How mortgages fuel corporate lending: It’s not magic, it’s covered bonds *

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Abstract

We use administrative and supervisory data at the bank-, loan- and firm-level to investigate the impact of covered bond issuances on bank lending and real economic outcomes. We show that the introduction of covered bonds leads to a rebalancing of bank portfolios from mortgages to corporate loans. We provide a theoretical framework for analyzing the impact of covered bonds on bank portfolio allocation, and highlight two opposing forces: On the one hand, covered bonds encourage banks to issue more mortgage loans due to lower funding costs. On the other hand, covered bonds enhance the liquidity of existing mortgages which allow banks to substitute mortgages with riskier corporate lending for higher yields. If initial bank liquidity is sufficiently low, the latter mechanism dominates. We provide empirical support for this by showing that the observed portfolio reallocation is driven by low-liquid banks. The increase in corporate credit leads to more favorable outcomes at the firm-level.

Keywords: Covered bond; Asset transfer; Portfolio rebalancing; Risk-taking
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1 Introduction

Covered bonds are debt instruments encumbered with primarily mortgage loans. Although a covered bond shares some characteristics with an asset-backed security (Jiménez et al., 2020) in that they both create financial securities backed by asset pools (often with residential mortgages), covered bonds differ substantially as issuers keep the collateral on their balance sheets instead of selling it to the market. Covered bonds is therefore securitization without explicit risk transfer.[1] The growth of covered bonds issued by banks since the 2000s, especially since the financial crisis of 2007-2008, has been substantial. By the end of 2019, the total volume of covered bonds outstanding worldwide corresponded to EUR 2.7 trillion (European Covered Bond Council, 2020). At the same time, roughly 36 % of all debt securities issued by European banks were covered bonds. 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 where 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 increasing usage of covered bonds has raised concerns about the implications for bank behavior and financial stability. Since covered bonds are perceived as relatively safe and thus carry a low risk premium, one concern is whether covered bonds provide cheap financing used by banks to expand mortgage credit in economies where house prices and household debt are already high and corporations are potentially credit constrained (Nicolaisen, 2017). However, covered bonds also lead to an increase in the liquidity of the existing mortgage portfolio, which in turn can relax bank liquidity constraints and induce banks to issue more illiquid loans such as corporate loans. Another concern relates to how asset encumbrance via covered bonds issuance affects bank appetite for credit risk. International Monetary Fund (2013) worries that risks may concentrate in unencumbered assets and this may enable banks to shift risks to uninsured creditors, encouraging excess risk taking, see also Ahnert et al. (2018), Banal-Estanol et al. (2018) and Garcia-Appendini et al. (2017). Yet, despite these different views and the the importance of covered bonds, there is limited empirical evidence on how covered bond financing affect bank lending and risk-taking.

In this paper we analyze how and why covered bonds affect bank lending and ultimately real economic outcomes. We focus on the introduction of covered bond legislation in Norway in 2007, which enabled Norwegian banks to issue covered bonds as part of their funding. As we show, the introduction of this legislation led to a boom in the issuance of covered bonds, 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 corporate loans and firm-level accounting data. This data-rich environment enables us to provide a comprehensive analysis of how and why covered bonds affect bank-level portfolio allocation and how the effects of covered bonds potentially filter through to the corporate sector via changes in loan terms

[1] Issuing asset-backed securities is associated with a bank business model of "originate to distribute", so that after a mortgage loan is originated its risk is transferred to market investors while the issuing bank earns a fee income. This risk transfer can encourage banks to excessively engage in mortgage lending, unambiguously crowding out bank lending to other sectors in the economy consistent with the evidence in Chakraborty et al. (2018). See also Carbó-Valverde et al. (2017) for a comparison of covered bonds versus asset-backed securities.

such as quantities and prices.

The analysis in this paper consists of five main steps. First, we exploit the fact that banks had different scope for issuing covered bonds due to different existing mortgage portfolios, thus implying that some banks were able to shift to covered bonds as a source of financing to a larger extent than others. Specifically, mortgages with an LTV below 75 % were eligible for being used 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 to other banks.

Second, we document that the relative increase in covered bond issuance translates into substantial changes in bank-level asset allocation. We find a relative increase of the ratio of firm lending after the introduction of covered bonds which corresponds to up to 7.4% of the average ratio of firm lending for high-exposure banks in the pre period, while there are no significant differences pre-reform. We find no significant difference in the growth of mortgages. This in turn implies that the increase in corporate lending is accompanied with a *portfolio rebalancing* away from mortgages to corporate loans. The introduction of covered bonds also leads high-exposure banks to increase their holdings of liquid financial assets, thus enhancing banks' liquidity.

Importantly, these bank-level changes are unlikely to be driven by other confounding factors, such as differential exposure to the financial crisis across banks.[2] 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 to other comparable countries (NOU, 2011). Moreover, the Norwegian financial sector did not experience substantial losses (Kragh-Sorensen 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 which our exposure measure is based upon is not correlated with 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.

Third, we show that the impact of covered bond issuance at the bank-level translates to more favorable lending conditions at the loan-level after the reform and in turn more favorable real economic outcomes at the firm-level. We use loan-level data on the universe of corporate loans in Norway to document that the growth in the outstanding loan balance is higher on loans issued by high-exposure banks. At the same time, interest rates tend to decline or remain unchanged, suggesting that demand factors are unlikely to drive these observations. Moreover, the results are robust to controlling for demand-side factors more directly, by either employing industry-location-size-times fixed effects as in Degryse et al. (2019) for the full sample of firms, or firm-time fixed effects as in Khwaja and Mian (2008) for the sample of firms borrowing from multiple banks. Importantly, we show that the issuance of covered bonds expand bank risk-taking. Specifically, we show that the increase in credit is not uniform across all corporate clients, but rather tailored towards firms with an ex.ante lower credit rating.

[2]We also discuss and address other potential confounding factors in section 3.3.

We link our loan-level data with firm-level data on all major balance sheet and income statement items and document that firms borrowing from high-exposure banks reduce their cash position, increase their wage bill and increase their R&D spending and capital investment after the reform. These findings suggest that the expansion in corporate lending due to covered bonds have significant effects on real economic outcomes for ex.ante riskier firms. Interestingly, we show that the ex.ante riskier firms become – if anything – more risky after this expansion in productive capacity, i.e. their credit rating deteriorates further with no sign of medium- to long-run improvement.

Fourth, we analyze our baseline bank-level findings through the lens of a simple theoretical framework. In the model, we consider a bank which provides liquidity services and extends mortgages and risky corporate loans. The bank is funded by uninsured depositors that have a preference for liquidity. Corporate loans are illiquid if a bad state of the economy materializes. Hence, banks that engage more in corporate lending face a higher risk premium by depositors. In line with the actual funding cost of covered bonds compared to other sources of mortgage financing, we model the introduction of covered bonds as an increase in the return from mortgage lending. Covered bonds therefore, on the one hand, increase banks' profit from mortgage lending by lowering their funding cost and thereby encourage banks to issue more mortgage loans. On the other hand, covered bonds reduce banks' liquidity risk by making it more likely that the bank can satisfy the liquidity need of depositors with the existing mortgage portfolio. Banks therefore have an incentive to substitute corporate for mortgage loans. This substitution effect is more likely to dominate when depositors have limited risk-aversion and when the credit risk in corporate lending is not too high. In addition, this effect varies with initial bank liquidity. Banks with low liquidity, which in our model is captured by a high cost of creating liquid assets, have stronger incentives to switch to corporate loans when the mortgage portfolio becomes more liquid.

In the fifth and final step, we return to the data and show support for our theoretical model by showing that the observed portfolio rebalancing from mortgages and to corporate loans is driven by banks with low initial liquidity. We also observe relatively lower funding costs for high exposed banks and conclude that despite banks' higher risk taking due to higher exposure to low rated borrowers, financial markets participants ask lower risk premia from banks which issue covered bonds and hence consider them as less risky due to their reduced liquidity risk.

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 asset-backed securities (ABS) provided liquidity relief for banks and allowed them to increase credit supply. They also show that during the credit boom, banks with higher exposure to the real estate sector increased their risk-taking. 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 an 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. (2017) 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-Estanol et al. (2018)

find that, after controlling for bank liquidity and capital ratios, higher asset encumbrance ratio relates to lower spreads in banks' credit default swaps (CDS). Our main contribution to this literature is to provide the first micro-level analysis of how covered bonds affect bank portfolio allocation *across* asset classes. Our stylized framework and empirical analysis emphasize how covered bonds—by enhancing bank liquidity—can lead to substantial reallocation across asset classes and contribute to more credit provisioning towards firms.

2 Introduction of covered bonds in Norway

A covered bond is a debt security that is issued by banks or mortgage companies and collateralized by a pool of assets with certain quality requirements. Special rules are imposed on covered bond issuance to ensure its safety from the perspective of investors. First, covered bonds are backed by an asset pool of high quality. For instance, mortgage loans that are included in the pool must have sufficiently low loan-to-value (LTV) ratios. The value of assets in the pool must exceed the face value of covered bonds backed by the pool, that is, covered bonds are over-collateralized. Second, the cover pool is dynamic in the following sense: if the quality of certain assets in the pool deteriorates and does not meet the quality requirement any longer, the issuer must replace these assets by other eligible assets or cash. Third and finally, if the issuer goes bankrupt throughout the maturity of a specific covered bond, its bond holders can seize the asset pool and recover their claims. If the liquidation value of the asset pool is not enough to clear their claims, covered bond holders are entitled to make further recourse against the issuer's remaining assets, with a higher seniority than the other creditors. As covered bond investors have recourse against both collateral and issuer's other assets, such feature is called *dual recourse*.

After the 2007-2009 global financial crisis, covered bond issuance started to gain momentum, especially after ECB accepted covered bonds as eligible collateral and included covered bond purchase in its QE program. As of 2019q4, covered bonds outstanding worldwide amounts to 2.705 trillion euro, about 90% of which is issued by banks in European countries (European Covered Bond Council, 2020).

In Norway, the necessary legislation for covered bonds issuance was adopted on June, 1 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). Following the introduction of covered bonds, issuance of covered bonds increased substantially. In the time period from the introduction of covered bond markets until 2012, which we focus on in our empirical analysis, the fraction of mortgages transferred to cover pools increased to approximately 55 %, as highlighted in Figure 1.

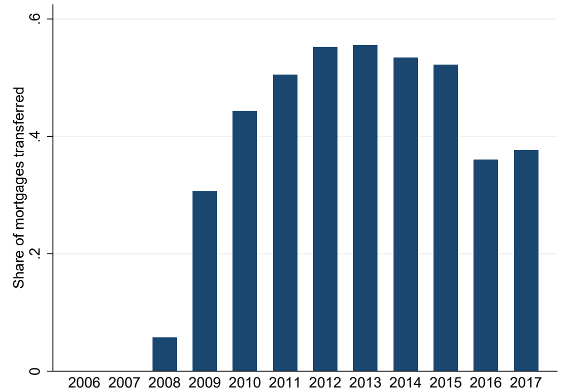


Figure 1: Share of total mortgages transferred

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

As we show in Figure 2, in the first two years, Norwegian covered bonds were mostly issued in foreign currencies and sold to foreign investors. The birth of the covered bond market was associated with a swap agreement that allows banks to exchange covered bonds for Treasury bills initiated by the Ministry of Finance in October 2008.

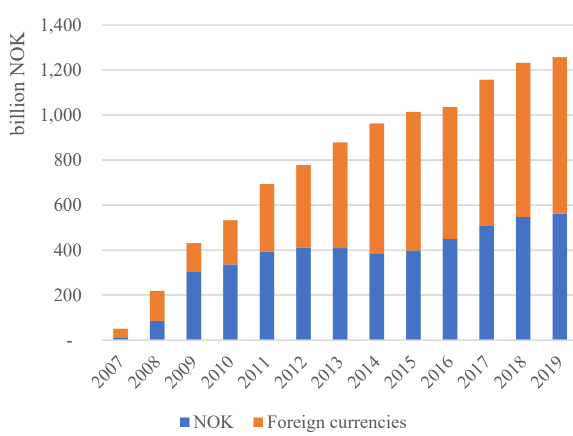


Figure 2: Outstanding debt and currency decomposition of Norwegian covered bonds

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: Finance Norway.

Although the swap arrangement last only until October 2009, covered bond issuance has increased substantially since then. As Figure 2 shows, the rapid growth in covered bond issuance after 2008 was largely driven by the demand of foreign investors. After our sample period ends, covered bond issuance has continued to experience fast growth. As of 2020q3, covered bonds outstanding in Norway amounts to 143 billion euro, equivalent to 43% of Norwegian GDP.

3 Data and methodology

In this section, we outline the data sources we use, in addition to describing our empirical approach.

3.1 Data

Our data is merged from three different datasets.

The first dataset is quarterly balance sheet data of Norwegian banks between 2003q1 and 2012q4 from ORBOF.[3] We exclude foreign branches or subsidiaries in Norway and consider only banks issuing mortgages. We drop banks which exist only before the introduction of covered bonds, and include new banks from their third quarter of existence onward (nine banks enter during our sample period).

The dataset covers 133 banks and 5,150 bank-quarter observations. Banks transfer mortgages to credit companies which maintain cover pools and issue covered bonds. ORBOF provides us with the volume of mortgage transfers from 2008q4 onward. There are 21 credit companies, 11 are single owned and 10 are owned by several banks. 11 banks are not linked to a credit company. We consolidate balance sheet items of credit companies and banks. If banks share a credit company, we consolidate on the basis of the share of mortgages stemming from bank i on the credit company's balance sheet. Between 2008-2012, banks transferred on average 15.17% of mortgages to credit companies. In aggregate, on average 30.51% of all mortgages issued were transferred (see Figure 1). Table 1 reports summary statistics on the bank-time level.

Further, we have information on the share of loans on the banks' balance sheets which have 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.

	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	5,148[4]	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
Funding costs						
Interest paid on total funding, yearly	1,251	2.723	1.049	0.57	2.399	6.307
Interest paid on subordinated funding, yearly	421	8.178	5.149	0.398	6.947	46.057

Table 1: Summary statistics on the bank 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.

[3] *Offentlig Regnskapsrapportering fra Banker og Finansieringsforetak*, i.e., Public Accounting Report from Banks and Financial Firms.

[4] For two bank-year observations, total loans over total assets exceeded 1. We set these two observations to missing.

Our second dataset is loan-level data obtained from the Norwegian Tax Administration (*Skatteetaten*). 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 which stem from 250,545 firms. We aggregate loans and deposits to 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 on the firm-bank-year level.

	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$\vert_{loan>0}$	457,962	1.566	1.950	1.000	1.000	310.000
Symmetric credit growth	1,355,289	-0.067	0.710	-2.000	0.000	2.000
Interest rate (in %)	401,673	6.614	3.595	0.000	6.166	35.473

Table 2: Summary statistics on firm-bank-year level
This table reports summary statistics for 275,323 firm-bank relationships, or 220,059 firms.

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

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

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 computed as

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

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.

Finally, we add firm balance sheet data to investigate whether the introduction of covered bonds affected firm outcomes. Firm-level data comes from the credit rating agency Bisnode. We exclude financial firms. Table 3 shows summary statistics. We merge 130,661 firms (933,746 firm-year observations). The median firm has total assets of approximately 2,782,000 NOK[5] and is 10 years old and has a A rating (AAA is 1 and C is 5). We define a 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). We compute symmetric growth rates for the following balance sheet variables as in equation (1): cash, research and development expenditures (RnD), tools as part of capital expenditures, sales and wage bill.

[5]Approximately 324'000 USD. 1 USD = 8.58 at the 5$^{\text{th}}$ of March, 2021.

	N	mean	sd	min	p50	max
Size and Age						
assets	933,746	42270.250	1,563,833	0.000	2782.000	>584mio
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
Symmetric growth rates						
cash	845,388	0.009	0.916	-2.000	0.000	2.000
rnd	848,552	0.000	0.144	-2.000	0.000	2.000
tools	848,422	-0.069	0.723	-2.000	0.000	2.000
sales	846,722	0.015	0.661	-2.000	0.000	2.000
wage bill	835,055	0.030	0.604	-2.000	0.000	2.000

Table 3: Summary statistics on firm-year level
This table reports summary statistics for 130,661 firms.

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% were eligible for being transferred to the covered bond pool. As a result, banks with different distributions of LTV 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 regulatory threshold of 75% for mortgages to be eligible for cover pools. We construct a treatment indicator which is equal to 1 for banks which 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.[6] On average, 84.2% of mortgages on banks' balance sheets have low LTVs. Banks which 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. On the firm level, we set $T_f = 1$ if firm f had a link to a high-exposure bank in 2006, and $T_f = 0$ otherwise. In a robustness check we use the continuous ratio of low LTV mortgages over total mortgages as the treatment measure and show that results remain the same. Table 4 shows summary statistics on our treatment indicators.

[6]Note that we slightly overestimate the share of eligible mortgages for *all* banks in our sample. We introduce measurement error only if high and low exposed banks differ systematically in terms of the shares of mortgages with LTVs between 75% and 80%.

	N	Mean	Sd	Min	Median	Max
Treatment on bank level						
T_b (treatment indicator)	5,150	0.496	0.500	0.000	0.000	1.000
Share of mortgages transferred to credit 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
Treatment indicator on *loan level:* T_b	1,355,289	0.880	0.325	0.000	1.000	1.000
Treatment indicator on *firm level*: T_f	933,746	0.909	0.288	0.000	1.000	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 observations and for 130,661 firms or 933,746 firm-year observations.

High-exposure banks transferred a substantially larger amount of their mortgages to the covered bond pool compared to other banks. In Figure 3, we show 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 highly exposed banks were approximately 70% larger compared to the less exposed banks. Note that our treatment definition does not exclude that low-exposure banks issue covered bonds. We merely capture the fact that high-exposure banks can 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.

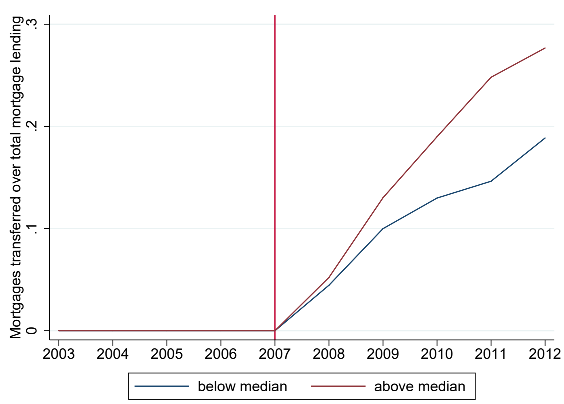


Figure 3: Share of mortgages transferred for high-exposure and low-exposure bank

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.

Over time also low-exposure banks can shift the supply of credit towards low LTV mortgages relative to high-exposure banks. This is likely to be a slow-moving process as shown in Figure 17 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 types. 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 is meant to capture exposure to the introduction of covered bonds in the short-run to medium-run. We therefore emphasize the impact of covered bonds on bank outcomes up until six years after the legal change was implemented.

The fraction of low LTV mortgages also well predicts post-treatment transfers when focusing on individual banks. In Table 5, we report the results from a univariate regression on the fraction of mortgages transferred post-treatment versus the pre-treatment fraction of eligible (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 well banks' subsequent issuance of covered bonds.

	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
Quarter-year FE	Yes

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 credit companies over total mortgages issued. The regression includes quarter-year fixed effects. *, **, *** indicate significant coefficients at the 10%, 5%, and 1% level, respectively.

Armed with this exposure measure, 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 banks with different values of the exposure measure in the absence of the introduction of covered bonds.

In Table 10 in Appendix B, we report summary statistics on a range of outcomes for banks defined as high-exposure and low-exposure in the pre-reform period. We also include the results from t-tests on the difference between the two groups. High-exposure banks are slightly larger in size, and issue slightly more mortgages and corporate loans. The share of loans over total assets is slightly lower for the high-exposure, though the difference amounts to 0.007 percentage point only. The difference is statistically significantly different from zero, though it is worth observing that the economic magnitude is small. The two groups do not differ in terms of mortgages and firm loans over total assets or over total loans, respectively. High-exposure banks hold less HTM (hold-to-maturity) assets over total assets, but more MM (marked-to-market) assets over total assets compared to 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 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 sub-sections, we outline our empirical strategy at the different levels of analysis.

3.2.2 Bank-level

We estimate the following dynamic estimation equation on 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 positions 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 assessing log-levels. The regression includes bank fixed effects (α_b) and quarter-year fixed effects (δ_τ). Standard errors are clustered on 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 on 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, decile of total assets and year to control for local, industry-specific and firm 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 make use of Khwaja and Mian (2008)'s approach and introduce firm-time fixed effects in the sample of multi-bank firms. Note that this approach reduces our sample size to 16.26% of firm-year observations.

3.2.4 Firm-level

We want to trace changes in banks' lending portfolios on firm balance sheets, and assess whether changes in firm lending is followed by real effects. We estimate the following dynamic estimation equation on the firm level:

$$Y_{f,t} = \alpha_f + \sum_{\tau} \delta_\tau \mathbf{1}_{t=\tau} + \sum_{\tau=2003, \tau\neq 2006}^{2012} \gamma_\tau \left(\mathbf{1}_{t=\tau} \times T_f\right) + \epsilon_{f,t}. \tag{5}$$

Dependent variables are firm rating and symmetric growth rates of firm level outcomes of firm f in year t. Treatment T_f equals 1 if firm f has a link to a high-exposure bank in 2006, and 0 otherwise. As before, we interact the treatment variable T_f with indicators for every year. We leave out 2006 as the base year before the introduction of covered bonds in 2007. We include firm fixed effects α_f and time fixed effects δ_τ. Standard errors are clustered at the firm level.

3.3 Threats to identification

Our empirical strategy is based on comparing outcomes at the bank-, loan- and firm-level according to different exposures to the covered bond reform at the bank-level. Conditional on the identifying assumption outlined in the previous section 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 demand shocks, confounding 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 corporate lending share throughout our sample period, we would estimate a positive and significant effect of low LTV mortgages on corporate lending.

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)-(5).

Confounding demand shocks The second threat to identification is that, even if banks with different exposures to the introduction of covered bonds are similar prior to the transition, they may have experienced different demand shocks after 2008. This is a concern as the introduction of covered bonds coincided with the financial crisis which could affect firms differently. Shocks to the corporate clients of banks, for instance, could affect our results if firms and banks are systematically linked. The main concern is that banks that are less exposed to the introduction of covered bonds lend more to export-oriented firms, or more generally to regions with a relatively high exposure to the international downturn associated with the financial crises. 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 of customers of low exposed banks rather than an increase in credit supply of high exposed banks.

In order to alleviate this concern, we control for firm demand shocks with an extensive sets 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. 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.

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

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 which potentially depreciated 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 a 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 and low exposed banks might be merely driven by changes in risk aversion over time. In order to adress this concern, we show that high and low exposed banks do not differ in terms of ex.ante risk taking behavior.

Another potential confounding 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. The reduction in risk-weights were on retail loans and mortgages with a low LTV. This could then imply that banks that were high-exposure according to our measure, also got a larger reduction in the effective capital requirement 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 corporate loans.[7] 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

[7]Risk weight on loan 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%.

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 17 in Appendix C it seems unlikely that banks selected 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 *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 Effects of covered bond issuance on bank, loan and firm outcomes

4.1 Bank-level

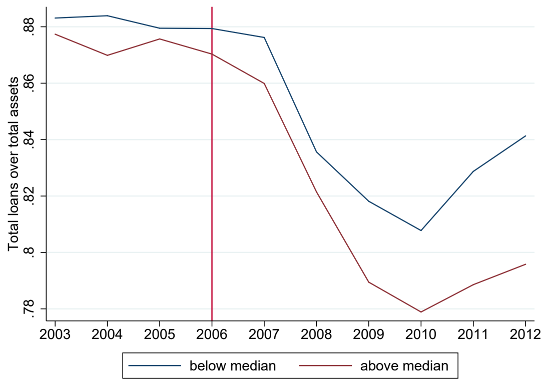
We start by comparing the evolution of bank-level outcomes, and show the main results at this level of aggregation in Figures 4 and 5. Accompanying statistics of the regression output are listed below in Table 6.

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, high-exposure banks and other banks, decreased the share of lending in total assets, however high-exposed banks even more than other banks. The coefficient plot in Figure 4b highlights that the reduction is significant: high-exposed 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 compared to base quarter-year 2006q4. 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 14b in Appendix B. The reduction is rather due to a relative increase in total assets, as we highlight in Figure 14a. By issuing covered bonds, high exposed banks extend their balance sheets relative to other banks.

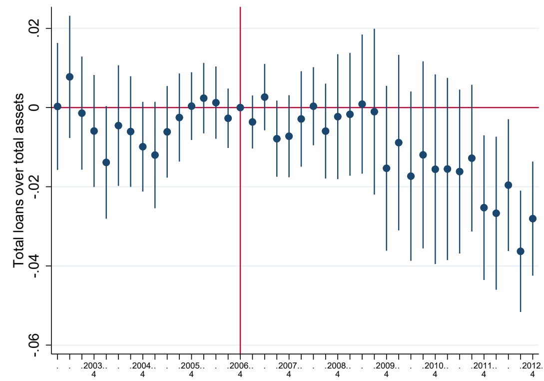
Figure 4c plots raw data of the share of mortgage lending over total loans. There is a divergence in mortgage lending between the two groups from 2008 onward. The difference is inconsistent with the view that covered bonds would lead to an expansion of mortgages—on the contrary, the high-exposure banks reduce the fraction of mortgages compared to 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 credit 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 to 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 14c 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 to other banks over the post-period. This compares to a pre-period mortgage share for high exposed 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 exposed banks in the pre period.

Next, we assess the fraction of corporate loans relative to total loans. In Figure 5a we illustrate that corporate 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 to the base quarter 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 exposed banks compared to other banks. The average share of firm lending for high-exposed banks in the pre period is 25.7%, so the relative increase corresponds to 7.4% of the average firm lending share of high exposed banks in the pre period. As total lending mildly increases for high-exposure banks relative to other banks, the increase in the corporate share is driven by an even larger relative increase in corporate lending, as we can confirm in Figure 14d in the Appendix B. The difference in log firm lending is statistically significantly different from zero from 2007q2 at the 5% level onward with varying significance levels between 1% in 2008q4 to 10% in 2012.

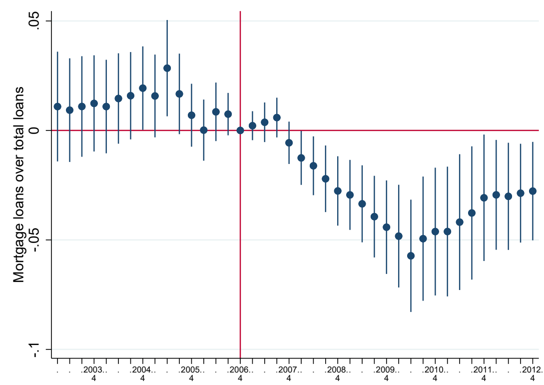


(a) Total loans over total assets



(b) Total loans over total assets

(c) Mortgages over total loans

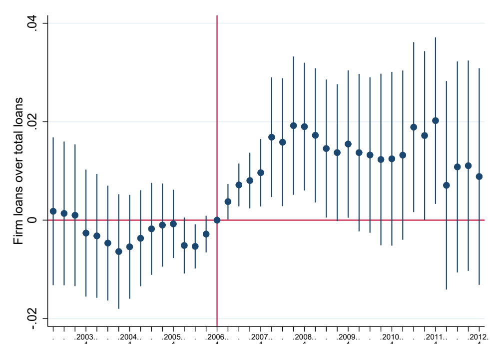


(d) Mortgages over total loans

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

In this figure we show the mean loan and the mean 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) Firm loans over total loans



(b) Firm loans over total loans

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

In this figure we show the mean corporate 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.

Dependent variable	Figure	N	No. of clusters	R2	Mean of dep. var.	Sd of dep. var.
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

Table 6: Regression information corresponding to Figures 4 and 5

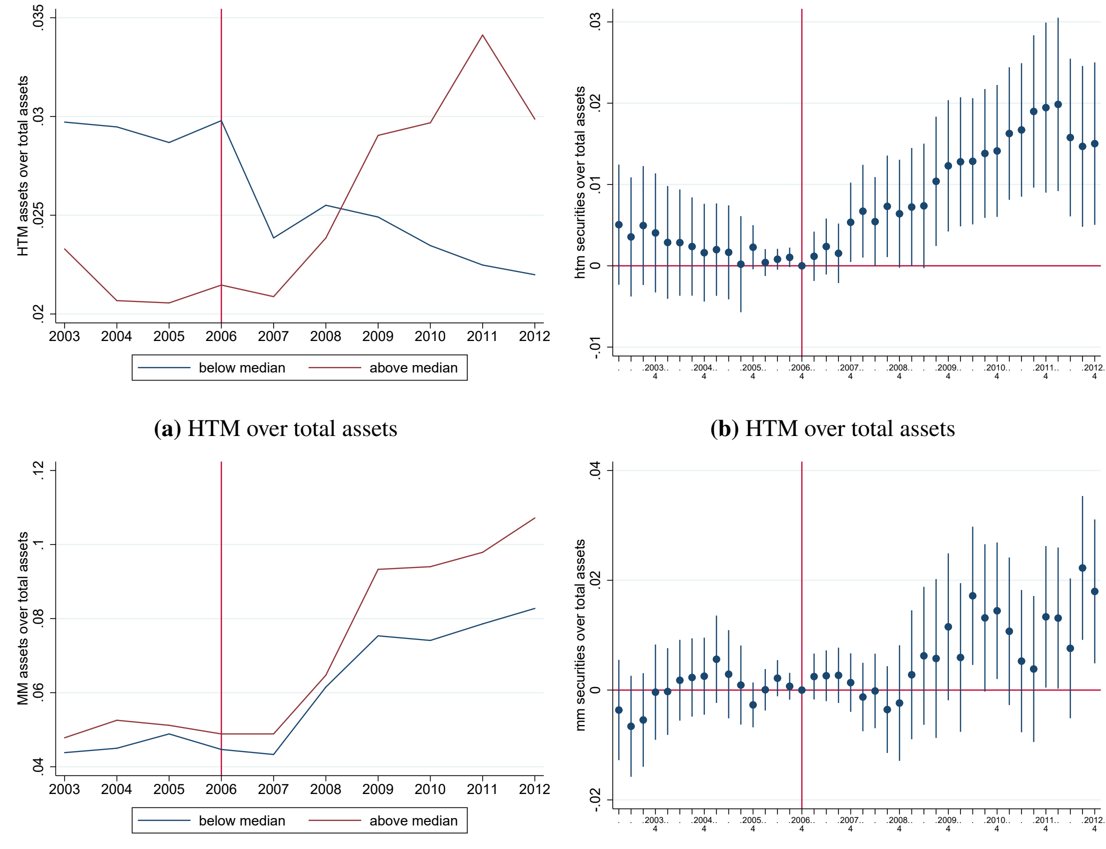
This table reports statistics from estimating equation (3). The second column ("Figure") refers to the corresponding coefficient plot.

Next, we assess whether there are changes in banks' investments in financial assets. In Figure 6 we show plots of the raw data in the left column, and coefficients from dynamic regressions in the right column. In the first row we show the evolution of hold-to-maturity (HTM) financial assets and the evolution of marked-to-market (MM) financial assets in the second row.

According to Figure 6a, high-exposure banks change their investment behavior after the introduction of covered bonds: the share of HTM assets over total assets increases relative to other banks. We show in Figure 6b that there are no statistically significant differences between the different bank types before the introduction of covered bonds. In the post period, the difference builds up 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 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. Given that banks extend their balance sheet when issuing covered bonds, i.e., the denominator, we should observe an even larger increase of the numerator. In Figure 14e in the Appendix B, we show that there is a statistically significant increase in the level of HTM assets for high-exposure banks compared to other banks at varying levels of significance up to 2010q1, and at the 1% level thereafter.

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, both groups increase their holdings of MM financial instruments. However, as highlighted in the right column, the relative increase is larger for high-exposure banks. The difference varies around 2 percentage points. Given that high-exposure had approximately 5% of their pre-period assets in MM financial instruments, the relative increase in MM asset holdings corresponds to 40% of the latter.

Overall, the results in Figure 6 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.



(a) HTM over total assets

(b) HTM over total assets

(c) MM over total assets

(d) MM over total assets

Figure 6: 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 7.

Dependent variable	Figure	N	No. of clusters	R2	Mean of dep. var.	Sd of dep. var.
HTM over total assets	6b	5,150	133	0.043	0.026	0.028
MM over total assets	6d	5,150	133	0.349	0.063	0.046

Table 7: Regression information corresponding to Figure 6.

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

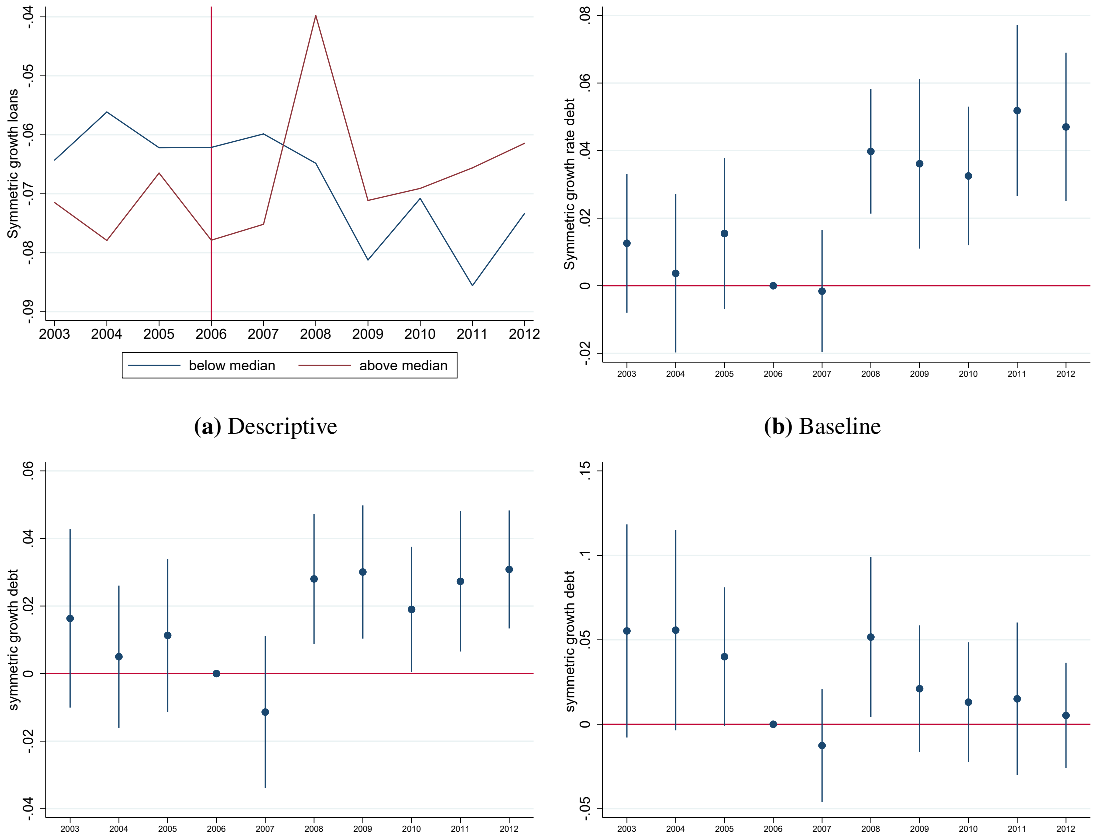
4.2 Loan-level

Next, we investigate the increase in corporate lending on the loan-level. Using loan-level data, we can (1) investigate whether the bank-level results stem from firms' switching banks or stem from an actual expansion of credit along the intensive and extensive margins, and (2) 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. Estimation results and accompanying statistics are reported in Table 12 in Appendix B.

In Figure 7a we show the mean 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-exposed banks increases, whereas loan growth decreases for loans from other banks. In Figure 7b we plot the coefficients from estimating equation (4) with symmetric growth of debt as the dependent variable. Loan growth does not differ in the pre-reform period between the two groups. From 2008 onward, loan growth from high exposed banks is larger than from other banks compared to base year 2006. The difference is statistically significantly different from zero at the 1% level for most years. High exposed 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-exposed banks in the pre-reform period of -0.073. The results confirm previous findings on the bank level that high-exposed banks issue relatively more firm loans.

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 7c 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-exposed 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-exposed 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-exposed firm-bank pairs in the pre-reform period for this sub sample is -0.048 we observe again a substantial relative increase.

Finally we follow Khwaja and Mian (2008) and introduce firm–year fixed effects for the sample of firms borrowing from multiple banks. In Figure 7d we show the corresponding coefficient plot. There are no differences between the two groups in the pre-period. And 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 to the estimates for the full sample. Specifically, loan growth increase by 0.052 for high-exposed firm-bank pairs compared to loan growth for other firm-bank pairs. Given that for high-exposed firm-bank pairs in this 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.



(a) Descriptive

(b) Baseline

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

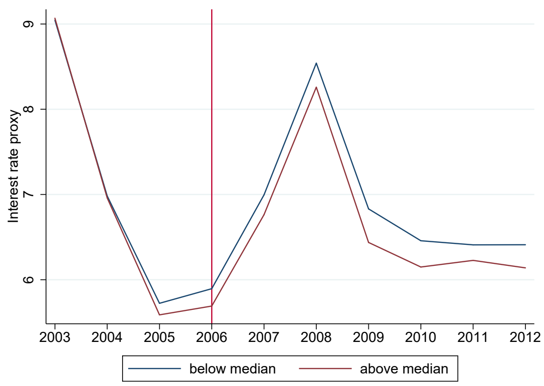
(d) Firm-time fixed effects

Figure 7: Changes on loan growth on the loan level.

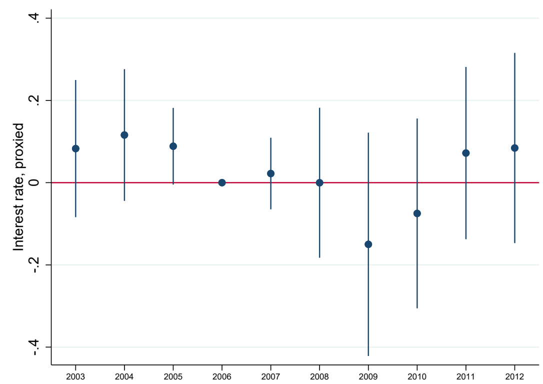
In Figure 7a we show mean symmetric loan growth for loans with high-exposure banks in red and loans with other banks in blue over time. In Figure 7b we show coefficient plots from estimating the dynamic regression equation (4) with confidence intervals at 90% with symmetric growth for loans as dependent variable. In Figure 7c we include industry-location-time fixed effects, and in Figure 7d firm-time fixed effects. Table 12 in Appendix B, columns I-III show the results.

To investigate whether banks changed their pricing behavior, we examine the impact of being linked to a high-exposure banks on the proxied interest rate. In Figure 8a we show the development of interest rates for high-exposed firm-bank pairs and other firm-bank pairs over time. Interest rates paid by firms have decreased until 2005, rise with the financial crisis in 2008, and decrease again thereafter. The raw data suggests that firms paid slightly lower interest rates after 2009 if the loan stemmed from a high-exposed bank. We estimate equation (4) with our proxy for the interest rate as dependent variable and plot the coefficients in Figure 8b. We can see a slight move towards lower interest rates for loans from high-exposed banks, however, the estimates are somewhat imprecise and we cannot reject the null hypothesis that coeficients are close to zero. As before, we follow Degryse et al. (2019) and introduce industry-location-size-time fixed effects and plot the corresponding coefficients in Figure 8c. Again, we see a negative difference between the two groups in the post-reform period, but the difference is not statistically significantly different from zero. Finally, we proceed by introducing firm-time fixed effects as in Khwaja and Mian (2008). Figure 8d shows the corresponding coefficient plot. Also for this sub-sample of multi-bank firms, we do not observe meaningful differences between the two groups.

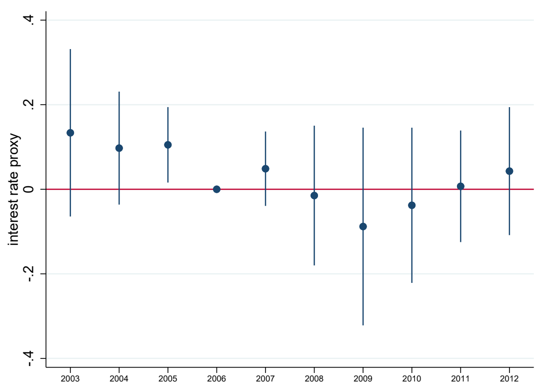
Importantly, the results in Figure 8 suggest that interest rates do not *increase* for loans from high-exposed banks. This, combined with the fact that point estimates decline, provides support for our interpretation of the results above, namely, that the increase in firm credit is coming from an expansion of credit supplied rather than an increase in credit demand.



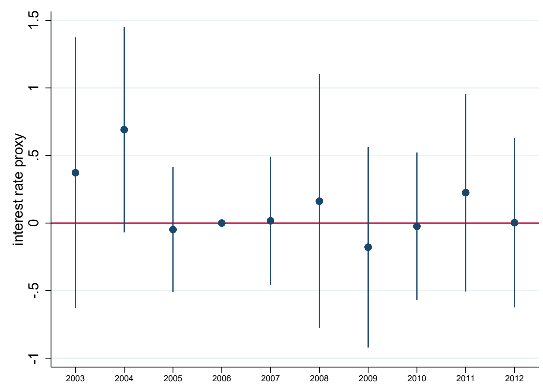
(a) Descriptive



(b) Baseline



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



(d) Firm-time fixed effects

Figure 8: Changes on interest rate proxy on the loan level.

In Figure 8a we show mean mean interest rate paid for loans with high-exposure banks in red and loans with other banks in blue over time. In Figure 8b 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 8c we include industry-location-time fixed effects, and in Figure 8d firm-time fixed effects. Table 12 in Appendix B, columns IV-VI show the results.

We want to assess which firms actually benefit from increases in loan supply. We partition our sample according to firm rating in 2006, the year before the introduction of covered bonds. We define low rated firms as firms with a rating of A or below (A, B, or C), and high rated firms as firms with a rating of AA or AAA. We re-estimate equation (4) for the sample of low and high rated firms respectively using the symmetric growth rate of loans as dependent variable. In Figure 9 we show the two coefficient plots within one graph. Table 13 in Appendix B shows regression results. We mark in blue differences between treated and control groups for ex.ante more risky firms with lower ratings. There is a positive differential effect from 2008 onward which lasts until the end of the sample period and amounts to up to 0.063. We show in red differential effects for ex.ante high rated firms. Treated high rated firms also show higher loan growth in the post period compared to non-treated high rated firms, however, the difference is only statistically significantly different from zero in 2008, and the effect levels off quickly. As we show in Table 8 on average the symmetric growth rate of debt increases by 0.05 for ex.ante low rated firms which are treated compared to low rated firms which are not treated. 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 exposed banks of 0.05 is again substantial. For high rated firms the average differential effect is close to zero.

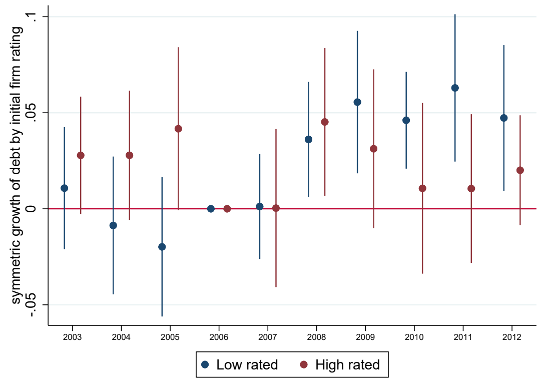


Figure 9: Changes on loan growth on the loan level conditional on firm rating.

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 in 2006. Low rated firms had a rating of A, B or C, and high rated firms a rating of AA or AAA. Table 8 shows the average differential effect in the post period for the two samples respectively. Table 13 in Appendix B shows the complete regression output.

	Low rated firms	High rated firms
Symmetric growth debt	0.050*** (0.012)	0.000 (0.011)

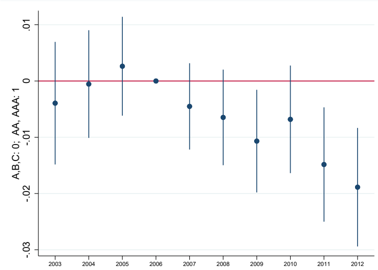
Table 8: Summarizing symmetric growth of debt across bank-firms

This table summarizes the estimated treatment effect from estimating equation (4) splitting the sample according to firm 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.

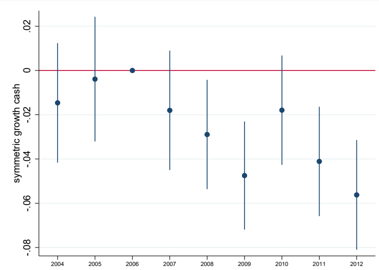
4.3 Firm level

Finally, we want to see whether changes in firm lending also have real effects. To investigate whether this is the case, we estimate equation (5) with firm rating as well as symmetric growth rates of firms' balance sheet, profits, and loss positions as dependent variables. We define a firm as treated if it had at least one link to a high-exposure bank in 2006, and as non-treated otherwise. We show the results in Figure 10. In Table 14 in Appendix B we provide the regression output underlying the figures.

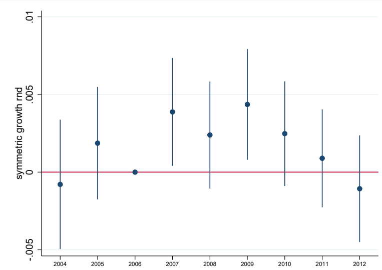
In Figure 10a we start with presenting results with a binary variable for firm rating as dependent variable. Rating equals 1 if the firm has a high rating of AAA or AA, and 0 with a low rating of A, B or C. Treated and non-treated firms do not show different ratings in the pre period compared to the base year 2006. In the post period, treated firms have a lower probability for a high rating compared to non-treated firms. In Figure 10b we plot the coefficients for cash holdings as the dependant variable. Firms do not differ in the pre-reform period. After the introduction of covered bonds, firms which had a link to a high-exposure bank hold less cash than other firms. The difference is statistically significantly different from zero at the 1% level for the years 2009, 2011 and 2012. The reduction in cash is consistent with cheaper credit reducing the need for precautionary savings. In Figure 10c we show the differences in terms of research and development expenditures of treated firms. Treated firms spend slightly more on R&D than non-treated firms in the post period. The effect is statistically significantly different from zero at the 10% level in 2007 and at the 5% level in 2009. Firms linked to high-exposure banks invest slightly more in tools (Figure 10d), and show higher sales (Figure 10e) in the post-reform period. Also, they expand their wage bill (Figure 10f).



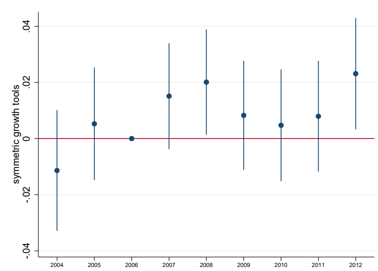
(a) Rating(0/1)



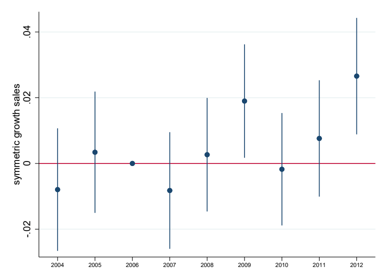
(b) Cash



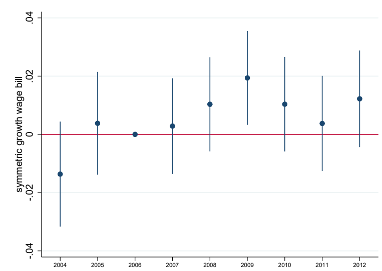
(c) RnD



(d) Tools



(e) Sales



(f) Wage bill

Figure 10: Firm level: Symmetric growth rates

In these figures we show coefficient plots with confidence intervals at 90% from estimating the dynamic regression equation (5) with firm rating as well as symmetric growth rate of cash, research and development (RnD), tools, sales, wage bill, lending to group, stocks, bonds and dividends as dependent variables. Regression results are reported in Table 14 in Appendix B.

4.4 Robustness

We address the concern of confounding demand shocks in our baseline approach by including extensive sets of fixed effects which control for firm loan demand. Also, we control for systemic differences between banks with bank fixed effects. Further, we observe differences between high exposed and low exposed banks which change over time compared to our base 2006q4 in the pre period, and can confirm that for most of our specifications there are no differential effects in the pre period which would violate the parallel trend assumption. 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 discuss 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.

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 18 in Appendix C, 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.

Further, we want to rule out that our results are driven by differences in risk taking behavior ex.ante which might change with the onset of the financial crisis as in Guiso et al. (2018). In Figure 19 in Appendix C we show the correlation of our treatment measure and risk indicators in 2006q4. In particular, in Figure 19a we show the correlation of our treatment measure with total funding costs, in Figure 19b with the changes in funding costs from 2006-2008 and in Figure 19c with funding costs on unsecured debt. Less risk averse banks should have higher funding costs and hence if high exposed 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. There is no correlation with the change of funding costs with 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 19d and 19e, respectively. If high exposed banks were more prudent we expect them to have a lower standard deviation of return on assets. Correlations are close to zero. Further we show correlations with the share of liquid assets and the share of net liquid assets in Figures 19f and 19g, respectively. If high exposed banks were more prudent before we expected 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 bank risk. Banks with a larger share of eligible mortgage loans show lower equity ratios in 2006q4 in Figure 19h. This in fact goes hand-in-hand with the definition of our treatment measure: banks which hold more high quality loans do need to hold less equity. Meanwhile these banks also have lower non-performing loans (NPL) ratios in Figure 19i 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 which might indicate higher risk aversion of high exposed banks: banks with higher share of eligible assets supply on average higher rated firms as can be seen in Figure 19j.

As discussed in Section 3.3, a further confounder of our results could be the transition to Basel II. In panel (c) of Figure 18 in Appendix C, we investigate the correlation with the capital requirement 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.

Throughout our analyses we use a binary indicator for bank exposure to covered bond markets. In a robustness check we use instead our actual continuous treatment measure, the share of eligible mortgages 2006q4, and re-estimate equation (3). We show results in Figure 15 and in Table 15 in Appendix B. The higher the share of low LTV mortgages over total mortgage loans the more banks reduce the share of mortgage loans and increase the share of corporate loans in the post period compared to low exposed banks. Similarly, results hold for financial asset holdings.

5 Inspecting the mechanism

5.1 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 like covered bonds which improves the liquidity of the assets that are subject to potential encumbrance. The bank provides two products that meet creditors' different risk appetites: safe demand deposit contract with non-state contingent return which is backed by encumbered safe assets (call it mortgage lending) and a risky financial security with state-contingent return which is backed by a risky project (call it corporate lending). Ideally, the bank prefers to invest more funds in the risky corporate 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 corporate loans. In equilibrium, the optimal credit allocation of the bank equates the marginal gain from corporate lending by the marginal increase in the risk premium.

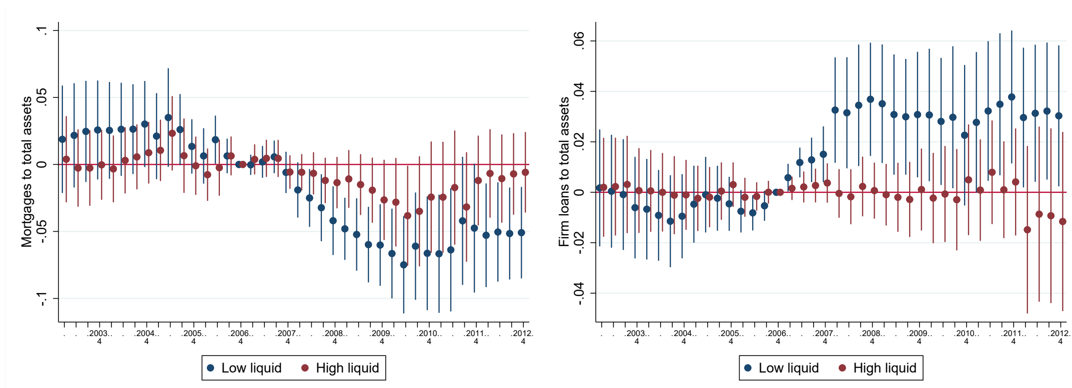
Asset encumbrance technology, such as covered bond, reduces the funding cost of mortgages while also increasing their liquidity. This generates two diverting effects on the optimal credit allocation: on the one hand, there is an *income effect* that encourages the bank to invest more in safer mortgages as the return from mortgage lending increases. However, there is also a *substitution effect* that encourages the bank to engage more in riskier corporate lending. This substitution effect occurs because a more liquid balance sheet reduces the risk premium that depositors charge banks when engaging in corporate lending. If the risk aversion of depositors is very high, the bank would choose to invest more in mortgage lending to reduce asset return volatility and the risk premium, i.e. the income effect dominates. If the risk aversion of depositors is very low, the bank would invest more in risky corporate lending for higher profit. Such effect is particularly strong for low-liquid banks (in our model, low-liquid banks are characterized with higher cost in liquidity management), given that covered bond improves balance sheet liquidity. In the lens of our model, we would therefore expect to see a larger shift from mortgages to corporate loans following the introduction of covered bonds for banks with low initial liquidity. We now turn to test this prediction.

5.2 Heterogeneous effects of the introduction of covered bonds

In order to test the predictions from the model outlined above, we partition banks into two groups based on their 2006q4 ratio of liquid assets to total assets. We then re-estimate equation (3) for the sample of low- and high-liquid banks respectively, using different bank-level portfolio shares as dependent variables.

In Figure 11 we show the result from this exercise, using the share of mortgages (left panel) and corporate loans (right panel). Starting with the left panel, the fraction of mortgages decline for high-exposure banks irrespective of whether we consider the low- or high-liquid sample. In terms of magnitudes, however, the drop is roughly three times the size of banks in the low-liquidity sample. In Table 9 we summarize the average treatment effect over the post-2007q6 period within the low- and high-liquid samples respectively. In the sample of high-liquid banks, the mortgage share decreases by approximately -2.0 percentage points on average. In the low-liquid sample, however, the drop in the mortgage share is approximately -6.5 percentage points on average.

In the right panel, we show the results focusing on corporate 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 increases the corporate lending share by approximately 3.3 percentage points on average. Generally speaking, the larger treatment effects on corporate lending is consistent with the model outlined above.



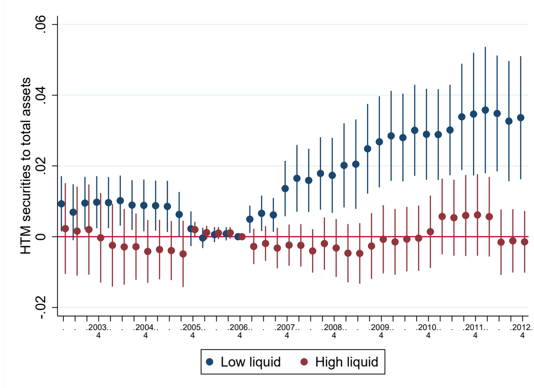
(a) Mortgages over total loans **(b)** Firm loans over total loans

Figure 11: Bank portfolio re-balancing according to liquidity: Lending

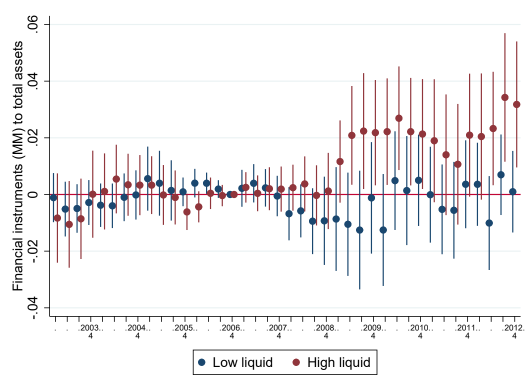
In these graphs we show coefficient plots from re-estimating equation (3) for the sample of low- and high-liquid banks respectively with confidence intervals at 90%.

Next, we consider other assets. Starting with the left panel in Figure 12, we show that high-exposure banks in the low-liquid sample increases HTM financial assets while there is no treatment effect in the high-liquid sample. 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-liquid banks, while high-liquid banks expand their relative holdings of financial instruments marked-to-market.

What can explain the differences in financial asset holdings? One plausible explanation is that the introduction of covered bonds implies a new financial assets that is attractive to invest in, but that firm 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 needs to be defined as held-to-maturity, whereas in the latter case they can be marked-to-market.



(a) HTM financial assets over total assets



(b) MM financial assets over total assets

Figure 12: 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-liquid banks respectively with confidence intervals at 90%.

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)
Corporate 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)

Table 9: 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 on the bank level and are depicted in parentheses. *, **, *** indicate significant coefficients at the 10%, 5%, and 1% level, respectively.

6 Discussion

One remaining question is what are overall implications for the Norwegian banking sector: did covered bonds introduce more risk taking due to more risky firm lending, or do covered bonds contribute to more liquid balance sheets and hence reduce liquidity risk? On the one hand, we find that higher exposure to covered bond markets leads banks to move their lending portfolio away from mortgage lending to riskier corporate lending. Further, the increases in loan supply are tailored towards lower rated firms. This points to higher risk taking of banks. On the other hand, high exposed banks also increase their HTM holdings, improving those banks' market liquidity which enables them for instance to pledge collateral for central bank reserves and allows them to raise more liquidity. In total, it is not clear how overall bank risk evolves, taken all these developments into consideration.

One way to analyze changes in bank risks over time is to examine how banks' funding costs evolve after the introduction of covered bonds, i.e., if one bank becomes riskier, market will require higher risk premium, leading to higher funding cost for the bank. We provide evidence on the evolution of funding costs of banks in Appendix B with Figure 16 and Table 16.

In Figure 16a we show the evolution of mean funding costs for high exposed banks in red and low exposed banks in blue over time. In Figure 16b we show the coefficient plot from estimating equation (3) with interest paid on total funding as dependent variable. Note that we use yearly data as the banks' income statements which we use to construct the funding cost measures are reported at an annual frequency. High exposed banks pay lower funding costs compared to low exposed banks. The negative differential effect is statistically significantly different up to the 1% level in 2011.[8] That is, the possibility to refinance mortgage loans with covered bonds lowers total funding costs of banks. However, do unsecured lenders in the market regard high exposed banks as riskier borrowers, given that these banks also increase lending to firms?

In Figure 16c we plot the mean interest rate paid by banks for subordinated debt. After the introduction of covered bond markets in 2007, there is a wedge building up between the two groups and high exposed banks show on average lower funding costs on subordinated debt. In Figure 16d we show that in fact high exposed banks pay even lower funding costs on subordinated debt compared to low exposed banks and the difference is statistically significantly different from zero at the 5% level in 2008 and 2009.[9] Note that not all banks use subordinated debt in every period, hence the number of observations is reduced.

Taken together, after the introduction of covered bonds market participants ask for lower risk premia from high exposed banks despite their increases in more risky firm lending. We conclude that the relief due to increases in liquid assets more than outweighs the higher risk exposure due to more firm lending. From the point of view of the unsecured creditor, banks issuing more covered bonds became less risky to invest in.

7 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* corporate loans. However not all corporations benefit from the increases in loan supply. In particular, banks tailor new loan supply to ex.ante low rated firms. We further find that banks which were more exposed to the reform and more readily able to issue covered bonds increased their holdings of financial instruments.

We sketched out a model which predicted that banks with low initial liquidity would use the possibility of covered bonds to raise liquidity and use it to extend more risky lending such as corporate lending. The empirical results are consistent with this prediction. Further we traced the increase in firm lending on to the loan and firm level, and found that firms increase their borrowings as a response to the credit supply shock and expand their productive capacity.

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[8] High exposed banks can reduce their total funding costs in the post period compared to low exposed banks by up to 0.21 percentage points. Given that mean funding costs in the pre-period for high exposed banks is 2.73%, the relative reduction corresponds to 7.69% of mean funding costs of high-exposed banks in the pre period.

[9] High exposed banks reduce funding costs on subordinated debt by up to 4.79 percentage points. Given that mean funding costs in the pre period for high exposed banks is 7.79%, the relative decrease corresponds to 61% of mean funding costs of high exposed banks in the pre period.

We conclude that despite the fact that banks increase their exposure to ex.ante more risky borrowers, they also improve their liquidity positions which investors reward with lower funding costs.

Our paper raises several related issues for future research. One is the implication of the covered bond issuance-induced shift to firm loans for bank risk. Another, more broad issue, is whether the impact of covered bond issuance on bank lending differ under different institutional and market setups. As our theoretical model predicts, covered bond issuing banks may also engage in excess mortgage lending and fuel housing boom if the risk in corporate lending is too high. Our paper thus encourages cross-country studies for better understanding how covered bonds influence market outcomes.

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: safe demand deposit contract with non-state contingent return which is backed by encumbered safe assets (call it mortgage lending), a risky financial security with state-contingent return which is backed by a risky project (call it corporate lending). Ideally, the bank prefers to invest more funds in the risky corporate lending for higher expected return, but this increases volatility in asset return as well as risk premium required by investors; such risk premium thus captures the punishment on bank's risk taking. In equilibrium, the bank will invest so much in corporate lending that its marginal gain from corporate lending is just offset by the marginal increase in risk premium.

Asset encumbrance technology, such as covered bond, increases liquidity of mortgage loans, generating two diverting effects on bank's balance sheet: *income effect* that encourages the bank to invest more in mortgage lending, and *substitution effect* that encourages the bank to engage more in riskier corporate 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 constraint; income effect thus dominates. If investors' risk aversion were very low so that the cost of paying risk premium were low, the bank would invest more in risky corporate lending for higher profit, and it would tend to adjust more in lending under tighter liquidity constraint; 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, which is operated by a banker. The bank does not have any initial wealth, but it has a risky investment technology—call it corporate 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 of corporate lending is not known in $t = 0$, and it will only be revealed in $t = 1$. Corporate lending is socially desirable, with Inada condition

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

  In addition, corporate 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 loan 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 loan 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 market, as Bianchi and Bigio (2020) show;

- One early consumer that is born in $t = 0$ with endowment e, and dies after $t = 2$;
- One late consumers that is born in $t = 1$ with endowment e each, and die 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 on 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.[10] More details are provided in the end of Section A.2.

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

$$u_E = u_L = \underline{u} = e + \alpha\overline{k}. \tag{6}$$

Consumers can also deposit in the bank, in order to access the high return from risky corporate lending. The expertise in corporate lending also justifies the role of the bank, 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 the need for liquidity insurance provided by the demand deposit contract, but she

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

also has the 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 corporate lending. To guarantee the repayment of the demand deposit contract, mortgage loan is encumbered to the early consumer; the risky financial security is backed by risky corporate loan. After collecting the funds, e, from early consumer, the bank invests an amount of θ in mortgage lending, and $e - \theta$ in corporate lending;

- In $t = 1$, the state of the world, or return of corporate lending in $t = 2$, is revealed. Early consumer can withdraw from the bank for consumption, including both deposits and return from risky security, and the bank fulfill her withdrawal demand by collecting realized return from the mortgage loan, as well as selling 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 from all assets.

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:

- If it is crisis state, the bank can collect $\theta\lambda r$ return from mortgage, and sell the claim on remaining mortgage loan at price $\theta(1-\lambda)r$ to the late consumer. As the corporate will return 0 in $t = 2$, the bank cannot sell it for any price higher than $s^B = 0$;
- If it is normal state, the bank can collect $\theta\lambda r$ return from mortgage, and sell the claim on remaining mortgage loan at price $\theta(1-\lambda)r$ to the late consumer, and sell the claim on corporate 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

$$\theta r + \alpha\theta r + p\left[s^G + \alpha\left(\overline{k} - \theta r\right)\right] \tag{7}$$

and she will only accept the offer, instead of staying in autarky, if her expected return in (7) exceeds her utility under autarky, (6)

$$\theta r + \alpha\theta r + p\left[s^G + \alpha\left(\overline{k} - \theta r\right)\right] \geq \underline{u}. \tag{8}$$

Solve (8) 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 seize 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 on selling the claim on corporate 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

$$\begin{aligned} \Pi &= pf(e-\theta) - \frac{1}{2}c(\theta r)^2 - p\underline{s}^G \\ &= pf(e-\theta) - \frac{1}{2}c(\theta r)^2 - p\left(\frac{e-\theta r}{p} + \frac{\alpha(1-p)\left(\overline{k} - \theta r\right)}{p}\right) \end{aligned} \tag{9}$$

and to maximize its expected return, its optimal choice in θ is given by the first-order condition of (9)

$$\frac{\partial \Pi}{\partial \theta} = -pf'(e-\theta) - c\theta r^2 + [r + \alpha r(1-p)] = 0 \tag{10}$$

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

The intuition behind our model can be easily seen from Figure 13, that illustrates the early consumer's utility as a function of her state-contingent consumption.[11] 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.

With the bank's investments in mortgage and corporate 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 a risk premium—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 corporate lending for higher return, it will be punished by increasing risk premium arising from higher consumption volatility. In equilibrium, the bank's investment in corporate lending shall be made when the marginal return from corporate lending is just offset by the marginal increase in risk premium.

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

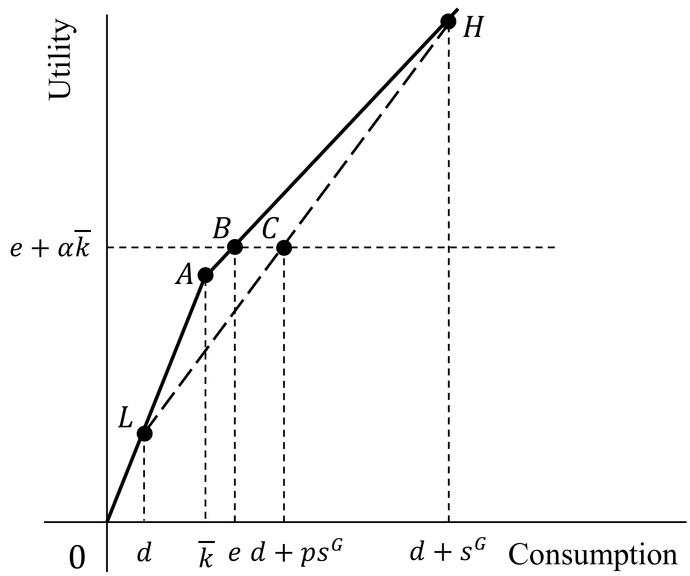


Figure 13: Global risk aversion and risk premium

A.3 Comparative Statics

A.3.1 Portfolio Adjustments

Now we conduct comparative analysis and see how the bank adjust its balance sheet in response to introducing covered bond technology. Covered bond is introduced as a technology that improves the bank's liquidity through a higher return r for the encumbered asset of mortgage loan. This captures the fact that introducing covered bond 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 bond may still increase credit risk in the *unencumbered* asset, as is to be shown below), instead, it increases bank liquidity by achieving lower funding cost (as Ahnert et al. (2018) demonstrate, although we do not explicit model the pricing of encumbered asset here), or, equivalently, higher profit from mortgage loan.

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 A.1. *After introducing covered bond technology,*

1. *The bank invests more in safe, liquid, mortgage lending when consumers are more risk averse, and/or credit risk of corporate lending is high, and/or liquidity creation is not costly;*
2. *The bank invests more in risky, illiquid, corporate lending when consumers are less risk averse, and/or credit risk of corporate lending is low, and/or liquidity creation is costly.*

Proof. Apply the implicit function theorem on the first-order condition (10),

$$\frac{d\theta}{dr} = -\frac{1 + \alpha(1 - p) - 2c\theta r}{pf''(e - \theta) - cr^2}. \tag{11}$$

Given that the denominator, $pf''(e - \theta) - cr^2$, is strictly negative, (11) 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 corporate lending (low p), or liquidity is less costly (low c). Covered bond leads 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 corporate lending (high p), or liquidity is more costly (high c). Covered bond leads to more investments in corporate lending, in order to benefit more from the high yields.

□

Intuitively, given that covered bond technology increases liquidity of mortgage loans, the bank may invest more in safer mortgage lending—call it *income effect*, but it may also invest more in riskier corporate lending—call it *substitution effect*. When 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; income effect dominates in this case. On the contrary, when investors' risk aversion were not high, the bank would find it more profitable to invest in high-yield corporate lending, without incurring too high risk premium; 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 positive liquidity shock must be affected by the efficiency in 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 A.2. *After introducing covered bond technology,*

1. *When consumers are more risk averse, and/or credit risk of corporate 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 more increase is in the bank's investment in safe, liquid, mortgage lending;*
2. *When consumers are less risk averse, and/or credit risk of corporate 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 more increase is in the bank's investment in risky, illiquid, corporate lending .*

Proof. Differentiate equation (11) with c and yield

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

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

- When $1+\alpha(1-p)-2c\theta r>0$ 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 $1 + \alpha(1-p) - 2c\theta r < 0$ so that $\frac{d\theta}{dr} < 0$, $\frac{d^2\theta}{drdc} < 0$ only if

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

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.

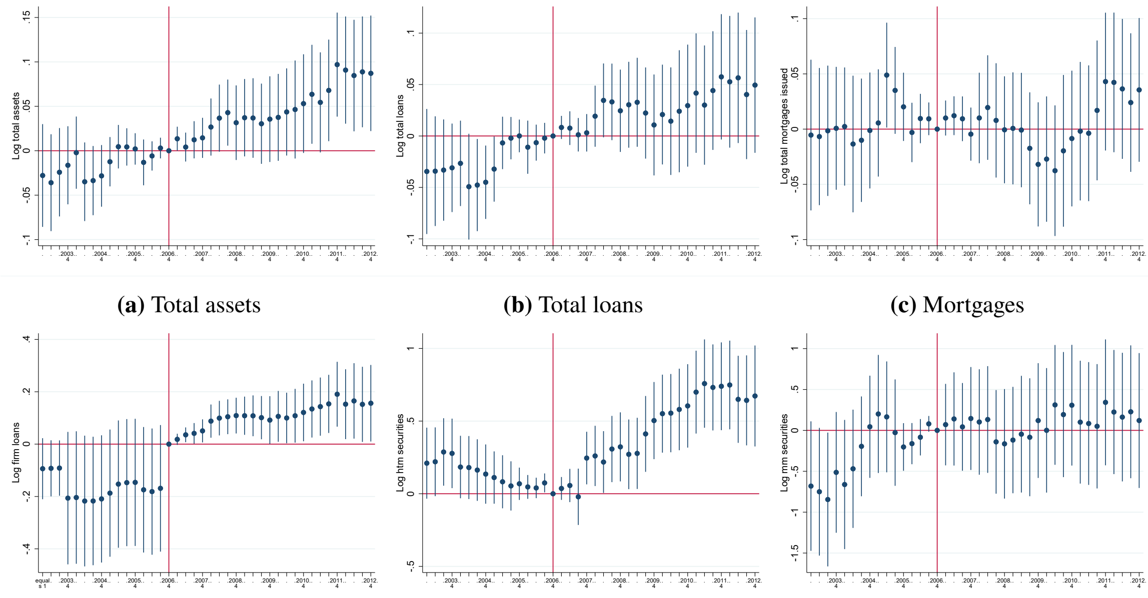
$\square$

B Further results

	$T_b = 0$ (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

Table 10: 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.



(a) Total assets **(b)** Total loans **(c)** Mortgages

(d) Firm loans **(e)** HTM assets **(f)** MM assets

Figure 14: 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 11 reports statistics accompanying the regression output.

Dependent variable	Figure	N observations	N cluster	R2	Mean dependent	SD dependent
Total assets	14a	5,150	133	0.882	14.957	1.409
Total loans	14b	5,150	133	0.859	14.781	1.380
Mortgages	14c	5,150	133	0.867	14.506	1.340
Firm loans	14d	5,150	133	0.357	13.327	1.688
HTM assets	14e	5,150	133	0.351	10.831	1.655
MM assets	14f	5,140	133	0.261	11.447	3.061

Table 11: Regression information corresponding to Figure 14.

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

	(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 12: Loan level: Table of results

This table reports results from estimating equation (4). Columns I-III reports 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 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. 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 on 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
T_b x 2003	0.011	0.028*
	(0.016)	(0.015)
T_b x 2004	-0.009	0.028
	(0.018)	(0.017)
T_b x 2005	-0.020	0.042*
	(0.018)	(0.021)
T_b x 2006	0	0
	(omitted)	(omitted)
T_b x 2007	0.001	0.000
	(0.014)	(0.021)
T_b x 2008	0.036**	0.045**
	(0.015)	(0.019)
T_b x 2009	0.056***	0.031
	(0.019)	(0.021)
T_b x 2010	0.046***	0.011
	(0.013)	(0.022)
T_b x 2011	0.063***	0.011
	(0.019)	(0.020)
T_b x 2012	0.047**	0.020
	(0.019)	(0.014)
Observations	564,073	425,250
R-squared	0.006	0.001
Firm-bank links	86,956	61,298
Firm-bank FE	Yes	Yes
Year FE	Yes	Yes

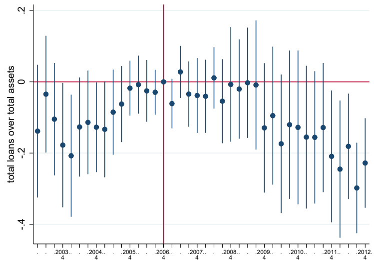
Table 13: Loan level: Table of results for sample split according to firm rating

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). 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 on the bank level and are depicted in parentheses. *, **, *** indicate significant coefficients at the 10%, 5%, and 1% level, respectively.

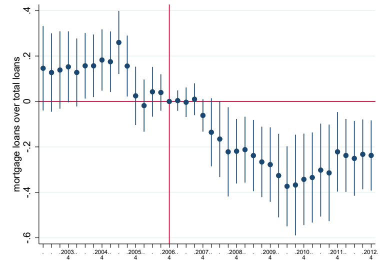
	(I) Rating	(II) Rating(0/1)	(III) Cash	(IV) RnD	(V) Tools	(VI) Sales	(VII) Wage bill
T_f x 2003	-0.013	-0.004					
	(0.012)	(0.007)					
T_f x 2004	-0.006	-0.001	-0.015	-0.001	-0.011	-0.008	-0.014
	(0.011)	(0.006)	(0.016)	(0.003)	(0.013)	(0.011)	(0.011)
T_f x 2005	-0.004	0.003	-0.004	0.002	0.005	0.003	0.004
	(0.009)	(0.005)	(0.017)	(0.002)	(0.012)	(0.011)	(0.011)
T_f x 2006	0	0	0	0	0	0	0
	(omitted)	(omitted)	(omitted)	(omitted)	(omitted)	(omitted)	(omitted)
T_f x 2007	-0.014*	-0.005	-0.018	0.004*	0.015	-0.008	0.003
	(0.008)	(0.005)	(0.016)	(0.002)	(0.011)	(0.011)	(0.010)
T_f x 2008	-0.007	-0.006	-0.029*	0.002	0.020*	0.003	0.010
	(0.010)	(0.005)	(0.015)	(0.002)	(0.011)	(0.010)	(0.010)
T_f x 2009	-0.005	-0.011*	-0.047***	0.004**	0.008	0.019*	0.019**
	(0.011)	(0.006)	(0.015)	(0.002)	(0.012)	(0.010)	(0.010)
T_f x 2010	-0.013	-0.007	-0.018	0.002	0.005	-0.002	0.010
	(0.011)	(0.006)	(0.015)	(0.002)	(0.012)	(0.010)	(0.010)
T_f x 2011	-0.032***	-0.015**	-0.041***	0.001	0.008	0.008	0.004
	(0.012)	(0.006)	(0.015)	(0.002)	(0.012)	(0.011)	(0.010)
T_f x 2012	-0.037***	-0.019***	-0.056***	-0.001	0.023*	0.027**	0.012
	(0.012)	(0.006)	(0.015)	(0.002)	(0.012)	(0.011)	(0.010)
Observations	933,746	933,746	845,388	848,552	848,422	846,722	835,055
R-squared	0.026	0.030	0.004	0.000	0.002	0.010	0.010
Number of firms	130,661	130,661	128,992	129,074	129,070	129,033	128,774
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 14: Firm-level: Table of results

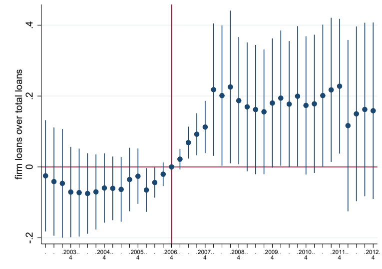
This table reports results from estimating equation (5) with firm rating and symmetric growth rates of balance sheet and profit& loss positions of firms. T_f equals 1 if the firm had at least one link to a treated bank in 2006. The regressions include firm and time fixed effects. Robust standard errors are clustered on the firm level and are depicted in parentheses. *, **, *** indicate significant coefficients at the 10%, 5%, and 1% level, respectively



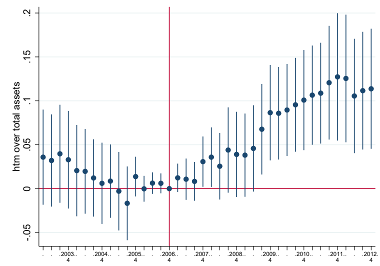
(a) Total loans over total assets



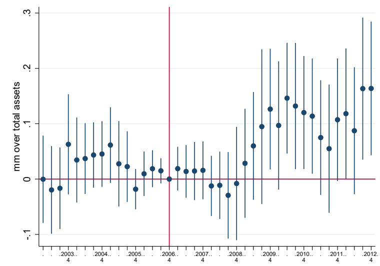
(b) Mortgages over loans



(c) Firm loans over loans



(d) HTM over total assets



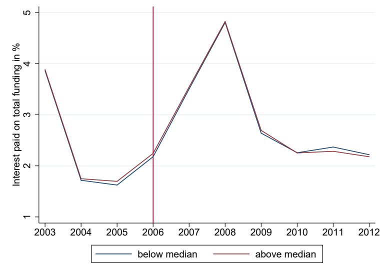
(e) MM over total assets

Figure 15: Bank-level: continuous treatment measure

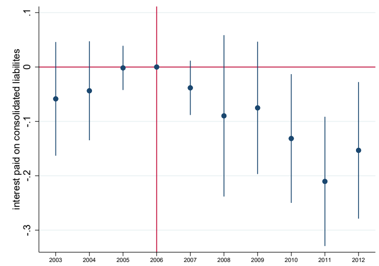
In these figures we show coefficient plots with confidence intervals at 90% from estimating the dynamic regression equation (3) with the continuous treatment measure Ratio of low LTV mortgages over total mortgages, 2006q4. Table 15 reports statistics accompanying the regression output.

Dependent variable	Figure	Observations	N cluster	R2	Mean dependent	SD dependent
Total loans over total assets	15a	5,148	133	0.357	0.843	0.081
Mortgages loans over total loans	15b	5,150	133	0.260	0.773	0.128
Firm loans over total loans	15c	5,150	133	0.076	0.260	0.102
HTM over total assets	15d	5,150	133	0.036	0.026	0.028
MM over total assets	15e	5,150	133	0.350	0.063	0.046

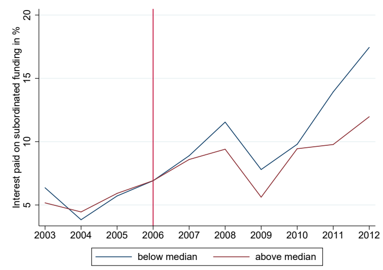
Table 15: Regression information corresponding to Figure 15.



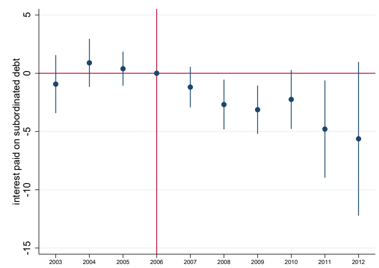
(a) Interest paid on total funding



(b) Interest paid on total funding



(c) Interest paid on subordinated funding



(d) Interest paid on subordinated funding

Figure 16: Bank-level: funding costs

In this figure we show mean total funding costs and the mean funding costs on subordinated debt 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) with funding costs as dependent variable with annual data. Table 16 reports the regression output.

	(1) Interest costs on total funding	(2) Interest costs on subordinated funding
T_b x 2003	-0.059	-0.934
	(0.063)	(1.490)
T_b x 2004	-0.044	0.896
	(0.055)	(1.239)
T_b x 2005	-0.002	0.389
	(0.025)	(0.874)
T_b x 2006	0	0
	(omitted)	(omitted)
T_b x 2007	-0.038	-1.188
	(0.030)	(1.045)
T_b x 2008	-0.090	-2.684**
	(0.090)	(1.280)
T_b x 2009	-0.075	-3.129**
	(0.073)	(1.244)
T_b x 2010	-0.131*	-2.245
	(0.071)	(1.514)
T_b x 2011	-0.210***	-4.791*
	(0.072)	(2.497)
T_b x 2012	-0.153**	-5.626
	(0.076)	(3.949)
Observations	1,251	421
R-squared	0.931	0.432
Number of banks	133	59
Bank FE	Yes	Yes
Year FE	Yes	Yes

Table 16: Bank-level: Table of results for funding costs

This table reports results from estimating equation (3) with yearly data. Column I reports results with interest paid on total funding as dependent variable. Column II reports results with 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 on the bank level and are depicted in parentheses. *, **, *** indicate significant coefficients at the 10%, 5%, and 1% level, respectively.

C Additional figures

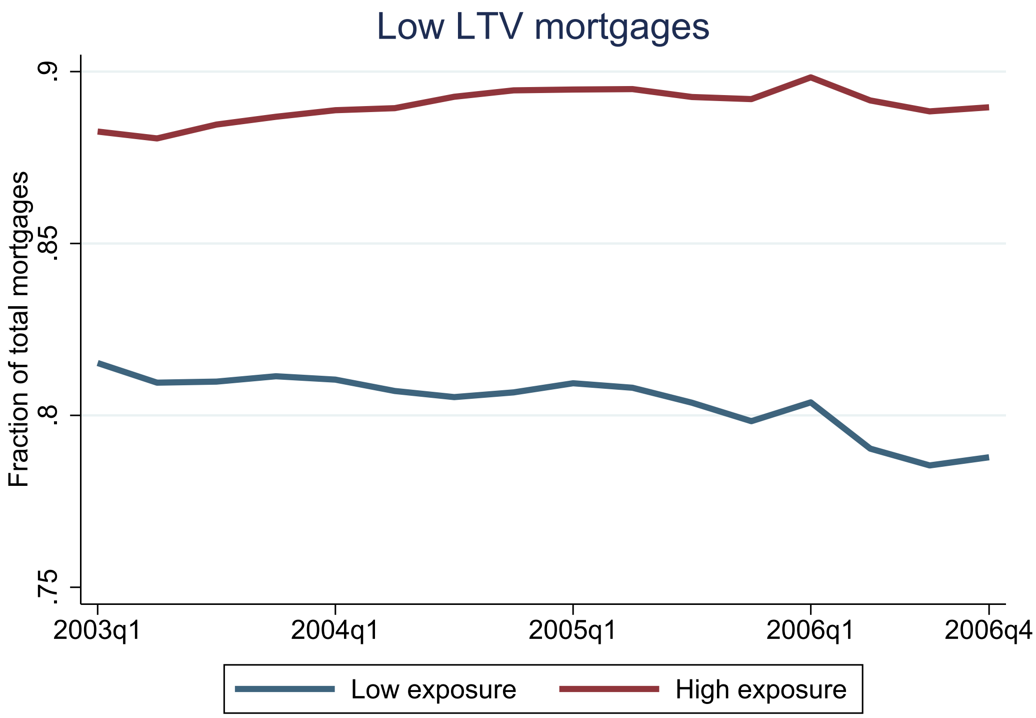
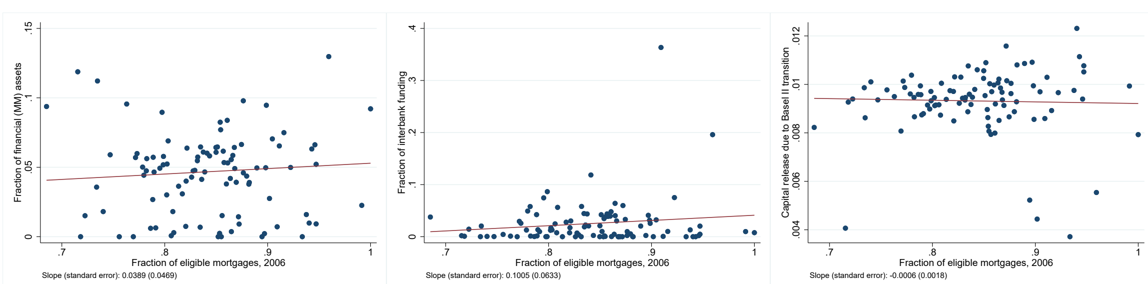


Figure 17: LTV-persistence

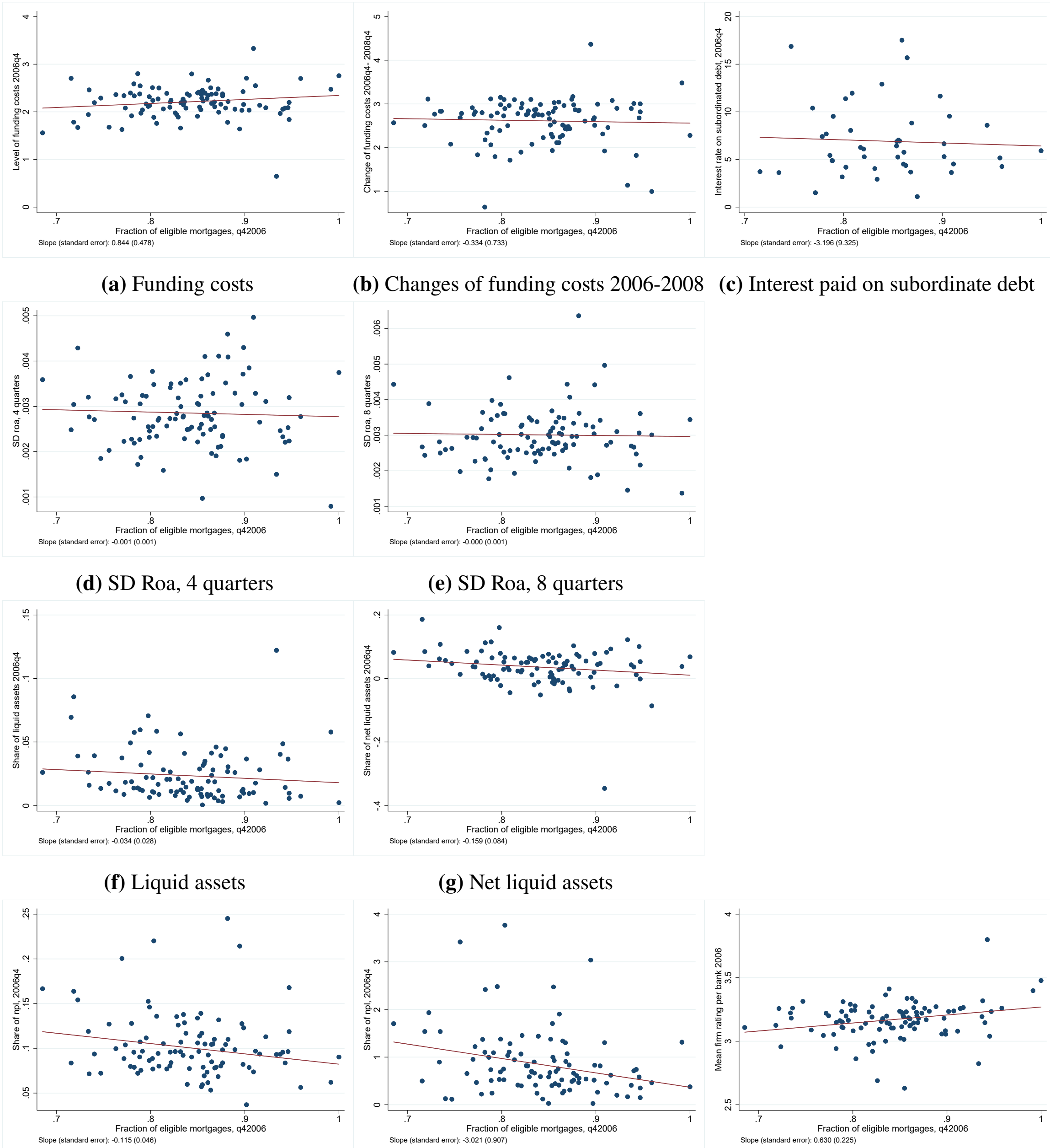
In this figure we show the evolution of low-LTV mortgages relative to total mortgages for high- and low-exposed banks.



(a) Financal instruments **(b)** Interbank borrowing **(c)** Capital requirement reduction

Figure 18: 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) Funding costs **(b)** Changes of funding costs 2006-2008 **(c)** Interest paid on subordinate debt

(d) SD Roa, 4 quarters **(e)** SD Roa, 8 quarters

(f) Liquid assets **(g)** Net liquid assets

(h) Equity ratio **(i)** NPL ratio **(j)** Mean firm rating

Figure 19: 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 of interest paid on total funding from 2006q4- 2008q4, (c) interest paid on subordinated funding, (d) standard deviation of return on asses (Roa) over past four quarters, (e) over past eight quarters, (f) share of liquid assets ((MM assets + central bank reserves)/ total assets), (g) share of net liquid assets (((MM assets + central bank reserves) - interbank borrowings - certificates)/ total assets), (h) equity ratio, (i) ratio of non-performing loans, (j) mean borrowers' rating.

References

Ahnert, Toni, Kartik Anand, Prasanna Gai, and James Chapman, "Asset encumbrance, bank funding, and fragility," *Review of Financial Studies*, September 2018, *32* (6), 2422–2455.

Banal-Estanol, Albert, Enrique Benito, and Dmitry Khametshin, "Asset encumbrance and CDS premia of European banks: Do capital and liquidity tell the whole story?," in Colin Mayer, Stefano Micossi, Marco Onado, Marco Pagano, and Andrea Polo, eds., *Finance and Investment: The European Case*, Oxford: Oxford University Press, 2018, chapter 21.

Bianchi, Javier and Saki Bigio, "Banks, liquidity management and monetary policy," *Econometrica*, 2020, p. forthcoming.

Carbó-Valverde, Santiago, Richard J Rosen, and Francisco Rodríguez-Fernández, "Are covered bonds a substitute for mortgage-backed securities?," *Journal of Economic Policy Reform*, 2017, *20* (3), 238–253.

Chakraborty, Indraneel, Itay Goldstein, and Andrew MacKinlay, "Housing price booms and crowding-out effects in bank lending," *Review of Financial Studies*, 07 2018, *31* (7), 2806–2853.

Dang, Tri Vi, Gary Gorton, Bengt Holmström, and Guillermo Ordoñez, "Banks as secret keepers," *American Economic Review*, April 2017, *107* (4), 1005–1029.

Degryse, Hans, Olivier De Jonghe, Sanja Jakovljević, Klaas Mulier, and Glenn Schepens, "Identifying credit supply shocks with bank-firm data: Methods and applications," *Journal of Financial Intermediation*, 2019, *40*, 100813.

European Covered Bond Council, *ECBC: European Covered Bond Fact Book 2020*, European Covered Bond Council, 2020.

Finance Norway, *Norwegian Covered Bonds*, Finance Norway, 2018.

Garcia-Appendini, Emilia, Stefano Gatti, and Giacomo Nocera, "Covered bonds, asset encumbrance and bank risk: Evidence from the European banking industry," 2017, pp. mimeo, Audencia Business School.

Gorton, Gary and George Pennacchi, "Banks and loan sales Marketing nonmarketable assets," *Journal of Monetary Economics*, 1995, *35* (3), 389–411.

Guiso, Luigi, Paola Sapienza, and Luigi Zingales, "Time varying risk aversion," *Journal of Financial Economics*, 2018, *128* (3), 403–421.

Hirshleifer, Jack, "The private and social value of information and the reward to inventive activity," *American Economic Review*, 1971, *61* (4), 561–574.

International Monetary Fund, "Global financial stability report: Transition challenges to stability," Global Financial Stability Report October 2013, International Monetary Fund 2013.

Jiménez, Gabriel, Atif Mian, José-Luis Peydró, and Jesús Saurina, "The real effects of the bank lending channel," *Journal of Monetary Economics*, 2020, *115*, 162–179.

Juelsrud, Ragnar E. and Elif C. Arbatli-Saxegaard, "Countercyclical capital requirement reductions, state dependence and macroeconomic outcomes," Working Paper 9/2020, Norges Bank 2020.

Khwaja, Asim Ijaz and Atif Mian, "Tracing the impact of bank liquidity shocks: Evidence from an emerging market," *American Economic Review*, 2008, *98* (4), 1413–1442.

Kragh-Sorensen, K and H Solheim, "What do banks lose money on during crises?," *Norges Bank Staff Memo 3/2014*, 2014.

Nicolaisen, Jon, "Covered Bonds and their impact on investors, banks and the real economy," 2017.

NOU, "Finanskriseutvalget," 2011.