Firm loans over total assets	1,056	0.223	1,046	0.225	-0.002	0.004	-0.471	0.638
Firm loans over total loans	1,056	0.257	1,046	0.260	-0.003	0.005	-0.702	0.483
HTM over total assets	1,056	0.030	1,046	0.022	0.008	0.001	6.354	0.000
MM over total assets	1,056	0.046	1,046	0.050	-0.004	0.001	-3.031	0.002

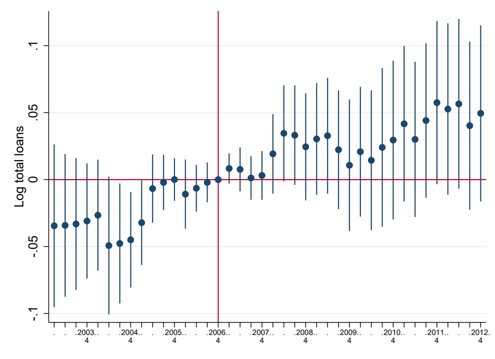
Figure B.1: Bank-level: Logs

These figures show coefficient plots with confidence intervals at 90% from estimating the dynamic regression equation (3) with dependent variables in log-levels. Table B.2 reports statistics accompanying the regression output.

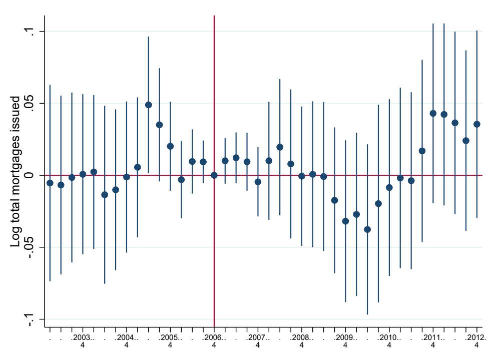
(a) Total assets



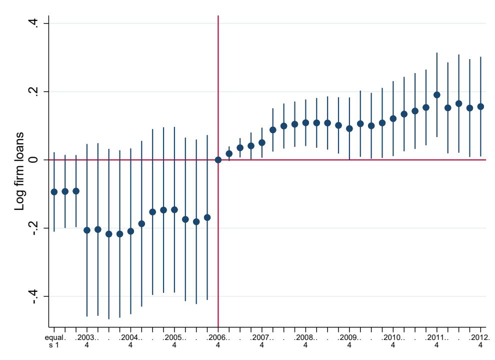
(b) Total loans



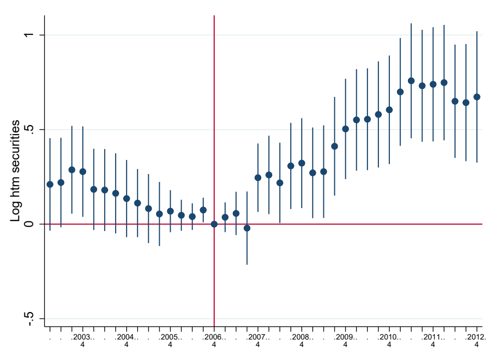
(c) Mortgages



(d) Firm loans



(e) HTM assets



(f) MM assets

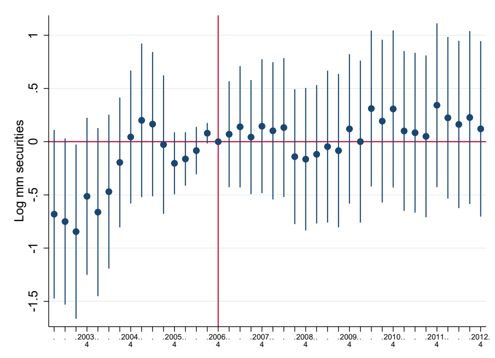


Table B.2: Regression information corresponding to Figure B.1.

This table reports statistics from estimating equation (3). The second column ("Figure") refers to the corresponding coefficient plot.

Dependent variable	Figure	N observations	N cluster	R2	Mean dependent	SD dependent
Total assets	B.1a	5,150	133	0.882	14.957	1.409
Total loans	B.1b	5,150	133	0.859	14.781	1.380
Mortgages	B.1c	5,150	133	0.867	14.506	1.340
Firm loans	B.1d	5,150	133	0.357	13.327	1.688
HTM assets	B.1e	5,150	133	0.351	10.831	1.655
MM assets	B.1f	5,140	133	0.261	11.447	3.061

Table B.3: Loan-level: Table of results

This table reports results from estimating equation (4). Columns I-III report results with systemic growth of loans as the dependent variable. Columns IV-VI report results with the interest rate proxy as dependent variable. T_b is a binary variable which is equal to 1 for banks that have a share of low LTV mortgages over total mortgages that is above the median of all banks in the pre-reform quarter-year 2006q4, and 0 otherwise. Regressions include firm-bank fixed effects. Column I and IV include further time fixed effects. Column II and V include industry-location-size-time fixed effects as in Degryse et al. (2019). Columns III and VI include firm-time fixed effects as in Khwaja and Mian (2008). Robust standard errors are clustered at the bank level and are depicted in parentheses. *, **, *** indicate significant coefficients at the 10 %, 5 %, and 1 % level, respectively.

	(I)	(II)	(III)	(IV)	(V)	(VI)
	symmetric growth loans			interest rate proxy		
T_b x 2003	0.013	0.016	0.055	0.083	0.134	0.372
	(0.012)	(0.016)	(0.038)	(0.100)	(0.119)	(0.604)
T_b x 2004	0.004	0.005	0.056	0.116	0.097	0.691
	(0.014)	(0.013)	(0.036)	(0.097)	(0.081)	(0.458)
T_b x 2005	0.016	0.011	0.040	0.089	0.105*	-0.049
	(0.014)	(0.014)	(0.025)	(0.056)	(0.054)	(0.279)
T_b x 2006	0	0	0	0	0	0
	(omitted)	(omitted)	(omitted)	(omitted)	(omitted)	(omitted)
T_b x 2007	-0.002	-0.011	-0.013	0.022	0.049	0.017
	(0.011)	(0.014)	(0.020)	(0.053)	(0.053)	(0.286)
T_b x 2008	0.040***	0.028**	0.052*	-0.000	-0.015	0.162
	(0.011)	(0.012)	(0.029)	(0.110)	(0.100)	(0.567)
T_b x 2009	0.036**	0.030**	0.021	-0.150	-0.088	-0.178
	(0.015)	(0.012)	(0.023)	(0.164)	(0.141)	(0.447)
T_b x 2010	0.033***	0.019*	0.013	-0.075	-0.038	-0.024
	(0.012)	(0.011)	(0.021)	(0.139)	(0.111)	(0.329)
T_b x 2011	0.052***	0.027**	0.015	0.072	0.007	0.225
	(0.015)	(0.013)	(0.027)	(0.126)	(0.080)	(0.441)
T_b x 2012	0.047***	0.031***	0.005	0.084	0.043	0.003
	(0.013)	(0.011)	(0.019)	(0.139)	(0.091)	(0.378)
Observations	1,355,289	1,086,275	294,050	401,673	273,612	14,966
Firm–bank links	275,323	258,716	64,356	102,231	60,141	4,265
R-squared	0.004	0.291	0.564	0.140	0.764	0.863
Firm-bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	No	No	Yes	No	No
Industry-Location-Size-Time FE	No	Yes	No	No	Yes	No
Firm-time FE	No	No	Yes	No	No	Yes

Table B.4: Loan-level: Table of results for sample split

This table reports results from estimating equation (4) with systemic growth of loans as the dependent variable. In column I we report results for firms which had a low rating in 2006 (A, B or C), and in column II we report results for firms which had a high rating in 2006 (AA or AAA). In column III we report results for firms below or equal to the median age of eight years, and in column IV for firms older than eight years. T_b is a binary variable which is equal to 1 for banks which have a share of low-LTV mortgages over total mortgages that is above the median of all banks in the pre-reform quarter-year 2006q4, and 0 otherwise. Regressions include firm-bank fixed effects and time fixed effects. Robust standard errors are clustered at the bank level and are depicted in parentheses. *, **, *** indicate significant coefficients at the 10 %, 5 %, and 1 % level, respectively.

	(I) Low-rated	(II) High-rated	(III) Young	(IV) Old
T_b x 2003	0.011	0.028*	0.024	0.006
	(0.016)	(0.015)	(0.025)	(0.012)
T_b x 2004	-0.009	0.028	-0.007	0.001
	(0.018)	(0.017)	(0.023)	(0.015)
T_b x 2005	-0.020	0.042*	-0.000	0.012
	(0.018)	(0.021)	(0.027)	(0.013)
T_b x 2006	0	0	0	0
	(omitted)	(omitted)	(omitted)	(omitted)
T_b x 2007	0.001	0.000	0.005	-0.006
	(0.014)	(0.021)	(0.017)	(0.013)
T_b x 2008	0.036**	0.045**	0.046**	0.034***
	(0.015)	(0.019)	(0.020)	(0.012)
T_b x 2009	0.056***	0.031	0.051**	0.030*
	(0.019)	(0.021)	(0.020)	(0.015)
T_b x 2010	0.046***	0.011	0.058***	0.008
	(0.013)	(0.022)	(0.016)	(0.015)
T_b x 2011	0.063***	0.011	0.056***	0.029*
	(0.019)	(0.020)	(0.020)	(0.015)
T_b x 2012	0.047**	0.020	0.052**	0.021
	(0.019)	(0.014)	(0.022)	(0.014)
Observations	564,073	425,250	446,090	673,438
R-squared	0.006	0.001	0.008	0.002
Firm-bank links	86,956	61,298	74,808	104,534
Firm-bank FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Table B.5: Bank-level: Table of results for profitability and bank risk

This table reports results from estimating equation (3) with yearly data. In column I we report results for net interest margin as dependent variable, in column II interest paid on total funding as dependent variable, and in column III interest paid on subordinated debt as dependent variable. T_b is a binary variable which is equal to 1 for banks which have a share of low-LTV mortgages over total mortgages that is above the median of all banks in the pre-reform quarter-year 2006q4, and 0 otherwise. Regressions include bank fixed effects and time fixed effects. Robust standard errors are clustered at the bank level and are depicted in parentheses. *, **, *** indicate significant coefficients at the 10 %, 5 %, and 1 % level, respectively.

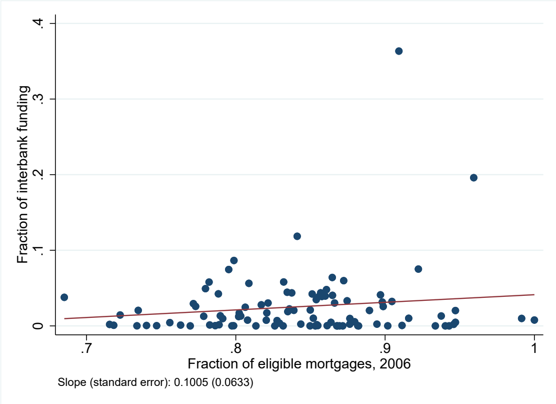
	(I) Net interest margin	(II) Interest paid total funding	(III) Interest paid sub. funding
T_b x2003	0.000	-0.059	-0.934
	(0.000)	(0.063)	(1.490)
T_b x2004	-0.000	-0.044	0.896
	(0.000)	(0.055)	(1.239)
T_b x2005	-0.000	-0.002	0.389
	(0.000)	(0.025)	(0.874)
T_b x 2006	0	0	0
	(omitted)	(omitted)	(omitted)
T_b x 2007	-0.000	-0.038	-1.188
	(0.000)	(0.030)	(1.045)
T_b x 2008	0.000	-0.090	-2.684**
	(0.000)	(0.090)	(1.280)
T_b x 2009	0.001	-0.075	-3.129**
	(0.000)	(0.073)	(1.244)
T_b x 2010	0.001*	-0.131*	-2.245
	(0.000)	(0.071)	(1.514)
T_b x 2011	0.000	-0.210***	-4.791*
	(0.000)	(0.072)	(2.497)
T_b x 2012	0.001	-0.153**	-5.626
	(0.000)	(0.076)	(3.949)
Observations	1,251	1,251	421
R-squared	0.830	0.931	0.432
Number of banks	133	133	59
Bank FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

Figure B.2: Treatment measure and exposure to the financial crisis and Basel II factors

In these figures we show the correlation of the fraction of mortgages eligible for mortgage transfers on banks' balance sheets in 2006q4 with (a) the share of MM assets over total assets, (b) the fraction of interbank funding over total assets, and (c) capital requirement reduction due to Basel II, all three in 2006q4.

(a) Financal instruments

(b) Interbank borrowing



(c) Capital requirement reduction

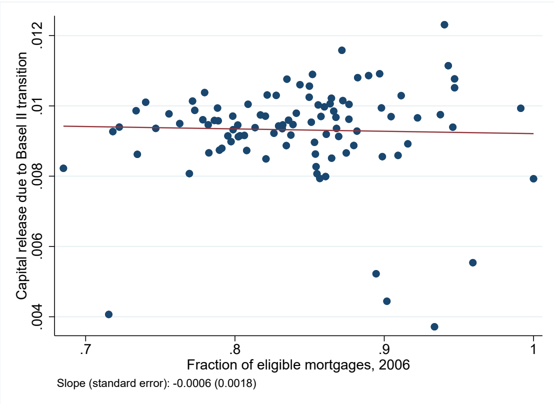
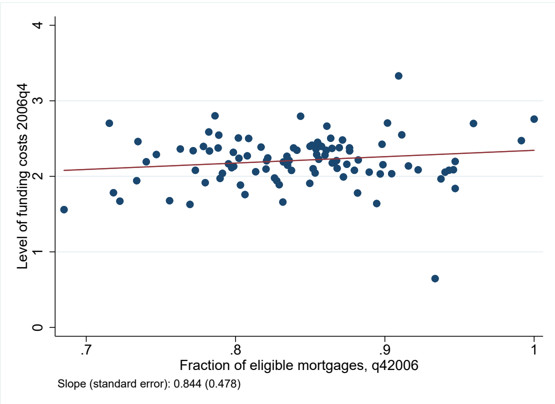


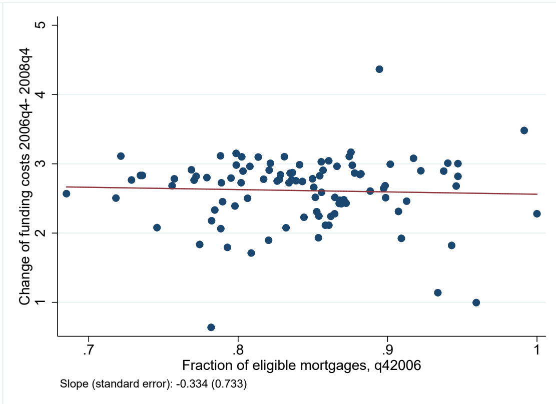
Figure B.3: Treatment measure and bank risk in the pre period

In these figures we show the correlation of the fraction of mortgages eligible for mortgage transfers on banks' balance sheets in 2006q4 with measures for bank risk in 2006q4. These are (a) interest paid on total funding, (b) the change in interest paid on total funding from 2006q4- 2008q4, (c) interest paid on subordinated funding, (d) standard deviation of return on assets (Roa) over past four quarters, (e) over past eight quarters.

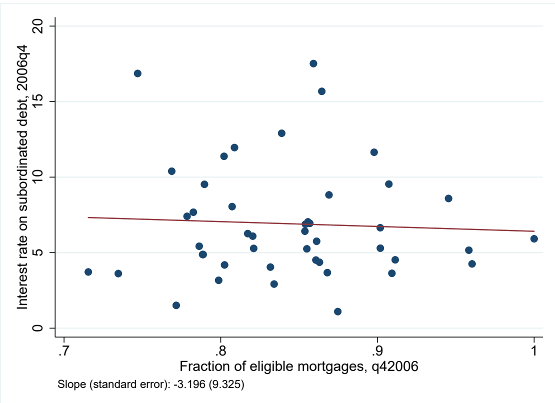
(a) Funding costs



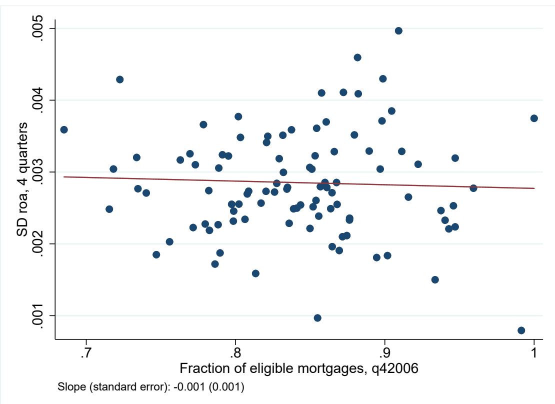
(b) Changes in funding costs 2006-2008



(c) Interest paid on subordinate debt



(d) SD Roa, 4 quarters



(e) SD Roa, 8 quarters

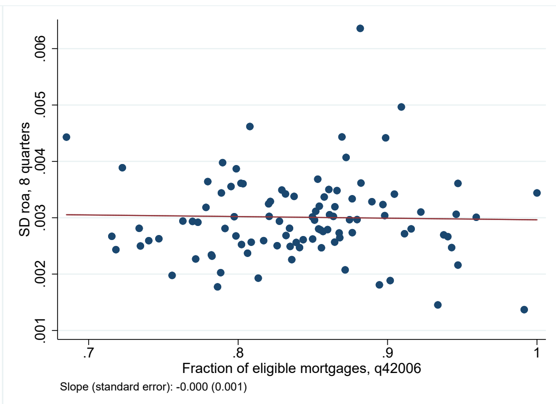
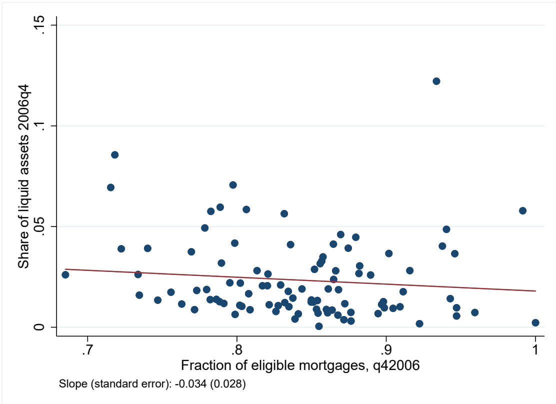


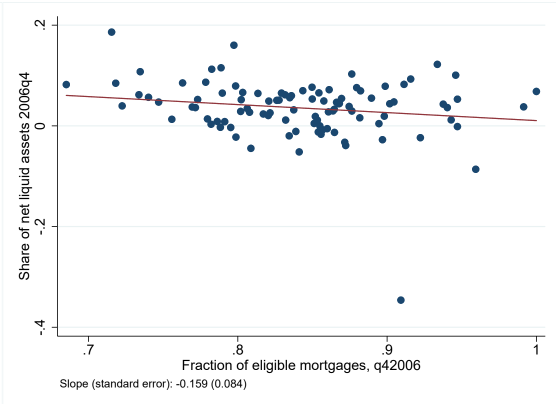
Figure B.4: Treatment measure and bank risk in the pre period continued

In these figures we show the correlation of the fraction of mortgages eligible for mortgage transfers on banks' balance sheets in 2006q4 with further measures for bank risk in 2006q4. These are (a) share of liquid assets ((MM assets + central bank reserves)/ total assets), (b) share of net liquid assets (((MM assets + central bank reserves) - interbank borrowings - certificates)/ total assets), (c) equity ratio, (d) ratio of non-performing loans, (e) mean borrowers' rating.

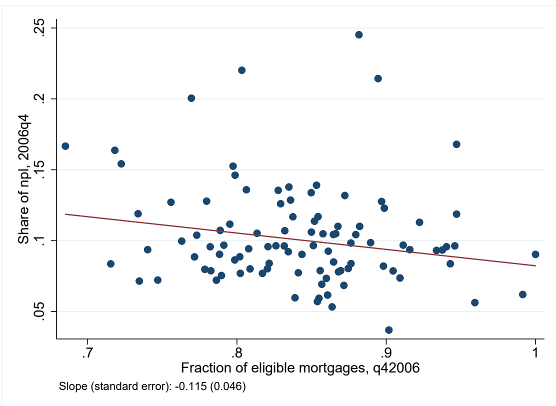
(a) Liquid assets



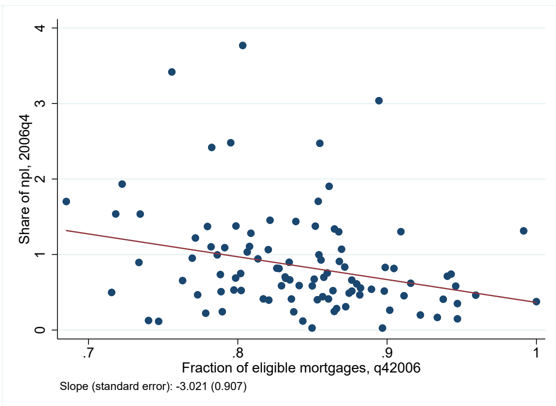
(b) Net liquid assets



(c) Equity ratio



(d) NPL ratio



(e) Mean firm rating

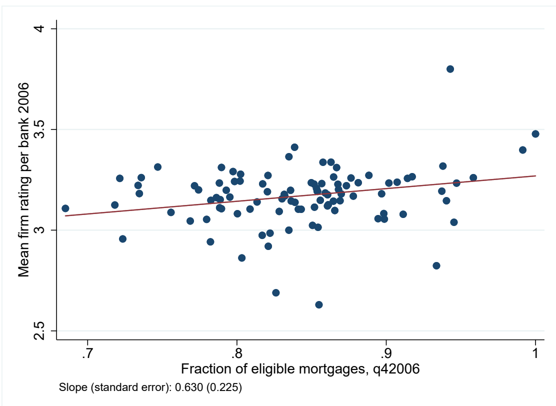
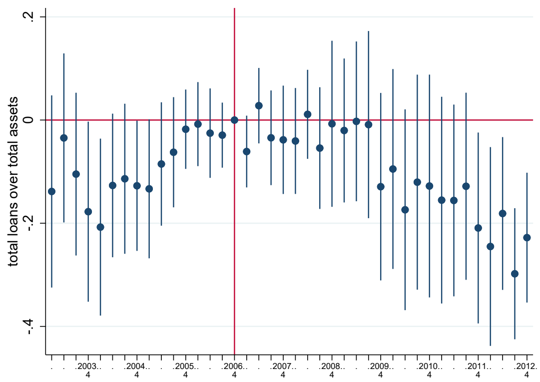


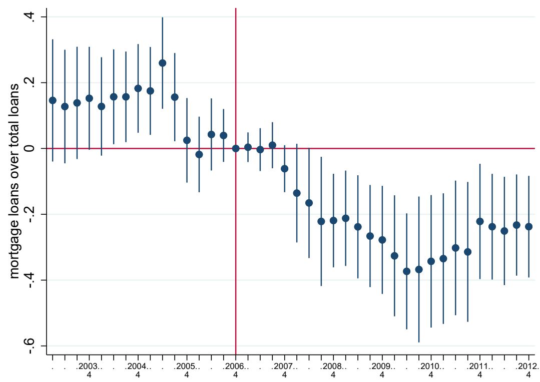
Figure B.5: Bank-level: continuous treatment measure

In these figures we show coefficient plots with confidence intervals at 90 % from estimating the dynamic regression equation (3) with the continuous treatment measure Ratio of low-LTV mortgages over total mortgages, 2006q4. Table B.6 reports statistics accompanying the regression output.

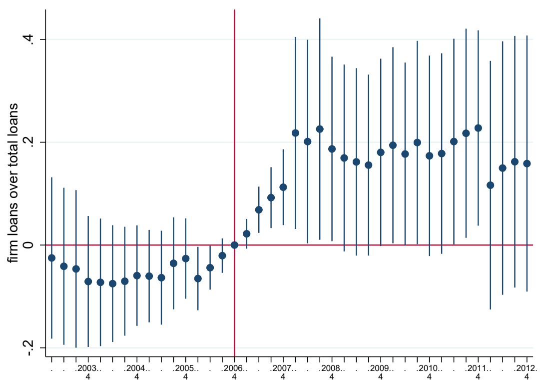
(a) Total loans over total assets



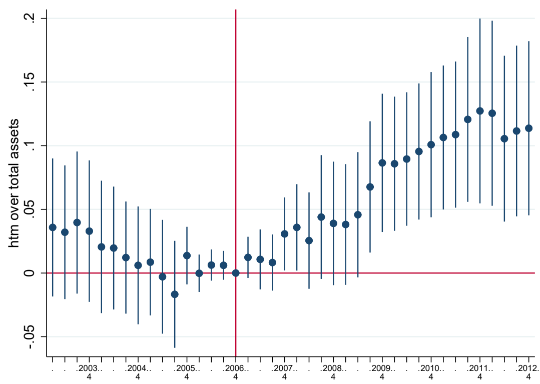
(b) Mortgages over loans



(c) Firm loans over loans



(d) HTM over total assets



(e) MM over total assets

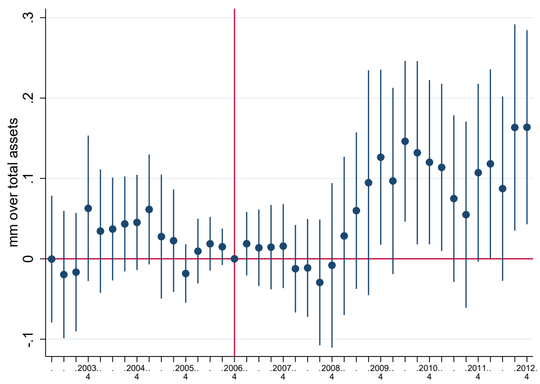


Table B.6: Regression information corresponding to Figure B.5.

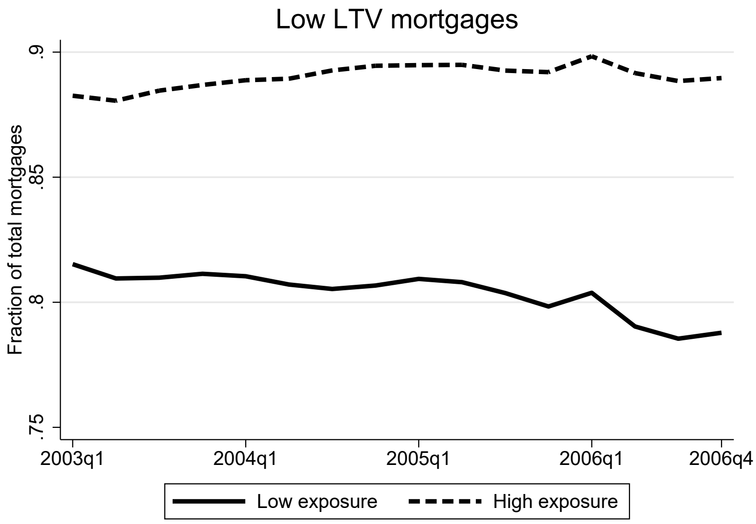
This table reports statistics from estimating equation (3) with the continuous treatment measure Ratio of low-LTV mortgages over total mortgages, 2006q4. The second column ("Figure") refers to the corresponding coefficient plot.

Dependent variable	Figure	Observations	N cluster	R2	Mean dependent	SD dependent
Total loans over total assets	B.5a	5,148	133	0.357	0.843	0.081
Mortgages loans over total loans	B.5b	5,150	133	0.260	0.773	0.128
Firm loans over total loans	B.5c	5,150	133	0.076	0.260	0.102
HTM over total assets	B.5d	5,150	133	0.036	0.026	0.028
MM over total assets	B.5e	5,150	133	0.350	0.063	0.046

C Additional figures

Figure C.1: LTV-persistence

In this figure we show the evolution of low-LTV mortgages relative to total mortgages for high- and low-exposure banks.



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Paper 2:

Follow-thy-neighbor? Spillovers of asset purchases within the real sector

Follow-thy-neighbor? Spillovers of asset purchases within the real sector*

Talina Sondershaus†

This Draft: June 17, 2022‡

Abstract

Unconventional monetary policy can stimulate lending from weak banks to weak firms. Do changes in lending behavior induce spillover effects between firms within agglomerations? By exploiting the first asset purchase program of the ECB, I show that firms linked to banks which benefit from asset purchases invest less and induce negative spillovers on firms operating in the same region and sector. The finding is important for two reasons: First, it provides evidence on how zombie lending can delay economic recovery. Second, it shows the importance to consider spillovers when assessing unconventional monetary policy because spillovers can cover up direct effects.

JEL Classification: D22, E58, G21

Keywords: Asset purchase programs, spillovers, small and medium sized enterprises, investments

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†Halle Institute for Economic Research (IWH), Kleine Märkerstraße 8, 06108 Halle (Saale), Germany, E-mail: talina.sondershaus@iwh-halle.de.

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1 Introduction

Does unconventional monetary policy (UMP) induce spillover effects among firms operating in agglomerates? Acharya et al. (2019) find a zombie lending behavior of banks exposed to the Outright Monetary Transaction Program (OMT) of the ECB in 2012. They show that firms borrowing from OMT banks do not change their investment behavior, and economic recovery remains weak. An explanation for the sluggish recovery during the sovereign debt crisis could be that zombie lending due to UMP causes spillover effects between market participants and thereby thwarting innovative processes.

In this paper I propose to enhance Acharya et al. (2019)'s analysis on the effects of UMP on firm investment behavior by taking spillover effects between firms which operate in agglomerates into account. This paper asks the question whether there are spillover effects of the ECB's first large asset purchase program, the securities markets program (SMP), on investment decisions of German small and medium-sized enterprises (SMEs) operating in the same region within the same sector. ”Treated firms”, i.e. firms with a link to a regional bank which held SMP eligible assets, benefit from increases in loan supply. To assess the real effects, I apply Berg et al. (2021)'s technique and compare investment behavior of treated firms to firms linked to banks which do not benefit from the SMP (”non-treated firms”) while taking spillover effects between the two groups of firms into account. On the one hand, concurrent spillovers can occur due to local aggregate demand effects, due to agglomeration spillovers or because firms use neighboring firms as a source of information. On the other hand, there could be diametrical spillovers because treated firms benefit from relatively lower financing costs and thereby crowd-out competitors (e.g. Bustamante and Frésard, 2021; Combes and Gobillon, 2015; Benoit, 1984).

As a pre-requisite to my study, I replicate Koetter (2020)'s finding that regional banks increase loan supply to corporate borrowers as a response to the SMP. In particular, I find that weakly capitalized banks increase lending to high leveraged firms, the ”zombie connection”. As a further pre-requisite I study aggregate developments after the introduction of the SMP. Regions in which a large share of firms were exposed to the SMP via their bank do not differ in terms of economic growth – similar to the finding of Acharya et al. (2019) for the impact of the OMT. However, high exposed regions show relatively lower unemployment rates after the introduction of the SMP, which is in line with Caballero et al. (2008)'s finding that additional financing enables zombie firms to hold onto workers.

Based on these findings, I study the investment behavior of firms. I observe that if spillovers between firms are ignored, differences in investment decisions between treated and control group are very small. In contrast, when taking spillovers into account I find that treated firms reduce their investment activities compared to non-treated firms. The relative reduction amounts to around 50% of average investment activities in the whole sample. My results are in line with findings by Marsh et al. (2020) who establishes a negative relationship between debt and investments if debt levels are already high. This applies to treated firms in my sample which are already particularly high leveraged. There are concurrent spillover effects on non-treated firms. A non-treated firm which operates in an averagely affected region–sector cluster reduces investments compared to non-treated firms without affected firms in their surroundings. The relative reduction in investments amounts to about 30% of average investments in the whole sample. My results speak to previous findings that firms are sensitive to the investment decision of neighbouring firms in the same industry, i.e. peer firms, and synchronize investment behavior (e.g. Bustamante and Frésard, 2021; Beck et al., 2021; Fracassi, 2017; Dougal et al., 2015).

There are indications for stronger competition among firms in affected clusters. The higher the share of treated peers which benefit from increases in loan supply, the lower are profits as well as market shares for *all* firms operating in the same region–industry. While investments are reduced and competition becomes stronger, treated firms increase their financial asset holdings such as financial claims vis-a-vis customers. Moreover, they also increase their workforce. This goes hand-in-hand with the lower unemployment rate on the regional level.

This paper discusses three channels for negative spillover effects: (1) Local aggregate demand effects force peer firms to reduce investments as well. I test whether non-tradeable industries drive negative spillovers which should be affected by local aggregate demand effects. There is no difference between tradeable and non-tradeable industries, and I conclude that local aggregate demand effects are not the sole driver for negative spillovers on non-treated firms. (2) Weakened agglomeration spillovers such as less benefits from lower transportation costs or infrastructure can be at work, as well as less knowledge spillovers. I argue that the first two rather materialize in the medium to long run and hence probably cannot be seen in my short sample period. For the latter I find that spillovers are not driven by high-tech industries which comprise mainly high-skilled labor for which knowledge spillovers should matter. (3) Firms can use their peers as a source of information. I cannot rule out that this channel is at work. In fact, Bustamante and Frésard (2021) argue that especially small firms, which comprise my sample, have less precise information and depend on their peers in judging about their future prospects.

There are two papers which consider spillover effects of UMP. Grosse-Rueschkamp et al. (2019) find that as a response to the corporate sector purchase program, small firms benefit from increased lending by their banks. The positive effect is induced by spillovers of large firms within the same bank which issued more bonds and freed up bank lending resources. Acharya et al. (2019) also investigate possible negative effects of zombie firms on their surroundings. They find that a larger share of zombie firms prevents healthy firms from investing and employing more. Schivardi et al. (2020) point to methodological difficulties when measuring the impact of the share of weak firms on neighboring strong firms: The share of weak firms is correlated with shocks that changes the performance of both groups. My study contributes to these papers by explicitly assessing spillovers *between firms*. I make use of a credit supply shock, which is exogenous to bank lending for German regional banks and investment decisions of firms linked to these banks. This allows me to study the effect of UMP on investment behavior of firms, and to draw conclusions about spillovers within region–sector clusters, while avoiding identification issues raised by Schivardi et al. (2020).

Previous papers show intended effects of the SMP. Researchers agree on that the SMP was successful in lowering government bond yields (Doran et al., 2013; Casiraghi et al., 2016; Gibson et al., 2016; Eser and Schwaab, 2016; Ghysels et al., 2016; De Pooter et al., 2018). Concerning side effects on banks and firms, Koetter (2020) shows that regional banks increase commercial lending as a response to the program and Cycon and Koetter (2015) find that corporate refinancing costs decreased. To the best of my knowledge, my paper is the first to study investment behavior of firms as a response to the SMP and spillovers between firms operating in the same sector and region.

The paper proceeds as follows: Section 2 describes the economic mechanism underlying the analysis and develops testable hypotheses. In Section 3, I describe data and identification approach. Section 4 presents the results: First I show changes in aggregate outcomes. Second, I summarize the replication exercise on lending behavior by banks. Third, I present the main results on investment behavior of firms. Section 5 provides robustness checks and Section 6 concludes.

2 Economic mechanism

In this section I outline the economic mechanism underlying my analysis and derive testable hypotheses on firms' investment behavior as well as spillovers to peer firms as a response to an UMP shock.[1] The discussion shall provide guidance how to empirically test spillovers and the channels through which spillovers can occur.

UMP may lead to a "zombie lending behavior" which is the continuation or increase in lending from weak banks to weak firms. As a result, directly affected (weak) firms might change their investment behavior. On the one hand, due to additional funding weak firms might be relieved from financial constraints and take up new borrowings in order to increase their investments.

H_1: Directly affected firms invest more.

On the other hand, weak firms which are defined according to leverage ratios might reduce investments due to a negative relationship between debt and investments which Marsh et al. (2020) demonstrate. High leveraged firms might not invest and forego possible projects with positive net present value because first, even higher debt levels reduce internal funds free to invest as these are being used to service debt payments. Second, owner's fear that benefits of investments only accrue to creditors and hence do not have incentives to invest (Marsh et al., 2020; Myers, 1977).

$Alternative\ H_1$: Directly affected (high leveraged) firms invest less.

There can arise agglomeration spillovers on peer firms' investment behavior. Firms tend to settle within agglomerations close to similar firms in the same regions (Combes and Gobillon, 2015). Firms benefit from each other due to knowledge spillovers, shared infrastructure, lower transportation costs, or deeper labor markets. These benefits materialize for firms operating within the same region within the same sector. For instance, Greenstone et al. (2010) show that total factor productivity increases for incumbent firms if there is a new plant opening in their neighborhood. Matray (2021) provides evidence for knowledge spillovers within geographical areas as a driver for innovation. Peer firms benefit from new technology employed and knowledge disseminated by workers, and conversely suffer if neighboring firms reduce production.

[1] As a pre-requisite to this study I outline the economic mechanism how UMP can induce changes in lending behavior and can lead to a so called "zombie lending behavior" in Appendix C.

Firms are also connected due to local aggregate demand effects (e.g. Shleifer and Vishny, 1988). For instance, when one firm extends its production site and employs more workers, local restaurants are facing higher demand. These linkages materialize within the same region, but may occur across sectors. Similarly, firms are linked due to input-output relationships. Increases in the production site of one firm can spill over upstream to suppliers who are faced with higher demand, and can spill over downstream to customer firms who are facing more supply (Ozdagli and Weber, 2021; Acemoglu et al., 2016). Moreover, firms might use peer firms as a source of information as in Bustamante and Frésard (2021) who find that in particular small firms use their product market peers as a source of information about future prospects and adjust their own investment decisions accordingly. Dougal et al. (2015) find that these information spillovers arise locally.

H_2: There are concurrent spillover effects to peer firms' investment behavior who are operating within the same region within the same sector.

Meanwhile UMP might strengthen market power for affected firms which reduces growth opportunities for peer firms. Benoit (1984) shows theoretically that firms which can afford it have incentives to prey on their competitors by lowering product market prices to drive their competitors out of the market. Donohoe et al. (2022) examine competitive externalities of a tax cut and find that firms which enjoy lower tax payments pressure their peers and depress their performance. The effect on peers is strongest for firms which are financially constraint and which produce similar products.

$Alternative\ H_2$: There are diametrical spillover effects to peer firms' investment behavior who are operating within the same region within the same sector.

3 Data and Identification

3.1 Monetary policy shock

The SMP was the first large scale asset purchase program (APP) that was conducted in the Eurozone. The ECB implemented the program in May 2010 and it lasted until September 2012. The ECB started purchasing Portuguese, Greek and Irish sovereign bonds and extended the program in 2011 to Spanish and Italian sovereign debt. They also purchased marketable debt of private entities incorporated in the Euro area, however, as will be described in Section 3.2, this does not affect firms in the sample of this paper which comprises only SMEs. In total, the program had a notional volume of 218 Billion Euro.

The SMP provides a good testing ground for establishing causal links between APPs and lending to firms and further spillover effects. First, in contrast to the Fed, the ECB was hesitating to intervene into financial markets until the SMP was established. Hence, the program was probably not expected by market participants (Stolz and Wedow, 2010). This condition is crucial to avoid self-selection into treatment group of especially risk-prone banks which loaded up with crisis bonds. Second, the SMP was a response to the sovereign debt crisis in Southern European countries and Ireland, and not to events in Germany. Third, the program aimed at lowering government bond yields and not to stimulate credit growth. The ECB describes this in their announcement of the program, and shows actions to keep aggregate reserves holdings stable by implementing sterilization measures. If there are changes in lending behavior in Germany as a response to the SMP, they are unintended side effects as they were neither the aim nor the reason for the program.

Data on the SMP purchases comes from the ECB and is combined with Bundesbank data on sovereign bond holdings and is taken from Koetter (2020) and Antoni and Sondershaus (2019). The data provides information on whether a bank held SMP eligible assets on a yearly basis during the program's years 2010-2012. Following Koetter (2020) I define a bank as treated if it held SMP eligible assets in 2010, the first year of the SMP. To reduce the probability of a selection bias, i.e., to rule out that banks and thereby also firms selected themselves into the group of the directly treated banks and firms, banks must have held SMP eligible assets in 2010. Banks which purchased assets only from 2011 or 2012 onward belong to the control group. Hence, it is possible that I underestimate the actual effect of the SMP, but I rule out that banks which selected into the treatment group after the start of the program confound my results. The sample covers 1,118 German savings and cooperative banks of which 17.98% are treated. I use regional banks only to ensure that banks are not specialized in security trading as are large commercial banks. To verify, I follow Abbassi et al. (2016) to approximate a bank's proficiency in trading. They assume that banks which are members of the German trading platform Eurex Exchange have a trading desk. There are four savings banks in Germany which are members of the Eurex[2]. They are excluded from my sample. In case of duplicates, bank-year observations which are consolidated are dropped to avoid double reporting.

[2]Kreissparkasse Ludwigsburg, Sparkasse Pforzheim, Kreissparkasse Köln and Hamburger Sparkasse

3.2 Firm data

The analyses on spillovers are based on the firm level. I use information on firms' bank links by Dafne from Bureau van Dijk for the time period 2007-2013. Dafne reports the names of the banks a firm has links to, however does not report on the nature or intensity of the relationship. To approximate lending volumes of banks to the firm, I reduce my sample to firms with one single bank relationship. This allows me to approximate bank loan volume by firms' balance sheet positions on outstanding debt. 59.05% of firms in Dafne report one single bank only. Kalemli-Ozcan et al. (2019) also report that it is common for German firms to have one bank only.

I add firm balance sheet data provided by Amadeus from Bureau van Dijk. For identification reasons I only include SMEs in the analysis. SMEs are largely bank dependent and changes in credit supply by their banks is relevant and cannot be substituted by capital markets. Moreover, in this way I can rule out that purchases of corporate bonds within the SMP by the ECB confound my analyses. As SMEs have a pivotal role as an engine of economic growth, employment and economic stability (BMWi, 2018), the study of SME's investment behavior is relevant for economic development in Germany. To identify SMEs, I use the definition provided by Amadeus: Firms are excluded if they are large or very large according to Amadeus. This concerns firms which have operating revenue $>=$ 10 million EUR, or their total assets are $>=$ 20 million EUR, or they have $>= 150$ employees. 99.49% of firms in my sample do have less than or equal to 150 employees. To avoid that misclassification by Amadeus confound my results, I leave out larger firms in robustness checks.

Also due to identification reasons, as described in Section 3.1, I keep only firms which link with regional banks. 66.38% of bank links of SMEs in the merged Dafne-Amadeus data set are to savings or cooperative banks, which shows the strong reliance of SMEs on regional banks. Finally, I exclude financial firms as well as industry sectors that are highly subsidized (agriculture, fishing and forestry), or which are closely linked to the state (health industry, education, and public administration).[3]

Table 1 reports summary statistics on the regional and on the firm level and Table D.1 in Appendix D shows variable definitions. I use a sample of firms for which all variables

[3]For detailed description of data preparation, see Appendix A.

necessary to calculate gross investments are available. The sample encompasses 11,809 SMEs or 38,661 firm-year observations. Gross investments is defined as

$$investments = log[(fias + 1) + depreciation]_t - log(fias + 1)_{t-1}, \tag{1}$$

which is log differences between fixed assets plus depreciation in period t and fixed assets in period $t - 1$. By this definition, replacement investments which substitute depreciated assets are captured as investments. The median firm has total asset size of around 0.935 million Euro and is 14 years old. I use further variables: ∆toas is the first difference of log total assets. ∆debt is first differences of log of current assets debt plus 1. ∆cash is first differences of log of cash plus 1. ∆ebta is first differences of log of earnings before interest, taxes, depreciation and amortization plus 1. ∆sales is first differences of log of operational revenue plus 1. $market\_share$ is the share of sales over total sales of *all* firms available in Amadeus for the same region-sector of firm i. ∆employment is the first differences of log employment. To avoid that outliers drive the results, investments, firm balance sheet and income variables, as well as employment are winsorized at the 1% and 99% by year.

– Insert Table 1 around here –

Treatment is defined similar to Koetter (2020)'s definition. He uses banks' exposure to SMP eligible assets in the first quarter of 2010. As I have yearly data on banks' SMP exposure, I define SMP equal to 1 if the bank, the firm is linked to, held eligible SMP assets in 2010. It equals 0 for banks that did not hold SMP eligible assets in 2010 as described in Section 3.1. 25.7% of firms are directly treated , i.e. $SMP = 1$.

Because agglomeration spillovers materialize locally within the same sector, as outlined in Section 2, I decide to model spillovers within regions within sectors. Meanwhile I aim to rule out that local aggregate demand effects, which can materialize across sectors, drive my results. As this analysis focuses on SMEs, which mainly operate locally, I refrain from modelling spillovers solely within sectors. To measure spillovers within region-sectors, I define space according to Brakman et al. (2005) and Brakman and van Marrewijk (2013). They show that agglomerations manifest especially on NUTS-3 level ("Kreis"). Sectors are identified with the two-digit NAICS code. Firms operate in 395 regions and 19 sectors in the analysis. The mean treatment share within region–cluster in 2010, $SMPshare$ is 29.0%. In the lending replication exercise I find that *certain* firms benefit from increases in loan supply: low leveraged firms, and high leveraged firms linked to weakly capitalized banks. I define the treatment variable $SMP\_precise$ which equals 1 only for firms which actually benefit, and 0 otherwise. $SMPshare\_precise$ is defined correspondingly. The mean treatment share within region–cluster according to this more precise definition is 26.7%.

According to Pasten et al. (2020), Ozdagli and Weber (2021) and Acemoglu et al. (2016) spillovers within input-output (IO) clusters are important mechanisms to transmit shocks through the economy. I alternatively measure spillover effects within IO relationships and define industry clusters according to Kelton et al. (2008) to capture IO linkages. They suggest 61 clusters of industries which are linked vertically but also horizontally. With this definition, firms are grouped in 60 clusters.[4] Each firm belongs to one industry according to the two-digit NAICS and is included at least in two, at the median in nine and at the maximum in 49 clusters. Note that sample size is reduced to 30,228 firm-year observations, or 9,276 firms, because Kelton et al. (2008) exclude wholesale (NAICS codes 42) and retail trade (NAICS codes 44 and 45) because they are too general to fit into IO categories. I estimate the share of treated firms within the same IO cluster within the same region, excluding firm i. Then for each firm I use the average of all IO clusters the firm operates in within the same region, excluding firm i, to obtain $SMPshare\_IO$. The average treatment share within region–industry IO clusters is 29.4%.

Further variables used in the analyses are the following: $Post$ is a binary variable which equals 0 in pre period 2007-2009 and 1 in the post period 2010-2013. $Non\_tradeable$ is a binary variable which equals 1 for firms which operate in an industry classified as producing non-tradeables according to Delgado et al. (2014), and 0 otherwise. They classify a sector as tradeable if more than 50% of products are traded. $High\_tech$ is a binary variable which equals 1 for firms which operate in an industry classified as high-tech according to Kile and Phillips (2009), and 0 otherwise. They classify ten industries according to the three-digit NAICS as high-tech.[5] $High\_tech\_Decker$ is a binary variable which equals 1 for firms which operate in an industry classified as high-tech according to Decker et al. (2020), and 0 otherwise. They define 14 industries according to the NAICS as high-tech.[6] 8.3% of observations according to the definition used by Decker et al. (2020), and 14.1% of observations according to the definition by Kile and Phillips (2009) belong to high-tech industries.

In aggregate analyses I assess whether there are changes to GDP growth, measured according to log differences of GDP, or the unemployment rate depending on how regions

[4] My sample does not contain firms from cluster 40 "insurance" as I exclude financial firms from my sample.

[5] NAICS 325, 334, 335, 339, 511, 513, 514, 517, 518, 541.

[6] NAICS 3254, 3341, 3342, 3344, 3345, 3364, 5112, 5161, 5179, 5181, 5182, 5413, 5415, 5417, definition provided by Heckler (2005).

are exposed to the SMP. Data on GDP and unemployment comes from Destatis. I define $SMPshare\_region$ as the overall share of all firms affected in region r, which is 34.5% on average. $SMPshare\_region\_SMEs$ is the share of all SMEs affected in region r, which is 17.2% on average. The share of affected SMEs is lower because SMEs rather bank with regional banks which were less affected by the SMP.

3.3 Identification

To gain an overview about the effect of the SMP on German regions, I follow Huber (2018) and assess first whether the macro economy shows changes in performance conditional on the extent how much regions are affected by the SMP. I therefore estimate the following model:

$$Y_{rt} = \gamma_1 \times SMPshare\_region_r \times Post_t + \alpha_r + \epsilon_{rt}. \tag{2}$$

Dependent variable is GDP growth, defined as log differences of GDP, and the unemployment rate of region r in year t. Regions are defined according to the NUTS-3 level. $SMPshare\_region$ is the overall share of treated firms of all firms in region r in year t. Alternatively, I measure the share of treated SMEs per region r in year t, $SMPshare\_region\_SMEs$ as described in Section 3.1.

Next I move to the firm level and assess how individual investment behavior of firms changes conditional on their bank being affected by the SMP and on their surrounding firms within their region–sector cluster. Figure 1 sketches the setting of studying spillover effects between SMEs.

– Insert Figure 1 around here –

Triangles are banks, squares are firms. Savings and cooperative banks operate in one confined region. SMEs have a single link to a regional bank and operate in one sector. I measure spillovers between firms within their specific region–sector cluster, marked with the dotted line. The black triangle is a bank which held SMP eligible assets in 2010 and hence is defined as treated, as well as the firms linked to the bank. I measure spillovers according to the share of treated firms within the cluster excluding $firm_i$. In the sketch, for $firm_{i=1}$ and $firm_{i=2}$ the share of treated firms within the cluster is 0.5. For $firm_{i=3}$ the share of treated firms within the cluster is 1. There can be heterogeneous spillover effects on non-treated and on treated firms, which will be captured in the econometric model.

To assess the effect of the SMP on firms operating in the same sector in close proximity, I estimate the following model which is in the vein of Berg et al. (2021):

$$\begin{aligned} Y_{it} &= \gamma_1 \times SMP_i \times Post_t \\ &+ \gamma_2 \times Post_t \times SMPshare_i \\ &+ \alpha_i + \alpha_{rt} + \alpha_{kt} + \epsilon_{it}. \end{aligned} \tag{3}$$

Dependent variable Y_{it} is investments, as defined in equation (1) of firm i in year t. The first line corresponds to a common difference-in-differences estimation: SMP is a binary variable which equals 1 if the firm's bank held SMP eligible assets in 2010, and 0 otherwise. $Post_t$ is an indicator which equals 0 in the years 2007-2009 and 1 in the years 2010-2013. γ_1 shows the direct effect of the treatment on firms linked to a bank which held SMP eligible assets in 2010. $SMPshare_i$ is the share of treated firms in the same region–sector of firm i excluding firm i. γ_2 shows homogeneous spillover effects on all firms, i.e. treated and non-treated, conditional on the share of treated firms within the same region–industry cluster. I augment equation (3) with heterogeneous spillover effects between treated and non-treated firms in equation (4):

$$\begin{aligned} Y_{it} &= \gamma_1 \times SMP_i \times Post_t \\ &+ \gamma_2 \times SMP_i \times Post_t \times SMPshare_i \\ &+ \gamma_3 \times (1 - SMP_i) \times Post_t \times SMPshare_i \\ &+ \alpha_i + \alpha_{rt} + \alpha_{kt} + \epsilon_{it}. \end{aligned} \tag{4}$$

Here, γ_2 captures spillover effects on treated firms, i.e. the effect of the $SMPshare$ on firms with SMP=1. γ_3 captures spillover effects on non-treated firms, i.e. firms with SMP=0.[7] As results on lending of banks as a response to the SMP show that there was a re-distribution of lending away from high leveraged firms linked to high capitalized banks towards low leveraged firms as well as towards high leveraged firms with low capitalized banks, I further apply the more precise treatment definition, $SMP\_precise$, which equals 1 only for firms linked to treated banks which belong to the group of firms which benefit from larger loan supply, and 0 otherwise. Equally, $SMPshare\_precise$ captures the share of treated firms according to the definition of $SMP\_precise$ within the same region–sector of firm i without firm i.

[7] In Appendix B, I compare equation (4) to a standard interaction model and give intuition on the interpretation of coefficients, explaining that equation (4) does not raise collinearity problems.

To control for unobserved heterogeneity across firms, firm fixed effects (α_i) are included. Region–time fixed effects (α_{rt}) and industry–time fixed effects (α_{kt}) control for region or industry demand shocks. I use the NAICS code for the industry classification and the NUTS-3 definition for regions. As the treatment variable $SMPshare$ varies on the region–sector level, standard errors are clustered on the region–sector level.

Verifying the parallel trend assumption in the pre period of treated and control firms is not easy when arguably the effect of the SMP is more complex due to spillovers and hence there are several treatment and control groups. This paper reports results from a dynamic version of equation (4) to show that the parallel trend assumption of treatment and control group in the pre period is not violated. To estimate a dynamic regression instead of estimating t-tests only between treated and control groups has the advantage that I can show parallel trends for all three coefficients of interest: direct effect, spillover on treated and spillover on non-treated firms instead of subsuming all in either treated or control group. Further, it allows interpretation on the dynamics of the effects over time:

$$\begin{aligned} Y_{it} = & \sum_{\tau=2007,\tau\neq 2009}^{2013} \gamma_{1\tau} \ (\mathbf{1}_{t=\tau} \times SMP_i) \\ & + \sum_{\tau=2007,\tau\neq 2009}^{2013} \gamma_{2\tau} \ (\mathbf{1}_{t=\tau} \times SMP_i \times SMPshare_i) \\ & + \sum_{\tau=2007,\tau\neq 2009}^{2013} \gamma_{3\tau} \ (\mathbf{1}_{t=\tau} \times (1 - SMP_i) \times SMPshare_i) \\ & + \alpha_i + \alpha_{rt} + \alpha_{kt} + \epsilon_{it}. \end{aligned} \tag{5}$$

I interact treatment variables with indicators for every year τ from 2007 until 2013 using year 2009 as the base year. In particular, $\gamma_{1\tau}$ can verify that treated and control firms for which $SMPshare = 0$ do not substantially differ in terms of outcome variables in the pre period compared to the base year 2009 conditional on the fixed effect structure. $\gamma_{2\tau}$ can verify that treated firms with low $SMPshare$ and treated firms with high $SMPshare$ do not differ substantially in the pre period compared to the base year 2009. Finally, $\gamma_{3\tau}$ can verify that non-treated firms with low $SMPshare$ and non-treated firms with high $SMPshare$ do not differ substantially in the pre period in terms of outcome variable compared to the base year 2009.

4 Results

4.1 Aggregate Results

Table 2 shows results for estimating equation (2) with GDP growth and unemployment rate as dependent variable.

– Insert Table 2 around here –

Column I and II report results for GDP growth as dependent variable. GDP growth changes neither when the exposure of regions is measured according to the share of all firms treated, nor when it is measured according to the share of treated SMEs. The coefficients are close to zero. Columns III and IV report results with the unemployment rate as dependent variable. The unemployment rate is lower in regions with high exposure compared to regions with low exposure to the SMP after the onset of the program. The difference is statistically significantly different at the 1% level. For a region with an average exposure of 34.5%, the unemployment rate is $0.345 \times (-\ 2.059) = -0.71$ percentage points (pp) lower compared to regions which are not affected by the SMP. Given that the average unemployment rate for the whole sample is 7.04%, the relative change corresponds to a reduction of the unemployment rate of around 10% for regions which are averagely affected compared to the mean unemployment rate.

The following analyses on the firm level provides evidence on why mean GDP growth does not pick up, while the unemployment is reduced in highly exposed regions.

4.2 Replicating lending behavior

As a pre-requisite to my study I replicate Koetter (2020)'s finding that regional banks increase corporate lending as a response to the SMP. In particular I want to assess whether also firms from my sample which are linked to a SMP bank benefit from increases in loan supply. In Appendix C I describe literature, hypotheses, data, and identification. As dependent variable I use first differences of log of long term debt holdings of firms, as well as short term loans. Note that I can only approximate long term and short term loans which originate from banks from observable balance sheet items provided by Amadeus as described in Section 3.2.

Similarly to Acharya et al. (2019) and Jiménez et al. (2014), I test whether there is a so called "zombie lending behavior" as a response to the SMP, which implies that especially weak banks increase lending to weak firms. Therefore I follow other authors and use the equity ratio banks as a proxy for the bank's weakness (Schivardi et al., 2020; Jiménez et al., 2014; Acharya et al., 2019; Peek and Rosengren, 2005). I define a bank as weak if it was below the median of the distribution of banks' equity ratios in the pre crisis and pre treatment year 2007. I define a firm as weak if it is highly leveraged following Schivardi et al. (2020). They claim to measure firms' default risk according to their leverage ratio. See Appendix C for further indication that firm leverage captures well firm vulnerability. I partition my sample at the sixth, seventh and eight percentile and define a firm as weak if it was at or above the respective decile in terms of mean leverage in the pre period within the sector it operates in. I use the mean over the whole pre period as some firms do not report leverage every year and hence I can obtain the highest coverage of firm-year observations.

– Insert Table 3 around here –

Table 3 shows the results for long term debt as dependent variable. Column I presents the result for a common difference-in-differences model without interactions. There is no differential effect between treated and non-treated banks in terms of their lending behavior. In column II, I show differential effects separately for firms linked to lowly capitalized bank and other firms. Again, there are no differential effects. From column III onward I report fully specified models. In column III a weak firm is defined as one with a mean leverage ratio in the pre period within the sector it operates in that is equal or above to the sixth decile. There is a positive differential effect on long term debt for firms linked to treated banks which are highly capitalized (Weak_bank = 0) and which belong to lower leveraged firms (Weak_firm = 0) compared to low leveraged firms with strong banks which were not treated. The differential effect is positive and statistically significantly different from zero at the 5% level (γ_1). These firms increase long term debt by 1.503 pp. Given that the standard deviation of long term debt growth for the whole sample is 4.115, the differential effect between treated and non-treated firms corresponds to more than 36% of one standard deviation of long term debt growth.

Further, I find that weak firms in general obtain less lending if they are linked to a treated bank (γ_3). The differential effects is negative and statistically significantly different from zero at the 5% level in columns III and IV, and at the 10% level in column V. The negative effect outweighs the general positive effect (γ_1) on long term lending. However, if weak firms are linked with weak banks, the so called ”zombie lending relationship”, they show *higher* loan growth if their bank is treated compared to weak firms which are linked to non-treated weak banks (γ_4). The results pertain when I change the definition of weak firms and move up the leverage distribution as I present in column IV and V. The coefficient is statistically significantly different from zero at the 10% level in all specifications. In total there is a positive effect on the growth rate of long term debt of weak firms linked to weak banks (γ_1 + γ_3 + $\gamma_4 > 0$).

To summarize, I find that lending is redistributed among firms: Strong firms, i.e. low leveraged firms, receive more lending. Weak firms linked to weak banks, the "zombie connection", also receive more lending. Weak firms with strong banks however, receive less lending. There is no effect on short term loans.[8] In the following, I investigate if changes in lending lead to changes in investment behavior of firms and whether there are spillover effects on firms operating in the same region–sector cluster.

4.3 Investments

Table 4 shows changes on investment behavior after the introduction of the SMP. The table builds up from a simple difference-in-differences analysis which ignores spillovers, to including spillover effect which are homogeneous for treated and non-treated firms as described in equation (3), to the fully specified model as described in equation (4).

– Insert Table 4 around here –

Column I reports the results from a common difference-in-differences model. There is no differential effects between treated and non-treated firms in terms of their investment behavior. In column II, I add homogeneous spillover effects, i.e. spillovers to all firms within the same region-sector. There is a negative spillover effect to peer firms which is statistically significantly different from zero at the 5% level. In column III I show results for the fully specified model in which I distinguish between spillovers on treated (γ_2) and non-treated firms (γ_3). γ_1 which captures the direct effect is negative and statistically significantly different form zero at the 5% level. Directly treated firms invest less and their investment behavior spills over to non-treated firms which operate in the same region–sector. In terms of economic magnitude, directly treated firms reduce their investments by 0.153 pp, which compares to mean investments in the whole sample of 0.336. That is, the relative reduction of investments of treated firms amounts to more than 50% of average investments activities.

Spillover effects are driven by spillovers on non-treated firms. Non-treated firms which operate in an averagely affected region–sector with a SMPshare of 0.290 reduce investments by 0.290$\times$0.350= 0.102 compared to non-treated firms without treated peers in their surroundings. That is, non-treated firms in an averagely affected region–sector reduce their

[8] Results are not reported here, but available upon request.

investments relative to non-treated firms without treated peers by around 30% compared to average investment activities.

In columns IV-VI I apply a more precise definition of the treatment. In the replication exercise on the lending behavior of banks as a response to the SMP, I show that there was a re-distribution of lending supply away from high leveraged firms with strong banks towards low leveraged firms in general, and high leveraged firms with weak banks (see Section 4.2). Following this finding, I define in columns IV -VI firms only as treated if they benefited from higher loan supply, which are the low leveraged firms as well as firms from what I call "zombie connections". As the treatment becomes more precise, the results also improve in precision: There is a negative direct effect which pertains across all specifications, though it becomes larger in the full model with all possible spillovers. Directly treated firms invest less, and the negative coefficient is statistically significantly differently from zero at the 1% level. The negative spillover effects also become more negative and are statistically significantly different from zero at the 1% level in column VI. In terms of economic magnitudes, non-treated firms which operate in an averagely affected region–sector with a SMP-share_precise of 0.267 reduce investments by 0.267$\times$0.465= 0.124 compared to non-treated firms without treated peers in their surroundings. That is, non-treated firms in an averagely affected region–sector reduce their investments relative to non-treated firms without treated peers by more than 36% compared to average investment activities.

– Insert Figure 2 around here –

Similar to Berg et al. (2021) I illustrate the results in a single graph as shown in Figure 2. I use the regression output from Table 4, column VI and plot predicted values of investments with 90% confidence intervals. The difference between E(Y_{SMP}) and E($Y_{(1-SMP)}$) at $SMPshare\_precise$ = 0 corresponds to the direct effect of the SMP on firm investments. The dotted line shows how non-treated firms are affected by spillovers and reduce investments the higher the share of treated firms in the same region–industry. The dotted-dashed line shows that also treated firms reduce investments more the higher $SMPshare\_precise$, but the confidence interval is large because there is a lot of variation across treated firms. The solid line shows the average reduction in investments for all firms. The figure illustrates that as spillover effects run in the same direction as direct effect, a common difference-in-differences specification without modelling spillovers cannot capture changes in investment behavior. The differential effect between treated and control group does not capture that both group of firms reduce their investment activities. Negative spillovers on the group of non-treated blurs treatment and control group in column I and IV in Table 4 and the effects on the single groups become only visible when taking spillovers into account.

The result that firms synchronize investment decisions is in line with previous findings: Dougal et al. (2015) show that investment decisions for public companies in the US are highly sensitive to their peers' investment choice which operate in the same agglomeration. Similarly, Bustamante and Frésard (2021) provide evidence that firms follow their peers' investment decisions. They argue that firms learn from their peers and use them as a source of information. The sensitivity is especially strong for SMEs. In Fracassi (2017)'s study information sharing among social peers drives concurrent investment decisions.

– Insert Table 5 around here –

Regression models in Table 4 include the whole fixed effect structure. In Table 5 I show results for estimating equation (4) with heterogeneous spillover effects and build up the fixed effect structure. Column I includes firm and time fixed effects, column II additionally industry–time fixed effects. There is a negative direct effect which is significantly different from zero for all specifications at the 5% level. Without including region–time fixed effects (column I and II), there is a positive spillover effect on treated firms. In fact, region–time effects cover up effects on treated as well as on non-treated firms: All coefficients become smaller (more negative) when region–time fixed effects are included. Region–time fixed effects control for local aggregate demand effects which are similar for all firms within the same region. Hence there are local aggregate demand effects which cover up negative spillovers.

– Insert Table 6 around here –

To refine the analysis and to capture IO linkages between firms across industries, I alternatively measure spillovers within IO clusters based on the two-digit NAICS code as defined by Kelton et al. (2008). Table 6 reports the results. There is a negative direct effect on investments for treated firms. There is a positive spillover effect on treated firms which could be induced by local aggregate demand effects which affect all firms operating in the same region. When region-time fixed effects are included from column III onward, the positive spillover effect on treated firms disappears and the negative spillover effect on non-treated firms becomes visible. In the full specification which includes all fixed effects, a directly treated firm invests 0.221 pp less compared to a non-treated firm which has no affected firms in its surroundings. Given that mean investments for the whole sample is 0.336, directly treated firms reduce investments relative to non-treated firms by more than 65% compared to average investments activities. Non-treated firms which operate in an averagely affected IO-cluster where 29.4% of firms are exposed to the SMP, reduces investments by $1.302 \times 0.294 = 0.38$, which corresponds to a relative reduction of more than 100% compared to non-treated firms with no exposure within their clusters and compared to average investment activities. I conclude that direct and spillover effects become even stronger, economically and statistically, when spillovers are measured within IO clusters. However, note three shortcomings: First, classification by Kelton et al. (2008) picks up IO linkages across industries – vertical links – , but also *horizontal* links, for instance common suppliers or common customers, which makes interpretation of results as *solely* driven by IO linkages difficult. Second, sample size is reduced by almost 39% as Kelton et al. (2008) leave out industries which are too broad. Third, the definition of IO clusters is based on US industry structures. Applying this classification to German data limits interpretabilty.

– Insert Table 7 around here –

A concern is that for the sake of identification I use a very specific sample of SMEs with only single bank links. I run an additional test to assess whether my results still hold in a sample of SMEs which include firms with multiple bank links. Treatment status is defined according to the first bank reported in Dafne, which I assume to be the main bank. Table 7 reports the results. Sample size almost doubles and increases to 21,806 firms or 74,589 firm-year observations. Direct and spillover effects become smaller in magnitudes, however they are still substantial in size. The statistical significance for the direct effects strengthens and is now at the 1% level valid. The statistical significance for the spillover effect weakens and is now valid at the 10% level. The direction of the effects pertains.

4.4 Discussion direct effect

4.4.1 Less investments

Why do firms directly affected by the SMP reduce investments when they can increase their borrowings? In Appendix C I show that in large parts it is the already high leveraged firms which can borrow more from their SMP banks. These high leveraged firms encompass the group of "treated" firms in the regressions on the effect of the SMP on investments. In fact, high leveraged firms have a particular behavior concerning investment decisions. Marsh et al. (2020) show a negative relationship between debt and investments of firms with high debt levels. His argument is in vein of Myers (1977) who establishes that firms with high debt ratios might pass by projects with positive net present value because the owners of the firm expect that all benefits of investments accrues only to creditors. Added to that, Marsh et al. (2020) argue that increases in debt and therefore interest payments reduce internal funds available which otherwise would have been used for investments. As German firms which benefited from additional funds due to the SMP were already highly leveraged, the observation that these firms decrease investments is in line with previous findings which establish the problem of underinvestments of firms with an already high debt burden.

4.4.2 Alternative dependent variables

What do directly treated firms do with the additional borrowing capacity offered by their SMP bank if they even reduce investments? Table 8 shows results from estimating equation (4) with alternative dependent variables.

– Insert Table 8 around here –

Directly treated firms shrink in size (column I). They load up on financial claims vis-a-vis debtors if they are exposed to other treated firms in the same region–sector cluster (column II). γ_2 is statistically significantly different from zero at the 10% level, and implies that firms linked to a SMP bank and which operate in an averagely affected region–industry cluster increase growth of debt relatively to treated firms without treated peers by $1.898 \times 0.29 = 0.55$. Given that average growth of current assets debt is 1.78 for the whole sample, treated firms increase relative debt growth by more than 30% compared to average debt growth in the whole sample. Directly affected firms become financial intermediaries themselves, however only if others in their surroundings do the same. Meanwhile treated firms hoard less precautionary savings and reduced cash (column III).

Also, the higher the share of treated firms within the same region–sector, the lower are profits measured according to earnings before taxes, depreciation, amortization, and interest payments (column IV). This holds for treated firms as well as non-treated firms. The higher the share of treated firms in the same cluster, the lower are growth of profits. Given that profit growth on average for the whole sample is 0.053, the relative changes for firms surrounded by many treated firms are substantial. For an averagely affected treated firm, profits shrink by $0.670 \times 0.29 = 0.194$ and hence shrink by more than three times of average profit growth. Also statistically they are meaningful: the coefficient for spillovers on treated firms in significantly different from zero at the 1% level, and the coefficient which measures spillovers on non-treated firms is statistically significantly different from zero at the 5% level. Moreover, the higher the share of treated firms within the cluster, the lower are market shares for treated and non-treated firms (column VI). Spillover effects are significantly different from zero at the 1% level. These results imply that competition among firms within the same cluster increases such that profits and market shares decrease.

Directly treated firms which are surrounded by many treated firms within the same cluster increase their work force (column VII). Spillover effects on treated firms for employment growth is positive and statistically significantly different from zero at the 5% level. Given that average employment growth is 0.028 for the whole sample, treated firms in an averagely affected cluster increase employment by $0.29 \times 0.262 = 0.08$ which implies a relative increase of employment growth which is almost three times as large as average employment growth compared to treated firms without treated peers in their surroundings. In Table 9 I show results for alternative dependent variables also with the more precise treatment measures. Results remain robust besides the effect on debt holdings.

– Insert Table 9 around here –

To sum up, firms increase their role as financial intermediaries and employ more. However, in both cases they only do so in sync with other firms in their surroundings which behave similarly. Competition among firms increases according to shrinking profits and market shares.

4.5 Discussion spillover effect

Why are there negative spillovers on the investment behavior of non-treated firms which operate in the same region–sector cluster? This section discusses three potential channels, as outlined in Section 2, which could drive my results: (1) local aggregate demand effects, (2) weakened agglomeration spillovers and (3) peers as a source of information.

Local aggregate demand effects. To control for local aggregate demand effects which are the same for all units in a region, I include region–time fixed effects. Then direct and spillover effects become stronger, i.e. more negative, in most specifications. This points at regional demand effects which work diametrically to direct and spillover effects. It is possible that firms which are directly treated and as a consequence strengthen their role as financial intermediaries themselves by extending credit to firms they supply or customers, and which increase their workforce, elicit positive demand effects within the region, which might cover up parts of the negative effects on investments.

As an additional test to differentiate between local aggregate demand effects and agglomeration spillovers, I interact equation (4) with an indicator variable $non\_tradeable$ which classifies industries according to Delgado et al. (2014) into industries which mainly produce tradeables versus industries which mainly produce non-tradeables as described in Section 3.2. The classification is based on U.S. firms and hinges on the industry structure of the U.S. Hence, interpretation of results when using German data has to be treated with care. 45.8% of firms in the sample are defined as producing non-tradeables. If my model picks up local aggregate demand effects only, I expect that spillovers should be driven by the non-tradeable industries only. Conversely, agglomeration spillovers should also affect tradeable industries. Table 10 reports the results. There are negative spillovers to non-treated firms which operate in an industry which produces mainly tradeables. There is no difference to firms operating in sectors that produce mainly non-tradeables. These results underline the conjecture that regression results after including region–time fixed effects are not driven by local aggregate demand effects.

– Insert Table 10 around here –

Weakened agglomeration spillovers. Another explanation for synchronized investments decisions are weakened agglomeration spillovers. If directly treated firms invest less, their peers also benefit less for instance from lower transportation costs or better developed infrastructure. However, both channels probably are active rather in the medium or long run. Infrastructure needs time to plan and build, and transportation costs might change if peers close down for instance. However, it is possible that firms benefit less from knowledge spillovers if their peers reduce investments. I follow Lerche (2019) and test whether spillovers are driven by information and communications technology (ICT) heavy industries which are high-skilled labor intensive and which should especially be affected by knowledge spillovers. I use the definition employed by Decker et al. (2020) and categorize 14 industries as high-tech as described in Section 3.2. Alternatively, I use the measure by Kile and Phillips (2009) and categorize ten industries as high-tech according to three-digit NAICS. I report the results in Table 10 columns II and III. As before there are negative direct effects on treated and negative spillover effects on non-treated firms. Triple and quadruple interactions with $high\_tech$ are not statistically significantly distinguishable from zero. This result holds for both classifications of ICT industries. There are no differential effects for firms operating in high-tech industries. Hence, I cannot rule out that it is not knowledge spillovers which drive my results.

Peers as a source of information. Another driver for concurrent spillovers on investments could be shared information. Bustamante and Frésard (2021) find that especially smaller firms in their sample, which composes US publicly-listed firms only, possess less precise information about their future prospects and hence use peer firms as a source of information for their investment decisions. It might be that as my sample composes only of SMEs that non-treated firms use the reduction in investments as a source of information for their own prospects and hence follow their peers. Also, SMEs in my sample operate within the same region in the same sector and hence it might also be that they have personal ties. In fact, Fracassi (2017) find that social ties between firm managers drive synchronized investment behavior, though again their study is on a sample of public companies only. Further, null results on sales as an alternative dependent variable might hint at an information channel: if, for instance, firms reduced demand for supplies, suppliers would reduce sales as a response. However, as can be seen in Table 8 column V, there are no differences in terms of sales for directly treated firms.

5 Robustness

For robustness, I discuss three concerns and propose tests to rule out that these drive my results: (1) different time trends, (2) SMP_share is correlated with regional characteristics and (3) time-varying bank characteristics.

There are no different time trends across groups. If treatment and control group show different time trends, the parallel trend assumption for estimating a difference-in-differences model is violated. In order to test the parallel trend assumption between treated and control group in the pre period, and to assess the dynamics of the effects on investments in the post period, Figure 3 presents coefficient plots from estimation the dynamic regression equation (5) with investments as dependent variable.

– Insert Figure 3 around here –

Panel 3a shows the evolution of the coefficient for the direct effect $\gamma_{1\tau}$. The regression estimation compares differences between treated and control group to the base year 2009. Confidence intervals are plotted at the 1% level. Differences between the two groups are close to zero in the pre period. In the post period, investments for treated compared to non-treated firms are lower especially in 2011, at the height of the SMP.

Panel 3b shows the evolution of the coefficient for the spillover effect on treated firms $\gamma_{2\tau}$. Differences between the two groups are close to zero in the pre as well as in the post period. Panel 3c shows the evolution of the coefficient for the spillover effect on non-treated firms $\gamma_{3\tau}$. Non-treated firms with low exposure do not differ from non-treated firms with a high SMP exposure from neighboring firms in the pre period. In the post period, the coefficient for spillovers on non-treated firms is negative from 2011 onward.

SMPshare is not correlated with regional characteristics. Another concern might be that the share of treated firms, $SMPshare$, is correlated with regional characteristics in the pre period and hence merely depicts differences across German regions. If these regions then develop differently according to these characteristics, my results cannot be ascribed to the SMP treatment, but merely to regional differences which coincide with my treatment status. Figure 4 shows correlations of regional characteristics with treatment status over time. I distinguish between high and low treated regions according to the mean of the $SMPshare$ per region. Regions are defined as high treated if their mean $SMPshare$ is above the median of all regions, and as low treated otherwise.

– Insert Figure 4 around here –

Panel (a) plots GDP per capita, and Panel (b) GDP growth over time including confidence bands at the 5% level. There are no substantial differences between high and low treated regions. If anything, high treated regions show slightly lower GDP per capita in the post period after 2010. In Panel (c) I show correlations of the unemployment rate with treatment status over time. High treated regions have a slightly higher unemployment rate throughout the sample period. However, confidence intervals overlap largely. In Panel (d) I show the change of the unemployment rate over time. There are no differences between the groups. Finally, Panel (e) depicts differences in industry composition of different regions measured by the share of tradeables. Again, confidence intervals largely overlap for the two groups, and there are no differences in terms of changes of the share of tradeables, as can be seen in Panel (f). Hence I conclude that there are no substantial systemic differences between high and low treated regions. For time-invariant level differences, such as in the unemployment rate, I can control for in the regression models by including firm fixed effects in which region fixed effects are nested as firms rarely change their region.

Spillovers are not driven by time-varying bank characteristics. Spillovers which I observe between firms might be driven by spillovers between treated and non-treated banks within the same region. For instance, a treated bank might increase its market share by offering lower loan rates after benefiting from the SMP thereby inducing negative spillovers on their competitor bank in the same region. Further, other time-varying bank specific characteristics such as new CEOs which change the lending policy of the local bank during the height of the sovereign debt crisis might confound my results if they are correlated with the treatment status of the bank. And finally, during the pre period, Lehman Brother collapsed which affected some regional savings banks in Germany due to the involvement in the MBS market of their Landesbank (Landesbanken are the central institutions of local savings banks). To control for time-varying bank characteristics, I include bank–time fixed effects to test whether spillovers between firms pertain. The sample size is slightly reduced as singletons are dropped in the regression, i.e. there must be several bank-firm-time observations in order for that bank to be included in the regression.

– Insert Table 11 around here –

Results are reported in Table 11. Spillovers on non-treated firms (γ_3) become just slightly smaller in terms of economic magnitude, and stay robust in terms of statistical significance. Negative spillovers on non-treated firms are not driven by spillovers of confounding factors on the bank level. Note that direct effects are not estimable in this setting as they are colinear with bank-time variations for the total treatment measures in column I-III. They are estimable in columns IV-VI when I use the precise treatment measure, because SMP banks are included in treatment and control group in case they are strong and serve weak as well as strong firms.

6 Conclusion

As a response to the SMP, regional bank increase corporate lending (Koetter, 2020). In my sample of German SMEs I find that there was a re-distribution of lending sources towards low leveraged firms as well as to high leveraged firms linked to weakly capitalized banks- what I call the ”zombie connection”. Already Acharya et al. (2019) find that after the OMT announcement of the ECB, there is an increase in zombie lending by European banks. They also assess investment behavior of firms linked to OMT banks and do not find changes in investment activities. My paper enhances their analysis by taking spillover effects between firms into account. In fact, I find that as a response to changes in lending behavior of banks exposed to the SMP, firms linked to these banks invest less and induce negative spillover effects on firms operating in the same region–sector clusters.

The finding is important for two reasons: One, common difference-in-differences estimations yield no results as concurrent spillovers cover up direct effects. In order to gain a more comprehensive understanding of the real effects of unconventional monetary policy, it is necessary to consider that firms are interconnected and react to changes of behavior of their peer firms. And two, the analyses provide indication for why there is only a sluggish economic recovery after UMP. Negative spillovers among firms drags on the economic recovery.

There are open issues for future research. In particular, what is the exact kind of spillovers that UMP induces? For instance, are spillovers due to information sharing among peer firms? Do firm managers know each other or do they infer information just by observing other firms? Moreover, as UMP affects banks first, are there also spillovers between banks operating in the same region on their lending behavior?

Tables and Figures

Table 1: Summary Statistics

This table reports summary statistics for regional and firm-level variables over the time period 2007-2013. $GDPgrowth$ is log changes of GDP of German NUTS-3 regions. Unemployment rate is also on regional level. $SMPshare\_region$ is the share of treated firms within regions (treatment defined as below), and $SMPshare\_region\_SMEs$ is the share of SMEs treated within regions. The firm level sample encompasses 11,809 small and medium sized German firms. $Investments$ is gross investments defined as log change of fixed assets plus depreciation. SMP is a binary treatment variable and equals 1 if the bank, the firm is linked to, held eligible SMP assets in 2010. It equals 0 for banks that did not hold SMP eligible assets in 2010. In $SMP\_precise$ only firms which benefit from increases in loan supply according to Table 3 are defined as treated. $SMPshare$ is the share of treated firms in the same region–sector in year 2010. $SMPshare\_precise$ captures the share of treated firms based on $SMP\_precise$. $SMPshare\_IO$ is the average share of treated firms within the same input-output clusters according to Kelton et al. (2008). $Post$ is a binary variable which equals 0 in pre period 2007-2009 and 1 in period 2010-2013. $Non\_tradeable$ is a binary variable which equals 1 for firms which operate in an industry classified as producing non-tradeables according to Delgado et al. (2014), and 0 otherwise. $High\_tech$ is a binary variable which equals 1 for firms which operate in an industry classified as high-tech according to Kile and Phillips (2009), and 0 otherwise. $High\_tech\_Decker$ is a binary variable which equals 1 for firms which operate in an industry classified as high-tech according to Decker et al. (2020), and 0 otherwise. Δtoas is the first difference of log total assets. Δdebt is first differences of log of current assets debt plus 1. Δcash is first differences of log of cash plus 1. Δebta is first differences of log of earnings before interest, taxes, depreciation and amortization plus 1. Δsales is first differences of log of operational revenue plus 1. $market\_share$ is the share of sales over total sales of all firms available in Amadeus for the same region-sector of firm i. Δemployment is the first differences of log employment. Investments, firm balance sheet variables, and employment are winsorized at the 1% and 99% per year.

	N	mean	sd	min	p50	max
GDP growth	2,726	0.025	0.047	-0.281	0.028	0.409
Unemployment rate	2,726	7.042	3.411	1.200	6.300	22.000
SMPshare_region	2,726	0.345	0.154	0.036	0.318	0.719
SMPshare_region_SMEs	2,726	0.172	0.210	0.000	0.064	0.770
Investments	38,661	0.336	0.660	-1.205	0.158	5.030
SMP	38,661	0.257	0.437	0.000	0.000	1.000
SMP_precise	38,661	0.236	0.425	0.000	0.000	1.000
SMPshare	38,661	0.290	0.302	0.000	0.156	1.000
SMPshare_precise	38,661	0.267	0.293	0.000	0.127	1.000
SMPshare_IO	30,228	0.294	0.294	0.000	0.149	0.995
Post	38,661	0.797	0.402	0.000	1.000	1.000
Non_tradeable	38,661	0.458	0.498	0.000	0.000	1.000
High_tech	38,661	0.141	0.348	0.000	0.000	1.000
High_tech_Decker	38,661	0.083	0.276	0.000	0.000	1.000
Δtoas	38,661	0.038	0.286	-1.132	0.018	1.189
Δdebt	38,536	1.780	4.803	-14.290	0.000	13.727
Δcash	37,337	0.087	1.573	-5.117	0.055	5.366
Δebta	25,259	0.053	0.732	-2.864	0.034	2.697
Δsales	24,664	0.040	0.288	-1.831	0.029	1.667
market_share	32,519	0.032	0.104	-0.002	0.005	1.000
Δemployment	22,103	0.028	0.212	-0.916	0.000	0.981

Table 2: Aggregate analyses

This table reports results from estimations $Y_{rt} = \alpha_r + \alpha_t + \gamma_1 Post_t \times \text{SMPshare}_r + \epsilon_{rt}$. $Post$ is a binary variable which equals 0 in the years 2007-2009 and 1 in the years 2010-2013. $SMPshare\_region$ is the share of firms in region r which are linked to a bank which hold SMP eligible assets in 2010. $SMPshare\_region\_SMEs$ is the share of small and medium sized firms in region r which are linked to a bank which hold SMP eligible assets in 2010. Dependent variables are GDP growth, defined as log differences of GDP of region r in year t in columns I and II, and the unemployment rate of region r in year t in columns III and IV. The regression includes region and time fixed effects. Robust standard errors are clustered on the region level and depicted in parentheses. *, **, *** indicate significant coefficients at the 10%, 5%, and 1% level, respectively.

	(I) GDP growth	(II) GDP growth	(III) Unempl.	(IV) Unempl.
Post×SMPshare_region	-0.010		-2.059***	
	(0.010)		(0.317)	
Post×SMPshare_region_SMEs		-0.001		-0.691***
		(0.008)		(0.260)
Observations	2,726	2,726	2,726	2,726
R-squared	0.438	0.438	0.972	0.971
Region FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes

Table 3: Heterogeneous lending behavior as a response to the SMP

This table reports results from estimating $Y_{it} = \alpha_i + \alpha_{rt} + \alpha_{kt} + \gamma_1 \times \text{SMP}_i \times Post_t + \gamma_2 \times \text{SMP}_i \times \text{Weak\_bank}_i \times Post_t + \gamma_3 \times \text{SMP}_i \times \text{Weak\_firm}_i \times Post_t + \gamma_4 \times \text{SMP}_i \times Post_t \times \text{Weak\_bank}_i \times \text{Weak\_firm}_i + \cdots + \epsilon_{it}$. Dependent variable is first differences of log of long term debt plus 1. SMP is a binary treatment variable and equals 1 if the bank, the firm is linked to, held eligible SMP assets in 2010. It equals 0 for banks that did not hold SMP eligible assets in 2010. $Post$ is a binary variable which equals 0 in the years 2007-2009 and 1 in the years 2010-2013. $Weak\_bank$ is an indicator variable which equals 1 if the bank was below median capitalization of all banks in the year 2007, and 0 otherwise. $Weak\_firm$ is an indicator which equals 1 for high leveraged firms and 0 otherwise. In particular, in column III it equals 1 for firms in upper four, in column IV in upper three and in column V in upper two deciles in terms of leverage of firms in the pre period within sector of firm i. Robust standard errors are clustered on the bank level and depicted in parentheses. *, **, *** indicate significant coefficients at the 10%, 5%, and 1% level, respectively.

	(I)	(II)	(III)	(IV)	(V)
	ΔLtdb	ΔLtdb	ΔLtdb	ΔLtdb	ΔLtdb
Firm leverage deciles			>=6.	>=7.	>=8.
SMP×Post	0.244	0.488	1.503**	1.320**	0.978**
	(0.245)	(0.409)	(0.664)	(0.595)	(0.496)
SMP×Post×Weak_bank		-0.345	-1.305	-1.108	-0.888
		(0.518)	(0.806)	(0.721)	(0.614)
SMP×Post×Weak_firm			-1.870**	-1.805**	-1.537*
			(0.795)	(0.790)	(0.801)
SMP×Post×Weak_bank×Weak_firm			1.759*	1.632*	1.756*
			(0.922)	(0.917)	(0.909)
Observations	38,663	38,663	38,663	38,663	38,663
R-squared	0.286	0.286	0.287	0.287	0.286
Weak_bank×Post	-	Yes	Yes	Yes	Yes
Weak_firm×Post	-	-	Yes	Yes	Yes
Weak_bank×Weak_firm×Post	-	-	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes
Region-Time FE	Yes	Yes	Yes	Yes	Yes
Industry-Time FE	Yes	Yes	Yes	Yes	Yes

Table 4: Direct and spillover effects on investments

This table reports results from estimations in the vein of Berg et al. (2021): $Y_{it} = \alpha_i + \alpha_{rt} + \alpha_{kt} + \gamma_1 \times \text{SMP}_i \times Post_t + \gamma_2 \times \text{SMP}_i \times Post_t \times \text{SMPshare}_i + \gamma_3 \times (1 - \text{SMP}_i) \times Post_t \times \text{SMPshare}_i + \epsilon_{it}$. Dependent variable is gross investments, defined as log differences of fixed assets plus depreciation of firm i in year t. SMP is a binary treatment variable and equals 1 if the bank, the firm is linked to, held eligible SMP assets in 2010. It equals 0 for banks that did not hold SMP eligible assets in 2010. $Post$ is a binary variable which equals 0 in the years 2007-2009 and 1 in the years 2010-2013. $SMPshare$ is the share of treated firms in the same region–sector, excluding firm i. Column I and IV report results from a common difference-in-differences estimation. Column II and V include homogeneous spillover effects, and from columns III and VI show results from the fully specified model. In columns IV-VI I apply more precise treatment definitions (SMP_precise and SMPshare_precise): Only firms which are low leveraged (which belong in the eighth or above decile in terms of mean leverage in the pre period) as well as firms which are high leveraged and linked to weak banks (which belong to the below median capitalized banks in 2007) and which banks held eligible SMP assets in 2010 are defined as treated and count into the share of treated firms. The regression includes firm fixed effects, region-time and industry-time fixed effects. Robust standard errors are clustered on the region–industry level and depicted in parentheses. *, **, *** indicate significant coefficients at the 10%, 5%, and 1% level, respectively.

	(I)	(II)	(III)	(IV) precise	(V) precise	(VI) precise
SMP×Post	-0.049	-0.048	-0.153**	-0.056*	-0.054*	-0.188***
	(0.031)	(0.032)	(0.062)	(0.033)	(0.033)	(0.064)
Post×SMPshare		-0.257**			-0.333**	
		(0.130)			(0.134)	
SMP×Post×SMPshare			-0.122			-0.172
			(0.138)			(0.139)
(1-SMP)×Post×SMPshare			-0.350**			-0.465***
			(0.141)			(0.147)
Observations	38,661	38,661	38,661	38,661	38,661	38,661
R-squared	0.567	0.567	0.567	0.567	0.567	0.567
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Region-Time FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 5: Direct and spillover effects on investments– build up of FE

This table reports results from estimations in the vein of Berg et al. (2021): $Y_{it} = \alpha_i + \alpha_{rt} + \alpha_{kt} + \gamma_1 \times \text{SMP}_i \times Post_t + \gamma_2 \times \text{SMP}_i \times Post_t \times \text{SMPshare}_i + \gamma_3 \times (1 - \text{SMP}_i) \times Post_t \times \text{SMPshare}_i + \epsilon_{it}$. Dependent variable is gross investments, defined as log differences of fixed assets plus depreciation of firm i in year t. SMP is a binary treatment variable and equals 1 if the bank, the firm is linked to, held eligible SMP assets in 2010. It equals 0 for banks that did not hold SMP eligible assets in 2010. $Post$ is a binary variable which equals 0 in the years 2007-2009 and 1 in the years 2010-2013. $SMPshare$ is the share of treated firms in the same region–sector, excluding firm i. The regression builds up on fixed effect structures: column I includes firm and time fixed effects, column II includes industry–time, and column IV region-time fixed effects. Robust standard errors are clustered on the region–industry level and depicted in parentheses. *, **, *** indicate significant coefficients at the 10%, 5%, and 1% level, respectively.

	(I)	(II)	(III)	(IV)
SMP×Post	-0.119**	-0.119**	-0.146**	-0.153**
	(0.048)	(0.050)	(0.059)	(0.062)
SMP×Post×SMPshare	0.150**	0.144**	-0.053	-0.122
	(0.064)	(0.067)	(0.128)	(0.138)
(1-SMP)×Post×SMPshare	-0.046	-0.048	-0.280**	-0.350**
	(0.045)	(0.046)	(0.128)	(0.141)
Observations	38,661	38,661	38,661	38,661
R-squared	0.513	0.531	0.548	0.567
Firm FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	-	-
Industry-Time FE	-	Yes	-	Yes
Region-Time FE	-	-	Yes	Yes

Table 6: Direct and spillover effects within input-output clusters

This table reports results from estimations in the vein of Berg et al. (2021): $Y_{it} = \alpha_i + \alpha_{rt} + \alpha_{kt} + \gamma_1 \times \text{SMP}_i \times Post_t + \gamma_2 \times \text{SMP}_i \times Post_t \times \text{SMPshare\_IO}_i + \gamma_3 \times (1 - \text{SMP}_i) \times Post_t \times \text{SMPshare\_IO}_i + \epsilon_{it}$. Dependent variable is gross investments, defined as log differences of fixed assets plus depreciation of firm i in year t. SMP is a binary treatment variable and equals 1 if the bank, the firm is linked to, held eligible SMP assets in 2010. It equals 0 for banks that did not hold SMP eligible assets in 2010. $Post$ is a binary variable which equals 0 in the years 2007-2009 and 1 in the years 2010-2013. $SMPshare\_IO$ is the mean of the shares of treated firms in the same input-output clusters according to Kelton et al. (2008) within the same region, excluding firm i. The regression includes firm fixed effects, region-time and industry-time fixed effects. Robust standard errors are clustered on the region–industry level and depicted in parentheses. *, **, *** indicate significant coefficients at the 10%, 5%, and 1% level, respectively.

	(I)	(II)	(III)	(IV)
SMP $\times Post$	-0.168***	-0.180***	-0.208***	-0.221***
	(0.058)	(0.062)	(0.071)	(0.077)
SMP $\times Post \times SMPshare\_IO$	0.234***	0.244***	-0.938	-0.989
	(0.081)	(0.085)	(0.629)	(0.662)
(1-SMP) $\times Post \times SMPshare\_IO$	0.010	0.003	-1.223*	-1.302**
	(0.049)	(0.050)	(0.629)	(0.663)
Observations	30,228	30,228	30,228	30,228
R-squared	0.529	0.547	0.572	0.590
Firm FE	Yes	Yes	Yes	Yes
Time FE	Yes	-	-	-
Industry-Time FE	-	Yes	-	Yes
Region-Time FE	-	-	Yes	Yes

Table 7: Direct and spillover effects on investments including firms with multiple banks

This table reports results from estimations in the vein of Berg et al. (2021): $Y_{it} = \alpha_i + \alpha_{rt} + \alpha_{kt} + \gamma_1 \times \text{SMP}_i \times Post_t + \gamma_2 \times \text{SMP}_i \times Post_t \times \text{SMPshare}_i + \gamma_3 \times (1 - \text{SMP}_i) \times Post_t \times \text{SMPshare}_i + \epsilon_{it}$. The sample includes also multi-bank firms and comprises 21,806 firms. Dependent variable is gross investments, defined as log differences of fixed assets plus depreciation of firm i in year t. SMP is a binary treatment variable and equals 1 if the bank, the firm is linked to, held eligible SMP assets in 2010. It equals 0 for banks that did not hold SMP eligible assets in 2010. $Post$ is a binary variable which equals 0 in the years 2007-2009 and 1 in the years 2010-2013. $SMPshare$ is the share of treated firms in the same region–sector, excluding firm i. Column I reports results from a common difference-in-differences estimation. Column II includes homogeneous spillover effects, and column III shows results from the fully specified model. The regression includes firm fixed effects, region-time and industry-time fixed effects. Robust standard errors are clustered on the region–industry level and depicted in parentheses. *, **, *** indicate significant coefficients at the 10%, 5%, and 1% level, respectively.

	(I)	(II)	(III)
SMP×Post	-0.023	-0.022	-0.070***
	(0.017)	(0.017)	(0.027)
Post×SMPshare		-0.086	
		(0.084)	
SMP×Post× SMPshare			-0.020
			(0.091)
(1-SMP)×Post×SMPshare			-0.151*
			(0.085)
Observations	74,589	74,589	74,589
R-squared	0.546	0.546	0.546
Firm FE	Yes	Yes	Yes
Industry-Time FE	Yes	Yes	Yes
Region-Time FE	Yes	Yes	Yes

Table 8: Direct and spillover effects on other dependent variables

This table reports results from estimations in the vein of Berg et al. (2021): $Y_{it} = \alpha_i + \alpha_{rt} + \alpha_{kt} + \gamma_1 \times \text{SMP}_i \times Post_t + \gamma_2 \times \text{SMP}_i \times Post_t \times \text{SMPshare}_i + \gamma_3 \times (1 - \text{SMP}_i) \times Post_t \times \text{SMPshare}_i + \epsilon_{it}$. Dependent variables are log differences of total assets, log differences of current assets debt (Δlog(debt + 1)), log differences of cash (Δlog(cash + 1)), log differences of earnings before depreciation, amortization and taxes (Δlog(ebta + 1)), log changes of sales (operational revenues) (Δlog(opre + 1)), the market share defined as sales of firm i over total sales of all firms within region–sector which are available in Amadeus and log differences of number of employees (Δlog(empl)) of firm i in year t. SMP is a binary treatment variable and equals 1 if the bank, the firm is linked to, held eligible SMP assets in 2010. It equals 0 for banks that did not hold SMP eligible assets in 2010. $Post$ is a binary variable which equals 0 in the years 2007-2009 and 1 in the years 2010-2013. $SMPshare$ is the share of treated firms in the same region–sector, excluding firm i. The regression includes firm fixed effects, region-time and industry-time fixed effects. Robust standard errors are clustered on the region–industry level and depicted in parentheses. *, **, *** indicate significant coefficients at the 10%, 5%, and 1% level, respectively.

	(I) Δtoas	(II) Δdebt	(III) Δcash	(IV) Δebta	(V) Δsales	(VI) market_share	(VII) Δempl
SMP×Post	-0.055*	-0.575	0.007	0.075	-0.026	0.001	-0.021
	(0.030)	(0.507)	(0.159)	(0.107)	(0.049)	(0.007)	(0.062)
SMP×Post×SMPshare	0.110	1.898*	-0.765*	-0.670***	-0.118	-0.083***	0.262**
	(0.071)	(1.137)	(0.427)	(0.221)	(0.092)	(0.031)	(0.116)
(1-SMP)×Post×SMPshare	0.024	0.607	-0.647	-0.462**	-0.153*	-0.081***	0.193
	(0.066)	(1.100)	(0.404)	(0.229)	(0.085)	(0.028)	(0.120)
Observations	38,661	38,498	37,133	20,882	19,898	32,152	19,656
R-squared	0.374	0.388	0.268	0.344	0.427	0.887	0.464
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region-Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 9: Direct and spillover effects on other dependent variables, more precise treatment measure

This table reports results from estimations in the vein of Berg et al. (2021): $Y_{it} = \alpha_i + \alpha_{rt} + \alpha_{kt} + \gamma_1 \times \text{SMP}_i \times Post_t + \gamma_2 \times \text{SMP}_i \times Post_t \times \text{SMPshare}_i + \gamma_3 \times (1 - \text{SMP}_i) \times Post_t \times \text{SMPshare}_i + \epsilon_{it}$. Dependent variables are log differences of total assets, log differences of current assets debt (Δlog(debt + 1)), log differences of cash (Δlog(cash + 1)), log differences of earnings before depreciation, amortization and taxes (Δlog(ebta + 1)), log changes of sales (operational revenues) (Δlog(opre + 1)), the market share defined as sales of firm i over total sales of all firms within region–sector which are available in Amadeus and log differences of number of employees (Δlog(empl)) of firm i in year t. $SMP\_precise$ is a binary treatment variable and equals 1 for low leveraged firms which are linked to banks which held eligible SMP assets in 2010, as well as for high leveraged firms which are linked to weakly capitalized banks which held eligible SMP assets in 2010. $Post$ is a binary variable which equals 0 in the years 2007-2009 and 1 in the years 2010-2013. $SMPshare\_precise$ is the share of treated low leveraged firms and treated high leveraged firms linked to weak banks in the same region–sector, excluding firm i. The regression includes firm fixed effects, region-time and industry-time fixed effects. Robust standard errors are clustered on the region–industry level and depicted in parentheses. *, **, *** indicate significant coefficients at the 10%, 5%, and 1% level, respectively.

	(I) Δtoas	(II) Δdebt	(III) Δcash	(IV) Δebta	(V) Δsales	(VI) market_share	(VII) Δempl
SMP_precise×Post	-0.054*	-0.038	0.145	0.073	-0.047	-0.001	-0.027
	(0.032)	(0.504)	(0.158)	(0.106)	(0.057)	(0.007)	(0.058)
SMP_precise×Post×SMPshare_precise	0.080	1.615	-1.048**	-0.676***	-0.072	-0.080**	0.188*
	(0.068)	(1.169)	(0.425)	(0.232)	(0.099)	(0.035)	(0.113)
(1-SMP_precise)×Post×SMPshare_precise	-0.001	0.963	-0.754*	-0.504**	-0.156	-0.082**	0.092
	(0.067)	(1.163)	(0.408)	(0.246)	(0.097)	(0.032)	(0.123)
Observations	38,661	38,498	37,133	20,882	19,898	32,152	19,656
R-squared	0.374	0.388	0.268	0.344	0.427	0.887	0.464
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region-Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 10: Direct and spillover effects on investments for non-tradeable or high-tech industries.

This table reports results from estimations in the vein of Berg et al. (2021): $Y_{it} = \alpha_i + \alpha_{rt} + \alpha_{kt} + \gamma_1 \times \text{SMP}_i \times Post_t + \gamma_2 \times \text{SMP}_i \times Post_t \times \text{SMPshare}_i + \gamma_3 \times (1 - \text{SMP}_i) \times Post_t \times \text{SMPshare}_i + \epsilon_{it}$. Dependent variable is gross investments, defined as log differences of fixed assets plus depreciation of firm i in year t. SMP is a binary treatment variable and equals 1 if the bank, the firm is linked to, held eligible SMP assets in 2010. It equals 0 for banks that did not hold SMP eligible assets in 2010. $Post$ is a binary variable which equals 0 in the years 2007-2009 and 1 in the years 2010-2013. $SMPshare$ is the share of treated firms in the same region–industry, excluding firm i. I further interact all coefficients with an $indicator$, which is $non - tradeable$ in column I. It equals 0 if firm i operates in an industry which according to Delgado et al. (2014) mainly produces tradeables, and 1 otherwise. In column II, $Indicator$ is $High\_tech$ which equals 1 if firm i operates in an ICT intense industry according to Kile and Phillips (2009). In column III, $Indicator$ is $High\_tech\_Decker$ which equals 1 if firm i operates in an ICT intense industry according to Decker et al. (2020). The regression includes firm fixed effects, region-time and industry-time fixed effects. Robust standard errors are clustered on the region–industry level and depicted in parentheses. *, **, *** indicate significant coefficients at the 10%, 5%, and 1% level, respectively.

	(I) $Tradeable$	(II) $High\_tech$	(III) $High\_tech\_Decker$
Post× Indicator	0	0	0
	(omitted)	(omitted)	(omitted)
SMP×Post	-0.132*	-0.136**	-0.150**
	(0.076)	(0.066)	(0.065)
SMP×Post×Indicator	-0.046	-0.089	-0.019
	(0.106)	(0.152)	(0.171)
SMP×Post×SMPshare	-0.157	-0.128	-0.115
	(0.149)	(0.136)	(0.137)
SMP×Post×SMPshare×Indicator	0.086	0.070	-0.115
	(0.139)	(0.213)	(0.253)
(1-SMP)×Post×SMPshare	-0.379***	-0.348**	-0.347**
	(0.146)	(0.142)	(0.142)
SMP×Post×SMPshare×Indicator	0.069	0.063	-0.047
	(0.099)	(0.166)	(0.243)
Observations	38,661	38,661	38,661
R-squared	0.567	0.567	0.567
Firm FE	Yes	Yes	Yes
Industry-Time FE	Yes	Yes	Yes
Region-Time FE	Yes	Yes	Yes

Table 11: Direct and spillover effects on investments including bank–time fixed effects

This table reports results from estimations in the vein of Berg et al. (2021): $Y_{it} = \alpha_i + \alpha_{rt} + \alpha_{kt} + \alpha_{bt} + \gamma_1 \times \text{SMP}_i \times Post_t + \gamma_2 \times \text{SMP}_i \times Post_t \times \text{SMPshare}_i + \gamma_3 \times (1 - \text{SMP}_i) \times Post_t \times \text{SMPshare}_i + \epsilon_{it}$. Dependent variable is gross investments, defined as log differences of fixed assets plus depreciation of firm i in year t. SMP is a binary treatment variable and equals 1 if the bank, the firm is linked to, held eligible SMP assets in 2010. It equals 0 for banks that did not hold SMP eligible assets in 2010. $Post$ is a binary variable which equals 0 in the years 2007-2009 and 1 in the years 2010-2013. $SMPshare$ is the share of treated firms in the same region–sector, excluding firm i. Column I and IV report results from a common difference-in-differences estimation. Column II and V include homogenous spillover effects, and from columns III and VI show results from the fully spedified model. In columns IV-VI I apply more precise treatment definitions (SMP_precise and SMPshare_precise): Only firms which are low leveraged (which belong in the eighth or above decile in terms of mean leverage in the pre period) as well as firms which are high leveraged and linked to weak banks (which belong to the below median capitalized banks in 2007) and which banks held eligible SMP assets in 2010 are defined as treated and count into the share of treated firms. The regression includes firm fixed effects, region-time, industry-time and bank-time fixed effects. Robust standard errors are clustered on the region–industry level and depicted in parentheses. *, **, *** indicate significant coefficients at the 10%, 5%, and 1% level, respectively.

	(I)	(II)	(III)	(IV) precise	(V) precise	(VI) precise
SMP×Post	0	0	0	-0.103	-0.102	-0.218**
	(omitted)	(omitted)	(omitted)	(0.088)	(0.088)	(0.106)
Post×SMPshare		-0.182			-0.180	
		(0.137)			(0.137)	
SMP×Post×SMPshare			-0.061			-0.021
			(0.160)			(0.150)
(1-SMP)×Post×SMPshare			-0.278*			-0.338**
			(0.156)			(0.162)
Observations	37,263	37,263	37,263	37,263	37,263	37,263
R-squared	0.628	0.628	0.628	0.628	0.628	0.628
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Region-Time FE	Yes	Yes	Yes	Yes	Yes	Yes

Figure 1: Setting

This graph shows the setting of my analysis. Triangles are regional banks which operate in one confined region. Squares are firms which are linked to one bank and operate each in one sector. A bank is defined as being treated if it held SMP eligible assets in 2010, and is makred with black in the graph. Firms linked to treated banks are also defined as directly treated, firms linked to non-treated banks are defined as non-treated. The dotted square shows a region–sector cluster in which three firms operate: $firm_{i=1}$ is faced with treatment share of $SMPshare_i = 0.5$ in its cluster. $firm_{i=2}$ has $SMPshare_i = 0.5$ and $firm_{i=3}$ has an $SMPshare_i = 1.0$.

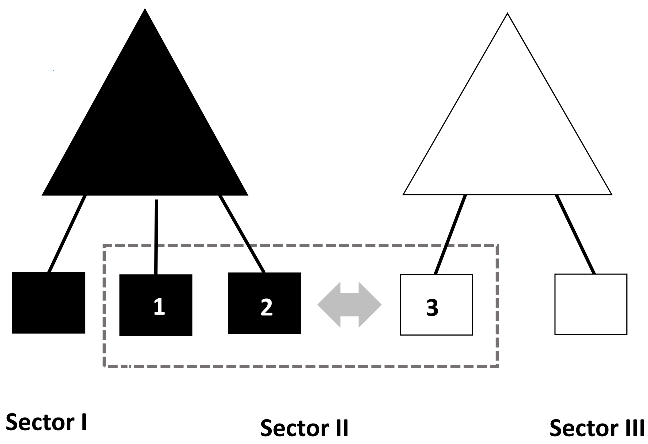


Figure 2: Illustrating spillover effects

This graph shows direct and spillover effects of the SMP on investment behavior of firms conditional on the share of treated firms within region–industry cluster in vein of Fig. 2 in Berg et al. (2021). It plots predicted values from estimating equation (4) with investments as dependent variable for directly treated firms (SMP_precise=1) and non-treated firms (SMP_precise=0) including spillover effects on each group (SMPshare_precise), which corresponds to regression output in Column VI in Table 4. Additional, I plot the average effect on investments, as well as 90% confidence intervals.

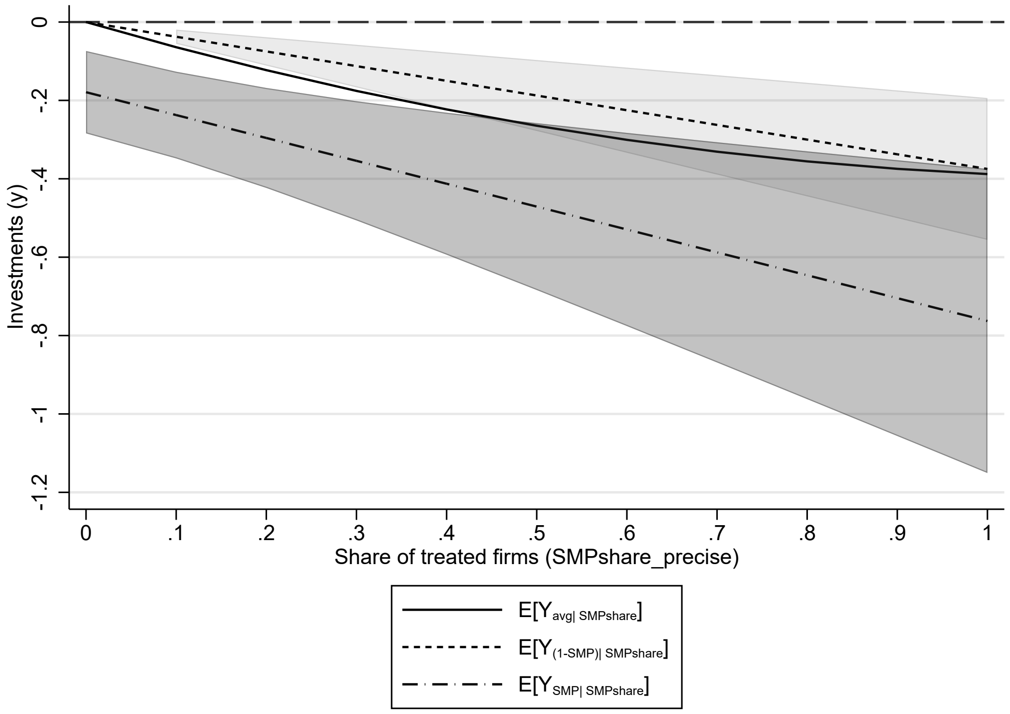
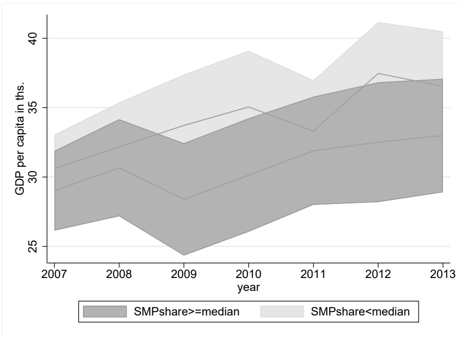


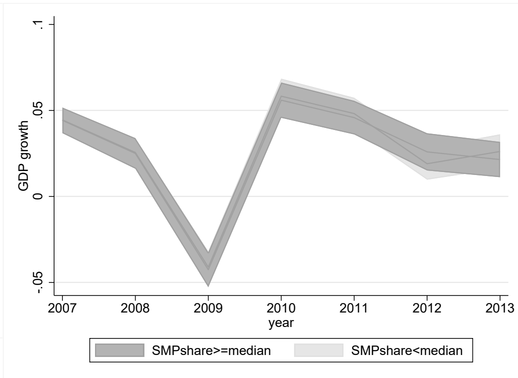
Figure 4: Regional characteristics and treatment status

This figure shows correlations of regional characteristics with treatment status. Regions are defined as high treated if the mean of $SMPshare$ per region is above the median of all regions, and as low treated otherwise.

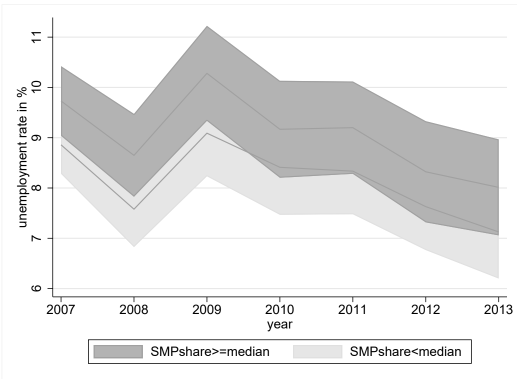
(a) GDP per capita



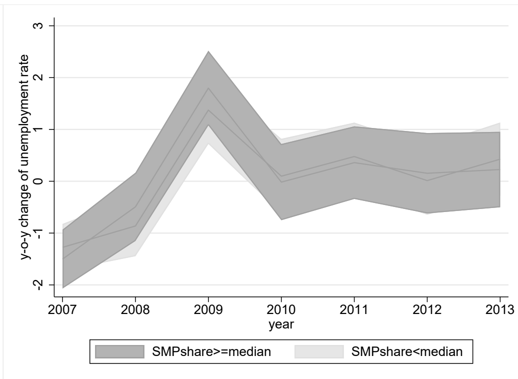
(b) GDP growth



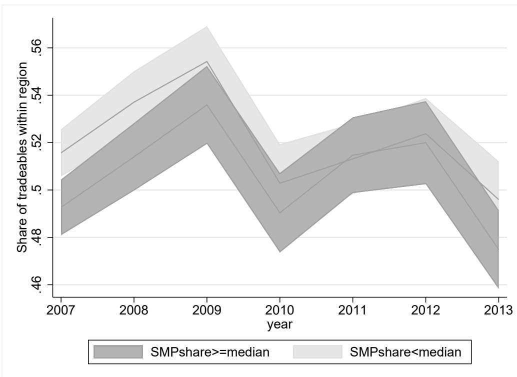
(c) Unemployment rate



(d) Change of unemployment rate



(e) Share of tradeables



(f) Change of share of tradeables

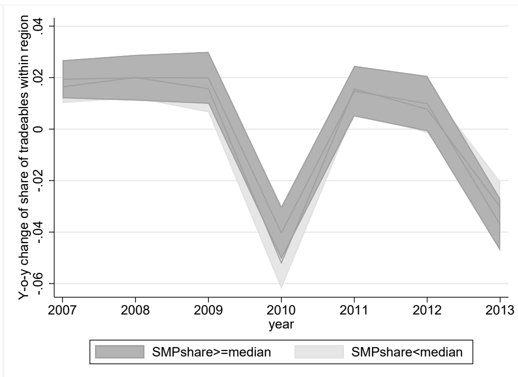
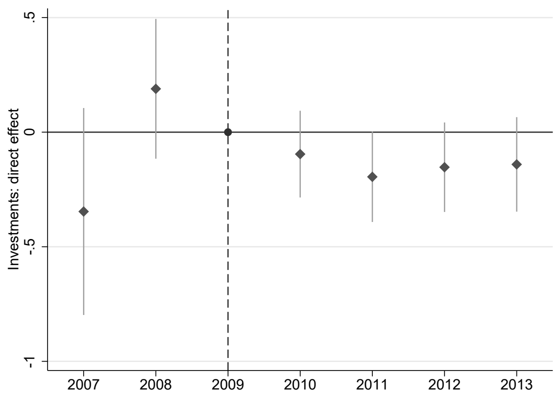


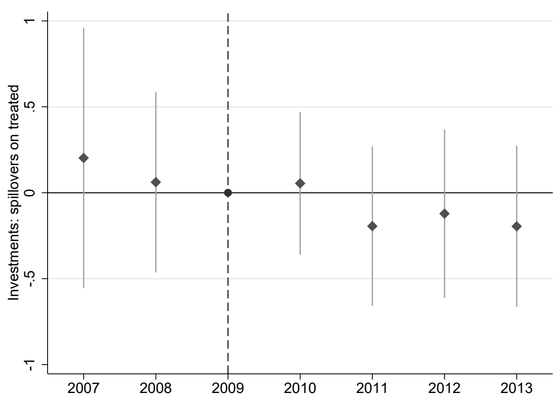
Figure 3: Coefficient plots for investments

These figures show coefficient plots from estimating dynamic equation (5) in the vein of Berg et al. (2021). Dependent variable is gross investments, defined as log differences of fixed assets plus depreciation of firm i in year t. SMP is a binary treatment variable and equals 1 if the bank, the firm is linked to, held eligible SMP assets in 2010. It equals 0 for banks that did not hold SMP eligible assets in 2010. I interact with binary variables for every year $\mathbf{1}_{t=year}$ excluding 2009. $SMPshare$ is the share of treated firms in the same region–sector, excluding firm i. The regression includes firm fixed effects, region-time and industry-time fixed effects. Robust standard errors are clustered on the region–sector level. Panel (a) plots $\gamma_{1\tau}$ for τ=2007 until τ=2013 with $\tau \neq$ 2009 which is the direct effect , panel (b) plots $\gamma_{2\tau}$ correspondingly which is the spillover effect on the treated, and panel (c) plots $\gamma_{3\tau}$ correspondingly which is the spillover effect on the non-treated. Confidence intervals are marked at the 1% level.

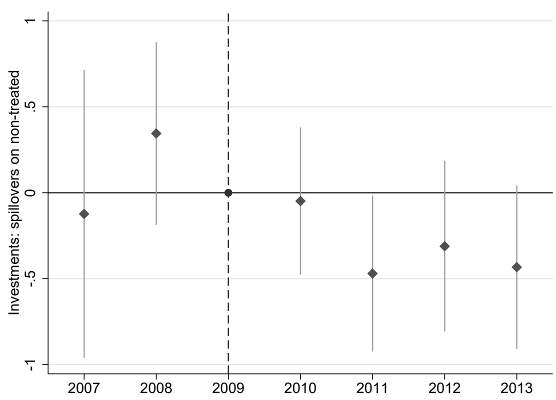
(a) Direct effect: $\gamma_{1\tau}$



(b) Spillover on treated: $\gamma_{2\tau}$



(c) Spillover on non-treated: $\gamma_{3\tau}$



Appendices

A Firm level data cleaning

The Dafne data set comprises more than 1.6 million firms of all sizes during the period 2007-2013. After merging with Amadeus, the data covers 1,019,047 firms. To derive a consistent data set, further data cleaning on the Amadeus firm financial data set is necessary: If there are firm-year duplicates, I keep the unconsolidated balance sheet information and drop consolidated data. Some firms have the same name but different IDs at Buerau van Dijk. This can be due to mergers. If name of firm, zip code and year is the same, but ID and consolidation code is different, the observations are dropped as I can assume that it is the same firm, but I do not know which report is the correct one. Further, observations with negative total assets are dropped. The merged and cleaned data comprises 793,601 SMEs. 373,975 SMEs fulfill my identification criteria meaning that they are linked to only one regional banks, however the linked bank may change over time.

B Note on Berg et al. (2021)'s regression specification

Berg et al. (2021)'s proposed regression specification is related to a common interaction model. I compare the approach to a standard interaction model and explain how the two relate. The following equation shows a common example of a difference-in-differences specification combined with an interaction model:

$$\begin{aligned} Y_{it} = {} & \alpha_1 \times \mathrm{T}_i \times Post_t \\ & + \alpha_2 \times \mathrm{T}_i \times Post_t \times \mathrm{M}_i \\ & + \alpha_3 \times \mathrm{M}_i \times Post_t \\ & + \cdots + \epsilon_{it}. \end{aligned} \tag{B.1}$$

Whereby T is a treatment variable, Post indicates a pre - post time dimension, and M is a modifier. This corresponds to T being SMP and M being SMPshare in equation (4). If we are interested in the marginal effect of M on Y, given that T=1 and Post=1, we derive the following: $\frac{\delta Y}{\delta M|_{T=1,Post=1}} = \alpha_2 + \alpha_3$.

In contrast, the specification by Berg et al. (2021) in equation (4) displays the marginal effect of M on Y given that T=1 and Post=1 directly with γ_2.

The marginal effect of M on Y given that T=0 and Post=1 corresponds to α_3 in equation (B.1), and also can be directly seen in equation (4) with γ_3. The advantage of equation (4) over equation (B.1) is hence that the effect of the SMPshare (corresponds to M here), is directly displayed for the group of the treated firms and the non-treated firms separately.

To put it differently, equation (4) splits the effects according to direct effect, effect of M given that T=1 and effect of M given that T=0. In contrast, equation (B.1) splits effects according to direct effect, the differential effect of M if T=1 compared to T=0, and the effect of M given that T=0.

C Replication exercise on bank lending

Previous literature finds that UMP has sparked increased bank lending. Koetter (2020) shows that German regional banks increase credit supply to corporate borrowers as a response to the SMP. Jiménez et al. (2014) find that in the low interest rate environment, especially weakly capitalized banks increase lending to low productive units. And Acharya et al. (2019) provide evidence for the so called zombie lending behaviour of European banks after the Outright Monetary Transaction Program announcement by the ECB in 2012. Again, it is the weakly capitalized banks which lend to low productive firms. In the following, I replicate Koetter (2020)'s analysis to assess whether also SMEs from my sub sample which link with regional banks and only have a single bank relationship increase borrowings. In particular, I assess whether there is also a zombie lending behavior as a response to the SMP, i.e. increased lending from weakly capitalized banks to weak firms. Further, firms in this sub sample must report fixed assets and depreciation in order to estimate their gross investments, as well as long term debt. So in contrast to Koetter (2020) I can only see borrowings from a small sub set of firms which make up the bank lending portfolios.

Hypotheses Exposure to SMP eligible assets is low among German savings and cooperative banks. On first sight, it is not clear why there should be a change in lending activity to firms, and further spillover effects. A bank that held eligible SMP assets could benefit in various ways. Either it sold the asset to the ECB and thereby obtained liquid reserves. Or it could benefit from a valuation effect. There are two building blocks why there could be a change in lending behavior for a specific group of banks: First, according to the zombie lending literature, lowly capitalized banks have an incentive to continue lending to troubled borrowers and thereby bet on the borrower's revival to avoid a loss to the own balance sheet (Caballero et al., 2008). An unexpected windfall gain might enable the bank to do so. Second, according to Diamond (2001), the size of the recapitalization is decisive to a change in behavior of a bank. It is especially these *small* windfall gains which lead to a gamble for resurrection instead of a healthy consolidation of banks' balance sheets (Keuschnigg and Kogler, 2020; Giannetti and Simonov, 2013).

H: There is an increase in lending which is driven especially by low capitalized banks to weak firms as a response of the SMP.

On the other hand, it is possible that exposures are very small, and that therefore the effect is so small that it is not perceivable.

Alternative H: There is no change in lending behavior of banks with exposure the SMP.

Data Information on the bank level comes from Bureau van Dijk's bankscope dataset. I follow other authors and use the equity ratio banks as a proxy for the bank's weakness (Schivardi et al., 2020; Jiménez et al., 2014; Acharya et al., 2019; Peek and Rosengren, 2005). I define a bank as weak if it was below the median of the distribution of banks' equity ratios in the pre crisis and pre treatment year 2007. 62% of firm-year observations are linked to a weak bank, as reported in Table C.1, i.e., weak banks are slightly larger in terms of customer base. I further add firm balance sheet data from Bureau van Dijk's Amadeus database and use the information on the firm-bank link by the Dafne database which also comes from Bureau van Dijk. I can only approximate lending via observable balance sheet positions that I have available from Amadeus. These are total long term debt, which proxies long term bank loans, and short term debt loans, which I assume are short term loans from firm i's only bank. Long term debt encompasses also other obligations than long term bank loans, and hence the effect might be greatly underestimated.

I define a firm as weak if it is highly leveraged following Schivardi et al. (2020). The degree of indebtedness of market participants plays an important role for financial and economic stability and economic development. Highly leveraged firms react more sensitive to decreased demand by reducing their labor force more quickly and thereby contributing to a propagation of adverse shocks (Sharpe, 1994). They performed worse in and after the great recession in terms of poorer sales growth, investment behavior and employment (Altunok and Oduncu, 2014; Kuchler, 2015; Giroud and Mueller, 2015). According to Traczynski (2017) firm leverage is one of the main explanatory variable for default risk. Cathcart et al. (2020) even claim it is the most important explanatory variable for default risk of SMEs. Banerjee and Hofmann (2020) and Hoshi (2006) show that zombie firms are higher levered compared to other firms, and Storz et al. (2017) provide evidence that especially zombie firms increased leverage further during the sovereign debt crisis in Europe.

In particular, I partition my sample at the sixth, seventh and eight percentile and define a firm as weak if it was at or above the respective decile in terms of mean leverage in the pre period within the sector it operates in. I use the mean over the whole pre period as some firms do not report every year and hence I can obtain the highest coverage of firm year observations.

Identification I estimate the following regression model to test whether banks change their lending behavior as a response to the SMP:

$$\begin{aligned} Y_{it} &= \alpha_i + \alpha_{rt} + \alpha_{kt} \\ &\quad + \gamma_1 \times \text{SMP}_i \times Post_t \\ &\quad + \gamma_2 \times \text{SMP}_i \times Post_t \times \text{Weak\_bank}_i \\ &\quad + \gamma_3 \times \text{SMP}_i \times Post_t \times \text{Weak\_firm}_i \\ &\quad + \gamma_4 \times \text{SMP}_i \times Post_t \times \text{Weak\_bank}_i \times \text{Weak\_firm}_i \\ &\quad + \cdots + \epsilon_{it}. \end{aligned} \tag{C.1}$$

As dependent variable I use log changes of long term debt of firm i in year t on firm i's balance sheet. Though SMEs rarely issue long term bonds (Moritz et al., 2016; Demary et al., 2016), they might be financed by long term leasing debt contracts which would also be included in this variable. Hence long term bank debt can only be interpreted as an approximation for long term loans. Further, I use and log changes of short term loans as an approximation of short term bank loans to firm i in year t.

SMP is a binary variable and indicates whether firm i is linked to a bank that held SMP eligible assets in 2010, and 0 otherwise. The dummy variable $Post$ equals 0 in the pre period 2007-2009, and 1 in the post period 2010-2013. $Weak\_bank$ and $Weak\_firm$ are defined as described above.

Results might be driven by demand shocks on the regional or industry level, as well as by time invariant unobservables on the firm level. To mitigate these concerns I include an extensive set of fixed effects: Firm fixed effects α_i, bank fixed effects α_b, region-time fixed effects α_{rt}, and industry-time fixed effects α_{kt}. As the treatment variable varies on the bank level I cluster standard errors are on the bank level.

Section 4.2 describes the results.

Table C.1: Summary Statistics on bank lending

This table reports summary statistics for a sample of 11,809 small and medium sized German firms. $\Delta\ ltdb$ is non-current liabilities debt plus 1 in logs (EUR). SMP is a binary treatment variable and equals 1 if the bank, the firm is linked to, held eligible SMP assets in 2010. It equals 0 for banks that did not hold SMP eligible assets in 2010. $Post$ equals 0 in pre period 2007-2009 and 1 in period 2010-2013. $Weak\_bank$ is an indicator variable which equals 1 if the bank was below the median capitalization of all banks in year 2007, and 0 otherwise. $Weak\_firm$ in an indicator which equals 1 if firm i is among the highest x decile in terms of mean leverage in the pre period within its sector, and 0 otherwise.

	N	mean	sd	min	p50	max
ΔLtdb	38,661	-0.288	4.115	-15.171	0.000	14.710
SMP	38,661	0.257	0.437	0.000	0.000	1.000
Post	38,661	0.797	0.402	0.000	1.000	1.000
Weak_bank	38,661	0.620	0.485	0.000	1.000	1.000
Weak_firm: $>=$6. decile	38,661	0.561	0.496	0.000	1.000	1.000
Weak_firm: $>=$7. decile	38,661	0.449	0.497	0.000	0.000	1.000
Weak_firm: $>=$8. decile	38,661	0.329	0.470	0.000	0.000	1.000

D Variable definitions

Table D.1: Variable definitions

Name	Unit	Description	Source
Investments	log differences	$log[(fias+1)+depr]_t - log(fias+1)_{t-1}$ with fixed assets (fias) and depreciation (depr). Winsorized at the 1 and 99% level by year.	Amadeus, own calculations
Post	0/1	Equals 0 in pre period 2007-2009, equals 1 in post period 2010-2013.	own calculations
SMP	0/1	Treatment variable equals 1 if firm has link to bank which held SMP eligible assets in 2010 and 0 otherwise.	Koetter (2020)
SMP_precise	0/1	Treatment variable equals 1 if firm has link to bank which held SMP eligible assets in 2010 and 0 otherwise. Defines only firms as treated which are low leveraged (mean leverage ratio in pre period < eight decile of all firms), or which are high leveraged and linked to a low capitalized bank ($Weak\_bank$).	Koetter (2020)
SMPshare_region	[0,1]	Share of treated firms per region in 2010 including *all* firms in Amadeus.	Koetter (2020), own calculations
SMPshare_region_SMEs	[0,1]	Share of treated SMEs per region in 2010 including *all* SMEs in Amadeus.	Koetter (2020), own calculations
SMPshare	[0,1]	Share of treated firms within same region–sector cluster in 2010 without firm i.	Koetter (2020), own calculations
SMPshare_precise	[0,1]	Share of treated firms within same region–sector cluster in 2010 without firm i. Includes only firms as treated which are low leveraged (mean leverage ratio in pre period < eight decile of all firms), or which are high leveraged and linked to a low capitalized bank ($Weak\_bank$).	Koetter (2020), own calculations
SMPshare_IO	[0,1]	Share of treated firms within same input-output clusters and the same region in 2010 according to Kelton et al. (2008) without firm i.	Koetter (2020), own calculations
Non_tradeable	0/1	Equals 1 if firm i operates in industry producing mainly tradeables according to Delgado et al. (2014), and 0 otherwise.	Amadeus
High_tech	0/1	Equals 1 if firm i operates in high-tech industry according to Kile and Phillips (2009), and 0 otherwise.	Amadeus
High_tech_Decker	0/1	Equals 1 if firm i operates in high-tech industry according to Decker et al. (2020), and 0 otherwise.	Amadeus
Δempl	log differences	First differences of log(number of employees). Winsorized at the 1 and 99% level by year.	Amadeus
Δsales	log differences	First differences of log(operational revenue (turnover) + 1). Winsorized at the 1 and 99% level by year.	Amadeus
Δebitda	log differences	First differences of log(earnings before interest, taxes, depreciation and amortization +1). Winsorized at the 1 and 99% level by year.	Amadeus
Δdebt	log differences	First differences of log(current assets debt +1). Winsorized at the 1 and 99% level by year.	Amadeus
Δcash	log differences	First differences of log(cash +1). Winsorized at the 1 and 99% level by year.	Amadeus
market_share	ratio	Operational revenue of firm i in year t over total sales of all firms available in Amadeus within same region–sector.	Amadeus, own calculations
ΔLtdb	log differences	Log of non-current liabilities long term debt plus 1. Winsorized at the 1 and 99% level by year.	Amadeus
Weak_bank	0/1	Equals 1 if bank of firm i was below median in terms of capitalization in 2007.	Bankscope, own calculations
Weak_firm	0/1	Equals 1 if firm i was equal or above the sixth, seventh or eighth decile in terms of mean leverage in the pre period.	Amadeus, own calculations
GDP per capita	log	Log of GDP per capita of region r in year t.	Destatis, own calculations.
GDP growth	log differences	Log of GDP of region r in year t minus log of GDP in region r in year $t-1$.	Destatis, own calculations.
Unemployment rate	%	Share of persons unemployed over total number of persons capable of work in region r in year t.	Destatis.
Share of tradeables	[0,1]	Share of industries classified as producing tradeables based on NAICS according to Delgado et al. (2014) in region r in year t.	Amadeus, own calculations.

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Paper 3:

DO ASSET PURCHASE PROGRAMS SHAPE INDUSTRY DYNAMICS? EVIDENCE FROM THE ECB'S SMP ON PLANT ENTRIES AND EXITS

Do asset purchase programs shape industry dynamics? Evidence from the ECB's SMP on plant entries and exits*

Manfred Antoni† Talina Sondershaus‡

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Abstract

Asset purchase programs (APPs) may allow banks to continue lending to unproductive customers. We use administrative plant and bank data to test whether APPs dampen industry dynamics in terms of plant entry and exit. Plants in Germany linked to banks with access to an APP are approximately 20% less likely to exit. In particular, unproductive plants connected to weak banks with APP access are less likely to close. Aggregate entry and exit rates in regional markets with high APP exposures are also lower. Thus, APPs seem to subdue Schumpeterian cleansing mechanisms by lowering factor reallocation.

JEL Classification: E58, G21, G28, G33

Keywords: Plant exits, extensive margin factor reallocation, asset purchase programs

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†Institute for Employment Research (IAB), Regensburger Strasse 104, 90478 Nuremberg, Germany, E-mail: manfred.antoni@iab.de.

‡Halle Institute for Economic Research (IWH), Kleine Märkerstraße 8, 06108 Halle (Saale), Germany, E-mail: talina.sondershaus@iwh-halle.de.

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1 Motivation

The reallocation of production factors from unproductive to more productive firms is crucial to maximize aggregate total factor productivity (TFP) growth (Hsieh and Klenow, 2009). Such reallocation implies that more productive firms become larger (Bartelsman et al., 2013) and that unproductive firms shrink and ultimately exit (Caballero and Hammour, 1994, 1996). However, how much of such a cleansing effect remains after ultra-loose monetary policy such as large asset purchase programs? In fact, as we show in Figure 1, the rates of market entries and exits for small firms have slowed down in Germany from 2010 onward, the time period when the European Central Bank (ECB) implemented its first large asset purchase program, the Securities Market Program (SMP).

Unconventional monetary policy such as large asset purchase programs (APPs) can lead to a ”zombie lending” behavior. Instead of cutting off low productive firms, weakly capitalized banks continue or increase lending to these borrowers thereby avoiding losses to their own balance sheets (Acharya et al., 2019). Zombie lending behavior induces factor misallocation among firms and may be followed by a productivity slowdown (Adalet McGowan et al., 2018; Schmidt et al., 2020). We provide the missing link between zombie lending induced by APPs and deterred productivity growth: the adaption of the economy at the *extensive* margin. Do APPs induce lower exit probabilities of unproductive firms or plants?

The novel combination of granular plant data and individual bank exposures to the SMP, the first APP conducted by the ECB between 2010 and 2012, covers the population of banks and a sample of German firms. The SMP stabilized asset prices (Doran et al., 2013; Gibson et al., 2016; Eser and Schwaab, 2016; Ghysels et al., 2016; De Pooter et al., 2018), caused increases in credit supply (Koetter, 2020), and together with other programs by the ECB stimulated the macroeconomy in Southern European countries (Casiraghi et al., 2016). The causal effects on plant and firm entries and exits, and thus industry dynamics, remain unclear. Our comprehensive data allow for the identification of the effects of APPs on individual plants and firms. To derive aggregate effects we supplement the data with 50% of the population of *all* German plants to provide micro-founded evidence on aggregate industry dynamics.

Plants that are connected to banks that benefited from the policy shock exhibit exit rates that are approximately 20% lower than plants connected to banks that were not exposed to the APP. In particular, unproductive plants connected to the least capitalized banks are the least likely to exit. This unhealthy coincidence of bad banks with access to APP helping weak firms to avoid exit is in line with evidence in Jiménez et al. (2014). They show that a loose (conventional) monetary stance in the Eurozone causally induced weak Spanish banks to inefficiently extend credit to unproductive firms in Spain. Our study complements their finding of inefficiently increasing credit by revealing an undue reduction in necessary churn. Quantitatively, the marginal effect of a weak bank having access to the SMP shock on unproductive plant exit probabilities is a 100 basis-point reduction, which is large in light of average exit rates of 2.3 percentage points during the sample period.

In addition to plant-level analyses of exit rates, we mobilize all ten million plant-year observations for the years 2007-2013 from the Establishment History Panel (BHP, Betriebshistorikpanel) for aggregate analyses at the region and sector levels. These administrative data cover half of the population of plants in Germany. Aggregate entry and exit rates are lower in regions and sectors with higher shares of plants connected to APP-exposed banks. This effect is amplified in unproductive regions, which is consistent with the plant-level evidence that unproductive firms tied to weakly capitalized banks exhibit lower exit rates. Thus, APPs to support stressed Eurozone members generally suppressed industry dynamics in the form of fewer exits and entries. The result that unproductive plants and regions exhibit less churn raises concerns of potential factor misallocation towards unproductive agents in non-stressed Eurozone economies.

However, APPs might not only reduce business dynamics. In line with Sette et al. (2022) we also assess ambiguous effects on the economy. We find that in particular small single-plant firms which receive more funding increase the number of employees. In order to draw more general conclusions on the effect of APPs we compare the unemployment rate and GDP per capita in regions which are highly exposed to the SMP with regions less exposed. We find that highly exposed regions show relatively lower unemployment rates, meanwhile exhibiting lower GDP per capita after the SMP was implemented. We conclude that the SMP slowed down business dynamics and therefore innovative processes which drags on economic growth. However, similar to Sette et al. (2022) we see that employment is sustained and even mildly increases at exposed small firms which can mitigate adverse effects on the economy.

Plant-level and aggregate results are based on the combination of data on German corporations, and administrative data on plants and banks, which is necessary to trace the transmission of the first European APP from the ECB via national (central) banking systems to corporate bank customers and, ultimately, their plants. First, we observe a unique sample from the universe of all plant closures in Germany based on the BHP between 2007 and

2013 (see Hethey and Schmieder, 2010), which are linked to firm identities (see Schild, 2016; Antoni et al., 2018). Second, we observe transaction data from the ECB during the SMP at the security level. Third, we identify banks that are exposed to the unexpected regime change by the ECB in the form of the SMP via the security holdings statistics of the German central bank as in Koetter (2020). Finally, we match firm identities to all banks – exposed and unexposed – based on bank-firm relationships reported in the Dafne database and supplement it with firm-level variables from Amadeus. To the best of our knowledge, we are the first to study such a granular chain from the financial to the real sector of a large, developed economy with respect to the implications of APPs for cleansing effects as reflected by absent attrition of unproductive plants.

More than 88% of observations in our sample come from single-plant firms for which the additional layer *plant* is identical with the firm-level. However, using plant-level data in addition to firm-level data enables us to draw implications of the effect of APPs on firm exits in two ways: First, plant-level data allows for a better identification of market exits. We use the technique by Hethey and Schmieder (2010) which allows us to distinguish market entries and exits from spin-offs or mergers. Second, plant-level data enables us to assess heterogeneous effects. We distinguish between exit probabilities of small single-plant and larger multi-plant firms. In fact, we find suppressed factor reallocation only for small, low productive single-plant firms linked to lowly capitalized banks. For multi-plant firms we demonstrate the possibility of efficiently lower plant exit rates of productive firms which are catered by well capitalized banks.

Previous literature has investigated the phenomenon of zombie lending and its macroeconomic consequences. Caballero et al. (2008) are the first to demonstrate the phenomenon of zombie lending behavior and its detrimental effect on productivity growth for the Japanese economy. Sette et al. (2022) show evidence for zombie lending behavior of Italian banks which impeded layoffs and prevented a further economic downturn. In contrast, Andrews and Petroulakis (2019) show for eleven European countries that zombie lending prevented more productive firms from growing and therefore reduced aggregate productivity growth. Acharya et al. (2020) show on the aggregate that the lower entry and exit rates the more zombie firms there are in a market. We contribute to this literature by providing *micro-level* evidence as well as micro-founded aggregate evidence on the role of unconventional monetary policy in changing market exit rates of low-productive plants as well as market entry rates.

Concerning the link between factor reallocation and productivity growth, Peters (2020) demonstrate the pitfalls of hampered exit and entry dynamics for aggregate productivity: a lower churn rate allows incumbent firms to gain monopoly power which lowers aggregate productivity. Gopinath et al. (2017) identify capital misallocation among Southern European firms due to a low interest rate environment and show how this leads to lower total factor productivity. According to Dosi et al. (2015) weak reallocation of market shares between firms impeded growth of total factor productivity already during the years before the global financial crisis. We contribute by showing how APPs can exacerbate already low levels of reallocation across firms.

This paper proceeds as follows. Section 2 sketches the economic mechanism which our analysis is based on. Section 3 describes the monetary policy, bank, firm and plant-level data which we use. In Section 4 we show micro-level evidence for changes in plant exits. In Section 5 we aggregate more than 10 million plant-year observations and present results on industry dynamics on the region and industry level. Section 6 concludes.

2 Economic mechanism

We proceed in two steps to outline the economic mechanism underlying our analysis: First, we describe how banks might change their lending behavior when affected by unconventional monetary policy. Second, we depict how market entry and exit probabilities might change for firms exposed to changes in credit supply by banks.

Unconventional monetary policy such as APPs can re-direct lending decisions and may thereby stimulate zombie lending behavior, i.e. lending from weakly capitalized banks to low productive firms (e.g., Acharya et al., 2020). The additional leeway to lending capacity for instance via recapitalization gains of banks need not be large. According to Giannetti and Simonov (2013) especially *small* recapitalization gains can lead to an evergreening of loans to non-viable borrowers. Low capitalized banks have an incentive to use small gains to continue lending to borrowers close to default instead of cutting them off, thereby avoiding loss on their own balance sheet. *Small* recapitalization gains allow weak banks to engage in the evergreening, but does not enable them to clean their balance sheets from non-viable borrowers.

Changes in lending behavior by banks to firms can influence the extensive margin. If less productive firms obtain more funding they can continue refinancing their production sites and refrain from closing or re-allocating resources across plants. In fact, Tracey (2021) demonstrates in a theoretical model how zombie lending translates into lower exit rates of low-productive firms. Acemoglu et al. (2018) model endogenous firm entries and exits with governmental interventions. They conclude that it can be welfare extending to subsidize exit of firms which can stimulate innovation for new entrants. In contrast, "subsidizing incumbents" can lead to welfare losses [1]. In fact, supporting incumbent low productive firms may prevent new firms from entering markets. For instance, Adalet McGowan et al. (2018) find that zombie firms congest markets and prevent new firms from entrance.

In a general equilibrium model as well as with macroeconomic time series data, Hartwig and Lieberknecht (2020) show how expansionary monetary policy can dampen exit probabilities of low productive firms due to increases in aggregate demand. We can test these considerations but extend their theoretical conjectures: We control for aggregate demand and test whether changes in lending behavior that directly affects firms' access to funding prevents factor reallocation by suppressing churn rates.

3 Data

3.1 Monetary policy and bank data

In response to soaring risk premia in May 2010, the ECB implemented the SMP "to restore an appropriate monetary policy transmission mechanism".[2] The ECB purchased sovereign bonds of Greece, Ireland and Portugal. It extended its purchases to Italian and Spanish bonds in August 2011. By September 2012, the ECB had purchased a notional volume of EUR 218 billion. The impact of the SMP on German plants is an ideal testing ground to isolate the causal impact of APPs on industry dynamics. Whereas the size of the SMP is small compared to subsequent APPs, the ECB's actions were unexpected. The ECB had been extremely reluctant to intervene in securities markets in contrast to the U.S. Federal Reserve, which started larges scale asset purchases already in November 2008. The beginning of the SMP thus marked an unexpected regime shift to reduce risk premia of sovereign bonds of *crisis*

[1] A large body of empirical research investigates how regulatory measures affect the entry of young firms and resulting industry dynamics. Cetorelli and Strahan (2006) show that lackluster banking market competition deters new entrants in U.S. markets. In related work, Kerr and Nanda (2010) show the branch deregulation in the U.S. enhanced competition, which causally increased entry rates of firms. Kerr and Nanda (2009) demonstrate that U.S. banking market deregulation increased not only market entry but also exit rates. Bertrand et al. (2007) provide evidence on European firms by showing that the deregulation of French banking markets also reduced the bailout of unproductive corporations by the financial sector and that industries with greater exposure to more competitive banking markets exhibit faster factor reallocation.

[2] See the ECB's press release from May 10, 2010:
https://www.ecb.europa.eu/press/pr/date/2010/html/pr100510.en.html.

countries and was a response to neither stressed firms nor troubled banks in Germany. This policy shock helps to isolate whether APPs had unintended effects on firms in non-stressed Eurozone countries.

We obtain exposure to the SMP from Koetter (2020), who matches ISIN codes from the ECB's purchase schedule to the security holdings reported by all German banks to the central bank to identify banks that hold eligible SMP assets. Exposures to SMP securities increase excess reserves and associated credit-generating capacity either through an unloading channel, if assets are sold to the ECB, or through a valuation channel, if they are retained but revalued at higher market prices (Eser and Schwaab, 2016). Koetter (2020) provides evidence that changes in lending behavior is driven by banks which continue holding SMP eligible assets and thereby benefited from evaluation gains, in contrast to banks which sold the SMP assets to the ECB.

Exposure to the SMP was generally low among regional banks (1% of securities portfolios at the median), but pervasive. Koetter (2020) shows that around 17% of German regional banks held SMP eligible assets in their securities portfolio while the program was in operation, and our sample shows that 7.37% of banks held SMP eligible assets in all three program years. Koetter (2020) finds that the average regional bank which was exposed to the SMP increases corporate lending by 4% compared to non-SMP banks. He argues that the effect of the SMP additionally worked through spillovers on value gains on exposure to other periphery sovereign debt and thereby strengthened the effect on regional bank lending. The SMP marked the commitment of the ECB to intervene also if other sovereign debt yields will soar.

To limit concerns about confounding policies, we focus on regional savings and cooperative banks that hold sovereign debt primarily as a store of liquidity given its regulatory treatment as a risk-free asset. Large German banks, in turn, engaged much more actively in (proprietary) securities trading and were subject to many confounding policy events, such as changes to the collateral framework, longer-term refinancing operations (LTROs), or even foreign policy measures that affected them via their cross-border activities (Buch et al., 2018).[3] Excluding these large financial institutions mitigates the possibility that banks in our sample purposefully accumulated Southern European bonds in anticipation of some form of rescue plan from the ECB or the EU. Moreover, the German economy is particularly useful to study regional responses of industry dynamics to APPs because the local banks

[3]According to Acharya and Steffen (2015) Southern European banks particularly benefited from LTROs and reduced their funding risk with borrowings from the ECB compared to Northern European banks. Further, we adjust our treatment definition as described in Section 3.2 to rule out that LTROs confound our results.

investigated here operate only in regional markets that largely coincide with county borders (German Council of Economic Experts, 2013). Local savings and cooperative banks are the relationship bankers of SMEs and, as such, are crucial for the transmission and mitigation of both shocks and policy (Koetter et al., 2020). In total we observe 909 German regional banks in our baseline sample.[4]

In addition to SMP exposure, we use financial account data from the Bankscope database provided by Bureau van Dijk (BvD) to control for bank size, (total assets), cost structure (cost-to-income ratio), profitability (return on assets) and liquidity. Further, we follow Acharya et al. (2019) and measure bank weakness with banks' equity ratio.

3.2 Firm and plant data

To identify the effect of the SMP on the real economy through plant exits, we link banks to non-financial corporations using BvD's Amadeus database. It contains financial information at the firm-level for 6,332,435 firm-year observations in our sample period from 2007 until 2013. Similar to Kalemli-Özcan et al. (2019), Kalemli-Özcan et al. (2016), Popov and Rocholl (2018), or Huber (2018), we use information on bank-firm links from Dafne by BvD which obtain the information from the rating agency Creditreform. Dafne reports firms' banks by reporting the banks' names.[5] To isolate the effect of the SMP shock, we only sample firms with a single bank relationship, which does not change during our sampling period. 66% of firms recorded by Dafne have a single bank and 60% fulfill both criteria – they only have one bank which they do not change over time, i.e. they are relationship borrowers. Especially small firms typically have only one or two bank relationships. According to a survey by Harhoff and Körting (1998), German firms with less than 5 employees report at the median one bank relationship, and according to Memmel et al. (2007) around 50% of German firms, including large firms, have one bank relationship only. Consequently, our sample comprises many SMEs – with a mean (median) number of employees of 11 (4) – which cannot substitute their non-treated bank with a link to a treated bank.[6]

[4]We extend to 1,091 regional banks in robustness checks where we include firms with multiple bank relationships additional to single-bank firms as described in Section 3.2.

[5]We extrapolate missing firm-bank links in early years using 2010 as a base year.

[6]Importantly, in robustness checks we include firms with multiple bank relationships which may vary over time. On the one hand, this sample is larger and therefore the results apply to a wider range of firms. On the other hand, the treatment definition of firms with multiple banks might introduce measurement error. We show that our results remain economically unchanged and even gain in statistical significance.

Neither Amadeus nor Dafne contain information on plants of these firms. Therefore, we use the linkage key generated by Schild (2016) and Antoni et al. (2018) to combine firm identifiers and traits from Amadeus with the administrative plant-level data of the Institute for Employment Research (IAB, Institut für Arbeitsmarkt- und Berufsforschung, Nuremberg). IAB's Establishment History Panel (BHP) aggregates worker-level social security notifications at the plant-level and covers the whole population of all German plants. These data provide information on the workforce composition and employee wage structure of plants.

Note that we use different samples depending on the level of analysis. The BHP data we use in the aggregate analyses in Section 5 is a 50% sample of all German plants. This version, henceforth called BHP 7514, corresponds to the dataset made available to the scientific community by the Research Data Centre (FDZ) of the German Federal Employment Agency at the IAB (see Schmucker et al., 2016). The data we use in plant-level analyses in Section 4 contain the same variables as the BHP 7514, but the special sample contains all German plants that are included in the linkage key mentioned in the previous paragraph. These data, henceforth referred to as linked BHP, are only available for replication purposes.

Plant-level data is necessary to identify market exits and entries of firms and plants correctly. We want to avoid capturing mergers or spin-offs, which we cannot distinguish from proper entries or exits by just observing entry and exit from the Amadeus dataset. With plant-level BHP data, we can follow Hethey and Schmieder (2010) and use worker flows to identify plant exits correctly. They detect plant spin-offs by tracking workers. If a significant share of employees remains employed in a plant, but the plant changes the ID, the supposed market exit and entry of the new ID is a spin-off. They also prevent us from considering mergers instead of plant exits: If a significant part of the work force of plant number one is employed together in another plant number two, then plant number one did not exit the market but merged with plant number two. We use their definition of "small and atomized deaths" to rule out that we mistake spin-offs and mergers for plant exits. In particular, plants with up to three employees that exit the market are classified as market exits. Plants with more than three employees, but of which no more than 30% of the work force is subsequently employed together in another plant, are also classified as market exits. If more than 30% of the work force is employed together in another plant, the previous establishment is not classified as a market exit, but it is assumed that is was merged. The same procedure is applied for identifying market entries: If a significant part of the workforce stems from one other plant, we do not consider this plant to be a new market entry. According to Hethey and Schmieder (2010), their method avoids a misclassification which applies to up to 65% of entries and exits of establishments in the BHP.

– Table 1 around here –

Table 1 summarizes the variables from plants and banks at the plant-year level: plant exits and observable traits as well as bank financials. In addition, we report summary statistics on bank and firm weakness indicators, as well as regional and sector aggregates. Table A.1 in the Appendix provides the definition and source of each variable.

The merged dataset contains 2,560,878 plant-year observations that belong to firms linked to one regional savings or cooperative bank. In addition, we condition on firm existence since 2006 and exclude firms from the forestry, agricultural, and financial sectors. The resulting sample comprises 593,357 German plant-year observations corresponding to approximately 85,000 plants per year between 2007 and 2013. All subsequent estimations on the micro-level use the most restrictive sample, in which we observe all indicators to distinguish between weak and strong banks and productive and unproductive firms. This final sample comprises 29,220 firms with 31,877 plants, or 202,386 plant-year observations.[7]

88.7 % of plant-year observations in our sample belong to single-plant firms. 96.8% of firms are single-plant firms The median plant employs four full-time-equivalent employees and is thus very small. This feature reflects the fact that our firms are mainly SMEs, which are more substantially affected by financial frictions than are large, listed multinationals. In Germany, 47% (66%) of plants have fewer than 5 (10) full-time-equivalent employees, and the vast majority of all firms are single-plant firms (Koch and Krenz, 2010). Hence, this sample of small firms mimics the population very well.

We define a bank as treated if it held an SMP asset in all three SMP years, 2010-2012. According to this definition, 11.6% of all observations or 10.7% of all plants are treated. We differ from the treatment definition in Koetter (2020) who defines a treated bank as one which holds SMP eligible assets in the first quarter of 2010, the quarter before the SMP was introduced. He finds that increases in corporate credit supply is driven by banks which continued holding SMP assets in contrast to banks which sold their SMP assets. With our treatment definition we can incorporate this finding and identify regional banks which actually increase firm lending as a response to the SMP. Further, with our treatment definition we rule out that banks purposefully loaded up on crisis bonds while observing the ECB's

[7] In robustness checks we include plants from firms with multiple bank relationships which yields 1,268,985 plant-year observations.

intervention and therefore select into the treatment group. Similarly, we also reduce the likelihood that banks took the chance to borrow in LTROs to purchase crisis bonds as in Acharya and Steffen (2015).

Because we estimate difference-in-differences models to isolate the effect of the SMP on industry dynamics, we test whether these two groups of plants are comparable by means of t-tests on selected variables at the plant- and bank-level.

– Table 2 around here –

Table 2 reports differences in levels across treated and non-treated observations for the pre and post period, respectively, as well as the corresponding difference-in-differences term. Both non-treated and treated plants show an average exit probability of 1.1% in the pre period. The exit rate for both groups increases in the post period, albeit more so for the non-treated group. As such, any potential effect of unconventional monetary policy that blocks the exit of plants tied to banks with additional credit-bearing capacity is not obviously visible from this non-parametric, unconditional comparison. Treated plants are larger than non-treated plants in terms of average number of employees (10.5 versus 14.3) and are slightly older (13.8 versus 14.2 years). Treated banks have slightly lower equity ratios and a lower return on assets, and while they are statistically significantly larger in size, this difference is economically negligible.

– Table 3 around here –

Treated and non-treated plants may differ in terms of covariate levels but must exhibit identical trends prior to treatment. Table 3 reports t-tests for changes in the respective variables. None of the plant, firm, or bank traits differ. The treatment and control groups exhibit parallel trends in observables prior to the SMP, and we employ a difference-in-differences approach in the following. As further evidence for parallel trends in the pre period we additionally provide results from a dynamic difference-in-differences estimation.

4 SMP effects on plant exit

4.1 Headline results

To quantify the effect of the SMP on plant closures, we use a difference-in-differences model to compare exits before and after the launch of the APP between plants with and without ties to SMP banks:

$$Exit_{it} = \alpha_i + \alpha_{rt} + \alpha_{kt} + \gamma\, SMP_i \times Post_t + \delta_x X_{it-1} + \epsilon_{it}. \tag{1}$$

The dependent variable $Exit_{it}$ is an indicator equal to 1 in year t when plant i exits. Plant fixed effects α_i gauge unobservable heterogeneity.[8] We also specify region-time fixed effects α_{rt} and sector-time fixed effects α_{kt} to control for local or industry specific time-varying changes in aggregate demand.

The variable SMP_i equals 1 if plant i is linked to a bank that held SMP-eligible assets in all three treatment years 2010-2012. It equals 0 if the bank did not hold SMP-eligible assets in all three years. $Post_t$ equals 1 in the period 2010-2013 after the SMP commenced, and 0 in the period 2007-2009. γ is our coefficient of interest and captures the difference-in-differences effect. We estimate the model with lagged bank-level controls and the second, third and fourth polynomial of firm age (X_{it-1}).[9] We cluster standard errors at the level of treatment, which is the bank level. Table 4 presents the headline results.

– Insert Table 4 around here –

The parsimonious specification in column I of Table 4 includes, in addition to plant and time fixed effects, only higher order polynomials of plant age as a control variable. The coefficient of interest is the interaction term, which is significant at the 10% confidence level and negative. The magnitude of -0.3 percentage points is economically meaningful, as average exit rates are on the order of 2.3 percentage points.

Irrespective of exposure to the SMP, plant exits may also depend on differences in bank health. Therefore, we add bank-specific CAMEL covariates plus bank size in column II to gauge financial profiles. The differential effect of the SMP on plant exits increases in size and is now statistically significant at the 5% level. Columns III and IV further scrutinize

[8] As most plants are operated by single-plant firms (96.8% of firms or 88.7% of plants), this fixed effect almost perfectly absorbs unobserved firm heterogeneity.

[9] Bank controls are defined in Table A.1 and follow the C(apitalization), A(sset quality), M(anagement skill), E(arnings), L(iquidity) taxonomy used, for example, by U.S. regulators to generate micro-prudential ratings of banks, plus bank size.

reduced plant exit rates due to the SMP by controlling for region-time and sector-time fixed effects. Controlling for unobservable shocks in regions or sectors entails an even larger, negative differential effect of the SMP on plant exits.

The magnitude of a reduction in mean exit rates by 0.5 percentage points is confirmed in the most conservative specification in column V, where we jointly control for all three types of fixed effects. Plants that are connected to firms with access to the SMP are almost 22% less likely to exit after the SMP started than plants without access to this APP. Note that the bank link manifests on the firm-level. We can observe exits on a more granular level, the plant-level. It is possible that credit constrained firms which are linked to a non-treated bank have to consolidate plants due to cost saving measures, which treated firms can avoid due to the support of their respective bank, and that is the reason why we observe lower exit rates for plants of treated firms.

To observe the dynamics of the effect and to test whether the parallel trend assumption holds in the pre period, we additionally estimate a dynamic version of equation (1) as in the following:

$$\begin{aligned} Exit_{it} &= \alpha_i + \alpha_{rt} + \alpha_{kt} \\ &+ \sum_{\tau=2007,\tau\neq 2009}^{2013} \gamma_{1\tau}\, D_\tau \times \mathrm{SMP}_i + \delta_x X_{it-1} + \epsilon_{it}. \end{aligned} \tag{2}$$

We interact treatment indicator SMP with yearly binary variables D_τ using τ= 2009 as base year. In Table 5 we report the results. Additionally, we present the results from column V, the most conservative estimation, for $\gamma_{1\tau}$ in a coefficient plot in Figure 2.

– Insert Table 5 around here –

– Insert Figure 2 around here –

Table 5 and Figure 2 confirm that the parallel trend assumption holds in the pre period. There are no differences in exit rates between treated and control group compared to base year 2009. The dynamics in the post period reveal that the negative effect on exit probabilities stems in particular from the second wave of the SMP starting in August 2011, which was more than twice as large as the first wave. The negative effect is most pronounced in 2013, the year after the end of the SMP.

4.1.1 Robustness

To determine the robustness of our results we further vary the fixed effect structure. In our baseline analyses, we use within-plant estimations when including plant-level fixed effects which reduces the influence of plants with no variation in the dependent variable. In an additional test we exclude plant fixed effects in order to test our hypothesis also *across* plants. We report the results in Table 6 in column I. The results remain unchanged though the statistical significance reduces to the 10% level.

Further, regional banks may arguably be similar in terms of size and business model, though we show in Table 2 that treated banks are slightly larger in size and are slightly less profitable. In Table 3 we demonstrate that differences in these characteristics do not change over time. In our main analysis, plant fixed effects absorb time invariant bank characteristics. For robustness we include bank fixed effects in our estimation which excludes plant fixed effects to control for time invariant differences across banks, for instance for the fact that savings banks are under governmental control whereas cooperatives can operate more freely. In Table 6 column II we show that our results remain unchanged.

– Insert Table 6 around here –

While the specification with many fixed effects should mitigate concerns of potentially confounding shocks, it remains important to ensure that it is indeed the SMP shock to which plant exit rates respond. To this end, we randomly assign placebo exposures to the SMP across plants that mimic the moments of the observed treatment distribution in the sample across plants and re-estimate the difference-in-differences model in equation (1).

– Insert Table 7 around here –

Column I in Table 7 reports the results for a placebo treatment that is assigned randomly across plants according to the overall treatment share. Column II shows the results for a placebo treatment that is assigned randomly for each year across plants according to the treatment share per year. Column III reports the results for a placebo treatment that is assigned randomly across plants and years. All three placebo estimations yield no significant results.

Due to identification reasons we include in our main specification only firms with a single bank link which does not change over time. To see whether our results hinge on this restricted sample, we include firms with multiple bank links which may change over time. The number of observations increases greatly to 1,268,985 plant-year observations. Treatment status of plant i is defined according to the first bank reported of the firm in Dafne which we assume to be the main bank. We show in Table 8 that the coefficient of interest γ becomes slightly smaller but the economic magnitude remains significant. The probability for exit of a treated plant decreases by 18.8% compared to the mean exit rate of 1.6% if the plant was exposed to the SMP. Statistically, the effect becomes even stronger: negative effects on exit probabilities are statistically significantly different from zero at the 1% level.

– Insert Table 8 around here –

We establish that for plants the probability to exit the market is reduced which is the *extensive* margin of how firms or plants react to the exposure to the SMP. We also provide checks for the *intensive* margin and assess whether the number of employees per plant change. On the one hand, instead of exiting the market, plants might only shrink and some workers move to more productive firms. On the other hand, additional funding might be used to employ more workers. As an alternative dependent variable we use the log of number of full-time equivalent workers of plant i in year t and re-estimate equation (1) and present results in Table 9.

– Insert Table 9 around here –

In column I in Table 9 we show that on average, affected plants do not change the number of employees. When we consider single-plant firms only in column Ia, the number of full-time equivalent employed persons is statistically significantly higher for affected plants compared to non-affected plants. This is a mild relative increase in terms of economic magnitudes by 0.78% compared to the average number of employees in the whole sample ((0.013/1.661)$\times$100). For multi-plant firms (column Ib) we do not observe differences across treated and control plants.[10] We conclude that plants do not shrink in size, on the contrary single-plant firms mildly increase the number of employees.

4.2 Channels

The finding that the SMP suppressed plant closures (which serve as an important cleansing mechanism) is consistent with other evidence that the provision of emergency liquidity to banks induces lending to unproductive firms that should have exited (Caballero et al., 2008). Similarly, Jiménez et al. (2014) demonstrate that loose (conventional) European monetary

[10] Note that the sum of plants from single and multi-plant firms is slightly lower than the whole sample from previous tables (202,015 versus 202,386). The reason is that additional singleton observations are dropped in sample splits. We use the sum of the reduced number of observations from columns Ia and Ib to estimate the average effect in column I.

policy contributed to the accumulation of credit risks in the Spanish financial system by misallocating credit via poorly capitalized banks to the least productive firms.

To test for such possible channels for adverse effects, we interact the baseline specification with an indicator for weak banks in equation (3):

$$Exit_{it} = \alpha_i + \alpha_{rt} + \alpha_{kt} + \cdots + \gamma\, SMP_i \times Post_t \times WB_i + \delta_x X_{it-1} + \epsilon_{it}. \quad (3)$$

We follow others (e.g. Schivardi et al., 2020; Jiménez et al., 2014; Acharya et al., 2019; Peek and Rosengren, 2005) and define bank weakness according to banks' capitalization. WB_i is an indicator equal to 1 if the bank was in the lowest quartile of the capitalization distribution in 2007, the last year before the financial crisis, which corresponds to an equity ratio below 5.56%. We extend the regression further by interacting with an indicator for weak firms in equation (4):

$$Exit_{it} = \alpha_i + \alpha_{rt} + \alpha_{kt} + \cdots + \gamma\, SMP_i \times Post_t \times WB_i \times WF_i + \delta_x X_{it-1} + \epsilon_{it}. \quad (4)$$

WF_i is an indicator equal to 1 if the firm was in the lowest quartile of the labor productivity distribution within its sector in 2007, the last year before the financial crisis. Labor productivity is defined as turnover per employee within each of the 66 sectors in our sample.[11] The variable turnover is only available at the firm-level from Amadeus; hence, WF_i is the same across plants within a given firm. Weak firms are not concentrated with weak banks. 24.4% of firms linked to strong banks, and 25.9% of firms linked to weak banks are classified as weak. We vary thresholds for weakness indicators in robustness checks. The quadruple difference-in-differences term gauges the effect of a weak bank being exposed to the policy shock on exit rates of plants of unproductive firms relative to the pre-SMP period. Standard errors are again clustered at the level of treatment, i.e., the bank. Table 10 reports marginal effects, which are derived from regression results shown in Table A.2 in the Appendix. For comparison, column I in Table 10 reproduces the headline results of Table 4.

– Insert Table 10 around here –

[11] According to OECD (2001) turnover per employee as measure of productivity entails the drawback that it correlates with outsourcing activities when labor inputs are substituted with intermediate inputs for instance. The upside of turnover per employee as productivity measure is that it does not require detailed data on intermediate inputs. It still captures more than just labor effort: the measure also covers changes in capital inputs, in intermediate inputs and total productivity as these raise turnover or increases turnover compared to number of employees. We compare turnover per employee within sectors such that level differences or trends such as outsourcing activities across sectors do not influence the result.

First, consider the marginal effects of a triple interaction, including a weak bank indicator in column II. Marginal effects are calculated separately for weak and strong SMP banks in the post-APP period. These results corroborate the general insight that plants are less likely to shut down if they are connected to SMP-supported banks. An important qualification here is that only the connection to the least capitalized banks entails a statistically significant reduction of exit probabilities. The economic magnitude of this effect increases drastically. Plants connected to weak SMP banks are on average 0.8 percentage points less likely to exit than non-treated plants. Thus, the transmission of emergency liquidity via weak banks is not a phenomenon confined to stressed Eurozone economies. Unconventional monetary policy also has the side effect that weaker intermediaries obtain the means to extend additional credit in stable economies such as Germany.

Column III specifies an additional indicator for weak firms, and we estimate marginal effects for each of the resulting four strata of weak/strong banks connected to unproductive/productive firms. Plants connected to well-capitalized banks do not exhibit changes in their exit probability, irrespective of their productivity. This result suggests that concerns about undesirable factor misallocation due to unconventional expansionary policy are less prevalent if banking systems are financially stable; see also Gopinath et al. (2017).

In contrast, plants connected to weak banks exhibit significantly lower exit probabilities. The marginal effect for productive firms connected to weak banks is 0.8 percentage points, whereas it equals 1 percentage point for plants of unproductive firms. Both differential effects represent a large reduction relative to the average exit rate of 2.3 percentage points. The numerically small difference between the effects for strong and weak firms might suggest that productivity differentials are not particularly relevant in the transmission of APP shocks. This is not the case. The group of productive firms includes all firms above the 25^{th} percentile, which still includes some fairly weak firms. We vary the threshold for weak firms in robustness checks in Section 4.2.1 and show that the effect is driven by firms below the median of the firm weakness indicator.

88.7% of our plant-level observations belong to small single-plant firms, and 11.3% to multi-plant firms. We want to identify whether suppressed churn rates go along with suppressed exits of small single-plant firms, or whether they are driven by reduced exit rates of plants within multi-plant firms. We split our sample accordingly and re-estimate equation (4) for single- and multi-plant firms, respectively. We present the results in Table 11.

– Insert Table 11 around here –

In columns 1a and 1b we show that multi-plant firms dominate the reduction in average exit rates. In fact, multi-plant firms which have a link to a well capitalized bank show lower probabilities of plant exit as we show in column IIb. In contrast, single-plant firms linked to weak banks show statistically significantly lower exit rates (column IIa). When turning to our fully specified model where we interact our difference-in-differences term with both weak bank and weak firm indicators, we can see that especially weak single-plant firms linked to lowly capitalized banks show lower exit rates (column IIIa). Plants from larger multi-plant firms show lower exit rates only if they are productive and linked to well capitalized banks (column IIIb).

We conclude that APPs raise survival probabilities especially for small weak firms dependent on weakly capitalized banks. Small capitalization gains as achieved with the SMP enables weak banks to continue lending to weak borrowers and keeps them alive despite their low productivity. Whereas larger low productive firms such as multi-plant firms do not benefit from increasing financial support. Well capitalized banks, in contrast, decide to strengthen relationships with productive larger firms and thereby buttress productive units in the economy. Therefore, APPs which affect well capitalized banks might even lead to (efficiently) lower factor reallocation *within* larger firms.

4.2.1 Robustness

In general, the unholy combination of weak (small) firms and weak banks drives the misallocation of resources in the form of unrealized plant exits. In Figures 3 and 4, we consider the entire range of thresholds to define weak financial profiles and unproductive plants, respectively.

– Insert Figure 3 around here –

First, we hold the threshold for the weak firm indicator constant and vary the threshold for weak banks across the entire distribution. Figure 3 shows the marginal effect and confidence bands at the 5% level of the treatment for unproductive plants connected to weak banks in the post period varying over different thresholds for the weak bank indicator. A bank is defined as weak if it is below the percentile threshold indicated on the horizontal axis. We depict point estimates of the marginal effects for re-estimations across the distribution of capitalization in one-percentile increments. The effect of the SMP in reducing the exit probabilities of unproductive firms prevails when defining weak banks as those that range approximately between the 5^{th} and the 30^{th} percentile. Thus, the main results reported for a threshold at the 25^{th} percentile are robust.

– Insert Figure 4 around here –

Second, we show marginal effects of the treatment for plants connected to weak banks for different firm productivity thresholds. In Figure 4, the threshold for the weak bank indicator is held constant, and we depict marginal effects and confidence bands at the 5% level across the distribution of productivity thresholds defined at different percentiles. In contrast to the bank stress threshold, the exit-dampening effect of the SMP prevails for a wide range of thresholds from the 15^{th} up and until the 60^{th} percentile. Hence, not only the very unproductive but also firms with moderate productivity are shielded from forced attrition due to harder-nosed monitoring styles by better capitalized SMP banks.

5 Regional and sector dynamics

The reduced average exit rates due to the SMP documented thus far may also be accompanied by more credit being available to new entrants that receive funding under a looser monetary policy stance. Or, in contrast, as incumbents receive more lending there might be less funding sources available for new entrants. Moreover, as incumbents remain longer in markets, new entrants might be blocked similar to findings by Adalet McGowan et al. (2018) and Andrews and Petroulakis (2019). Because new entrants, by definition, do not yet report an existing bank relationship, we cannot test this hypothesis using plant-level data. Therefore, we next consider whether aggregate industry dynamics – entry and exit rates per region and sector – differ significantly conditional on the share of SMP exposed banks.

5.1 Aggregation of microdata

We do so by mobilizing all 10,085,408 plant-year observations in the BHP 7514 during the years 2007-2013 to estimate the aggregate effects of the SMP on industry dynamics. The exposure of counties or sectors to the SMP shock is gauged by the share of SMP-affected plants $SMPshare$ per county or sector. We use the entire sample of banks, including commercial banks, and obtain the share of treated plants from our matched bank-firm-plant dataset. We extrapolate the total share of treated plants to the region or sector level. In Figure O.1 in the Online Appendix we show a heat map with 402 German regions defined according to the NUTS-3 level. German regions differ in terms of exposure to the SMP. Figure 5 depicts the number of incumbent plants (stock), the number of entering firms (entries), and the number of exiting firms (exits) per year by regions above and below the median of SMP-exposed plants during the treatment period 2010-2012. Entry and exit dynamics do not differ visibly between exposed and unexposed counties before and after the SMP shock.

– Insert Figure 5 around here –

To reveal possibly less-obvious changes in aggregate entries and exits, we apply difference-in-differences regressions at the aggregate level. To account for the feature that SMP-exposed regions host more incumbent plants, we specify region fixed effects.

First, we calculate for each of the 402 German counties ("Kreise") average plant entry and exit rates per year. In addition to regional aggregates, we calculate entry and exit rates by sector to test whether entry and exit rates differ systematically across sectors conditional on greater exposure to the SMP. Table O.1 in the Online Appendix reports sectors according to the 2-digit North American Industry Classification System (NAICS), a description of the sector, the SMP share and the number of plants per sector as of 2009. A lower cost of external funding may affect industry dynamics more in sectors with technologies that rely more heavily on capital as a production factor than in sectors that are less exposed to this change in relative factor prices. Table 12 presents tests of the parallel trends assumption at the aggregate level.

– Insert Table 12 around here –

We report differences in levels as well as compare year-on-year changes in the dependent and control variables between 2007 and 2009. Highly exposed regions have higher entry (5.8% versus 5.1%) as well as exit rates (5.7% versus 5.0%). They are larger in terms of the average number of plants per region but also in terms of the average number of full-time equivalent employees per plant (8.1 versus 6.7). They show higher GDP per capita but also higher unemployment rate (9.6% versus 5.9%). In regression analyses, we employ region fixed effects to control for level differences. When we compare changes, most level differences vanish. Only highly exposed regions show a stronger reduction of the unemployment rate in the pre period. Most importantly, t-tests clearly reject that aggregate entry and exit rates differ significantly prior to the launch of the SMP.

Concerning differences across sectors we observe that high exposure sectors are smaller in terms of average number of plants (11,446 versus 19,228), while comprising of larger firms in terms of average number of full-time equivalent employees per plant (41.6 versus 9.4). In regression analyses, we also employ sector fixed effects to control for level differences.

When we compare changes, high exposure sectors also report different changes in these variables. However, in terms of changes in entry and exit rates, which we use as dependent variables in the following, t-tests again clearly reject that these differ in the pre period.

5.2 SMP effects across regions and sectors

To estimate the changes in aggregate entry and exit rates in response to the policy shock, we gauge the SMP exposure of regions and sectors by the respective share of treated plants in the 402 regions and 66 sectors, respectively, and specify:

$$Y_{rt/kt} = \alpha_{r/k} + \alpha_t + \gamma\, SMPshare_{r/k} \times Post_t + \epsilon_{rt/kt}. \tag{5}$$

The dependent variable is the mean entry or exit rate in region r or sector k in year t. We extrapolate the share of treated plants per region $SMPshare_r$ or sector $SMPshare_k$ from the granular sample of firms that includes relationships to all banks. The share of treated plants per region (sector) is interacted with an indicator $Post_t$ that equals 0 for the pre period, 2007-2009, and 1 for the post period, 2010-2013. We include region (sector) fixed effects and time fixed effects and cluster standard errors at the region (sector) level.

– Insert Table 13 around here –

Columns I and II of Table 13 report results at the regional level. Plant entry rates after the launch of the SMP are significantly lower in counties with larger shares of SMP-exposed plants than in the three years preceding this policy shock. The economic impact depends on the $SMPshare$, which equals 42% in the average county. The point estimates imply a reduced entry rate of 0.418 $\times$ (-0.007), or -0.29 percentage points. Against the backdrop of average entry rates on the order of 5 percentage points, this implies a substantial reduction of 5.8%. Expansionary policy shocks in the form of APP not only depress average (unproductive) plant exit rates but also block the entry of new competitors. In the vein of Cetorelli and Strahan (2006), these results may indicate that an erosion of competitive pressure due to APP support for (weak) banks has detrimental effects on the real economy. Lower refinancing costs for banks due to the APP may induce them to prefer the provision of credit to incumbent, possibly less productive customers rather than lending to new, more innovative, but also more costly to screen entrants as in Cetorelli and Gambera (2001). Similarly, our findings are in line with observations by Adalet McGowan et al. (2018) and Andrews and Petroulakis (2019) that weak firms might congest markets and prevent new firms from entering.

Column II reports the impact of the share of treated plants in the region on average exit rates. In line with the plant-level results, aggregate regional plant attrition also declines. Averagely exposed regions have exit rates which are by 0.17 percentage points reduced (0.418 × (-0.004)) compared to regions which are not exposed to the SMP. Compared to the a mean attrition of 5.5 percent, a reduction by 0.17 percentage points corresponds to a contraction of average exit rates of 3%. Thus, having a larger share of regional SMP exposure has economically substantial restrictive effects on regional business dynamics.

Columns III and IV report aggregate results at the sector level. Qualitatively, the effect of relatively more SMP-exposed plants on sectoral entry and exit rates mimic the effects at the regional level. However, the effect on subdued entry rates is no longer significant, possibly reflecting the substantially lower number of observations. Therefore, the almost seven-fold estimate of the economic magnitude for the effect of the SMP share on sectoral plant attrition rates should be interpreted with caution.

Note that in contrast to the plant-level exercise in which multiple plants from diverse sectors are nested within each county, we cannot saturate the aggregate regional analyses with an equally tight grid of fixed effects to control for unobservables. In the regional analysis, for example, we account for a federal business cycle and for time-invariant traits of regions but not for systematic differences for each county over time. To challenge the assumption that a difference-in-differences approach at the aggregate level is valid beyond the tests of the parallel trends assumption shown in Table 12, we therefore estimate leads and lags models. Specifically, we interact the share of treated plants, $SMPshare_r$, with indicator variables for the years 2007-2013, excluding the immediate pre-treatment year 2009:

$$Y_{rt} = \alpha_r + \alpha_t + \sum_{t=2007,\, t\neq 2009}^{2013} \gamma_t \, D_t \times SMPshare_k + \cdots + \epsilon_{rt}. \tag{6}$$

D_t are year indicators, and $SMPshare$ is the share of treated plants per region or sector. We show results in Table 14.

– Insert Table 14 around here –

Columns I and II report the results at the regional level, while columns III and IV report those at the sector level. The effects of lower entry and lower exit rates are virtually all concentrated in the years after the SMP commenced, thereby confirming the parallel trends assumption.[12]

5.2.1 Robustness

The aggregate analysis may suffer more from potential bias than the plant-level results due to the presence of financial centers in selected counties. Hosts of financial centers may benefit over-proportionally from APP and experience specific economic conditions tied to the financial industry. Therefore, we re-estimate Equation (5) and exclude the local financial centers of Hamburg, Frankfurt (Main), Munich, Duesseldorf, and Stuttgart from the regional analysis. In the sector-level estimations, we exclude plants from these regions before aggregating plant observations. Tables O.2 through O.5 in the Online Appendix confirm that entry and exit rates at the regional and sectoral levels are each unaffected by this approach.

In sum, the evidence highlights quite clear adverse effects of APP in terms of industry dynamics and thus factor reallocation: (unproductive) firms connected to weak banks survive, new competitors cannot enter the market, and turnover rates decrease.

5.3 Heterogeneous aggregate transmission

The impact of the SMP on industry dynamics likely depends on the plant population within regions and sectors. Counties that host fewer but relatively many large plants may exhibit even stronger declines in (unproductive) plant attrition if additional bank funding made available by APPs is routed to these fewer customers by banks exposed to the program. Analogously, regions and sectors characterized by relatively low productivity at the time of the shock may suffer even more from suspended innovative renewal because SMP banks may seek to protect their incumbent customers.

To test whether and how regional and sectoral differences affect the transmission of the SMP to aggregate entry and exit, we augment Equation (5) with additional indicators that gauge differences in the respective plant population:

$$Y_{rt} = \alpha_r + \alpha_t + \gamma SMPshare_r \times Post_t \times Indicator_r + \cdots + \epsilon_{rt}. \tag{7}$$

[12]Only regional entry rates differ in the pre-period year 2007.

The binary variable $Indicator_r$ captures whether region or sector r is above the mean average plant size or below the mean labor productivity in the pre period across regions or sectors described below.

– Insert Table 15 around here –

At the regional level, columns I and II of Table 15 report the results when entry rates are the dependent variable. Columns III and IV present the results when exit rates are the dependent variable. We find no evidence of significantly different entry rates due to asset purchases between regions with large or small plants. Reduced exit rates are entirely driven by regions with large plants. Large plants can make use of liquidity injected into the economy by asset purchases and cause lower exit rates at the aggregate level. Lower exit rates driven by regions with large plants drag more heavily on renewal dynamics than would be the case if they were driven by small plants.

In columns II and IV, $Indicator_r$ equals one if mean labor productivity, measured according to the turnover per employee, is below the mean of all regions. As turnover is not available for all plants, the variable is extrapolated from firm information available from Amadeus. We find that lower entry rates are driven by both, low and high productive regions, however the estimate for low productive regions is twice as large. Lower exit rates are entirely driven by regions that show low productivity. Regions that are in need of innovation due to their low productivity exhibit even lower renewal rates after they benefited from asset purchases. These results match the preceding plant-level analysis. In the plant-level estimations (see Table 10) we show that weak firms connected to weak banks are the main driver of lower productivity differentials among plants. This is reflected in the estimations at the aggregate level, where low-productivity regions show lower churn rates.

– Insert Table 16 around here –

Table 16 reports results for observations aggregated at the sector level. As before, we do not find effects for entry rates in column I and II. In column III and IV we show results for exit rates. Similar to estimations at the region level, we find that sectors with large plants drive the result of lowered exit rates. Large plants benefit from asset purchases and remain in the market. The potential for adverse effects due to reduced Schumpeterian destruction is therefore large. Columns III and VI show the results for productivity measures. At the sector level, we find that high- and low-productivity sectors show reduced exit rates when plants are treated by the SMP. In contrast to the regional level, it is not the low-productivity sectors that are primarily responsible for the results.

5.4 GDP per capita and unemployment rate

On the one hand, micro-level evidence points to longer survival periods of low productive plants, and macro level evidence additionally shows lower entry rates, which could impede innovative processes. On the other hand, longer survival time of plants might sustain employment and prevent layoffs. In fact, we even observe a mild positive effect on the number of employees for small single-plant firms. To draw more general conclusions from the effect of the SMP on the economy, we assess how GDP per capita and the unemployment rate in highly affected regions develops compared to low affected regions. We re-estimate equation (5) with log of GDP per capita and the unemployment rate for region r as dependent variables. We report results in Table 17.

– Insert Table 17 around here –

In column I we report that the unemployment rate is lower for regions highly exposed to the SMP. The effect is statistically significant at the 1% level. The unemployment rate decreases by 0.67 percentage points in regions which are averagely affected by the SMP with a $SMPshare$ of 0.414 (-1.607×0.414 = -0.67) compared to regions not affected by the SMP. Compared to a mean unemployment rate of 7.062% in the whole sample, the effect corresponds to a reduction of the unemployment rate by around 9.5%.[13]

In column II we show results for the log of GDP per capita as dependent variable. The more regions are affected by the SMP, the lower is GDP per capita. Again, the effect is statistically significant at the 1% level. In averagely affected regions with a SMPshare of 0.414, the effect corresponds to -0.022 (-0.053×0.414). GDP per capita in the post period is 2.2% lower in regions which are averagely affected compared to regions which are not affected by the SMP (-0.022×100).

From these findings we conclude that the SMP causes low productive plants to remain longer in the market, which prevents layoffs and thereby sustains employment. Hence, the unemployment rate is lower the more strongly affected regions are. On the other hand, less exits of low productive plants as well as lower aggregate entry rates seem to subdue innovative processes resulting in lower GDP per capita overall.

[13] We interpret these results with caution. T-tests have shown that highly exposed regions reduce unemployment in the pre period more than low exposed regions, see Table 12.

6 Conclusion

Between May 2010 and September 2012, the European Central Bank (ECB) launched its first asset purchase program and absorbed sovereign debt from stressed Eurozone economies in secondary markets under the securities markets program (SMP). Meanwhile, entry and exit rates for very small firms in Germany declined. Based on a unique combination of granular data on plant exits and equally granular data on financial firms and security transactions between 2007 and 2013, we trace the SMP and show that it indeed dampened industry dynamics in Germany, a large Eurozone economy that was not targeted by this unconventional policy tool.

Difference-in-differences analyses at the plant-level clearly show that exit probabilities for plants connected to banks that are exposed to an APP decrease. These reduced exit rates are attributable to unproductive firms that are connected to weakly capitalized banks, which is robust to the use of a wide range of thresholds to define weak banks and firms. Detrimentally low market exits are triggered by low capitalized banks catering small low productive firms. Well capitalized banks, in contrast, induce lower churn rates for productive multi-plant firms. This result corroborates earlier evidence on the misallocation of credit to so-called zombie firms when monetary policy is overly loose and hits a weakly capitalized banking system. Indications for deterred factor reallocation only stem from firms linked to weakly capitalized banks.

We also assess aggregate industry dynamics in regional markets and 66 two-digit sectors of the German economy. This aggregate perspective exploits more than 10 million plant-year observations and permits analyses of average entry and exit activities in regions and sectors. Both average entry and exit rates are significantly lower in regions that host more banks that are exposed to the SMP shock. This result is qualitatively confirmed at the sector level. The results are driven by regions and sectors with large plants, which underlines the importance for the aggregate economy. Reflecting plant-level analyses, we further find that low-productivity regions, which should be the ones with the largest need and potential for innovative renewal, are the main drivers of the reduction in entries and exits.

We also trace ambiguous effects of the SMP. We observe that in particular small single-plant firms exposed to the SMP increase the number of employees. On the aggregate, unemployment rates are lower in regions more exposed to the SMP. Meanwhile, economic development measured according to GDP per capita is lower. Our evidence thus indicates that one economic cost imposed by asset purchase programs is to subdue the factor reallocation facilitated by financial institutions, namely, the exit of unproductive plants and the entry of new competitors. We conclude that the SMP hinders efficient factor reallocation across firms and thereby contributes to a slow economic recovery. Nonetheless, APPs also contribute to preventing layoffs and sustaining employment in the short term. The question whether inefficiently lower churn rates offset beneficial labor market effects in the long run remains open for future research.

Tables and Figures

Table 1: Summary statistics

This table reports summary statistics for 29,220 firms with 31,877 plants, or 202,386 plant-year observations, for the years 2007-2013. Variables on the plant-level are the following: $Exit$ is an indicator that equals 1 if plant i exits in year t, Age reports plant age in years, and $Number\ FTE$ is the number of employees in full-time equivalents. Variables on the bank level are the following: $Equity$ is the share of equity over total assets (in %), $Cost\text{-}to\text{-}income$ is the cost to income ratio (in %), $Return\ on\ assets$ is the return on total assets (in %), and $Liquidity$ is the share of liquid assets over total assets (in %). All bank-level variables are winsorized at the top and bottom 1% percentile. Furthermore, $Assets$ is the log of total assets (in million EUR). Total assets is winsorized before taking logs at the top and bottom 1% percentile. We use the following indicator variables: SMP equals 1 if the bank to which the firm is connected held SMP-eligible assets in all three treatment years 2010-2012. It equals 0 if the bank did not hold SMP-eligible assets in all three years. WB is a bank weakness indicator that equals 1 if the bank was in the lower 25% percentile in terms of equity ratio in the year 2007. WF is a firm weakness indicator that equals 1 if the firm was in the lower 25% percentile in terms of labor productivity, measured according to the turnover per employee in its sector in the year 2007. $Post$ equals 0 in 2007-2009 and 1 in 2010-2013. Variables at the regional and sector levels are as follows: $SMPshare$ is the share of treated plants in a region or sector. $Entry\ rate$ is the mean entry rate of plants per region or sector, and $Exit\ rate$ is the mean exit rate of plants per region or sector. $Unemployment\ rate$ is the number of unemployed persons over the number of all persons capable of work. $GDP\ per\ capita$ is GDP per capita at the region level in logs. Note that 13 regions fail to report the unemployment rate 2006-2008, and seven regions do so 2007-2011. Two regions do not report GDP per capita.

	Obs	Mean	Std. Dev.	Min	Max
Plant					
Exit	202,386	0.023	0.150	0.000	1.000
Age	202,386	15.825	10.023	1.000	38.000
Number FTE	202,386	11.441	52.794	0.000	9911.000
Bank					
Assets	202,386	7.954	1.327	5.142	12.470
Equity	202,386	6.656	1.795	2.538	12.331
Cost-to-income	202,369	69.296	10.027	44.640	145.120
Return on assets	202,384	0.199	0.155	-1.310	0.880
Liquidity	202,386	13.617	8.656	2.144	66.974
Indicators					
SMP	202,386	0.116	0.320	0.000	1.000
WF	202,386	0.243	0.429	0.000	1.000
WB	202,386	0.383	0.486	0.000	1.000
Post	202,386	0.548	0.498	0.000	1.000
Region					
SMPshare	2,814	0.418	0.188	0.100	0.921
Entry rate	2,814	0.050	0.010	0.024	0.088
Exit rate	2,814	0.055	0.009	0.029	0.100
Unemployment rate	2,741	7.062	3.418	1.200	22.000
GDP per capita	2,741	10.259	0.352	9.450	11.763
Sector					
SMPshare	462	0.476	0.106	0.212	0.805
Entry rate	462	0.055	0.030	0.000	0.253
Exit rate	462	0.055	0.028	0.000	0.154

Table 2: T-tests on levels of plant- and bank-level variables

This table reports the results of t-tests on mean levels of plant- and bank-level variables in the pre and post periods between treated and control groups. The last two columns report the difference-in-differences tests between the means of the two groups over both periods (DiD). The sample covers the years 2007-2009 in the pre period and 2010-2013 in the post period. The table reports tests on the following plant-level variables: $Exit$ is an indicator that equals 1 if plant i exits in year t, $Number\ FTE$ is the number of employees in full-time equivalents, and Age reports plant age in years. Tests on the following bank-level variables are reported: $Equity$ is the share of equity over total assets (in %), $Cost\text{-}to\text{-}income$ is the cost to income ratio (in %), $Return\ on\ assets$ is the return on total assets (in %), and $Liquidity$ is the share of liquid assets over total assets (in %). All bank-level variables are winsorized at the top and bottom 1% percentile. Furthermore, $Assets$ is the log of total assets (in million EUR). Total assets is winsorized before taking logs at the top and bottom 1% percentile. *, **, *** indicate significant differences at the 10%, 5%, and 1% level, respectively.

		Pre period				Post period					
LEVELS	N	Non-treated	Treated	Diff	SE	Non-treated	Treated	Diff	SE	DiD	SE
Plant											
Exit	202,386	0.011	0.011	0.000	0.002	0.033	0.031	-0.002	0.001	-0.002	0.002
Number FTE	202,386	10.511	14.318	3.808***	0.545	11.310	15.940	4.63***	0.495	0.822	0.737
Age	202,386	13.825	14.198	0.373***	0.102	17.377	17.940	0.563***	0.093	0.190	0.138
Bank											
Equity	6,265	6.382	5.939	-0.443***	0.129	7.771	7.481	-0.289**	0.113	0.154	0.172
Cost-to-income	6,263	71.954	72.058	0.104	0.617	67.251	66.893	-0.357	0.617	-0.431	0.820
Return on assets	6,264	0.233	0.193	-0.039***	0.013	0.286	0.249	-0.038***	0.011	0.001	0.017
Liquidity	6,265	15.520	15.815	0.294	0.560	12.253	13.129	0.877*	0.489	0.582	0.743
Assets	6,265	6.414	6.718	0.304***	0.083	6.517	6.797	0.280***	0.073	-0.024	0.111

Table 3: T-tests on changes of plant- and bank-level variables

This table reports the results of t-tests on year-to-year changes in plant- and bank-level variables in the pre and post periods between treated and control groups. The last two columns report the difference-in-differences tests between the means of the two groups over both periods (DiD). The sample covers the years 2007-2009 in the pre period and 2010-2013 in the post period. For first differences in year 2007, observations from 2006 are also considered. The table reports tests on the plant-level variable $Number\ FTE$, which is the year-to-year change in the number of employees in full-time equivalents. Tests on the following bank-level variables are reported: $Equity$ is the year-to-year change in the share of equity over total assets, $Cost\text{-}to\text{-}income$ is the year-to-year change in the cost to income ratio, $Return\ on\ assets$ is the year-to-year change in the return on total assets, and $Liquidity$ is the year-to-year change in the share of liquid assets over total assets. All bank-level variables are winsorized at the top and bottom 1% percentile. Furthermore, $Assets$ is the year-to-year change in the log of total assets (in million EUR). Total assets is winsorized before being transformed into logs at the top and bottom 1% percentile. *, **, *** indicate significant differences at the 10%, 5%, and 1% level, respectively.

		Pre period				Post period					
CHANGES	N	Non-treated	Treated	Diff	SE	Non-treated	Treated	Diff	SE	DiD	SE
Plant											
Number FTE	202,386	0.245	0.278	0.033	0.173	0.176	0.242	0.066	0.157	0.033	0.233
Bank											
Equity	5,351	0.012	0.101	0.089	0.056	0.551	0.575	0.023	0.040	-0.065	0.068
Cost-to-income	5,350	-1.776	-1.797	-0.021	0.576	-0.348	-0.392	-0.044	0.410	-0.023	0.707
Return on assets	5,351	0.011	0.015	0.004	0.012	0.001	0.002	0.001	0.009	-0.003	0.015
Liquidity	5,351	-1.018	-0.992	0.026	0.403	-0.757	-0.645	0.111	0.286	0.085	0.494
Assets	5,351	0.036	0.029	-0.007	0.006	0.025	0.022	-0.003	0.004	0.004	0.008

Table 4: Plant exit probabilities

This table reports the results from difference-in-differences analyses at the plant-level from the following regression: $Exit_{it} = \alpha_i + \alpha_{rt} + \alpha_{kt} + \gamma SMP_i \times Post_t + \delta_x X_{it-1} + \epsilon_{it}$. The sample comprises 29,220 firms with 31,877 plants, or 202,386 plant-year observations, for the years 2007-2013. The dependent variable $Exit$ is an indicator that equals 1 if plant i exits the market in year t and 0 otherwise. SMP is an indicator that equals 1 if the bank to which the firm is connected held SMP-eligible assets in all three treatment years 2010-2012. It equals 0 if the bank did not hold SMP-eligible assets in all three years. $Post$ is an indicator that equals 0 for the years 2007-2009 and 1 for the years 2010-2013. All estimations include the second, third and fourth polynomial of plant age. We add lagged bank controls (X_{it-1}) including the equity ratio, cost-to-income ratio, return on assets, liquidity ratio and log of total assets (in million EUR). Bank-level variables are winsorized at the lower and upper 1% percentile. Furthermore, plant (α_i), region-time (α_{rt}), and sector-time (α_{kt}) fixed effects are added. $Mean\ Exit$ reports the mean of the dependent variable in the regression sample, and $SD\ Exit$ is the standard deviation. Standard errors are clustered at the bank level and reported in parentheses. *, **, *** indicate significant coefficients at the 10%, 5%, and 1% level, respectively.

	I	II	III	IV	V
Post×SMP	-0.003*	-0.004**	-0.005**	-0.005**	-0.005**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Firm age	Yes	Yes	Yes	Yes	Yes
Bank controls	-	Yes	Yes	Yes	Yes
Plant FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	-	-	-
Region-Time FE	-	-	Yes	-	Yes
Sector-Time FE	-	-	-	Yes	Yes
N	202,386	202,386	202,386	202,386	202,386
R2	0.248	0.248	0.250	0.251	0.253
Mean Exit	0.023	0.023	0.023	0.023	0.023
SD Exit	0.150	0.150	0.150	0.150	0.150

Table 5: Probability of default of plants in a dynamic setting

This table reports the results from dynamic difference-in-differences analyses at the plant-level from the following regression: $Exit_{it} = \alpha_i + \alpha_{rt} + \alpha_{kt} + \sum_{\tau=2007,\tau\neq 2009}^{2013} \gamma_{1\tau}\ D_\tau \times \text{SMP}_i + +\delta_x X_{it-1} + \epsilon_{it}$. The sample comprises 29,220 firms with 31,877 plants, or 202,386 plant-year observations, for the years 2007-2013. The dependent variable $Exit$ is an indicator that equals 1 if plant i exits the market in year t and 0 otherwise. SMP is an indicator that equals 1 if the bank to which the firm is connected held SMP-eligible assets in all three treatment years 2010-2012. It equals 0 if the bank did not hold SMP-eligible assets in all three years. D_τ are indicator variables for years 2007-2013, leaving out 2009 as base year. All estimations include the second, third and fourth polynomial of plant age. We add lagged bank controls (X_{it-1}) including the equity ratio, cost-to-income ratio, return on assets, liquidity ratio and log of total assets (in million EUR). Bank-level variables are winsorized at the lower and upper 1% percentile. Furthermore, plant (α_i), region-time (α_{rt}), and sector-time (α_{kt}) fixed effects are added. $Mean\ Exit$ reports the mean of the dependent variable in the regression sample, and $SD\ Exit$ is the standard deviation. Standard errors are clustered at the bank level and reported in parentheses. *, **, *** indicate significant coefficients at the 10%, 5%, and 1% level, respectively.

	I	II	III	IV	V
2007×SMP	0.000	0.000	-0.001	0.001	0.000
	(0.003)	(0.003)	(0.004)	(0.003)	(0.004)
2008×SMP	0.000	0.000	0.000	0.001	0.001
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
2009×SMP	0	0	0	0	0
	(omitted)	(omitted)	(omitted)	(omitted)	(omitted)
2010×SMP	-0.003	-0.003	-0.004	-0.003	-0.004
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
2011×SMP	0.001	0.000	0.001	0.000	0.001
	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)
2012×SMP	-0.003	-0.004	-0.006	-0.004	-0.006
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
2013×SMP	-0.009***	-0.011***	-0.012***	-0.011***	-0.013***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Firm age	Yes	Yes	Yes	Yes	Yes
Bank controls	-	Yes	Yes	Yes	Yes
Plant FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	-	-	-
Region-Time FE	-	-	Yes	-	Yes
Sector-Time FE	-	-	-	Yes	Yes
N	202,386	202,386	202,386	202,386	202,386
R2	0.248	0.248	0.250	0.251	0.253
Mean Exit	0.023	0.023	0.023	0.023	0.023
SD Exit	0.150	0.150	0.150	0.150	0.150

Table 6: Varying the fixed effects structure

This table reports the results from difference-in-differences analyses at the plant-level from the following regression: $Exit_{it} = (\alpha_b) + \alpha_{rt} + \alpha_{kt} + \gamma SMP_i \times Post_t + \delta_x X_{it-1} + \epsilon_{it}$. The sample comprises 29,220 firms with 31,877 plants, or 202,386 plant-year observations, for the years 2007-2013. The dependent variable $Exit$ is an indicator that equals 1 if plant i exits the market in year t and 0 otherwise. SMP is an indicator that equals 1 if the bank to which the firm is connected held SMP-eligible assets in all three treatment years 2010-2012. It equals 0 if the bank did not hold SMP-eligible assets in all three years. $Post$ is an indicator that equals 0 for the years 2007-2009 and 1 for the years 2010-2013. All estimations include the second, third and fourth polynomial of plant age. We add lagged bank controls (X_{it-1}) including the equity ratio, cost-to-income ratio, return on assets, liquidity ratio and log of total assets (in million EUR). Bank-level variables are winsorized at the lower and upper 1% percentile. Furthermore, region-time (α_{rt}), sector-time (α_{kt}) and bank fixed effects (α_b, column II) are added. $Mean\ Exit$ reports the mean of the dependent variable in the regression sample, and $SD\ Exit$ is the standard deviation. Standard errors are clustered at the bank level and reported in parentheses. *, **, *** indicate significant coefficients at the 10%, 5%, and 1% level, respectively.

	excl. plant FE I	incl. bank FE II
Post×SMP	-0.003*	-0.004*
	(0.002)	(0.002)
Firm age	Yes	Yes
Bank controls	Yes	Yes
Plant FE	-	-
Region-Time FE	Yes	Yes
Industry-Time FE	Yes	Yes
Bank FE	-	Yes
N	202,386	202,386
R2	0.018	0.025
Mean Exit	0.023	0.023
SD Exit	0.150	0.150

Table 7: Placebo estimations

This table reports the results from placebo difference-in-differences analyses at the plant-level from the following regression: $Exit_{it} = \alpha_i + \alpha_{rt} + \alpha_{kt} + \gamma SMPplacebo_i \times Post_t + \delta_x X_{it-1} + \epsilon_{it}$. The sample comprises 29,220 firms with 31,877 plants, or 202,386 plant-year observations, for the years 2007-2013. The dependent variable $Exit$ is an indicator that equals 1 if plant i exits the market in year t and 0 otherwise. $Post$ is an indicator that equals 0 for the years 2007-2009 and 1 for the years 2010-2013. In column I, the treatment $SMPplacebo$ is assigned randomly across plants according to the overall treatment share. In column II, the treatment $SMPplacebo$ is assigned randomly across plants per year according to the yearly treatment share. In column III, the treatment $SMPplacebo$ is assigned randomly across plants and years according to the overall treatment share. All estimations include the second, third and fourth polynomial of plant age. We add lagged bank controls (X_{it-1}) including the equity ratio, cost-to-income ratio, return on assets, liquidity ratio and log of total assets (in million EUR). Bank-level variables are winsorized at the lower and upper 1% percentile. Furthermore, plant (α_i), region-time (α_{rt}), and sector-time (α_{kt}) fixed effects are added. $Mean\ Exit$ reports the mean of the dependent variable in the regression sample, and $SD\ Exit$ is the standard deviation. Standard errors are clustered at the bank level and are reported in parentheses. *, **, *** indicate significant coefficients at the 10%, 5%, and 1% level, respectively.

	I	II	III
Post×SMPplacebo	0.001	0.002	0.001
	(0.002)	(0.002)	(0.002)
Firm age	Yes	Yes	Yes
Bank controls	Yes	Yes	Yes
Plant FE	Yes	Yes	Yes
Region-Time FE	Yes	Yes	Yes
Sector-Time FE	Yes	Yes	Yes
N	202,386	202,386	202,386
R2	0.253	0.253	0.253
Mean Exit	0.023	0.023	0.023
SD Exit	0.150	0.150	0.150

Table 8: Probability of default of plants including multi-bank firms

This table reports the results from difference-in-differences analyses at the plant-level from the following regression: $Exit_{it} = \alpha_i + \alpha_{rt} + \alpha_{kt} + \gamma SMP_i \times Post_t + \delta_x X_{it-1} + \epsilon_{it}$. The sample comprises 192,929 firms with 213,519 plants, or 1,268,985 plant-year observations, for the years 2007-2013. The dependent variable $Exit$ is an indicator that equals 1 if plant i exits the market in year t and 0 otherwise. SMP is an indicator that equals 1 if the first bank reported by the firm held SMP-eligible assets in all three treatment years 2010-2012. It equals 0 if the first bank reported did not hold SMP-eligible assets in all three years. $Post$ is an indicator that equals 0 for the years 2007-2009 and 1 for the years 2010-2013. All estimations include the second, third and fourth polynomial of plant age. We add lagged bank controls which are averages of all banks the firm has a link to (X_{it-1}) including the equity ratio, cost-to-income ratio, return on assets, liquidity ratio and log of total assets (in million EUR). Bank-level variables are winsorized at the lower and upper 1% percentile. Furthermore, plant (α_i), region-time (α_{rt}), and sector-time (α_{kt}) fixed effects are added. $Mean\ Exit$ reports the mean of the dependent variable in the regression sample, and $SD\ Exit$ is the standard deviation. Standard errors are clustered at the bank level and reported in parentheses. *, **, *** indicate significant coefficients at the 10%, 5%, and 1% level, respectively.

	I	II	III	IV	V
Post×SMP	-0.004***	-0.002**	-0.003***	-0.003***	-0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Firm age	Yes	Yes	Yes	Yes	Yes
Bank controls	-	Yes	Yes	Yes	Yes
Plant FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	-	-	-
Region-Time FE	-	-	Yes	-	Yes
Sector-Time FE	-	-	-	Yes	Yes
N	1,268,985	1,268,985	1,268,985	1,268,985	1,268,985
R2	0.272	0.272	0.273	0.274	0.274
Mean Exit	0.016	0.016	0.016	0.016	0.016
SD Exit	0.127	0.127	0.127	0.127	0.127

Table 9: Employment

This table reports the results from difference-in-differences analyses at the plant-level from the following regression: $Y_{it} = \alpha_i + \alpha_{rt} + \alpha_{kt} + \gamma SMP_i \times Post_t + \delta_x X_{it-1} + \epsilon_{it}$. The sample comprises 29,212 firms with 31,863 plants, or 202,015 plant-year observations, for the years 2007-2013. The dependent variable $Employees$ is the log number of full time equivalents plus 1 of plant i in year t. SMP is an indicator that equals 1 if the bank to which the firm is connected held SMP-eligible assets in all three treatment years 2010-2012. It equals 0 if the bank did not hold SMP-eligible assets in all three years. $Post$ is an indicator that equals 0 for the years 2007-2009 and 1 for the years 2010-2013. All estimations include the second, third and fourth polynomial of plant age. We add lagged bank controls (X_{it-1}) including the equity ratio, cost-to-income ratio, return on assets, liquidity ratio and log of total assets (in million EUR). Bank-level variables are winsorized at the lower and upper 1% percentile. Furthermore, plant (α_i), region-time (α_{rt}), and sector-time (α_{kt}) fixed effects are added. $Mean\ Dependent$ reports the mean of the dependent variable in the regression sample, and $SD\ Dependent$ is the standard deviation. Standard errors are clustered at the bank level and reported in parentheses. *, **, *** indicate significant coefficients at the 10%, 5%, and 1% level, respectively.

	All I	Single-plant firms Ia	Multi-plant firms Ib
Post×SMP	0.010	0.013**	0.041
	(0.007)	(0.007)	(0.026)
Firm age	Yes	Yes	Yes
Bank controls	Yes	Yes	Yes
Plant FE	Yes	Yes	Yes
Region-Time FE	Yes	Yes	Yes
Sector-Time FE	Yes	Yes	Yes
N	202,015	179,336	22,679
R2	0.951	0.948	0.965
Mean Dependent	1.705	1.661	2.048
SD Dependent	1.071	1.035	1.267

Table 10: Marginal effects conditional on weak banks and firms

This table reports marginal effects of the treatment SMP in the post period 2010-2013 derived from the following estimation: $Exit_{it} = \alpha_i + \alpha_{rt} + \alpha_{kt} + \cdots + \gamma SMP_i \times Post_t \times WB_i \times WF_i + \delta_x X_{it-1} + \epsilon_{it}$. The sample comprises 29,220 firms with 31,877 plants, or 202,386 plant-year observations, for the years 2007-2013. Table A.2 reports the underlying regression table. The dependent variable $Exit$ is an indicator that equals 1 if plant i exits the market in year t and 0 otherwise. SMP is an indicator that equals 1 if the bank to which the firm is connected held SMP-eligible assets in all three treatment years 2010-2012. It equals 0 if the bank did not hold SMP-eligible assets in all three years. $Post$ is an indicator that equals 0 for the years 2007-2009 and 1 for the years 2010-2013. WB is a bank weakness indicator that equals 1 if the bank was in the lower 25% percentile in terms of the equity ratio in the year 2007. WF is a firm weakness indicator that equals 1 if the firm was in the lower 25% percentile in terms of labor productivity, measured according to the turnover per employee in its sector in 2007. All estimations include the second, third and fourth polynomial of plant age. We add lagged bank controls (X_{it-1}) including the equity ratio, cost-to-income ratio, return on assets, liquidity ratio and log of total assets (in million EUR). Bank-level variables are winsorized at the lower and upper 1% percentile. Furthermore, plant (α_i), region-time (α_{rt}), and sector-time (α_{kt}) fixed effects are added. Column I reports the marginal effects of SMP for all firm-bank observations. Column II reports the marginal effects of SMP conditional on the bank weakness indicator WB. Column III reports the marginal effects of SMP conditional on bank and firm weakness. $Mean\ Exit$ reports the mean of the dependent variable in the regression sample, and $SD\ Exit$ is the standard deviation. Standard errors are clustered at the bank level and reported in parentheses *, **, *** indicate significant coefficients at the 10%, 5%, and 1% level, respectively.

		I	II	III
All		-0.005**		
		(0.002)		
Banks	strong		-0.002	
			(0.003)	
	weak		-0.008***	
			(0.003)	
Strong banks	strong firms			-0.005
				(0.003)
	weak firms			0.004
				(0.006)
Weak banks	strong firms			-0.008**
				(0.003)
	weak firms			-0.010**
				(0.004)
N		202,386	202,386	202,386
R2		0.253	0.253	0.253
Mean Exit		0.023	0.023	0.023
SD Exit		0.150	0.150	0.150

Table 11: Marginal effects conditional on weak banks and firms, sample split

This table reports marginal effects of the treatment SMP in the post period 2010-2013 derived from the following estimation: $Exit_{it} = \alpha_i + \alpha_{rt} + \alpha_{kt} + \cdots + \gamma SMP_i \times Post_t \times WB_i \times WF_i + \delta_x X_{it-1} + \epsilon_{it}$. We split the sample according to single-plant firms and multi-plant firms. The sample of single-plant firms encompasses 28,167 firms or plants, or 179,336 plant-year observations for the years 2007-2013. The sample of multi-plant firms encompasses 1,459 firms, 4,106 plants or 22,679 plant-year observations. Table A.3 reports the underlying regression table. The dependent variable $Exit$ is an indicator that equals 1 if plant i exits the market in year t and 0 otherwise. SMP is an indicator that equals 1 if the bank to which the firm is connected held SMP-eligible assets in all three treatment years 2010-2012. It equals 0 if the bank did not hold SMP-eligible assets in all three years. $Post$ is an indicator that equals 0 for the years 2007-2009 and 1 for the years 2010-2013. WB is a bank weakness indicator that equals 1 if the bank was in the lower 25% percentile in terms of the equity ratio in the year 2007. WF is a firm weakness indicator that equals 1 if the firm was in the lower 25% percentile in terms of labor productivity, measured according to the turnover per employee in its sector in 2007. All estimations include the second, third and fourth polynomial of plant age. We add lagged bank controls (X_{it-1}) including the equity ratio, cost-to-income ratio, return on assets, liquidity ratio and log of total assets (in million EUR). Bank-level variables are winsorized at the lower and upper 1% percentile. Furthermore, plant (α_i), region-time (α_{rt}), and sector-time (α_{kt}) fixed effects are added. Column Ia and Ib report the marginal effects of SMP across banks and firms. Column IIa and IIb report the marginal effects of SMP conditional on the bank weakness indicator WB. Column IIIa and IIIb report the marginal effects of SMP conditional on bank and firm weakness. $Mean\ Exit$ reports the mean of the dependent variable in the regression sample, and $SD\ Exit$ is the standard deviation. Standard errors are clustered at the bank level and reported in parentheses *, **, *** indicate significant coefficients at the 10%, 5%, and 1% level, respectively.

		Ia single-plant	Ib multi-plant	IIa single-plant	IIb multi-plant	IIIa single-plant	IIIb multi-plant
All		-0.004	-0.021***				
		(0.003)	(0.008)				
Banks	strong			-0.000	-0.036***		
				(0.003)	0.009		
	weak			-0.009**	-0.013		
				(0.004)	(0.011)		
Strong banks	strong firms					-0.002	-0.038***
						(0.004)	(0.010)
	weak firms					0.005	-0.024
						(0.007)	(0.018)
Weak banks	strong firms					-0.007*	-0.016
						(0.004)	(0.010)
	weak firms					-0.012**	0.031
						(0.005)	(0.046)
N		179,336	22,679	179,336	22,679	179,336	22,679
R2		0.248	0.323	0.248	0.323	0.248	0.323
Mean Exit		0.022	0.028	0.022	0.028	0.022	0.028
SD Exit		0.147	0.1651	0.147	0.1651	0.147	0.1651

Table 12: T-tests on levels and mean changes at the region and sector level

This table shows t-tests on levels as well as year-to-year changes in variables at the region and sector levels during the pre period between treated and control groups. Regions or sectors are defined as treated if the treatment share is above the median of all regions or sectors. The control group consists of regions or sectors that have a treatment share that is below the median. The sample covers the years 2007-2009. For first differences in the year 2007, observations from the year 2006 are also considered. The table reports tests on the following variables: $Entry$ is the mean year-to-year change in entry rates at the region or sector level. $Exit$ is the exit rate at the region or sector level. $Number\ of\ plants$ is the number of plants per region or sector. $FTE\ per\ plant$ is the number of employees per plant in full-time equivalents. $GDP\ per\ capita$ is GDP per capita at the region level in logs. $Unemployment\ rate$ is the number of unemployed persons over the number of all persons capable of work. *, **, *** indicate significant differences at the 10%, 5%, and 1% level, respectively. Data for GDP and unemployment come from Destatis. Note that 13 regions fail to report the unemployment rate 2006-2008, and seven regions do so 2007-2011. Two regions do not report GDP per capita. The sample in these tests encompasses all region-year observations for which we observe both variables.

	High treat	N	Low treat	N	Difference	t-stat
Region						
-Levels-						
Entry	0.058	603	0.051	603	-0.006***	-12.463
Exit	0.057	603	0.050	603	-0.007***	-15.581
Number of plants	4,139	603	2,931	603	-1207***	-5.354
FTE per plant	8.072	603	6.703	603	-1.369***	-11.363
GDP per capita	10.229	597	10.169	603	-0.060**	-2.942
Unemployment rate	9.631	559	5.874	600	-3.757***	-20.047
-Changes-						
Entry	-0.002	603	-0.001	603	0.000	0.792
Exit	-0.001	603	0.000	603	0.001	1.425
Number of plants	55.566	603	44.050	603	-11.516*	2.461
FTE per plant	-0.053	603	-0.040	603	0.013	0.869
GDP per capita	351.672	597	303.561	603	-48.111	0.495
Log (GDP per capita)	0.015	597	0.013	603	-0.002	-0.551
Unemployment rate	-0.568	364	-0.267	400	0.301***	4.132
Sector						
-Levels-						
Entry	0.064	108	0.053	90	-0.011*	-2.297
Exit	0.047	108	0.042	90	-0.005	-1.093
Number of plants	11,446	108	19,288	90	7,842*	-2.068
FTE per plant	41.605	108	9.423	90	-32.182***	-6.685
-Changes-						
Entry	-0.000	99	0.002	99	0.002	0.571
Exit	0.018	99	0.017	99	-0.002	-0.423
Number of plants	427.626	99	1321.131	99	893.505**	3.221
FTE per plant	-1.435	99	-0.200	99	1.235**	2.769

Table 13: Aggregated effects of SMP on entry and exit rates

This table reports the results from difference-in-differences estimations at the aggregate level from the following regression: $Y_{rt/kt} = \alpha_{r/k} + \alpha_t + \gamma SMPshare_{r/k} \times Post_t + \epsilon_{rt/kt}$. The underlying sample comprises 10,085,408 plant-year observations, covering the years 2007-2013, which are aggregated at the region r or sector k level. The dependent variables are mean entry and mean exit rates per region or sector. The data cover 402 regions and 66 sectors. $Post$ is an indicator that equals 0 for the years 2007-2009 and 1 for the years 2010-2013. $SMPshare$ is the share of treated plants per region or sector. $Mean\ dependent$ reports the mean of the dependent variable in the regression sample, and $SD\ dependent$ is the standard deviation. $Mean\ SMPshare$ reports the mean of the SMP share over all regions or sectors, and $SD\ SMPshare$ is the standard deviation. Standard errors are clustered at the region or sector level and are reported in parentheses. *, **, *** indicate significant coefficients at the 10%, 5%, and 1% level, respectively.

	Region		Sector	
	Entry	Exit	Entry	Exit
	I	II	III	IV
Post×SMPshare	-0.007***	-0.004***	-0.023	-0.027**
	(0.001)	(0.001)	(0.022)	(0.012)
Time FE	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	-	-
Sector FE	-	-	Yes	Yes
N	2,814	2,814	462	462
R2	0.782	0.746	0.782	0.880
Mean dependent	0.050	0.055	0.055	0.055
SD dependent	0.010	0.009	0.030	0.028
Mean SMPshare	0.418	0.418	0.476	0.476
SD SMPshare	0.188	0.188	0.106	0.106

Table 14: Aggregated effects of SMP on entry and exit rates in a dynamic setting

This table reports the results from leads and lags estimations at the aggregate level from the following regression: $Y_{rt/kt} = \alpha_{r/k} + \alpha_t + \sum_{t=2007,\, t\neq 2009}^{2013} \gamma_t \, D_t \times SMPshare_{r/k} + \cdots + \epsilon_{rt/kt}$. The underlying sample comprises 10,085,408 plant-year observations, covering the years 2007-2013, which are aggregated at the region r or sector k level. The dependent variables are the mean entry and mean exit rates of a region or sector. The data cover 406 regions and 66 sectors. D_t are year indicators, excluding year 2009. $SMPshare$ is the share of treated plants per region or sector. $Mean\ dependent$ reports the mean of the dependent variable in the regression sample, and $SD\ dependent$ is the standard deviation. $Mean\ SMPshare$ reports the mean of the SMP share over all regions or sectors, and $SD\ SMPshare$ is the standard deviation. Standard errors are clustered at the region or sector level and are reported in parentheses. *, **, *** indicate significant coefficients at the 10%, 5%, and 1% level, respectively.

	Region		Sector	
	Entry	Exit	Entry	Exit
	I	II	III	IV
2007×SMPshare	0.004**	0.001	0.004	-0.008
	(0.002)	(0.002)	(0.015)	(0.032)
2008×SMPshare	0.000	0.000	0.044	0.030
	(0.002)	(0.002)	(0.041)	(0.022)
2010×SMPshare	-0.004**	-0.002	-0.026*	-0.011
	(0.002)	(0.002)	(0.013)	(0.008)
2011×SMPshare	-0.003*	-0.003**	-0.028**	-0.047***
	(0.002)	(0.002)	(0.011)	(0.010)
2012×SMPshare	-0.006***	-0.007***	-0.026	0.002
	(0.002)	(0.002)	(0.016)	(0.019)
2013×SMPshare	-0.008***	-0.003	0.054	-0.022
	(0.002)	(0.002)	(0.040)	(0.016)
Region FE	Yes	Yes	-	-
Sector FE	-	-	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
N	2,814	2,814	462	462
R2	0.784	0.747	0.792	0.884
Mean Dependent	0.050	0.055	0.055	0.055
SD Dependent	0.010	0.009	0.030	0.028
Mean SMPshare	0.418	0.418	0.476	0.476
SD SMPshare	0.188	0.188	0.106	0.106

Table 15: Heterogeneous aggregate transmission in regions

This table reports the results from difference-in-differences estimations at the aggregate level from the following regression: $Y_{rt} = \alpha_t + \alpha_r + \gamma SMPshare_r \times Post_t \times Indicator_r + \cdots + \epsilon_{rt}$. The underlying sample comprises 10,085,408 plant-year observations, covering the years 2007-2013, which are aggregated at the region level. The dependent variables are mean entry rates (columns I and II) and mean exit rates (columns III and IV). The data cover 402 regions. $Post$ is an indicator that equals 0 for the years 2007-2009 and 1 for the years 2010-2013. $SMPshare$ is the share of treated plants per region. $Indicator$ equals 1 in column I if the mean plant size in terms of the number of employees in full-time equivalents in region r is above the mean of all regions, 0 otherwise. In column II, $Indicator$ equals 1 if mean labor productivity, measured according to the turnover per employee, is below the mean of all regions. Turnover is extrapolated from firm information available from Amadeus from our matched bank-firm-plant sample. In columns III and IV, $Indicator$ is defined accordingly. $Mean\ dependent$ reports the mean of the dependent variable in the regression sample, and $SD\ dependent$ is the standard deviation. $Mean\ SMPshare$ reports the mean of the SMP share over all regions, and $SD\ SMPshare$ is the standard deviation. Standard errors are clustered at the region level and are reported in parentheses. *, **, *** indicate significant coefficients at the 10%, 5%, and 1% level, respectively.

	Entry		Exit	
	Size	Turn	Size	Turn
	I	II	III	IV
Post×SMPshare	-0.005***	-0.004***	-0.002	-0.002
	(0.002)	(0.001)	(0.001)	(0.001)
Post×Indicator	0.000	0.002*	0.001	0.002***
	(0.001)	(0.001)	(0.001)	(0.001)
Post×SMPshare×Indicator	-0.002	-0.004**	-0.004*	-0.005**
	(0.002)	(0.002)	(0.002)	(0.002)
Time FE	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes
Sector FE	-	-	-	-
N	2,814	2,814	2,814	2,814
R2	0.783	0.783	0.747	0.747
Mean dependent	0.050	0.050	0.055	0.055
SD dependent	0.010	0.010	0.009	0.009
Mean SMPshare	0.418	0.418	0.418	0.418
SD SMPshare	0.188	0.188	0.188	0.188

Table 16: Heterogeneous aggregate transmission in sectors

This table reports results from difference-in-differences estimations at the aggregate level from the following regression: $Y_{kt} = \alpha_t + \alpha_k + \gamma SMPshare_k \times Post_t \times Indicator_k + \cdots + \epsilon_{kt}$. The underlying sample comprises 10,085,408 plant-year observations, covering the years 2007-2013, which are aggregated at the sector level. The dependent variables are mean entry rates (columns I and II) and mean exit rates (columns III and IV). The data cover 66 sectors. $Post$ is an indicator that equals 0 for the years 2007-2009 and 1 for the years 2010-2013. $SMPshare$ is the share of treated plants per sector. $Indicator$ equals 1 in column I if the mean plant size in terms of the number of employees in full-time equivalents in sector k is above the mean of all sectors, 0 otherwise. In column II, $Indicator$ equals 1 if mean labor productivity, measured according to the turnover per employee, is below the mean of all sectors. Turnover is extrapolated from firm information available from Amadeus from our matched bank-firm-plant sample. In columns III and IV, $Indicator$ is defined accordingly. $Mean\ dependent$ reports the mean of the dependent variable in the regression sample, and $SD\ dependent$ is the standard deviation. $Mean\ SMPshare$ reports the mean of the SMP share over all sectors, and $SD\ SMPshare$ is the standard deviation. Standard errors are clustered at the sector level and are reported in parentheses. *, **, *** indicate significant coefficients at the 10%, 5%, and 1% level, respectively.

	Entry		Exit	
	Size	Turn	Size	Turn
	I	II	III	IV
Post×SMPshare	-0.036	-0.018	0.015	-0.039**
	(0.025)	(0.034)	(0.014)	(0.015)
Post×Indicator	-0.003	0.004	0.021**	-0.015
	(0.018)	(0.016)	(0.009)	(0.010)
Post×SMPshare×Indicator	0.012	0.005	-0.053***	0.035*
	(0.041)	(0.038)	(0.019)	(0.020)
Time FE	Yes	Yes	Yes	Yes
Region FE	-	-	-	-
Sector FE	Yes	Yes	Yes	Yes
N	462	462	462	462
R2	0.782	0.784	0.883	0.881
Mean dependent	0.055	0.055	0.055	0.055
SD dependent	0.030	0.030	0.028	0.028
Mean SMPshare	0.476	0.476	0.476	0.476
SD SMPshare	0.106	0.106	0.106	0.106

Table 17: Unemployment and GDP per capita

This table reports results from difference-in-differences estimations at the aggregate level from the following regression: $Y_{rt} = \alpha_t + \alpha_r + \gamma SMPshare_r \times Post_t + \cdots + \epsilon_{rt}$. The sample comprises 402 regions over the time period 2007-2013. The dependent variables are the unemployment rate in region r in column I and the log of GDP per capita in region r in column II. For 13 regions we do not have information on the unemployment rate 2006-2008, and for seven regions 2007-2011. For two regions we do not have GDP per capita in the pre period. The sample in this regression encompasses all region-year observations for which we observe both variables. $Post$ is an indicator that equals 0 for the years 2007-2009 and 1 for the years 2010-2013. $SMPshare$ is the share of treated plants per sector. $Mean\ dependent$ reports the mean of the dependent variable in the regression sample, and $SD\ dependent$ is the standard deviation. $Mean\ SMPshare$ reports the mean of the SMP share over regions, and $SD\ SMPshare$ is the standard deviation. Standard errors are clustered at the region level and are reported in parentheses. *, **, *** indicate significant coefficients at the 10%, 5%, and 1% level, respectively.

	Unemployment I	GDP per capita II
Post×SMPshare	-1.670***	-0.053***
	(0.257)	(0.014)
Time FE	Yes	Yes
Region FE	Yes	Yes
N	2,741	2,741
R2	0.972	0.989
Mean Dependent	7.062	10.259
SD Dependent	3.418	0.352
Mean treatment	0.414	0.414
SD treatment	0.187	0.187

Figure 1: Business dynamics in Germany for small firms

In this figure we show the number of births of enterprises (left axis) and deaths of enterprises (right axis) for enterprises with 1-4 employees in Germany over the time period 2006-2013. Source: Eurostat business demography statistics, own illustration.

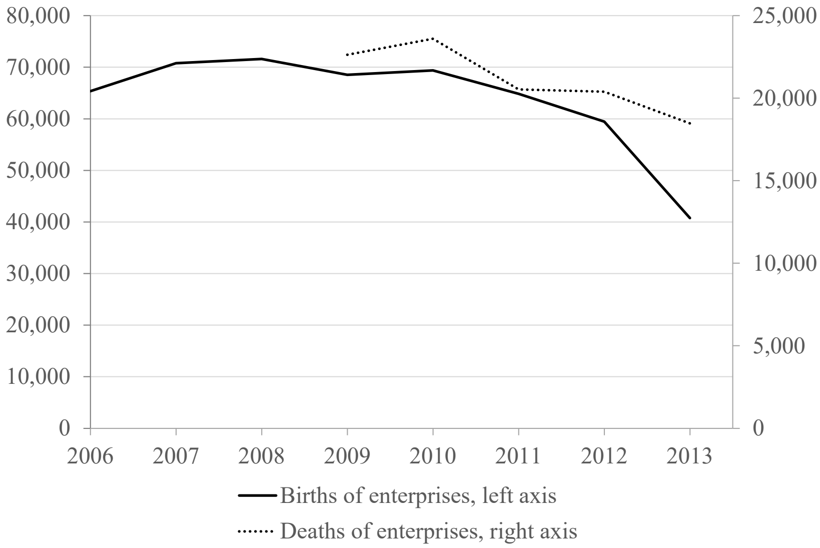


Figure 2: Probability of default of plants in a dynamic setting

In this figure we show the coefficient plot from estimating the following dynamic difference-in-differences analysis at the plant-level: $Exit_{it} = \alpha_i + \alpha_{rt} + \alpha_{kt} + \sum_{\tau=2007,\tau\neq 2009}^{2013}(\gamma_{1\tau}\,\mathbf{1}_{t=\tau} \times \text{SMP}_i) + \delta_x X_{it-1} + \epsilon_{it}$. The sample comprises 29,220 firms with 31,877 plants, or 202,386 plant-year observations, for the years 2007-2013. The dependent variable $Exit$ is an indicator that equals 1 if plant i exits the market in year t and 0 otherwise. SMP is an indicator that equals 1 if the bank to which the firm is connected held SMP-eligible assets in all three treatment years 2010-2012. It equals 0 if the bank did not hold SMP-eligible assets in all three years. $\mathbf{1}_{t=\tau}$ are indicator variables for years 2007-2013, leaving out 2009 as base year. All estimations include the second, third and fourth polynomial of plant age. We add lagged bank controls (X_{it-1}) including the equity ratio, cost-to-income ratio, return on assets, liquidity ratio and log of total assets (in million EUR). Bank-level variables are winsorized at the lower and upper 1% percentile. Furthermore, plant (α_i), region-time (α_{rt}), and sector-time (α_{kt}) fixed effects are added. Standard errors are clustered at the bank level. We depict confidence intervals at the 10% level.

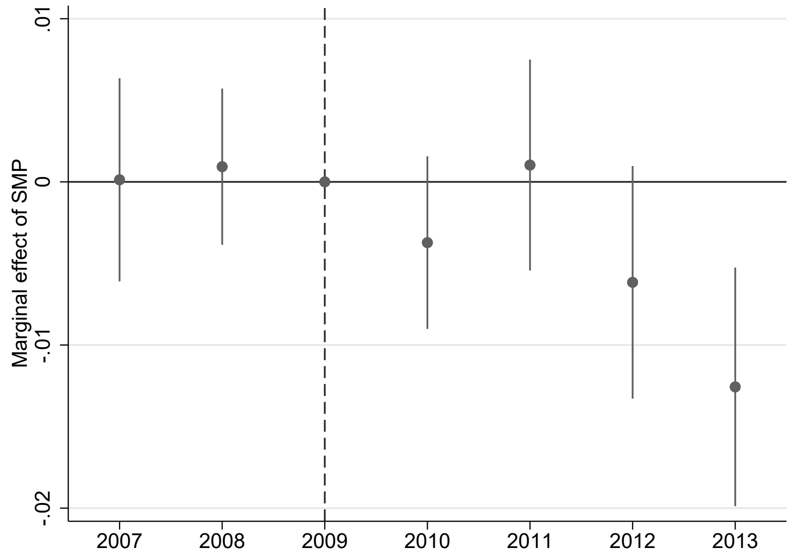


Figure 3: Varying weak bank indicator

This figure depicts marginal effects and confidence bands at the 5% level of the treatment SMP in the post period 2010-2013 conditional on varying weak bank indicators derived from the following estimations: $Exit_{it} = \alpha_i + \alpha_{rt} + \alpha_{kt} + \cdots + \gamma SMP_i \times Post_t \times WB\_X_i \times WF_i + \delta_x X_{it-1} + \epsilon_{it}$. The sample comprises 29,220 firms with 31,877 plants, or 202,386 plant-year observations, for the years 2007-2013. The dependent variable $Exit$ is an indicator that equals 1 if plant i exits the market in year t and 0 otherwise. SMP is an indicator that equals 1 if the bank to which the firm is connected held SMP-eligible assets in all three treatment years 2010-2012. It equals 0 if the bank did not hold SMP-eligible assets in all three years. $Post$ is an indicator that equals 0 for the years 2007-2009 and 1 for the years 2010-2013. WF is a firm weakness indicator that equals 1 if the firm was in the lower 25% percentile in terms of labor productivity, measured according to the turnover per employee in its sector in 2007. WB_X is a bank weakness indicator that equals 1 if the bank was in the lower X% percentile in terms of the equity ratio in the year 2007. We run 99 regressions and vary WB_X over 99 percentiles. All estimations include the second, third and fourth polynomial of plant age. We add lagged bank controls (X_{it-1}) including the equity ratio, cost-to-income ratio, return on assets, liquidity ratio and log of total assets (in million EUR). Bank-level variables are winsorized at the lower and upper 1% percentile. Furthermore, plant (α_i), region-time (α_{rt}), and sector-time (α_{kt}) fixed effects are added. Standard errors are clustered at the bank level. "b" reports the marginal effect, "lb" is the lower bound of the 5% confidence interval and "up" reports the upper bound of the confidence interval.

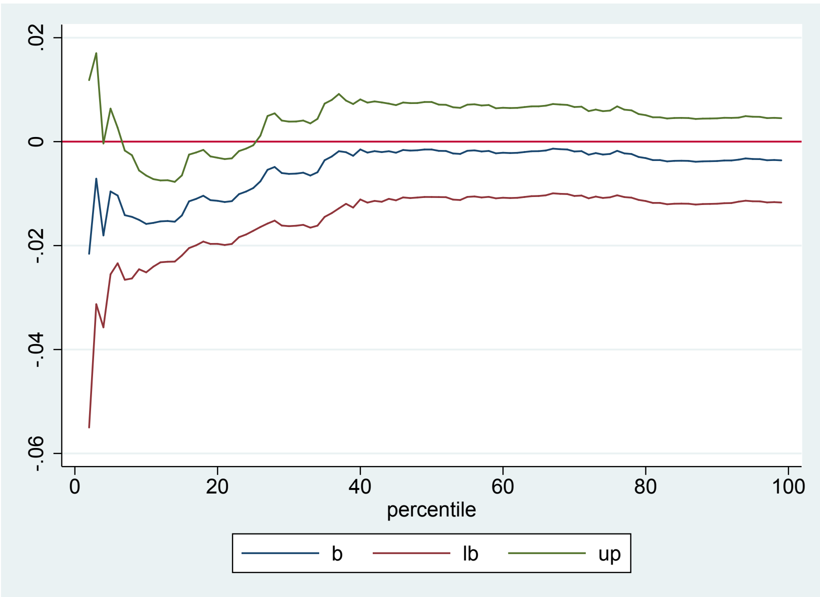


Figure 4: Varying weak firm indicator

This figure depicts marginal effects and confidence bands at the 5% level of the treatment SMP in the post period 2010-2013 conditional on varying weak firm indicators derived from the following estimations: $Exit_{it} = \alpha_i + \alpha_{rt} + \alpha_{kt} + \cdots + \gamma SMP_i \times Post_t \times WB_i \times WF\_X_i + \delta_x X_{it-1} + \epsilon_{it}$. The sample comprises 29,220 firms with 31,877 plants or 202,386 plant-year observations for the years 2007-2013. The dependent variable $Exit$ is an indicator that equals 1 if plant i exits the market in year t and 0 otherwise. SMP is an indicator that equals 1 if the bank to which the firm is connected held SMP-eligible assets in all three treatment years 2010-2012. It equals 0 if the bank did not hold SMP-eligible assets in all three years. $Post$ is an indicator that equals 0 for the years 2007-2009 and 1 for the years 2010-2013. WB is a bank weakness indicator that equals 1 if the bank was in the lower 25% percentile in terms of equity ratio in the year 2007. WF_X is a firm weakness indicator that equals 1 if the firm was in the lower X% percentile in terms of labor productivity, measured according to the turnover per employee in its sector in 2007. We run 99 regressions and vary WF_X over 99 percentiles. All estimations include the second, third and fourth polynomial of plant age. We add lagged bank controls (X_{it-1}) including the equity ratio, cost-to-income ratio, return on assets, liquidity ratio and log of total assets (in million EUR). Bank-level variables are winsorized at the lower and upper 1% percentile. Furthermore, plant (α_i), region-time (α_{rt}), and sector-time (α_{kt}) fixed effects are added. Standard errors are clustered at the bank level. "b" reports the marginal effect, "lb" is the lower bound of the 5% confidence interval and "up" reports the upper bound of the confidence interval.

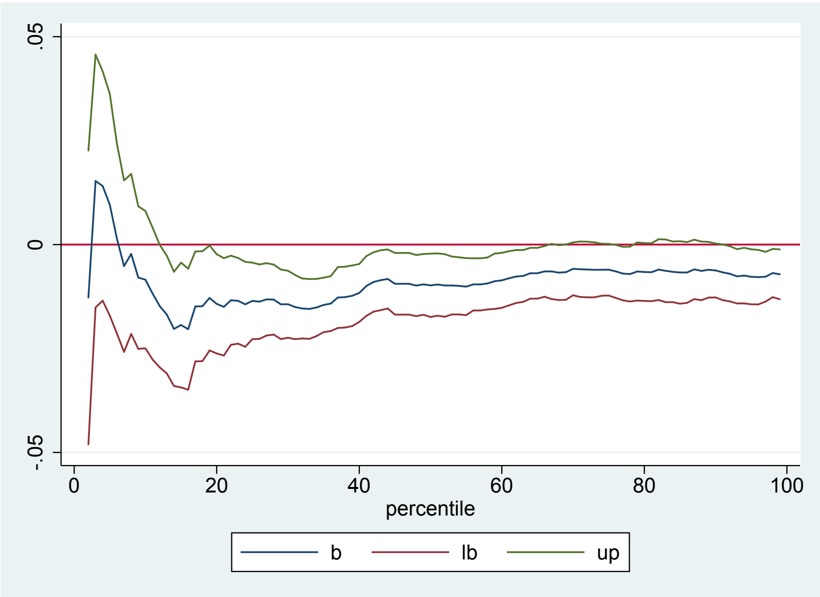
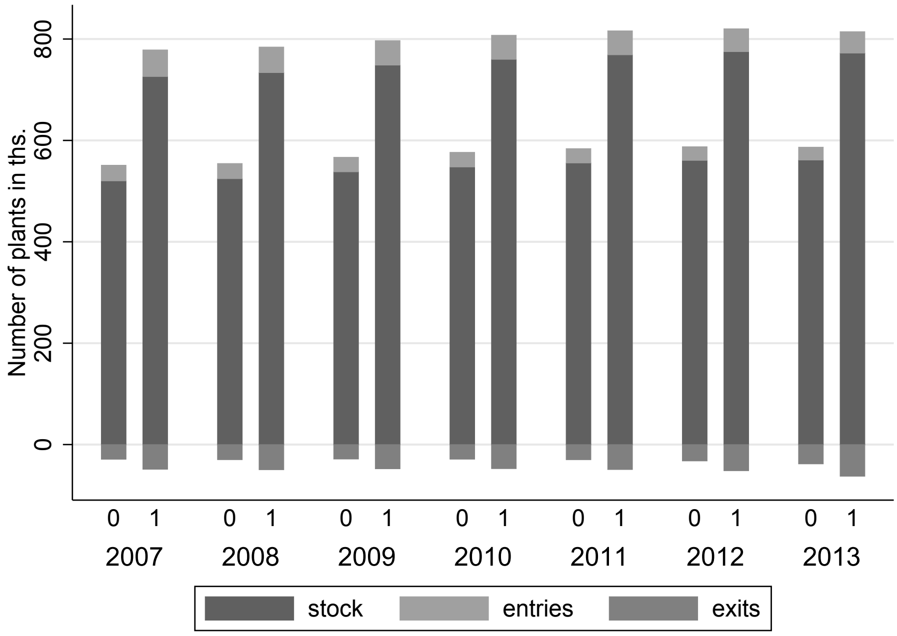


Figure 5: Number of plants per year conditional on treatment share of region

This figure depicts the number of plants per year in thousands. We categorize plants as belonging to the stock of plants, entering that year (entries), or exiting that year (exits). Furthermore, we distinguish between exposed and unexposed regions. Regions in which the share of treated plants based on our matched bank-firm-plant sample is below the median are considered to be unexposed (0), while regions that exhibit a treatment share above the median are considered to be exposed (1).



A Variable definitions and additional tables

Table A.1: Variable descriptions

Variable	Unit	Description
Plant variables. Source: IAB.		
Exit	0/1	Equals 1 in the year a plant exits the market, 0 otherwise. We use the definition of Hethey and Schmieder (2010) on small and atomized deaths.
Age	Years	Age of plant in years.
Number FTE	Employees	Number of employees in full-time equivalents.
Employees	Log	Log number of employees in full-time equivalents + 1.
Bank variables, winsorized at lower and upper 1%. Source: Bankscope.		
Equity ratio	%	Equity over total assets.
Cost-to-income ratio	%	Overhead over net interest revenue plus other operating income.
Return on assets	%	Net income over total assets.
Liquidity ratio	%	Liquid assets over total assets.
Log of assets	Log mil EUR	Log million EUR total assets, winsorized before taking logs.
Aggregate variables. Source: IAB, Statistische Landesämter.		
Entry rate	[0;1]	Mean entry rate per region (sector).
Exit rate	[0;1]	Mean exit rate per region (sector).
(Log) GDP per capita	EUR	GDP per capita per region in (Log) Euros.
Unemployment rate	%	Number of unemployed persons over all persons capable of work per region.
Bank Weakness Indicator. Source: Bankscope.		
WB	0/1	Equals 1 if a bank's equity ratio was in the lower 25% percentile in 2007.
Firm Weakness Indicator. Source: Amadeus and IAB.		
WF	0/1	Equals 1 if a firm's turnover/employee was in the lower 25% percentile in 2007 in its sector. As turnover is available only at the firm-level, the WF indicator is the same within firms across plants.

Variable descriptions continued

Variable	Unit	Description
Treatment variables. Source: Bundesbank and ECB.		
SMP	0/1	Equals 1 if bank held SMP-eligible assets in all three treatment years 2010, 2011 and 2012. Equals 0 if bank did not hold SMP eligible-assets in all three years.
SMPshare	[0;1]	Average share of treated plants in a region or sector during treatment period 2010-2012. Extrapolated from merged sample of plant-level data with firm and bank information.
Time indicator		
Post	0/1	Equals 0 in years 2007-2009 and 1 in years 2010-2013.

Table A.2: Regression results conditional on weak banks and firms

This table reports results from difference-in-differences analyses at the plant-level from the following regression: $Exit_{it} = \alpha_i + \alpha_{rt} + \alpha_{kt} + \cdots + \gamma SMP_i \times Post_t \times WB_i \times WF_i + \delta_x X_{it-1} + \epsilon_{it}$. The sample comprises 29,220 firms with 31,877 plants, or 202,386 plant-year observations, for the years 2007-2013. Table 10 reports the marginal effects of SMP conditional on time, firm and bank weakness. The dependent variable $Exit$ is an indicator that equals 1 if plant i exits the market in year t and 0 otherwise. SMP is an indicator that equals 1 if the bank to which the firm is connected held SMP-eligible assets in all three treatment years 2010-2012. It equals 0 if the bank did not hold SMP-eligible assets in all three years. $Post$ is an indicator that equals 0 for the years 2007-2009 and 1 for the years 2010-2013. WB is a bank weakness indicator that equals 1 if the bank was in the lower 25% percentile in terms of the equity ratio in the year 2007. WF is a firm weakness indicator that equals 1 if the firm was in the lower 25% percentile in terms of labor productivity, measured according to the turnover per employee in its sector in 2007. All estimations include the second, third and fourth polynomial of plant age. We add lagged bank controls (X_{it-1}) including the equity ratio, cost-to-income ratio, return on assets, liquidity ratio and log of total assets (in million EUR). Bank-level variables are winsorized at the lower and upper 1% percentile. Furthermore, plant (α_i), region-time (α_{rt}), and sector-time (α_{kt}) fixed effects are added. $Mean\ Exit$ reports the mean of the dependent variable in the regression sample, and $SD\ Exit$ is the standard deviation. Standard errors are clustered at the bank level and reported in parentheses *, **, *** indicate significant coefficients at the 10%, 5%, and 1% level, respectively.

	I	II	III
Post×SMP	-0.005**	-0.002	-0.005
	0.002	0.003	0.003
Post×Weak_bank		-0.001	0.000
		0.002	0.002
Post×SMP×Weak_bank		-0.006	-0.003
		0.004	0.004
Post×Weak_firm			-0.003
			0.002
Post×SMP×Weak_firm			0.008
			0.007
Post×Weak_bank×Weak_firm			-0.002
			0.003
Post×SMP×Weak_bank×Weak_firm			-0.011
			0.008
Firm age	Yes	Yes	Yes
Bank controls	Yes	Yes	Yes
Plant FE	Yes	Yes	Yes
Region-Time FE	Yes	Yes	Yes
Sector-Time FE	Yes	Yes	Yes
N	202,386	202,386	202,386
R2	0.253	0.253	0.253
Mean Exit	0.023	0.023	0.023
SD Exit	0.150	0.150	0.150

Table A.3: Regression results conditional on weak banks and firms, sample split

This table reports results from difference-in-differences analyses at the plant-level from the following regression: $Exit_{it} = \alpha_i + \alpha_{rt} + \alpha_{kt} + \cdots + \gamma SMP_i \times Post_t \times WB_i \times WF_i + \delta_x X_{it-1} + \epsilon_{it}$. We split the sample according to single-plant firms and multi-plant firms. single-plant firms encompasses 28,167 firms and plants, or 179,336 plant-year observations for the years 2007-2013. multi-plant firms encompasses 1,459 firms , 4,106 plants or 22,679 plant-year observations. Table 11 reports the marginal effects of SMP conditional on time, firm and bank weakness. The dependent variable $Exit$ is an indicator that equals 1 if plant i exits the market in year t and 0 otherwise. SMP is an indicator that equals 1 if the bank to which the firm is connected held SMP-eligible assets in all three treatment years 2010-2012. It equals 0 if the bank did not hold SMP-eligible assets in all three years. $Post$ is an indicator that equals 0 for the years 2007-2009 and 1 for the years 2010-2013. WB is a bank weakness indicator that equals 1 if the bank was in the lower 25% percentile in terms of the equity ratio in the year 2007. WF is a firm weakness indicator that equals 1 if the firm was in the lower 25% percentile in terms of labor productivity, measured according to the turnover per employee in its sector in 2007. All estimations include the second, third and fourth polynomial of plant age. We add lagged bank controls (X_{it-1}) including the equity ratio, cost-to-income ratio, return on assets, liquidity ratio and log of total assets (in million EUR). Bank-level variables are winsorized at the lower and upper 1% percentile. Furthermore, plant (α_i), region-time (α_{rt}), and sector-time (α_{kt}) fixed effects are added. $Mean\ Exit$ reports the mean of the dependent variable in the regression sample, and $SD\ Exit$ is the standard deviation. Standard errors are clustered at the bank level and reported in parentheses *, **, *** indicate significant coefficients at the 10%, 5%, and 1% level, respectively.

	Ia single-plants	Ib multi-plants	IIa single-plants	IIb multi-plants	IIIa single-plants	IIIb multi-plants
Post×SMP	-0.004	-0.021***	-0.000	-0.036***	-0.002	-0.038***
	(0.003)	(0.008)	(0.003)	(0.009)	(0.004)	(0.010)
Post×Weak_bank			-0.000	-0.003	0.000	-0.003
			(0.002)	(0.007)	(0.002)	(0.008)
Post×SMP×Weak_bank			-0.008*	0.024*	-0.005	0.021
			(0.005)	(0.014)	(0.005)	(0.014)
Post×Weak_firm					-0.002	-0.020**
					(0.002)	(0.010)
Post×SMP×Weak_firm					0.007	0.014
					(0.007)	(0.021)
Post×Weak_bank×Weak_firm					-0.003	0.004
					(0.003)	(0.015)
Post×SMP×Weak_bank×Weak_firm					-0.012	0.034
					(0.009)	(0.052)
Firm age	Yes	Yes	Yes	Yes	Yes	Yes
Bank controls	Yes	Yes	Yes	Yes	Yes	Yes
Plant FE	Yes	Yes	Yes	Yes	Yes	Yes
Region-Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Sector-Time FE	Yes	Yes	Yes	Yes	Yes	Yes
N	179,336	22,679	179,336	22,679	179,336	22,679
R2	0.248	0.323	0.248	0.323	0.248	0.323
Mean Exit	0.022	0.028	0.022	0.028	0.022	0.028
SD Exit	0.147	0.165	0.147	0.165	0.147	0.165

Online appendix

Table O.1: Treatment shares across sectors

This table reports North American Industry Classification System (NAICS) codes, description of sectors, treatment shares per sector $SMPShare$, and number of plants per sector as of the year 2009.

NAICS	Description	SMPshare	Number of plants
10	Manufacture of food products	0.343	4,106
11	Manufacture of beverages	0.400	768
12	Manufacture of tobacco products	0.805	29
13	Manufacture of textiles	0.496	1,143
14	Manufacture of wearing apparel	0.487	534
15	Manufacture of leather and related products	0.449	238
16	Manufacture of wood and of products of wood and cork, except furniture; manufacture and plaiting materials	0.337	2,160
17	Manufacture of paper and paper products	0.598	905
18	Printing and reproduction of recorded media	0.406	3,859
19	Manufacture of coke and refined petroleum products	0.684	100
20	Manufacture of chemicals and chemical products	0.652	1,946
21	Manufacture of basic pharmaceutical products and pharmaceutical preparations	0.693	362
22	Manufacture of rubber and plastic products	0.501	3,719
23	Manufacture of other non-metallic mineral products	0.500	3,514
24	Manufacture of basic metals	0.556	1,880
25	Manufacture of fabricated metal products, except machinery and equipment	0.399	14,253
26	Manufacture of computer, electronic and optical products	0.564	4,139
27	Manufacture of electrical equipment	0.525	2,810
28	Manufacture of machineryand equipment n.e.c.	0.545	8,880
29	Manufacture of motor vehicles, trailers and semi-trailers	0.600	1,304
30	Manufacture of other transport equipment	0.522	466
31	Manufacture of furniture	0.314	2,019
32	Other manufacturing	0.416	5,228
33	Repair and installation of machinery and equipment	0.399	3,465
35	Electricity, gas, steam and air conditioning supply	0.528	2,464
36	Water collection, treatment and supply	0.470	260
37	Sewerage	0.397	400
38	Waste collection, treatment and disposal activities; materials recovery	0.472	2,406
39	Remediation activities and other waste management services	0.483	79
41	Construction of buildings	0.276	11,062
42	Civil engineering	0.357	3,469
43	Specialised construction activities	0.300	43,422
45	Wholesale and retail trade and repair of motor vehicles and motorcycles	0.350	18,044
46	Wholesale trade, except of motor vehicles and motorcycles	0.506	42,796
47	Retail trade, except of motor vehicles and motorcycles	0.482	41,449
49	Land transport and transport via pipelines	0.337	6,403
50	Water transport	0.395	555
51	Air transport	0.653	140
52	Warehousing and support activities for transportation	0.567	10,158
53	Postal and courier activities	0.458	712
55	Accommodation	0.362	2,935
56	Food and beverage service activities	0.410	6,862
58	Publishing activities	0.516	2,729
59	Motion picture	0.582	1,673
60	Programming and broadcasting activities	0.546	200
61	Telecommunications	0.597	572
62	Computer programming	0.499	14,359
63	Information service activities	0.496	1,343
68	Real estate activities	0.449	15,721
69	Legal and accounting activities	0.498	5,317
70	Activities of head offices; management consultancy activities	0.532	13,395
71	Architectural and engineering activities; technical testing and analysis	0.456	13,262
72	Scientific research and development	0.567	1,545
73	Advertising and market research	0.476	6,120
74	Other professional scientific and technical activities	0.466	2,182
75	Veterinary activities	0.212	47
77	Rental and leasing activities	0.483	3,873
78	Employment activities	0.557	5,396
79	Travel agency	0.480	3,298
80	Security and investigation activities	0.520	1,062
81	Services to buildings and landscape activities	0.390	7,057
82	Office administrative	0.510	4,715
92	Gambling and betting activities	0.391	1,546
93	Sports activities and amusement and recreation activities	0.313	2,514
95	Repair of computers and personal and household goods	0.427	1,271
96	Other personal service activities	0.470	5,307

Figure O.1: Exposure of German regions ("Kreise") to the SMP

This map shows 402 German regions according to the NUTS-3 level and their exposure to the SMP, measured according to the share of treated plants within the region. The higher the share, the darker the region.

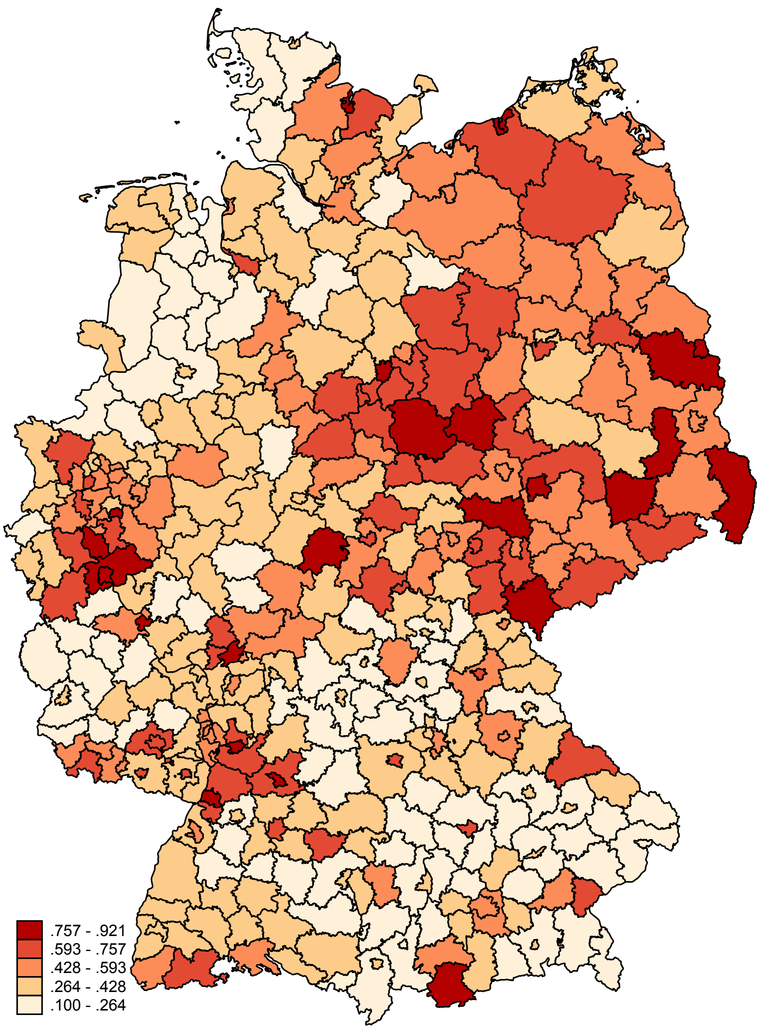


Table O.2: Results on entry rates on regional level remain robust without financial centers

This tables reports results from difference-in-differences estimations on the aggregate level from the following regression: $Y_{rt} = \alpha_r + \alpha_t + \gamma SMPshare_r \times Post_t + \epsilon_{rt}$. The underlying sample comprises 10,085,408 plant-year observations, covering the years 2007-2013, which are aggregated on the region level. The dependent variable is the mean entry rate. The data covers 402 regions minus financial centers. Column I excludes Hamburg (HH), column II Frankfurt (Main), column III Munich, column IV Duesseldorf, column V Stuttgart and column VI all five. $Post$ is an indicator which equals 0 for the years 2005-2009, and 1 for the years 2010-2013. $SMPshare$ is the share of treated plants per region. $Mean\ Entry$ reports the mean of the dependent variable in the regression sample and $SD\ Entry$ the standard deviation. $Mean\ treatment$ reports the mean of the treatment variable in the regression sample and $SD\ treatment$ the standard deviation. Standard errors are clustered on the region level and reported in parentheses. *, **, *** indicate significant coefficients at the 10%, 5%, and 1% level, respectively.

	HH I	FFM II	MUE III	DUE IV	ST V	ALL VI
Post×SMPshare	-0.007***	-0.007***	-0.007***	-0.007***	-0.007***	-0.007***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Region FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
N	2,807	2,807	2,807	2,807	2,807	2,779
R2	0.780	0.778	0.780	0.781	0.782	0.772
Mean Entry	0.050	0.050	0.050	0.050	0.050	0.050
SD Entry	0.010	0.009	0.010	0.010	0.010	0.009
Mean treatment	0.417	0.417	0.417	0.417	0.417	0.415
SD treatment	0.188	0.187	0.188	0.188	0.187	0.187

Table O.3: Results on exit rates on regional level remain robust without financial centers

This tables reports results from difference-in-differences estimations on the aggregate level from the following regression: $Y_{rt} = \alpha_r + \alpha_t + \gamma SMPshare_r \times Post_t + \epsilon_{rt}$. The underlying sample comprises 10,085,408 plant-year observations, covering the years 2007-2013, which are aggregated on the region level. The dependent variable is the mean exit rate. The data covers 402 regions minus financial centers. Column I excludes Hamburg (HH), column II Frankfurt (Main), column III Munich, column IV Duesseldorf, column V Stuttgart and column VI all five. $Post$ is an indicator which equals 0 for the years 2005-2009, and 1 for the years 2010-2013. $SMPshare$ is the share of treated plants per region. $Mean\ Exit$ reports the mean of the dependent variable in the regression sample and $SD\ Exit$ the standard deviation. $Mean\ treatment$ reports the mean of the treatment variable in the regression sample and $SD\ treatment$ the standard deviation. Standard errors are clustered on the region level and reported in parentheses. *, **, *** indicate significant coefficients at the 10%, 5%, and 1% level, respectively.

	HH I	FFM II	MUE III	DUE IV	ST V	ALL VI
Post*SMPshare	-0.004***	-0.004***	-0.004***	-0.004***	-0.004***	-0.004***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Region FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
N	2,807	2,807	2,807	2,807	2,807	2,779
R2	0.745	0.743	0.745	0.745	0.746	0.739
Mean Exit	0.055	0.055	0.055	0.055	0.055	0.055
SD Exit	0.009	0.009	0.009	0.009	0.009	0.009
Mean treatment	0.417	0.417	0.417	0.417	0.417	0.415
SD treatment	0.188	0.187	0.188	0.188	0.187	0.187

Table O.4: Results on entry rates on sector level remain insignificant without financial centers

This tables reports results from difference-in-differences estimations on the aggregate level from the following regression: $Y_{kt} = \alpha_k + \alpha_t + \gamma SMPshare_k \times Post_t + \epsilon_{kt}$. The underlying sample comprises 10,085,408 plant-year observations, covering the years 2007-2013, which are aggregated on the sector level. The dependent variable is the mean entry rate. The data covers 66 sectors. Column I excludes Hamburg (HH), column II Frankfurt (Main), column III Munich, column IV Duesseldorf, column V Stuttgart and column VI all five. $Post$ is an indicator which equals 0 for the years 2005-2009, and 1 for the years 2010-2013. $SMPshare$ is the share of treated plants per sector. $Mean\ Entry$ reports the mean of the dependent variable in the regression sample and $SD\ Entry$ the standard deviation. $Mean\ treatment$ reports the mean of the treatment variable in the regression sample and $SD\ treatment$ the standard deviation. Standard errors are clustered on the sector level and reported in parentheses. *, **, *** indicate significant coefficients at the 10%, 5%, and 1% level, respectively.

	HH I	FFM II	MUE III	DUE IV	ST V	ALL VI
Post×SMPshare	-0.023	-0.021	-0.022	-0.022	-0.022	-0.019
	(0.023)	(0.021)	(0.022)	(0.022)	(0.022)	(0.020)
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
N	462	462	462	462	462	462
R2	0.782	0.782	0.782	0.782	0.782	0.781
Mean Entry	0.055	0.055	0.055	0.055	0.055	0.055
SD Entry	0.030	0.030	0.030	0.030	0.030	0.030
Mean treatment	0.475	0.474	0.474	0.475	0.474	0.466
SD treatment	0.106	0.106	0.105	0.106	0.106	0.104

Table O.5: Results on exit rates on sector level remain robust without financial centers

This tables reports results from difference-in-differences estimations on the aggregate level from the following regression: $Y_{kt} = \alpha_k + \alpha_t + \gamma SMPshare_k \times Post_t + \epsilon_{kt}$. The underlying sample comprises 10,085,408 plant-year observations, covering the years 2007-2013, which are aggregated on the sector level. The dependent variable is the mean exit rate. The data covers 66 sectors. Column I excludes Hamburg (HH), column II Frankfurt (Main), column III Munich, column IV Duesseldorf, column V Stuttgart and column VI all five. $Post$ is an indicator which equals 0 for the years 2005-2009, and 1 for the years 2010-2013. $SMPshare$ is the share of treated plants per sector. $Mean\ Exit$ reports the mean of the dependent variable in the regression sample and $SD\ Exit$ the standard deviation. $Mean\ treatment$ reports the mean of the treatment variable in the regression sample and $SD\ treatment$ the standard deviation. Standard errors are clustered on the sector level and reported in parentheses. *, **, *** indicate significant coefficients at the 10%, 5%, and 1% level, respectively.

	HH I	FFM II	MUE III	DUE IV	ST V	ALL VI
Post×SMPshare	-0.028**	-0.027**	-0.027**	-0.026**	-0.027**	-0.029**
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
N	462	462	462	462	462	462
R2	0.881	0.88	0.88	0.88	0.88	0.881
Mean Exit	0.055	0.055	0.055	0.055	0.055	0.055
SD Exit	0.028	0.028	0.028	0.028	0.028	0.028
Mean treatment	0.475	0.474	0.474	0.475	0.474	0.466
SD treatment	0.106	0.106	0.105	0.106	0.106	0.104

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Paper 4:

COMPLEXITY AND BANK RISK DURING THE FINANCIAL CRISIS

Complexity and bank risk during the financial crisis.*

Thomas Krause† Talina Sondershaus‡ Lena Tonzer§

This Draft: March 3, 2022¶

Abstract

We construct a novel dataset to measure banks' complexity and relate it to banks' riskiness. The sample covers stock listed Euro-area banks from 2007 to 2014. Bank stability is significantly affected by complexity, whereas the direction of the effect differs across complexity measures.

JEL Classification: G01, G20, G33

Keywords: Bank risk, complexity, globalization

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†Danmarks Nationalbank, Langelinie Allee 47 DK-2100 København, Denmark. E-mail: thk@nationalbanken.dk.

‡Halle Institute for Economic Research (IWH), Kleine Märkerstraße 8, 06108 Halle (Saale), Germany. E-mail: talina.sondershaus@iwh-halle.de.

§VU Amsterdam, School of Business and Economics, De Boelelaan 1105, 1081 HV Amsterdam, Netherlands. E-mail: l.tonzer@vu.nl.

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1 Introduction

Over recent years, the European banking system has become more financially integrated and expanded its business activities toward securitization or the insurance sector (Cetorelli et al., 2014; Poszar et al., 2010). This has increased banks' complexity. Complexity can dampen the impact of shocks emerging in one country or business sector. However, shocks can be propagated in interlinked and complex systems. This might have adverse consequences for bank stability. Also, supervision and regulation, as well as the resolution of complex banks become more difficult.

Despite the relevance of the topic, there exists limited empirical research on the relationship between bank complexity and financial stability.[1] We use a novel dataset on parent banks' subsidiary structure to determine four proxies for banks' complexity and relate them to bank risk. The dataset covers stock listed banks in the Euro area for the period 2007-2014. Following Cetorelli and Goldberg (2014), we compute parent banks' business and geographical complexity. Hence, complexity is conceptually defined by the variety of business types and geographical regions of banks' subsidiaries: banks are more complex if they have subsidiaries across different business types/ regions. We extend the set of complexity measures to cover the share of non-bank/ foreign subsidiaries because these are useful complements in explaining key dynamics in the before mentioned measures.[2] The results show that banks have increased their number of subsidiaries. However, this has not necessarily translated into higher complexity. The effect of complexity on bank stability depends on the choice of the complexity measure.

Cetorelli and Goldberg (2014) calculate complexity measures for the year 2012 and show that banks' degree of complexity varies across countries and institutions; a common feature is a concentration of subsidiaries in the home country of the parent bank. We extend this literature by computing complexity measures over time and relate them to bank stability. Gong et al. (2015) show that effective capital ratios of US banks are lower than reported ones if minority-owned subsidiaries would be consolidated. Undercapitalization increases bank risk, suggesting that banks arbitrage regulation. Cetorelli and Goldberg (2016) take the perspective of foreign branches in the US being part of a larger, global conglomerate. They find that the more complex the conglomerate, the lower is the lending sensitivity of branches to funding shocks. Liu et al. (2015), based on a sample of US bank holding companies, show

[1] Higher complexity can simultaneously imply a higher degree of diversification. We use the term complexity throughout the paper.

[2] A more detailed survey about the concept of complexity is provided by Carmassi and Herring (2014).

that higher complexity increases banks' stability. This is in contrast to our results and might be driven by a different sample composition and calculation of complexity.

2 Bank Complexity

The analysis is based on a sample of 80 stock listed banks in the Euro area over 2007-2014.[3] For these banks, we have obtained data from the Bankscope Ownership Module containing information on banks' domestic and foreign subsidiaries like their business area, location, and percentage of ownership. We only consider majority-owned (>50%) subsidiaries that are directly owned by the parent bank. We compute four complexity measures:

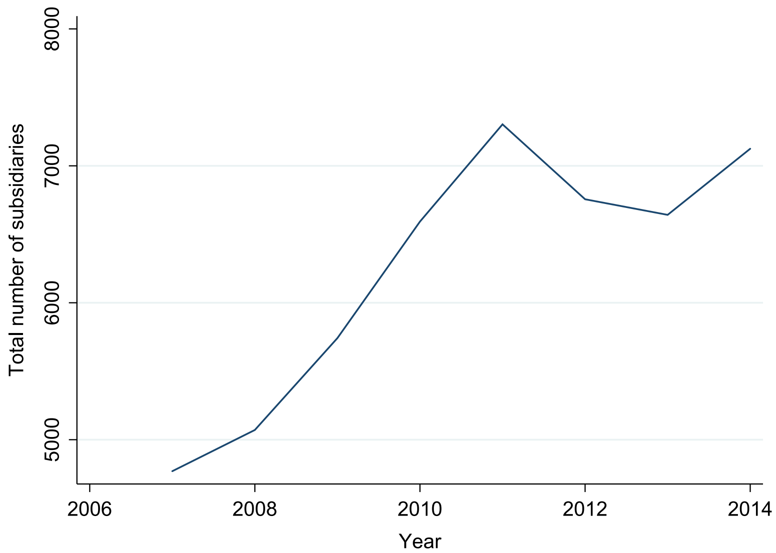
- **Business complexity** is a normalized Herfindahl index (*HHI*) depending on the number of subsidiaries by business types relative to the total number of subsidiaries: $HHI_{it} = \frac{T}{T-1}\left(1 - \sum_{\tau=1}^{T}\left(\frac{count^{it\tau}}{totalcount^{it}}\right)^2\right)$ with T being the number of subsidiary types. The index is defined between zero and one, higher values reflect a higher degree of complexity. Subsidiary types include banks, insurance companies, mutual and pension funds, other financial subsidiaries, non-financial subsidiaries (Cetorelli and Goldberg 2014). A more complex subsidiary network might entail economies of scale and buffer against the occurrence of losses in one sector. However, transaction and monitoring costs can increase, which might incentivize banks to take more risks.
- **Geographical complexity** is a normalized HHI depending on the number of subsidiaries by region relative to the total number of subsidiaries: $HHI_{it} = \frac{R}{R-1}\left(1 - \sum_{r=1}^{R}\left(\frac{count^{itr}}{totalcount^{it}}\right)^2\right)$ with R being the number of geographical regions. Higher values indicate a higher degree of complexity in the sense that the parent bank's subsidiaries are equally distributed across various regions. Regions include the Euro area, the UK, Japan, South Korea, China, Canada, the USA, Taiwan, Middle East, other Americas, other Europe, Eastern Europe, other Asia, other. Higher geographical complexity can help withstand local shocks but it can also increase agency problems and exposure to global shock spillovers. This would result into increased risk-taking before a crisis and higher vulnerability during a crisis.
- **Non-bank subsidiaries** is the ratio of a parent bank's non-bank subsidiaries to total subsidiaries. Non-bank subsidiaries can be used to become active in other activities than the traditional financial intermediation process such as securitization.

[3]Details on the sample composition are available in Table A1 in the supplementary appendix.

- **Foreign subsidiaries** is the ratio of a parent bank's foreign subsidiaries to total subsidiaries. A larger share of foreign subsidiaries contains possibilities for regulatory arbitrage -in general, subsidiaries fall under the regulation of their host country- and cause coordination problems among regulators from different countries in case a bank has to be resolved.

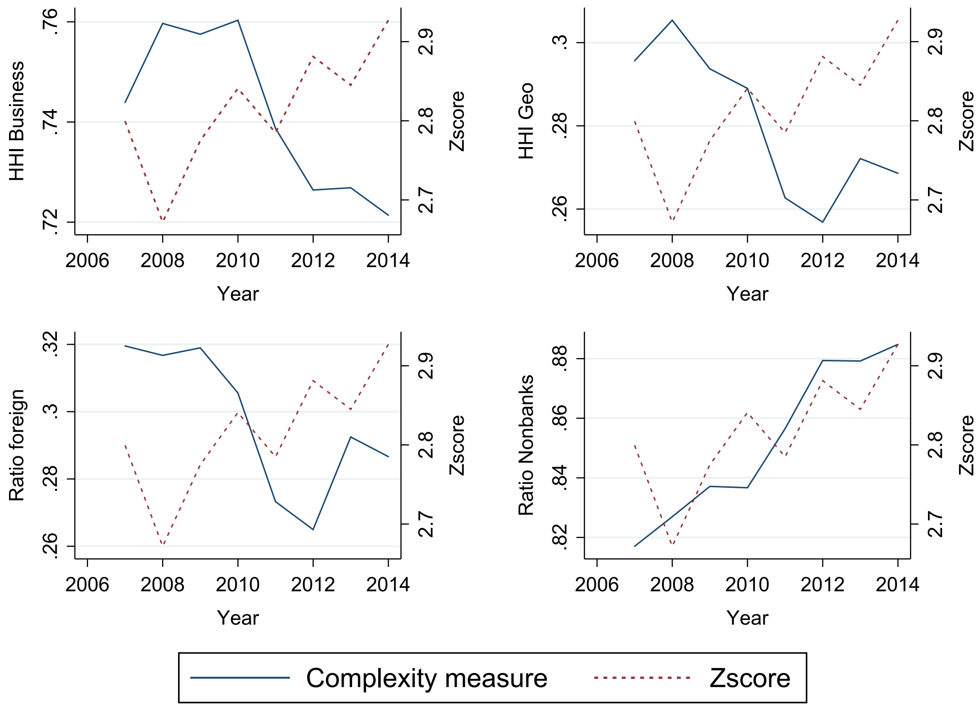
Figure 1 shows that banks have increased their number of subsidiaries (like in Carmassi and Herring 2014). However, this has not resulted in an increase of all complexity measures (Figure 2). Business and geographical complexity, and the share of foreign subsidiaries have declined. The reason for this downward trend is that banks have extended the ownership of non-bank/ local subsidiaries relatively more than the one of bank/ foreign subsidiaries. This implies a higher degree of concentration in one sector/ region and thus a decline in the HHIs.

Figure 1: Number of Banks' Subsidiaries.



Notes: This graph shows the number of majority-owned subsidiaries by parent banks.

Figure 2: Complexity and Zscore.



Notes: This graph shows the average pattern of a complexity measure (left axis; blue solid line) and the Zscore (right axis; red dotted line).

3 Main Results

3.1 Zscore

To evaluate the relationship between banks' complexity and riskiness during the recent crisis period, we estimate the following model:

$$\begin{aligned} Zscore_{ij,average08-10} &= \alpha + \beta_1 X_{ij,2007} + \beta_2 Country_{j,2007} \\ &+ \beta_3 Complex_{ij,2007} + \epsilon_{ij} \end{aligned} \tag{1}$$

where $Zscore_{ij,average08-10}$ is the average Zscore for bank i located in country j during the financial crisis period from 2008 to 2010. To ensure linearity, the Zscore is defined as $Zscore_{ij} = \log(1 + \widehat{Zscore}_{ij})$, whereas higher values indicate higher stability.[4]

[4] $\widehat{Zscore}_{ij}$ is calculated as $\frac{\mu_{RoA,i}+equ_{it}}{\sigma_{RoA,i}}$, with $\mu_{RoA,i}$ being the mean and $\sigma_{RoA,i}$ being the standard deviation of return on assets over 2007-2014, equ_{it} denotes the equity to assets ratio (Lepetit and Strobel, 2013). The pattern of the $Zscore$ is depicted in Figure 2.

We add pre-crisis values of bank-level controls $(X_{ij,2007})$ obtained from Bankscope including the log of total assets, the CAMEL variables (Cole and White, 2012), and a complexity measure $(Complex_{ij,2007})$.[5] At the country-level $(Country_{j,2007})$, we control for GDP growth and inflation, and an indicator variable for the GIIPS countries (Greece, Ireland, Italy, Portugal, Spain). This estimation approach reduces simultaneity concerns (Laeven et al., 2016).

The results in Table 1 show that two of the four complexity measures have a significant coefficient. Higher geographical complexity and a higher share of foreign subsidiaries before the crisis can be associated with higher bank risk (or a lower Zscore) during the crisis. Hence, negative effects due to higher monitoring costs and agency problems, as well as global shock spillovers during the recent crisis significantly outweigh positive effects going back to being diversified across regions. Business complexity and the share of non-bank subsidiaries remain insignificant suggesting that diversification advantages are equalized by disadvantages arising from specialization losses. Our results remain robust differentiating by crisis period, whereas geographical complexity shows a stronger effect during the financial crisis compared to the sovereign debt crisis.[6]

[5] We exclude the equity ratio and return on assets because they are part of our dependent variable. To correct for outliers, we keep only observations with non-missing assets. We drop observations with negative values for assets, equity, or loans, and if ratios take implausible values (e.g. greater than 100%). All CAMEL variables are winsorized at the top and bottom percentile. For summary statistics, see the supplementary appendix (Tables A2-A4).

[6] See Table A7. Our results remain also robust for a set of robustness tests like running univariate or panel regressions as well as using a systemic risk measure as dependent variable (see supplementary appendix, Tables A5-A9).

Table 1: Regression Results - Zscore.

	(1)	(2)	(3)	(4)
Log $assets_{2007}$	0.027	0.121	0.02	0.096
	-0.065	-0.09	-0.066	-0.087
NPL_{2007}	-0.08	-0.084**	-0.076	-0.075*
	-0.049	-0.04	-0.047	-0.042
Cost-to-income2007	0.002	0.006	0.002	0.005
	-0.01	-0.009	-0.011	-0.008
Liquid $assets_{2007}$	-0.005	-0.002	-0.008	-0.005
	-0.01	-0.009	-0.011	-0.01
GDP_{2007}	0.038	0.03	0.02	0.017
	-0.137	-0.132	-0.153	-0.135
$Inflation_{2007}$	-0.870***	-0.725***	-0.895***	-0.784***
	-0.264	-0.233	-0.266	-0.257
GIIPS $Country_{2007}$	0.259	0.238	0.227	0.181
	-0.423	-0.43	-0.435	-0.417
HHI $Business_{2007}$	-0.206			
	-0.511			
HHI Geo_{2007}		-1.057**		
		-0.442		
Ratio $Nonbanks_{2007}$			0.221	
			-0.485	
Ratio $Foreign_{2007}$				-0.853*
				-0.487
Observations	54	54	54	54
R^2	0.316	0.371	0.316	0.356

Notes: This table reports cross-sectional regressions. The dependent variable is a bank's average Zscore over 2008-2010. Robust standard errors are depicted in parentheses. The p-values are: *** p<0.01, ** p<0.05, * p<0.1.

3.2 State Aid

Alternatively, we test whether bank complexity affected the probability to be in the need of state aid during 2008-2014 (Cole and White, 2012; Shaffer, 2012). The state aid indicator is a more precise signal that a bank had serious problems:

$$\begin{aligned} Stateaid_{ij,t} &= \alpha + \beta_1 X_{ij,t-1} + \beta_2 Country_{j,t} \\ &+ \beta_3 Complex_{ij,t-1} + \theta_t + \epsilon_{ij,t} \end{aligned} \tag{2}$$

where the dependent variable is a dummy equaling one if bank i has received state aid in period t, e.g. recapitalization or asset guarantees, and zero otherwise. Information on state aid requests comes from the *State Aid Register* of the European Commission. The explanatory variables are defined as above. Global developments are captured by time fixed effects θ_t.

In Table 2, it can be seen that higher geographical complexity and a higher share of foreign subsidiaries increase the probability of a state aid request. This finding is consistent with the previous results and most prevalent during the sovereign debt crisis period. From a supervisory perspective, this implies that coordinated actions across national borders can help detect problems at international banks earlier and intervene before a bank requests state aid. A higher share of non-bank subsidiaries significantly reduces the probability of state aid. This suggests risk-sharing possibilities: shocks in the financial system can be mitigated by being active in other sectors; internal cross-funding possibilities within a bank holding company including different subsidiaries types can reduce liquidity strains during crisis times.

Table 2: Regression Results - State Aid.

	(1)	(2)	(3)	(4)
HHI Business$_{t-1}$	0.788			
	(1.614)			
HHI Geo$_{t-1}$		3.452***		
		(1.14)		
Ratio Nonbanks$_{t-1}$			-3.738***	
			(1.189)	
Ratio Foreign$_{t-1}$				2.505**
				(1.01)
Controls	Yes	Yes	Yes	Yes
Observations	399	400	399	400
# Banks	75	75	75	75

Notes: This table reports probit regressions. The dependent variable equals one if the bank received state aid and zero otherwise. Standard errors clustered at the bank level are depicted in parentheses. The p-values are: *** p<0.01, ** p<0.05, * p<0.1.

4 Conclusion

The recent financial crisis has brought the issue of bank complexity on the agenda of policymakers. We find that banks have steadily increased their number of (non-bank) subsidiaries. However, this has not necessarily translated into higher complexity regarding the diversification of subsidiaries across regions and business types. When evaluating the relationship between bank complexity and stability, the results show a heterogeneous picture. Higher geographical complexity and a higher share of foreign subsidiaries increase banks' riskiness. In contrast, a higher share of non-bank subsidiaries has stabilizing effects. This advises against the use of a single complexity measure.

A Supplementary Appendix

A.1 Sample Composition

The following list in Table A.1 contains information on the sample composition. The first column contains the names of the banks included in the sample. The second column indicates the bank type. The status information in the third column shows that there is no bank that died within our sample period.[7] The fourth column lists the country in which the bank is located. The last column shows the average weight of each bank's capitalization to the total capitalization of all banks in the respective country over the period 2007-2014. Except for Slovakia, the banks included in our sample cover on average more than 85% of total market capitalization.[8] As of July 2014, 111 banks were stock listed in the Euro area according to Datastream. To correct the sample from outliers, we drop banks with insufficient variation in the stock market data and institutions with a market capitalization of less than 100 million Euros as of 31 December 2007. Finally, we drop banks that could not be matched to Bankscope. For the remaining 80 banks, we can thus ensure to have sufficient variation in the data to obtain reasonable estimates of ΔCoVaR. We match stock market data of these 80 banks to balance sheet information provided by Bankscope by using the ISIN number. For this final sample of banks, we have obtained information from the Bankscope Ownership Module on banks' domestic and foreign subsidiaries over the period 2007-2014. This allows the calculation of complexity measures. The number of banks included in the regressions can be smaller than 80 due to missing values for explanatory variables.

[7] Although POHJOLA PANKKI A bank died on October 1st 2014, we still have non-missing values of the variables in 2014.

[8] The aggregated sum of market capitalization across all banks in one country can be slightly larger than 100% in selected cases due to taking average values across the whole period.

Table A.1: Sample Composition.

Name of Bank	Type	Status	Country	Market Value (avg.)
BK.FUR TIROL UND VBG.	Equity	Active	Austria	2.59%
BKS BANK	Equity	Active	Austria	3.11%
ERSTE GROUP BANK	Equity	Active	Austria	52.36%
OBERBANK	Equity	Active	Austria	6.93%
RAIFFEISEN BANK INTL.	Equity	Active	Austria	34.77%
DEXIA	Equity	Active	Belgium	18.94%
KBC GROUP	Equity	Active	Belgium	66.43%
BANK OF CYPRUS	Equity	Active	Cyprus	79.64%
HELLENIC BANK	Equity	Active	Cyprus	16.25%
COMMERZBANK	Equity	Active	Germany	19.73%
DEUTSCHE BANK	Equity	Active	Germany	63.39%
DEUTSCHE POSTBANK	Equity	Dead (23/12/15)	Germany	11.86%
IKB DEUTSCHE INDSTRBK.	Equity	Active	Germany	1.20%
OLDENBURGISCHE LB.	Equity	Active	Germany	1.74%
QUIRIN BANK	Equity	Active	Germany	0.14%
BANCO DE SABADELL	Equity	Active	Spain	4.09%
BANCO POPULAR ESPANOL	Equity	Active	Spain	4.83%
BANCO SANTANDER	Equity	Active	Spain	47.65%
LIBERBANK	Equity	Active	Spain	0.69%
BANKIA	Equity	Active	Spain	5.66%
BANKINTER 'R'	Equity	Active	Spain	2.14%
BBV.ARGENTARIA	Equity	Active	Spain	28.55%
CAIXABANK	Equity	Active	Spain	9.73%
AKTIA 'A'	Equity	Active	Finland	11.50%
ALANDSBANKEN 'A'	Equity	Active	Finland	4.68%
POHJOLA PANKKI A	Equity	Dead (01/10/14)	Finland	86.70%
BANQUE REUNION	Equity	Dead (07/05/15)	France	0.13%
BNP PARIBAS	Equity	Active	France	44.38%
CIC 'A'	Equity	Active	France	4.07%
CR.AGR.SUD RHONE ALPES	GDR	Active	France	0.07%
CR.AGRICOLE MORBIHAN	Equity	Active	France	0.06%
CRCAM ATLANTIQUE VENDEE	Equity	Active	France	0.07%
CREDIT AGRICOLE BRIE PICARDIE	Equity	Active	France	0.25%
CRCAM ILLE-VIL.CCI	Equity	Active	France	0.09%
CRCAM LANGUED CCI	Equity	Active	France	0.07%
CRCAM NORD DE FRANCE CCI	Equity	Active	France	0.22%
CRCAM NORMANDIE SEINE	GDR	Active	France	0.06%
CREDIT AGR.ILE DE FRANCE	Equity	Active	France	0.42%
CREDIT AGR.TOULOUSE	Equity	Active	France	0.07%
CREDIT AGR.TOURAINE	Equity	Active	France	0.05%
CREDIT AGRICOLE	Equity	Active	France	18.94%
NATIXIS	Equity	Active	France	8.37%
SOCIETE GENERALE	Equity	Active	France	22.17%
ALPHA BANK	Equity	Active	Greece	20.75%
ATTICA BANK	Equity	Active	Greece	1.47%
BANK OF PIRAEUS	Equity	Active	Greece	15.39%
EUROBANK ERGASIAS	Equity	Active	Greece	15.47%
GENERAL BANK OF GREECE	Equity	Active	Greece	1.39%
NATIONAL BK.OF GREECE	Equity	Active	Greece	41.43%
ALLIED IRISH BANKS	Equity	Active	Ireland	67.78%
BANK OF IRELAND	Equity	Active	Ireland	32.22%
BANCA CARIGE	Equity	Active	Italy	2.40%
BANCA FINNAT EURAMERICA	Equity	Active	Italy	0.18%
BANCA MONTE DEI PASCHI	Equity	Active	Italy	5.10%
BANCA POPOLARE DI MILANO	Equity	Active	Italy	1.95%
BANCA PPO.ETRURIA LAZIO	Equity	Active	Italy	0.23%
BANCA PROFILO	Equity	Active	Italy	0.24%
BANCA PPO.DI SONDRIO	Equity	Active	Italy	1.97%
BANCA PPO.DI SPOLETO	Equity	Active	Italy	0.10%
BANCA PPO.EMILIA ROMAGNA	Equity	Active	Italy	2.51%
BANCO DI SARDEGNA RSP	Equity	Active	Italy	0.07%
BANCO POPOLARE	Equity	Active	Italy	3.76%
BNC.DI DESIO E DELB.	Equity	Active	Italy	0.44%
CREDITO EMILIANO	Equity	Active	Italy	1.72%
BCA.PICCOLO CDT.VALTELL	Equity	Active	Italy	0.90%
INTESA SANPAOLO	Equity	Active	Italy	32.50%
MEDIOBANCA BC.FIN	Equity	Active	Italy	6.91%
UNIONE DI BANCHE ITALIAN	Equity	Active	Italy	5.40%
UNICREDIT	Equity	Active	Italy	33.30%
BANK OF VALLETTA	Equity	Active	Malta	38.60%
HSBC BANK MALTA	Equity	Active	Malta	47.59%
LOMBARD BANK	Equity	Active	Malta	5.11%
ING GROEP	Equity	Active	Netherlands	97.10%
VAN LANSCHOT	Equity	Active	Netherlands	2.90%
BANCO BPI	Equity	Active	Portugal	19.24%
BANCO COMR.PORTUGUES 'R'	Equity	Active	Portugal	37.91%
BANCO ESPIRITO SANTO DEAD	Equity	Dead (03/02/16)	Portugal	42.54%
VSEOBECNA UVEROVA BANKA	Equity	Active	Slovakia	24.93%
ABANKA VIPA	Equity	Active	Slovenia	36.70%
NOVA KREDITNA BANKA MARIBOR	Equity	Active	Slovenia	63.30%

Table A.2: Summary Statistics - Full Sample.

VARIABLES	N	mean	sd	skewness	kurtosis	min	max
Dependent variables							
Zscore	608	2.82	1.07	0.18	2.43	0.25	5.11
Stateaid	610	0.05	0.21	4.34	19.83	0	1
ΔCoVaR	601	0.01	0.01	0.62	3.02	0	0.05
Complexity measures							
HHI Business	587	0.74	0.24	-1.82	5.84	0	0.99
HHI Geo	589	0.28	0.27	0.41	1.78	0	0.85
Ratio Nonbanks	587	0.85	0.16	-1.4	5.7	0	1
Ratio Foreign	589	0.3	0.26	0.5	2.26	0	1
Bank-level controls							
Log assets	610	17.8	1.97	0.07	2.46	13.28	21.66
Equity	610	7.34	3.5	1.28	6.73	1.45	24.6
NPL	520	7.94	8.32	2.24	8.29	0.41	42.58
Cost-to-income	579	60.93	12.01	0.6	3.11	36.73	96.01
RoA	610	0.3	1.26	-2.69	12.65	-5.98	2.36
Liquid assets	610	15.22	11.64	1.71	6.09	2.51	61.56
Macroeconomic variables							
Inflation	610	1.85	1.29	-0.11	2.88	-1.71	5.65
GDP	610	0.03	2.7	-0.59	3.74	-8.86	10.68

Notes: This table shows summary statistics for the dependent variables Zscore, Stateaid and ΔCoVaR, bank-level control variables, as well as macroeconomic control variables. The sample consists of 80 banks listed on the stock market in the Euro area and covers the years 2007-2014. Zscore is the log of the Zscore calculated as in Lepetit and Strobel (2013). Stateaid denotes a dummy, which equals one if the bank received state aid following the State Aid Register of the European Commission and zero otherwise. ΔCoVaR is calculated following Benoit et al. (2016) and market data are obtained from Datastream. HHI Business indicates diversification of banks across different business activities, HHI Geo indicates diversification of banks across geographical regions, Ratio Nonbanks gives the number of nonbank subsidiaries over the total number of subsidiaries, and Ratio Foreign is the number of subsidiaries that are located in a different country than the bank holding company over the total number of subsidiaries. Due to lack of information on subsidiary type for the year 2011, we take the average of the preceding and succeeding year for the HHI Business and the Ratio Nonbanks. Log assets denotes the logarithm of bank assets in thousands of USD. Equity is the equity to total assets ratio (in %). In order to measure asset quality, NPL is used which is defined as the fraction of impaired loans relative to gross loans (in %). Cost-to-income is a measurement of the management quality defined as the cost to income ratio (in %). Earnings are measured by the return on assets (RoA) which is the ratio of operating profits to total assets (in %). Liquid assets is the share of liquid assets in total assets (in %). The inflation rate (in %) and GDP growth (in %) of the bank holding company's country of location are used as macroeconomic controls.

Table A.3: Summary Statistics - Regression Sample.

VARIABLES	N	mean	sd	skewness	kurtosis	min	max
Dependent variable							
Zscore	74	2.72	1.07	0.24	2.39	0.56	4.94
Complexity measures							
HHI Business	70	0.74	0.26	-1.77	5.42	0	0.99
HHI Geo	70	0.3	0.28	0.31	1.6	0	0.8
Ratio Nonbanks	70	0.82	0.21	-1.91	7.61	0	1
Ratio Foreign	70	0.32	0.27	0.47	2.24	0	1
Bank-level controls							
Log assets	74	17.82	1.98	0.16	2.42	13.28	21.66
Cost-to-income	73	57.1	9.98	0.71	5.08	36.73	96.01
NPL	57	3.22	2.86	2	8.32	0.41	15.27
Equity	74	7.71	3.98	1.4	6.11	2.04	24.6
RoA	74	1.06	0.66	-1.75	10.64	-2.24	2.36
Liquid assets	74	19.25	13.36	1.57	5.36	2.51	61.56
Macroeconomic variables							
Inflation	74	2.12	0.56	0.31	3.5	0.7	3.61
GDP	74	3.08	1.55	1.94	9.59	1.47	10.68

Notes: This table shows summary statistics for the dependent variable Zscore, bank-level control variables, as well as macroeconomic control variables. The sample consists of 74 banks listed on the stock market in the Euro area. Explanatory variables are from the year 2007. Zscore (in logs) is calculated as in Lepetit and Strobel (2013) and averaged across the crisis years 2008-2010. HHI Business indicates diversification of banks across different business activities, HHI Geo indicates diversification of banks across geographical regions, Ratio Nonbanks gives the number of nonbank subsidiaries over the total number of subsidiaries, and Ratio Foreign is the number of subsidiaries that are located in a different country than the bank holding company over the total number of subsidiaries. Log assets denotes the logarithm of bank assets in thousands of USD. Equity is the equity to total assets ratio (in %). In order to measure asset quality, NPL is used which is defined as the fraction of impaired loans relative to gross loans (in %). Cost-to-income is a measurement of the management quality defined as the cost to income ratio (in %). Earnings are measured by the return on assets (RoA) which is the ratio of operating profits to total assets (in %). Liquid assets is the share of liquid assets in total assets (in %). The inflation rate (in %) and GDP growth (in %) of the bank holding company's country of location are used as macroeconomic controls.

Table A.4: Correlations.

	Zscore	Stateaid	ΔCoVaR	HHI Business	HHI Geo	Ratio Nonbanks	Ratio Foreign	Log Assets	Equity	NPL	Cost-to-income	RoA	Liquid assets
Zscore	1												
Stateaid	-0.2	1											
ΔCoVaR	-0.35	0.06	1										
HHI Business	-0.43	0.11	0.53	1									
HHI Geo	-0.33	0.2	0.51	0.52	1								
Ratio Nonbanks	0.24	-0.01	-0.26	-0.31	-0.22	1							
Ratio Foreign	-0.31	0.19	0.44	0.4	0.87	-0.15	1						
Log assets	-0.05	0.16	0.52	0.53	0.66	-0.22	0.58	1					
Equity	0.41	-0.2	-0.29	-0.52	-0.48	0.15	-0.42	-0.56	1				
NPL	-0.37	0.25	-0.06	-0.05	-0.11	-0.03	-0.05	-0.12	0	1			
Cost-to-income	-0.25	0.12	-0.08	0.15	0.13	-0.18	0.1	0.06	-0.27	0.21	1		
RoA	0.41	-0.28	0.05	-0.13	-0.1	0.08	-0.14	-0.03	0.25	-0.7	-0.51	1	
Liquid assets	-0.13	-0.09	0.06	0.15	0.26	-0.01	0.2	0.1	-0.12	-0.2	0.16	-0.02	1

Notes: This table shows pairwise correlations between the dependent and explanatory variables at the bank level for the period 2007-2014. The Zscore (in log) is calculated as in Lepetit and Strobel (2013). The dummy Stateaid equals one if the bank received state aid following the State Aid Register of the European Commission and zero otherwise. $\Delta CoVaR$ is calculated following Benoit et al. (2016) and market data are obtained from Datastream. Bank-level data on complexity are obtained from the Bankscope Ownership Module: HHI Business, indicating diversification of banks across different business activities, HHI Geo indicating diversification of banks across geographical regions, number of nonbank subsidiaries over the total number of subsidiaries (Ratio Nonbanks), and the number of subsidiaries that are located in a different country than the bank holding company over the total number of subsidiaries (Ratio Foreign). Further bank characteristics are obtained from Bankscope and comprise: Log assets denotes the logarithm of bank assets in thousands of USD. Equity is the equity to total assets ratio (in %). In order to measure asset quality, NPL is used, which is defined as the fraction of impaired loans relative to gross loans (in %). Cost-to-income is a measurement of the management defined as the cost to income ratio (in %). Earnings are measured by the return on assets (RoA), which is the ratio of operating profits to total assets (in %). Liquid assets is the share of liquid assets in total assets (in %).

Table A.5: Univariate Cross-Sectional Regression Results - Zscore.

	(1)	(2)	(3)	(4)	(5)
HHI $Business_{2007}$	-1.691***				-1.473***
	(0.586)				(0.454)
HHI Geo_{2007}		-1.311***			-0.942
		(0.385)			(0.657)
Ratio $Nonbanks_{2007}$			1.062**		1.116**
			(0.463)		(0.542)
Ratio $Foreign_{2007}$				-0.986**	0.409
				(0.463)	(0.769)
Constant	3.976***	3.106***	1.850***	3.033***	3.050***
	(0.488)	(0.187)	(0.324)	(0.204)	(0.497)
Observations	70	70	70	70	70
R-squared	0.165	0.119	0.044	0.063	0.250

Notes: This table reports cross-sectional regressions that are based on yearly data of stock listed banks of Euro area countries. The dependent variable is a bank's average Zscore over the years 2008-2010. The complexity measures are from the year 2007 and include: HHI Business indicates diversification of banks across different business activities, HHI Geo indicates diversification of banks across geographical regions, the ratio of non-bank subsidiaries over the total number of subsidiaries (Ratio Nonbanks), and the ratio of subsidiaries that are situated in a foreign country over the total number of subsidiaries (Ratio Foreign). Robust standard errors are depicted in parentheses. The p-values are as follows: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A.6: Cross-Sectional Regression Results by Year - Zscore (HHI Business).

	(1) **2008**	(2) **2009**	(3) **2010**	(4) **2011**	(5) **2012**	(6) **2013**	(7) **2014**
Log assets$_{t-1}$	0.046	0.136**	0.081	0.108**	0.128**	0.097**	0.083*
	(0.08)	(0.063)	(0.061)	(0.05)	(0.056)	(0.042)	(0.042)
NPL$_{t-1}$	-0.049	-0.102*	-0.074*	-0.065**	-0.104***	-0.087***	-0.056***
	(0.059)	(0.053)	(0.037)	(0.027)	(0.02)	(0.018)	(0.01)
Cost-to-income$_{t-1}$	-0.005	0.007	-0.015*	-0.003	-0.009	-0.019***	-0.018***
	(0.015)	(0.007)	(0.008)	(0.007)	(0.007)	(0.007)	(0.006)
Liquid assets$_{t-1}$	0.007	0.028*	-0.002	-0.007	-0.017**	-0.018**	-0.023***
	(0.015)	(0.015)	(0.015)	(0.008)	(0.008)	(0.009)	(0.007)
GDPt	0.207	0.126*	0.184**	0.158***	0.190**	0.024	-0.062
	(0.139)	(0.069)	(0.079)	(0.042)	(0.071)	(0.059)	(0.055)
Inflation$_t$	-0.432**	0.333**	0.071	0.431**	0.474**	-0.035	-0.069
	(0.188)	(0.158)	(0.174)	(0.172)	(0.2)	(0.189)	(0.145)
GIIPS Country$_t$	0.432	0.205	0.136	0.137	0.188	-0.396**	-0.645***
	(0.4)	(0.266)	(0.262)	(0.201)	(0.193)	(0.198)	(0.215)
HHI Business$_{t-1}$	-0.855	-2.159	-1.333	-1.943**	-1.414**	-1.349***	-0.744*
	(0.566)	(1.285)	(0.896)	(0.76)	(0.566)	(0.482)	(0.435)
Constant	3.719*	1.594	3.075**	1.418	1.963	4.678***	4.558***
	(1.993)	(1.389)	(1.448)	(1.176)	(1.423)	(0.824)	(0.68)
Observations	54	52	55	55	50	62	69
R-squared	0.194	0.335	0.344	0.607	0.657	0.678	0.722

Notes: This table reports cross-sectional regressions that are based on yearly data of stock listed banks of Euro area countries by year as indicated in the column head. The dependent variable is a bank's Zscore. Explanatory variables include bank-level controls: Log assets is the log of total assets, NPL is the ratio of non-performing loans to total loans (in %), the cost-to-income ratio (in %), and liquid assets to total assets (in %). Macro controls of the bank holding company's country of location include: GDP growth (in %), the inflation rate (in %), and a dummy that equals one if the bank holding company is located in a GIIPS Country, i.e. Greece, Ireland, Italy, Portugal, or Spain. The complexity measure is the HHI Business indicating diversification of banks across different business activities. Bank-level variables are lagged by one period. Robust standard errors are depicted in parentheses. The p-values are as follows: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A.7: Cross-Sectional Regression Results by Year - Zscore (HHI Geo).

	(1) **2008**	(2) **2009**	(3) **2010**	(4) **2011**	(5) **2012**	(6) **2013**	(7) **2014**
Log assets$_{t-1}$	0.204**	0.172***	0.102	0.116**	0.084	0.120**	0.096**
	(0.098)	(0.061)	(0.067)	(0.053)	(0.052)	(0.048)	(0.046)
NPL$_{t-1}$	-0.047	-0.100**	-0.073**	-0.075**	-0.112***	-0.096***	-0.058***
	(0.041)	(0.044)	(0.031)	(0.029)	(0.018)	(0.017)	(0.008)
Cost-to-income$_{t-1}$	0.002	0.006	-0.016*	-0.003	-0.007	-0.014**	-0.017***
	(0.011)	(0.007)	(0.009)	(0.007)	(0.007)	(0.007)	(0.006)
Liquid assets$_{t-1}$	0.009	0.027**	0.004	0	-0.012	-0.018*	-0.020***
	(0.012)	(0.011)	(0.014)	(0.01)	(0.01)	(0.009)	(0.008)
GDPt	0.240**	0.162**	0.121	0.138***	0.218***	0.052	-0.05
	(0.118)	(0.07)	(0.098)	(0.044)	(0.068)	(0.066)	(0.049)
Inflation$_t$	-0.480***	0.272*	-0.016	0.32	0.216	-0.178	-0.158
	(0.152)	(0.143)	(0.195)	(0.215)	(0.207)	(0.16)	(0.142)
GIIPS Country$_t$	0.536	0.059	-0.022	-0.033	0.165	-0.611***	-0.766***
	(0.38)	(0.26)	(0.29)	(0.241)	(0.191)	(0.195)	(0.189)
HHI Geo$_{t-1}$	-1.928***	-1.469***	-0.953	-1.175**	-0.803*	-1.216***	-0.790**
	(0.451)	(0.464)	(0.599)	(0.441)	(0.437)	(0.432)	(0.338)
Constant	0.478	-0.014	2.196	0.507	2.483*	3.664***	3.960***
	(2.366)	(1.285)	(1.514)	(1.585)	(1.413)	(0.976)	(0.813)
Observations	54	52	55	55	51	62	69
R-squared	0.364	0.397	0.339	0.552	0.622	0.684	0.725

Notes: This table reports cross-sectional regressions that are based on yearly data of stock listed banks of Euro area countries by year as indicated in the column head. The dependent variable is a bank's Zscore. Explanatory variables include bank-level controls: Log assets is the log of total assets, NPL is the ratio of non-performing loans to total loans (in %), the cost-to-income ratio (in %), and liquid assets to total assets (in %). Macro controls of the bank holding company's country of location include: GDP growth (in %), the inflation rate (in %), and a dummy that equals one if the bank holding company is located in a GIIPS Country, i.e. Greece, Ireland, Italy, Portugal, or Spain. The complexity measure is HHI Geo indicating diversification of banks across geographical regions. Bank-level variables are lagged by one period. Robust standard errors are depicted in parentheses. The p-values are as follows: *** p<0.01, ** p<0.05, * p<0.1.

Table A.8: Cross-Sectional Regression Results by Year - Zscore (Ratio Nonbanks).

	(1) **2008**	(2) **2009**	(3) **2010**	(4) **2011**	(5) **2012**	(6) **2013**	(7) **2014**
Log assets$_{t-1}$	0.007	0.072	0.009	0.013	0.021	0.019	0.051
	(0.08)	(0.056)	(0.05)	(0.042)	(0.043)	(0.041)	(0.04)
NPL$_{t-1}$	-0.056	-0.097*	-0.064**	-0.064*	-0.110***	-0.089***	-0.056***
	(0.059)	(0.052)	(0.03)	(0.033)	(0.021)	(0.019)	(0.009)
Cost-to-income$_{t-1}$	-0.001	0.005	-0.018**	-0.005	-0.009	-0.017**	-0.021***
	(0.015)	(0.007)	(0.008)	(0.007)	(0.007)	(0.008)	(0.006)
Liquid assets$_{t-1}$	0.008	0.032**	0.001	-0.01	-0.022**	-0.026***	-0.024***
	(0.015)	(0.014)	(0.016)	(0.011)	(0.009)	(0.009)	(0.008)
GDPt	0.219	0.089	0.183**	0.181***	0.263***	0.092	-0.064
	(0.15)	(0.069)	(0.078)	(0.045)	(0.069)	(0.067)	(0.059)
Inflation$_t$	-0.391*	0.276*	0.027	0.292	0.255	-0.185	-0.023
	(0.203)	(0.16)	(0.177)	(0.231)	(0.223)	(0.203)	(0.152)
GIIPS Country$_t$	0.361	0.032	-0.003	0.028	0.224	-0.607***	-0.651***
	(0.45)	(0.28)	(0.285)	(0.257)	(0.197)	(0.216)	(0.24)
Ratio Nonbanks$_{t-1}$	-0.832	-0.634	-0.486	0.143	-0.181	-0.064	0.832
	(0.553)	(0.551)	(0.523)	(0.572)	(0.484)	(0.613)	(0.714)
Constant	4.054*	1.465	3.920***	2.055	3.778**	5.497***	3.987***
	(2.08)	(1.163)	(1.385)	(1.645)	(1.682)	(1.109)	(0.959)
Observations	54	52	55	55	50	62	69
R-squared	0.199	0.299	0.314	0.512	0.606	0.634	0.712

Notes: This table reports cross-sectional regressions that are based on yearly data of stock listed banks of Euro area countries by year as indicated in the column head. The dependent variable is a bank's Zscore. Explanatory variables include bank-level controls: Log assets is the log of total assets, NPL is the ratio of non-performing loans to total loans (in %), the cost-to-income ratio (in %), and liquid assets to total assets (in %). Macro controls of the bank holding company's country of location include: GDP growth (in %), the inflation rate (in %), and a dummy that equals one if the bank holding company is located in a GIIPS Country, i.e. Greece, Ireland, Italy, Portugal, or Spain. The complexity measure is the ratio of nonbank subsidiaries over the total number of subsidiaries (Ratio Nonbanks). Bank-level variables are lagged by one period. Robust standard errors are depicted in parentheses. The p-values are as follows: *** p<0.01, ** p<0.05, * p<0.1.

Table A.9: Cross-Sectional Regression Results by Year - Zscore (Ratio Foreign).

	(1) **2008**	(2) **2009**	(3) **2010**	(4) **2011**	(5) **2012**	(6) **2013**	(7) **2014**
Log assets$_{t-1}$	0.134	0.162***	0.083	0.092*	0.07	0.124**	0.066
	(0.106)	(0.053)	(0.056)	(0.054)	(0.058)	(0.048)	(0.046)
NPL$_{t-1}$	-0.036	-0.090**	-0.049	-0.057*	-0.108***	-0.090***	-0.057***
	(0.047)	(0.038)	(0.03)	(0.033)	(0.018)	(0.015)	(0.009)
Cost-to-income$_{t-1}$	0	0.005	-0.017*	-0.005	-0.007	-0.016**	-0.018***
	(0.012)	(0.007)	(0.009)	(0.007)	(0.007)	(0.007)	(0.006)
Liquid assets$_{t-1}$	0.006	0.026**	0.007	-0.001	-0.014	-0.018**	-0.024***
	(0.014)	(0.01)	(0.013)	(0.011)	(0.01)	(0.009)	(0.007)
GDPt	0.189	0.155**	0.094	0.143***	0.212***	0.038	-0.048
	(0.129)	(0.063)	(0.1)	(0.048)	(0.066)	(0.066)	(0.052)
Inflation$_t$	-0.409**	0.267*	-0.068	0.339	0.153	-0.159	-0.132
	(0.178)	(0.151)	(0.209)	(0.208)	(0.212)	(0.156)	(0.14)
GIIPS Country$_t$	0.329	-0.035	-0.167	-0.115	0.11	-0.712***	-0.813***
	(0.385)	(0.242)	(0.29)	(0.238)	(0.171)	(0.188)	(0.193)
Ratio Foreign$_{t-1}$	-1.258**	-1.738***	-1.173**	-1.064**	-0.843	-1.392***	-0.446
	(0.563)	(0.5)	(0.502)	(0.473)	(0.556)	(0.47)	(0.363)
Constant	1.546	0.37	2.744*	0.893	3.017*	3.713***	4.522***
	(2.443)	(1.167)	(1.481)	(1.527)	(1.515)	(0.959)	(0.806)
Observations	54	52	55	55	51	62	69
R-squared	0.256	0.444	0.378	0.545	0.622	0.689	0.711

Notes: This table reports cross-sectional regressions that are based on yearly data of stock listed banks of Euro area countries by year as indicated in the column head. The dependent variable is a bank's Zscore. Explanatory variables include bank-level controls: Log assets is the log of total assets, NPL is the ratio of non-performing loans to total loans (in %), the cost-to-income ratio (in %), and liquid assets to total assets (in %). Macro controls of the bank holding company's country of location include: GDP growth (in %), the inflation rate (in %), and a dummy that equals one if the bank holding company is located in a GIIPS Country, i.e. Greece, Ireland, Italy, Portugal, or Spain. The complexity measure is the ratio of subsidiaries that are situated in a foreign country over the total number of subsidiaries (Ratio Foreign). Bank-level variables are lagged by one period. Robust standard errors are depicted in parentheses. The p-values are as follows: *** p<0.01, ** p<0.05, * p<0.1.

Table A.10: Different Crisis Periods - Zscore.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log $assets_{2007}$	0.019	0.115	0.012	0.088	0.072	0.159*	0.061	0.137
	(0.066)	(0.09)	(0.067)	(0.088)	(0.064)	(0.092)	(0.065)	(0.087)
NPL_{2007}	-0.08	-0.084**	-0.076	-0.075*	-0.078	-0.082*	-0.073	-0.072
	(0.049)	(0.04)	(0.047)	(0.042)	(0.051)	(0.043)	(0.048)	(0.045)
Cost-to-$income_{2007}$	0.002	0.006	0.002	0.004	0.009	0.012	0.009	0.011
	(0.01)	(0.009)	(0.011)	(0.008)	(0.01)	(0.009)	(0.01)	(0.009)
Liquid $assets_{2007}$	-0.008	-0.004	-0.01	-0.007	-0.003	0	-0.006	-0.003
	(0.01)	(0.01)	(0.012)	(0.01)	(0.01)	(0.009)	(0.011)	(0.009)
GDP_{2007}	0.025	0.017	0.007	0.004	0.105	0.095	0.082	0.081
	(0.142)	(0.136)	(0.158)	(0.14)	(0.115)	(0.112)	(0.135)	(0.115)
$Inflation_{2007}$	-0.866***	-0.721***	-0.892***	-0.781***	-0.932***	-0.795***	-0.965***	-0.848***
	(0.272)	(0.24)	(0.275)	(0.265)	(0.234)	(0.21)	(0.232)	(0.231)
GIIPS $Country_{2007}$	0.244	0.222	0.211	0.165	0.356	0.322	0.309	0.264
	(0.428)	(0.434)	(0.439)	(0.421)	(0.401)	(0.416)	(0.418)	(0.4)
HHI $Business_{2007}$	-0.214				-0.319			
	(0.504)				(0.586)			
HHI Geo_{2007}		-1.067**				-1.026**		
		(0.443)				(0.479)		
Ratio $Nonbanks_{2007}$			0.216				0.27	
			(0.487)				(0.474)	
Ratio $Foreign_{2007}$				-0.854*				-0.865*
				(0.493)				(0.488)
Constant	4.192**	2.106	4.147**	2.837	2.695	0.694	2.641*	1.327
	(1.646)	(2.139)	(1.584)	(2.016)	(1.63)	(2.176)	(1.557)	(2.038)
Observations	54	54	54	54	54	54	54	54
R-squared	0.311	0.367	0.311	0.351	0.334	0.379	0.333	0.369

Notes: This table reports cross-sectional regressions that are based on yearly data of stock listed banks of Euro area countries. The dependent variable in columns (1)-(4) is a bank's average Zscore over 2008 and 2009. The dependent variable in columns (5)-(8) is a bank's average Zscore over 2010, 2011 and 2012. Explanatory variables as of the year 2007 include bank-level controls: Log assets is the log of total assets, NPL is the ratio of non-performing loans to total loans (in %), the cost-to-income ratio (in %), and liquid assets to total assets (in %). Macro controls of the bank holding company's country of location as of the year 2007 include: GDP growth (in %), the inflation rate (in %), and a dummy that equals one if the bank holding company is located in a GIIPS Country, i.e. Greece, Ireland, Italy, Portugal, or Spain. The complexity measures are from the year 2007 and include: HHI Business indicates diversification of banks across different business activities, HHI Geo indicates diversification of banks across geographical regions, the ratio of nonbank subsidiaries over the total number of subsidiaries (Ratio Nonbanks), and the ratio of subsidiaries that are situated in a foreign country over the total number of subsidiaries (Ratio Foreign). Robust standard errors are depicted in parentheses. The p-values are as follows: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A.11: Panel Regression Results - Zscore.

	(1)	(2)	(3)	(4)
Log assets$_{t-1}$	-0.621***	-0.605***	-0.597***	-0.573***
	(0.149)	(0.14)	(0.123)	(0.125)
NPL$_{t-1}$	-0.003	-0.003	-0.003	-0.004
	(0.005)	(0.005)	(0.004)	(0.004)
Cost-to-income$_{t-1}$	0	0	0	0
	(0.002)	(0.002)	(0.001)	(0.001)
Liquid assets $_{t-1}$	0.003	0.002	0.001	0.001
	(0.004)	(0.004)	(0.003)	(0.004)
GDP$_t$	0.030***	0.029***	0.023**	0.023**
	(0.009)	(0.01)	(0.009)	(0.009)
Inflation$_t$	0.021	0.016	0.009	0.004
	(0.019)	(0.02)	(0.017)	(0.017)
Crisis (0/1)	-0.389***	-0.347***	0.211***	0.228***
	(0.089)	(0.088)	(0.056)	(0.053)
HHI Business$_{t-1}$	-0.066*			
	(0.035)			
Crisis (0/1)*HHI Business$_{t-1}$	0.007			
	(0.03)			
HHI Geo$_{t-1}$		-0.007		
		(0.051)		
Crisis (0/1)*HHI Geo$_{t-1}$		-0.057**		
		(0.024)		
Ratio Nonbanks$_{t-1}$			0.019	
			(0.023)	
Crisis (0/1)*Ratio Nonbanks$_{t-1}$			-0.070***	
			(0.022)	
Ratio Foreign$_{t-1}$				0.017
				(0.032)
Crisis (0/1)*Ratio Foreign$_{t-1}$				-0.048**
				(0.022)
Constant	14.056***	13.764***	13.229***	12.792***
	(2.745)	(2.576)	(2.25)	(2.27)
Bank fixed effects	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes
Observations	397	398	443	444
R-squared	0.347	0.354	0.349	0.326
Number of banks	75	75	75	75

Notes: This table reports fixed effects regressions that are based on yearly data of stock listed banks of Euro area countries for the period 2007-2014. The dependent variable is a bank's Zscore (in logs). Explanatory variables include bank-level controls: Log assets is the log of total assets, NPL is the ratio of non-performing loans to total loans (in %), the cost-to-income ratio (in %), and liquid assets to total assets (in %). Macro controls of the bank holding company's country of location include: GDP growth (in %), the inflation rate (in %), and a dummy that equals one if the bank holding company is located in a GIIPS Country, i.e. Greece, Ireland, Italy, Portugal, or Spain. The complexity measures are standardized and include: HHI Business indicates diversification of banks across different business activities, HHI Geo indicates diversification of banks across geographical regions, the ratio of nonbank subsidiaries over the total number of subsidiaries (Ratio Nonbanks), and the ratio of subsidiaries that are situated in a foreign country over the total number of subsidiaries (Ratio Foreign). All bank-level variables are lagged by one period. The complexity measures are interacted with the dummy variable Crisis (0/1), which equals one in the years 2008, 2009 and 2010, and zero otherwise. The regressions take into account bank and year fixed effects. Cluster-robust standard errors are depicted in parentheses. The p-values are as follows: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A.12: Regression Results - ΔCoVaR.

	(1)	(2)	(3)	(4)
Log assets$_{2007}$	0.002***	0.002***	0.003***	0.002***
	0.	(0.001)	0.	(0.001)
Equity$_{2007}$	0	0	0	0
	0.	0.	0.	0.
NPL$_{2007}$	0.001	0.001*	0.001	0.001*
	(0.001)	0	(0.001)	0
Cost-to-income$_{2007}$	0	0	0	0
	0	0	0	0
RoA$_{2007}$	0.003	0.006**	0.006*	0.005*
	(0.003)	(0.003)	(0.003)	(0.003)
Liquid assets$_{2007}$	0	0	0	0
	0	0	0	0
GDP$_{2007}$	0	0	-0.001	0
	(0.001)	(0.001)	(0.001)	(0.001)
Inflation$_{2007}$	0.004	0.003	0.004	0.003
	(0.003)	(0.002)	(0.002)	(0.002)
GIIPS Country$_{2007}$	0.003	0.004	0.004	0.005**
	(0.003)	(0.003)	(0.003)	(0.003)
HHI Business$_{2007}$	0.008			
	(0.006)			
HHI Geo$_{2007}$		0.012***		
		(0.004)		
Ratio Nonbanks$_{2007}$			0.007	
			(0.004)	
Ratio Foreign$_{2007}$				0.013***
				(0.004)
Constant	-0.046***	-0.03	-0.059***	-0.029
	(0.016)	(0.019)	(0.017)	(0.018)
Observations	54	54	54	54
R-squared	0.582	0.641	0.58	0.682

Notes: This table reports cross section regressions that are based on yearly data of stock listed banks of Euro area countries. The dependent variable is a bank's average ΔCoVaR over the years 2008-2010. Explanatory variables are from the year 2007 and include bank-level controls: Log assets is the log of total assets, equity is the ratio of equity to total assets (in %), NPL is the ratio of non-performing loans to total loans (in %), the cost-to-income ratio (in %), return on assets (RoA, in %), and liquid assets to total assets (in %). Macro controls of the bank holding company's country of location include: GDP growth (in %), the inflation rate (in %), and a dummy that equals one if the bank holding company is located in a GIIPS Country, i.e. Greece, Ireland, Italy, Portugal, or Spain. The complexity measures are also from year the 2007 and include: HHI Business indicates diversification of banks across different business activities, HHI Geo indicates diversification of banks across geographical regions, the ratio of nonbank subsidiaries over the total number of subsidiaries (Ratio Nonbanks), and the ratio of subsidiaries that are situated in a foreign country over the total number of subsidiaries (Ratio Foreign). Robust standard errors are depicted in parentheses. The p-values are as follows: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A.13: Regression Results - State aid.

	(1)	(2)	(3)	(4)
Log assets$_{t-1}$	0.513**	0.316	0.632**	0.427*
	(0.257)	(0.238)	(0.311)	(0.245)
Equity$_{t-1}$	-0.297***	-0.297***	-0.350***	-0.291***
	(0.112)	(0.109)	(0.105)	(0.101)
NPL$_{t-1}$	0.135***	0.143***	0.149***	0.128***
	(0.046)	(0.036)	(0.051)	(0.033)
Cost-to-income$_{t-1}$	-0.009	-0.015	-0.011	-0.009
	(0.02)	(0.019)	(0.022)	(0.02)
RoA$_{t-1}$	-0.21	-0.342	-0.311	-0.207
	(0.211)	(0.218)	(0.238)	(0.214)
Liquid assets$_{t-1}$	-0.103**	-0.112**	-0.119**	-0.116**
	(0.049)	(0.05)	(0.053)	(0.052)
GDP$_t$	0.138	0.145	0.166	0.166
	(0.105)	(0.104)	(0.115)	(0.108)
Inflation$_t$	-1.021**	-0.794**	-1.161***	-0.927**
	(0.402)	(0.348)	(0.395)	(0.376)
GIIPS Country$_t$	-1.083	-0.943	-1.386**	-0.86
	(0.693)	(0.605)	(0.707)	(0.602)
HHI Business$_{t-1}$	0.788			
	(1.614)			
HHI Geo$_{t-1}$		3.452***		
		(1.14)		
Ratio Nonbanks$_{t-1}$			-3.738***	
			(1.189)	
Ratio Foreign$_{t-1}$				2.505**
				(1.01)
Constant	-5.543	-2.791	-9.044	-9.528*
	(5.777)	(5.027)	(6.127)	(5.175)
Time fixed effects	Yes	Yes	Yes	Yes
Observations	399	400	399	400
Number of banks	75	75	75	75

Notes: This table reports random effects probit regressions that are based on yearly data of stock listed banks of Euro area countries for the period 2007-2014. The dependent variable is a dummy for state aid, which equals one if the bank received state aid that year following the State Aid Register of the European Commission, and zero otherwise. Explanatory variables include bank-level controls: Log assets is the log of total assets, equity is the ratio of equity to total assets (in %), NPL is the ratio of non-performing loans to total loans (in %), the cost-to-income ratio (in %), return on assets (RoA, in %), and liquid assets to total assets (in %). Macro controls of the bank holding company's country of location include: GDP growth (in %), the inflation rate (in %), and a dummy that equals one if the bank holding company is located in a GIIPS Country, i.e. Greece, Ireland, Italy, Portugal, or Spain. The complexity measures comprise: HHI Business indicates diversification of banks across different business activities, HHI Geo indicates diversification of banks across geographical regions, the ratio of nonbank subsidiaries over the total number of subsidiaries (Ratio Nonbanks), and the ratio of subsidiaries that are situated in a foreign country over the total number of subsidiaries (Ratio Foreign). All bank-level variables are lagged by one period. Regressions include time fixed effects. Standard errors clustered at the bank level are depicted in parentheses. The p-values are as follows: *** p<0.01, ** p<0.05, * p<0.1.

Table A.14: Different Crisis Periods - State aid.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log assets$_{t-1}$	0.496*	0.324	0.705**	0.431*	0.506*	0.312	0.638**	0.432*
	(0.26)	(0.241)	(0.349)	(0.239)	(0.259)	(0.237)	(0.319)	(0.255)
Equity$_{t-1}$	-0.292***	-0.343***	-0.404***	-0.314***	-0.298***	-0.287***	-0.352***	-0.299***
	(0.109)	(0.113)	(0.103)	(0.102)	(0.113)	(0.108)	(0.105)	(0.1)
NPL$_{t-1}$	0.136***	0.162***	0.159***	0.130***	0.133***	0.139***	0.151***	0.136***
	(0.046)	(0.04)	(0.054)	(0.033)	(0.045)	(0.035)	(0.052)	(0.037)
Cost-to-income$_{t-1}$	-0.01	-0.025	-0.01	-0.015	-0.009	-0.015	-0.011	-0.008
	(0.02)	(0.019)	(0.023)	(0.018)	(0.021)	(0.019)	(0.022)	(0.02)
RoA$_{t-1}$	-0.217	-0.454*	-0.271	-0.241	-0.221	-0.365	-0.306	-0.179
	(0.21)	(0.238)	(0.243)	(0.208)	(0.225)	(0.235)	(0.239)	(0.209)
Liquid assets$_{t-1}$	-0.100**	-0.112**	-0.128**	-0.114**	-0.101**	-0.113**	-0.121**	-0.115**
	(0.049)	(0.05)	(0.059)	(0.052)	(0.05)	(0.049)	(0.054)	(0.052)
GIIPS Country$_{t}$	-1.047	-0.838	-1.425*	-0.776	-1.047	-0.971	-1.403*	-0.811
	(0.699)	(0.619)	(0.8)	(0.586)	(0.701)	(0.611)	(0.719)	(0.598)
GDP$_{t}$	0.151	0.196**	0.144	0.192**	0.141	0.136	0.168	0.158
	(0.108)	(0.098)	(0.128)	(0.097)	(0.105)	(0.1)	(0.115)	(0.112)
Inflation$_{t}$	-0.996***	-0.699**	-1.241***	-0.860**	-1.022**	-0.810**	-1.160***	-0.901**
	(0.384)	(0.342)	(0.431)	(0.352)	(0.397)	(0.342)	(0.399)	(0.365)
HHI Business$_{t-1}$	0.335				0.093			
	(0.458)				(0.439)			
Crisis(0/1)*HHI Business$_{t-1}$	-0.432				0.523			
	(0.604)				(0.638)			
HHI Geo$_{t-1}$		1.234***				0.876**		
		(0.299)				(0.348)		
Crisis(0/1)*HHI Geo$_{t-1}$		-1.036***				0.237		
		(0.335)				(0.393)		
Ratio Nonbanks$_{t-1}$			-0.311				-0.659***	
			(0.259)				(0.221)	
Crisis(0/1)*Ratio Nonbanks$_{t-1}$			-0.670*				0.124	
			(0.362)				(0.237)	
Ratio Foreign$_{t-1}$				0.749***				0.727**
				(0.244)				(0.294)
Crisis(0/1)*Ratio Foreign$_{t-1}$				-0.422				-0.348
				(0.328)				(0.297)
Constant	-4.561	-0.845	-13.405*	-8.560*	-4.798	-1.664	-12.330*	-9.158*
	(5.221)	(5.184)	(7.)	(5.08)	(5.163)	(5.051)	(6.618)	(5.437)
ME complexity, crisis=1	**-0.004**	**0.006**	**-0.040*****	**0.013**	**0.03**	**0.051****	**-0.022****	**0.015****
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	399	400	399	400	399	400	399	400
Number of banks	75	75	75	75	75	75	75	75

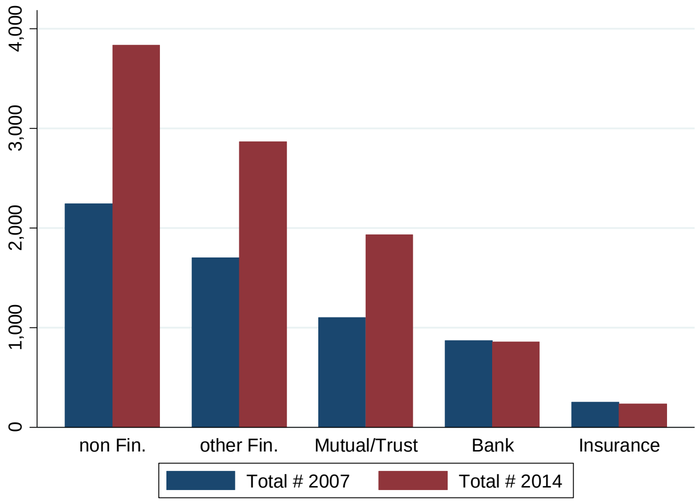
Notes: This table reports random effects probit regressions that are based on yearly data of stock listed banks of Euro area countries for the period 2007-2014. The dependent variable is a dummy for state aid, which equals one if the bank received state aid that year following the State Aid Register of the European Commission, and zero otherwise. In columns (1)-(4), the complexity measures are interacted with the dummy variable Crisis (0/1), which equals one in the years 2008 and 2009 and zero otherwise. In columns (5)-(8), the dummy variable Crisis (0/1) equals one in the years 2010, 2011 and 2012 and zero otherwise. Marginal effects (ME) for the complexity measures in case of crisis are reported below. Explanatory variables are defined as before. The complexity measures comprise: HHI Business indicates diversification of banks across different business activities, HHI Geo indicates diversification of banks across geographical regions, the ratio of nonbank subsidiaries over the total number of subsidiaries (Ratio Nonbanks), and the ratio of subsidiaries that are situated in a foreign country over the total number of subsidiaries (Ratio Foreign). All bank-level variables are lagged by one period. Regressions include time fixed effects. Standard errors clustered at the bank level are depicted in parentheses. The p-values are as follows: *** p<0.01, ** p<0.05, * p<0.1.

Table A.15: Regression Results - State Aid and Restructuring Power.

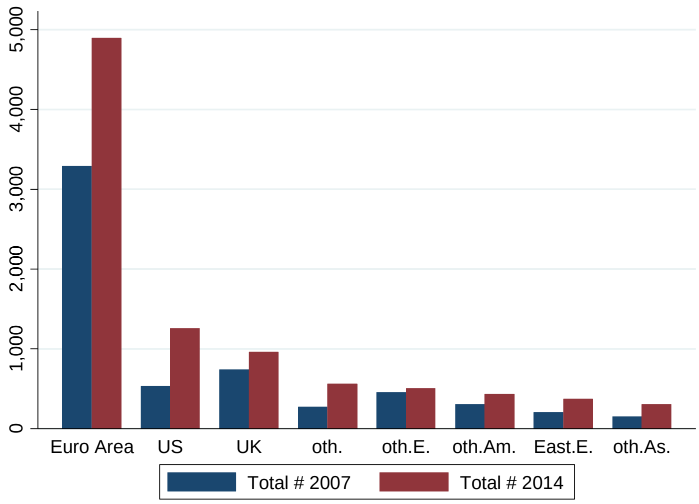
	(1)	(2)	(3)	(4)
Log assets$_{t-1}$	0.472**	0.251	0.597**	0.384
	(0.232)	(0.223)	(0.298)	(0.238)
Equity$_{t-1}$	-0.253**	-0.268**	-0.329***	-0.263***
	(0.103)	(0.106)	(0.103)	(0.1)
NPL$_{t-1}$	0.135***	0.146***	0.150***	0.128***
	(0.047)	(0.04)	(0.055)	(0.036)
Cost-to-income$_{t-1}$	-0.002	-0.005	-0.003	0
	(0.019)	(0.018)	(0.021)	(0.019)
RoA$_{t-1}$	-0.14	-0.264	-0.218	-0.117
	(0.195)	(0.201)	(0.214)	(0.188)
Liquid assets$_{t-1}$	-0.107**	-0.117**	-0.123**	-0.121**
	(0.048)	(0.05)	(0.055)	(0.053)
GIIPS Country$_t$	-1.135*	-0.969*	-1.358*	-0.861
	(0.673)	(0.575)	(0.702)	(0.584)
GDP$_t$	0.149	0.187*	0.182	0.200*
	(0.11)	(0.106)	(0.122)	(0.113)
Inflation$_t$	-0.845*	-0.458	-0.991**	-0.667
	(0.494)	(0.406)	(0.488)	(0.438)
Restructuring Power$_t$	-0.061	-0.153	-0.077	-0.112
	(0.143)	(0.112)	(0.127)	(0.105)
HHI Business$_{t-1}$	1.78			
	(2.033)			
HHI Geo$_{t-1}$		3.884***		
		(1.272)		
Ratio Nonbanks$_{t-1}$			-3.524***	
			(1.14)	
Ratio Foreign$_{t-1}$				2.662**
				(1.05)
Constant	-6.568	-3.227	-8.902	-9.189*
	(5.843)	(5.043)	(5.919)	(5.292)
Time fixed effects	Yes	Yes	Yes	Yes
Observations	393	394	393	394
Number of banks	75	75	75	75

Notes: This table reports random effects probit regressions that are based on yearly data of stock listed banks of Euro area countries for the period 2007-2014. The dependent variable is a dummy for state aid, which equals one if the bank received state aid that year following the State Aid Register of the European Commission, and zero otherwise. Explanatory variables include bank-level controls: Log assets is the log of total assets, equity is the ratio of equity to total assets (in %), NPL is the ratio of non-performing loans to total loans (in %), the cost-to-income ratio (in %), return on assets (RoA, in %), and liquid assets to total assets (in %). Macro controls of the bank holding company's country of location include: GDP growth (in %), the inflation rate (in %), and a dummy that equals one if the bank holding company is located in a GIIPS Country, i.e. Greece, Ireland, Italy, Portugal, or Spain. We include Restructuring Power provided by the World Bank Surveys on Bank Regulation to control for cross-country heterogeneity of regulation. The complexity measures comprise: HHI Business indicates diversification of banks across different business activities, HHI Geo indicates diversification of banks across geographical regions, the ratio of nonbank subsidiaries over the total number of subsidiaries (Ratio Nonbanks), and the ratio of subsidiaries that are situated in a foreign country over the total number of subsidiaries (Ratio Foreign). All bank-level variables are lagged by one period. Regressions include time fixed effects. Standard errors clustered at the bank level are depicted in parentheses. The p-values are as follows: *** p<0.01, ** p<0.05, * p<0.1.

Figure A.1: Complexity measures decomposed 2007 versus 2014.



Notes: This graph shows the number of subsidiaries by type for the years 2007 and 2014.



Notes: This graph shows the number of subsidiaries by region for the years 2007 and 2014.

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