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Covered bonds and bank portfolio rebalancing

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Covered bonds and bank portfolio rebalancing ^{*}

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Abstract

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

Keywords: Asset encumbrance; Covered bond; Portfolio rebalancing; Liquidity management

JEL Classification: G21, G23, G28

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1 Introduction

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

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

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

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

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

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

bond issuance on bank portfolios at a granular level.

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

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

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

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

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

effect also varies with initial bank liquidity. Banks with low initial liquidity have stronger incentives to switch to firm loans when the mortgage portfolio becomes more liquid. We then return to the data and show support for our theoretical model: The observed portfolio rebalancing from mortgage loans to firm loans is indeed driven by banks with low initial liquidity as well as by banks with relatively low initial firm credit risk.

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

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

Focusing on banks' encumbrance choice, Ahnert et al. (2018) show that asset encumbrance allows banks to raise cheaper funding through secured debt. At the same time, however, it reduces banks' scope for repaying unsecured creditors out of unencumbered assets in the event of market stress, increasing the likelihood of bank failure. Using cross-country data with more than 100 listed banks in Europe over 2004-2013, Garcia-Appendini et al. (2017) find that a bank's default risk is positively correlated with its covered bond

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

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

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, a higher asset encumbrance ratio relates to lower spreads in banks' credit default swaps (CDS).

Our main contribution to the literature is to document how covered bond issuance affects bank portfolios, considering a wide set of outcomes and what the overall implications for bank risk are. Our results highlight an interesting tension between the effects of covered bond issuance on credit risk and liquidity risk: on the one hand credit risk increases in line with [Ahnert et al. \(2018\)](#) and [International Monetary Fund \(2013\)](#), whereas on the other hand liquidity risk decreases. As a result, the implications of covered bond issuance for overall bank risk are ambiguous. When focusing on the risk premium on unsecured bond funding, we show that overall risk declines despite an increase in credit risk. The empirical findings are therefore consistent with the seemingly different views in [Ahnert et al. \(2018\)](#) and [Garcia-Appendini et al. \(2017\)](#) versus [Banal-Estanol et al. \(2018\)](#).

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

2 Institutional background

A covered bond is a debt security issued by banks or mortgage companies that is collateralized by a pool of assets ("cover pool"). Mortgage companies are owned by banks and its sole purpose is the issuance of covered bonds. Specifically, when a bank initiates the issuance of a covered bond, the cover pool is transferred from the bank to the mortgage company, which then issues the covered bond.⁵ A covered bond and the underlying cover pool is subject to three important types of restrictions. First, the quality of the underlying collateral must be high. Mortgage loans that are included in the cover pool must have sufficiently low loan-to-value (LTV) ratios. The value of the assets in the cover pool must exceed the face value of the covered bond itself, i.e. covered bonds are over-collateralized. Second, the cover pool is dynamic: if the quality of certain assets in the covered pool deteriorates and violates the quality requirements, the issuer must replace these assets by other eligible assets or cash. Third and finally, if the issuer goes bankrupt throughout the maturity of a covered bond, the covered bond holders can seize the asset pool and recover their claims. If the liquidation value of the cover pool is not enough to satisfy their claims, the covered bond holders have further recourse against the issuer's remaining assets with a higher seniority than other uninsured creditors. As covered bond investors have recourse against both the cover pool and the issuer's other assets, they have *dual recourse*.

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

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

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

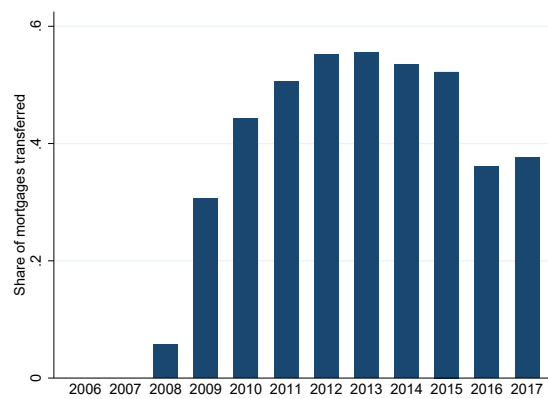


Figure 1: Share of total mortgages transferred

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

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

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

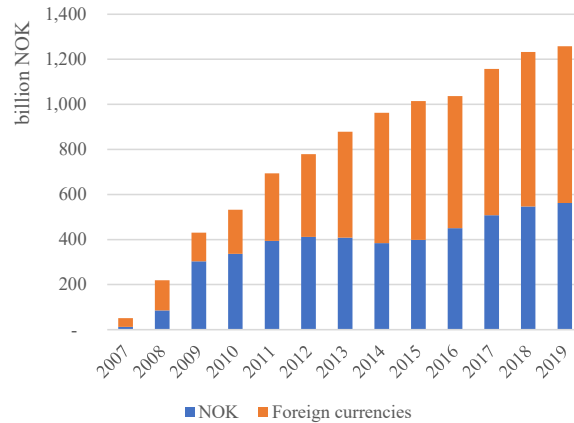


Figure 2: Outstanding debt and currency decomposition of Norwegian covered bonds

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

Although the swap arrangement only lasted until October 2009, covered bond issuance continued to increase substantially. As Figure 2 shows, the rapid growth in covered bond issuance after 2008 was largely driven by demand from foreign investors. After the end of our sample period, covered bond issuance has continued to experience fast growth. As at 2020q3, covered bonds outstanding in Norway amount to 143 billion euros, equivalent to 43 % of Norwegian GDP.

3 Data and methodology

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

3.1 Data

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

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

⁷Nine banks enter the market during our sample period.

constructing our treatment indicator, as highlighted in Section 3.2. Table 1 reports summary statistics at the bank-time level.

	N	Mean	Sd	Min	Median	Max
<i>Logs</i>						
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
<i>Ratios</i>						
Total loans over total assets	5,148	0.843	0.081	0.301	0.861	0.997
Mortgage loans over total assets	5,150	0.654	0.123	0.044	0.676	0.954
Mortgage loans over total loans	5,150	0.773	0.128	0.051	0.793	1.000
Firm loans over total assets	5,150	0.218	0.084	0.000	0.209	0.810
Firm loans over total loans	5,150	0.260	0.102	0.000	0.251	0.935
HTM over total assets	5,150	0.026	0.037	0.000	0.014	0.329
MM over total assets	5,150	0.063	0.027	-0.005	0.059	0.314
Net liquidity over total assets	5,135	0.053	0.078	-0.553	0.056	0.386
Balance sheet liquidity over total assets	5,150	-0.324	0.074	-0.648	-0.324	-0.046
<i>Interest income</i>						
Mean interest on firm lending in %, yearly	1,006	5.890	0.699	3.140	5.909	7.720
Ratio interest firm over interest other lending, yearly	1,006	1.269	0.221	0.545	1.250	2.130
<i>Funding costs</i>						
Interest paid on total funding in %, yearly	1,251	2.723	1.049	0.57	2.399	6.307
Interest paid on subordinated funding in %, yearly	421	8.178	5.149	0.398	6.947	46.057
<i>Profitability</i>						
Net interest margin, yearly	1,251	0.020	0.006	0.001	0.020	0.040

Table 1: Summary statistics at 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. We define net liquidity over total assets as the share of net liquid assets over total assets as (marked-to-market (MM) assets + central bank reserves - interbank borrowings - certificates) / total assets. We define balance sheet liquidity over total assets as the negative of Berger and Bouwman (2009)'s definition of liquidity creation. We use Berger and Bouwman (2009)'s definition and adapt it to the availability of our balance sheet data. Illiquid assets encompass firm loans, intangible HTM assets, HTM owner assets and other assets. Liquid assets are assets at the central bank, HTM bonds, other HTM assets, and MM assets. Illiquid liabilities are subordinated debt and equity. Liquid liabilities are deposits and deposits from the central bank. We add the sum of illiquid assets and the sum of liquid liabilities with weights of 0.5 and subtract the sum of liquid assets and illiquid liabilities with weights of 0.5. We divide by total consolidated assets and multiply the index by -1. We estimate the interest on total funding costs in % as the share of interest costs over total liabilities, and the interest on subordinated funding in % as interest costs on subordinated funding over total subordinated debt. We truncate interest paid on subordinated debt at the 1st and the 99th percentile per year due to outliers and set negative values to missings. ⁸

Our second data source is loan-level data obtained from the Norwegian Tax Administration. By the end of each year, all banks report all outstanding loan and deposit accounts to the tax administration for tax purposes.

⁸We consolidate balance sheet positions from banks with their mortgage companies on the basis of the share of mortgage transfers to the mortgage company. As this is only an approximation of the exact positions, it might be that the sum of average ratios exceeds 1. In two instances, total loans over total assets exceeded 1. We set these two observations to missing.

In total, we observe 3,885,845 firm-account-bank-year observations, based on 250,545 limited liability firms.⁹ 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 at 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 _{loan>0}	457,962	1.566	1.950	1.000	1.000	310.000
Symmetric credit growth ($\Delta L_{b,f,t}$)	1,355,289	-0.067	0.710	-2.000	0.000	2.000
Interest rate ($i_{b,f,t}$, in %)	401,673	6.614	3.595	0.000	6.166	35.473

Table 2: Summary statistics at 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 the symmetric growth rate of credit as dependent variable, defined as

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

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

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

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

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 1st and the 99th percentile.

Our third and final data source is firm-level data from a major credit rating agency on all major balance sheet items and other information on the universe of Norwegian limited liability firms. We add information on firm age, rating and balance sheet variables to investigate the role of firm characteristics in explaining banks' potential change in credit allocation following the introduction of covered bonds. We exclude financial firms. Table 3 shows summary statistics. We merge 130,661 firms (933,746 firm-year observations). The median firm has total assets of approximately NOK 2,782,000¹⁰, is 10 years old and has a A rating.¹¹ 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).

⁹Limited liability firms represent the vast majority of the Norwegian private sector. In most of the years in our sample, these firms employ roughly 90 % of the private sector labor force.

¹⁰Approximately USD 324,000. 1 USD = 8.58 on 5 March, 2021.

¹¹AAA (coded as 1) is the top rating a firm can achieve, while C (coded as 5) is the worst rating.

	N	Mean	Sd	Min	p50	Max
<i>Size and Age</i>						
Assets (in 1000s of NOK)	933,746	42,270.250	1,563,833	0.000	2,782.000	5.84×e ⁸
Age	933,738	13.71379	13.00164	0.000	10.000	169.000
<i>Rating</i>						
Rating (AAA:5 - C:1)	933,746	3.278	0.991	1.000	3.000	5.000
Rating(0/1)	933,746	0.425	0.494	0.000	0.000	1.000

Table 3: Summary statistics at 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 % ("low LTVs") were eligible for being transferred to the cover pool. As a result, banks with different initial distributions of LTVs in their mortgage portfolios had different scope for issuing covered bonds. As described in Section 3.1 we observe the breakdown of the volume of mortgages with an LTV below and above 80 %. We use this information to approximate the fraction of loans for each bank below the regulatory threshold of 75 %. We construct a treatment indicator equal to 1 for banks that had a share of low LTV mortgages over total mortgages that is above the median of all banks in the quarter before the covered bond introduction (2006q4), i.e. $T_b = 1$. We set $T_b = 0$ for all other banks and refer to them as "low-exposure banks" or "other banks" throughout the text.¹² On average, 84.2 % of mortgages on banks' balance sheets have low LTVs. Banks that we define as high-exposure had on average 89.2 % low LTV mortgages, while other banks had on average 79.2 % low LTV mortgages in 2006q4. In line with Callaway et al. (2021), we also use the continuous ratio of low LTV mortgages over total mortgages as the treatment measure in a robustness exercise and show that the results remain qualitatively similar. Table 4 shows summary statistics on our treatment indicators.

	N	Mean	Sd	Min	Median	Max
T_b (treatment indicator at <i>bank level</i>)	5,150	0.496	0.500	0.000	0.000	1.000
Share of mortgages transferred to mortgage companies, 2007-2012	3,048	0.106	0.140	0.000	0.038	0.869
Ratio of low LTV mortgages over total mortgages, 2006q4	133	0.842	0.064	0.662	0.850	1.000
Ratio of low LTV mortgages over total mortgages, 2006q4, $T_b = 1$	67	0.892	0.039	0.850	0.876	1.000
Ratio of low LTV mortgages over total mortgages, 2006q4, $T_b = 0$	66	0.792	0.039	0.662	0.799	0.844
T_b (treatment indicator at <i>loan level</i>)	1,355,289	0.880	0.325	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 and for 275,323 firm-bank links.

Note that our treatment definition does not exclude the possibility that low-exposure banks issue covered bonds. We merely capture the fact that high-exposure banks could more readily issue covered bonds due to the availability of eligible mortgages on their balance sheets. Hence, we capture the difference in the intensity

¹²Note that we slightly overestimate the share of eligible mortgages for *all* banks in our sample and hence introduce a slight measurement error in T_b .

of exposure to the introduction in covered bonds. To illustrate this difference, we show in Figure 3 the fraction of mortgages transferred to the cover pools for high-exposure banks and other banks, respectively. By 2011, the fraction of mortgages transferred by high-exposure banks was approximately 70 % larger compared with other banks.

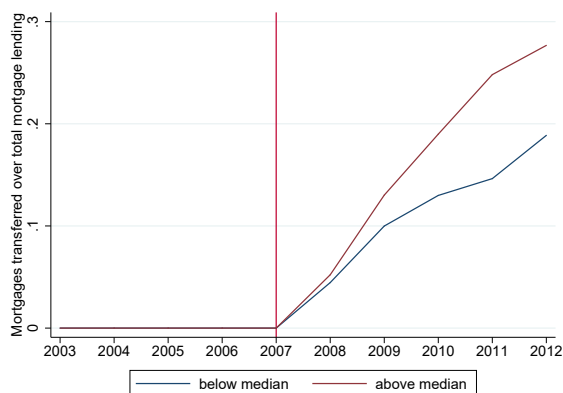


Figure 3: Share of mortgages transferred for high-exposure and low-exposure banks

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

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

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

	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

Table 5: Share of eligible mortgages predict mortgage transfers

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

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

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

3.2.2 Bank level

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

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

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

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

3.2.3 Loan level

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

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

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

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

3.3 Threats to identification

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

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

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

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

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

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

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

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

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

A final potential confounding credit supply shock is the transition to Basel II. The transition to Basel II

took place in 2007, and entailed for most banks a reduction in average risk-weights, applied to retail loans and mortgages with a low LTV. This could then imply that there was also a larger reduction in the effective capital requirement for banks that were high-exposure according to our measure and that this relative reduction in the capital requirement is driving our results. The largest absolute reduction in risk weights for banks computing risk weights under the standard method was for retail firm loans.¹³ As a robustness check, we therefore use balance sheet information and actual changes in risk weights to compute—bank by bank—the actual reduction in the capital requirement due to the Basel II transition. We can then correlate the capital requirement reduction with our treatment measure to investigate whether banks that were more exposed to the Basel II transition were also more exposed to the introduction of covered bonds.

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

4 Results

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

4.1 Results on portfolio rebalancing

4.1.1 Credit at bank level

We start by comparing the evolution of credit at the bank level, and show the main results at this level of aggregation in Figure 4 and Figure 5. Accompanying statistics of the regression output are listed 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 decreased the share of lending to total assets, while the decline was largest for high-exposure banks. The coefficient plot from estimating equation (3) in Figure 4b highlights that the relative reduction is statistically significant: high-exposure banks show a statistically significantly lower ratio of total loans over total assets compared to

¹³The risk weight on loans in the retail portfolio was lowered from 100 % to 75 %. The risk weight on mortgages with an LTV below 80 % was reduced from 50 % to 35 %.

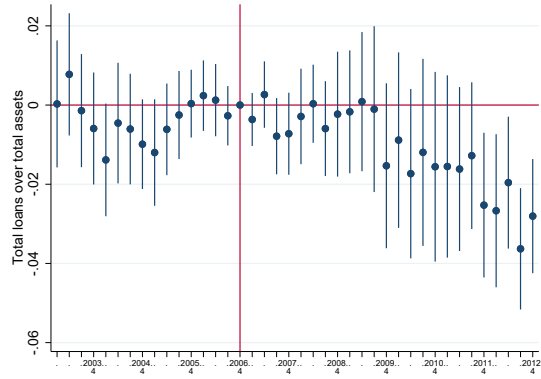
other banks in the post period from 2011q4 onward, whereas there are no differences in the pre period. The relative reduction in loans over assets for high-exposed banks is not driven by a reduction in total lending; there is even a mild relative increase in total lending as we show in Figure B.1b in Appendix B. The reduction is rather due to a relative increase in total assets, as we highlight in Figure B.1a. By issuing covered bonds, high-exposure banks expand their balance sheets relative to other banks.

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

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



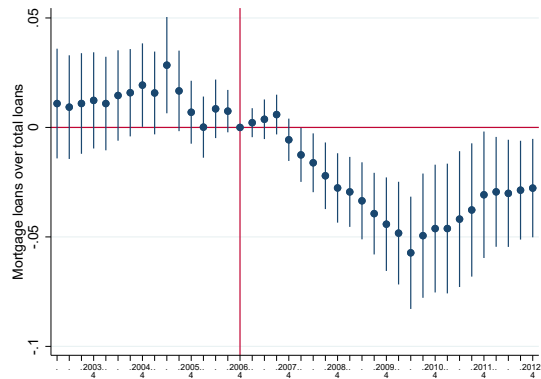
(a) Total loans over total assets



(b) Total loans over total assets



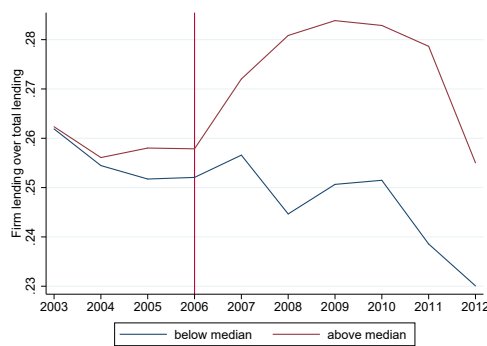
(c) Mortgages over total loans



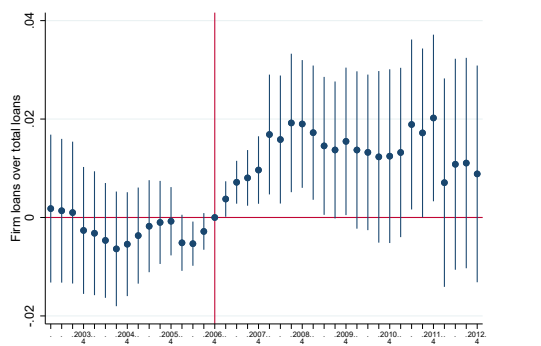
(d) Mortgages over total loans

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

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



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

Dependent variable	Figure	N	No. of banks	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.

4.1.2 Credit at loan level

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

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

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

Finally we follow Khwaja and Mian (2008) and introduce firm-year fixed effects for the sample of firms borrowing from multiple banks. In Figure 6d we show the corresponding coefficient plot. There are no differences between the two groups in the pre period. Although our estimates become more imprecise,

we still observe a positive difference between the two groups for the post-treatment year 2008, which is statistically significantly different from zero at the 10 % level. In terms of economic magnitude, the effect becomes stronger compared with the estimates for the full sample. Specifically, loan growth increase by 0.052 for high-exposure firm-bank pairs compared with loan growth for other firm-bank pairs. Given that for high-exposure firm-bank pairs in this sub-sample the average symmetric growth rate in the pre-reform period is -0.059, we observe again a substantial relative increase of the loan growth rate.

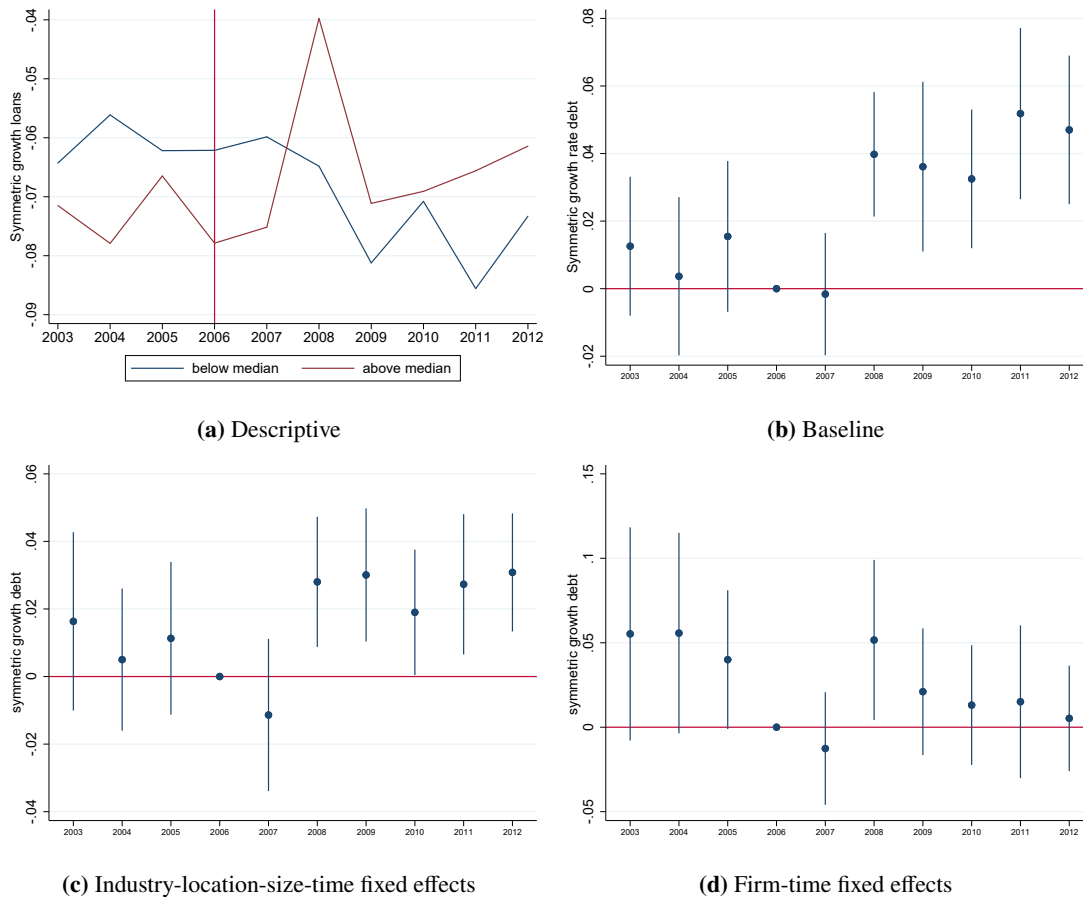


Figure 6: Changes on loan growth on the loan level.

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

To investigate whether banks changed their pricing behavior, we next examine the impact of being linked to a high-exposure bank on the proxied interest rate. In Figure 7a we show the development of interest rates for high-exposure firm-bank pairs and other firm-bank pairs over time. The raw data suggest that firms paid slightly lower interest rates after 2009 if the loan stemmed from a high-exposure bank. In Figure 7b we show the coefficient estimates from estimating equation (4) with our proxy for the interest rate as dependent variable. We can see a slight move towards lower interest rates for loans from high-exposure banks. The estimates, however, are somewhat imprecise, and we cannot reject the null hypothesis that the coefficients are

zero. As before, we follow [Degryse et al. \(2019\)](#) and introduce industry-location-size-time fixed effects and plot the corresponding coefficients in [Figure 7c](#). Again, we see a negative difference between the two groups in the post-reform period, but the difference is imprecisely measured. Finally, we proceed by introducing firm-time fixed effects as in [Khwaja and Mian \(2008\)](#). [Figure 7d](#) shows the corresponding coefficient plot. The results are in line with the previous findings.

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

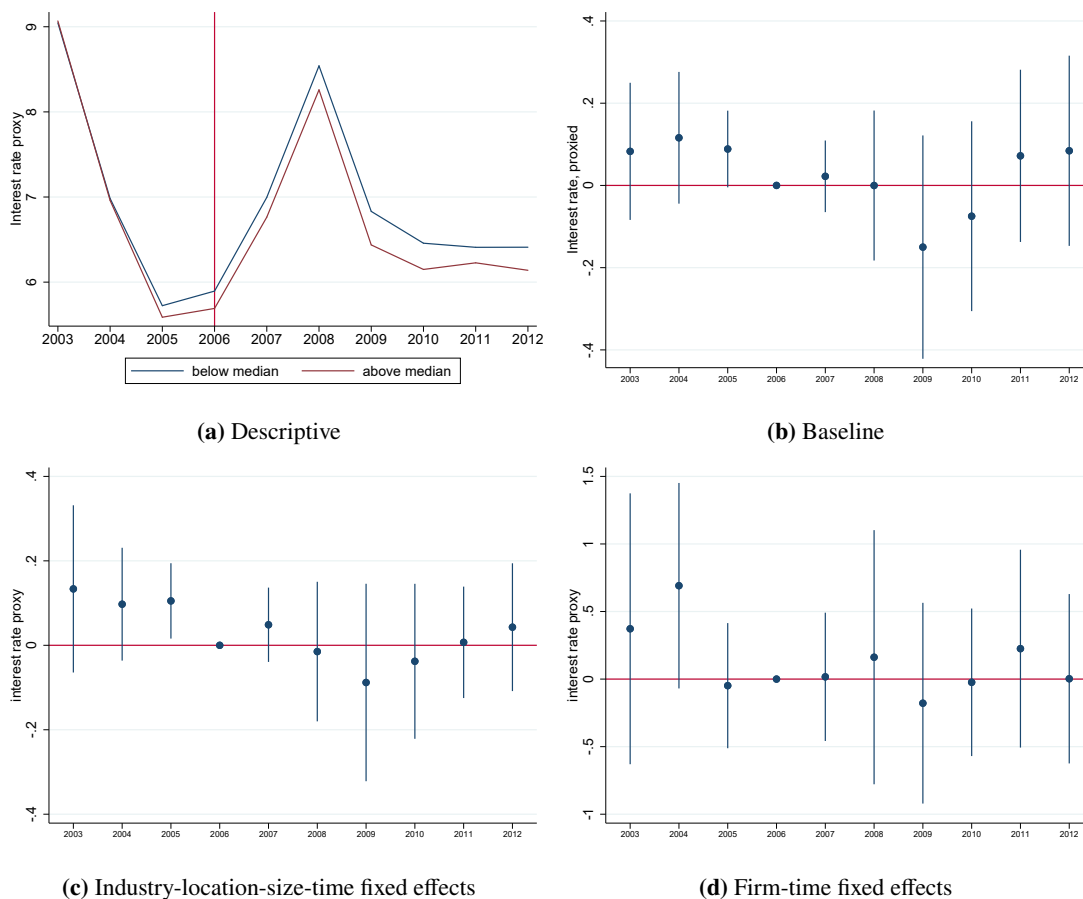


Figure 7: Changes in interest rate proxy at the loan level.

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

Low-rated and young firms obtain more lending Next, we assess whether the increase in firm credit is uniform across all firms or driven by a subset of firms. Two important dimensions for understanding the heterogeneous impact of credit supply expansions in the existing literature are firm risk and firm age ([Gertler and Gilchrist, 1994](#); [Holmström and Tirole, 1997](#)). We therefore group the firms in our sample according to

firm rating and firm age in 2006. We define a firm as low-rated if it has a rating of A or below (A, B, or C), and a firm as high-rated if it has a rating of AA or AAA. We define a firm as young if it has an age below or equal to the median firm age (eight years), and a firm as old if it has an age above the median. We re-estimate equation (4) for the sample of low- and high-rated firms, as well as young and old firms separately, using the symmetric growth rate of loans as dependent variable.

In Figure 8 we show coefficient plots and in Table B.4 in Appendix B regression results. In Figure 8a we show that for the sample of low-rated firms there is a positive differential effect between high-exposure and low-exposure banks from 2008 and onward, which lasts until the end of the sample period and amounts to up to 0.063. For ex ante high-rated firms, there is a significant difference in 2008, which levels off quickly. As we show in Table 7, the symmetric growth rate of debt on average increases by 0.05 for ex ante low-rated firms that borrow from high-exposure banks compared with other banks. Given that the average growth rate for all treated firm-bank pairs in the pre period is -0.073, the differential effect between high- and low-exposure banks of 0.05 is again substantial. For the sample of high-rated firms the average differential effect is close to zero.

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

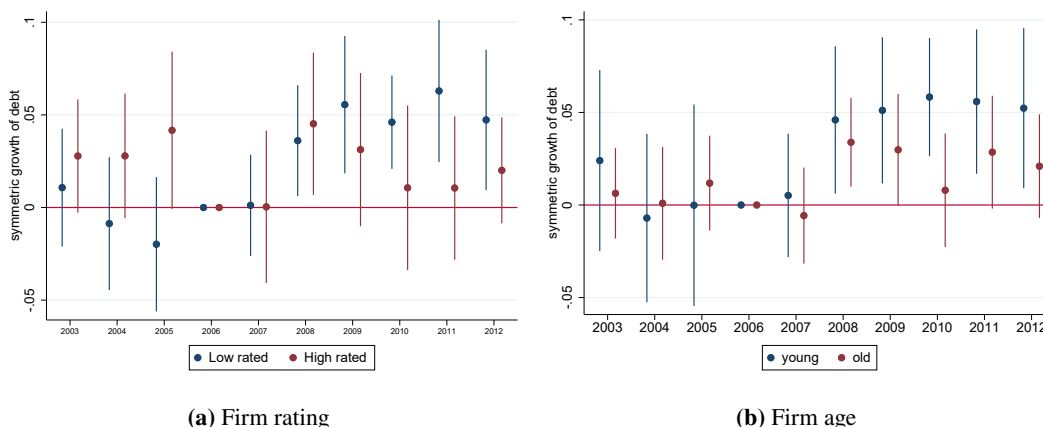


Figure 8: Changes in loan growth at the loan level conditional on firm rating and age.

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

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

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

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

4.1.3 Asset liquidity at bank level

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

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

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

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

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

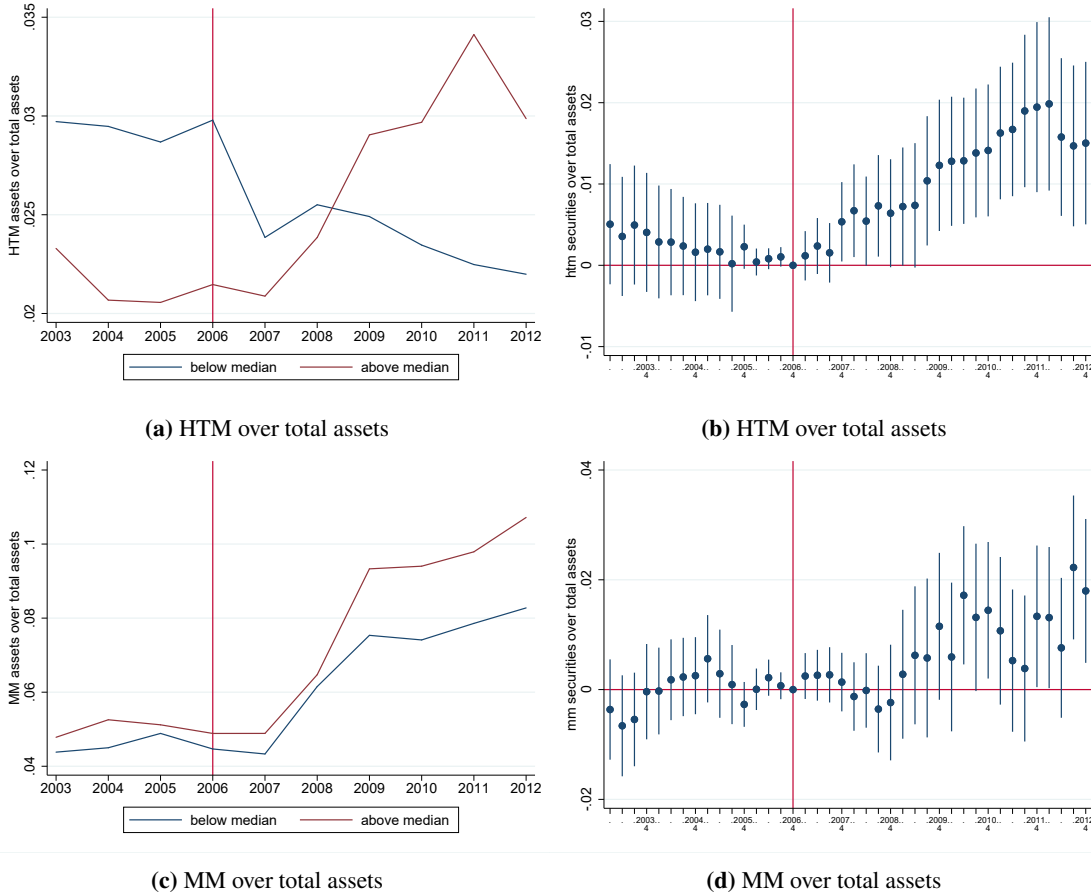


Figure 9: Bank portfolio re-balancing: Financial assets

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

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

Table 8: Regression information corresponding to Figure 9.

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

4.2 Results on bank balance sheet liquidity, risk and profitability

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

Liquidity versus credit risk Covered bonds can increase banks' funding liquidity as covered bonds are a source of long-term funding, as well as market liquidity as they allow banks to raise cash. To get a comprehensive view of the overall liquidity position of the banks in our sample, we use [Berger and Bouwman \(2009\)](#)'s definition of liquidity creation, which encompasses both the liquidity of assets and liabilities. We take the negative of this index as a measure of banks' overall balance sheet liquidity. In [Figure B.3a](#) we plot the average balance sheet liquidity for high-exposure banks in red and other banks in blue. Both groups of banks increase their balance sheet liquidity after the introduction of covered bonds. In [Figure B.3b](#) we show the coefficient plot from estimating equation (3) with balance sheet liquidity as dependent variable. Though both groups increase balance sheet liquidity, there is a relative increase for high-exposure banks especially after 2009.¹⁴

While balance sheet liquidity improves, we also document that covered bond issuance increases credit risk. It is therefore not clear how *overall* bank risk evolves. The risk premia asked by unsecured creditors provides us with an indication of the market's perception of overall bank risk. In [Figure B.3c](#) we plot the average interest rate paid by banks for subordinated debt.¹⁵ After the introduction of covered bonds in 2007, we see a wedge building up between the two groups, with high-exposure banks showing on average lower funding costs on subordinated debt. In [Figure B.3d](#) we show results from estimating equation (3) with interest paid on subordinated debt as dependent variable. High-exposure banks pay lower funding costs on subordinated debt compared with other banks and the difference is statistically significantly different from zero at the 5 % level in 2008 and 2009.¹⁶ We conclude that covered bond issuance reduces bank risk, suggesting that any positive effects from increased balance sheet liquidity offset any potential increase in credit risk due to more firm lending.

Bank profitability Finally, covered bonds have sizable effects on bank profitability. In [Figure B.3e](#) we show the evolution of average total funding costs over time and in [Figure B.3f](#) the coefficient plot from estimating equation (3) with interest paid on total funding as dependent variable. Covered bonds lower funding costs on secured debt, and as we have shown in the previous paragraph also on subordinated debt. This is reflected in the evolution of total funding costs: High-exposure banks pay lower total funding costs compared with other banks. The negative differential effect is statistically significantly different up to the 1 % level in 2011.¹⁷

In [Figure B.3g](#) we assess net interest margins defined as net interest income over total assets as a measure of banks' profitability. Net interest margins decrease for both groups, but less so for high-exposure banks. In fact, there is a mild positive differential effect as we show in [Figure B.3h](#).¹⁸

¹⁴High-exposure banks increase balance sheet liquidity compared with low-exposure banks by up to 0.03 percentage points. Given that mean balance sheet liquidity for high exposed banks in the pre period is -0.34, the relative increase corresponds to 8.8 % of the latter.

¹⁵Note that yearly data such as the banks' income statements that we use to construct the funding cost measures are reported in annual frequency and that not all banks use subordinated debt in every period, hence the number of observations is reduced.

¹⁶High-exposure banks reduce funding costs on subordinated debt compared with other banks by up to 4.79 percentage points. Given that mean funding costs in the pre period for high-exposure banks is 5.70 %, the relative decrease corresponds to 84 % of the latter.

¹⁷High-exposure banks reduce their total funding costs in the post period compared with other banks by up to 21 basis points. Given that average funding costs in the pre-period for high-exposure banks is 2.38 %, the relative reduction corresponds to 8.8 % of the latter.

¹⁸High-exposure banks increase their net interest margin in the post period compared with low-exposure banks by up to 0.001. Given that mean interest margins in the pre-period for high-exposure banks is 0.022, the relative increase corresponds to 4.5 % of the latter.

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

4.3 Inspecting the mechanism

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

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

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

Asset encumbrance technology, such as covered bonds, reduces the funding cost of mortgages while also increasing their liquidity. This generates two diverting effects on the optimal credit allocation: on the one hand, there is an *income effect* that encourages the bank to invest more in safer mortgages as the return from mortgage lending increases. However, there is also a *substitution effect* that encourages the bank to engage more in riskier firm lending due to the enhanced balance sheet liquidity. This liquidity effect occurs because a more liquid balance sheet reduces the risk premium that depositors charge banks when engaging in firm lending. If the risk aversion of depositors is very high and/or firm risk is high, the bank would choose to invest more in mortgage lending to reduce asset return volatility and the risk premium, i.e. the return effect dominates. If the risk aversion of depositors is very low and/or firm risk is sufficiently low, the bank would invest more in risky firm lending for higher profit. Such effect is particularly strong for banks with low initial liquidity. In the lens of our model, we would therefore expect to see a larger shift from mortgages to firm loans following the introduction of covered bonds for banks with low initial liquidity. We refer to this testable hypothesis as H1.

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

The bank in our model balances the trade-off between higher returns and higher funding costs when considering the optimal firm lending share. On the one hand, a higher firm lending share would increase bank profits due to higher yields. On the other hand, more firm lending would increase the risk premium the bank is charged by its depositors. If the existing firm lending is sufficiently safe, the former effect dominates the latter

in our model and we would therefore expect that banks with initially safer borrowers would have stronger incentives to reallocate their portfolio towards firm lending. We refer to this testable hypothesis as H2.

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

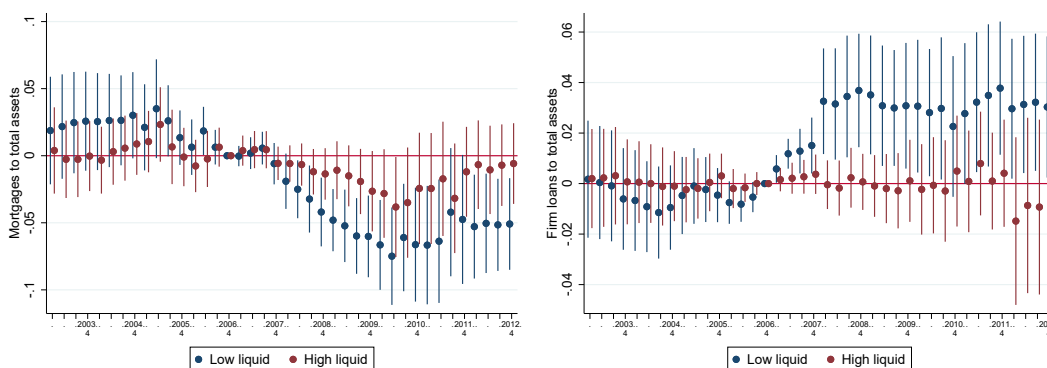
We now turn to test these predictions.

4.3.2 Heterogeneous effects of the introduction of covered bonds

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

In Figure 10 we show the result from this exercise, using the share of mortgages (left panel) and firm loans (right panel). Starting with the left panel, the fraction of mortgages declines for high-exposure banks irrespective of whether we consider the low- or high-liquidity sample. In terms of magnitudes, however, the drop is roughly three times the size for banks in the low-liquidity sample. In Table 9 we summarize the average treatment effect over the post-2007q6 period within the low- and high-liquidity samples respectively. In the sample of high-liquidity banks, the mortgage share decreases by approximately -2.0 percentage points on average. In the low-liquidity sample, however, the drop in the mortgage share is approximately -6.5 percentage points on average.

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



(a) Mortgages over total loans

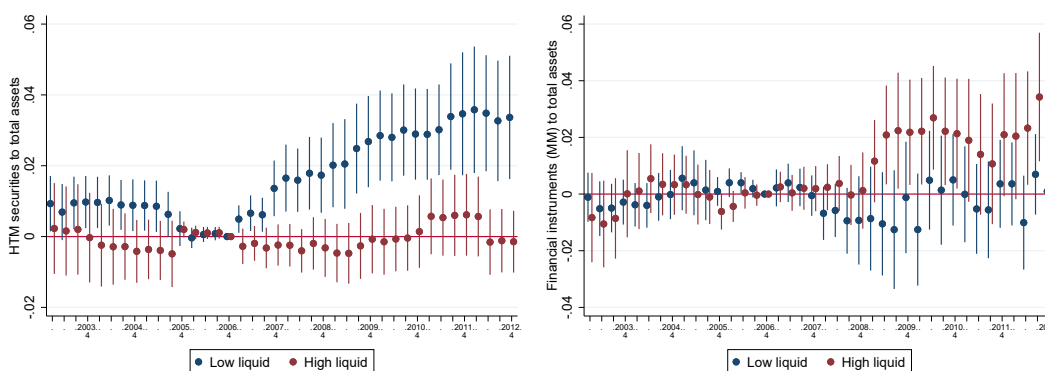
(b) Firm loans over total loans

Figure 10: Bank portfolio re-balancing according to liquidity: Lending

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

Next, we consider other assets. Starting with the left panel in Figure 11, we show that high-exposure banks in the low-liquid sample increase HTM financial assets, while there is no treatment effect in the high-liquidity sample. This qualitative difference is completely switched when focusing on financial assets that are marked-to-market. In this case, there is no treatment effect for low-liquidity banks, while high-liquidity banks expand their relative holdings of financial instruments marked-to-market.

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



(a) HTM financial assets over total assets

(b) MM financial assets over total assets

Figure 11: Bank portfolio re-balancing according to liquidity: Financial assets.

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

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

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

H2: Credit risk A second testable prediction of our model is that banks are more likely to switch to firm lending when the returns from doing so are high. In our model, the bank is risk-neutral, so a higher marginal return on firm credit would incentivize banks to engage more in firm lending. In fact, for most banks and in most time periods, firm lending is more profitable than mortgage lending. In 92 % of bank-year observations the approximated interest rate on firm lending is higher than on other lending.¹⁹ Further, according to SSB

¹⁹We approximate the average interest rate on firm lending per bank from our loan-level data set as in equation (2) and average over all firm-bank observations per bank in 2006. We derive interest on all other lending by subtracting total interest paid by firms per bank

(Statistics Norway) the average interest rate margin on loans to non-financial corporations between 2014q1 and 2021q1 was 2.22 % and while it was 1.60 % on mortgages, which also reflects higher yields on firm lending on average. However, according to our model, banks have to balance higher yields from firm lending with higher funding costs due to higher risk premia. We examine prediction *H2* from our model that banks rather turn to firm lending if credit risk is relatively low. We measure credit risk according to interest yield on firm lending and divide our sample at the median.

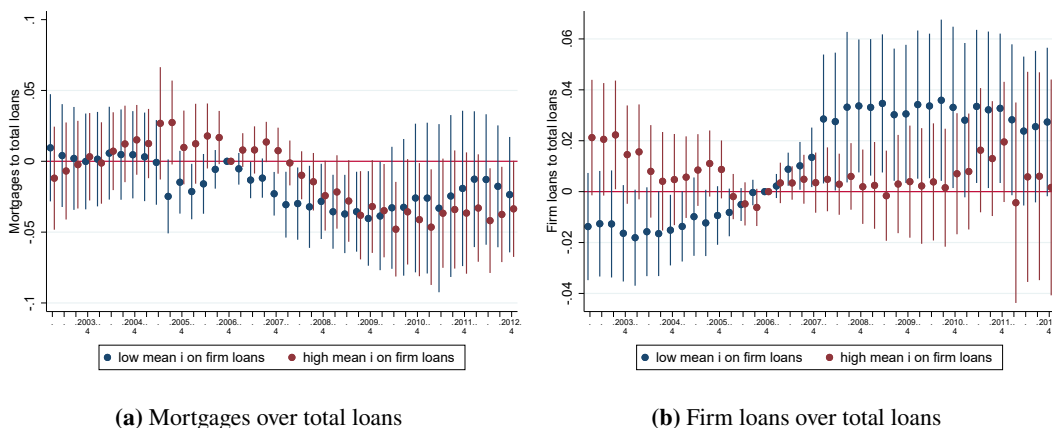


Figure 12: Bank portfolio re-balancing according to credit risk and profitability of firm lending

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

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

Table 10: Summarizing portfolio rebalancing across banks

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

We show in blue in Figure 12a that banks with low firm yields decrease the share of mortgages over total lending quicker than banks with high firm yields. However, when taking averages over the whole post period, banks with high firm yields reduce mortgage lending by -1.3 percentage points more than banks with low firm yields, as can be seen in Table 10. Nevertheless, we show in Figure 12b that the increase in firm lending following the introduction of covered bonds is driven by banks with initially lower yields on firm loans. On average, these banks increase the share of firm lending by 3.9 percentage points as reported in Table 10, whereas banks with high-yield firm loans do not increase firm lending. We conclude that banks with lower initial credit risk have more credit risk capacity and hence increase firm lending to more risky borrowers as a response to the introduction of covered bonds.

from total interest income from loans in banks' income statements and divide it by total lending minus total firm lending.

4.4 Robustness

We address the concern of confounding demand shocks in our baseline approach at the loan level in Section 4.1.2 by including an extensive sets of fixed effects in our regression estimations to control for firm loan demand. Also, we control for systemic differences between banks with bank fixed effects in estimations at the bank level. Further, we observe whether differences between high-exposure and other banks change in the pre period, and can confirm that for most of our specifications the empirical evidence is consistent with parallel trends in the pre period. However, the analysis above cannot exclude the possibility that there are potentially other confounding *supply-side* (e.g. bank) shocks that affect our results. In Section 3.3 we discussed three potential concerns: exposure to the ongoing financial crisis, changes in relative risk aversion due to the financial crisis, and exposure to the capital requirement reduction due to the transition to Basel II. Below, we show the robustness of our results to these potentially confounding factors. Finally, we also present results with a continuous treatment measure in line with Callaway et al. (2021).

Exposure to the financial crisis To investigate the correlation between our treatment measure and the exposure to the financial crisis, we compute a bank's ratio of marked-to-market financial instruments to total assets and the ratio of interbank borrowing to total assets in 2006q4. These measures are aimed at capturing the two main channels of exposure to the financial crisis, as discussed in Section 3.3. In panels (a) and (b) of Figure C.2 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.

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

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

There is only a mild negative correlation with net liquid assets.

Finally, we present three further measures to gauge the correlation between our treatment measure and bank risk. Banks with a larger share of eligible mortgage loans show lower equity ratios in 2006q4 in Figure C.3h. This in fact goes hand-in-hand with the definition of our treatment measure: banks that hold more high-quality loans do need to hold less equity. Meanwhile these banks also have lower non-performing loan (NPL) ratios in Figure C.3i, which also reflects the fact that they have more high-quality mortgage loans on their balance sheets. According to these two indicators, banks seem on the one hand less risk-averse due to lower equity ratios, but on the other hand more risk-averse due to lower NPL ratios. There is only one indicator that might indicate higher risk aversion for high-exposure banks: banks with a higher share of eligible assets supply on average higher-rated firms, as can be seen in Figure C.3j.

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

Continuous treatment measure Throughout our analyses we use a binary indicator to measure banks' exposure to the introduction of covered bonds. For robustness, we use our actual continuous treatment measure, the share of eligible mortgages 2006q4, and re-estimate equation (3) in line with Callaway et al. (2021). We show the results in Figure B.2 and in Table B.5 in Appendix B. The results are consistent with the results in the preceding paragraphs.

5 Conclusion

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

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

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

Appendices

A Model

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

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

A.1 Agents, preferences, and technologies

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

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

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

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

The bank also has a safe investment technology—call it mortgage lending: for one unit investment in $t = 0$, the gross return from mortgage lending is r , $r \geq 1$, but only a share of λ ($0 < \lambda < 1$) returns in $t = 1$, and the rest $1 - \lambda$ returns in $t = 2$. Liquidity creation by issuing mortgage loans is costly—for example, the bank has to exert effort in screening through loan applications—so that the bank incurs a

convex cost of $\frac{1}{2}c\phi^2$, $c > 0$ being a constant, for mortgage loans with face value ϕ . c thus captures the bank's cost efficiency in liquidity management. For instance, in reality, banks with tighter liquidity constraints usually have higher c , as these banks rely more on costly funding from interbank markets, as [Bianchi and Bigio \(2020\)](#) show;

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

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

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

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

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

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

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

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

$$u_L = c_{L1} + c_{L2} + \alpha \min \{c_{L2}, \bar{k}\}.$$

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

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

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

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

- In $t = 0$, the early consumer deposits her endowment in the bank, and the bank gives her a “take-it-or-leave-it” offer that includes a fixed, demand deposit contract and a risky financial security with state-contingent return. Here we should interpret the consumer of our economy rather as a *representative* consumer: she has a need for liquidity insurance provided by the demand deposit contract, but she also

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

has a need for higher return from risky financial investment. To fulfill its agreement with the early consumer, in $t = 0$, the bank invests in a portfolio that consists of safe mortgage lending and risky firm lending. To guarantee the repayment of the demand deposit contract, the mortgage loan is encumbered to the early consumer; the risky financial security is backed by a risky firm loan. After collecting the funds, e , from the early consumer, the bank invests an amount of θ in mortgage lending, and $e - \theta$ in firm lending;

- In $t = 1$, the state of the world, or return on firm lending in $t = 2$, is revealed. The early consumer can withdraw funds from the bank for consumption, including both deposits and return on the risky security, and the bank meets her withdrawal demand by collecting the realized return on the mortgage loan, as well as selling the early consumer's other claims to the late consumer who enters the market: suppose the bank does so by giving the late consumer a “take-it-or-leave-it” offer.
- In $t = 2$, the late consumer is repaid by the bank using collected returns on all assets.

A.2 Equilibrium Analysis

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

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

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

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

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

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

Solve (A.3) for the security price

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

Since the bank is assumed to have full bargaining power in its “take-it-or-leave-it” offer and seizes all the rent,

the equilibrium price must be

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

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

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

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

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

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

The intuition behind our model can be easily seen in Figure A.1, which illustrates the early consumer’s utility as a function of her state-contingent consumption.²¹ Liquidity preference gives her higher marginal utility on consumption from 0 to \bar{k} —the OA part in her utility curve with a slope of $\alpha > 1$, and her marginal utility is lower for consumption exceeding \bar{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 firm lending in $t = 0$, in $t = 1$, the early consumer receives a fixed return from deposit contract $d = \theta r$, plus $s^G > 0$ in good state (with total consumption as point H shows) or $s^B = 0$ in bad state (with total consumption as point L shows), and point C denotes her expected consumption, $d + ps^G$. In order to induce the consumer to provide funding, the bank must ensure her expected utility is as least as high as her utility under autarky, implying that a risk premium—the distance between B and C—must be incurred to compensate the consumer. As a result, although the bank is willing to invest in more risky firm lending for higher return, it will be punished by increasing risk premia arising from higher consumption volatility. In equilibrium, the bank’s investment in firm lending should be made when the marginal return from firm lending is just offset by the marginal increase in risk premium.

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

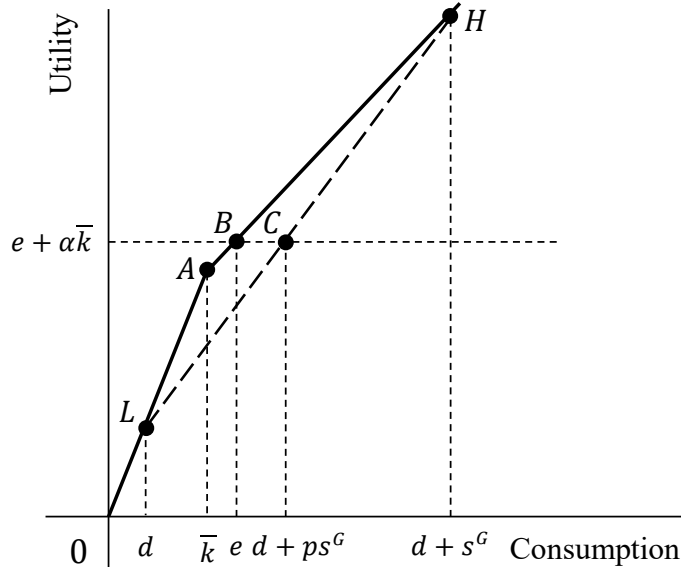


Figure A.1: Global risk aversion and risk premium

A.3 Comparative statics

A.3.1 Portfolio Adjustments

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

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

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

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

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

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

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

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

□

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

A.3.2 Sensitivity analysis

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

Proposition A.2. *After introducing covered bond technology,*

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

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

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

Given that the denominator is positive and the first term in the 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

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

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.

□

B Further results

	$T_b = 0$ (low exposure)		$T_b = 1$ (high exposure)		Difference	Std. error	t-statistic	p-value
	N	Average	N	Average				
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 B.1: Summary statistics of bank level variables in the pre-reform period 2003-2006

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

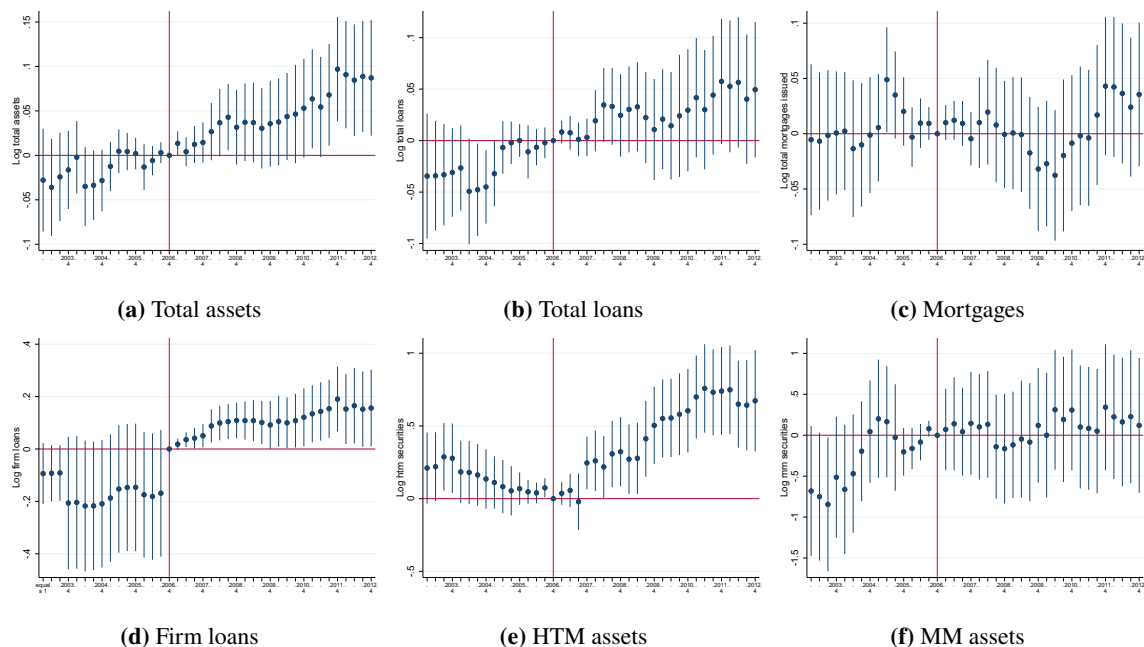


Figure B.1: Bank-level: Logs

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

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

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

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

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

Table B.3: Loan level: Table of results

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

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

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

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

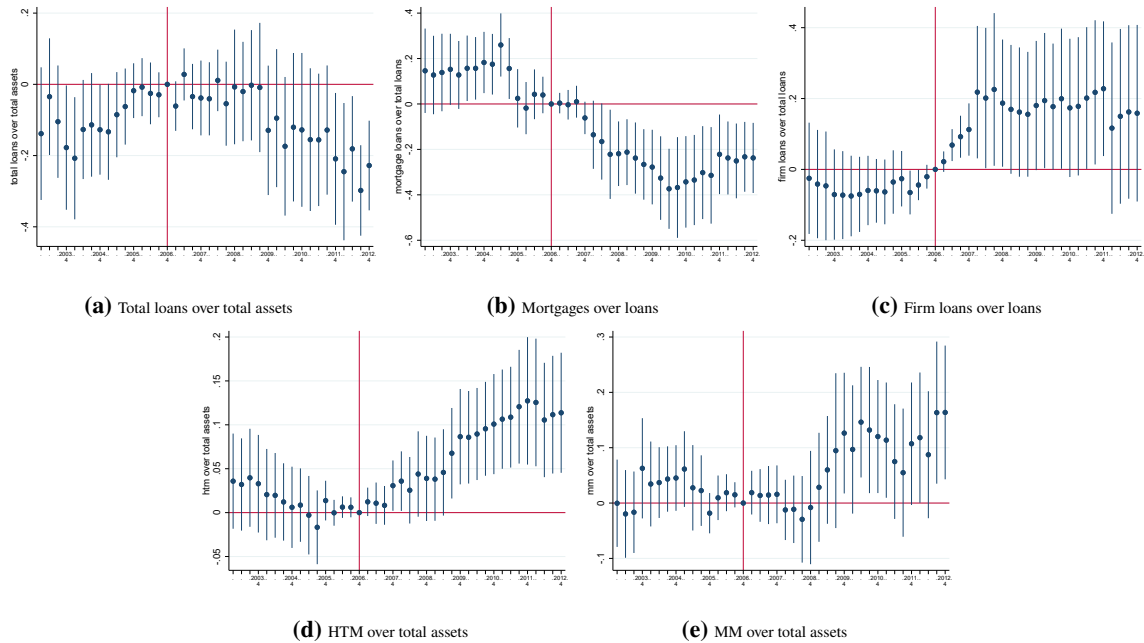


Figure B.2: Bank-level: continuous treatment measure

In these figures we show coefficient plots with confidence intervals at 90 % from estimating the dynamic regression equation (3) with the continuous treatment measure Ratio of low-LTV mortgages over total mortgages, 2006q4. Table B.5 reports statistics accompanying the regression output.

Dependent variable	Figure	Observations	N cluster	R2	Mean dependent	SD dependent
Total loans over total assets	B.2a	5,148	133	0.357	0.843	0.081
Mortgages loans over total loans	B.2b	5,150	133	0.260	0.773	0.128
Firm loans over total loans	B.2c	5,150	133	0.076	0.260	0.102
HTM over total assets	B.2d	5,150	133	0.036	0.026	0.028
MM over total assets	B.2e	5,150	133	0.350	0.063	0.046

Table B.5: Regression information corresponding to Figure B.2.

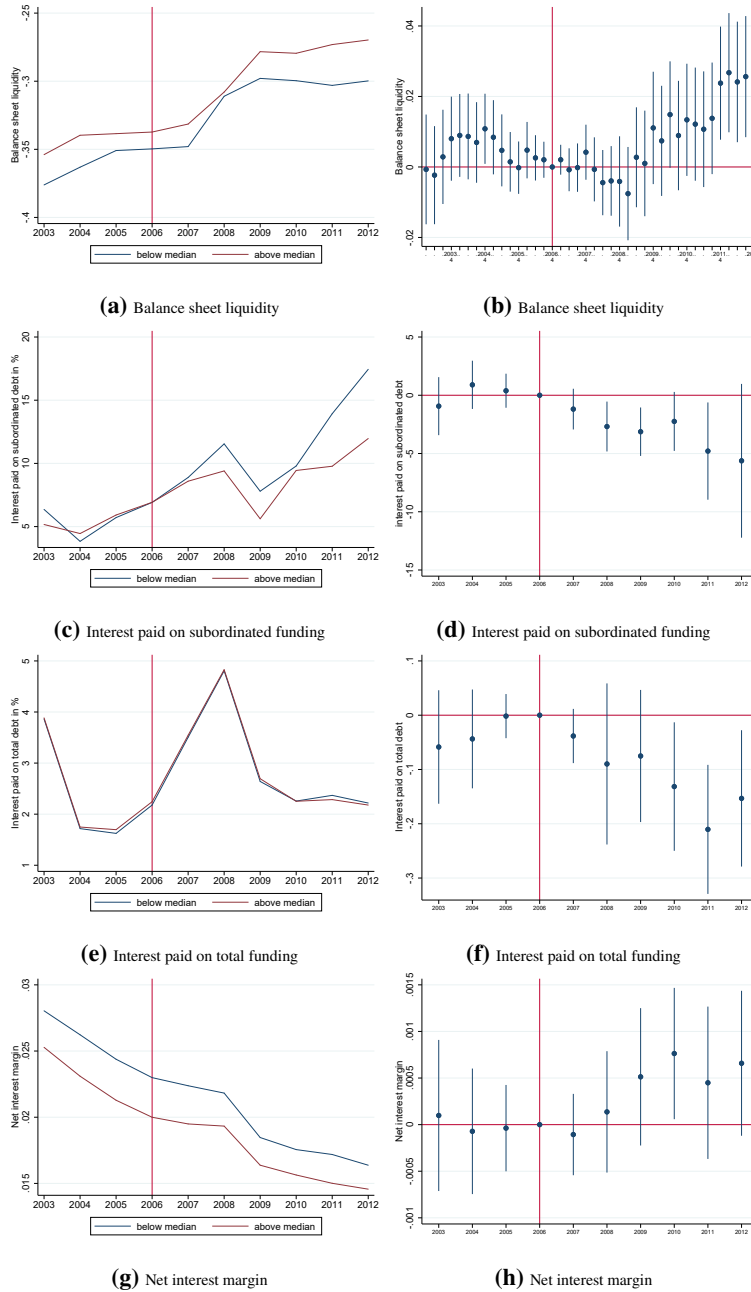


Figure B.3: Bank-level: Funding costs and profitability

In this figure we show mean dependent variables of raw data over time in the left column. In the right column we show coefficient plots with confidence intervals at 90% from estimating equation (3) with annual data. Table B.6 reports regression statistics for Figure B.3b and Table B.7 reports the regression output for Figures B.3d, B.3f and B.3h.

Dependent variable	Figure	Observations	N cluster	R2	Mean dependent	SD dependent
Balance sheet liquidity	B.3b	5,150	133	0.447	-0.324	0.074

Table B.6: Regression information corresponding to Figure B.3b.

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

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

Table B.7: Bank-level: Table of results for profitability and bank risk

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

C Additional figures

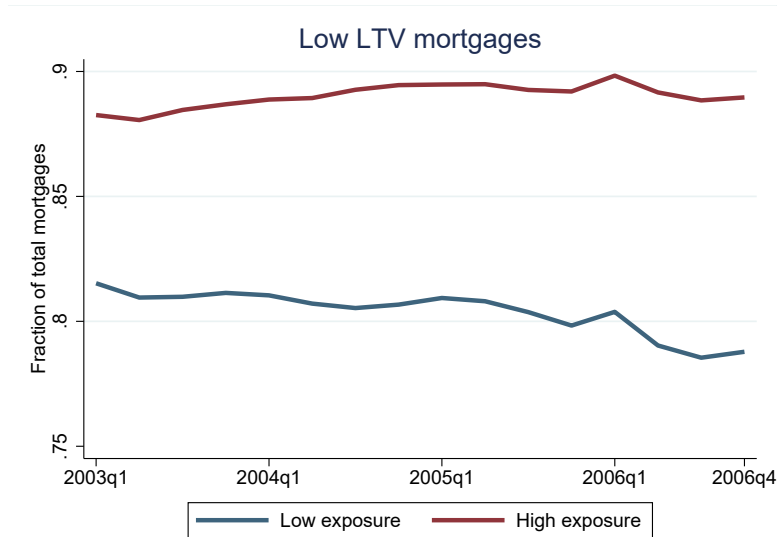


Figure C.1: LTV-persistence

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

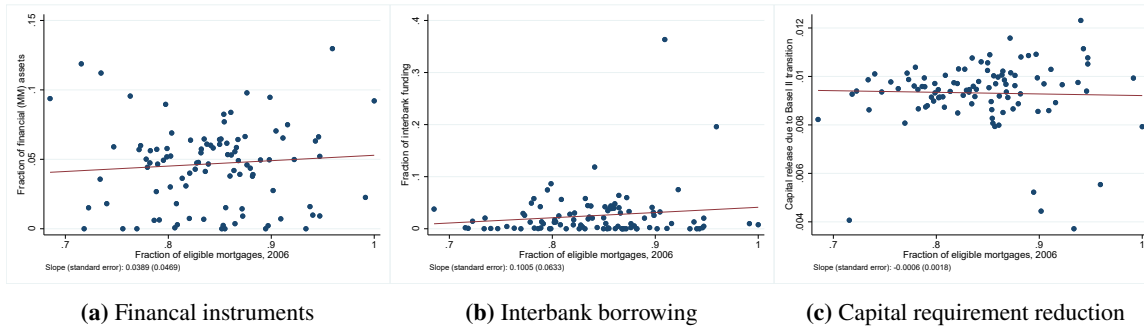


Figure C.2: Treatment measure and exposure to the financial crisis and Basel II factors

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

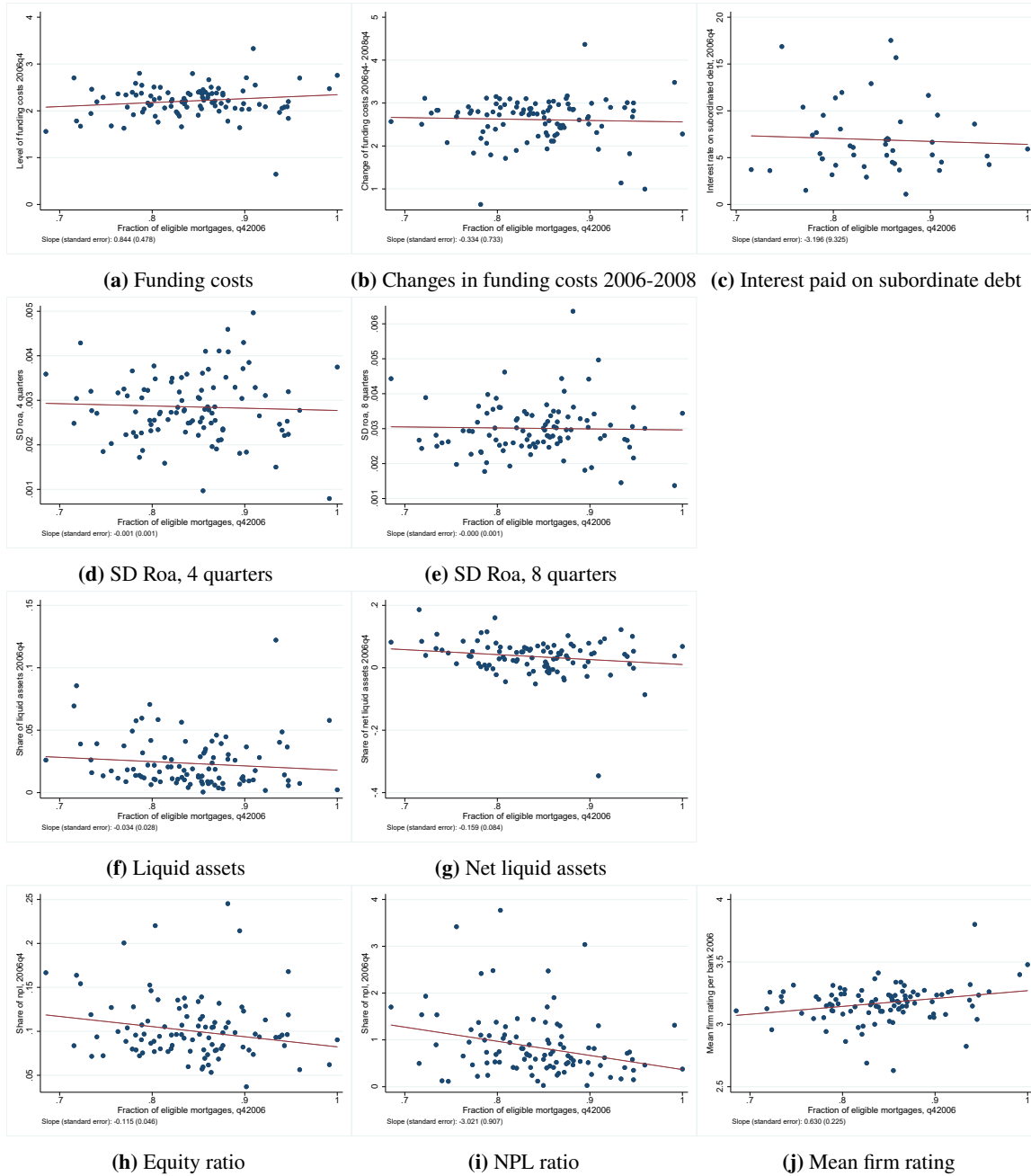


Figure C.3: Treatment measure and bank risk in the pre period

In these figures we show the correlation of the fraction of mortgages eligible for mortgage transfers on banks' balance sheets in 2006q4 with measures for bank risk in 2006q4. These are (a) interest paid on total funding, (b) the change in interest paid on total funding from 2006q4- 2008q4, (c) interest paid on subordinated funding, (d) standard deviation of return on assets (Roa) over past four quarters, (e) over past eight quarters, (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.
- Berger, Allen N. and Christa H. S. Bouwman**, “Bank liquidity creation,” *Review of Financial Studies*, 2009, 22 (9), 3779–3837.
- Bianchi, Javier and Saki Bigio**, “Banks, liquidity management and monetary policy,” *Econometrica*, 2020, p. forthcoming.
- Callaway, Brantly, Andrew Goodman-Bacon, and Pedro HC Sant’Anna**, “Difference-in-Differences with a Continuous Treatment,” *arXiv preprint arXiv:2107.02637*, 2021.
- 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.
- ECB**, “Covered bonds in the EU financial system,” *ECB December 2008*, 2008.
- 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.
- Gertler, Mark and Simon Gilchrist**, “Monetary policy, business cycles, and the behavior of small manufacturing firms,” *Quarterly Journal of Economics*, 1994, 109 (2), 309–340.
- 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.
- Holmström, Bengt and Jean Tirole**, “Financial intermediation, loanable funds, and the real sector,” *Quarterly Journal of Economics*, 1997, 112 (3), 663–691.
- 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-Sørensen, Kasper and Haakon Solheim**, “What do banks lose money on during crises?,” *Norges Bank Staff Memo 3/2014*, 2014.
- Mian, Atif and Amir Sufi**, “The consequences of mortgage credit expansion: Evidence from the US mortgage default crisis,” *Quarterly Journal of Economics*, 2009, 124 (4), 1449–1496.
- Nicolaisen, Jon**, “Covered Bonds and their impact on investors, banks and the real economy,” 2017.
- NOU**, “Finanskriseutvalget,” 2011.
- Purnanandam, Amiyatosh**, “Originate-to-distribute model and the subprime mortgage crisis,” *Review of Financial Studies*, 2011,

24 (6), 1881–1915.

Van Rixtel, Adrian and Gabriele Gasperini, “Financial crises and bank funding: recent experience in the euro area,” *BIS Working Paper No. 406*, 2013.

Webb, David C., “The impact of liquidity constraints on bank lending policy,” *Economic Journal*, 2000, *110* (460), 69–91.