Three Essays on Bank Risk-taking from a Portfolio Perspective

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Abstract

This dissertation studies three distinct aspects of bank risk-taking from a novel portfolio perspective. First, I provide compelling evidence demonstrating that banks with high industry exposure adeptly adapt loan contract design to prevent potential adverse effects on loan portfolio value arising from the interaction between rival borrowers. Second, I stress the importance of banks' pre-existing exposure and asset concentration in characterizing the risk-shifting incentives of banks enjoying government guarantees coverage. Last, I show that government guarantees coverage prompts bank risk-shifting at the intensive margin, and induces borrowers to leverage excessively, overinvest, and engage in low-quality projects. Altogether, I highlight the importance of pre-existing exposure in shaping banks' risk management incentives and its connection to two key issues: the rise in bank concentration and the extent of government guarantees coverage. These findings carry noteworthy implications for bank lending behavior and loan contract design, ultimately impacting borrowers' corporate policy and potentially giving rise to unintended policy consequences.

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Chapter 1

Introduction

The recent failures of Silicon Valley Bank and Signature Bank, along with the orchestrated acquisition of First Republic Bank, have reignited public attention to the banking sector. This renewed focus is fueled by the enduring memory of the global financial crisis. As a result, the recurrence of such episodes has prompted new scrutiny of banks' propensity for excessive risk-taking. At the same time, it has also highlighted the ongoing implications of government efforts to mitigate the adverse effects of bank failures. Moreover, the limited effectiveness of heightened regulation in averting the current crisis indicates that comprehension of the incentives driving bank risk-taking remains incomplete. Altogether, these recent events revive long-lasting discussions and sustain the subject of bank risk-taking as an intriguing topic, calling for further examination and research to enhance our understanding of the underlying factors involved.

In this dissertation, I contribute to this purpose through the examination of three distinct aspects of bank risk-taking that highlight the importance of pre-existing exposure in shaping banks' risk-taking incentives, in combination with two key matters: the rise in bank concentration and the extent of government guarantees coverage.

Firstly, I provide empirical evidence demonstrating that banks with high exposure adeptly adapt their loan contract design to effectively manage their portfolio risk, taking into account the potential detrimental effects that the interaction between competing borrowers can have on their loan portfolio value. Next, I emphasize the importance of banks' pre-existing exposure in explaining the risk-shifting incentives of protected banks, as opposed to focusing on the idiosyncratic risk associated with new assets. Lastly, I argue that the funding cost advantage enjoyed by protected banks encourages increased risk-taking at the intensive margin, thereby influencing their borrowers to engage in excessive leverage and further investment in low-quality projects.

By analyzing these three facets of bank risk-taking from a portfolio perspective, this dissertation contributes to a deeper understanding of the complexities involved. These insights carry noteworthy implications for bank lending behavior and loan contract design, ultimately impacting the corporate policies of borrowers and potentially giving rise to unintended policy consequences.

To delve further into these implications, I provide a brief overview of the forthcoming chapters in the dissertation.

In the second chapter of my dissertation, titled "It's Not You, It's Them: Industry Spillovers and Loan Portfolio Optimization," I provide compelling evidence that lenders with substantial exposure to a specific industry impose stricter covenant requirements on firms operating within that industry. Specifically, these lenders adopt a more cautious approach by incorporating capital-based covenants and tangible net worth requirements, effectively deterring debt-funded growth and encouraging more conservative behavior among borrowers. This empirical finding suggests that lenders internalize industry spillovers arising from product market competition, utilizing loan contract terms as a means to manage borrowers' growth appetite and mitigate the risk associated with their overall industry exposure.

Importantly, these results are robust and not driven by time-varying unobserved factors at the bank or industry level. By exploiting exogenous changes in lender exposure resulting from bank mergers, I address endogeneity concerns and alternative explanations, further confirming the relationship between lender exposure and covenant strictness.

Furthermore, this study extends the existing literature by shedding light on the impact of industry spillovers on bank risk-taking from a portfolio perspective. Previous research has focused on the role of covenants in mitigating borrowers' agency risk and their potential wealth extraction from lenders after loan origination. This study reveals that banks strategically increase the strictness of non-monetary terms beyond the optimal level from a bilateral perspective, providing valuable insights into loan portfolio optimization.

The third chapter of my dissertation, "Concentrating on Bailouts: Government Guarantees and Bank Asset Composition," examines the link between expected bailout guarantees and bank portfolio concentration. In collaboration with my co-authors, Christian Eufinger and Björn Richter, we emphasize the importance of banks' pre-existing portfolios in characterizing the risk-shifting incentives of protected banks.

Government guarantees reduce creditors' concerns about the bank's liquidation value in insolvency states. We show that this creates an incentive for banks to increase asset concentration by loading up on assets whose failure would already bring down the bank, given its previous exposure to these asset classes. Consequently, we argue that government guarantees incentivize banks to take on more risk by increasing the correlation of the marginal asset in their portfolio to the bank's survival but not necessarily acquiring assets of higher idiosyncratic risk.

In this way, government guarantees significantly alter the trade-off between specialized and diversified asset portfolios (Boyd & Prescott, 1986; Diamond, 1984; Winton, 1999) and foster asset concentration, especially for banks that already have a high exposure to a particular asset class relative to their equity capitalization.

We confirm our model predictions in the context of the U.S. banking system, exploiting exogenous variations in banks' expected government guarantees induced by changes in the composition of the influential U.S. Senate Committee on Banking, Housing and Urban Affairs (BHUA Senate Committee) (Kostovetsky, 2015). We show that banks that gain representation in the BHUA Senate committee increase their portfolio concentration by further loading up on loan classes to which they are already highly exposed. In contrast, banks that lose representation reduce their exposure to these asset classes.

Overall, this chapter sheds light on the relationship between government guarantees, bank portfolio concentration, and banks' risk-taking behavior. By providing empirical evidence from the U.S. banking system, I contribute to the understanding of how government policies influence bank asset composition and risk management practices.

In the fourth chapter of my dissertation, titled "*Banking on Bailouts*: How Public Guarantees affect Loan Contracts and Borrower Investments," I shed light on how government guarantees shape banks' incentives and promote risk-shifting at the intensive margin. In collaboration with Christian Eufinger and Zhiqiang Ye, we demonstrate that the moral hazard issues stemming from government guarantees incentivize banks to exploit their funding-cost advantage, crowding out direct market-based finance. Consequently, they increase lending to existing borrowers, influencing bank-firm relationships and loan contract design. Thereby, government guarantees lead banks to encourage excessive leverage among borrowers, resulting in overinvestment and involvement in inferior high-risk projects.

Exploiting changes in the BHUA Senate Committee, we analyze the behavior of banks in the context of the U.S. syndicated loan market. We find that protected banks increase their wholesale funding and translate this into more lending. Moreover, firms indirectly protected through their credit relationships witness a growth in debt-based funding and overall investment, potentially exceeding the optimal expected levels and ultimately resulting in reduced productivity. These findings corroborate the notion that protected banks drive borrowers to assume excessive leverage and overinvest in low-quality projects.

This chapter contributes to the broader understanding of the multidimensional consequences of government guarantees within the banking sector. It builds upon the existing literature that primarily focuses on how government guarantees encourage risk-taking at the extensive margin and expands the perspective to include the intensive margin and its impact on loan contract design and borrower investment efficiency.

Chapter 2

It's Not You, It's Them: Industry Spillovers and Loan Portfolio Optimization

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I provide evidence that lenders with high exposure to a particular industry extend loans with a higher covenant strictness to the firms in this industry. Specifically, these lenders deter debt-funded growth and induce a more conservative behavior by including more capital-based covenants and tangible net worth requirements. This is consistent with lenders internalizing industry spillovers arising from product market competition, using loan contract terms to tame borrowers' growth appetite, thus reducing the risk of their overall industry exposure. These results are not driven by time-varying unobserved heterogeneity at the bank or industry level. Exploiting bank mergers as an exogenous change in lender exposure, I verify that these findings are robust to endogeneity concerns and alternative explanations.

2.1 Introduction

Under a traditional view, a lender will maximize the expected value of a new loan by combining the interest rate with a specific covenant structure that limits the firm's risk (Bradley & Roberts, 2015; Demerjian, 2011). Nevertheless, consolidation and increased concentration in the banking sector (Vives, 2016) have led to significant industry-wide exposures of bank portfolios, often resulting in a bank lending to rival borrowers in the same market.[1] Consequently, departing from a strictly bilateral lender-borrower perspective can provide new insights, as lenders with significant exposure to multiple firms in the same industry are also affected by spillovers arising from product market competition (Saidi & Streitz, 2021).[2] Specifically, when a borrower of a lender with high exposure to the borrower's peers implements a pro-competitive growth strategy, the borrower's success will likely be detrimental to its peers and, thus, to the lender's portfolio value.

How do lenders that are significantly exposed to several firms competing in the same industry (in the following, for simplicity, called high-exposure banks) mitigate negative spillovers to their loan portfolio when extending a new loan to a borrower in this industry? In this paper, I argue that these lenders increase the strictness of their loan contract terms to curb growth appetite and tame product market competition between rival borrowers, thereby maximizing their portfolio expected returns by reducing the overall risk of their industry exposure.

The strictness of loan covenants is a key monitoring tool used by lenders because borrowers have strong incentives to avoid breaching them. Lenders increase the strictness of the loan covenants by narrowing the borrower's distance to technical default when originating the loan (Demerjian & Owens, 2016), thus, inducing borrowers to operate more conservatively, even well outside of payment default states (Nini, Smith, & Sufi, 2012).[3]

Previous literature has mainly emphasized the role of covenants in limiting borrower's agency risk (P. Demerjian, 2019) of extracting wealth from lenders after loan origination (Jensen & Meckling, 1976a). In this way, stricter covenants can lead to an increase in firm value by reducing agency conflicts (Smith Jr & Warner, 1979).[4] However, this bi-

[1] U.S. banking became increasingly concentrated over the last decades, with a decline in the total number of banks (Janicki & Prescott, 2006) and an increased market share of large banks (Vives, 2016), with the five largest banks representing less than 15% of total assets in 1992 but over a 40% in 2014. Kroszner and Strahan (2014) document that the decrease in the number of banks is related to a sharp increase of bank concentration at the national level, but also to a slight decrease in within-state local concentration.

[2] For example, recent empirical evidence demonstrates the consequences of fire sales and industry contagion, both from the perspective of the lender (Giannetti & Saidi, 2019) and the borrower (Carvalho, 2015), as well as the risk of sensitive information leakage (Asker & Ljungqvist, 2010).

[3] Covenant violation is costly for the borrower as it allows the lender to accelerate their claims and initiate costly renegotiations (Chodorow-Reich & Falato, 2022; Dichev & Skinner, 2002), in turn resulting in a higher influence of the lender on the borrower's corporate policy (Chava & Roberts, 2008; Ersahin, Irani, & Le, 2021). This motivates even very solvent firms to actively avoid technical default (Bradley & Roberts, 2015).

[4] See Jensen and Meckling (1976a) for a description of the incentives of risky debtors extracting wealth from creditors. See also Smith Jr and Warner (1979); Garleanu and Zwiebel (2009); Demerjian (2011) for

lateral lender-borrower view overlooks the additional consequences of a borrower's pro-competitive actions on its industry peers, to which the bank might also be exposed. Given a high industry exposure, a bank's optimal covenant strictness of a marginal loan will thus depend on its pre-existing loan portfolio. High-exposure banks will prefer to increase covenant strictness over and above the level that would be optimal from a bilateral lender-borrower perspective. That is, to curb borrowers' growth appetite when there is the risk that externalities of product market competition deteriorate its exposures to the borrower's peers.

To test my conjecture, I obtain loan-level data from DealScan on large private corporate debt extended by lenders in the U.S. (Schwert, 2018) for the period 1990-2018. I include information on the strictness of loan covenants at the deal level (Demerjian & Owens, 2016),[5] outstanding capital expenditure restrictions (Nini, Smith, & Sufi, 2009) and borrower characteristics (Compustat). Altogether, this dataset comprises 35,730 loan packages granted to 7,836 borrowers by 90 bank holding companies, with the average bank extending 460 loans deals to 72 different industries, which translates into an exposure of 3.1 borrowers per industry.[6]

I explore differences in loan contract terms between bank-industry pairs conditional on the lenders' industry exposure. I compare loans at origination, assuming exposure matters until maturity, and control for loan and borrower characteristics. To rule out other confounding factors, I include bank-quarter fixed effects to capture time-varying unobserved heterogeneity across banks (e.g., differences in credit supply), as well as industry-time fixed effects to control for differences in loan demand at the industry level (Khwaja & Mian, 2008).

To measure the extent of lenders' incentives to internalize industry competition spillovers, I use the share of the outstanding debt extended by a particular lender in the total outstanding debt extended to the industry by all lenders (for simplicity, lending share). I find

further discussions on how contractual provisions limit agency risk.

[5]Covenant strictness is estimated at the loan package, and measures the aggregate probability of covenant violation at inception date. The probability of violation ranges from 0 to 100 percentage points. It is estimated based on the number of covenants, the estimated distance of each financial ratio to the covenant's threshold, and the covariance between financial ratios (Murfin, 2012). Covenant strictness is also estimated specifically for capital related covenants.

[6]Each bank-industry pair is defined at the 3-digit SIC level. Following the literature, I focus on lead arrangers (Chakraborty, Goldstein, & MacKinlay, 2018). I exclude loans granted to the government, financial or utilities sector.

that high-exposure banks extend loans with stricter covenants: a lending share higher by one standard deviation translates into a 2.9 percentage points (pp) increase in covenant strictness (Demerjian & Owens, 2016). I verify that this result is robust to different specifications.[7]

To rule out that the lender share and loan covenant strictness are jointly determined, for example, because banks actively adjust loan contract terms to gain lending share in the industry, I exploit plausibly exogenous changes in lending shares stemming from bank mergers in an IV setting. Because of their nature and size, these mergers are unlikely to be driven by the interest of the acquirer in a particular industry.[8] The results of the IV estimation confirm that the results are robust to endogeneity concerns.[9]

There are two alternative explanations for this result, in addition to high-exposure banks, including stricter covenants to tame product market competition. First, these lenders may lend to smaller firms in atomized industries. These firms will be limited in their ability to influence their industry peers through a more conservative behavior, and consequently, including stricter covenants will not reduce product market competition. Instead, the stricter terms may respond to a lower quality of these borrowers that firm-risk controls do not capture it. Second, a high industry exposure may give lenders a competitive advantage from industry specialization, allowing them to impose stricter terms.

Still, my results remain robust after controlling for the number of firms in the industry, using an alternative measure for industry exposure that accounts for the borrower's size within the industry, and including different proxies for industry specialization in the regression. This indicates that these alternative explanations are not the primary driver of my findings.

I provide further evidence by looking at two settings in which the incentives of high-exposure banks to curb the growth appetite of their borrowers should be more relevant.

[7]More specifically, by looking at broader time fixed effects (year instead of quarter level), taking averages at the industry level, comparing the loan contract design of different banks to the same firm using bank-firm and time fixed effects, and computing the lending share without including the borrower (only its industry peers) as a proxy for lender's incentives to internalize industry spillovers.

[8]First, because corporate lending generally represents only a fraction of the balance sheet of these banks. Additionally, I define industry at a granular level (3-digit SIC), for which the lender's exposure to a particular industry should also be immaterial for the merger decision.

[9]In the appendix, I present additional robustness checks using different specifications.

First, given the asymmetric payoff structure of debt, high-exposure banks will be mainly concerned about the bankruptcy risk of borrower's peers. Second, high-exposure banks should increase the covenant strictness of new loans when borrower's growth strategies are more likely to harm industry peers.

Consistent with this, high-exposure banks are only stricter when the industry peers of the borrower to which the lender is exposed have a high bankruptcy risk.[10] Moreover, they are not additionally stricter when the borrower itself is riskier, which rules out the possibility that the banks could use covenants to force poor-performing firms into bankruptcy. Also, these banks are stricter when dealing with borrowers in more concentrated or mature industries, where growth opportunities are scarcer, and firm growth likely leads to intense competition for market share, to the detriment of other peers.

Next, I carry out a detailed analysis of how high-exposure banks curb borrowers' growth strategies. To deter competition, these lenders could make a stricter use of capital covenants. Capital covenants limit debt-funded growth and align the incentives of the contracting parties 'ex-ante', inducing a more conservative behavior after the loan is granted (Aghion & Bolton, 1992). Indeed, I find that high-exposure banks are stricter on capital covenants. Also, they make more use of capital-based covenants (Christensen & Nikolaev, 2012) and demand borrowers put more 'skin-in the-game' by including additional net worth covenants and tangible net worth requirements.

To deter borrowers from growing excessively, high-exposure banks could also make more use of covenants that reduce investment incentives. I find these lenders are less likely to include dividend payout limits and their borrowers are more likely to have capital expenditure restrictions, both curbing investing incentives.[11]

Altogether, these results are consistent with high-exposure banks limiting debt-funded growth and inducing a more conservative behavior in their borrowers, which tames competition and protects their lending portfolios. I further analyze different implications consistent with this conjecture.

As high-exposure banks aim to have a greater influence on the behavior of their bor-

[10] Measured as the average Z-score of rival borrowers within the industry.

[11] Dividend payout restrictions place a minimum on investment expenditures, making profitable projects less likely to be turned down (Kalay, 1982; Smith Jr & Warner, 1979). On the contrary, the absence of these restrictions implies a reduced incentive for borrowers to reinvest profits. Capital expenditure covenants limit the amount assigned to investment projects or restrict them directly (Nini et al., 2009).

rowers, they could substitute the use of stricter covenants with a reduction in the maturity of their new loans when there are no covenants in the deal. Shorter maturities allow lenders to revise the terms of loan renewal more often (Bhattacharya & Chiesa, 1995; Billett, King, & Mauer, 2007; Myers, 1977), increasing monitoring frequency and preventing their borrowers from taking risks that could affect their industry peers. Altogether, I find that high-exposure banks extend loans with shorter maturities when loans do not include covenants.

A subsequent question that follows the previous results is why borrowers accept these stricter terms. If stricter terms are merely imposed by rent-extracting banks, we should see that lenders with high industry exposure exert market power by also charging higher interest rates to compensate for the additional indirect risk that the borrower brings to its loan portfolio (Cetorelli et al., 2001). Alternatively, these lenders may need to share the benefits of reduced risk in their overall exposure with borrowers to be able to include stricter terms (Bradley & Roberts, 2015). I examine this question by looking at interest rate spreads of new loans and the 'spreads-to-strictness' ratio.[12] Consistent with the latter explanation, I find evidence suggesting that these lenders extend cheaper loans to incentivize borrowers to accept stricter terms.[13]

Finally, if high-exposure banks incentivize their borrowers to be more conservative, this should result in a lower risk for industry peers. Using the average CDS spreads of the borrower's peers as a proxy, I estimate the effect of loan announcements on industry risk, conditional on the lender's industry exposure. I find that the industry peers of the borrower experience a relative reduction in CDS spreads when the loan announced is arranged by a bank with a high, rather than low, exposure to this industry.

The findings of this paper contribute to two theoretical discussions. First, the literature on bank concentration has a long tradition of analyzing the consequences of concentration on markets and industries. Petersen and Rajan (1995) analyze how bank concentration could shape lending relationships and credit availability, with consequences for firm entry

[12]This is, the ratio between the logarithm of the interest rate spread and covenant strictness of the loan, as measured in Demerjian and Owens (2016).

[13]This is consistent with findings in Saidi and Streitz (2021), who argue that a lower interest rate serves as an implicit collusion mechanism between borrowers from a common lender. This is because cheaper rates reduce the limited-liability effect of debt (Brander & Lewis, 1986) and allow borrowers to commit to a less competitive output strategy. Distinct to their contribution, I present an explicit though non-mutually exclusive mechanism through which common lenders can deter borrowers from taking growth strategies that would negatively affect their overall industry exposure.

and competition. Related to this, Cetorelli and Strahan (2006) provide direct empirical evidence on the implications of bank concentration on industry structure.[14]

More recently, a stream of the literature has revised the implications of bank concentration, emphasizing the relevance of lenders' ex-post incentives to internalize the industry spillovers of their own credit decisions. These incentives increase with the pre-existing exposure of the lender and have consequences that can accrue a benefit for the borrower as well. In particular, Saidi and Streitz (2021) relate bank concentration to lower product market competition, reflected in lower industry output and higher mark-ups, and find that firms may actively seek a lending relationship with these banks.[15]

I contribute to this discussion by presenting an explicit mechanism through which concentrated lenders tame product market competition, that is, by increasing the strictness of loan contract terms. Moreover, I find evidence suggesting that these lenders exchange stricter covenants for cheaper loans rather than just imposing these terms.

A second contribution relates to the literature on loan contracting, specifically, on the purpose and use of debt loan covenants. This literature studies the role of loan contract terms in overcoming agency conflicts between debt and equity holders (Jensen & Meckling, 1976a) through interest alignment or decision rights reallocation (Aghion & Bolton, 1992; Garleanu & Zwiebel, 2009). From a bilateral lender-borrower perspective, it also studies how lenders optimally combine contract terms to maximize the value of the loan (Bradley & Roberts, 2015). In this direction, most of the empirical efforts have been directed towards understanding borrower-side determinants for covenant type and tightness (Christensen & Nikolaev, 2012; Demerjian, 2011), with a strong focus on the consequences of covenant violation (Chava & Roberts, 2008; Ersahin et al., 2021; Gu, Mao, & Tian, 2017; Nini et al., 2012).

Instead, I turn attention to the importance of the lender's pre-existing portfolio as a determinant of the loan contract terms for the marginal loan. I contribute by showing that high-exposure banks redesign loan contract terms to manage the risk of their over-

[14]See Cetorelli et al. (2001) for a discussion on the heterogeneous effects of concentration across other industries.

[15]See also Favara and Giannetti (2017), who find that lenders with a high share of collateralized mortgage debt in their loan portfolios are more inclined to renegotiate their debt to avoid price-default spirals affecting non-distressed neighboring houses, and Giannetti and Saidi (2019), who find that banks with a high concentration in a particular industry are more prone to lend during downturns to avoid fire sales of specific assets used as collateral.

all industry exposure optimally. Hence, they increase loan covenant strictness over and above the level that would be optimal from a bilateral lender-borrower perspective to curb growth appetite and protect other firms to which they are also exposed. This finding is closer to more recent papers looking at the role played by lender attributes in contract terms (Murfin, 2012) and loan renegotiation (Chodorow-Reich & Falato, 2022).

Lastly, the literature on common ownership also depicts a setting where a financial agent has incentives to reduce competition (Bernheim & Whinston, 1985). This literature studies the implications of institutional investors owing shares across rival firms. For instance, Azar, Schmalz, and Tecu (2018) provide empirical evidence on the anti-competitive implications of common equity holdings in the airline industry. Antón, Ederer, Giné, and Schmalz (2018) extend these findings and elaborate on the managerial incentives behind this behavior.[16]

However, while the potential consequences of common ownership resemble those discussed in this paper, the mechanism presented here reflects a different set of incentives. As debt-holders do not participate in the upside of firm performance, lenders exposed to several borrowers in the same industry will only influence competition incentives when the borrower's peers are at risk of entering the bankruptcy region. In this way, the findings presented here add evidence to the discussion about the relationship between bank concentration and product market competition, for which one channel is the existence of a common lender (Saidi & Streitz, 2021).

The rest of the paper is organized as follows. In the following section, I expand on the theoretical background. In Section 2.3, I explain how my database is constructed and present descriptive statistics. In Section 2.4, I present the main results supporting the conjecture that high-exposure banks extend loans with stricter covenants. I exploit exogenous changes in lending shares to show that previous findings are robust to endogeneity concerns. In Section 2.5, I present a more granular analysis to pin down the mechanism behind my finding, looking at different capital-based and negative covenants. In Section 2.6, I corroborate the use of stricter covenants is consistent with other contract terms, such as loan maturity and interest rate spreads, and show that industry risk is relatively lower

[16]These findings have been a matter of debate. For example, Dennis, Gerardi, and Schenone (2021) criticize the findings on anti-competitive effects in the airline industry, arguing they derive from measurement error and misinterpretation of the seminal work of O'Brien and Salop (2000).

when a high-exposure bank is involved. Finally, I present the conclusions of my findings in Section 2.7 and include complementary material in the Appendix 6.

2.2 Theoretical Background

To understand how banks can deter product market competition by increasing debt covenant strictness, it is useful to review first how a lender defines loan contract terms when interacting with a single borrower. Consider a lender that has agreed to extend a loan to a risky borrower. When defining the initial contract terms, the lender will assess the likelihood that the borrower will stop repaying the loan. After evaluating the expected payoffs in each scenario and its probabilities, the lender will estimate a required interest rate in accordance with the risk assumed.

At the same time, the lender can include provisions into the loan contract (i.e., financial covenants) that compel the borrower to guarantee its financial health will stay within pre-established thresholds or circumscribe its actions in a predetermined way.[17] Their inclusion limits lender's uncertainty about borrower's default risk (Demerjian, 2011) and, consequently, the required interest rate (Bradley & Roberts, 2015). Altogether, the lender will combine these contract terms to maximize the expected value of its loan exposure.

The lender may include different covenants, adjusting the exact definition and tightness of the pre-established thresholds (Demerjian & Owens, 2016) to its needs. As an illustrative example of covenant provisions in a loan contract, consider the case of Centex Corp., a home building company headquartered in Texas, USA. In August 7th, 2003, the firm borrowed $800 million U.S. dollars from a syndicated loan led by Bank of America.[18] The deal included three financial covenants that compelled the firm to have a maximum leverage ratio of 55%, a tangible net worth that is not below a composite value based on net income and net proceeds from future equity issuance, and a minimum interest coverage ratio of 2.0.[19]

[17]This is, “financial” or “negative" covenants, respectively

[18]Information obtained from SEC Filings for Centex

[19]Specifically, leverage ratio is defined as the ratio between unsubordinated debt over the sum of consolidated debt and tangible net worth. The minimum interest coverage ratio is defined as the ratio of EBITDA over interest expenses. Tangible net value should not be below the sum between $1.7 Billion USD and the average between the cumulative consolidated net income and the net proceeds from any future equity issuance.

To comply with the contract, Centex is obliged to meet all three provisions in each quarterly report. In a hypothetical situation in which any of these covenants is breached, Centex will be in 'technical default', giving Bank of America the right to accelerate the payments of the loan. A situation like this would increase the bank's bargaining power and its capacity to reassess the whole deal (Chodorow-Reich & Falato, 2022).

The possibility of a costly renegotiation generates strong incentives for borrowers to comply with its debt covenants. Moreover, if a breach occurred, the threat of harder consequences would allow the lender to increase its monitoring activity and even intervene in the firm (Chava & Roberts, 2008; Nini et al., 2009). In sum, the consequences of their infringement make covenants a useful tool to influence borrowers' corporate policy, even well outside payment default states (Nini et al., 2012).[20]

Thus, the lender can calibrate its control over the firm by defining how close to technical default the borrower will be when originating the loan. By introducing 'stricter' covenants in the contract, the lender reduces the agency uncertainty associated with the loan (P. Demerjian, 2019), the risk arising from the borrower's actions after loan origination. Stricter covenants will induce the borrower to be more conservative, protecting the value of the lender's exposure by, for example, deterring the borrower from embarking on an aggressive investment that exposes both, lender and borrower, to a risk that exceeds what was previously agreed.

Then, under a strictly bilateral perspective, the optimal strictness will be determined by the risk represented by the borrower over the loan value (Demerjian & Owens, 2016). However, this view overlooks the additional impact of the borrower on other firms to which the lender also has exposure.

When the lender has a high industry exposure, its reactiveness to competition between rival borrowers becomes more acute. Following the previous example, in 2003, Bank of America extended a loan to Centex while also being exposed to D.R. Horton, another home building company to which it had recently committed $775 million U.S. dollars.[21] All else equal, if Centex had decided to grow and gain market share, the bank would have been affected both directly and indirectly.

[20] This motivates even very solvent firms to actively avoid technical default (Bradley & Roberts, 2015)

[21] Through a revolving credit agreement granted in January 2002. Obtained from SEC Filings for D.R. Horton

To start with, Bank of America would be negatively impacted by D.R. Horton's bankruptcy risk being augmented since its margins are being threatened by Centex. In addition, D.R. Horton's incentives to retaliate increase, pushing the firm to invest in ambitious projects, reduce margins and increase its leverage, exacerbating its original risk. This amplifies competition within the industry and reduces Bank of America's loan portfolio. On top, borrowers' success in outperforming their peers provides little benefit to the lender, who mostly cares about borrowers' repayment capacity.

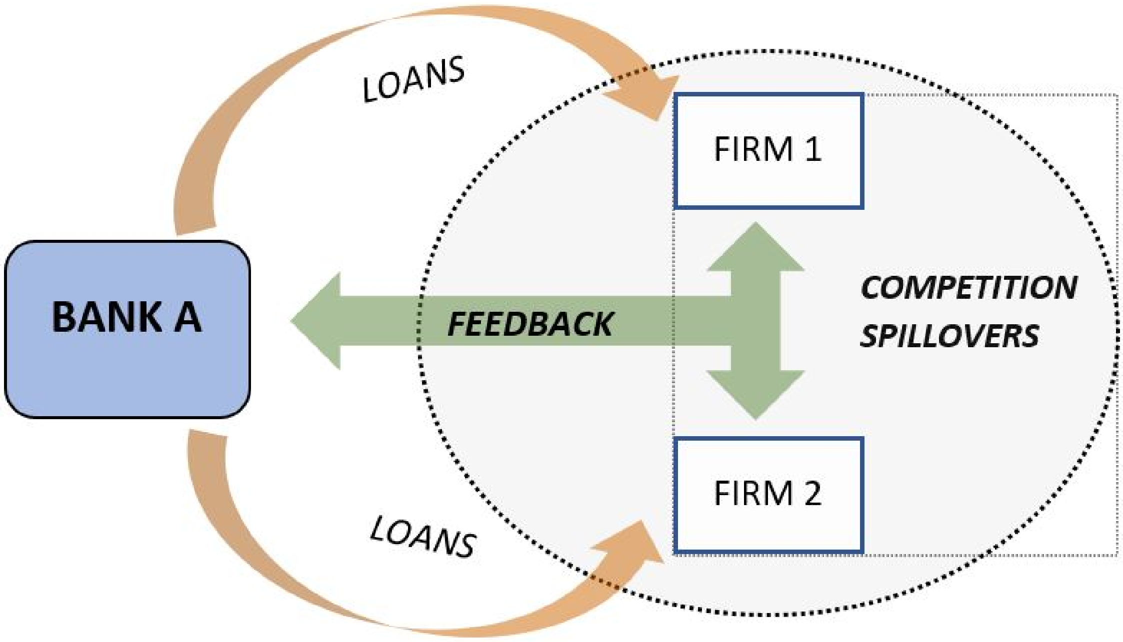
More generally, when a borrower implements a pro-competitive growth strategy, its success will be to the detriment of industry peers to which the bank is also exposed. Unlike equity holders, creditors will receive little benefit if the former succeeds. However, they will be negatively affected by their exposure to competing borrowers. At the same time, such a strategy will result in retaliation and borrowers taking additional risk.

While rational for the borrower, from the perspective of the bank, this level of competition will be excessive as it has an overall negative effect on its industry exposure. Therefore, to maximize the expected returns of its loan portfolio, the bank will redesign the contract terms of the marginal loan conditioned by its pre-existing portfolio (Figure 2.1) , taking into account the spillovers of its own lending decision. Specifically, increasing covenant strictness will reduce competition externalities by deterring borrowers from adopting growth strategies that could jeopardize the value of the bank's debt holdings at the industry level.

This idea follows previous discussions in the literature. For example, when analyzing the interaction between a firm's financial conditions and industry peers, Carvalho (2015) shows that borrowers suffer from greater valuation losses if the long-term debt of a competitor is maturing during an industry downturn, amplifying the shock through a reduction in their collateral value. Giannetti and Saidi (2019) find evidence on how industry negative externalities "feed back" into bank's lending decision, where banks with high lending shares are more likely to provide liquidity during downturns to avoid fire sales ignition within the industry. Moreover, they observe that lenders also provide liquidity to new borrowers if this industry is in distress.

In this direction, Saidi and Streitz (2021) argue that bank concentration is associated with reduced product market competition, reflected in lower industry output and higher

Figure 2.1: **Feedback Effect.** Diagram on the internalization of competition spillovers on bank's lending decision



mark-ups. The authors show that common lenders extend cheaper loans, which works as an implicit mechanism that moderates the competitive effect of debt. Assuming higher marginal returns in better states of the world, a higher cost of debt would pre-commit borrowers to a more aggressive output strategy (i.e., limited-liability effect (Brander & Lewis, 1986)). However, by providing cheaper loans, common lenders moderate the limited liability effect of debt and implicitly allow firms to commit to relatively less aggressive output strategies.

Following this discussion, I present an explicit mechanism through which high-exposure banks deter product market competition, complementary and non-mutually exclusive with this previous explanation. In short, I show that these lenders tend to provide loans with stricter covenants, reducing both the risk of the borrower and its competitors. Stricter covenants provide them with tighter control over borrowers' corporate policy, inducing a more conservative behavior and deterring debt-based growth that could reduce the overall value of the bank's exposure.

To demonstrate this, in the following sections, I will compare the covenant strictness (Demerjian & Owens, 2016) of loans granted by banks with different lending shares in each industry and expand on other loan contract terms, which allows me to characterize their behavior in more detail.

2.3 Data Sources and Descriptive Statistics

To test for differences in loan contract terms conditional on the bank's industry exposure, I incorporate information on corporate loans, borrowers, and lenders. I obtain information on private corporate debt extended in the U.S. during 1990-2018 from DealScan, which has the most extensive coverage on loan deals with comprehensive historical information on contract terms and loan pricing. I aggregate loan information at the loan deal level, and identify the industry of the borrower at the 3-digit SIC.[22]

I get financial information on borrowing firms from Compustat, including quarterly information on firms' balance sheets and income statement figures and other characteristics relevant to the analysis (e.g., rating scores). I follow Chava and Roberts (2008) to merge borrower characteristics with loan-level data. I incorporate information on firm-level CDS spreads, which I obtain from Markit. A relevant part of my analysis is centered around different measures of loan covenant strictness, which I obtain from Demerjian and Owens (2016).[23] Also, I include information about restrictions on capital expenditures from Nini et al. (2009).[24]

I follow Schwert (2018) to identify lenders across time, which allows me to track their loan portfolios at the bank holding level in a quarterly basis. Following the prevailing literature, I attribute the whole amount of the loan to the lead arranger of the deal, in charge of its active management (Ivashina, 2009), and distribute it in equal parts if there

[22] I exclude loans granted to the government, financial, or utilities sector. Also, I assume the industry to be its most frequently reported industry at that period to correct for the cases in which a firm reports to have more than one industry during the same period. These assumptions do not significantly affect my results, which are robust to this correction.

[23] Authors provide estimates on the loan package aggregate probability of covenant violation at inception date. Murfin (2012) is the first to estimate the aggregate probability of financial covenants violation (or covenant "strictness") based on the number of covenants, the estimated slack at inception for each covenant, and the co-variance between financial ratios. Demerjian and Owens (2016) build on this to calculate a non-parametrically measure for a broader set of deals, including more covenant categories and minimizing the measurement error arising from covenant-specific definitions. Covenant strictness is also estimated separately for capital and performance related covenants. In all cases, the probability of violation ranges from 0 to 100 percentage points. The measure is available for loans with covenants originated from 1994 till 2020.

[24] I match restrictions on capital expenditures for all the firms that have loans with at least one covenant (i.e. Covenants = "Yes") on my sample.

is more than one leader. To identify lead arrangers, I follow Chakraborty et al. (2018), who rank lenders in a loan based on the variables “lead arranger" and “lead arranger credit".[25] I compare loans when first originated, and assume exposure matters until the end of maturity. To approximate the time lag between the effective moment in which banks and firms commit to loan contract terms and the reported start date, I follow Murfin (2012), and consider the origination date of a package 90 days prior to the one reported in DealScan.

Mainly, I conjecture that high-exposure banks extend loans with stricter covenants to curtail pro-competitive growth strategies from rival borrowers that can adversely affect the lender's loan portfolios. My variable of interest is bank's lending share at the industry, which I use to proxy for the lender's industry-wide exposure and its incentives to internalize the negative spillovers from product market competition through the redesign of loan contract terms. Similar to Giannetti and Saidi (2019) and Saidi and Streitz (2021), I define the bank's lending share as the proportion of outstanding loans originated by lender b in industry i, divided by all outstanding loans issued to the industry, both estimated as the average dollar amounts over the previous five years:

$$Lending\ Share_{b,i,t} = \frac{\sum Outstanding\ loans\ from\ bank_{b,l,i,t}}{\sum Total\ Outstanding\ loans_{i,l,t}} \tag{2.1}$$

In Table 1, I present the definition of the main variables used in the empirical section, together with relevant descriptive statistics associated with these variables in Table 2.[26]

Altogether, I end up with information on 35,730 loan packages granted to 7,836 bor-

[25]Authors develop a ranking hierarchy. For each loan package, the lender(s) with the highest ranking is (are) considered the lead arranger(s). The ranking is the following: 1) lender is denoted as “Admin Agent”, 2) lender is denoted as “Lead bank”, 3) lender is denoted as “Lead arranger”, 4) lender is denoted as “Mandated lead arranger”, 5) lender is denoted as “Mandated arranger”, 6) lender is denoted as either “Arranger” or“Agent” and has a “yes” for the lead arranger credit, 7) lender is denoted as either “Arranger” or “Agent” and has a “no” for the lead arranger credit, 8) lender has a “yes” for the lead arranger credit but has a role other than those previously listed (“Participant” and “Secondary investor” are also excluded), 9) lender has a “no” for the lead arranger credit but has a role other than those previously listed (“Participant” and “Secondary investor” are also excluded), and 10) lender is denoted as a “Participant” or “Secondary investor”". Similarly to the authors finding, approximately 90% of the sample loan packages have a lender ranked six or higher. I exclude any loan for which I cannot identify at least one lead arranger. Results are robust to using the categories in the lender role description, as in Ivashina (2009).

[26]As a first control on the joint determination between bank lending share and loan contract terms, I lag the explanatory variable by one year or four quarters. Based on the average maturity of a loan, I consider the average share over five years. That is, twenty quarters, from $t-4$ to $t-23$. I verify that my results are robust to alternative time frames on the explanatory variable in the Appendix section.

Table 2.1: Definition of main variables

Panel A: Explanatory variables and controls

Variable	***Description***
$Lending\ Share^{*}_{b,t-4}$	Bank lending volume to industry over total lending volume to industry
$Size_{f,t-1}$	Natural logarithm of assets
$Leverage_{f,t-1}$	Total debt over equity
$Tangible\ N.W._{f,t-1}$	Tangible net worth over assets
$Debt\text{-}to\text{-}Cash\text{-}Flow_{f,t-1}$	EBIT over total debt
$Debt\ Service\ Ratio_{f,t-1}$	EBIT over interest expenses and current debt obligations
$Profitability_{f,t-1}$	EBITDA over assets
$Rating_{f,t-1}$	Firm rating. Categorical variable. Non-rated coded as zero
$Loan\ Maturity_{l,t}$	Log of loan maturity (months)
$Loan\ Amount_{l,t}$	Log of loan amount (thousand USD)
$Number\ of\ leaders_{l,t}$	Total leaders in loan
$Loan\ type_{l,t}$	Term loan, credit loan, both or special type
$Market\text{-}to\text{-}Book\ Ratio_{f,t-4}$	Assets plus difference of market and book value of equity, all divided by assets
$Z\text{-}score_{f,t-4}$	Z-score at the firm level is estimated as: $1.2 \times \frac{cash\ holdings}{assets} + 1.4 \times \frac{undistributed\ profit}{assets} + 3.3 \times \frac{EBIT}{assets}$ $+1 \times \frac{market\ value\ of\ equity}{liabilities} + 0.6 \times \frac{common\ equity}{liabilities}$. An average Z-score below 3.00 indicates having risk of entering into bankruptcy

Panel B: Outcome Variables

Variable	***Description***
$Covenant\ Strictness_{l,t}$	Ex-ante probability of default of loan based on the slack, variability, number and co-variance of its financial covenants (Demerjian & Owens, 2016) (pp)
$Capital\ Strictness_{l,t}$	Same measure for sub-group of capital-based covenants, as defined in Christensen and Nikolaev (2012) (pp)
$Average\ Drawn\ Spreads_{l,t}$	Logarithm of loan average drawn spread over base rate, as reported in DealScan
$Capital\ Intensity_{l,t}$	Count measure on capital-based covenants
$Net\ Worth\ Intensity_{l,t}$	Count measure on covenants with net worth requirements
$Tangible\ Net\ Worth\ Intensity_{l,t}$	Count measure on covenants with tangible net worth requirements
$Payout\ Restriction_{l,t}$	Inclusion of dividend payout restriction
$Capex\ Restriction_{f,t}$	Borrower has a capital expenditures restriction in t (Nini et al., 2009)
$CDS\ Spreads_{i,f,d(t)}$	Δ log of average CDS spreads at industry level (exc. borrower f), accumulated with respect to day 4 previous to loan announcement (5 year Maturity)

All continuous variables are winsorized at 1%

* *Lending Share is calculated on a 20-quarter rolling average up to* $t-4$ *before origination*

Table 2.2: Descriptive statistics

	Observations	Mean	Std. Dev.	10 %	50 %	90 %
Panel A: Bank-Industry Metrics and Explanatory variables						
Deals per bank	90	460.3	1030.9	28.5	167	902
Industries per bank	90	72.2	57.4	15	65.5	148
Lending share (at origination, %)	34,001	19.95	23.56	0.50	10.30	53.67
Avg. borrowers per bank-industry pair	6,502	3.07	2.09	1.47	2.41	5.78
Panel B: Explained variables						
Covenant strictness	13,664	37.8	41.7	0.0	12.6	99.7
Capital strictness	13,664	10.3	26.1	0.0	0.0	31.3
Int. drawn spreads (bps.) (weighted by tranche size)	31,125	199.7	143.9	40.0	175.0	375.0
Capital intensity	17,241	0.71	0.80	0.0	1.0	2.0
N.W. intensity	17,244	0.18	0.37	0.0	0.0	1.0
Tangible N.W. intensity	17,244	0.21	0.41	0.0	0.0	1.0
Capex restriction	2,944	0.3	0.5	0.0	0.0	1.0
Payout restriction	15,351	0.8	0.4	0.0	1.00	1.0
Spreads-to-Strictness	12,602	3.88	1.05	2.63	3.88	5.30
Panel C: Firm and Loan level risk controls						
Size (log)	36,585	6.95	1.94	4.37	6.93	9.58
Leverage	36,390	1.06	4.06	0.00	0.71	2.85
Tangible N.W.	36,564	0.33	3.49	0.09	0.38	0.68
Cash-flow-to-debt	32,534	0.34	1.13	0.02	0.09	0.45
Debt service ratio	36,108	3.76	14.43	-0.38	0.600	7.15
Profitability	34,145	0.03	0.03	0.01	0.03	0.07
Rating	18,427	10.44	3.55	6.00	10.00	15.00
Total leaders	33,814	1.19	0.79	1.00	1.00	2.00
Loan maturity (months)	33,878	47.2	24.3	15.0	48.0	78.0
Loan amount (log)	38,397	18.92	1.66	16.76	19.09	20.95
Market-to-book	28,548	1.69	0.99	0.91	1.37	2.81
Z-score	16,223	2.41	2.98	0.77	1.79	4.33
Δ Log(CDS spreads$_{t+3}$) (pp)	9,001	-0.04	4.60	-4.83	-0.09	4.94

rowers by 90 Bank Holding Companies.[27] Observations are unique at the bank-deal level, with loans arranged by one or more lenders to a single firm in a particular industry.

In my sample, the average bank extended 460 loans deals to 72 different industries. The average Bank-Industry pair is exposed to 3.1 (2.4) borrowers per industry in average (median), and its average (median) industry lending share is 19.9% (10.4%) at loan origination. The average loan has a general strictness of 37.8 (on a scale of 0 to 100), a capital strictness of 10.4, a capital intensity of 0.71, a maturity of 47 months, and an average spread of approximately 199 basic points.

2.4 Loan Covenant Strictness

2.4.1 Baseline Results

According to my conjecture, high-exposure will be negatively affected by the competition between rival borrowers, thus, having incentives to use contract terms to tame product market competition. By including harsher terms, these banks will have tighter control over borrowers' corporate policy (Chodorow-Reich & Falato, 2022; Nini et al., 2012), inducing conservatism and curbing pro-competitive growth strategies that could reduce the overall value of the bank's exposure to the industry.

To test this, I begin by comparing the covenant strictness on new loans conditional on the industry exposure of the bank. As a lender holds a larger share of the outstanding debt extended to the industry, it is more likely to be affected by the interaction between competing borrowers and assigning an increasing weight to the spillovers of its own lending decision (Giannetti & Saidi, 2019). Therefore, I expect banks with a higher lending share to extend loans with stricter covenants.

To rule out other confounding factors, I include bank-quarter fixed effects to capture time-varying unobserved heterogeneity across banks (e.g., differences in credit supply), loan and borrower risk characteristics, and industry-time fixed effects, to control for selection and differences in loan demand at the industry level (Khwaja & Mian, 2008). While

[27] For the purpose of comparison, I keep those lenders with at least 15 loans across the sample. However, this assumption does not affect the results in any significant way. When I refer to the bank, bank holding company or lender, I mean the lead arranger of the loan (Schwert, 2018).

variations apply, the main empirical test is specified as follows:

$$\begin{aligned} Loan\ Covenant\ Strictness_{b,l,i,t} &= \beta Lending\ Share_{b,i,\overline{t-4}} \\ &+ \gamma firm\ controls_{l,i,t-1} + \delta Loan\ controls_{l,i,t} \\ &+ \alpha_b \times \alpha_t + \alpha_i \times \alpha_t + \varepsilon_{b,l,i,t} \end{aligned} \tag{2.2}$$

Where *Loan Covenant Strictness* is obtained from Demerjian and Owens (2016) and defined as the ex-ante probability of loan technical default at origination, based on the slack, variability, number and co-variance of its financial covenants. *Lending Share* proxies the industry exposure of the bank, as defined in Equation 2.1. I control for firm and loan characteristics, including size, leverage, tangibility, cash-flow-to-debt ratio, interest coverage, and profitability, all winsorized at 1%. Also, I control for firm rating (Non-rated are coded as zero) and loan characteristics, including loan type, the log of loan maturity, the log of loan amount, and the number of total leaders.

Results are presented in Table 2.3. My main results of interest are shown in column 2, where I find that a higher lending share by one standard deviation translates into a 2.9pp increase in the covenant strictness of the new loans extended, and 1.4pp when only using Bank-Year fixed effects (column 1). Results are robust when comparing bank-firm pairs across time and controlling for general economic conditions (column 3) using Bank-Firm and Year fixed effects. Also, consistent with high-exposure banks internalizing industry spillovers, I find a similar relationship when considering banks' exposure to rival borrowers only (i.e., excluding the borrower itself from the proxy), with one standard deviation increase in their lending share over rival borrowers translating into a 1.3pp increase in covenant strictness (column 4). Complementary to this, I find a similar effect when performing the empirical analysis at the bank-industry level (columns 5 and 6), with one standard deviation increase in lending share translating into a 3.0pp increase in average covenant strictness, and banks on the top 25% of lending share extending loans with 4.5pp higher average covenant strictness.

Alternative explanations. There are two alternative explanations for this result, in addition to high-exposure banks including stricter covenants to tame product market compe-

Table 2.3: Bank industry exposure on covenant strictness

	Covenant Strictness					
	Bank-Loan Level				Bank-Ind. Level	
Lending Share	1.45***	2.94***	0.99*		2.99***	
	(0.006)	(0.002)	(0.054)		(0.000)	
Lending Share (exc. borrower)				1.33**		
				(0.041)		
Top Share (25%)						4.46***
						(0.000)
Fixed Effects:						
Bank-Year	Yes	No	No	No	No	No
Bank-Quarter	No	Yes	No	Yes	Yes	Yes
Industry-Quarter	No	Yes	No	Yes	Yes	Yes
Bank-Firm	No	No	Yes	No	No	No
Year	No	No	Yes	No	No	No
N	8,422	4,373	6,003	4,368	41,619	41,619
R^2	0.260	0.691	0.665	0.690	0.468	0.467

This table presents estimation results from Specification 2 for the period 1990-2018, at the bank-loan level (columns 1-4) and bank-industry level (columns 5-6). I include Bank-Year (Column 1), Bank-Quarter and Industry-Quarter (Columns 2 and 4-6), and Bank-Firm and Year fixed effects (Column 3). The dependent variable is the loan covenant strictness as reported in Demerjian and Owens (2016). The variable *Lending Share* represents the importance of the lender in the industry (zero to one) measured as the dollar amount of outstanding debt in the industry originated by the lender over the total outstanding debt in the industry, averaged across the previous 20 quarters $[t-4, t-23]$ and standardised. In Column 4, *Lending Share* is re-estimated excluding the borrower, following the same methodology, capturing the exposure of the bank to borrower's peers. The variable *Top Share* is a binary variable that identifies the bank-industry pairs at the top 25% of the lending share distribution (Column 6), compared at period t on the lending shares estimated over quarters $[t-4, t-23]$. Additionally, I incorporate a set of lagged control variables, including firm risk measures as size, leverage, tangibility, debt-to-cash-flow ratio, debt service ratio, profitability (all winsorized at 1%), and rating, plus controls on loan characteristics: type, log maturity, log amount, and total leaders. Firm and loan level characteristics are averaged at the industry level for bank-industry level regressions (Cols. 5-6). Standard errors are clustered at bank level and p-values are reported in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

tition. First, high-exposure banks may be lending to relatively smaller firms in atomized industries. These firms will be limited in their ability to influence their industry peers through a more conservative behavior, and consequently, including stricter covenants on new loans to these borrowers will not permit the lender to tame product market competition. Rather, the stricter terms may respond to the lower quality of these borrowers.

To control for this, I first consider the number of firms in the industry. Additionally, I use an alternative measure for the bank's internalization incentives that captures the borrower's relevance. I proxy the extent of the bank's exposure to influential borrowers in the industry by looking at the "*Bank-Industry HHI*" of each bank-industry pair. I construct this metric by summing a bank's squared lending shares with respect to each firm (Bank-firm lending share. For simplicity: *BFLS*).

$$BFLS_{b,f,t} = \frac{\sum Outstanding\ loans\ from\ bank\ to\ firm_{b,l,f,t}}{\sum Total\ Outstanding\ loans\ to\ firm_{f,l,t}} \tag{2.3}$$

Where *BFLS* is estimated as the outstanding loans extended by bank b over total outstanding loans extend to the firm by all banks, both measures in dollar amounts and estimated over the previous five years (twenty quarters, from $t-4$ to $t-23$). *BFLS* is then summed at the industry level and weighted by the relevance of the firm in the industry, as reflected by its market share in terms of sales:

$$Bank\ Industry\ HHI_{b,i,t} = \sum [Firm\ market\ share_{f,i,t} \times (BFLS_{b,f,t})^2] \tag{2.4}$$

Another concern may arise if higher lending shares capture additional factors besides the ex-post incentives to internalize competition spillovers. In particular, it may capture an information advantage from bank specialization in the industry. An information advantage allows the lender to reduce uncertainty more efficiently, inducing these lenders to provide loans with more lenient conditions (Giometti & Pietrosanti, 2022). However, this efficiency may also provide a competitive advantage that allows them to impose stricter covenants, which would entangle the interpretation of the findings presented above.

I account for this explanation of the results in two different ways. First, I control for the relative share of the industry in the bank's portfolio, which indicates a relative focus on the bank's monitoring resources within the bank's exposures. Second, I measure bank specialization based on abnormally large lending shares on a particular industry (Paravisini, Rappoport, & Schnabl, 2020), which better captures an information advantage of the bank over other potential lenders.

Results in Table 2.4 dissipate the previously described concerns. I find that after controlling for the number of firms, the higher strictness observed for highly-exposed banks remains practically unchanged (column 1). At the same time, the effect of the *Bank-industry HHI* remains significant, with one standard deviation increase in the measure being associated with a 2.6pp rise in covenant strictness (column 2). This indicates that my results are not driven by high-exposure banks lending to small firms in atomized industries.

As shown in column 3, the coefficient of interest remains unaltered when controlling for portfolio concentration, with one standard deviation increase in lending share translating into a 3.4pp increase in covenant strictness. Interestingly, when using abnormally large lending shares to proxy for bank specialization, I find that the relevance of the internalization of competition spillovers is stronger, with a lending share higher by one standard deviation translating into a 4.9pp increase in covenant strictness (column 4). This suggests that the effect is rather non-monotonic and driven by less extreme values of my proxy for banks' incentives to internalize industry spillovers.[28]

Altogether, these empirical results are consistent with the conjecture that high-exposure banks internalize industry spillovers by extending loans with stricter covenants to tame competition. At the same time, other alternative explanations do not appear to be the main driver of this finding.

Industry cross section I explore further implications of this conjecture. High-exposure banks should be stricter when extending loans to firms that are more likely to jeopardize the value of their exposure to rival borrowers. To test this, I look at conditions at the industry level where lenders' incentives to prevent competition spillovers should be more substantial.

Given the asymmetric payoff structure of debt, banks will be mostly concerned about the bankruptcy risk of their borrowers. At the same time, banks will perceive little benefit from any additional upside on firm performance, conditional on borrowers being in the capacity to repay their debt obligations. Consequently, high-exposure banks should have the incentives to increase the covenant strictness of new loans only when borrowers' growth is more likely to increase the bankruptcy risk of industry peers.

First, I test if lenders extend loans that are stricter when the borrower's peers, to which the lender is also exposed, have a higher bankruptcy risk. I estimate the average risk of all the competing borrowers of the firm to which the loan is extended, using Altman's Z-Score to proxy for firm risk. I then interact the *Lending Share* of the bank with the average risk of rival borrowers.

[28] At the same time, specialized banks extend loans with more lenient covenants, which is consistent with findings in (Giometti & Pietrosanti, 2022).

Table 2.4: Bank industry exposure on covenant strictness

	Covenant Strictness			
Lending Share	3.18***		3.39***	4.86***
	(0.000)		(0.001)	(0.001)
Bank-Industry HHI		2.55**		
		(0.039)		
Total firms in industry	-0.19			
	(0.299)			
Portfolio Share			-22.90	
			(0.394)	
Bank Specialization				-12.39***
				(0.007)
Fixed Effects:				
Bank-Quarter	Yes	Yes	Yes	Yes
Industry-Quarter	Yes	Yes	Yes	Yes
N	4,126	4,373	4,373	4,373
R^2	0.701	0.691	0.691	0.692

This table presents estimation results from Specification 2 for the period 1990-2018. I include Bank-Time and Industry-Time fixed effects. The dependent variable is covenant strictness as reported in Demerjian and Owens (2016). The variable *Lending Share* represents the importance of the lender in the industry (zero to one) measured as the dollar amount of outstanding debt in the industry originated by the lender over the total outstanding debt in the industry, averaged across the previous 20 quarters $[t-4, t-23]$ and standardized. The variable *Total firms in industry* (Column 1) is a count variable on the number of firms in the industry on the previous year $(t-4)$. The variable *Bank-industry HHI* (Column 2) follows equation 4. This variable represents the importance of the lender in the industry (zero to one) when accounting for the size of the borrower in the industry, and is averaged across the previous 20 quarters $[t-4, t-23]$ and standardized. The variable *Portfolio Share* (Column 3) represents the importance of the industry on the lender portfolio measured in terms of the dollar amounts of its outstanding debt-holdings (zero to one), averaged across the previous 20 quarters $[t-4, t-23]$. Bank *Specialization* (Column 4) is a dummy variable that identifies a bank as specialized if its lending share has been higher than the 75^{th} percentile plus 1.5 times the inter-quantile range of the lending shares at some quarter during the previous 20 quarters $[t-4, t-23]$ (Giometti & Pietrosanti, 2022; Paravisini et al., 2020). Additionally, I incorporate a set of lagged control variables, including firm risk measures as size, leverage, tangibility, debt-to-cash-flow ratio, debt service ratio, profitability (all winsorized at 1%), and rating, plus controls on loan characteristics: type, log maturity, log amount, and total leaders. Standard errors are clustered at the bank level, and *p*-values are reported in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

$$\begin{aligned} Loan\ Covenant\ Strictness_{b,l,i,t} &= \beta_1 Lending\ Share_{b,i,\overline{t-4}} + \beta_2 Risky\ Peers_{i,t-4} \\ &+ \beta_3 Lending\ Share_{b,i,\overline{t-4}} \times Risky\ Peers_{i,t-4} \\ &+ \gamma firm\ controls_{l,i,t-1} + \delta Loan\ controls_{l,i,t} \\ &+ \alpha_b \times \alpha_t + \alpha_i \times \alpha_t + \varepsilon_{b,l,i,t} \end{aligned} \tag{2.5}$$

Where *Risky Peers* is a dummy variable capturing the average risk of other borrowers in the industry to which the bank is also exposed, estimated at the time of loan origination to the borrower. Firm risk is measured using Altman's Z-score in the previous year (at $t-4$).[29] For ease of interpretation, I split safe vs. risky borrowing peers, with an average Z-score below 3.00, indicating rival borrowers have a significant risk of entering into bankruptcy. The rest of the equation follows the same empirical Specification (2.2). The coefficient of interest is β_3, which captures the additional effect of the bank's *lending share* on loans extended to firms with risky borrowing peers.

Results in Table 2.5 indicate that, as expected, high-exposure banks include stricter covenants when the borrower's peers are closer to bankruptcy, and could therefore be more affected if the borrower initiated a pro-competitive growth strategy. As shown in column 2, high-exposure banks provide loans with stricter covenants only when borrowing peers are risky, with a lending share higher by one standard deviation translating into a 5.7pp increase in covenant strictness when the borrower has risky rival borrowers in the same industry. At the same time, the effect is not significantly different from zero if the rival borrowers are safe. This is consistent with the incentives of the lender to prevent competition spillovers only being relevant when the rival borrowers of the firm have a high bankruptcy risk.

An alternative interpretation could be that high-exposure banks increase the strictness of covenants in new loans to force the bankruptcy of poorly performing firms. By doing this, banks could encourage better-performing rivals to which they are also exposed. To test this, I follow Specification (2.5), substituting *Risky Peers* for the risk of the borrower ("*Risky Borrower*"). The evidence shown in column 1 rules out this explanation. If anything, high-exposure banks tend to be less strict with poorly performing borrowers.

Based on my conjecture, high-exposure banks should be stricter when lending to borrowers in mature or more concentrated industries. In mature industries, growth opportunities are limited, and the expansion of a firm is more likely to be successful only at the expense of the market share from the borrower's peers. Similarly, markets should be less contestable in more concentrated industries, and high-exposure banks' influence should be more effective in deterring competition. In consequence, high-exposure banks will have higher incentives to deter pro-competitive growth strategies in these industries.

[29] Z-score at the firm level is estimated as $1.2 \times \frac{cash}{assets} + 1.4 \times \frac{undistributed profit}{assets} + 3.3 \times \frac{EBIT}{assets} + 1 \times \frac{market value of equity}{liabilities} + 0.6 \times \frac{common equity}{liabilities}$.

Table 2.5: Bank industry exposure on covenant strictness: cross-section tests

	Covenant Strictness			
Lending Share	4.62**	-2.13	1.68*	2.29**
	(0.023)	(0.292)	(0.065)	(0.028)
Lending Share x Risky Borrower (1/0)	-2.96			
	(0.114)			
Lending Share x Risky Peers (1/0)		5.74***		
		(0.006)		
Lending Share x Concentrated Industry (1/0 - Top 25%)			4.21**	
			(0.027)	
Lending Share x Mature Industry (1/0 - Bottom 25%)				6.10***
				(0.002)
Fixed Effects:				
Bank-Quarter	Yes	Yes	Yes	Yes
Industry-Quarter	Yes	Yes	Yes	Yes
N	3,544	3,086	4,357	4,357
R^2	0.720	0.691	0.691	0.692

This table presents estimation results from Specifications (2.5) (columns 1-2) and Specification (2.6) (columns 3-4) for the period 1990-2018. I include Bank-Time and Industry-Time fixed effects. The dependent variable is the general covenant strictness of the deal, as estimated by Demerjian and Owens (2016). The variable *Lending Share* represents the importance of the lender in the industry (zero to one), averaged across the previous 20 quarters $[t-4, t-23]$ and standardized. The variable *Peers' Risk* is a continuous variable (Column 2) capturing the average Z-score of all firms in industry *i* that are peers of the borrower and to which bank *b* has an outstanding lending exposure (i.e., excluding the borrower of the loan itself). The variable *Risky Borrower* is equal to one if the average Z-score of the borrower is below 3.00 at $t-4$ (Column 1). The variable *Risky Peers* is equal to one if the average Z-score of the borrower's peers is below 3.00 at $t-4$, indicating rival borrowers can have a significant risk of entering into bankruptcy (Column 2). Z-score at the firm level is estimated as $1.2 \times \frac{cash}{assets} + 1.4 \times \frac{undistributed\ profit}{assets} + 3.3 \times \frac{EBIT}{assets} + 1 \times \frac{market\ value\ of\ equity}{liabilities} + 0.6 \times \frac{common\ equity}{liabilities}$, and averaged as explained in $t-4$. *Concentrated Industry* is a dummy variable identifying those industries in the top 25^{th} percentile of industry concentration, measured as the squared sum of industry market share (based on sales) at $t-4$ (Column 3). *Mature Industry* is a dummy variable identifying those industries in the bottom 25^{th} percentile of growth opportunities across industries (Column 4). Growth opportunities are measured as the median market-to-book ratio at $t-4$. Additionally, I incorporate a set of lagged control variables, including firm risk measures such as size, leverage, tangibility, debt-to-cash-flow ratio, debt service ratio, profitability (all winsorized at 1%), and rating, plus controls on loan characteristics: type, log maturity, log amount, and total leaders. Standard errors are clustered at the bank level, and p-values are reported in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

To test this, I split industries by their degree of maturity and concentration, which allows the identification of differences in lenders' incentives, as reflected in the strictness of their loan covenants. I use the following empirical specification:

$$
\begin{aligned}
Loan\ Covenant\ Strictness_{b,l,i,t} &= \beta_1 Lending\ Share_{b,i,\overline{t-4}} \\
&+ \beta_2 Lending\ Share_{b,i,\overline{t-4}} \times Mature\ Industry_{i,t-4} \\
&+ \gamma firm\ controls_{l,i,t-1} + \delta Loan\ controls_{l,i,t} \\
&+ \alpha_b \times \alpha_t + \alpha_i \times \alpha_t + \varepsilon_{b,l,i,t} \qquad (2.6)
\end{aligned}
$$

Where *Mature Industry* is a dummy variable identifying those industries in the bottom 25^{th} percentile of growth opportunities across industries. Growth opportunities are measured as the median market-to-book ratio previous to loan origination (at $t-4$).[30] Alternatively, we replace *Mature Industry* variable for *Concentrated Industry*,a dummy variable identifying those industries in the top 25^{th} percentile of industry concentration, measured as the squared sum of industry market share (based on sales). Again, I include the same control variables and fixed effects as those in Specification (2.2). The coefficient of interest is β_2, which captures the additional effect of the bank's *lending share* on loans extended to firms in mature and concentrated industries.

Results in Table 2.5 corroborate that lenders are stricter when growth opportunities are limited, and the industry is more concentrated. As observed in Column 3 of Table 5. I find that a lending share higher by one standard deviation translates into a 4.2pp increase in covenant strictness when the borrower is in a concentrated Industry. This effect is 2.7 times larger than for non-concentrated industries (1.7 pp). Results in Column 4 also confirm that high-exposure banks are stricter with borrowers in mature industries. A lending share higher by one standard deviation translates into a 6.1pp increase in loan covenant strictness for borrowers at industries in the bottom 25% of the maturity measure. This effect is 2.6 times larger than when growth opportunities are more abundant and borrower's expansion is less likely to be compromising for the solvency of its competitors by 2.3pp.

All findings in Table 2.5 support the view that high-exposure banks deter competition when the expansion of a borrower is necessarily linked with the increase of the bankruptcy

[30] In the appendix, I present similar results when looking at alternative measures such as the industry sales growth and the change in the log market-to-book ratio, and alternative time frames. Results are consistent when using a continous measure for growth opportunities.

risk of other competing borrowers in the same industry. Consequently, banks' incentives to internalize competition spillovers are stronger.

2.4.2 Bank Mergers

The evidence provided so far shows that banks with a high lending share extend loans with relatively stricter covenants, particularly when firm growth can negatively affect the financial health of industry peers to which the bank is also exposed. This is consistent with high-exposure banks using the contract terms of new loans to induce conservative behavior from their borrowers, preventing competition spillovers, thus, maximizing the expected returns of their lending portfolios.

Still, a concern may be raised about contract terms and lending shares being jointly determined.[31] In the previous tests, I cope with this by measuring lending shares with a lag of four quarters with respect to loan origination. To further rule out this concern, I repeat the analysis on loan contract strictness using a two-staged IV regression based on exogenous changes in lending shares stemming from bank mergers.

Because of their nature and size, these mergers are unlikely to be driven by the interest of the acquirer in a particular industry. First, because I define industry at a granular level (3-digit SIC), for which the lender's exposure to a particular industry should also be immaterial for the merger decision. Additionally, corporate lending generally represents only a fraction of the balance sheet of these banks.

Therefore, I exploit 28 hand-collected bank mergers taking place between 1994-2016, which endogenously increased the lending share of the surviving banks across industries. Following a similar approach to Saidi and Streitz (2021), if the bank had a merger or acquisition in a particular year, I instrument the survivor's lending share as the sum of the historical share of the two entities, on the last quarter of the pre-merger year.[32] I code the rest of the observations as zero. Using this IV measure for lending share ('Lending Share IV'), I estimate its impact on Loan Covenant Strictness over loans extended within the first three years after loan origination.[33]

[31] The setting of loan contract terms may be an active strategy of the bank to actively gain lending share in a particular industry (Petersen & Rajan, 1995).

[32] This is, using the average lending share of the previous twenty quarters.

[33] For example, if a bank experienced a merger on 1998-3q, the lending share, which averages 1993-

The empirical specification goes as follows:

$$
\begin{aligned}
Loan\ Covenant\ Strictness_{b,l,i,t+h} &= \beta Lending\ Share\ IV_{b,i,\overline{t-4}} \\
&+ \gamma\, firm\ controls_{l,i,t-1} + \delta\ Loan\ controls_{l,i,t} \\
&+ \gamma firm\ controls_{l,i,t-1} + \delta Loan\ controls_{l,i,t} \\
&+ \alpha_b \times \alpha_t + \alpha_i \times \alpha_t + \varepsilon_{b,l,i,t} \qquad (2.7)
\end{aligned}
$$

Where *Loan Covenant Strictness* is observed during the three subsequent years after the bank merger starting at t, i.e., through quarters $t+h$ for $h = 0,...,11$, and *Lending Share IV* refers to the incremental lending share of bank b at industry i as a consequence of a bank merger in the same year as $t-4$. Control variables and fixed effects follow those in Specification (2.2).

The results presented in Table 2.6 show that a lending share increase of one standard deviation, instrumented through increments stemming from a previous merger or acquisition, translates into a 9.1 pp increase in covenant strictness (column 2). This result indicates that the main conjecture on high-exposure banks including stricter covenants remains robust to the endogeneity concerns mentioned above.

I further verify that this result is robust to two different concerns. First, I check that the effect is not uniquely driven by extreme increments in the lending share after a bank merger. Second, I verify that the effect is not driven uniquely by mergers taking place at a particular moment in time. For example, several mergers took place during the financial crisis of 2008-2009 after government intervention. Also, many bank mergers occurred the year 1998.

To rule out these additional concerns, I repeat the test formulated in equation 7 by, first, winsorizing lending shares at the top 10%, and, second, excluding exclude each of these episodes from the instrumental variable approach.[34] As shown in Table 7, the results

4q-1998-3q, is instrumented with the sum of the average lending shares of each merging side between 1993-1q-1997-4q. In this way, any new contract in 1999, 2000, and 2001 is going to be regressed on the additional lending shares obtained from the acquired bank. In the Appendix, I corroborate that results are robust by only looking at the first year after the merger took place.

[34]In the appendix, I also verify that results remain robust to considering only a single year ahead of the bank merger shock. Then, I show that results are robust to including overlapping mergers - that is, mergers that took place sequentially and were too close to each other to be included in the main analysis. Finally,

Table 2.6: Bank industry exposure on loan covenant strictness: IV estimates

	Covenant Strictness	
Merger-Implied	0.73***	
Lending Share	(0.000)	
Lending Share		9.07***
(IV Estimate)		(0.001)
Fixed Effects:		
Bank-Quarter	Yes	Yes
Industry-Quarter	Yes	Yes
F-stat (1 St.)	131.00	
N	4,377	4,377

This table presents estimation results from Specification (2.7) for the period 1990-2018. I include Bank-Time and Industry-Time fixed effects. The dependent variable is covenant strictness as estimated in Demerjian and Owens (2016). *Merger-Implied Lending Share* is the instrumentation of survivor's lending share using the sum of corresponding lending shares of prior entities at the last quarter of the pre-merger year, for contracts taking place on the three years after the merger took place. Otherwise, it is coded as zero (Column 1). The variable *Lending Share - IV Estimate* represents the importance of the lender in the industry (zero to one), averaged across the previous 20 quarters $[t-4, t-23]$ and instrumented by the incremental share of bank mergers (Column 2). Additionally, I incorporate a set of lagged control variables, including firm risk measures such as size, leverage, tangibility, debt-to-cash-flow ratio, debt service ratio, profitability (all winsorized at 1%), and rating, plus controls on loan characteristics: type, log maturity, log amount, and total leaders. Standard errors are clustered at the bank level, and p-values are reported in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

remain robust after taking into account these additional concerns.

2.5 Capital Covenants and Investment Incentives

In this section, I intend to pin down the different ways in which high-exposure banks induce conservative behavior in their borrowers and deter pro-competitive growth strategies. To do so, I go into more detail on the type of financial covenants used by these lenders, and on which they are more strict.

2.5.1 Capital covenants

Financial covenants require that one or more financial ratios remain within previously established thresholds, which can restrain the borrower's actions. In particular, financial covenants based on capital ratios (in the following, capital-based covenants) align

using a similar IV approach, I provide evidence on other contract terms analyzed in the following sections (e.g., capital covenant strictness, interest rate spreads, 'spreads-to-strictness' ratio).

debt and shareholders' incentives by imposing costly restrictions on borrowers' capital structure that deter debt-funded growth (Christensen & Nikolaev, 2012). Everything else equal, the compulsory provision of equity will make shareholders more sensitive to losses, motivating borrowers to behave more conservatively as they have more 'skin-in-the-game'. (Aghion & Bolton, 1992; Jensen & Meckling, 1976a).

As previously conjectured, high-exposure lenders will be interested in preventing borrowers from taking growth strategies that increase the default probability of industry peers and the risk of retaliation by the latter. Consequently, I expect that they provide loans with stricter capital-based covenants to limit borrowers' debt capacity and growth appetite, while also increasing borrowers' carefulness to peers' retaliation.

To test for this, I use the following empirical specification:

$$\begin{aligned} Capital\ Strictness_{b,l,i,t} &= \beta Lending\ Share_{b,i,\overline{t-4}} \\ &+ \gamma firm\ controls_{l,i,t-1} + \delta Loan\ controls_{l,i,t} \\ &+ \alpha_b \times \alpha_t + \alpha_i \times \alpha_t + \varepsilon_{b,l,i,t} \end{aligned} \tag{2.8}$$

Where *Capital Strictness* refers to capital-based covenant strictness, as defined in Demerjian and Owens (2016). Control variables and fixed effects follow those in Specification (2.2).

I complement this test by looking at alternative covenant measures. In previous literature, relevant studies have relied on empirical strategies based on covenant count measures to test their hypothesis (Bradley & Roberts, 2015; Christensen & Nikolaev, 2012; Demerjian, 2011). While these measures are less accurate than covenant strictness ones provided in Demerjian and Owens (2016), they are available for a broader set of loan deals and allow for a more granular analysis of the exact type of covenants used.

I expand on which covenants are more used by high-exposure banks by looking at the 'intensity' of covenants. The conjecture that these banks require borrowers more 'skin-in-the-game' can be tested by checking on those covenants that require a higher equity stake. First, I count all capital covenants. Secondly, I look at whether these lenders tend to include more covenants that track the net worth of the firm. Secondly, I test if they are more inclined to require net worth to be tangible, which would implicate borrowers to a higher degree.

Therefore, I create 'intensity' measures for all capital covenants, net worth covenants, and tangible net worth covenants in each loan contract. To test for this, I use the following empirical specification:

$$\begin{aligned} Covenant\ Intensity_{b,l,i,t} &= \beta Lending\ Share_{b,i,\overline{t-4}} \\ &+ \gamma firm\ controls_{l,i,t-1} + \delta Loan\ controls_{l,i,t} \\ &+ \alpha_b \times \alpha_t + \alpha_i \times \alpha_t + \varepsilon_{b,l,i,t} \end{aligned} \tag{2.9}$$

Here, the dependent variable *Covenant Intensity* refers to count measures on the number of certain types of covenants included in a loan contract, where *Capital Covenants Intensity* indicates the number of all capital-based covenants, and *Net Worth Intensity* refers to the number of net worth related covenants, either by requiring a minimum net worth or a maximum debt over net worth. Additionally, I split the latter measure for the cases in which there is an explicit requirement for this net worth to be tangible. For ease of interpretation, dependent variables are standardized.[35] Control variables and fixed effects follow those in Specification (2.2).

Results are shown in Table 2.7. As shown in column 1, high-exposure banks are more inclined to extend loans with stricter capital-based covenants, with a higher lending share by one standard deviation translating into a 1.2 pp increase in strictness. This result provides further support to the initial conjecture on high-exposure banks internalizing competition spillovers, as it shows that these lenders are interested in limiting debt-funded growth and deterring competition ´ex-ante', which would also prevent any retaliation effect for increased aggressiveness affecting the borrower itself.

As observed in Column 2, high-exposure banks tend to include more capital-based covenants to prevent competition spillovers in the industry. I find that a lending share higher by one standard deviation is related to a higher capital-covenant intensity by 6.3%

[35]To address any potential issues with using linear regression over count variables (Cohn, Liu, & Wardlaw, 2021), I repeat the tests presented in equation 9 and equation 10 using Poisson models and present the results in the appendix.

Table 2.7: Bank industry exposure on capital covenants

	Capital Strictness	Capital Intensity	Net Worth Covenants	Tangible N.W.	Unspecified N.W.
Lending Share	1.19**	6.29***	4.01**	4.30**	0.01
	(0.031)	(0.005)	(0.043)	(0.041)	(0.762)
Fixed Effects:					
Bank-Quarter	Yes	Yes	Yes	Yes	Yes
Industry-Quarter	Yes	Yes	Yes	Yes	Yes
N	4,373	6,035	6,035	6,035	6,035
R^2	0.644	0.718	0.714	0.642	0.575

This table presents estimation results from Specifications (2.8) (column 1), and Specification (2.9) (columns 2 to 5) for the period 1990-2018. I include Bank-Time and Industry-Time fixed effects. The dependent variables are: the strictness of capital covenants as defined in Demerjian and Owens (2016) (column 1), and count variables on the total number of capital-based covenants ("Capital Intensity") (column 2), covenants requiring net worth (N.W.), either as a Min. N.W. or a Max. Debt over N.W. (column 3), and covenants explicitly requiring tangible N.W. (column 4) or not specified N.W. (column 5). All dependent variables are standardized. The variable *Lending Share* represents the importance of the lender in the industry (zero to one), averaged across the previous 20 quarters $[t-4, t-23]$ and standardized. Additionally, I incorporate a set of lagged control variables, including firm risk measures such as size, leverage, tangibility, debt-to-cash-flow ratio, debt service ratio, profitability (all winsorized at 1%), and rating, plus controls on loan characteristics: type, log maturity, log amount, and total leaders. Standard errors are clustered at the bank level, and p-values are reported in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

of a standard deviation, in accordance with the previous finding on capital strictness.

As observed in columns 3 to 5, high-exposure banks also include more covenants limiting net worth levels, which restricts debt-funded growth, with one standard deviation increase in lending share implying a 4.0% of a standard deviation increase in total net worth covenants. On the same direction, I verify that these lenders are mostly concerned about increasing the strictness of tangible net worth covenants, requiring borrowers more ‘skin-in-the-game’, with a slightly stronger effect of 4.3% of a standard deviation increase. On the contrary, there is no significant difference in the use of "unspecified" net worth covenants, which just refer to net worth without distinguishing it from intangible assets.

These results provide both robustness and granularity to the findings presented in the previous section, allowing to better understand how high-exposure banks prevent competition spillovers by redesigning loan contract terms. By demanding borrowers with a larger equity stake, in particular in the form of tangible assets, lenders can limit borrowers’ debt capacity and growth appetite, while also increasing their sensitivity to peers’ retaliation. Altogether, this is consistent with a reduction of overall industry risk, which would maximize the expected returns of the loan portfolios of high-exposure banks.

2.5.2 Negative covenants

High-exposure banks can also curb investment-based growth strategies, including negative covenants such as dividend payout and capital expenditure restrictions. These restrictions can reshape the incentives and ability of the firm to undertake investment projects and sustain a pro-competitive growth strategy.

On the one hand, payout restrictions can lead to a marginal increase in the equity stake if shareholders cannot distribute as much as they would have preferred. On the other hand, fewer chances of including dividend restrictions may decrease shareholders' incentives to reinvest gains. In this way, the inclusion of payout restrictions places a minimum on investment expenditures, making profitable projects less likely to be turned down (Kalay, 1982; Smith Jr & Warner, 1979). Consequently, the lack of this restriction could reflect that high-exposure banks are more lenient towards the distribution of profits and prone to reduce the incentives of the borrowers to reinvest them.

In addition, having restrictions on capital expenditures can limit borrowers on the magnitudes and types of investments they make (Nini et al., 2009), also reducing their ability to embark on and sustain ambitious investment-based growth strategies.

To compare the likelihood of including payout restrictions in a loan or that a firm has a capex restriction, I present below a set of tests following linear probability models with interacted fixed effects, similar to previous specifications. I include additional tests in the appendix, using non-linear probability models (Probit and Poisson) consistent with the approach in Nini et al. (2009)[36]. To test this, I follow this specification:

$$\begin{aligned} Loan\ Contract\ Restriction_{b,l,i,t} &= \beta Lending\ Share_{b,i,\overline{t-4}} \\ &+ \gamma firm\ controls_{l,i,t-1} + \delta Loan\ controls_{l,i,t} \\ &+ \alpha_b \times \alpha_t + \alpha_i \times \alpha_t + \varepsilon_{b,l,i,t} \end{aligned} \tag{2.10}$$

[36]Specifically, probit models controlling for relevant characteristics such as growth opportunities, sequentially adding bank-time fixed effects. However, probit models can be inconsistent with FE (Arellano, Hahn, et al., 2005). Consequently, my main approach is based on linear probability models. To account for non-linearity while considering fixed effects, I also replicate these tests using Poisson models (more in Appendix).

Where *Loan Contract Restriction* is a binary dummy that accounts alternatively for the inclusion of payout restriction in a loan or a borrower having a capex restriction at the moment the loan is originated.[37] When looking at payout restrictions, control variables, and fixed effects follow those in Specification (2.2). When looking at capital restrictions, I control for growth opportunities and only include Bank-Time fixed effects due to the reduced sample size.

Table 2.8: Bank industry exposure on negative covenants

	Payout Restriction	Capex Restriction
Lending Share	-1.60**	2.70**
	(0.017)	(0.017)
Fixed Effects:		
Bank-Quarter	Yes	Yes
Industry-Quarter	Yes	Yes
N	13,640	1,412
R^2	0.617	0.485

This table presents estimation results from Specification (2.10) for the period 1990-2018. The dependent variable is a binary variable equal to one if the deal Dividend Payout (column 1) restriction or the firm has a capital expenditure restriction (column 2). The variable *Lending Share* represents the importance of the lender in the industry (zero to one), averaged across the previous 20 quarters $[t-4, t-23]$ and standardized. I include Bank-Time (columns 1 and 2) and Industry-Time (column 1) fixed effects. Additionally, I incorporate a set of lagged control variables, including firm risk measures as size, leverage, tangibility, market-to-book ratio (Column 2), debt-to-cash-flow ratio, debt service ratio, profitability (all winsorized at 1%), and rating, plus controls on loan characteristics: type, log maturity, log amount, and total leaders. Standard errors are clustered at the bank level, and *p*-values are reported in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Results are shown in Table 2.8. I find lending share is negatively related to loan provisions impeding dividend payouts and positively related to the probability that the borrower has a restriction in its capital expenditures. As shown in Column 1, a higher lending share by one standard deviation translates into a 1.6 pp decrease in the probability of including a payout restriction, reflecting the lender's leniency towards the distribution of profits, which reduces the borrower's incentives to reinvest.

Based on previous evidence, the possibility that lenders are more restrictive on dividend payouts would have been consistent with their requirements for a higher equity stake from shareholders to align risk-taking incentives. However, considering previous evidence, this is already required through stricter capital covenants (Christensen & Nikolaev, 2012). In this way, payout leniency is more likely to act as a disincentive to rein-

[37] This is information is obtained from Nini et al. (2009) and allows to identify if the borrower has a capex restriction at a particular year and quarter

vesting profits. Additionally, this could also explain how increased mark-ups from lower competition (Saidi & Streitz, 2021) are channeled to shareholders.

In column 2, I show that a higher lending share by one standard deviation translates into a 2.7 pp increase in the probability of the borrower having a capital expenditures restriction, suggesting it is more likely lenders limit the firm's ability to implement ambitious investment projects. As a direct consequence, this restrains borrowers' capacity to initiate and sustain growth strategies to gain market share, protecting other borrowers to which the bank also has exposure.

Altogether, these results corroborate that high-exposure banks make use of these negative covenants to deter investment-based growth and tame product market competition between rival borrowers.

2.6 Further Implications

In this section, I verify the implications of my conjecture on other contract terms and overall industry risk. I begin by analyzing if high-exposure banks extend loans with shorter maturities, which would be consistent with the use of stricter covenants to influence borrowers' corporate policy. Following, I shed additional light on the reasons behind borrowers accepting these stricter terms, and how high-exposure lenders may incentivize them to do so. Finally, I provide evidence consistent with high-exposure banks reducing industry risk, which is a key implication of their intention to induce more conservative behavior in their borrowers.

2.6.1 Other contract terms

Loan Maturity. As high-exposure banks aim to induce a more conservative behavior on their borrowers, they may as well reduce the maturity of their new loans.

Shorter maturities allow lenders to revise the terms of loan renewal more often (Bhattacharya & Chiesa, 1995; Billett et al., 2007; Myers, 1977), increasing monitoring frequency and preventing their borrowers from taking risks that could affect their industry peers. At the same time, frequent renegotiation of contracts implies higher costs for the lender. On the other hand, high-exposure banks may extend loans with longer maturities if including stricter covenants reduce their uncertainty. To see if high-exposure banks make use of shorter to increase their monitoring and deter inconvenient growth strategies, I first carry out a test similar to Specification (2.2) substituting the dependent variable for loan maturity. Furthermore, to test if these banks use covenants as substitutes or complements, I test for differential effects on loans with and without covenants, using the following empirical specification:

$$\begin{aligned} Loan\ Maturity_{b,l,i,t} &= \beta_1 Lending\ Share_{b,i,\overline{t-4}} + \beta_2 Has\ Covenants_{l,t} \\ &+ \beta_3 Lending\ Share_{b,i,\overline{t-4}} \times Has\ Covenants_{l,t} \\ &+ \gamma firm\ controls_{l,i,t-1} + \delta Loan\ controls_{l,i,t} \\ &+ \alpha_b \times \alpha_t + \alpha_i \times \alpha_t + \varepsilon_{b,l,i,t} \end{aligned} \tag{2.11}$$

Where *Loan Maturity* is the logarithm of the loan maturity at origination, measured in months, and *Has Covenants* is a dummy equal to one when the loan includes covenants and zero otherwise. The coefficient of interest is β_3, which captures the differential effect of *Lending Share* on the loan maturity of the loan. Control variables and fixed effects follow those in Specification (2.2), except for loan maturity.

As shown in Table 2.9, lenders with higher incentives to internalize spillovers appear to complement the use of covenant strictness with a relatively lower maturity in their loans, with a higher lending share by one standard deviation translating into a 1.1% reduction in loan maturity. This result suggests that in addition to stricter covenants, high-exposure banks make use of shorter maturities. At the same, results in column 2 indicate that this effect is mainly driven by those loans that do not include covenants, with a higher lending share by one standard deviation translating into a 3.5% reduction in loan maturity. On the contrary, they don't seem to reduce maturity over and above the optimal level from a bilateral perspective if the loan already contains covenants. Altogether, this indicates that high-exposure banks use this alternative as a substitute, which allows them to check on their borrowers more often and have an earlier awareness of how much risk they are taking and how this could affect other firms to which they are exposed.

Average Loan Spreads and 'Spreads-to-strictness' Ratio. Following the results presented so far, a subsequent question is why borrowers accept these stricter terms.

If stricter terms are merely imposed by rent-extracting banks, we should see that lenders with high industry exposure exert market power by also charging higher interest rates (Cetorelli et al., 2001). Alternatively, these lenders may need to share the benefits of reduced risk in their portfolios with borrowers to be able to include stricter terms (Bradley & Roberts, 2015; Smith Jr & Warner, 1979).[38]

I examine if, indeed, banks share part of these benefits with their borrowers by reducing the cost of debt, measured as the average interest rate spread of the loan. Additionally, I analyze the relationship between these spreads and covenant strictness using the ratio between the variables (i.e., the 'spreads-to-strictness' ratio), which should increase with the cost of debt and decrease as covenant strictness increases.

I test this using the following empirical specification:

$$\begin{aligned} Loan\ Spread_{b,l,i,t} &= \beta Lending\ Share_{b,i,\overline{t-4}} \\ &+ \gamma firm\ controls_{l,i,t-1} + \delta Loan\ controls_{l,i,t} \\ &+ \alpha_b \times \alpha_t + \alpha_i \times \alpha_t + \varepsilon_{b,l,i,t} \end{aligned} \tag{2.12}$$

Where *Loan Spreads* refers alternatively to the logarithm of the average drawn spreads at the loan level, weighted by the relative size of each tranche within the loan (whenever this tranche includes information about interest rates spreads), and the 'Spreads-to-strictness' ratio, which is the ratio between the logarithm of the interest rate spread and covenant strictness of the loan, as measured in Demerjian and Owens (2016).[39]. Control variables and fixed effects follow those in Specification (2.2).

As shown in Table 2.9, I find evidence suggesting that these lenders extend cheaper loans to incentivize borrowers to accept stricter covenants. I find that a lending share higher by one standard deviation translates into an approximately 3.0% reduction in loan

[38] Smith Jr and Warner (1979) argue that even if covenants are costly for borrowers, their inclusion can increase the value of the firm by reducing agency conflicts, with this cost-reducing benefits accruing to shareholders. Bradley and Roberts (2015) show that this benefit translates into a lower cost of debt, with covenant inclusion being negatively associated with corporate bond yields.

[39] In the appendix, I verify this result is robust to alternative definitions.

Table 2.9: Bank industry exposure on other contract terms

	Loan Maturity		Average Loan Spread	Spread-to Strictness
Lending Share	-1.13*	-3.48***	-2.97**	-0.09***
	(0.072)	(0.005)	(0.012)	(0.007)
Has Covenants x Lending Share		-0.40		
		(0.586)		
Fixed Effects:				
Bank-Quarter	Yes	Yes	Yes	Yes
Industry-Quarter	Yes	Yes	Yes	Yes
N	13,650	12,324	12,904	4,207
R^2	0.581	0.617	0.856	0.683

This table presents estimation results from Specification (2.12) for the period 1990-2018. The dependent variables are the logarithm of loan maturity (column 1), the logarithm of the average deal spread (column 2), weighted by the relative size of the tranche within the deal, and the ratio between the average loan spread and loan covenant strictness of the loan, the denominator obtained from Demerjian and Owens (2016) (column 3). The variable *Lending Share* represents the importance of the lender in the industry (zero to one), averaged across the previous 20 quarters $[t-4, t-23]$ and standardized. I include Bank-Time and Industry-Time fixed effects. Additionally, I incorporate a set of lagged control variables, including firm risk measures as size, leverage, tangibility, debt-to-cash-flow ratio, debt service ratio, profitability (all winsorized at 1%), and rating, plus controls on loan characteristics: type, log maturity, log amount, and total leaders. Standard errors are clustered at the bank level, and p-values are reported in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

spreads (column 2). I also verify this by showing that the new loans extend by high-exposure banks have a lower 'Spreads-to-Strictness' ratio, with a lending share higher by one standard deviation translating into an approximately 0.09 standard deviations reduction of the ratio. Altogether, these results are consistent with findings in Bradley and Roberts (2015) and Saidi and Streitz (2021), and indicate that these lenders provide relatively cheaper loans alongside stricter terms.[40]

2.6.2 CDS Spreads

Here, I study the consequences of high-exposure banks' behavior on borrowers' peers. If high-exposure banks incentivize their borrowers to be more conservative, this should result in a lower risk for industry peers. The evidence shown so far presents a clear picture

[40]Saidi and Streitz (2021) argue that a lower interest rate serves as an implicit collusion mechanism between borrowers from a common lender. This is because cheaper rates reduce the limited-liability effect of debt (Brander & Lewis, 1986) and allow borrowers to commit to a less competitive output strategy. Distinct to their contribution, I present an explicit though non-mutually exclusive mechanism through which common lenders can deter borrowers from taking growth strategies that would negatively affect their overall industry exposure.

of how banks use contract terms to account for the competition externalities in industries in which they have high exposure. In short, it appears that high-exposure banks provide stricter but cheaper loans, curb debt-funded growth strategies by requiring borrowers to have more 'skin-in-the-game', and limit the ability of borrowers to invest.

Yet, a question that remains is if, indeed, these banks are able to reduce industry risk in order to maximize their loan portfolio returns. To analyze this, I test if the risk of industry peers is relatively lower when one of these banks extends a loan to a firm in this industry. In this way, I look at the change in CDS spreads at the industry level, using the following empirical specification:

$$\begin{aligned} \Delta log(CDS\ Spreads)_{b,l,i,d(t)+v} &= \beta Lending\ Share_{b,i,\overline{t-4}} \\ &+ \gamma\ industry\ controls_{l,i,d(t-1)} + \delta\ Loan\ controls_{l,i,d(t)} \\ &+ \alpha_b + \alpha_i + \alpha_t + \varepsilon_{b,l,i,d(t)+v} \end{aligned} \tag{2.13}$$

Where the dependent variable $\Delta log(CDS\ Spreads)_{b,l,i,d(t)+v}$ is the change in the logarithm of the average CDS spreads of borrower's peers in industry i (excluding the borrower itself), accumulated with respect to base day $d-4$, during the v days d before and after public announcement of loan origination, respectively, for different leads, $v = \{-3,...,3\}$. CDS Spreads have a 5-year maturity, and the changes are trimmed at 1% to control for extreme values. Additionally, I include industry time-varying controls and loan controls, plus bank, industry, and time fixed effects.

Results are displayed in table 2.10 and plotted in Figure 2.2 for further clarity. As observed, the change in CDS spreads is relatively lower after a loan is announced when the loan was originated by a high-exposure bank. I find that a higher lending share by one standard deviation translates into a 0.13% reduction in industry peers' average CDS spreads after three days of loan announcement.

Table 2.10: Bank industry exposure on industry CDS spreads

	Accumulated industry $\Delta log(CDS\ Spreads)$					
	-3	-2	-1	1	2	3
Lending Share	-0.02%	0.00%	-0.00%	-0.10%***	-0.09%*	-0.13%**
	(0.288)	(0.995)	(0.408)	(0.004)	(0.094)	(0.022)
Fixed Effects:						
Bank	Yes	Yes	Yes	Yes	Yes	Yes
Quarter	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes	Yes
N	6,569	6,577	6,571	6,559	6,560	6,565
R^2	0.094	0.097	0.131	0.147	0.155	0.173

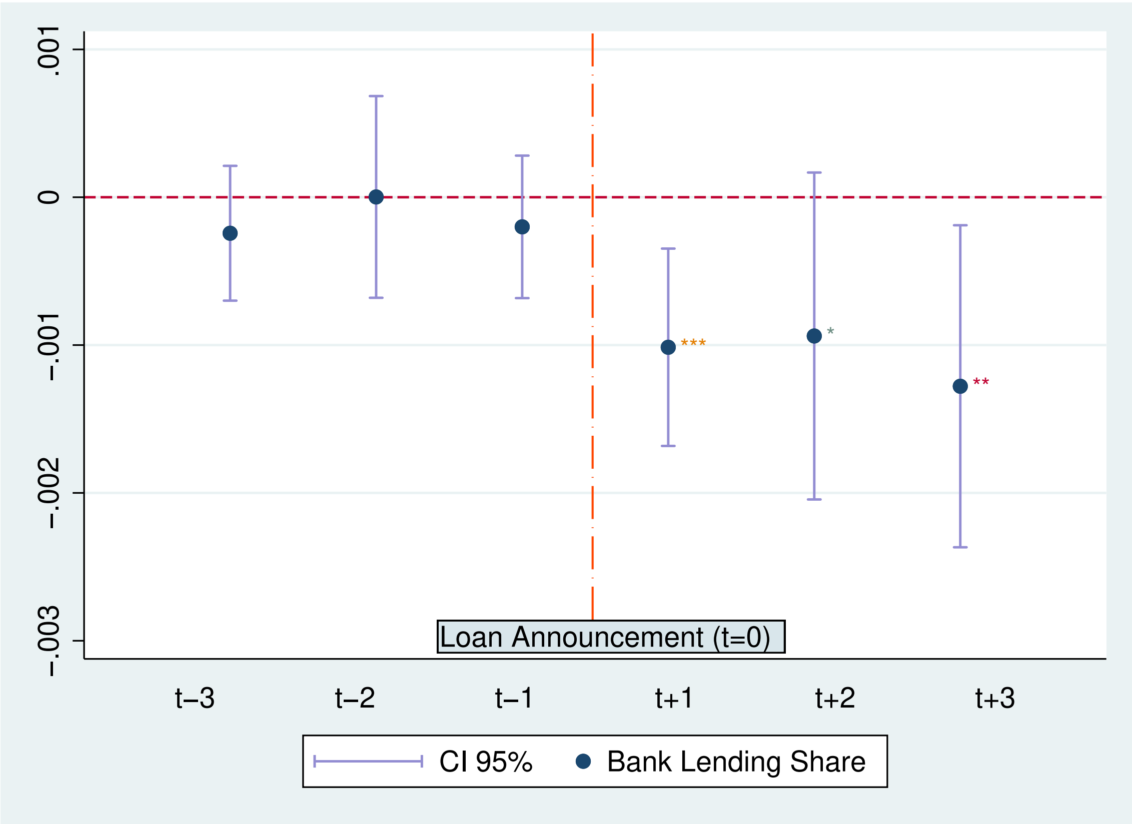
This table presents estimation results from Specification (2.13) for the period 1990-2018. The dependent variable is the change in the log of the average of the 5-year maturity CDS spreads (closing value) for all those industry peers of the borrower, using the accumulated change on average spreads with respect to four days before loan announcement, and shown over the three days previous and posterior to loan announcement (on each column respectively), where loan announcement occurs between day $t-1$ and $t+1$. The variable *Lending Share* represents the importance of the lender in the industry (zero to one), averaged across the previous 20 quarters $[t-4, t-23]$ and standardized. I include Bank, Time, and Industry fixed effects. Additionally, I incorporate a set of lagged control variables at the industry level, including the industry average for size, leverage, and profitability (all winsorized at 1%), plus previous quarter rating, and controls on loan characteristics: type, log maturity, and log amount. Standard errors are clustered at the bank level, and p-values are reported in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

2.7 Conclusions

Altogether, the evidence provided in this paper supports the conjecture that high-exposure banks maximize the expected returns of their lending portfolios, increasing the strictness of the conditions on their loan contracts to account for competition externalities between rival borrowers.

High-exposure banks are more prone to internalize the spillovers from their own lending decisions (Giannetti & Saidi, 2019), especially those arising from product market competition (Saidi & Streitz, 2021). I present an explicit channel through which these lenders can influence corporate policy and induce further conservatism. I show that these lenders extend loans with stricter contract terms, in particular those related to capital requirements, while charging lower spreads (Bradley & Roberts, 2015) and 'Spreads-to-strictness' ratio. Stricter covenants allow lenders to have relatively tighter control on borrowers' corporate policy after loan origination (Demerjian and Owens (2016); Nini et al. (2012)). Consistent with the previous, I also find that these lenders complement their strategy with relatively shorter maturities. Altogether, this curbs debt-funded growth strategies and reduces product market competition, thus protecting the bank's overall exposure at the industry level.

Figure 2.2: Industry risk reduction after loan announcement. Industry risk is measured as the change in the logarithm of the average CDS spreads of all industry peers of the borrower after the loan announcement, accumulated from the three days prior to the three days after the loan announcement.



Consistent with this, I confirm that high-exposure banks become stricter when lending to firms in mature industries, where growth opportunities are limited, and when rival borrowers are at a higher risk of bankruptcy. Also, these lenders are more inclined to include capital expenditure restrictions, and less inclined to include dividend payout ones, lowering the incentives to reinvest profits and sustain investment-based growth strategies. Lastly, I find that high-exposure banks provide loans that are more intense in capital covenants, being more likely to restrain the issue of additional debt and prone to require a higher tangible stake from borrowers, thus reducing risk-taking incentives by requiring more 'skin-in-the-game'.

Altogether, these results shed light on banks' loan contracting strategies when departing from a strictly bilateral lender-borrower and taking into account the previous exposure of the lender, showing how high-exposure banks use covenants not only to restrict borrower's agency risk (P. Demerjian, 2019), but also to prevent the consequences of borrowers' pro-competitive actions on industry peers to which the bank also has a lending exposure.

Chapter 3

Concentrating on Bailouts: Government Guarantees and Bank Asset Composition

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This paper studies the link between government guarantees for banks and bank asset concentration. We show theoretically that these guarantees, when combined with high leverage, incentivize banks to further invest in asset classes they are already heavily exposed to. We confirm these predictions using U.S. panel data, exploiting exogenous changes in banks' political connections for variation in bailout expectations. At the bank level, we find that higher bailout probabilities are associated with higher portfolio concentration. At the bank-loan class level, we find that banks respond to an increase in their bailout expectations by further loading up on loan classes that already have a high weight in their portfolio.

3.1 Introduction

The origins of many banking crises can be traced back to banks' exposures to particular asset classes, or even to the default of a few large borrowers.[1] As a result, regulators today

[1]Historical examples are manyfold: In 1890, large exposures to the struggling Argentinian economy triggered the near-default of Barings bank and sparked banking panics around the world. The German crisis of 1931 erupted when Darmstädter Nationalbank (Danatbank), then second-largest German bank,

impose limits on the exposure a bank can have to one single counterparty.[2] Nevertheless, concentrated exposures in particular asset classes contributed significantly to the two main banking crises in the 21st century: exposures to U.S. subprime mortgages were at the heart of the 2007–2008 global financial crisis (Brunnermeier, 2009), and large sovereign debt exposures severely deepened Europe's debt crisis of 2011–2012 (Acharya & Steffen, 2015 and Brunnermeier et al., 2016). With these risks associated, why do banks often choose to concentrate their portfolio in particular asset classes?

The existing literature considers banks' asset concentration to be a result of the trade-off between specialized (e.g., Winton, 1999) versus diversified asset portfolios (e.g., Diamond, 1984 and Boyd & Prescott, 1986). In this paper, we show (theoretically and empirically) that government guarantees significantly alter this trade-off and may contribute to bank asset concentration, especially for banks that already have a high exposure to a particular asset class relative to their equity capitalization.

Specifically, government guarantees lower the value that bank creditors attribute to liquidation values in the banks' insolvency states. Thereby, guarantees incentivize protected banks to increase exposures towards assets that increase returns in their solvency states and that only lead to additional losses in their insolvency states. In other words, an incentive to increase asset concentration by loading up on assets whose failure would already bring down the bank given its exposure to these asset classes.

We confirm our model predictions in the context of the U.S. banking system, exploiting exogenous variation in banks' expected government guarantees induced by changes in the composition of the influential U.S. Senate Committee on Banking, Housing, and Urban Affairs (BHUA Senate committee). Senators in this committee are heavily involved in bank bailout decisions. Specifically, we conjecture that having at least one senator from its home state in the BHUA Senate committee increases a bank's expected government guarantee value. We show that banks that gain representation in the BHUA Senate committee increase their portfolio concentration by further loading up on loan classes to

faced the default of its largest borrower Nordwolle, with the exposure amounting to 80% of Danatbank's capital (Doerr, Gissler, Peydro, & Voth, 2021).

[2]See, e.g., Basel Committee on Banking Supervision (2019a) and Basel Committee on Banking Supervision (2019b) on credit concentration and large exposure risks. For regulators, these risks are difficult to monitor: Benediktsdóttir, Eggertsson, and þórarinsson (2017) provides a detailed account how Icelandic banks worked around these rules prior to the financial crises of 2008, and how 20% of the loan book at the time of default can be traced back to six large counterparties.

which they are already highly exposed. In contrast, banks that lose representation reduce their exposure to these asset classes.

This mechanism has important implications for financial stability and policy. While technological advances allow banks to diversify across sectors, asset classes, and countries, they may actually forgo these diversification opportunities when benefiting from government guarantees, instead tilting their portfolios towards a higher asset concentration. A prime example for the importance of this mechanism is the eurozone, where policymakers currently debate whether to expand deposit insurance (by introducing the European Deposit Insurance Scheme; EDIS), while banks' sovereign exposures are highly concentrated.[3] Our results highlight that this step may be associated with unintended consequences, as banks may be incentivized to further load up on domestic assets.

Model preview and results. We lay out the effects of government guarantees on banks' investment behavior in a corporate finance framework. Specifically, we consider an economy that consists of two dates $t = 1, 2$ and three risk-neutral parties: the government, a bank, and a creditor. The bank has a risky legacy investment and needs to refinance some legacy debt at $t = 1$. The bank can borrow funds from the creditor.

Moreover, the bank has two mutually exclusive investment possibilities at $t = 1$. The returns of these two risky marginal assets and the bank's legacy asset are statistically dependent and the marginal assets differ with respect to their return correlation with the bank's legacy asset.

Depending on the bank's leverage and legacy exposure, there exist a low- and a high-exposure case. In the low-exposure case, the bank only defaults if its legacy investment and the marginal asset both fail. In this case, the extent of the return correlation between the bank's marginal assets and its legacy asset has an ambiguous effect on the bank's expected return; the sign depends on the extent of the government guarantee.

In the high-exposure case, the bank defaults whenever its legacy asset fails. In this case, a higher return correlation between marginal and legacy asset has two opposing effects on the bank's expected return. First, it increases the bank's expected cash flows in solvency states (the cash flow channel); second, it lowers the expected liquidation value in insolvency states, leading to higher financing costs as the creditor demands a higher

[3] Véron (2017) shows that 60% of European banks hold domestic sovereign debt in excess of their Tier-1 capital.

interest rate (the financing costs channel). Without government guarantees, these two channels exactly offset each other.

A government guarantee, however, drives a wedge into this relationship. With the protection provided by the government guarantee, the creditor assigns a lower value to the positive cash flows from the marginal asset in the bank's default states, which decreases the importance of the financing costs channel. As a result, the cash flow channel dominates the financing costs channel, which gives the bank an incentive to invest in the marginal asset that has a higher return correlation with its legacy exposure.

Our model thus predicts that banks with a concentrated risk exposure (i.e., a large exposure to a particular asset class relative to their equity capitalization) tend to further concentrate their portfolio in this asset class when their government guarantee coverage increases. We bring this model prediction to the data in our empirical analysis.

Empirical analysis and results. Identifying banks' portfolio reallocations in response to changes in the extent of their government guarantees is empirically challenging. First, effects on banks' investment behavior arise from expectations about the value of their guarantees, which are usually not observable. Second, the extent of a bank's government guarantee protection may be endogenous to its investment behavior and portfolio risk. For our analysis, we thus require some measurable variation in banks' expected government guarantee value that is otherwise uncorrelated with their investment behavior. To this end, we draw from the recent literature on the role of political connections in bank bailout decisions, which uses banks' geography-based political representation to proxy for bailout expectations (Duchin & Sosyura, 2014; Kostovetsky, 2015).

In particular, building on Kostovetsky (2015), we conjecture that having a senator from its state of incorporation as a member in the BHUA Senate committee increases expectations about the likelihood of receiving government assistance in times of distress. In recent decades, this committee has been paramount for U.S. government bailout decisions. Importantly for our analysis, representation in the BHUA Senate committee is dispersed across different states with significant exogenous variation over time.

We measure changes in banks' expected government guarantee coverage using a bank-specific time-variant dummy, *GG*, that is equal to one if at least one senator from the respective state of incorporation is a member in the BHUA Senate committee in that year.

For better readability, we refer to the case in which this dummy is equal to one or switches to one/zero as "high government guarantee coverage" and "gaining/losing government guarantee coverage", respectively.

To track changes in the banks' portfolio holdings, we employ data from the BHC Call Report Database, provided by the Federal Reserve System. We calculate different measures for loan portfolio composition based on granular data on banks' exposures to fourteen different loan classes. Our final sample consists of 3,205 unique banks and spans the years 1996 to 2016.

We run empirical analyses at the bank-year level and at the bank–loan-class–year level. At the bank-year level, we test the effects of changes in the government guarantee proxy on banks' asset concentration, where we use the Herfindahl-Hirschman index (*HHI*) and an entropy diversification measure (*EDM*) to measure portfolio concentration. For this analysis, we employ time and bank fixed effects to absorb time-invariant bank characteristics and common shocks.

We find that high government guarantee coverage is associated with higher portfolio concentration. A *GG* equal to one implies a 0.292 higher HHI value, which represents 13.5% of the average within-bank standard deviation (SD) of the HHI. We find similar evidence for the portfolio EDM measure.[4] At the bank–loan-class–year level, banks move to a higher loading towards loan classes to which they already have a high pre-existing exposure when the guarantee proxy increases. Specifically, gaining government guarantee coverage is associated with a 0.23pp higher portfolio weight on loan classes to which the respective bank has a high pre-existing exposure (i.e., the top 25% of the distribution). This change represents 7.8% of the average within-bank SD of the portfolio weight changes. Similarly, banks that gain government guarantee coverage increase their loan volume to high-exposure loan classes on average by 1.92pp, which is 2.7% of the average within-bank SD of the loan volume changes.

We conduct several validity checks. First, our results on the moderating effect of banks' pre-existing exposures are robust to including state-time fixed effects. Second, we run placebo tests for the pre-treatment period and validate the parallel trends assumption. Third, we exclude all banks that are treated most of the time. Fourth, we exclude one

[4] This portfolio reallocation intensifies up to the third year after the change in the government guarantee coverage.

sample year at a time. The results remain robust in these alternative specifications. Fifth, we build on the diagnostic tests suggested by De Chaisemartin and d'Haultfoeuille (2020) to show that our setting is not materially affected by the "negative weighting problem" that can occur in staggered difference-in-differences (DiD) specifications.

Finally, we employ a modified DiD design to evaluate to what extent our results are driven by banks that gain government guarantee coverage ("gainers") versus banks that lose coverage ("losers") and to rule out "forbidden comparisons" (see, e.g., De Chaisemartin & D'Haultfoeuille, 2022). Specifically, in the spirit of De Chaisemartin and d'Haultfoeuille (2020), we exclude banks that switch treatment more than once and, using a coerced matching technique, restrict the analysis to two types of comparisons: (i) gainers vs. banks that are never represented in the BHUA Senate committee, and, (ii), losers vs. banks that are always represented during our sample period.

The modified DiD design confirms our main results, both qualitatively and quantitatively. Moreover, the results show that the effect of a change in government guarantee coverage on banks' lending behavior is fairly symmetrical in magnitude. While gainers tend to further increase their exposure towards loan classes to which they already had a high pre-existing exposure, losers reduce their exposure to these loan classes.

Related literature. First, our paper adds to the literature that studies the effects of government guarantees on bank investment behavior. Generally, government guarantees aim to prevent bank runs (e.g., Diamond & Dybvig, 1983) and to avoid the social cost of bank failures (e.g., Gorton & Huang, 2004). Early papers showed that government guarantees create moral hazard problems (e.g., Kareken & Wallace, 1978 and Merton, 1977; see Allen, Carletti, & Leonello, 2011 for a review), while more recent literature links government guarantees and systemic risk (Farhi & Tirole, 2012; Bianchi, 2016; Keister, 2016; and Davila & Walther, 2019).[5]

Empirically, Karels and McClatchey (1999) finds no relation between deposit insurance and bank risk-taking, while Gropp and Vesala (2004) finds even lower risk-taking. Most studies, however, find that government guarantees are associated with higher bank risk-taking (e.g., Dam & Koetter, 2012, Brandao-Marques, Correa, & Sapriza, 2013, and

[5]Farhi and Tirole (2012) demonstrates that guarantees induce herding incentives, resulting in financial fragility. Bianchi (2016) shows that targeted bailouts exacerbate banks' moral hazard. Keister (2016) considers bailouts with limited commitment. Davila and Walther (2019) shows that large banks anticipate that their actions affect bailout decisions and thus leverage more than smaller banks.

Gropp, Gruendl, & Guettler, 2014). Gropp, Hakenes, and Schnabel (2011) documents that guarantees undermine competition in the banking sector, which increases risk-taking also by non-guaranteed banks. We highlight that government guarantees can induce banks to increase their asset concentration, a more subtle form of risk-taking, and provide empirical evidence for this mechanism.

Second, our paper contributes to the literature studying bank asset concentration and specialization. Several papers study determinants of specialization[6] and implications for bank risk.[7] Most closely related to our paper, there is evidence showing that distressed banks increase their asset concentration. De Jonghe, Dewachter, Mulier, Ongena, and Schepens (2020) shows that banks facing a negative funding shock reallocate their loan portfolio to sectors where they have a high market share and to sectors in which they are more specialized. Using Mexican loan data, Agarwal, Correa, Morais, Roldán, and Ruiz Ortega (2020) shows that after a collapse of energy prices in 2014, banks exposed to the energy sector increased their exposure to these borrowers even more. We contribute to this literature by showing that perceptions of government guarantee coverage shape banks' portfolio concentration.

3.2 Model framework

We lay out the effects of government guarantees on banks' investment choices in a corporate finance–style framework. In our model, government guarantees distort shareholders' preferences towards investments that pay off more in states of nature where the firm does not default. We consider an economy that consists of two dates $t = 1, 2$ and three risk-neutral parties: the government, a bank, and a creditor.

[6] Burietz and Ureche-Rangau (2020) shows that banks lend more to domestic borrowers and familiar industries. Duquerroy, Mazet-Sonilhac, Mésonnier, and Paravisini (2022) shows that banks specialize locally by industry. Paravisini, Rappoport, and Schnabl (2015) find that firms take bank specialization into account when selecting their lenders. Acharya, Hasan, and Saunders (2006) and Tabak, Fazio, and Cajueiro (2011) find a positive link between portfolio concentration and bank performance.

[7] Goetz, Laeven, and Levine (2016) shows that lower geographic concentration reduces bank risk. Galaasen, Jamilov, Juelsrud, and Rey (2020) finds that banks pass on granular credit shocks to the real economy, which suggests that credit concentration induces negative economic outcomes on average. Boeve, Duellmann, and Pfingsten (2010) shows that specialization can have opposing effects on portfolio risk, negative through improved monitoring and positive due to concentration risk. Beck, De Jonghe, and Mulier (2022) finds that systemic risk exposure decreases with specialization. De Jonghe, Mulier, and Samarin (2021) finds that bank specialization is associated with less zombie lending.

3.2.1 Setup

The creditor is endowed with d units of capital at $t = 1$. The bank has an equity endowment of e and it can borrow additional funds from the creditor. Moreover, the bank has a legacy investment of size l in risky asset L, and it needs to refinance the legacy debt d_l.

The creditor can either lend to the bank or invest in a risk-free asset that yields a gross return of $R_f = 1$ at $t = 2$. The contract between the creditor and the bank is a standard debt contract that specifies the loan amount d as well as the interest D to be paid at $t = 2$; and which cannot be made contingent on the realization of the state of nature. The bank's total available funds at $t = 1$ are thus $K = e + d$. Moreover, we assume that the bank is protected by limited liability and that it has all the bargaining power vis-a-vis the creditor.[8]

At $t = 1$, two mutually exclusive investments possibilities arise for the bank: an investment in asset $\overline{A}$ or $\underline{A}$. In the following, we use $A = \{\overline{A}, \underline{A}\}$ as abbreviation for this set of assets. Both assets have a fixed investment size of x and mature at $t = 2$. For simplicity, we normalize the bank's total liquidity demand to $d_l + x = 1$ and specify that $K = 1$. The bank's legacy asset L and the assets $\overline{A}$ and $\underline{A}$ generate a return $R_i > 1$ (where $i = \{L, A\}$) per unit of invested capital with probability λ_i and zero otherwise.

We specify that both of the bank's investment opportunities have the same expected return, that is, $\lambda_{\overline{A}} R_{\overline{A}} = \lambda_{\underline{A}} R_{\underline{A}} = R$, where λ_A is a random variable with support $\{\underline{\lambda}, \overline{\lambda}\}$ and $E[\lambda_A] = \lambda$. Moreover, without loss of generality, we assume that the bank has a non-pecuniary benefit/cost, Δ, when choosing asset $\underline{A}$, which is uniformly distributed with $\Delta \sim U(-\delta, \delta)$ and $E[\Delta] = 0$. This random non-pecuniary benefit allows us to determine an ex-ante likelihood for the bank to choose either asset investment.[9]

The bank learns the realizations of the random variables at $t = 1$ before it has to decide between its two investment possibilities. We assume that investing in either investment opportunity is always superior compared to not investing, that is, $(R - \delta) > R_f$. Since we are interested in the implication of a sizeable pre-existing loan exposure on the bank's investment behavior, we specify that $lR_L \geq xR_i$ (i.e., the legacy exposure is larger than the marginal investment) and focus our analysis on the case where the bank does not default

[8] Shifting the bargaining power to the creditor does not affect bank behavior qualitatively, it only changes the distribution of the gains from exploiting the government guarantee. When having the bargaining power, the creditor will increase the interest rate until the bank just breaks even in expectations.

[9] We specify that $\delta > xR/\lambda$, which ensures that the ex-ante likelihood that the bank chooses the legacy asset over the alternative asset is always a continuous function of the government insurance coverage, α.

when the legacy asset is successful.

To study the effect of a government guarantee on the bank's investment incentives given a specific pre-existing portfolio and investment opportunity set, we assume that the risky returns of assets L and A are dependent with the joint success probabilities shown in Table 3.1. The joint probability that both assets are successful at the same time (i.e., the realization where $\widetilde{R}_L = R_L$ and $\widetilde{R}_A = R_A$) is given by ρ_A, where we assume without loss of generality that $\rho_{\underline{A}} < \rho_{\overline{A}} \leq \underline{\lambda}$. That is, asset $\overline{A}$ has a higher return correlation with the legacy asset L than asset $\underline{A}$. Moreover, it follows that $(\lambda_L - \rho_A)$ is the probability that asset L is successful and A is not, while $(\lambda_A - \rho_A)$ is the probability that asset A is successful and L is not. The joint probability that both assets fail at the same time is $(1 - \lambda_L - \lambda_A + \rho_A)$.[10] The return correlation of the bank's marginal investment opportunities with its legacy asset are thus increasing with ρ_A.

Finally, we assume that bank debt is guaranteed by the government through the possibility of a public intervention in case of default. In particular, if the bank would default on its debt liabilities, the government rescues the bank with probability $\alpha \in [0, 1]$, that is, the government injects enough funds to fully settle the bank's liabilities.[11] Hence, α is a measure of the government insurance coverage for the bank's debt liabilities. There is full deposit insurance when $\alpha = 1$, bank debt is not guaranteed when $\alpha = 0$, and all intermediate cases, $\alpha \in (0, 1)$, correspond to an implicit government bailout guarantee in which the government bails out a bank with probability α.

3.2.2 Bank maximization

The bank's maximization problem is to optimally choose its investment at $t = 1$. In the following, we first determine the bank's expected profit from investing in asset $\underline{A}$ and $\overline{A}$ at $t = 1$, respectively. In a second step, we analyze how a change in the extent of the bank's government guarantee affects the likelihood that the bank invests in either asset.

In general, we have to distinguish between two different cases depending on the bank's

[10] We stipulate that $1 - \lambda_L - \lambda_A + \rho_A \geq 0$, which ensures that all joint probabilities are non-negative for all $\rho_A \in [0, \underline{\lambda}]$.

[11] This can be interpreted either as (i) the government takes over the bank and thus becomes the residual claimant (i.e., receives possible returns) and then settles the bank's liabilities or (ii) the bank remains private and the government injects the shortfall of funds needed to settle the bank's liabilities. Both assumptions yield the same results.

Table 3.1: Joint probabilities for the bank's return realizations of the risky assets

Asset $\overline{A}$

		$\widetilde{R}_{\overline{A}}$	
		$R_{\overline{A}}$	0
$\widetilde{R}_L$	R_L	$\rho_{\overline{A}}$	$\lambda_{\overline{A}} - \rho_{\overline{A}}$
	0	$\lambda_L - \rho_{\overline{A}}$	$1 - \lambda_L - \lambda_{\overline{A}} + \rho_{\overline{A}}$

Asset $\underline{A}$

		$\widetilde{R}_{\underline{A}}$	
		$R_{\underline{A}}$	0
$\widetilde{R}_L$	R_L	$\rho_{\underline{A}}$	$\lambda_{\underline{A}} - \rho_{\underline{A}}$
	0	$\lambda_L - \rho_{\underline{A}}$	$1 - \lambda_L - \lambda_{\underline{A}} + \rho_{\underline{A}}$

leverage and pre-existing legacy asset exposure:

(i) Low-exposure case: the bank has a low exposure to the legacy asset relative to the size of its equity capitalization, that is, the bank only defaults if both its investments (i.e., the legacy asset L and A) fail at the same time.

(ii) High-exposure case: the bank has a high exposure to the legacy asset relative to the size of its equity capitalization, that is, the bank defaults whenever the investment in the legacy asset L fails.

Low-exposure case.

We first consider the low-exposure case, for which the bank's expected profit at $t = 1$ is given by

$$\begin{aligned}\Pi_{A,lo} &= \Delta_A + \rho_A\left[lR_L + xR_A - dD\right] + (\lambda_L - \rho_A)\left[lR_L - dD\right] \\ &+ (\lambda_A - \rho_A)\left[xR_A - dD\right] - e, \end{aligned} \tag{3.1}$$

where $\Delta_{\overline{A}} = 0$ and $\Delta_{\underline{A}} = \Delta$. With probability ρ_A both assets (i.e., L and A) are successful at the same time, and with probability $(\lambda_L - \rho_A)$ and $(\lambda_A - \rho_A)$, respectively, only one of the two assets is successful. If at least one investment is successful, the bank receives the residual asset cash flows after the repayment to the creditor. Note that the bank's probability of staying solvent, $\rho_A + (\lambda_L - \rho_A) + (\lambda_A - \rho_A)$, depends negatively on the return correlation ρ_A.

To borrow the necessary funds from the creditor (i.e, $d = d_l + x - e$), the bank must offer an interest rate that makes the creditor at least indifferent between lending to the bank and investing in the risk-free asset. The bank can repay the creditor if either asset investment is successful. When both of the bank's investments are unsuccessful, which happens with probability $(1-\lambda_L-\lambda_A+\rho_A)$, the government steps in and settles the creditor's claim with probability α. Hence, the creditor's participation constraint at $t=1$ is given by

$$\rho_A dD+(\lambda_L-\rho_A)\,dD+(\lambda_A-\rho_A)\,dD+(1-\lambda_L-\lambda_A+\rho_A)\alpha dD\geq d. \tag{3.2}$$

The creditor is fully repaid if at least one of the assets is successful (first three terms) or if both investments fail but the bank is rescued by the government (fourth term).

As the creditor's participation constraint will be binding in the optimum (the bank has the bargaining power), the respective interest rate follows from solving Constraint (3.2) for D:

$$D_{A,lo}=\frac{1}{\rho_A+(\lambda_L-\rho_A)+(\lambda_A-\rho_A)+(1-\lambda_L-\lambda_A+\rho_A)\alpha}. \tag{3.3}$$

Plugging the binding creditor's participation constraint from Eq. (3.2) and $D_{A,lo}$ from Eq. (3.3) into Eq. (3.1) and simplifying yields for the bank's expected return:

$$\begin{aligned}\Pi^*_{A,lo}=\Delta_A+&\underbrace{(\lambda_L lR_L+\lambda_A xR_A)}_{=PV_{A,lo}}\\ &+\underbrace{(1-\lambda_L-\lambda_A+\rho_A)\alpha\frac{d}{\rho+(\lambda_L-\rho_A)+(\lambda_A-\rho_A)+(1-\lambda_L-\lambda_A+\rho_A)\alpha}}_{=G_{A,lo}}-1,\end{aligned} \tag{3.4}$$

where we already incorporated that $e+d=d_l+x=1$.

Eq. (3.4) consists of the following parts: The investments in assets L and A yield in expectations $\lambda_L lR_L$ and $\lambda_A xR_A$, respectively (first term), denoted $PV_{A,lo}$. The second term in Eq. (3.4) represents the value of the government guarantee, denoted $G_{A,lo}$, which equals the expected transfer of funds from the public to the private sector. In particular, the government repays the bank's creditor with probability α in case the bank fails (which happens with probability $1-\lambda_L-\lambda_A+\rho_A$). As the bank has the bargaining power vis-a-vis the creditor, it appropriates the full value of the government guarantee subsidy.

Eq. (3.4) implies the following Lemma.

Lemma 1. *Investing in the asset $\overline{A}$ dominates investing in asset $\underline{A}$ at $t = 1$ in the low-exposure case if*

$$\begin{aligned} \Delta \leq \Delta^*_{lo} \equiv & \frac{(1-\lambda_L-\lambda_{\overline{A}}+\rho_{\overline{A}})\alpha d}{\rho_{\overline{A}}+\left(\lambda_L-\rho_{\overline{A}}\right)+\left(\lambda_{\overline{A}}-\rho_{\overline{A}}\right)+(1-\lambda_L-\lambda_{\overline{A}}+\rho_{\overline{A}})\alpha} \\ & - \frac{(1-\lambda_L-\lambda_{\underline{A}}+\rho_{\underline{A}})\alpha d}{\rho_{\underline{A}}+\left(\lambda_L-\rho_{\underline{A}}\right)+\left(\lambda_{\underline{A}}-\rho_{\underline{A}}\right)+(1-\lambda_L-\lambda_{\underline{A}}+\rho_{\underline{A}})\alpha}, \end{aligned} \tag{3.5}$$

where Δ^*_{lo} is negative when $\left(\lambda_{\overline{A}}-\rho_{\overline{A}}\right) > \left(\lambda_{\underline{A}}-\rho_{\underline{A}}\right)$ and vice versa. The ex-ante expected value for the threshold value, Δ^*_{lo}, is

$$\begin{aligned} E[\Delta^*_{lo}] = & \frac{(1-\lambda_L-\lambda+\rho_{\overline{A}})\alpha d}{\rho_{\overline{A}}+\left(\lambda_L-\rho_{\overline{A}}\right)+\left(\lambda-\rho_{\overline{A}}\right)+(1-\lambda_L-\lambda+\rho_{\overline{A}})\alpha} \\ & - \frac{(1-\lambda_L-\lambda+\rho_{\underline{A}})\alpha d}{\rho_{\underline{A}}+\left(\lambda_L-\rho_{\underline{A}}\right)+\left(\lambda-\rho_{\underline{A}}\right)+(1-\lambda_L-\lambda+\rho_{\underline{A}})\alpha} > 0. \end{aligned} \tag{3.6}$$

Proof. See Appendix A.

From Eqs. (3.5) and (3.6), it follows that the ex-ante probability that the bank invests in asset $\overline{A}$ and $\underline{A}$ is given by

$$F_{\overline{A},lo} \equiv P(\Delta \leq \Delta^*_{lo}) = \frac{E[\Delta^*_{lo}]}{2\delta}, \tag{3.7}$$

$$F_{\underline{A},lo} \equiv P(\Delta > \Delta^*_{lo}) = 1 - \frac{E[\Delta^*_{lo}]}{2\delta}, \tag{3.8}$$

respectively. Consequently, a lower $E[\Delta^*_{lo}]$ implies that it is more likely that the bank invests in asset $\overline{A}$ (instead of asset $\underline{A}$) at $t = 1$. The following lemma states that the effect of a change in the government guarantee coverage on the bank's investment behavior (i.e., the likelihood of the bank choosing asset $\overline{A}$ vs $\underline{A}$) is ambiguous in the low-exposure case.

Lemma 2. *The derivative of $F_{\overline{A},lo}$ with respect to α is given by*

$$\begin{aligned} \frac{\partial F_{\overline{A},lo}}{\partial \alpha} = & \frac{1}{2\delta}\frac{d(\lambda_L+\lambda-\rho_{\overline{A}})(1-\lambda_L-\lambda+\rho_{\overline{A}})}{(\rho_{\overline{A}}+\left(\lambda_L-\rho_{\overline{A}}\right)+\left(\lambda-\rho_{\overline{A}}\right)+(1-\lambda_L-\lambda+\rho_{\overline{A}})\alpha)^2} \\ & - \frac{1}{2\delta}\frac{d(\lambda_L+\lambda-\rho_{\underline{A}})(1-\lambda_L-\lambda+\rho_{\underline{A}})}{(\rho_{\underline{A}}+\left(\lambda_L-\rho_{\underline{A}}\right)+\left(\lambda-\rho_{\underline{A}}\right)+(1-\lambda_L-\lambda+\rho_{\underline{A}})\alpha)^2}, \end{aligned} \tag{3.9}$$

which can be positive or negative.

Proof. See Appendix A.

High-exposure case.

Next, we assess the high-exposure case for which the bank's expected return at $t = 1$ becomes

$$\Pi_{A,hi} = \Delta_A + \rho_A \left[lR_L + xR_A - dD \right] + (\lambda_L - \rho_A) \left[lR_L - dD \right] - e. \tag{3.10}$$

In the high-exposure case, the face value of debt, dD, is higher than the bank's cash flow in the state where only asset A is successful. Hence, the bank only remains solvent if the legacy asset L is successful and fails otherwise. Eq. (3.10) shows that the bank's expected asset cash flows in success states increase with ρ_A: a higher return correlation between the marginal and the legacy asset raises the likelihood that the bank receives returns from asset A in states in which the bank is solvent (i.e., in state in which asset L is successful).

For the high-exposure case, the creditor's participation constraint becomes

$$\begin{aligned} &\rho_A dD + (\lambda_L - \rho_A) dD + (\lambda_A - \rho_A) \left[\alpha dD + (1-\alpha) xR_A \right] \\ &+ (1 - \lambda_L - \lambda_A + \rho_A) \alpha dD \geq d. \end{aligned} \tag{3.11}$$

The creditor receives full repayment in all states in which either asset L is successful (first two terms of Eq. 3.11) or the bank fails but the government intervenes. Additionally, even if the bank's investment in asset L fails and the bank is not rescued, the creditor receives at least a partial repayment if the bank's investment in asset A is successful as the creditor receives the bank's liquidation value (i.e., xR_A) in this case.

Again, the creditor's participation constraint has to be binding in the optimum. Solving the binding Constraint (3.11) for D yields the creditor's interest rate for the high-exposure case:

$$D_{A,hi} = \frac{1 - \frac{1}{d} (\lambda_A - \rho_A) (1-\alpha) xR_A}{\lambda_L + (1-\lambda_L)\alpha}. \tag{3.12}$$

Moreover, Eq. (3.11) shows that the value of the creditor's additional hedge provided by an investment in asset A decreases with the asset correlation ρ_A: a higher asset correlation between the marginal and the legacy asset decreases the likelihood that the creditor receives at least a partial repayment in the event that the bank's investment in asset L fails. As a result, the creditor's interest rate increases with ρ_A, as shown by Eq. (3.12). Through this funding cost channel, a higher return correlation has a negative effect on the bank's expected return as it leads to higher financing costs.

Comparing Eqs. (3.3) and (3.12) shows that the creditor's interest rate is always lower in the low-exposure case compared to the high-exposure case. In the latter case, the creditor is not fully repaid if solely asset A is successful and the bank is not rescued.

Plugging the binding creditor's participation constraint from Eq. (3.11) and $D_{A,hi}$ from Eq. (3.12) into Eq. (3.10) and simplifying yields for the bank's expected return at $t = 1$ in the high-exposure case

$$\begin{aligned}
\Pi^*_{A,hi} &= \Delta_A + \underbrace{(\lambda_L l R_L + \lambda_A x R_A)}_{=PV_{A,hi}} \\
&+ \underbrace{(1-\lambda_L)\alpha \frac{d - (\lambda_A - \rho_A)(1-\alpha) x R_A}{\lambda_L + (1-\lambda_L)\alpha} - (\lambda_A - \rho_A)\, \alpha x R_A}_{=G_{A,hi}} - 1. \qquad (3.13)
\end{aligned}$$

where we again used that $e + d = d_l + x = 1$. Taking the derivative of $\Pi^*_{A,hi}$ with respect to the asset correlation ρ_A yields

$$\frac{\partial \Pi^*_{A,hi}}{\partial \rho_A} = \frac{\alpha x R_A}{\lambda_L + (1-\lambda_L)\alpha} > 0. \qquad (3.14)$$

Hence, the bank's expected return at $t = 1$ positively depends on the asset correlation if $\alpha > 0$.

The intuition for this result is as follows: a higher return correlation has two opposing effects on the bank's expected return in the high-exposure case. On the one hand, a higher return correlation increases the bank's expected asset cash flows in states in which the bank is solvent (see Eq. 3.10); on the other hand, it leads to higher financing costs, as the bank's creditor demands a higher interest rate (see Eq. 3.12). Without government guarantees, these two channels exactly offset each other (i.e., $\partial \Pi^*_{A,hi}/\partial \rho_A(\alpha = 0) = 0$), as shown by Eq. (3.14). Whatever the bank gains in higher expected asset cash flows in success states due to a higher return correlation, the creditor loses in expectations as liquidation value. The latter increases the bank's funding costs such that it exactly offsets the increase in expected asset returns.

Government guarantees drive a wedge into this relationship. With government guarantees, the hedge for the creditor provided by the possible asset A return is not as valuable as it is without government guarantees. Specifically, since the creditor always receives full repayment if the bank receives public support, the creditor does not value asset A's return in these states. Hence, if the government provides at least a partial guarantee, a change in the asset correlation has a smaller effect on the creditor's interest rate. As a result, if $\alpha > 0$, the cash flow channel (i.e., a higher return correlation leads to a higher expected asset cash flow in success states) dominates the financing costs channel (i.e., a higher return correlation leads to higher financing costs) and thus $\Pi^{*}_{A,hi}$ increases with the asset correlation.

The result also directly follows from the Modigliani-Miller intuition. As the bank has all the bargaining power vis-a-vis its creditor, it fully appropriates the value of the government guarantee subsidy. Therefore, the bank's expected return increases and decreases one-to-one with the bank's total firm value (i.e., the sum of the value generated by its asset investment and the value of the government guarantee).

Eq. (3.13) shows that, while the asset return correlation ρ_A has no effect on the net present value (NPV) generated by the assets ($PV_{A,hi}$), the value of the government guarantee ($G_{A,hi}$) increases with the return correlation if $\alpha > 0$. The intuition for this mechanism is as follows. The bank defaults in two states in the high-exposure case: (i) if both assets fail and (ii) if asset L fails but asset A is successful. In state (i) the government has to inject the amount $dD_{A,hi}$ if it decides to rescue the bank. However, in state (ii) asset A yields the return xR_A; thus, the government only has to inject the amount $dD_{A,hi} - xR_A$ in this state.

With a higher asset return correlation state (i) becomes more and state (ii) less likely. The size of the expected public injection (and, in turn, the value of the government guarantee) thus increases with the return correlation ρ_A. In other words, the bank "loses" less expected asset return to the government when the correlation is high (see second last term of Eq. 3.13). As a result, the bank's expected return increases with the return correlation between the marginal and the legacy asset.

Finally, comparing Eq. (3.13) for the high and low asset correlation asset (i.e., assets $\overline{A}$ and $\underline{A}$, respectively), yields the following Lemma.

Lemma 3. *Investing more in asset $\overline{A}$ dominates investing in asset $\underline{A}$ if Δ is sufficiently low, that is,*

$$\Delta \leq \Delta_{hi}^{*} \equiv \alpha \frac{(\lambda_{\underline{A}}\rho_{\overline{A}} - \lambda_{\overline{A}}\rho_{\underline{A}})xR}{\lambda_{\overline{A}}\lambda_{\underline{A}}(\alpha + (1-\alpha)\lambda_L)}. \tag{3.15}$$

Otherwise, investing in asset $\underline{A}$ dominates. The ex-ante expected value for the threshold value, Δ_{hi}^{*}, is

$$E[\Delta_{hi}^{*}] = \alpha \frac{(\rho_{\overline{A}} - \rho_{\underline{A}})xR}{\lambda(\alpha + (1-\alpha)\lambda_L)}. \tag{3.16}$$

From Eq. (3.16), it follows that the ex-ante probability that the bank invests in asset $\overline{A}$ at $t = 1$ in the high-exposure case is given by

$$F_{\overline{A},hi} \equiv P(\Delta \leq \Delta_{hi}^{*}) = \frac{E[\Delta_{hi}^{*}]}{2\delta}. \tag{3.17}$$

Taking the derivative of $F_{\overline{A},hi}$ with respect to α yields

$$\frac{\partial F_{\overline{A},hi}}{\partial \alpha} = \frac{1}{2\delta} \frac{\lambda_L(\rho_{\overline{A}} - \rho_{\underline{A}})xR}{\lambda(\lambda_L + (1-\lambda_L)\alpha)^2} > 0. \tag{3.18}$$

Therefore, an increase in the extent of the government guarantee always raises the ex-ante likelihood that the bank decides to invest in asset $\overline{A}$ (the high asset correlation asset) in the high-exposure case.

3.2.3 Comparison low- and high-exposure case.

In a last step, we compare the marginal change in the bank's propensity to invest in the high versus low return correlation marginal asset for the two exposure cases, which yields the following proposition.

Proposition 4. *An increase in the bank's government guarantee coverage, α, increases* *the propensity that the bank invests in asset $\overline{A}$ versus asset $\underline{A}$ more in the high-exposure case (compared to the low-exposure case), that is, it always holds that*

$$\frac{\partial F_{\overline{A},hi}}{\partial \alpha} > \frac{\partial F_{\overline{A},low}}{\partial \alpha}. \tag{3.19}$$

Proof. See Appendix A.

The result summarized in Proposition 4 predicts that banks with a concentrated asset exposure (i.e., a large exposure relative to their equity capitalization) tend to further concentrate their exposure more strongly when their government guarantee coverage increases compared to banks with a less concentrated exposure.

3.3 Data and Institutional Setting

We test our model predictions in the context of the U.S. banking system. Our sample period spans the years 1996 to 2016. We employ information about the U.S. Senate committee composition to measure changes in banks' expected government guarantee value and obtain bank financial and portfolio information from the BHC Call Report Database. The following chapter describes the data in more detail.

3.3.1 Measuring changes in banks' bailout expectations

Identifying banks' portfolio reallocations in response to changes in the extent of their government guarantee coverage is empirically challenging. First, effects on the banks' investment behavior arise from expectations about the value of government guarantees, which are usually not observable. Second, the extent of a bank's government guarantee protection is largely endogenous to its investment behavior and portfolio risk.

Econometrically, we thus require some measurable variation in banks' expected government guarantee value that is otherwise uncorrelated with their investment behavior. To this end, we draw from the recent literature on political connections and bank bailouts, and use changes in banks' geography-based political connections to identify arguably exogenous variation in their bailout expectations (Duchin & Sosyura, 2014 and Kostovetsky, 2015).[12]

Exploiting banks' geography-based political connections as an instrument for bailout approvals, Duchin and Sosyura (2014) studies applications to the Troubled Asset Relief Program (TARP) and finds that bailed-out banks started to originate riskier mortgages. Using a similar geography-based measure, Kostovetsky (2015) finds that politically connected banks have a lower bankruptcy probability, as well as a higher leverage, stock price volatility, and co-movement with the stock market.

We build on the geography-based political connection measure from Kostovetsky (2015) to identify variation in banks' expected government guarantee values. The results therein are consistent with the conjecture that having a senator from its state of incorporation in the BHUA Senate committee significantly increases a bank's likelihood of receiving government assistance in times of distress.

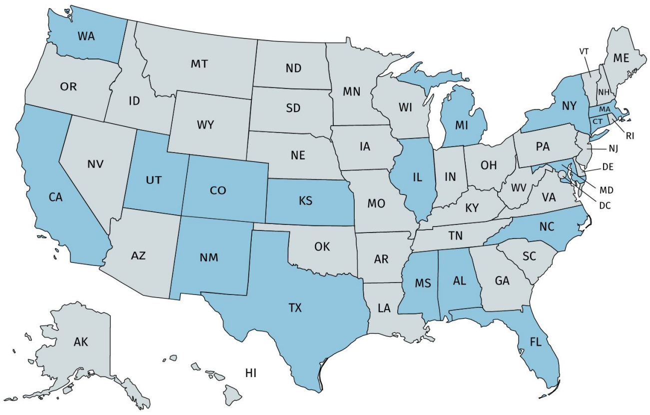
With every new congress, senators are assigned to committees in the U.S. Senate, which, within assigned areas, monitor ongoing governmental operations, identify issues suitable for legislative review, gather and evaluate information, and recommend courses of action. The BHUA Senate committee is one of twenty standing committees, and it has jurisdiction over banks and other financial institutions. In recent decades, this committee has played a decisive role for U.S. government bailout decisions.

Although senators are formally elected to standing committees by the entire membership of the Senate, in practice each party conference is largely responsible for determining which of its members will sit on each committee. Party conferences appoint a "committee on committees" or a "steering committee" to make committee assignments, considering seniority, areas of expertise, as well as preferences and prior committee assignments. The committee assignments need to adhere to limits that the Senate places on the number and types of panels any one senator may serve on and chair.

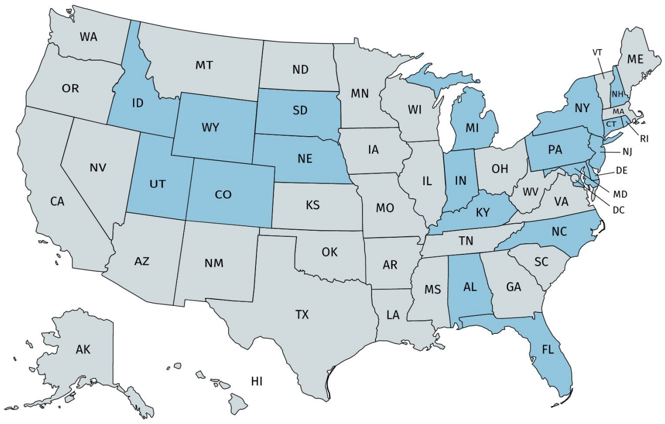
The number of seats a party holds in the Senate determines its share of seats on each committee. Hence, besides party considerations and senators' qualifications and committee preferences, shifts in the proportion of Republican and Democrat senators might also lead the parties to reorganize committee memberships. Moreover, changes in committee membership are triggered by a senator's decision to focus on other tasks (e.g., electoral

[12]Relatedly, Dam and Koetter (2012), Duchin & Sosyura, 2012, and Blau, Brough, and Thomas (2013) show that politically connected banks are more likely to benefit from government rescue measures.

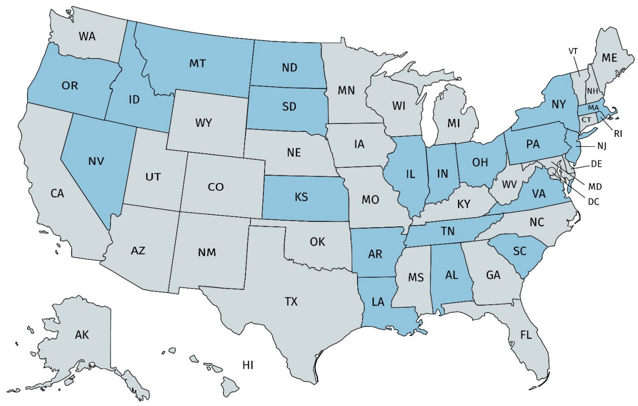
Figure 3.1: **BHUA Senate committee.** States with a senator in the Committee (in light blue) in 1996, 2006, and 2016.



(a) As of 1996



(b) As of 2006



(c) As of 2016

campaigns) or by a senator's retirement.

As of 2022, the BHUA Senate committee has 24 members, 12 from the Democratic Party and 12 from the Republican Party. We draw historical membership of the BHUA Senate committee from annual volumes of the Official Congressional Directory. Figure 3.1 shows that state representation in the committee is dispersed across different regions with significant variation over time.

The process and the factors that determine the composition of Senate committees, as well as the fact that banks rarely move across state lines (we exclude the few banks that moved during our sample period), make it reasonable to conjecture that a bank's geography-based committee representation is not directly linked to its investment behavior and asset composition, except through the effect on bailout expectations. Exploiting this exogenous variation allows us to estimate causal effects of changes in banks' expectations about their government guarantee coverage on their portfolio concentration.

Specifically, we use the information about the composition of the BHUA Senate committee to construct two proxies to capture changes in the banks' bailout expectations. For regressions at the bank–year level, we employ the dummy $GG_{b,t}$ (for **G**overnment **G**uarantee) as proxy for changes in the banks' expected government guarantee coverage, which is equal to one if at least one senator from bank b's state of incorporation is a member in the BHUA Senate committee in year t. For regressions at the bank–loan-class–year level, we employ $\triangle GG_{b,t}$, which can take the values $\{-1,0,1\}$: 0 when there was no change in $GG_{b,t}$ in year t, 1 if $GG_{b,t}$ changed from zero to one, and -1 if $GG_{b,t}$ changed from one to zero. Overall, 1,270 out of the 3,205 banks in our sample (i.e., 39.6%) experienced a change in $GG_{b,t}$ during our sample period.

3.3.2 Measuring banks' asset composition

We obtain bank portfolio data, detailed financial information, and general bank information (e.g., about headquarter locations) from the U.S. Federal Reserve's publicly available Consolidated Financial Statements for Bank Holding Companies (FR Y-9C). These are reported quarterly and publicly disclosed for U.S. Bank Holding Companies (BHCs) and contain detailed information on banks' activities and financial statements. The dataset includes all domestic bank holding companies with total consolidated assets of $150 million or more and all multibank holding companies with debt outstanding to the general public or engaged in certain nonbanking activities. We consider top-tier U.S. Bank Holding Companies identified based on the "RSSD ID".

We condense information at the year level using year-end values and drop observations with missing or negative assets and/or equity. Moreover, we exclude banks that changed their headquarter state during our sample period (to ensure treatment exogeneity), as well as bank-year observations where a bank's assets increase by more than 50% in a single year (such a large change is likely due to a merger or a major acquisition).

We determine banks' loan portfolio composition based on data about their exposure to fourteen different loan classes. Banks often use this portfolio segmentation in the Comprehensive Capital Analysis and Review (CCAR) exercises (Siarka, 2021). These loan classes include: residential real estate (three different sub-classes), commercial real estate (three different sub-classes), two agricultural loan classes, two consumer credit classes, two commerce and industry loan classes, loans to financial firms, and loans to foreign governments.

We first compute two different concentration measures commonly used in the literature at the bank level: the Herfindahl-Hirschman index (*HHI*) and an entropy diversification measure (*EDM*). Both measures build on the relative weight of each loan class in the lender's portfolio, the class weight (*CW*) at time t, calculated as

$$CW_{b,c,t} = \frac{Lending\ Volume\ to\ Class_{b,c,t}}{Total\ Lending\ Volume_{b,t}}. \tag{3.20}$$

The *HHI* is then calculated as the sum of the squared portfolio share of each loan class, while the *EDM* is calculated as the sum of the product between the share of each loan class c times its logarithm:

$$Portfolio\ HHI_{b,t} = \sum [CW_{b,c,t}^2] \times 100 \tag{3.21}$$

$$Portfolio\ EDM_{b,t} = \sum [CW_{b,c,t} * Log(CW_{b,c,t})] \times 100. \tag{3.22}$$

A higher *HHI* and *EDM* both correspond to a higher asset concentration in the bank's loan portfolio. Table 3.2 provides an overview over the definitions of our dependent, independent, and control variables and Table 3.3 presents summary statistics for portfolio

Table 3.2: Variable Definitions

Variable	Description
Panel A: Explanatory variables and controls	
$GG_{b,t}$	Bank has headquarter in state represented in BHUA Senate committee.
$Size_{b,t}$	Natural logarithm of one plus assets.
$Wholesale\ Debt_{b,c,t}$	Assets minus equity and deposits, scaled by assets.
$Liquidity_{b,t}$	Cash and short-term investments, over assets.
$ROA_{b,t}$	Income before interests and taxes, over assets.
$Dividends_{b,t}$	Dummy variable identifying dividend payers.
$State\ GDP_{b,t}$	Natural logarithm of the GDP of bank *b*'s state of incorporation.
$Lending\ Exposure_{b,t}$	Total loan volume, scaled by Tier-1 capital.
$Exposure\ Ratio_{b,c,t}$	Asset holdings of loan class *c*, scaled by Tier-1 capital.
Panel B: Lender Outcomes	
$CW_{b,c,t}$	$\frac{Lending\ Volume\ to\ Class_{b,c,t}}{Total\ Lending\ Volume_{b,t}}$.
$Portfolio\ HHI_{b,t}$	$\sum[CW^2_{b,c,t}] \times 100$.
$Portfolio\ EDM_{b,t}$	$\sum[CW_{b,c,t} * Log(CW_{b,c,t})] \times 100$.
$\Delta Log(1+PW)_{b,c,t}$	Change in log of one plus loan class *c* portfolio weight, multiplied by 100.
$\Delta Log(1+LCV)_{b,c,t}$	Change in log of one plus loan volume to loan class *c*, multiplied by 100.

concentration measures, as well as our set of control variables.

The loan-class breakdown allows us to test our model prediction that banks with a concentrated exposure to a particular loan class have an incentive to further load up on this class when their government guarantee coverage increases. A higher concentration in a specific loan class ceteris paribus increases default correlations in the portfolio as borrowers' default events are generally more correlated within a specific loan class than across different loan classes (Boeve et al., 2010).[13]

[13]For example, Hansen, van Vuuren, Ramadurai, and Verde (2008) empirically estimates asset correlations for each internal ratings-based approach (IRB) asset class, finding that the correlation across asset classes is low. Regarding within asset class correlation, Calem, Follain, et al. (2003) and Carazo Hitos, Lamas Naveira, Muruais Fernández, and García Cascales (2010) find a default correlation within mort-

Table 3.3: Descriptive Statistics on BHC Call Report Data

	Observations	Mean	Std. Dev.	10%	50%	90%
GG	25,203	0.407	0.491	0.000	0.000	1.000
Size	25,203	13.390	1.322	12.124	13.134	14.925
Wholesale Debt	25,203	0.104	0.092	0.016	0.081	0.213
Liquidity	25,071	0.048	0.034	0.019	0.038	0.087
ROA	25,203	0.023	0.018	0.007	0.024	0.041
Dividends	25,203	0.770	0.421	0.000	1.000	1.000
State GDP	25,203	12.53	0.94	11.28	12.59	13.70
Portfolio HHI	25,203	24.72	7.35	16.33	22.94	34.05
Portfolio EDM	25,203	-164.75	23.64	-192.00	-168.16	-133.23
Lending Exposure	25,067	7.595	3.285	3.948	7.161	11.604
Exposure Ratio	259,629	0.725	1.012	0.012	0.263	2.118
$\Delta Log(1+PW)$	219,075	-0.002	1.485	-1.438	-0.016	1.468
$\Delta Log(1+LCV)$	219,075	5.694	41.718	-29.916	3.220	44.343

3.4 Bank level analysis

Before analyzing granular changes in the banks' loan class composition, we begin our empirical analysis by testing the effects of changes in our government guarantee proxy on banks' overall asset concentration.

3.4.1 Empirical setup

Based on our model predictions, we expect that having $GG = 1$ is associated with banks targeting a higher asset concentration in their loan portfolios. We employ the following staggered DiD specification to test this prediction:

$$y_{b,t+1} = \alpha_t + \alpha_b + \beta_1 GG_{b,t} + \delta X_{b,t} + \varepsilon_{b,t}, \tag{3.23}$$

where $y_{b,t+1}$ is either $HHI_{b,t+1}$ or $EDM_{b,t+1}$. Accordingly, our coefficient of interest is β_1, which captures the effect of GG on the banks' portfolio concentration.

The vector $X_{b,t}$ includes the control variables log of state GDP, size (logarithm of

gages of around 15%, which is in line with the correlation assumption in Basel II. Similarly, McNeil and Wendin (2007) find within sector correlations for a sample of U.S. corporate loans to be around 11%.

one plus assets), ROA (earnings before interest and taxes, scaled by assets), liquidity (cash holdings and short-term investments, scaled by assets), wholesale debt (assets minus equity and deposits, scaled by assets), dividends (dummy variable identifying dividend payers), number of loan classes, and lending exposure (total loans over Tier-1 capital). All continuous control variables are winsorized at 1%. Moreover, we include time and bank fixed effects to absorb time-invariant bank characteristics and common shocks.

To further investigate our model prediction that banks with larger lending exposures concentrate their assets more strongly as a result of government guarantee protection (compared to banks with less lending exposure), we employ the following regression specification:

$$\begin{aligned} y_{b,t+1} &= \alpha_t + \alpha_b + \beta_1 GG_{b,t} + \beta_2 Lending\ Exposure_{b,t} \\ &+ \beta_3 GG_{b,t} \times Lending\ Exposure_{b,t} + \delta X_{b,t} + \varepsilon_{b,t}, \end{aligned} \tag{3.24}$$

Where we again employ the banks' portfolio HHI and EDM as dependent variables. The variable *Lending Exposure* is defined as bank *b*'s total loans over Tier-1 capital, which allows us to analyze the interaction of our government guarantee measure with the size of the banks' overall loan exposure relative to their equity capitalization. Again, we control for the same set of control variables as in Specification (3.23) and include time and bank fixed effects. Here, our coefficient of interest is β_3, which gauges the additional effect of *GG* for banks with a high lending exposure.

Testing the prediction that banks with larger lending exposures react more strongly does not require us to simultaneously measure responses of banks across treated and non-treated states. Hence, we can test this prediction on banks within the same state by including state-time fixed effects. We employ the following functional form for this refinement:

$$\begin{aligned} y_{b,t+1} &= State_s \times \alpha_t + \alpha_b + \beta_1 Lending\ Exposure_{b,t} \\ &+ \beta_2 GG_{b,t} \times Lending\ Exposure_{b,t} + \delta X_{b,t} + \varepsilon_{b,t}. \end{aligned} \tag{3.25}$$

Given that our treatment is at the state level, we cluster standard errors conservatively at this level in all regression specifications. Our results are also robust to clustering standard errors at the bank level.

3.4.2 Results

Table 3.4 shows the regression results for Specification (3.23). In line with our model predictions, we find that a higher government guarantee coverage is associated with a higher portfolio concentration, that is, a higher HHI (column 1) and EDM (column 4). More specifically, a *GG* equal to one implies a 0.292 higher HHI value, which represents 13.5% of the average within-bank SD of the HHI. Equivalently, *GG* equal to one is associated with banks having a 0.742 higher portfolio EDM, which amounts to 10.9% of the average within-bank SD of the EDM.

To test whether the effect of a higher government guarantee coverage on banks' lending behavior is stronger for banks with higher lending exposure, we first conduct sample split tests dividing banks into high and low exposure banks. To this end, we flag banks that are in each sample year above the median of the *Lending Exposure* distribution as "high exposure" banks, and the remaining banks as "low exposure".[14] This split leaves us with 988 high exposure banks (results reported in columns 2 and 5 of Table 3.4) and 2,203 low exposure banks (results reported in columns 3 and 6). The results for both concentration measures confirm that, indeed, the effect is stronger for banks with high loan exposures, both in terms of the economic magnitude as well as the statistical significance.

Employing Specification (3.24), we further investigate whether the outcome differences between banks with high vs. low lending exposures are statistically different (see Panel A of Table 3.5). Columns (1)-(3) show the estimates for the HHI and columns (4)-(6) for the EDM. In columns (1) and (4), we employ *Lending Exposure* as a continuous variable. For the HHI and EDM, we find that β_3 is significant at the 10% and 5% level, respectively. The asset concentration effect of government guarantees is, hence, stronger for banks that have higher loan exposures relative to equity.

Our model predicts that this effect is non-linear, being particularly strong for banks with very high lending exposures. Accordingly, we employ dummies indicating a very

[14] The group of "low exposure" banks, hence, also includes banks that are in some, but not all, years above the median in the lending exposure distribution. We adopt this definition to avoid banks moving between the high and low exposure subsamples to be able to perform the diagnostic tests following De Chaisemartin and d'Haultfoeuille (2020) as described in Section 3.4.3.

Table 3.4: Portfolio Concentration

	Portfolio HHI			Portfolio EDM		
	Full Sample	High Ex.	Low Ex.	Full Sample	High Ex.	Low Ex.
GG	0.292**	0.505**	0.242*	0.742*	1.515**	0.592
	(0.032)	(0.039)	(0.087)	(0.053)	(0.019)	(0.141)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
N	20,861	4,351	16,510	20,861	4,351	16,510
R^2	0.840	0.907	0.824	0.870	0.921	0.855
$T1$	0.306	0.436	0.267	0.779	1.310	0.652
$T2$	3.933	4.991	3.185	10.007	14.982	7.787
Weight $(+)$	83.9%	79.4%	84.5%	83.9%	79.4%	84.5%
Sum $(+)$	1.019	1.030	1.020	1.019	1.030	1.020
Sum $(-)$	-0.019	-0.030	-0.020	-0.019	-0.030	-0.020

This table presents estimation results from Specification (3.23) for the period 1996-2016. The dependent variable in columns (1)-(3) is the Herfindahl-Hirschman index measure of bank b's lending portfolio in (t+1) from Eq. (3.21). The dependent variable in columns (4)-(6) is the entropy measure of bank b's lending portfolio in (t+1) from Eq. (3.22). Columns (1) and (4) use the full sample. In columns (2)-(3) and (5)-(6) we conduct sample splits, where we distinguish between banks that are above the median of the *Lending Exposure* distribution during the whole sample period ("high exposure" banks) and other banks ("low exposure" banks), where *Lending Exposure* is defined as total loans over Tier-1 capital. The dummy $GG_{b,t}$ is equal to one if at least one senator from bank b's state of incorporation is a member in the BHUA Senate committee in year t. The regressions include a set of one-period lagged control variables: log of state GDP, size (proxied as the logarithm of assets), return on assets (earnings before interest and taxes, scaled by assets), liquidity (measured as cash holdings and short-term investments, scaled by assets), dividends (dummy variable identifying dividend payers), lending exposure (total loans over Tier-1 capital), number of loan classes, and wholesale debt (assets minus equity and deposits, divided by assets). Standard errors are clustered at the state level. p-values are reported in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The last five columns report diagnostic test results following De Chaisemartin and d'Haultfoeuille (2020), which are discussed in detail in Section 3.4.3.

high lending exposure, where we consider the top 25% (columns 2 and 5) and the top 10% (columns 3 and 6) of the *Lending Exposure* distribution in the previous year as cutoffs, respectively. The results for both concentration measures again confirm that the effect is stronger for highly exposed banks. For example, the estimates in columns (3) and (6) of Table 3.5 imply that for banks with a *Lending Exposure* in the top 10%, $GG = 1$ is associated with a 0.99 higher HHI and a 3.05 higher EDM, which amounts to 45.5% of the average within-bank SD of the HHI and 44.9% of the average within-bank SD of the EDM, respectively.

Panel B of Table 3.5 shows that the results on the moderating effect of banks' lending exposure on the change in their portfolio concentration is robust to including state-time fixed effects. This evidence suggests that our results are not just driven by statewide economic developments that are reflected in bank balance sheets.

Table 3.5: Portfolio Concentration Conditional on Lending Exposure

Panel A: Inter-State	Portfolio HHI			Portfolio EDM		
GG	-0.199	0.191	0.213	-0.807	0.468	0.475
	(0.439)	(0.169)	(0.106)	(0.296)	(0.224)	(0.194)
GG x Lending Exposure	0.065^{*}			0.207^{**}		
(Continuous)	(0.059)			(0.042)		
GG x Lending Exposure		0.384^{**}			0.994^{**}	
(Top 25%)		(0.013)			(0.040)	
GG x Lending Exposure			0.773^{***}			2.572^{***}
(Top 10%)			(0.008)			(0.005)
$\hat{\beta}_1 + \hat{\beta}_3$		0.575^{***}	0.986^{***}		1.461^{***}	3.048^{***}
		(0.001)	(0.001)		(0.007)	(0.001)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
N	20,861	20,861	20,861	20,861	20,861	20,861
R^2	0.840	0.839	0.839	0.870	0.869	0.869

Panel B: Intra-State	Portfolio HHI			Portfolio EDM		
GG x Lending Exposure	0.070^{**}			0.212^{**}		
(Continuous)	(0.046)			(0.047)		
GG x Lending Exposure		0.399^{**}			1.019^{**}	
(Top 25%)		(0.010)			(0.041)	
GG x Lending Exposure			0.721^{**}			2.421^{***}
(Top 10%)			(0.013)			(0.009)
State-Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
N	20,799	20,799	20,799	20,799	20,799	20,799
R^2	0.855	0.854	0.854	0.882	0.881	0.881

This table presents estimation results from Specification (3.24) (Panel A) and Specification (3.25) (Panel B) for the period 1996-2016. The dependent variables in columns (1)-(3) is the Herfindahl-Hirschman index measure of bank b's lending portfolio in (t+1) from Eq. (3.21). The dependent variables in columns (4)-(6) is the entropy measure of bank b's lending portfolio in (t+1) from Eq. (3.22). The dummy $GG_{b,t}$ is equal to one if at least one senator from bank b's state of incorporation is a member in the BHUA Senate committee in year t. *Lending Exposure* is defined as total loans over Tier-1 capital. In columns (1) and (4), we employ it as a continuous exposure. In columns (2) and (5) we compare the Top 25% vs. Bottom 75% and in columns (3) and (6) we compare the Top 10% vs. Bottom 90%. The regressions include a set of one-period lagged control variables: log of state GDP, size (proxied as the logarithm of assets), return on assets (earnings before interest and taxes, scaled by assets), liquidity (measured as cash holdings and short-term investments, scaled by assets), dividends (dummy variable identifying dividend payers), number of loan classes, and wholesale debt (assets minus equity and deposits, divided by assets). Standard errors are clustered at the state level. p-values are reported in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

3.4.3 Validity

To further assess the identification assumptions of our DiD specification and the robustness of our results, we conduct a set of validity and robustness tests. We start investigating whether trends for treatment and control groups are parallel in the pre-treatment period with a placebo test (Angrist & Pischke, 2009). Specifically, we perform an additional DiD estimation “treating” banks three years before the actual treatment.[15]

Table 3.B.1 presents the placebo test results for the effect on banks’ portfolio concentration from Table 3.4 and Table 3.B.2 for the effects conditional on banks’ lending exposure from Table 3.5. All DiD estimates in the pre-treatment period are statistically indistinguishable from zero, supporting the equal trends assumption.

Recent advances in econometric theory suggest that, under certain conditions, staggered DiD designs might not provide valid estimates of the causal estimands of interest even if the equal trends assumption holds (e.g., De Chaisemartin & d’Haultfoeuille, 2020; Callaway & Sant’Anna, 2021; Goodman-Bacon, 2021; Imai & Kim, 2021; Sun & Abraham, 2021; Athey & Imbens, 2022). The intuition is that already treated units can act as effective comparison units, and changes in their outcomes over time are subtracted from the changes of later-treated units. As a result, staggered DiD estimates could obtain the opposite sign compared to the true effect.

In general, staggered DiD designs produce estimates of weighted averages of many different treatment effects (Baker, Larcker, & Wang, 2022). De Chaisemartin and D’Haultfoeuille (2022) demonstrates that the phenomenon of estimating opposite signs compared to the true effect can only arise when some of these weights are negative. We employ the diagnostic tests suggested by De Chaisemartin and d’Haultfoeuille (2020) to assess the extent of this issue in our setting.

We start our diagnosis with estimating the weights attached to our full sample regressions in Table 3.4 (reported at the end of the table). We find that 83.9% of the weights are strictly positive and the negative weights sum to only -0.019, alleviating the negative weights concern. Next, we derive the two diagnostic measures suggested by De Chaisemartin and d’Haultfoeuille (2020).

The first measure corresponds to the minimal value of the standard deviation of the treatment effect across treated units and time periods under which beta and the average treatment effect on the treated (ATT) could be of opposite signs. In the following, we denote this measure $T1$. When $T1$ is large, the likelihood that beta and ATT are of opposite sign is rather small. Specifically, when $T1$ is large, beta and ATT can only be of opposite

[15]Our results from Section 3.5 suggest that the effects take three years to build up.

sign under a very large treatment effect heterogeneity. For both concentration measures it holds that $|\beta| < \sqrt{3} \times T1$ (the threshold suggested by De Chaisemartin & d'Haultfoeuille, 2020), suggesting that $T1$ is in both cases an implausibly high amount of treatment effect heterogeneity.

The second measure corresponds to the minimal value of the standard deviation of the treatment effect across treated units and time periods under which beta could be of a different sign than the treatment effect in all treated units and time periods. In the following, we denote this measure $T2$. For both concentration measures, HHI and EDM, it holds that $|\beta| < 2\sqrt{3} \times T2$ (the threshold suggested by De Chaisemartin & d'Haultfoeuille, 2020), suggesting that $T2$ would imply implausibly large treatment effect heterogeneity.

Hence, our full sample results in Table 3.4 pass both diagnostic tests. Note that the interaction specifications in Table 3.5 does not allow us to conduct the diagnostic tests outlined in De Chaisemartin and d'Haultfoeuille (2020). We thus follow the suggestion to alternatively conduct the tests separately for the groups with heterogeneous treatment effects. To this end, we conduct the diagnostic tests for splits into high and low exposure banks in columns (2) and (5) as well as (3) and (6) of Table 3.4, respectively, which closely resemble the tests from Table 3.5. Again, our results pass both diagnostic tests.

3.5 Bank & loan-class level analysis

Given the evidence that government guarantee coverage incentivizes banks to concentrate their assets, especially for banks that have a high lending exposure, we next investigate the underlying portfolio adjustments in more detail.

3.5.1 Empirical setup

To this end, we study the changes in portfolio weights and lending volumes of different loan classes for banks which experience a change in the government guarantee proxy (*GG*), conditional on their pre-existing exposure to the respective loan class. Specifically, our model predicts that, in response to an increase in expected government guarantee value, banks further load up on asset classes (i.e., increase the invested volume and portfolio weight of the asset class) to which they already have a high exposure.

We employ the following staggered DiD specification for this analysis:

$$\begin{aligned} y_{b,c,t+h} &= \alpha_b + Class_c \times \alpha_t + \beta_1 \triangle GG_{b,t} + \beta_2 Exposure\ Ratio_{b,c,t} \\ &+ \beta_3 \triangle GG_{b,t} \times Exposure\ Ratio_{b,c,t} + \delta X_{b,t} + \varepsilon_{b,c,t}. \end{aligned} \tag{3.26}$$

Here, the dependent variable is the change in the logarithm of either one plus bank b's portfolio weight of loan class c, i.e., $\Delta Log(1+PW)_{b,c,t+h}$, or one plus bank b's lending volume to loan class c, i.e., $\Delta Log(1+LCV)_{b,c,t+h}$, from year t to year $t+h$ for $h=\{1,2,3\}$. The interval variable ΔGG can take the values $\{-1,0,1\}$: equal to 0 when there was no change in $GG_{b,t}$ in year t; equal to 1 if $GG_{b,t}$ changed from zero to one; and equal to -1 if $GG_{b,t}$ changed from one to zero.

The variable $Exposure\ Ratio_{b,c,t}$ is a continuous measure for bank b's pre-existing exposure to a particular loan class, which we calculate as the ratio of bank b's holdings of loan class c over its Tier-1 equity capital. To account for the predicted non-linear moderating effect of the banks' pre-existing loan class exposure on the link between government guarantee coverage and lending behavior, we further employ the dummy variable *Top 25% Exposure*, which flags loan classes to which the respective bank already has a high exposure. Specifically, the dummy is equal to one for bank-class pairs above the 25% percentile of the *Exposure Ratio* distribution in the previous three years.

In addition to the set of control variables from Specification (3.23), we also include bank and loan class-time fixed effects in this regression. This stringent fixed effects setting absorbs time-invariant bank characteristics and loan class-specific shocks, here most importantly demand shocks. Specifically, this fixed effects setting allows us to compare the changes in bank asset holdings of a particular loan class between banks that gain/lose government guarantee coverage relative to banks that do not experience any change in their expected government guarantee value, holding constant the time-varying demand at the loan class level.

The coefficients of interest in Specification (3.26) are β_1 and β_3. Coefficient β_1 captures the effect of a change in GG on loan class c holdings for a bank without exposure to this loan class. The coefficient β_3 captures the additional effect of a change in GG when the bank has a pre-existing exposure to this loan class.

Testing the prediction that banks with a higher pre-existing exposure to a particular loan class have stronger incentives to load up on this loan class when the extent of their government guarantee coverage increases does not require us to simultaneously measure responses of banks across treated and non-treated states. Hence, we can test this prediction comparing banks in the same states by including state-time fixed effects. Specifically, for this refinement we employ the following functional form:

$$\begin{aligned} y_{b,c,t+h} &= \alpha_b + Class_c \times \alpha_t + State_s \times \alpha_t + \beta_1 Exposure\ Ratio_{b,c,t} \\ &+ \beta_2 \triangle GG_{b,t} \times Exposure\ Ratio_{b,c,t} + \delta X_{b,t} + \varepsilon_{b,c,t}. \end{aligned} \tag{3.27}$$

3.5.2 Results

We present first results with portfolio weights as the dependent variable, and study subsequently loan volumes.

Portfolio weights

Table 3.6 presents the results for the effect of a change in *GG* on the banks' portfolio weights; on the left side of the table for the continuous *Exposure Ratio* measure (columns 1-3) and on the right for the dummy variable *Top 25% Exposure* (columns 4-6). Panel A shows the results for Specification (3.26) and Panel B for Specification (3.27).

The table shows that banks which experience an increase in their government guarantee coverage tend to further concentrate their portfolio, while banks that experience a decrease in their coverage tend to lower their portfolio concentration. Specifically, banks that gain government guarantee coverage (i.e., $\triangle GG$ equal to one) further increase the portfolio weight of loan classes to which they already have a high pre-existing exposure and decrease the weight of classes to which they have a low exposure. The portfolio reallocation is reversed for banks that lose government guarantee coverage (i.e., $\triangle GG$ equal to minus one). These portfolio reallocations intensify over the first three years after a change in the government guarantee coverage.

Panel B of Table 3.6 shows that these relationships remain robust when we include state-time fixed effects. This result provides further evidence that differences in state characteristics and state-level economic developments are not driving the relationship.

Table 3.6: Change in Portfolio Weights on Loan Class Level

	Continuous Exposure			Top 25% Exposure		
Panel A: Inter-State	ΔPW (t+1)	ΔPW (t+2)	ΔPW (t+3)	ΔPW (t+1)	ΔPW (t+2)	ΔPW (t+3)
△GG	-0.025	-0.061**	-0.111***	-0.010	-0.036*	-0.073***
	(0.101)	(0.012)	(0.003)	(0.383)	(0.080)	(0.005)
△GG x Exposure Ratio	0.034*	0.083***	0.144***			
	(0.052)	(0.006)	(0.003)			
△GG x Top 25% Exposure				0.043	0.168*	0.305**
				(0.401)	(0.072)	(0.013)
$\hat{\beta}_1 + \hat{\beta}_3$				0.032	0.131*	0.232**
				(0.413)	(0.069)	(0.014)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Class-Time FE	Yes	Yes	Yes	Yes	Yes	Yes
N	184,062	156,198	132,980	184,062	156,198	132,980
R^2	0.089	0.142	0.185	0.087	0.136	0.175
Panel B: Intra-State	ΔPW (t+1)	ΔPW (t+2)	ΔPW (t+3)	ΔPW (t+1)	ΔPW (t+2)	ΔPW (t+3)
△GG x Exposure Ratio	0.033*	0.081***	0.140***			
	(0.056)	(0.007)	(0.003)			
△GG x Top 25% Exposure				0.041	0.166*	0.301**
				(0.418)	(0.075)	(0.011)
State-Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Class-Time FE	Yes	Yes	Yes	Yes	Yes	Yes
N	184,062	156,198	132,980	184,062	156,198	132,980
R^2	0.087	0.139	0.181	0.086	0.134	0.172

This table presents estimation results from Specification (3.26) (Panel A) and Specification (3.27) (Panel B) for the period 1996-2016. The dependent variable is the change in the log of one plus the weight of loan class c over total lending of bank b from year t to $t+h$ ($\Delta Log(1+PW)_{b,c,t+h}$). We present results for $h = 1,2,3$, respectively. $\triangle GG$ can take the values $\{-1,0,1\}$: 0 when there was no change in $GG_{b,t}$ in year t, 1 if $GG_{b,t}$ changed from zero to one, and -1 if $GG_{b,t}$ changed from one to zero. The dummy $GG_{b,t}$ is equal to one if at least one senator from bank b's state of incorporation is a member in the BHUA Senate committee in year t. *Exposure Ratio* is the ratio between bank b's holdings of loan class c and its Tier-1 equity capital. The variable *Top 25% Exposure* is a dummy variable identifying bank-class pairs above the 25% percentile of the *Exposure Ratio* distribution in the previous three years. The regressions include a set of one-period lagged control variables: log of state GDP, size (proxied as the logarithm of assets), ROA (return on assets, measured as earnings before interest and taxes, scaled by assets), liquidity (measured as cash holdings and short-term investments, scaled by assets), dividends (dummy variable identifying dividend payers), number of loan classes, and wholesale debt (assets minus equity and deposits, divided by assets). Standard errors are clustered at the state level, p-values are reported in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure 3.2 shows that three-year changes in portfolio weights after treatment are significantly higher for loan classes with an *Exposure Ratio* above one, that is, when the bank's pre-treatment exposure to this loan category exceeds its Tier-1 capital. This threshold corresponds roughly to the 75% percentile of the *Exposure Ratio* distribution. Conversely, banks that experience an expansion in their government guarantee coverage significantly decrease the portfolio weight for loan classes for which they have an *Exposure Ratio* below 0.6 (which corresponds to the 65% percentile).

Regarding the economic magnitude of the portfolio shift towards high-exposure asset classes (i.e., the top 25% of the *Exposure Ratio* distribution), the estimates in column (6) of Table 3.6, Panel A suggest that gaining (losing) government guarantee coverage is associated with a 0.23pp higher (lower) portfolio weight on these classes. This change represents 7.8% of the average within-bank SD of portfolio weight changes.

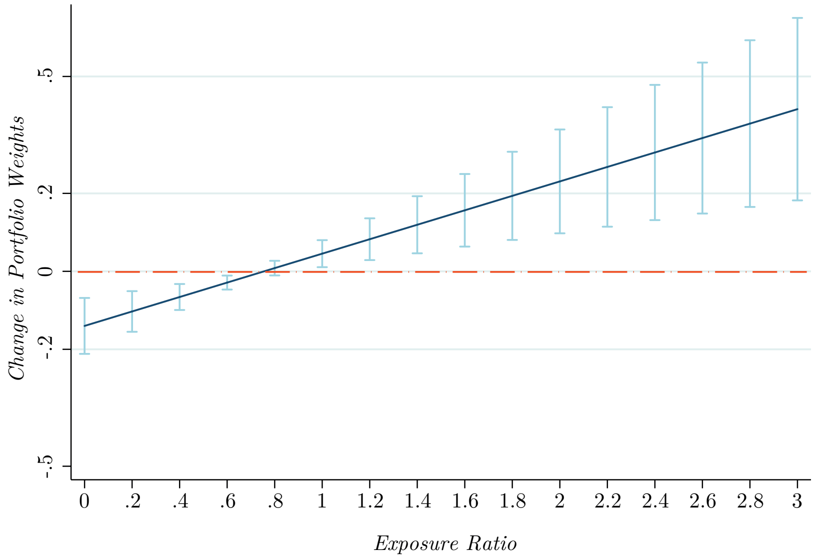
Loan volumes

We find corresponding evidence for shifts in banks' lending volume across loan classes. Specifically, the results in Table 3.7 show that banks which experience an increase in their government guarantee coverage subsequently increase the volume of lending in high-exposure loan classes, and decrease the volume of lending in low-exposure classes.

Figure 3.3 plots the average aggregate effect of a change in the government guarantee coverage (i.e., ΔGG) on three-year changes in banks' lending volume post treatment for different *Exposure Ratio* levels. The results suggest that, in response to gaining government guarantee coverage, banks significantly raise their lending volumes of loan classes for which their *Exposure Ratio* is above two, which is roughly the 90% percentile of the *Exposure Ratio* distribution. Conversely, banks significantly decrease lending to loan classes for which they have a *Exposure Ratio* below 0.6, which corresponds to the 65% percentile.

The estimates in column (6) of Table 3.7, Panel A suggest that three years after a positive change in *GG*, banks increase their loan volume to high-exposure loan classes on average by 1.92pp (which is 2.7% of the average within-bank SD of the loan volume changes), while they decrease their low-exposure loan class volume on average by 2.11pp (which equals 2.9% of the average within-bank SD of the loan volume changes).

Figure 3.2: **Change in Portfolio Weights at** $t = 3$.



This figure presents post-estimation results derived from Specification (3.26) for the period 1996-2016. The dependent variable is the change in the log of one plus the weight of loan class c over total lending of bank b from year t to $t+3$ ($\Delta Log(1+PW)_{b,c,t+3}$). The blue line represents the predicted additional change in the dependent variable when bank b experiences a change in $GG_{b,t}$ in t, (i.e., $|\triangle GG|$ = 1), estimated in absolute terms over different levels of *Exposure Ratio* to loan class c (90% confidence interval, light blue). The dotted red line plots the zero change in the dependent variable. The dummy $GG_{b,t}$ is equal to one if at least one senator from bank b's state of incorporation is a member in the BHUA Senate committee in year t. $\triangle GG$ can take the values $\{-1, 0, 1\}$: 0 when there was no change in $GG_{b,t}$ in year t, 1 if $GG_{b,t}$ changed from zero to one, and -1 if $GG_{b,t}$ changed from one to zero. *Exposure Ratio* is the ratio between bank b's holdings of loan class c and its Tier-1 equity capital. The regressions include a set of one-period lagged control variables: log of state GDP, size (proxied as the logarithm of assets), ROA (return on assets, measured as earnings before interest and taxes, scaled by assets), liquidity (measured as cash holdings and short-term investments, scaled by assets), dividends (dummy variable identifying dividend payers), number of loan classes, and wholesale debt (assets minus equity and deposits, divided by assets). Standard errors are clustered at the state level.

3.5.3 Validity

We first verify the build-up of the effect over time (i.e., over three years) focusing on the subsample of banks for which the full three-year horizon in outcomes can be observed. Tables 3.B.3 and 3.B.4 show that the results from Tables 3.6 and 3.7 are robust to this restriction.

Next, we confirm that our results are not driven by certain years. Table 3.B.5 shows the estimation results for the analyses from Table 3.6 and 3.7 but excluding one year at a time. Our results are robust across all specifications.

For our validity analysis we again conduct placebo tests where we "treat" banks three years before the actual treatment. Table 3.B.6 presents the placebo test results for the change in portfolio weights and Table 3.B.7 for the change in loan volumes. All DiD estimates in the pre-treatment period are again statistically indistinguishable from zero. Figures 3.4 and 3.5 visualize the placebo test results together with the DiD results from Tables 3.6 and 3.7, respectively.

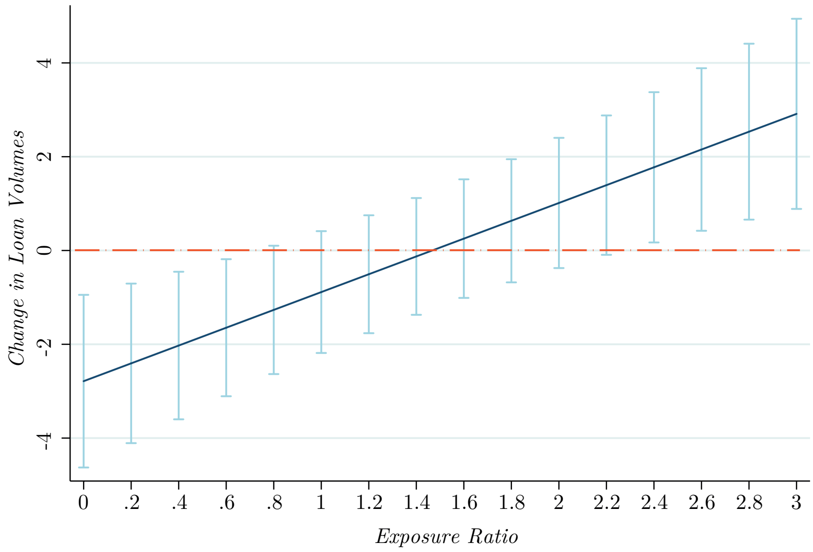
Table 3.7: Change in Loan Volumes on Loan Class Level

	Continuous Exposure			Top 25% Exposure		
Panel A: Inter-State	ΔLCV (t+1)	ΔLCV (t+2)	ΔLCV (t+3)	ΔLCV (t+1)	ΔLCV (t+2)	ΔLCV (t+3)
$\triangle$GG	-0.231	-1.744*	-2.634**	-0.165	-1.391	-2.110**
	(0.639)	(0.090)	(0.029)	(0.715)	(0.120)	(0.031)
$\triangle$GG x Exposure Ratio	0.132	1.131**	1.903***			
	(0.617)	(0.018)	(0.002)			
$\triangle$GG x Top 25% Exposure				0.019	2.221**	4.032***
				(0.976)	(0.014)	(0.000)
$\hat{\beta}_1 + \hat{\beta}_3$				-0.146	0.830	1.922**
				(0.768)	(0.311)	(0.049)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Class-Time FE	Yes	Yes	Yes	Yes	Yes	Yes
N	184,062	156,198	132,980	184,062	156,198	132,980
R^2	0.075	0.134	0.185	0.074	0.131	0.180
Panel B: Intra-State	ΔLCV (t+1)	ΔLCV (t+2)	ΔLCV (t+3)	ΔLCV (t+1)	ΔLCV (t+2)	ΔLCV (t+3)
$\triangle$GG x Exposure Ratio	0.044	0.956*	1.761***			
	(0.873)	(0.062)	(0.009)			
$\triangle$GG x Top 25% Exposure				-0.314	1.353	3.382***
				(0.638)	(0.141)	(0.000)
State-Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Class-Time FE	Yes	Yes	Yes	Yes	Yes	Yes
N	184,062	156,198	132,980	184,062	156,198	132,980
R^2	0.055	0.093	0.126	0.054	0.091	0.123

This table presents estimation results from Specification (3.26) (Panel A) and Specification (3.27) (Panel B) for the period 1996-2016. The dependent variable is the change in the log one plus the loan volume of loan class c from year t to $t+h$ ($\Delta\, Log(1+LCV)_{b,c,t+h}$). We present results for h=1,2,3, respectively. $\triangle GG$ can take the values $\{-1,0,1\}$: 0 when there was no change in $GG_{b,t}$ in year t, 1 if $GG_{b,t}$ changed from zero to one, and -1 if $GG_{b,t}$ changed from one to zero. The dummy $GG_{b,t}$ is equal to one if at least one senator from bank b's state of incorporation is a member in the BHUA Senate committee in year t. *Exposure Ratio* is the ratio between bank b's holdings of loan class c and its Tier-1 equity capital. The variable *Top 25% Exposure* is a dummy variable identifying bank-class pairs above the 25% percentile of the *Exposure Ratio* distribution in the previous three years. The regressions include a set of one-period lagged control variables: log of state GDP, size (proxied as the logarithm of assets), ROA (return on assets, measured as earnings before interest and taxes, scaled by assets), liquidity (measured as cash holdings and short-term investments, scaled by assets), dividends (dummy variable identifying dividend payers), number of loan classes, and wholesale debt (assets minus equity and deposits, divided by assets). Standard errors are clustered at the state level, p-values are reported in parentheses. Significance levels: * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

The staggered DiD design that we employ for the analysis in Section 3.5 could, in general, be affected by the "negative weighting" problem discussed in Section 3.4.3, which in extreme cases can result in the estimand having the "wrong sign". The loan class-time and state-time fixed effects, as well as the interaction terms that we utilize in Specification (3.26), however, do not allow us to implement the weight decomposition from De Chaise-

Figure 3.3: **Change in Lending Behavior at** $t = 3$.



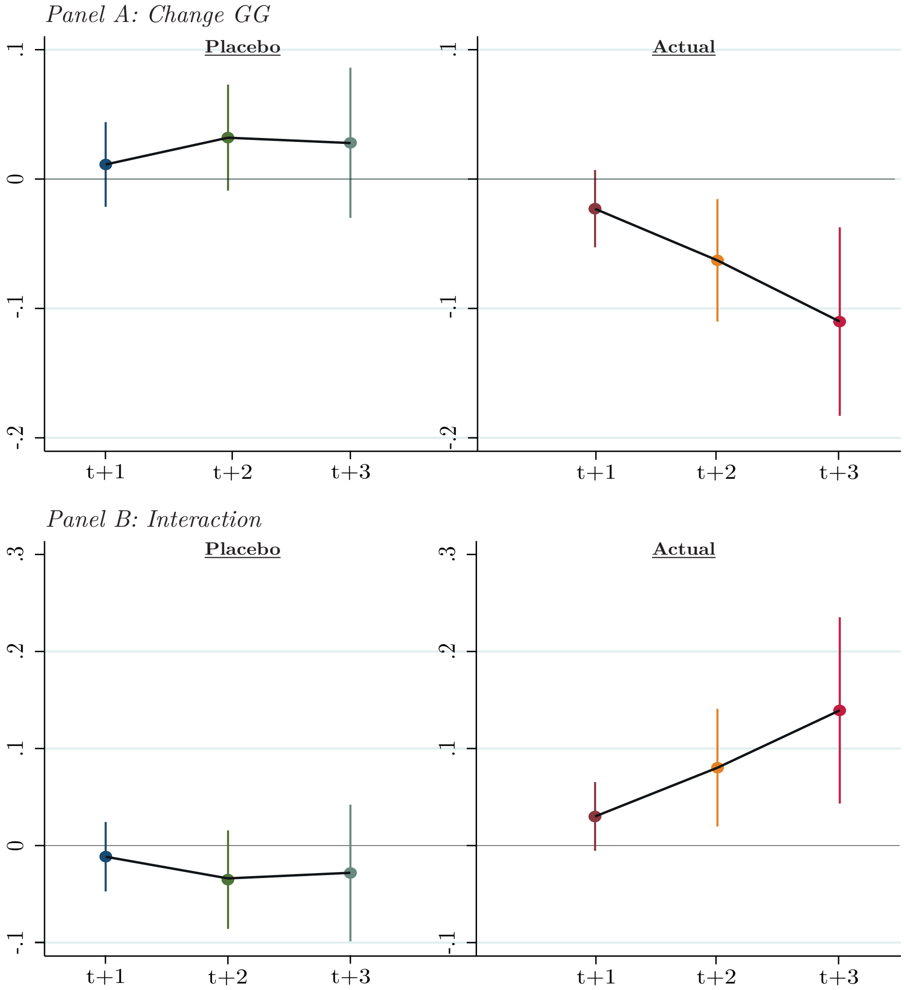
This figure presents post-estimation results derived from Specification (3.26) for the period 1996-2016. The dependent variable is the change in the log of one plus the weight of loan class c over total lending of bank b from year t to $t+3$ ($\Delta Log(1+LCV)_{b,c,t+3}$). The blue line represents the predicted additional change in the dependent variable when bank b experiences a change in $GG_{b,t}$ in t, (i.e., $|\triangle GG| = 1$), estimated in absolute terms over different levels of *Exposure Ratio* to loan class c (90% confidence interval, light blue). The dotted red line plots the zero change in the dependent variable. The dummy $GG_{b,t}$ is equal to one if at least one senator from bank b's state of incorporation is a member in the BHUA Senate committee in year t. $\triangle GG$ can take the values $\{-1,0,1\}$: 0 when there was no change in $GG_{b,t}$ in year t, 1 if $GG_{b,t}$ changed from zero to one, and -1 if $GG_{b,t}$ changed from one to zero. *Exposure Ratio* is the ratio between bank b's holdings of loan class c and its Tier-1 equity capital. The regressions include a set of one-period lagged control variables: log of state GDP, size (proxied as the logarithm of assets), ROA (return on assets, measured as earnings before interest and taxes, scaled by assets), liquidity (measured as cash holdings and short-term investments, scaled by assets), dividends (dummy variable identifying dividend payers), number of loan classes, and wholesale debt (assets minus equity and deposits, divided by assets). Standard errors are clustered at the state level.

martin and d'Haultfoeuille (2020), which we apply in Section 3.4 to test for the prevalence of negative weights in our bank level analysis.

Therefore, we have to take a different route to check the validity of our results in Section 3.5. De Chaisemartin and D'Haultfoeuille (2022) shows that all weights are likely positive when there is no group that is treated most of the time, and no time periods where most groups are treated. In our setting, there are no time periods where most groups are treated. There are, however, some states where banks are treated in most years during our sample period (i.e., banks whose state of incorporation is always/almost always represented in the BHUA Senate committee): New York, Alabama, Rhode Island, Nebraska, and South Dakota. In such cases, De Chaisemartin and D'Haultfoeuille (2022) suggests to drop the most of the time treated groups to mitigate or eliminate negative weights, if there are any. Hence, in Tables 3.B.8 and 3.B.9 we exclude banks from the abovementioned states, which does not materially change our results.

Moreover, De Chaisemartin and D'Haultfoeuille (2022) shows that a binary treatment, compared to a non-binary treatment, decreases the likelihood of negative weights.

Figure 3.4: Portfolio Weights. Visualization of Results



This figure visualizes the results from Table 3.6 (the two panels on the right) and the corresponding placebo test three years before the actual treatment from Table 3.B.6 (the two panels on the left). The dots indicate the estimated coefficients, Panel A for β_1 in Specification (3.26) and Panel B for β_3, respectively. We plot the 95% confidence interval for each coefficient.

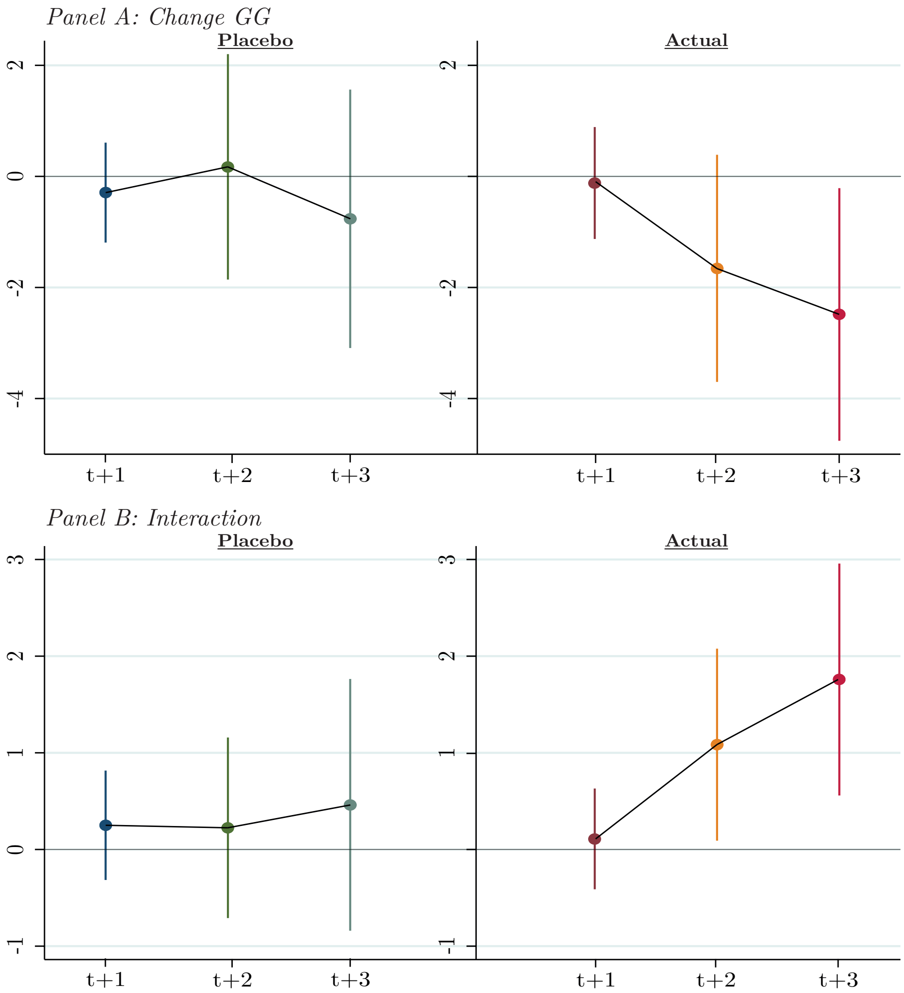
The fact that our results are even stronger for our binary treatment in columns (4)-(6) of Tables 3.6 and 3.7, compared to the continuous treatment of columns (1)-(3) thus further mitigates concerns about the negative weighting problem.

While these robustness tests suggest that the negative weighting problem is not material in our setting, we cannot completely rule out that it affects our estimates. We thus address the negative weighting problem further in the next section.

3.6 Gainers versus losers

The reason why treatment effects for some units and time periods can receive negative weights in staggered DiD designs are so-called "forbidden comparisons" (see, e.g.,

Figure 3.5: Loan Volume. Visualization of Results



This figure visualizes the results from Table 3.7 (the two panels on the right) and the corresponding placebo test three years before the actual treatment from Table 3.B.7 (the two panels on the left). The dots indicate the estimated coefficients, Panel A for β_1 in Specification (3.26) and Panel B for β_3, respectively. We plot the 95% confidence interval for each coefficient.

Borusyak, Jaravel, & Spiess, 2021; Goodman-Bacon, 2021; De Chaisemartin & D'Haultfoeuille, 2022). Specifically, there are two different forbidden comparisons: first, the comparison between a group that switches into the treatment and a control group that is treated before and after the treatment group switches. Second, when the treatment is not binary, comparing the outcome evolution of a group whose treatment increases more to the outcome evolution of another group whose treatment increases less.

Therefore, we proceed by confirming the robustness of our results by employing a modified DiD design where we adjust the set of effective comparison units such that we can rule out forbidden comparisons. Moreover, this modified DiD assign allows us to investigate to what extent our results are driven by banks that gain government guarantee coverage ($\Delta GG = 1$; the "gainers") and banks that lose government guarantee coverage

($\Delta GG = -1$; the "losers").

3.6.1 Empirical setup

Specifically, in the spirit of De Chaisemartin and d'Haultfoeuille (2020), we utilize two types of comparisons. First, we compare the outcome evolution of gainers with the evolution of banks that are not represented in the BHUA Senate committee before and after the gainers switch (i.e., $GG = 0$). Second, we compare the outcome evolution of losers and of banks represented in the BHUA Senate committee before and after the losers switch (i.e., $GG = 1$).

To allow for dynamic effects, which the De Chaisemartin and d'Haultfoeuille (2020) estimator does not accommodate, we go a step further by implementing a more stringent control group selection to avoid comparisons where later-treated banks are compared to the earlier-treated banks. Specifically, while the De Chaisemartin and d'Haultfoeuille (2020) estimator considers as control groups units that are treated/untreated in the pre- and post-treatment year, we further limit the control groups to banks that are never represented in the BHUA Senate committee for gainers, and to always-represented banks for losers. Moreover, we exclude banks that experience more than one change in their government guarantee coverage during our sample period.

Within the respective group of control candidates, we use a coerced matching technique to compare gainers and losers with comparable banks based on their size, leverage, liquidity, and the number of loan classes to which the bank is exposed.[16] For every treated bank (i.e., gainers and losers), we then track the difference in the portfolio reallocation from three years before to three years after the treatment relative to the respective control group. Specifically, we employ the following functional form for this analysis:

$$\begin{aligned} y_{b,c,t+1} = {} & \alpha_b + Class_c \times \alpha_t + \beta_1 Treated_b + \beta_2 Post_t + \beta_3 Exposure\ Ratio_{b,c,t} \\ & + \beta_4 Treated_b \times Post_t + \beta_5 Treated_b \times Exposure\ Ratio_{b,c,t} \\ & + \beta_6 Post_t \times Exposure\ Ratio_{b,c,t} \\ & + \beta_7 Treated_b \times Post_t \times Exposure\ Ratio_{b,c,t} + \delta X_{b,t} + \varepsilon_{b,c,t}, \end{aligned} \tag{3.28}$$

[16] All variables measured in the year of treatment. We match 386 losers to 452 always represented banks and 316 gainers to 851 never represented banks.

Table 3.8: “Losers” and “Gainers”

	Losers		Gainers	
Panel A	ΔPW	ΔPW	ΔPW	ΔPW
Treated x Post	0.098*	0.067	-0.098**	-0.072**
	(0.096)	(0.128)	(0.036)	(0.038)
Treated x Post x Exposure Ratio	-0.125**		0.128**	
	(0.029)		(0.022)	
Treated x Post x Top 25% Exposure		-0.261**		0.289**
		(0.022)		(0.013)
N	22,979	22,989	34,565	34,583
R^2	0.219	0.217	0.260	0.257
Panel B:	ΔLCV	ΔLCV	ΔLCV	ΔLCV
Treated x Post	3.122	2.627	-2.166	-1.886
	(0.196)	(0.261)	(0.401)	(0.395)
Treated x Post x Exposure Ratio	-1.874**		2.548**	
	(0.043)		(0.021)	
Treated x Post x Top 25% Exposure		-3.902**		5.964***
		(0.046)		(0.003)
N	22,979	22,989	34,565	34,583
R^2	0.228	0.227	0.242	0.240
Bank FE	Yes	Yes	Yes	Yes
Class-Time FE	Yes	Yes	Yes	Yes

This table presents estimation results from Specification (3.28) for the period 1996-2016. The dependent variables are the annual change in the log of one plus the weight of loan class *c* over total lending of bank *b* ($\Delta Log(1+PW)_{b,c,t+1}$) (Panel A) and the annual change in the log one plus the loan volume of loan class *c* ($\Delta Log(1+LCV)_{b,c,t+1}$) (Panel B). We include observations that lie within a window of three years before and three years after bank *b*'s treatment. In columns (1) and (2), the dummy $Treated_b$ is equal to one if bank *b* loses representation in the BHUA Senate committee (“Losers”), and it is equal to zero if this remains unchanged. In columns (3) and (4), the dummy $Treated_b$ is equal to one if bank *b* gains representation in the BHUA Senate committee (“Gainers”), and it is equal to zero if this remains unchanged. Treated bank *b* is matched with comparable non-treated banks based on size (proxied as the logarithm of assets), wholesale debt (assets minus equity and deposits, divided by assets), liquidity (measured as cash holdings and short-term investments, scaled by assets), and the number of loan classes to which the bank is exposed, all measured in the year of the treatment. The variable $Post_{b,t}$ is a dummy that takes unity in the three years after bank *b*'s treatment and zero for the years before treatment. *Exposure Ratio* is the ratio between bank *b*'s holdings of loan class *c* and its Tier-1 equity capital. The variable *Top 25% Exposure* is a dummy variable identifying bank-class pairs above the 25% percentile of the *Exposure Ratio* distribution in the previous year. The regressions include a set of one-period lagged control variables: log of state GDP, size (proxied as the logarithm of assets), ROA (return on assets, measured as earnings before interest and taxes, scaled by assets), liquidity (measured as cash holdings and short-term investments, scaled by assets), dividends (dummy variable identifying dividend payers), number of loan classes, and wholesale debt (assets minus equity and deposits, divided by assets). Standard errors are clustered at the state level, p-values are reported in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

where we include observations of bank *b* and its matched control group that lie within a window of three years before and three years after bank *b*'s treatment, and the dependent variables are the one-year change in bank *b*'s portfolio weights and loan volumes for the different loan classes.

The variable $Treated_b$ is equal to one if bank b is either a loser or a gainer and equal to zero if the bank does not experience a change in *GG*, but is part of the matched control group. The variable $Post_{b,t}$ is a dummy that takes unity in the three years after bank b's treatment and zero for the years before treatment. As before, the variable *Exposure* $Ratio_{b,c,t}$ is calculated as the ratio of bank b's holdings of loan class c over its Tier-1 equity capital. Alternatively, we employ the dummy variable *Top 25% Exposure*, which is equal to one for bank-class pairs above the 25% percentile of the *Exposure Ratio* distribution in the previous year. We again include bank and loan class-time fixed effects and the same set of controls as in Specification (3.26). Here, the coefficients of interest are β_4 and β_7, which capture the effect of a change in the expected government guarantee on the portfolio weight and lending volume to loan class c, conditional on the bank's pre-existing exposure to this loan class.

3.6.2 Results

Table 3.8 presents the results of this analysis: Panel A for changes in portfolio weights and Panel B for changes in loan volumes. Columns (1) and (2) show the results for losers, where the dummy $Treated_b$ is equal to one if bank b loses representation in the BHUA Senate committee and equal to zero for non-switchers. Columns (3) and (4) show the results for gainers, where the dummy $Treated_b$ is equal to one if bank b gains representation in the BHUA Senate committee and again equal to zero for non-switchers.

There are two main takeaways from this exercise. First, the results from our modified DiD design confirm the evidence from Section 3.5, both qualitatively and quantitatively. Second, the evidence shows that the effect of a change in government guarantee coverage on banks' lending behavior is fairly symmetrical. While gainers tend to further increase their exposure towards loan classes to which they already had a high pre-existing exposure, losers reduce the portfolio weight of these loan classes.

In a final step, we combine both types of DiD comparisons in a joint regression, that is, gainers and banks that are never represented in the BHUA Senate committee, as well as losers and banks always represented in the BHUA Senate committee. To this end, we re-code the variable $Treated_b$ as follows: $Treated_b$ is equal to minus one if bank b is a loser, equal to zero if the bank does not experience a change in *GG*, and equal to one if bank b is a gainer.

Table 3.B.10 presents the results for this joint analysis, in columns (1) and (2) for the change in the portfolio weights and in columns (3) and (4) for the change in loan volumes. The evidence confirms our previous results.

3.6.3 Validity

To analyze the validity of our analysis, we perform a placebo test for the modified DiD design, where we again move the treatment three years before the actual treatment. The results in Tables 3.B.11 and 3.B.12 suggest that the parallel trends assumption also holds for the modified DiD design.

3.7 Conclusion and policy implications

While previous literature on government guarantees has mostly focused on the individual riskiness of new investments when analyzing banks investment behavior, in this paper we highlight the importance of taking banks' pre-existing exposures into account. Once these are accounted for, we show theoretically that the risk-taking incentives created by government guarantees have an important portfolio dimension: they give banks an incentive to further load up on assets to which they are already highly exposed.

Exploiting plausibly exogenous variation in perceived government guarantees arising from the assignment of senators to the U.S. Senate committee that is paramount for bank bailout decisions, we find strong empirical support for this portfolio dimension of risk taking. Going forward, the mechanism may have important implications for current policy initiatives.

A good example of the relevance of the mechanism is the eurozone, where many banks' exposures are tilted towards sovereign debt of countries in the European periphery. On average, before the European sovereign debt crisis, the maximum exposure to a single periphery sovereign amounted to 11 times their equity for banks from periphery countries (Acharya, Eisert, Eufinger, & Hirsch, 2018). Even for non-periphery banks the maximum exposure to a single periphery sovereign was, on average, 1.35 times their equity. Partly driven by moral hazard, banks further increased their exposures to periphery sovereigns in the run-up to the European sovereign debt crisis (Acharya & Steffen, 2015 and Acharya et al., 2018), despite widening yield spreads. The resulting highly concentrated exposures significantly deepened the European sovereign debt crisis.

To attenuate the resulting vicious circle between banks and sovereigns (Brunnermeier et al., 2016), policymakers seek to introduce a common deposit insurance scheme in the eurozone (the European Deposit Insurance Scheme; EDIS). This scheme is supposed to implement a risk-sharing mechanism among euro countries to, at least partially, reduce the link between sovereign health and bank failures.

Our model framework and our empirical results suggest that, by making banks' guarantee coverage more extensive, such a common deposit insurance scheme could have unintended side-effects: it could actually reinforce banks' portfolio risk-taking incentives and lead to a further concentration of exposures.

Chapter 4

Banking on Bailouts: How Public Guarantees affect Loan Contracts and Borrower Investments

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This paper demonstrates that government guarantees prompt banks to engage in risk-shifting at the intensive margin. Theoretically, we show that banks exploit the funding-cost advantage arising from government guarantees by acting as intermediaries between investors and ultimate borrowers. This mechanism leads to a crowding-out of direct market finance and to inefficient capital allocation by their borrowers. We validate our findings in the context of the U.S. syndicated loan data, using exogenous changes in banks' political connections to capture variations in expectations regarding potential bailouts. At the bank level, we observe that higher bailout probabilities correspond to increased wholesale funding and lending. At the firm level, we find that borrowers respond to indirect government guarantees by leveraging more and overinvesting in suboptimal high-risk projects.

4.1 Introduction

Mark Twain's aphorism, "History doesn't repeat itself, but it often rhymes," seems strikingly fitting when considering government support policies aimed at mitigating the negative externalities of bank failures. Although the specific measures vary, time and again, regulators offer government support to struggling banks, as evidenced by recent cases involving Silicon Valley Bank and Credit Suisse. Such bailouts continue to occur despite previous assurances from authorities that "this time is different" and bailouts are rendered obsolete due to the implementation of stress tests, the enforcement of more stringent capital and liquidity requirements, along with the introduction of novel resolution mechanisms such as bail-in provisions and living wills. Nevertheless, bailouts remain a constant feature in the banking landscape, and it appears that government guarantees for banks are now more extensive than ever before.

The existing literature has established that explicit and implicit government guarantees incentivize banks to engage in riskier behavior at the extensive margin, which includes investment in high-risk assets and extending credit to riskier borrowers (e.g., see Dam and Koetter (2012), and Gropp et al. (2014)). Our paper shows that government guarantees can also induce banks to engage in risk-shifting at the intensive margin, thereby negatively affecting the nature of bank-firm relationships.

We contend that government guarantees not only impact the overall risk appetite but also permeate the banks' loan contract design. By strategically leveraging their guarantee-induced funding-cost advantage, banks can act by just intermediating funds between investors and ultimate borrowers. Consequently, banks have a strong incentive to fulfill all of the firm's funding demands, thereby crowding out market-based finance. Furthermore, banks can maximize their total expected profit by encouraging the firm to assume disproportionate leverage, overinvest, and engage in suboptimal high-risk projects. This comprehensive perspective on risk-shifting underscores the multidimensional consequences of government guarantees within the banking sector.

We validate our model predictions using data from the U.S. syndicated loan market, taking advantage of exogenous variations in banks' expected government guarantees resulting from changes in the composition of the influential U.S. Senate Committee on Banking, Housing, and Urban Affairs (BHUA Senate Committee). The senators in this committee play a significant role in bank bailout decisions. Our conjecture is that if a bank has at least one senator from its home state in the BHUA Senate committee, it increases the bank's expected government guarantee value.

Our findings demonstrate that banks gaining representation in the BHUA Senate committee experience an increase in their wholesale funding, which is subsequently channeled into higher overall lending as well as lending to corporate entities. Additionally, these banks that benefit from indirect protection through bank-firm relationships tend to leverage more and expand their investment expenditures. Consequently, this expansion is accompanied by higher levels of firm overinvestment and a decrease in firm productivity.

Overall, our paper highlights that the moral hazard problems caused by government guarantees not only affects the banks' credit allocation at the extensive margin (i.e., riskier and worse firms are financed) but that these guarantees also have negative welfare effects for the behavior of existing borrowers at the intensive margin (i.e., overinvestment and inferior project choice within existing lending relationships).

A prominent example for this mechanism is the behavior of the government-sponsored enterprises Fannie Mae and Freddie Mac in the run-up of the global financial crisis. Due to their implicit bailout guarantees, these firms were able to borrow at interest rates that were well below the competitive market rate (see Acharya, Richardson, Van Nieuwerburgh, & White, 2011).[1] This funding-cost advantage fueled Fannie and Freddie's mortgage growth, since it allowed them to systemically exploit the spread between the interest yield on their mortgage investments and the interest rate on their issued debt. As a result, their market share increased to almost 70% before the burst of the subprime mortgage crisis. Ultimately, the U.S. government had to inject \$187 billion to bailout the two mortgage giants.

Model preview. We analyze the interplay between government guarantees, bank finance and market-based finance within a classical corporate finance framework, building on Holmstrom and Tirole (1997). In particular, we consider an economy with two dates and four different risk-neutral parties: a firm, a bank, a government, and competitive household investors (henceforth called investors for simplicity).

In the first period, the firm can choose to invest either in a good or in a bad real project. Both projects have decreasing returns to scale and two possible return states in the second period: success and failure. A good project has a positive net return when the investment size is not too large, while a bad project always has a negative net return. Although the bad project has a higher failure probability, it yields a higher return in case of success,

[1] Passmore (2005) estimates a present value of the government subsidy to Fannie and Freddie over 25 years of roughly \$122 to \$182 billion, which almost equals their market value.

which creates a moral hazard problem for the firm.

In addition to its equity endowment, the firm can raise external funds for its real investment, either directly from investors (i.e., market-based funding) or indirectly from the bank that, in turn, can raise funds from investors (i.e., bank-based funding). The investors provide a perfectly elastic amount of funds whenever their expected investment return is at least equal to their cost of capital. If the firm borrows from the bank, the bank can decide to monitor the firm and implement the good project, thereby resolving the firm's moral hazard problem. Monitoring, however, involves a non-pecuniary fixed cost. Moreover, the bank incurs an intermediary cost that increases with the loan amount. The loan contract between the bank and the firm is a standard debt contract, which stipulates the loan amount and the interest rate. The bank has the bargaining power vis-a-vis investors and the firm.

Finally, when the bank fails in the second period, the government has to decide whether to rescue the bank. For this decision, the government has to weigh the costs of raising distortionary taxes to bail out the bank versus the negative externalities of letting the bank default. Since these negative externalities are uncertain ex-ante, all parties expect in the first period that the bank is rescued with a positive probability in case it fails in the second period.

Results preview. Without any monitoring, the firm prefers to implement the good instead of the bad project only when the payment promised to investors is below a certain threshold. Therefore, the firm's moral hazard problem limits the amount the firm can borrow when it solely relies on market-based funding, which leads to an inefficiently low investment level $\bar{I}$.

To overcome this inefficiency, the firm can borrow funds from the bank, which can monitor the firm. With bank monitoring, the firm's attainable investment level is thus no longer constrained at $\bar{I}$, which increases the attainable net return of the firm's good project. Without a government guarantee, the bank's optimal loan contract involves extracting the monitoring-induced net return increase of the firm's project through the loan interest rate, while keeping the loan size as small as possible to minimize intermediary costs. If the loan amount is insufficient for the firm to reach the efficient investment level I^*, it optimally obtains additional market-based funding. Therefore, in the absence of a government guarantee, bank-based funding always achieves investment efficiency and thereby increases social welfare.

In contrast, with a government bailout guarantee, bank-based funding can lead to the firm overinvesting and choosing the bad instead of the good project. First, we consider the case where bank monitoring is compulsory. When the bank's marginal lending costs (i.e., the sum of the banks' funding costs per unit of loaned funds and the marginal intermediary costs) are equal to or greater than the investors' cost of capital, the bank's optimal strategy is the same as in the case without a government guarantee: extracting the increased project net return through the loan interest rate, while minimizing the loan volume.

However, if the bank's bailout probability is high enough such that the resulting funding-cost reduction lowers the bank's marginal lending costs below the investors' cost of capital, the bank's loan provision incentive flips. Now, the bank can exploit the spread between its marginal lending costs and the investors' cost of capital by simply channeling funds from investors to the firm. Hence, the bank has an incentive to intermediate all of the firm's funding demand, thereby crowding out market-based finance.

Moreover, since now intermediating funds provides the bank with an additional profit source (besides extracting the monitoring-induced increase in the firm's project net return), the bank can maximize its total expected profit by incentivizing the firm to implement an investment level that is higher than the efficient level I^*. As a result, the firm overinvests, and its leverage increases compared to the case without a government guarantee.

Finally, we consider the case where the bank is protected by a government guarantee and bank monitoring is not compulsory. Our results show that if the bank's bailout probability is sufficiently high, the bank stops monitoring and incentivizes the firm to implement the bad instead of the good project. The key intuition for this result is that a higher bank default probability is associated with a higher expected government guarantee value, which can be exploited by the bank. In particular, a switch by the firm from the good to the bad project has two opposing effects on the bank's expected profit: an income-reducing and a cost-saving effect.

First, the switch to the bad project decreases the bank's expected loan income, since the loan repayment is linked to the firm's project net return, which is lower for the bad project. Second, the project switch increases the bank's default probability and thus decreases the probability that the bank has to honor its debt repayment obligations. While the increased default probability also increases the bank's funding rate, it does so only to a limited extent due to the government guarantee, which makes the bank's funding rate less sensitive to changes in its default probability. Overall, the switch to the bad project thus decreases the bank's *expected* funding costs and, in turn, its expected marginal lending costs. Hence, the bank prefers financing the bad project whenever this cost-saving effect dominates the income-reducing effect.

Empirical analysis and results. Empirically, it is challenging to identify the portfolio reallocations of banks in response to changes in the level of their government guarantees. This difficulty arises from two main factors. Firstly, the effects on banks' investment behavior stem from their expectations regarding the value of guarantees, which are typically not directly observable. Secondly, the extent of a bank's government guarantee protection may be influenced by and, in turn, influence its investment behavior and portfolio risk, leading to endogeneity concerns.

In order to conduct our analysis, it is crucial for us to identify a measurable variation in banks' expected government guarantee value that is independent of their investment behavior. To achieve this, we leverage insights from the recent literature that explores the influence of political connections on bank bailout decisions. Specifically, we employ banks' geographic-based political representation as a proxy for their expectations of receiving bailouts. This approach allows us to establish a source of exogenous variation in banks' anticipated government guarantee value, which is not directly influenced by their investment behavior.

Drawing on the findings of Kostovetsky (2015), we conjecture that the presence of a senator from a bank's state of incorporation in the BHUA Senate committee heightens the bank's expectations regarding the probability of obtaining government assistance during times of financial turmoil. Over the past few decades, the BHUA Senate committee has played a pivotal role in shaping bailout decisions made by the U.S. government. Significantly, for our analysis, the composition of the BHUA Senate committee exhibits a dispersed distribution across various states, resulting in substantial exogenous variation over time that is crucial for our research.

To quantify the shifts in banks' anticipated government guarantee coverage, we employ a bank-specific time-varying binary variable, denoted as *GG*. This variable takes a value of one if the bank's state of incorporation has at least one senator serving on the BHUA Senate committee in a given year. In the interest of clarity, we use the terms "government guarantee coverage" to describe the scenario when *GG* equals one, and "gaining/losing government guarantee coverage" to refer to instances when the *GG* variable switches from zero to one or vice versa, respectively. Lastly, we refer to "indirect government guarantee coverage" to describe the scenario when borrowers' protection obtained through credit relationships, *Indirect GG*, is positive. This terminology enhances readability and aids in comprehending the shifts in banks' anticipated government guarantee status.

To track changes in the banks' funding and lending behavior, we use both aggregated data from the BHC Call Report Database, provided by the Federal Reserve System, and granular data from the U.S. syndicated loan market. Using aggregate data, we look at banks' funding and lending policies. Leveraging on the granularity of syndicated loan data, we then look at changes in bank lending behavior at the industry and firm levels and analyze real effects at the firm level. Our final sample consists of 99 unique banks and 5560 unique borrowers and spans the years 1996 to 2016.

We run empirical analyses at the bank–year level, bank–industry–year and bank–firm–year level, and at the firm–year level. At the bank–year level, we look at banks' wholesale funding, total lending, and lending to business enterprises. For this analysis, we employ time and bank fixed effects to absorb time-invariant bank characteristics and common shocks.

We find that high government guarantee coverage is associated with an increase in wholesale funding and enhanced growth in total lending and lending to business enterprises. A *GG* equal to one implies an additional 6.2pp growth in wholesale funding, which represents 31.4% of the average within-bank standard deviation (SD) of wholesale funding growth. Conversely, a *GG* equal to one is associated with an additional 2.2pp growth in total lending and a 3.0pp increase in lending to business enterprises, which represents 26.0% and 26.7% of the average within-bank SD of each variable, respectively. To validate our results, we build on the diagnostic tests suggested by De Chaisemartin and d'Haultfoeuille (2020) to show that our setting is not materially affected by the "negative weighting problem" that can occur in staggered difference-in-differences (DiD) specifications.

Next, we look at granular changes in bank loan volume to industries and firms, aggregating syndicated loan market data at the bank–industry–year and bank–firm–year level, respectively. For this analysis, we employ bank fixed effects, plus either industry-time or firm-time fixed effects to absorb time-invariant bank characteristics and common shocks. Altogether, banks display a lending behavior consistent with the evidence for aggregate data. Specifically, gaining government guarantee coverage is associated with an additional 2.9pp growth in loan volume at the industry–level, and an additional 2.1pp growth in loan volume at the bank–firm level. These changes represent a 8.1% and a 8.2% of their respective average within-bank SD.

Finally, we look at the real effects of borrowers' "indirect government guarantee coverage" obtained through their credit relationships. For this analysis, we aggregate syndicated loan market data at firm–year level and include firm, industry-time, and region-time fixed effects to absorb time-invariant firm characteristics and common shocks. Consistent with our predictions, borrowers gaining indirect government guarantee coverage experience an increase in their debt-over-assets ratio of 2.0-2.2 points and grow their debt-based funding by 4.1-4.3pp, which represents 5.9-6.5% and a 7.3-7.7% of the average within-firm SD for each measure, respectively.

Additionally, we find that borrowers that gain indirect government guarantees coverage increase their capital expenditures over assets by an additional 0.19-0.26 points, and their investment over assets by an additional 0.69-1.02 points, which represents between 5.3-7.2% and 5.1-7.5% of the average within-firm SD for the respective investment expenditure measure. Moreover, this behavior appears to be associated with higher excess investments over assets, estimated as the difference between actual and expected investment, by an additional 0.25-0.33 points, which represents between 6.1-8.0% of the average within-firm SD. Ultimately, overinvesting in low-quality projects leads to a reduction in firms' productivity by 0.8-1.2pp, which represents 4.8-7.2% of the average within-firm SD.

In line with this evidence, our results show that greater government guarantees (usually predominant in countries with a large banking sector) lead to more intermediated credit and, in turn, efficiency losses due to overinvestment and worse project selection. This interpretation is also consistent with the findings of Cournède and Denk (2015), who show that periods of more intermediated credit are associated with larger implicit bank debt guarantees, stronger credit issuance by banks compared to other intermediaries, a lower credit quality, and slower economic growth. Similarly, Denk, Schich, and Cournède (2015) find that situations where bank credit reaches levels that reduce economic growth are more prevalent in OECD countries with greater bailout guarantees.

Related literature. Risk-shifting incentives have been widely studied since the seminal work of Jensen and Meckling (1976b). This problem is particularly relevant for banks due to their high leverage, the ease with which they can change their portfolio risk, and the fact that they are protected by implicit and/or explicit government guarantees (e.g., Kareken & Wallace, 1978; Merton, 1977).[2]

Diamond and Rajan (2002) distinguish between well-targeted bailouts (which can be beneficial) and poorly-targeted bailouts that can lead to a systemic crisis. Relatedly, Bianchi (2016) shows that non-targeted and systemic bailouts are preferred to targeted ones since the latter exacerbate banks' moral hazard. Farhi and Tirole (2012) demonstrate that bailouts generate incentives to correlate risks, resulting in financial fragility. Davila and Walther (2019) find that large banks leverage more than small banks because they internalize that their decisions affect bailout policies. Allen, Carletti, Goldstein, and Leonello (2018) show that, although guarantees can distort bank behavior, they increase welfare because they induce banks to improve liquidity provision. Keister (2016) finds that commitment to a no-bailout policy induces banks to become excessively illiquid.

The existing theoretical literature thus mainly focuses on the effect of government guarantees on the banks' risk-taking behavior at the extensive margin, that is, their portfolio and capital structure choices. We highlight that government-insured banks also have risk-shifting incentives at the intensive margin that lead to knock-on real effects for their borrowers, that is, higher firm leverage, overinvestment, and worse project selection.

Various papers have also empirically investigated the effect of government guarantees on banks' risk-taking decisions. Brandao-Marques et al. (2013), Dam and Koetter (2012), and Gropp et al. (2014) provide evidence showing that government guarantees

[2]Such government guarantees aim to prevent bank runs (e.g., Diamond & Dybvig, 1983) and to avoid the social cost of bank failures (e.g., Gorton & Huang, 2004).

are associated with more bank risk-taking. Gropp et al. (2011) document that government guarantees undermine competition in the banking sector, which also increases risk-taking by non-guaranteed banks. Nier and Baumann (2006) find that government safety nets result in lower capital buffers.

Our paper also contributes to the literature that investigates how firms choose between bank and market finance.[3] Diamond (1991) develops a model of bank loan demand asserting that new borrowers borrow from an informed bank that monitors rather than from an arm's length lender that does not. Rajan (1992) argues that while bank financing is more efficient, a firm's optimal funding structure circumscribes the banks' bargaining power. Besanko and Kanatas (1993) show that when banks cannot precommit to a particular monitoring level, there is a unique credit market equilibrium with firms being financed with a combination of bank and market finance. In Boot and Thakor (1997), the trade-off is between the market's ability to aggregate information and banks' ability to resolve moral hazard. Their results show that a financial system in its infancy will be bank-dominated, and that increased financial market sophistication diminishes bank lending. Holmstrom and Tirole (1997) study a model of financial intermediation and market finance in which firms and intermediaries are capital constrained, and use it to investigate the lending behavior in response to a capital tightening.

In the model of Bolton and Freixas (2000), if a firm's default is likely, banks can investigate its future profitability through monitoring. Bond finance avoids intermediation costs, but bond holders always liquidate the borrower. As a result, low (high) quality firms do (do not) value the banks' monitoring ability and thus rely primarily on bank debt (bond or equity financing). Finally, Donaldson et al. (2019) show that the banks' funding-cost advantage can exacerbate soft-budget-constraint problems, making it costly to finance innovative projects. The high cost of capital of non-banks works as a commitment device to withhold capital, solving soft-budget-constraint problems and thereby allowing them to finance innovative projects.

[3] See Donaldson, Piacentino, and Thakor (2019) for a comprehensive literature overview.

4.2 Baseline Model Setup

We analyze the interplay between government guarantees, bank finance, and market-based finance within a classical corporate finance framework, building on Holmstrom and Tirole (1997). In particular, we consider an economy that consists of two dates, $t = \{0, 1\}$, and several risk-neutral parties: a firm, a bank, a government, and numerous competitive household investors.

4.2.1 Players and Timing

The firm has an equity endowment $E > 0$ and can invest in scalable real projects.[4] The real projects are represented by a pair of project characteristics $\{F(I), P\}$, where I represents the firm's investment level at $t = 0$, $F(I)$ the return at $t = 1$ if the project succeeds, and P the project's success probability. For simplicity, we assume that all projects yield a return of zero when they fail. Whether a project succeeds or not is observable at $t = 1$.

Whenever the firm wants to implement an investment level $I > E$, it can raise additional external funds either directly from household investors (i.e., market-based funding, which can be interpreted as either equity or corporate bonds) or indirectly from the bank that, in turn, can also raise funds from household investors (hereafter called investors for simplicity). We assume that all parties have a cost of capital equal to $(1+r)$.[5] Investors provide a perfectly elastic amount of funds to the bank and/or the firm whenever their expected return is at least equal to their cost of capital. Since investors are competitive, we assume that they have no bargaining power vis-a-vis the firm or the bank.

If the firm decides to borrow from the bank, they can write a loan contract that specifies a pair of contract elements $\{R_B, L\}$, where R_B is the gross loan repayment at $t = 1$, while L denotes the borrowed amount at $t = 0$. Moreover, we assume that the bank can resolve the firm's moral hazard problem (explained in detail in Section 4.2.2) through monitoring. Similar to Holmstrom and Tirole (1997), we assume that the bank manager (for simplicity,

[4]The firm can be interpreted as a representative firm representing numerous identical firms. In Section **??**, we consider the case where the economy consists of multiple independent firms. In Section **??**, we relax the assumption of an exogenous equity endowment and consider an endogenous equity choice. Both changes do not affect our results qualitatively.

[5]In Appendix C, we show that our results are also robust to assuming that all parties have the outside option of investing in a risk-free technology that generates a safe return of $1+r$.

in the following called bank) can derive a non-pecuniary benefit γ if it does not monitor the firm.

To clearly convey the intuition of the model, we assume in our baseline setup that the bank has no initial capital endowment.[6] Moreover, we assume that the bank has full bargaining power vis-a-vis the firm and assume that the bank incurs a pecuniary intermediary cost β for each unit of intermediated funds.[7] The intermediary costs justify the co-existence of bank finance and market-based funding. Without these costs there would be no need for market-based finance (see, e.g., Bolton & Freixas, 2000).

Finally, we assume that the government provides an implicit bailout guarantee and thus has to decide whether to rescue the bank (by settling its debt liabilities) if the bank defaults on its debt at $t = 1$. We follow the bailout literature and assume that, when making this decision, the government must trade off the costs of transferring funds from the public to the private sector (e.g., deadweight costs that originate from taxation; see Ballard, Shoven, & Whalley, 1985 and Feldstein, 1999) and the social costs of a bank's failure (e.g., Freixas, 1999). In particular, we assume that the costs of transferring funds from the public to the private sector are χ times the transferred funds. The social costs of a bank's failure are given by the fraction κ of the bank's balance sheet size and thus are assumed to increase with the bank's size. These costs can be interpreted as fire sale costs due to rapid asset liquidation, legal expenditures, or costs that result from breaking a loan originator-borrower relationship (e.g., Acharya & Yorulmazer, 2007).

Because the costs arising from the bank's failure are driven by bank-specific factors that are revealed only in times of distress (such as the availability of outside investors, asset liquidity, and lending relationships with the non-financial sector), we assume that at $t = 0$, only the distribution of κ is known. Specifically, κ follows a uniform distribution between zero and an upper limit $\overline{\kappa} \geq \chi$ at $t = 0$, that is, $\kappa = \mathscr{U}(0, \overline{\kappa})$. Therefore, at $t = 1$, the government decides to bail out the bank if, and only if

$$\chi L \quad \leq \quad \kappa L. \tag{4.1}$$

[6] We relax this assumption in Section **??** where we consider positive bank equity capital.

[7] In practice, banks serve more than one firm, so it is reasonable to allocate the bargaining power to the bank. In Section **??**, we show that shifting the bargaining power to the firm will not affect our main results.

As a result, the ex-ante bailout probability at $t = 0$ if the bank defaults at $t = 1$ is equal to

$$\alpha = 1 - \chi/\overline{\kappa}, \tag{4.2}$$

which increases with the government's ability to raise bailout funds and with the expected negative externalities of a bank's failure. Accordingly, there is an explicit full government guarantee (e.g., a deposit insurance scheme) when $\alpha = 1$, while $\alpha \in (0, 1)$ corresponds to an implicit government bailout guarantee in which the government bails out a bank with probability α.

4.2.2 Firm Projects and Moral Hazard

We follow Diamond (1991) to implement a firm moral hazard problem in our setup. In particular, the firm has two investment possibilities in $t = 0$, a good and a bad project. The good project is represented by project characteristics $\{f(I), p_H\}$, that is, $F(I) = f(I)$ and $P = p_H$:

$$\text{Return of the good project} = \begin{cases} f(I) & \text{with prob. } p_H \\ 0 & \text{with prob. } (1 - p_H). \end{cases} \tag{4.3}$$

We assume that $f(I)$ is a decreasing returns to scale technology. Specifically, we assume that $f'(I) > 0$, $f''(I) < 0$, and $f(0) = f'(\infty) = 0$. The good project is "good" in the sense that it has a positive net return, defined as $p_H f(I) - I(1 + r)$, if the investment level I is not too high. Formally, we thus assume that:

Assumption 1. $p_H f'(E) > (1 + r)$.

Assumption 1 implies that the good project's marginal expected return is still higher than the cost of capital, $(1 + r)$, even if the firm invests its entire initial equity endowment E. Hence, there is a benefit of raising additional outside funds.

The bad project has the project characteristics $\{\delta f(I), p_L\}$, that is, $F(I) = \delta f(I)$ and

$P = p_L$:

$$\text{Return of the bad project} = \begin{cases} \delta f(I) & \text{with prob. } p_L \\ 0 & \text{with prob. } (1 - p_L), \end{cases} \tag{4.4}$$

where $\delta > 1$ and $p_L < p_H$. Hence, the bad project is less likely to succeed but yields a higher return in the event of success. The bad project is "bad" because it always generates a negative net return, irrespective of the investment level, which we formalize in the following assumption:

Assumption 2. $p_L \delta f'(0) < (1+r)$.

Note that this assumption also implies that $p_L \delta < p_H$. Without outside monitoring, the firm thus implements the good project if and only if

$$p_H \left[f(I) - R \right] \geq p_L \left[\delta f(I) - R \right], \text{[Firm Incentive Compatibility Constraint (IC)]} \tag{4.5}$$

where R represents the gross return the firm promises to outside fund providers (the bank or investors) in case of success. The left-hand side (LHS) and the right-hand side (RHS) of Condition (4.5) represent the firm's expected residual return from the good and the bad project, respectively.

The possibility of investing in the bad project thus creates a moral hazard problem for the firm, which becomes more severe, the higher the promised payment to outside fund providers, R. The intuition directly follows from Condition (4.5), which shows that the bad project's relative to the good project's residual return increases with R. This moral-hazard-induced condition imposes the following upper bound for the amount the firm can promise to outside fund providers without any monitoring:

$$R \leq \frac{p_H - p_L \delta}{\triangle p} f(I) \equiv \overline{R} < f(I), \tag{4.6}$$

where $\triangle p \equiv p_H - p_L$.

4.3 Without a Government Guarantee

In this section, we consider the benchmark case where the government never intervenes. First, we analyze the case where the firm finances its project purely through market-based finance, that is, by raising funds directly from investors. In a second step, we consider the case in which the firm can borrow funds from both, investors and the bank.

4.3.1 Market Finance

Let R_I denote the gross repayment that the firm promises to investors at $t = 1$. Since the project payoff in the bad state is zero, market-based finance can be interpreted as either equity finance or corporate bonds.[8]

Let R_I denote the gross repayment that the firm promises to investors at $t = 1$. Since the project payoff in the bad state is zero, market-based finance can be interpreted as either equity finance or corporate bonds.[9]

Due to Condition (4.5), the firm implements the good project if and only if $R_I \leq \overline{R}$. Hence, $\overline{R}$ is the maximum amount that can be pledged to investors.[10] As a result, the firm's optimization problem becomes:

$$\pi_f^m = \max_{I,R_I} p_H \left[f(I) - R_I\right] - E(1+r), \tag{4.7}$$

$$s.t.$$

$$R_I \leq \overline{R} \qquad \text{[Firm IC]} \tag{4.8}$$

$$p_H R_I \geq (I-E)(1+r) \qquad \text{[Investor Participation Constraint (PC)]} \tag{4.9}$$

where π_f^m denotes the firm's maximum expected profit in the market finance case. The good project is successful with probability p_H, in which case the bank receives the residual project return, after having repaid the investors (first term in Eq. 4.7). Moreover, the firm's equity incurs the cost of capital (second term in Eq. 4.7). Investors are willing to

[8] For the equity interpretation, the firm can sell θ shares of the firm's return to investors, guaranteeing that $R_I = \theta F(I)$. For the corporate bond interpretation, R_I represents the bullet repayment.

[9] For the equity interpretation, the firm can sell θ shares of the firm's return to investors, guaranteeing that $R_I = \theta F(I)$. For the corporate bond interpretation, R_I represents the bullet repayment.

[10] Any higher amount cannot be promised to investors; otherwise, the firm would invest in the bad project, which has a negative net return and is thus not implementable because it cannot ex-ante satisfy the break-even conditions of both, the firm and investors.

finance the firm only if their expected return (LHS in PC 4.9) is greater or equal to their cost of capital (RHS in PC 4.9).

Since the firm has the bargaining power vis-à-vis investors, the Investor PC (4.9) must be binding in the optimum. By plugging this condition into Eq. (4.7), we can simplify the firm's optimizing problem to

$$\pi_f^m = \max_{I,R_I} p_H f(I) - I(1+r), \text{ s.t. } R_I \leq \overline{R}, \tag{4.10}$$

which corresponds to maximizing the good project's net return subject to the Firm IC (4.8). If the Firm IC is not binding, the first-order condition for the firm is simply

$$f'(I^*)p_H = (1+r), \tag{4.11}$$

where I^* is the optimal unconstrained investment level. Eq. (4.11) implies that optimal unconstrained investment level should equate the good project's marginal expected return, $f'(I)p_H$, to the cost of capital, $1+r$. Hence, I^* is also the welfare optimal investment level because it balances the marginal benefit of investing with the social cost of capital.

However, if the Firm IC (4.8) is binding, jointly solving the Firm IC and the Investor PC (4.9) yields the following condition for the firm's optimal constrained investment level, $\bar{I}$:

$$\frac{(\bar{I}-E)(1+r)}{p_H} = \frac{p_H - p_L\delta}{\triangle p} f(\bar{I}). \tag{4.12}$$

To focus our analysis on the most interesting case, that is, the case in which the firm's optimal unconstrained investment level is not achievable through pure market-based finance, we assume in the following that:

Assumption 3. *$\bar{I} < I^*$,*

which implies that the Firm IC (4.8) is always binding.

4.3.2 Bank Finance

To overcome the inefficiency caused by the firm's moral hazard problem, the firm can borrow funds from the bank that is able to monitor the firm and enforce the implementation of the firm's good project.

If the bank implements a loan contract $\{R_B, L\}$ with a loan amount $L > 0$, it needs to borrow from investors to raise enough funds to provide the loan to the firm. If the bank monitors the firm, investors' gross interest rate paid in case of success, $(1+r_d)$, has to satisfy

$$p_H(1+r_d) \geq (1+r). \qquad \text{[Investor PC]} \tag{4.13}$$

to incentivize investors to lend funds to the bank.

The bank breaks even only if its expected return from giving the loan at least equals the sum of its funding and intermediary cost, that is,

$$p_H R_B \geq p_H L(1+r_d) + L\beta, \qquad \text{[Bank PC]} \tag{4.14}$$

where β is the intermediary cost for each unit of bank loan. Condition (4.14) implies that $R_B/L > (1+r_d)$. Hence, without government guarantee, bank finance is strictly more expensive than market-based finance for the firm.

The condition that guarantees that the bank monitors the firm and enforces the implementation of the good project is given by

$$p_H R_B \geq p_L R_B + \gamma \Leftrightarrow R_B \geq \frac{\gamma}{\triangle p}, \qquad \text{[Bank IC]} \tag{4.15}$$

where γ is the non-pecuniary benefit derived from waiving monitoring. Bank IC (4.15) implies that the bank monitors and enforces the implementation of the good project only if its expected return from doing so is equal or greater than the sum of her expected return in the case that the firm implements the bad project and the private no-monitoring benefit. Since the bank has full bargaining power when contracting with the firm, the bank chooses $\{R_B, L\}$ to maximize:

$$\pi_b^{ng} = \max_{R_B, L \geq 0} p_H \left[R_B - L(1+r_d)\right] - L\beta, \tag{4.16}$$

$$s.t. \text{ Constraints (4.13), (4.14), (4.15), and}$$

$$\max_{I \geq L+E} \underbrace{p_H \left[f(I) - \frac{(I-L-E)(1+r)}{p_H} - R_B \right] - E(1+r)}_{\substack{\text{Expected firm profit} \\ \text{with bank finance}}} \geq \underbrace{p_H f(\bar{I}) - \bar{I}(1+r)}_{\substack{\text{Expected firm profit} \\ \text{without bank finance}}}, \quad \text{[Firm PC]} \tag{4.17}$$

where π_b^{ng} denotes the bank's maximum expected profit in the case with no government guarantee. Constraint (4.17) is the firm's PC, that is, the firm accepts the loan contract $\{R_B, L\}$ only if its expected return with bank finance is at least equal to its expected return with pure market-based finance.

If the firm accepts the loan contract $\{R_B, L\}$, there can be two different cases: (i) the loan amount is insufficient to cover the firm's investment target (i.e., $L+E \leq I^*$) and the firm will borrow additional funds ($I^* - L - E$) from investors until the marginal benefit of investment reaches the cost of capital; and (ii) the loan contract already excessively satisfies the firm's funding needs (i.e., $L+E > I^*$) and the firm does not borrow any additional funds from investors since the investment level is already inefficiently high.

In our benchmark case, without a government guarantee, we want to ensure a benchmark in which the involvement of a bank (monitoring) is able to restore investment efficiency. Therefore, we assume in the following that

Assumption 4. $p_H \frac{\gamma}{\triangle p} - \underbrace{\left[p_H f(I^*) - I^*(1+r) - \left(p_H f(\bar{I}) - \bar{I}(1+r) \right) \right]}_{\equiv \triangle NR} + E(1+r) \leq I^*(1+r)$,

which ensures that $L+E < I^*$ holds in our benchmark case without the government guarantee. The expression $\triangle NR$ denotes the incremental net return increase of the good project enabled by bank monitoring and the resulting increase in the firm's attainable investment level from $\bar{I}$ to I^*. Intuitively, Assumption 4 requires that γ, the non-pecuniary benefit of giving up monitoring, is not too large.[11]

The following proposition characterizes the bank's optimal loan contract and the resulting firm investment decision for the benchmark case without a government bailout guarantee.

[11]The second case (i.e., $L+E > I^*$) only occurs if the bank offers a loan contract with a very high loan volume L. However, our analysis in Proposition 1 shows that in the benchmark case, the bank minimizes L to avoid the intermediary cost, and thus the only force that pushes L upwards is a large γ. If γ is sufficiently low, the second case will never occur in the benchmark case.

Proposition 1. *Under Assumptions 1-4, the bank participates if and only if*

$$\triangle NR \geq \frac{p_H\gamma}{(1+r+\beta)\triangle p}\beta. \tag{4.18}$$

If the bank participates, the bank's optimal contract $\{R_B^{ng}, L^{ng}\}$ is given by:

$$R_B^{ng} = \max\left\{\frac{\gamma}{\triangle p}, \frac{\triangle NR}{p_H}\right\}, \tag{4.19}$$

$$L^{ng} = \max\left\{\frac{1}{1+r}\left(\frac{p_H\gamma}{\triangle p} - \triangle NR\right), 0\right\}. \tag{4.20}$$

If the bank participates, the bank's maximum expected profit π_b^{ng} is given by

$$\pi_b^{ng} = \min\left\{\triangle NR, \left(1+\frac{\beta}{1+r}\right)\Delta NR - \frac{p_H\gamma}{(1+r)\triangle p}\beta\right\} \geq 0. \tag{4.21}$$

The investment level of the firm is I^* ($\bar{I}$) if the bank participates (does not participate).

Proof. See the Appendix.

The intuition for the result is as follows. With bank monitoring, the net return of the firm's project increases by $\triangle NR$. Hence, the bank's best strategy is to extract $\triangle NR$ through raising the loan repayment, R_B, while keeping the loan size, L, as small as possible to minimize the intermediary costs.

When the private benefit from waiving monitoring, γ, is small (i.e., $\gamma \leq (\triangle p/p_H)\triangle NR$), the Bank IC (4.15) is not binding. Therefore, the bank simply chooses $L^{ng} = 0$ to avoid intermediary costs, while setting $R_B^{ng} = \triangle NR/p_H$ to extract all incremental project net return. In this case, the optimal loan contract reduces to a fee contract, where the bank charges the fee R_B^{ng} and provides the monitoring service to lift the firm's moral-hazard-induced borrowing capacity constraint.

When γ is high (i.e., $\gamma > (\triangle p/p_H)\triangle NR$), $R_B = \triangle NR/p_H$ is insufficient to incentivize the bank to monitor. Without monitoring, there is no incremental net return the bank could extract. Therefore, to guarantee that the bank has enough incentive to monitor the firm, R_B must be increased to at least $\gamma/\triangle p$. If, however, L would be kept at zero while R_B increases, the contract would lose attractiveness for the firm. Hence, to again satisfy the Firm PC (4.17), the bank must increase L to $1/(1+r)(p_H\gamma/\triangle p - \triangle NR)$.

If the bank participates (and monitors), the firm's borrowing capacity is no longer constrained by the moral hazard problem. Since the loan amount is insufficient for the firm to reach its optimal investment level (see Assumption 4), the firm optimally borrows additional funds from investors until its investment level reaches I^*.

Note that waiving monitoring can never be optimal for the bank. Without monitoring, the firm's moral hazard problem remains even if the firm borrows from the bank. Hence, without monitoring, the value of the good project cannot exceed $p_H f(\bar{I}) - \bar{I}(1+r)$, that is, the net return also attainable with pure market finance.[12] Since the shareable profits (or economic rents) of the firm and the bank are solely derived from the good project, the bank can only extract value from the loan contract if, through monitoring, it increases the good project's attainable net return. The following corollary summarizes this analysis.

Corollary 1. *In the absence of a government guarantee, a necessary condition for the bank to make a positive profit is that the bank monitors the firm.*

Finally, note that the bank, when it participates, always (weakly) increases the firm's investment efficiency, but sometimes incurs intermediary costs. However, the bank only participates when the benefits dominate the costs. Therefore, we obtain the following result with regard to social welfare.

Corollary 2. *In the absence of a government guarantee, social welfare always increases if the bank participates and makes a positive expected profit.*

4.4 With a Government Guarantee

Next, we analyze the case where the government provides a public guarantee for the bank. First, we investigate the case where the bank, if it participates, always monitors the firm and enforces the implementation of the good project without considering whether it is optimal to do so. In a second step, we analyze the case where the bank also decides whether to monitor or not.

[12] Due to the intermediary costs, the amount of funding the firm can raise is even lower than $\bar{I} - E$ when it borrows from the bank and the bank does not monitor.

4.4.1 Optimal Contract with Compulsory Monitoring

In this subsection, we study the case where the bank always monitors and implements the good project when it participates; in other words, monitoring is compulsory.[13] With the public guarantee, the government settles the bank creditors' claims with probability α when the bank fails (which happens with probability $1 - p_H$). Hence, investors lend funds to the bank only if

$$p_H L(1+r_d) + (1-p_H)\alpha L(1+r_d) \geq L(1+r), \qquad \text{[Investor PC]} \tag{4.22}$$

where the LHS is the expected payoff to investors if they lend the amount L to the bank that offers a deposit rate $1+r_d$, while the RHS represents investors' total cost of capital. The bank's and the firm's PC (i.e., Constraints 4.14 and 4.17, respectively), and the bank's IC (i.e., Constraint 4.15) are unaffected by the possibility of a government bailout.

Therefore, the bank's maximum expected profit in the case with government guarantee, monitoring, and the implementation of the high probability success project (i.e., the good project) results from the following loan contracting problem:

$$\pi_b^{gmH} = \max_{R_B, L \geq 0} p_H \left[R_B - L(1+r_d)\right] - L\beta,$$

$$s.t.\ (4.14),\ (4.15),\ (4.17),\ \text{and}\ (4.22).$$

We characterize the bank's optimal loan contract and the resulting firm investment decision in the following proposition.

Proposition 2. *With a government guarantee and Assumptions 1-4, there are two possible cases:*

(i) If for the bank's expected marginal lending cost (MLC^H) it holds that

$$MLC^H \equiv p_H \frac{1+r}{p_H + (1-p_H)\alpha} + \beta \geq 1+r, \tag{4.23}$$

[13]This does not mean that the bank's IC can be neglected. Instead, compulsory bank monitoring means the bank must satisfy the bank's IC whenever it participates

the bank participates if and only if

$$\frac{MLC^H}{1+r}\triangle NR - \frac{p_H\gamma}{(1+r)\triangle p}\left(MLC^H-(1+r)\right)\geq 0. \tag{4.24}$$

If the bank participates, the bank's optimal loan contract $\{R_B^{gm\overline{H}}, L^{gm\overline{H}}\}$ *in this case equals* $\{R_B^{ng}, L^{ng}\}$ *(given in Proposition 1). The bank's maximum expected profit is thus given by*

$$\pi_b^{gm\overline{H}} = \begin{cases} \triangle NR & \text{if } \triangle NR \geq \frac{p_H\gamma}{\triangle p} \\ \frac{MLC^H}{1+r}\triangle NR - \frac{p_H\gamma}{(1+r)\triangle p}\left(MLC^H-(1+r)\right) & \text{if } \triangle NR < \frac{p_H\gamma}{\triangle p} \end{cases} \tag{4.25}$$

The investment level of the firm is I^* *(*$\bar{I}$*) if the bank participates (does not participate).*

(ii) If for the bank's expected marginal lending cost it holds that

$$MLC^H < 1+r, \tag{4.26}$$

the bank always participates. The bank's optimal loan contract $\{R_B^{gm\underline{H}}, L^{gm\underline{H}}\}$ *is then given by the unique solution of the following system of equations:*

$$p_H f'(L^{gm\underline{H}}+E) = MLC^H \tag{4.27}$$

$$p_H R_B^{gm\underline{H}} = p_H f(L^{gm\underline{H}}+E) - E(1+r) - \left(p_H f(\bar{I}) - \bar{I}(1+r)\right). \tag{4.28}$$

The bank's maximum expected profit in this case is given by

$$\pi_b^{gm\underline{H}} = p_H f(L^{gm\underline{H}}+E) - E\,(1+r) - \left(p_H f(\bar{I}) - \bar{I}\,(1+r)\right) - L^{gm\underline{H}}MLC^H.$$

The firm's investment level is $L^{gm\underline{H}}+E > I^*$*. The firm no longer borrows from investors, that is, bank finance completely crowds out market-based finance.*

Proof. See the Appendix.

To see why MLC^H represents the bank's marginal lending costs in the compulsory monitoring case note that the investors' PC (Condition 4.22) must be binding in the optimum (as shown in the proof of Proposition 2), which implies that

$$MLC^H = \underbrace{p_H(1+r_d)}_{\substack{\text{Expected marginal}\\ \text{borrowing cost}}} + \underbrace{\beta}_{\substack{\text{Marginal}\\ \text{intermediary cost}}} . \tag{4.29}$$

Hence, MLC^H is the sum of the expected return investors require from the bank for each unit of loaned funds, $p_H(1+r_d)$, and the intermediary cost that the bank incurs for providing a unit of loans, β.

The intuition of the results outlined in Proposition 2 is as follows. When the bank's marginal lending costs, MLC^H, are equal or greater than investors' cost of capital, $1+r$ (i.e., $MLC^H \geq 1+r$), the bank's optimal strategy is the same as the one described in Proposition 1: extracting the increased project net return through the loan repayment, R_B, while minimizing the loan volume, L. Therefore, we have $\{R_B^{gm\overline{H}}, L^{gm\overline{H}}\} = \{R_B^{ng}, L^{ng}\}$. The government guarantee, however, reduces the bank's expected marginal cost of providing loans from $1+r+\beta$ to MLC^H, and thus increases the bank's expected profit, which loosens the bank's PC (i.e., Condition 4.24 is less restrictive than Condition 4.18).

In contrast, if $MLC^H < 1+r$, the bank's incentive regarding the provision of loans flips. Now, if the bank intermediates funds from investors to the firm, the bank's marginal lending costs are lower than the firm's market-based funding option, $1+r$. Since the bank has full bargaining power, it can extract the positive spread between $1+r$ and MLC^H by simply channeling funds from investors to the firm. Hence, to maximize its profits, the bank has an incentive to intermediate all funds the firm requires, thereby eliminating the firm's incentive to borrow additional funds from investors after accepting the loan contract. As a result, market-based finance is completely crowded out.

Moreover, since the spread between $1+r$ and MLC^H provides the bank with an additional source of profit besides the incremental project net return ($\triangle NR$), the bank prefers a firm investment level that is higher than I^* when $MLC^H < 1+r$ to maximize its total profit from both sources.

Figure 4.1 shows how the bank's profit depends on the government bailout probability α. Generally, the bank's profit (weakly) increases with α, which is intuitive since the government guarantee reduces the bank's marginal lending costs, MLC^H. Figure 4.1

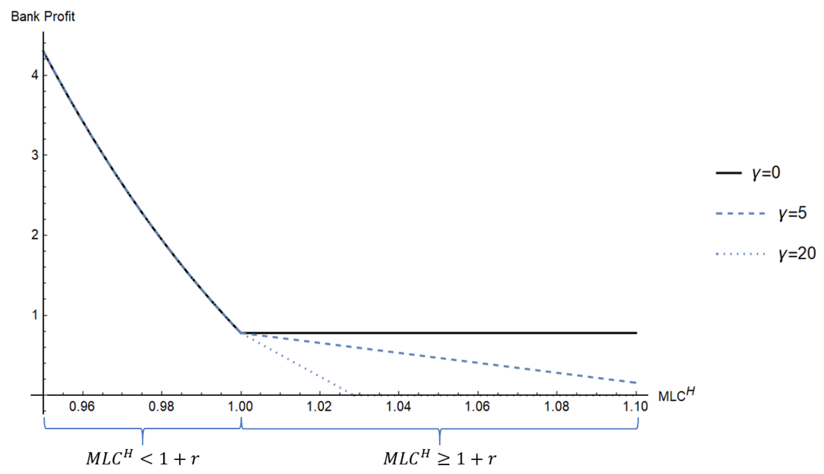


Figure 4.1: **Bank Profit with Compulsory Monitoring.** This figure plots the bank's profits against the government bailout probability α when monitoring is compulsory. The solid/dashed/dotted curve describes the bank's profit when $\gamma = 0/\gamma = 5/\gamma = 20$. The function $f(I)$ is specified as $f(I) \equiv A(1+I)^{1-c} - A$. The remaining parameter values are: $E = 10, p_H = 0.7, p_L = 0.2, p_L\delta = 0.4, r = 0, c = 0.1, A = 2.4, \beta = 0.1$.

also highlights that, the higher the bailout probability α, the higher the likelihood that $MLC^H < 1+r$ (i.e., case ii of Proposition 2) and thus that the bank incentivizes the firm to overinvest.

Since MLC^H decreases with α, Proposition 2 also implies the following corollary that characterizes the firm's leverage:

Corollary 3. *If it holds that $MLC^H < 1+r$, we have:*

(i) the firm's leverage, $(L^{gm\underline{H}} + E)/E$, is higher than in the case where the firm's investment level is efficient;

(ii) the firm's leverage increases with the bailout probability, α.

Moreover, Figure 4.1 shows that the evolution of the bank's profit also depends on γ, the non-pecuniary private benefit of waiving monitoring. According to Proposition 2, when γ is low (solid line), the bank's profit is fixed at $\triangle NR$ when $MLC^H \geq 1+r$, and the bank always participates. For medium γ (dashed line), the bank's IC can be binding in the region $MLC^H \geq 1+r$, which reduces the bank's profit. For high γ (dotted line), the bank's incentive problem is so severe that the bank does not participate when α is not sufficiently high (i.e., the dotted line lies on the horizontal axis).

In contrast, when $MLC^H < 1+r$, the bank's IC is no longer binding, and the bank can extract additional benefits from the spread between MLC^H and $1+r$. Therefore, for

$MLC^H < 1+r$ the three lines overlap and increase rapidly with α.

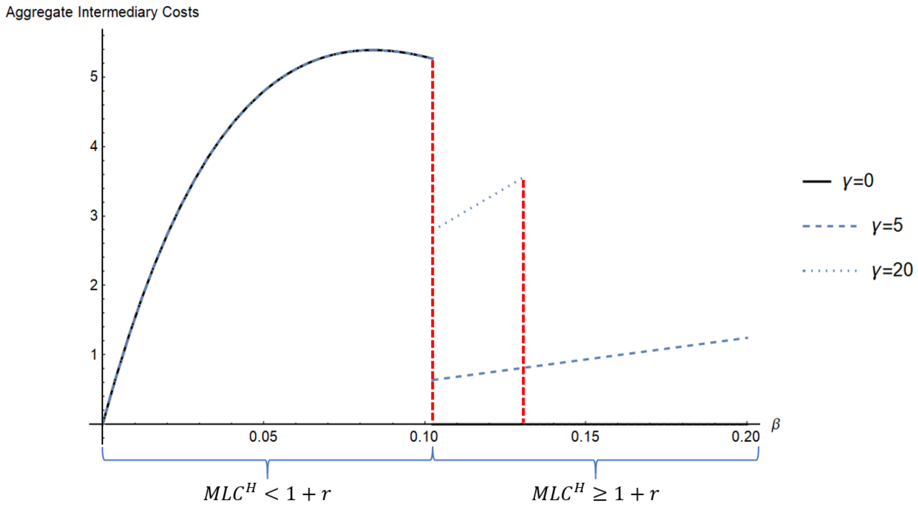


Figure 4.2: Aggregate Intermediary Costs with Compulsory Monitoring. This figure plots the aggregate intermediary costs (i.e., $L\beta$) against β when monitoring is compulsory. The solid/dashed/dotted curve describes the aggregate intermediary costs for $\gamma = 0/\gamma = 5/\gamma = 20$, respectively. The function $f(I)$ is specified as $f(I) \equiv A(1+I)^{1-c} - A$. The remaining parameter values are: $\alpha = 0.35, E = 10, p_H = 0.7, p_L = 0.2, p_L\delta = 0.4, r = 0, c = 0.1, A = 2.4$.

Another interesting implication of Proposition 2 is that lower marginal intermediary costs (i.e., lower β) may actually lead to higher aggregate intermediary costs (i.e., higher $L\beta$) due to a resulting larger loan volume, as shown in Figure 4.2.

When γ is relatively low (solid line) and β relatively high (such that $MLC^H \geq 1+r$), the loan contract reduces to a fee contract that specifies zero loan volume and thus avoids intermediary costs. As long as $MLC^H \geq 1+r$, decreasing β has no effect on the aggregate intermediary costs since the loan volume remains zero. However, if β further decreases such that $MLC^H < 1+r$, the bank's lending attitude switches from minimizing the loan amount to enlarging it (to exploit the spread between $1+r$ and MLC^H) and, as a result, the aggregate intermediary costs suddenly jump up.

When γ is at a medium level (dashed line) and β relatively high (such that $MLC^H \geq 1+r$), the bank's IC becomes binding, and thus, the optimal loan volume is positive. Therefore, in this region, the aggregate intermediary costs decrease as β decreases, since the loan volume is independent of β. Again, when β is sufficiently low such that $MLC^H < 1+r$, the aggregate intermediary costs jump up since the bank's attitude towards lending flips.

When γ is very high (dotted line) and β sufficiently large, the bank's incentive problem is so severe that the bank does not participate. When β is small enough such that the bank participates, the aggregate intermediary costs follow a similar pattern as in the medium γ case.

Finally, Figure 4.2 also highlights that lower marginal intermediary costs increase the likelihood that $MLC^H < 1+r$ (i.e., case ii of Proposition 2), and thus make it more likely that the bank incentivizes the firm to overinvest and to increase its leverage. This finding highlights a potential downside of the increased intermediation efficiency of the banking sector in recent decades. Paired with a government guarantee, it can backfire and lead to an overinvestment in the real sector.

4.4.2 Optimal Contract without Compulsory Monitoring

In the previous subsection, we consider the case where the bank, when participating, always monitors the firm and enforces the implementation of the good project. In this subsection, we analyze under which conditions it is actual optimal for the bank to monitor or not to monitor the firm and whether inducing the firm to implement the good project is always preferable for the bank. l The following lemma shows that, when protected by a government guarantee, the bank is indeed able to make a positive expected profit even if it does not monitor the firm.

Lemma 5.

(i) If the bank does not monitor the firm, but wants to incentivize the firm to implement the good project, the bank can make a positive profit if and only if

$$MLC^H < 1+r. \tag{4.30}$$

If Condition (4.30) holds, the bank's maximum expected return for the case with government guarantee, without monitoring, and an implementation of the high success probability project (i.e., the good project) is

$$\pi_b^{gw\underline{H}} = \left(1+r-MLC^H\right)\left(\bar{I}-E\right), \tag{4.31}$$

and the corresponding optimal loan contract is given by $\left\{R_B^{gw\underline{H}}, L^{gw\underline{H}}\right\}$*, where*

$$R_B^{gw\underline{H}} = \frac{(1+r)\left(\bar{I}-E\right)}{p_H} \text{ and } L^{gw\underline{H}} = \bar{I}-E. \tag{4.32}$$

(ii) If the bank does not monitor the firm and the firm implements the bad project, the bank's expected marginal lending cost is

$$MLC^L \equiv p_L \frac{1+r}{p_L+(1-p_L)\alpha} + \beta. \tag{4.33}$$

A necessary condition for the bank to make a positive profit in this case is

$$MLC^L < 1+r. \tag{4.34}$$

Define a function $\pi_b^{gwL}(L)$ *as:*

$$\pi_b^{gwL}(L) = p_L \delta f(L+E) - p_H f(\bar{I}) + \left(\bar{I}-E\right)(1+r) - MLC^L L, \tag{4.35}$$

and let L^{gwL} *be the unique solution of*

$$p_L \delta f'(L^{gwL}+E) = MLC^L. \tag{4.36}$$

If the bank does not monitor the firm and the firm implements the bad project after accepting the bank's loan contract, the bank's maximum expected profit is $\pi_b^{gwL}\left(\max\left\{L^{gwL},0\right\}\right)$*. Therefore, the bank has a positive expected profit if and only if*

$$\pi_b^{gwL}\left(\max\left\{L^{gwL},0\right\}\right) > 0, \tag{4.37}$$

in which case it always holds that $L^{gwL} > 0$*. Whenever the bank's expected profit is positive, the bank's optimal contract is* $\{R_B^{gwL}, L^{gwL}\}$*, where* R_B^{gwL} *solves:*

$$p_L[\delta f(L^{gwL}+E) - R_B^{gwL}] - E(1+r) = p_H f(\bar{I}) - \bar{I}(1+r).$$

Proof. See the Appendix.

Lemma 5 states that, under certain conditions, the bank can achieve a positive expected profit even if it does not monitor the firm, irrespective of whether the firm implements the good or the bad project. Note that the bank never has a positive expected profit if it does not monitor the firm and there is no government guarantee (i.e., $\alpha = 0$), since in this case Conditions (4.30) and (4.37) are both violated.

The intuition behind Item (i) of Lemma 5 is straightforward. If the bank does not monitor the firm, the firm can borrow at most the amount $\bar{I} - E$ from investors. However, when the bank's expected marginal lending cost (i.e., MLC^H) is lower than investors' cost of capital $1 + r$, the bank is able to exploit the spread between $1 + r$ and MLC^H by intermediating funds from investors to the firm. Since the bank does not monitor the firm, the firm's moral hazard problem remains. Therefore, the bank is able to intermediate at most $\bar{I} - E$ units of funds if it wants the firm to implement the good project.

The intuition behind Item (ii) is slightly more subtle. As the bad project has a negative net return, there is no loan contract that can guarantee non-negative expected profits for both the firm and the bank, in the absence of a government guarantee. With a bailout possibility, however, the government may inject public funds when the bank fails, which effectively increases the expected value of the bad project for the three private sector parties: the firm, the bank, and investors. Hence, when the bailout likelihood is sufficiently high, the bank can offer a loan contract that guarantees positive expected profits for both the firm and the bank, and a zero profit for investors, even if the firm implements the bad project.

However, even if the bank is able to make a positive profit without monitoring the firm, it does not yet imply that waiving monitoring yields a higher expected bank profit than in the case where the bank monitors the firm. The following proposition shows that indeed it may be optimal for the bank to give up monitoring.

Proposition 3.

(i) *Whenever $\pi_b^{gw\underline{H}} > 0$, it holds that $\pi_b^{gw\underline{H}} < \pi_b^{gm\underline{H}}$. Therefore, the bank never gives up monitoring if it wants the firm to implement the good project.*

(ii.1) *When $MLC^H < 1 + r$, there exists a parameter set $\{\beta, \alpha, E\}$ with which the bank waives monitoring and offers the contract $\left\{R_B^{gwL}, L^{gwL}\right\}$ (given in Lemma 5) if it holds that $f'(0) < \frac{1+r}{1-p_L\delta/p_H}$.*

(ii.2) *When $MLC^H \geq 1+r$, there exists a parameter set $\{\alpha, E\}$ with which the bank waives monitoring and offers the contract $\left\{R_B^{gwL}, L^{gwL}\right\}$ if it holds that $f'(0) < \frac{(1-p_L)(1+r)-\beta}{p_H - p_L\delta}$.*

(iii) *If the bank gives up monitoring and offers the contract $\left\{R_B^{gwL}, L^{gwL}\right\}$, the firm implements the bad project after taking the contract, and market-based finance is crowded out.*

Proof. See the Appendix.

Item (i) of Proposition 3 is quite intuitive. When the bank gives up monitoring, but incentivizes the firm to implement the good project, the maximum project net return is still constrained at $p_H f(\bar{I}) - \bar{I}(1+r)$ since the firm's moral hazard problem remains. Therefore, the bank's sole profit source is exploiting the spread between $1+r$ and MLC^H (see Lemma 5). But even if $MLC^H < 1+r$, the bank cannot optimally exploit the spread because the loan volume is constrained at $\bar{I} - E$ due to the firm's moral hazard problem.

In contrast, when the bank monitors the firm, it can extract the incremental project net return. Moreover, if it monitors, the bank derives more value from the spread between $1+r$ and MLC^H since the loan volume is no longer limited to $\bar{I} - E$. For these reasons, giving up monitoring but incentivizing the firm to implement the good project can never be optimal.

Items (ii.1), (ii.2), and (iii) of Proposition 3, however, state that the bank may prefer to waive monitoring and to implement the bad project in some cases. The key intuition for this result is that a higher bank default probability is associated with a higher expected value of the government guarantee, which can be exploited by the bank.

In particular, if the firm switches from the good to the bad project, this has two opposing effects on the bank's expected profit: an income-reducing and a cost-saving effect. First, this switch reduces the bank's expected loan repayment, since the loan repayment value is linked to the firm's project net return, which is lower when the firm invests in the bad project. Second, the switch increases the value of the government guarantee and, thereby, decreases the bank's expected marginal lending cost from MLC^H to MLC^L. More specifically, the project switch increases the bank's default probability and thus decreases the probability that the bank has to honor its debt repayment obligations. While the increased default probability also increases the bank's funding rate, it does so only to a limited extent due to the government guarantee, which makes the bank's funding rate less sensitive to changes in its default probability.

Overall, the bank thus prefers financing the bad project when the cost-saving effect dominates the income-reducing effect, in which case the bank gives up monitoring and offers the loan contract $\left\{R_B^{gwL}, L^{gwL}\right\}$ to incentivize the firm to implement the bad project (see Item iii of Proposition 3).[14]

Next, we numerically explore how the different model parameters affect the bank's decision whether to incentivize the firm to invest in the bad or good project. Figure 4.3 shows that the bad project dominates the good project whenever the bank's bailout probability α exceeds a certain threshold. This result is intuitive because the value of the government guarantee and, in turn, the bank's expected return is more sensitive to α when the bad project is implemented due to its higher default probability. Hence, if the bank's bailout probability is sufficiently high, the firm implements the bad project not because of moral hazard at the firm level, but because the bank prefers to finance the bad project and incentivizes the firm to implement it.

Moreover, Figure 4.3 shows that this critical threshold level of α above it becomes optimal for the bank to incentivize the firm to invest in the bad project increases with the firm's equity E. Recall that, when the bad project is implemented, the bank's profit solely originates from the spread between the cost of capital,$1+r$, and the bank's expected marginal lending cost, MLC^L, which makes the bank's profit very sensitive to the volume of intermediated funds. Since a higher firm equity level implies a lower loan volume, the bank's profit decreases quickly with E when the bad project is implemented. As a result, a higher firm equity level makes the bad project less attractive from the bank's perspective.

The effect of a change in p_L (keeping $p_L\delta$ constant) on the bank's profit is shown in Figure 4.4. A higher p_L (i.e., a lower failure probability for the bad project) implies a lower attractiveness of the bad project for the bank. This result is quite intuitive. When keeping $p_L\delta$ constant, the bad project's intrinsic expected return for any given investment

[14]Note that, when solving for the bank's optimal strategy, we do not take into account the non-pecuniary private benefit of giving up monitoring, γ, to illustrate the bank's tradeoff more clearly. However, including γ would actually strengthen the result that the bank may optimally give up monitoring and implement the bad project, since waiving monitoring would generate an additional benefit.

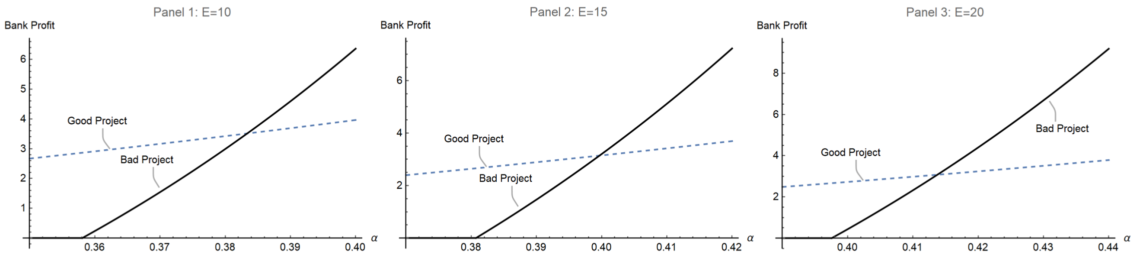


Figure 4.3: **Bank Profits for Good versus Bad Project: Effect of E.** This figure plots the bank's profits against the government bailout probability α. Panels 1 to 3 show this relationship for different levels of E. The solid/dashed lines represent the bank's profit when the firm implements the bad/good project. The function $f(I)$ is specified as $f(I) \equiv A(1+I)^{1-c} - A$. The remaining parameter values are: $\gamma = 0.1, p_H = 0.7, p_L = 0.2, p_L\delta = 0.4, r = 0, c = 0.1, A = 2.4, \beta = 0.1$.

level remains constant even when we vary p_L. However, the value of the government guarantee decreases with p_L, which reduces the attractiveness of the bad project for the bank.

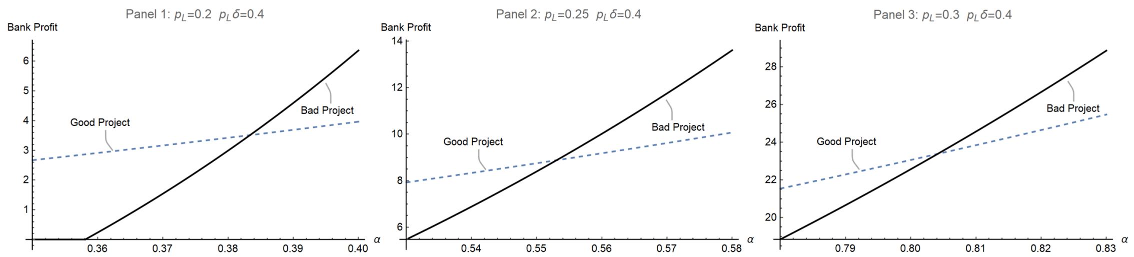


Figure 4.4: **Bank Profits for Good versus Bad Project: Effect of p_L.** This figure plots the bank's profits against the government bailout probability α. Panels 1 to 3 show this relationship for different levels of p_L (keeping $p_L\delta$ constant). The solid/dashed lines represent the bank's profit when the firm implements the bad/good project. The function $f(I)$ is specified as $f(I) \equiv A(1+I)^{1-c} - A$. The remaining parameter values are: $E = 10, \gamma = 0.1, p_H = 0.7, p_L\delta = 0.4, r = 0, c = 0.1, A = 2.4, \beta = 0.1$.

Finally, we analyze how the effect of the concavity of the projects' payoff function $f(I)$ on the bank's expected return. Figure 4.5 shows that, as the concavity of $f(I)$ increases, implementing the bad firm project becomes less attractive for the bank. Specifically, the marginal returns of both the good and the bad projects decrease faster with the firm's investment size for a higher concavity of $f(I)$. As a result, the firm's investment level will be lower if the concavity of $f(I)$ is high. When the firm invests in the bad project, the bank's expected return solely originates from exploiting the spread between the cost of capital and its marginal lending cost. This makes the bank's expected return quite sensitive to the bank's loan volume, which, in turn, is determined by the firm's investment level. Therefore, a higher concavity of $f(I)$ lowers the firm's investment level, thereby decreasing the bank's loan volume, which makes the bad project less attractive for the bank relative to the good project.

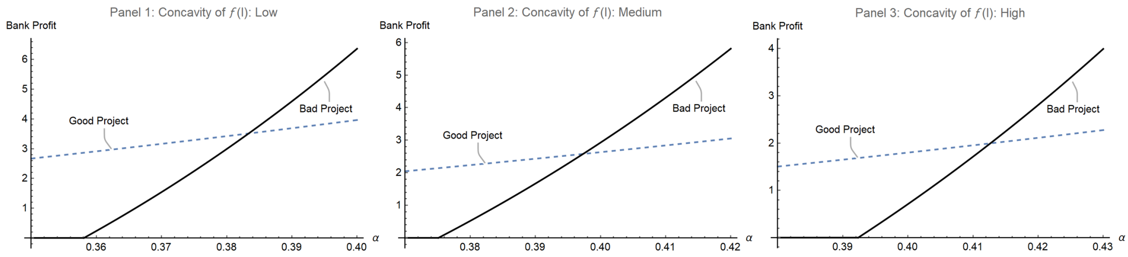


Figure 4.5: **Bank Profits for Good Project versus Bad Project: Effect of the Concavity of $f(I)$.** This figure plots the bank's profits against the government bailout probability α. Panels 1 to 3 show this relationship for different concavities of function $f(I)$. The solid/dashed lines represent the bank's profit when the firm implements the bad/good project. The function $f(I)$ is specified as $f(I) \equiv A(1+I)^{1-c} - A$. In Panel 1/Panel 2/Panel 3, we have $c = 0.1/c = 0.105/c = 0.11$. The remaining parameter values are: $E = 10, \gamma = 0.1, p_H = 0.7, p_L = 0.2, p_L\delta = 0.4, r = 0, A = 2.4, \beta = 0.1$.

4.5 Data and Institutional Setting

We test our model predictions in the context of corporate lending in the U.S. banking system during the period 1996-2016. We use bank financial information from the BHC Call Report Database and employ information about the U.S. Senate committee composition to capture banks' expected government guarantee coverage changes. We use LPC Dealscan to identify bank activity in the syndicated loan market and obtain borrower financial information from Compustat. The following chapter describes the data in more detail.

4.5.1 Measuring changes in banks' bailout expectations

Identifying banks' portfolio reallocations in response to changes in the extent of their government guarantee coverage is empirically challenging. First, effects on the banks' investment behavior arise from expectations about the value of government guarantees, which are usually not observable. Second, the extent of a bank's government guarantee protection is largely endogenous to its investment behavior and portfolio risk.

Econometrically, we thus require some measurable variation in banks' expected government guarantee value that is otherwise uncorrelated with their investment behavior. To this end, we draw from the recent literature on political connections and bank bailouts, and use changes in banks' geography-based political connections to identify arguably exogenous variation in their bailout expectations (Duchin & Sosyura, 2014 and Kostovetsky, 2015).[15]

Exploiting banks' geography-based political connections as an instrument for bailout approvals, Duchin and Sosyura (2014) studies applications to the Troubled Asset Relief Program (TARP) and finds that bailed-out banks started to originate riskier mortgages. Using a similar geography-based measure, Kostovetsky (2015) finds that politically connected banks have a lower bankruptcy probability, as well as higher leverage, stock price volatility, and co-movement with the stock market.

We build on the geography-based political connection measure from Kostovetsky (2015) to identify variations in banks' expected government guarantee values. The results therein are consistent with the conjecture that having a senator from its state of incorporation in the BHUA Senate committee significantly increases a bank's likelihood of receiving government assistance in times of distress.

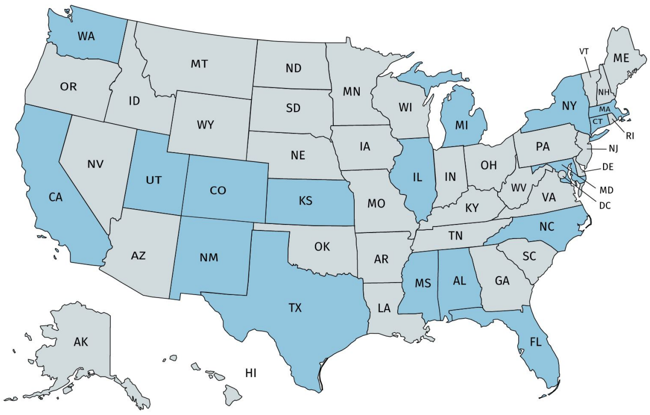
With every new congress, senators are assigned to committees in the U.S. Senate, which, within assigned areas, monitor ongoing governmental operations, identify issues suitable for legislative review, gather and evaluate information, and recommend courses of action. The BHUA Senate committee is one of twenty standing committees, and it has jurisdiction over banks and other financial institutions. In recent decades, this committee has played a decisive role in U.S. government bailout decisions.

Although senators are formally elected to standing committees by the entire membership of the Senate, in practice each party conference is largely responsible for determining which of its members will sit on each committee. Party conferences appoint a "committee on committees" or a "steering committee" to make committee assignments, considering seniority, areas of expertise, as well as preferences and prior committee assignments. The committee assignments need to adhere to limits that the Senate places on the number and types of panels any one senator may serve on and chair.

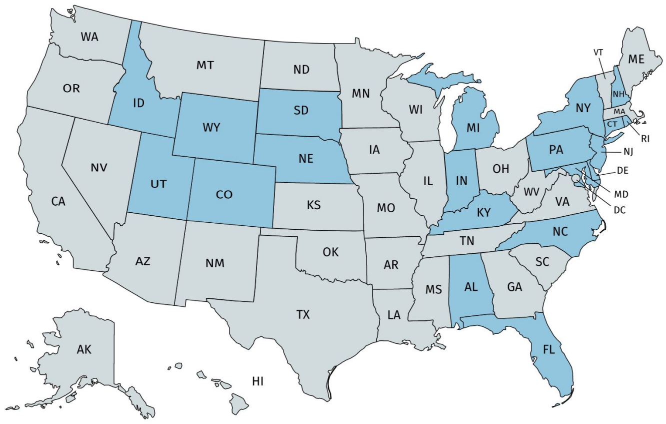
The number of seats a party holds in the Senate determines its share of seats on each committee. Hence, besides party considerations and senators' qualifications and committee preferences, shifts in the proportion of Republican and Democrat senators might also

[15]Relatedly, Dam and Koetter (2012), Duchin & Sosyura, 2012, and Blau et al. (2013) show that politically connected banks are more likely to benefit from government rescue measures.

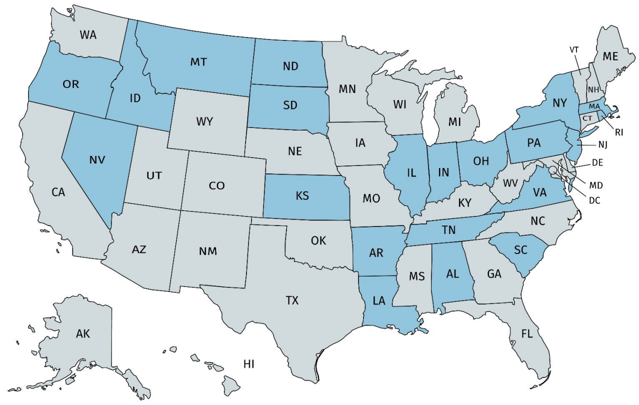
Figure 4.6: **BHUA Senate Committee.** States with a senator in the committee (in light blue) in 1996, 2006, and 2016.



(a) As of 1996



(b) As of 2006



(c) As of 2016

lead the parties to reorganize committee memberships. Moreover, changes in committee membership are triggered by a senator's decision to focus on other tasks (e.g., electoral campaigns) or by a senator's retirement.

As of 2022, the BHUA Senate committee has 24 members, 12 from the Democratic Party and 12 from the Republican Party. We draw historical membership of the BHUA Senate committee from annual volumes of the Official Congressional Directory. Figure 3.1 shows that state representation in the committee is dispersed across different regions with significant variation over time.

The process and the factors that determine the composition of Senate committees, as well as the fact that banks rarely move across state lines, make it reasonable to conjecture that a bank's geography-based committee representation is not directly linked to its investment behavior and asset composition, except through the effect on bailout expectations. Exploiting this exogenous variation allows us to estimate causal effects of changes in banks' expectations about their government guarantee coverage on their portfolio concentration.

Specifically, we exploit the modifications of the BHUA Senate committee composition with two purposes: capturing changes in the banks' bailout expectations and capturing changes in borrowers' indirect protection.

For regressions at the bank–year level, we employ the dummy $GG_{b,t}$ (for **G**overnment **G**uarantee) as proxy for changes in the banks' expected government guarantee coverage, which is equal to one if at least one senator from bank b's state of incorporation is a member in the BHUA Senate committee in year t. For regressions at the bank–industry–year and bank–firm–year level, we employ $\triangle GG_{b,t}$, which can take the values $\{-1,0,1\}$: 0 when there was no change in $GG_{b,t}$ in year t, 1 if $GG_{b,t}$ changed from zero to one, and -1 if $GG_{b,t}$ changed from one to zero. Overall, 35 out of the 99 banks in our sample (i.e., 35.3%) experienced a change in $GG_{b,t}$ during our sample period.

For regressions at the firm–year level, we employ the continuous variable *Indirect GG*, bounded between 0 and 1. We measure non-financial non-utility borrowers' incidental advantages of *GG*, weighting by the relative size of their credit relationships.[16] That is,

[16]Information on the contribution of each lender in a syndicated loan is partially populated in the database. Consequently, we estimate the lending share of each lender in each loan when this information is not reported. To do this, we employ OLS estimates regressing the available lending shares on the

for each bank-firm pair at year t, we estimate the borrowing share as the ratio between the funding obtained by firm f from bank b over the total funding obtained by the firm from all banks:

$$Borrowing\ Share_{b,f,t} = \frac{Borrowed\ Volume\ from\ Bank_{b,f,t}}{Total\ Borrowed\ Volume_{f,t}} \tag{4.38}$$

We then calculate the firm's weighted sum of the coverage obtained through their credit relationships, defined as $Indirect\ GG_{f,t}$ and calculated at the firm and year level:

$$Indirect\ GG_{f,t} = \sum Borrowing\ Share_{b,f,t} * GG_{b,t} \tag{4.39}$$

Overall, 2587 out of the 5560 borrowers in our sample (i.e., 46.5%) experienced a change in $GG_{f,t}$ during our sample period.

4.5.2 Measuring banks' and firms' behavior

We obtain bank financial and general (i.e., on headquarters locations) information from the U.S. Federal Reserve's publicly available Consolidated Financial Statements for Bank Holding Companies (FR Y-9C), publicly disclosed for U.S. Bank Holding Companies (BHCs). We identify top-tier U.S. Bank Holding Companies based on their "RSSD ID" and match them with Dealscan (Schwert, 2018) to track their activity in the syndicated loan market.

We condense information at the year level using year-end values and drop observations with missing or negative assets and/or equity. Moreover, we exclude bank-year observations when the bank's assets increase by more than 50% in a single year (such a large change is likely due to a merger or a major acquisition) or if they changed their headquarter state during our sample period.

Based on this bank-level information, we test our model prediction that banks with *GG* will have the incentive to increase their wholesale funding and channel this into more lending. We define wholesale funding as the difference between assets and equity plus deposits and consider the change in the logarithm of bank b's wholesale funding, i.e.,

dollar amount of the deal, the number of lead lenders and participants, and the lender's primary role. Our results are consistent when using a 'pro-rata' allocation of the deal amount across lenders.

$\triangle Log(WF)_{b,t+1}$. Similarly, we estimate the change in lending behavior by looking at either the logarithm of bank b's total lending, i.e., $\triangle Log(TL)_{b,t+1}$, or bank b's commercial and industrial lending, i.e., $\triangle Log(CI)_{b,t+1}$, estimated year-over-year.[17] To mitigate the impact of extreme values for such a small sample, we winsorize all outcome variables at 3%. Alternatively, we create a dummy variable for each outcome of interest, equal to one when the change in the bank's outcome is above the median change for all banks in that year, and zero otherwise.

Next, we leverage on the granularity of syndicated loan data from LPC Dealscan to further analyze banks' response to *GG* coverage. We follow Schwert (2018) to construct loan portfolios for each bank holding company on a yearly basis, using loans extended in the U.S. to non-financial non-utility firms. We attribute each loan to its lead arranger(s), in charge of its active management (Ivashina, 2009), which we identify following Chakraborty et al. (2018) based on the variables "lead arranger" and "lead arranger credit".[18]

Aggregating this information at the bank-industry and bank-firm level, we analyze if changes in *GG* protection lead to an adjustment of banks' lending behavior in the syndicated loan market. In two separate analyses, we estimate lending behavior using the logarithm of bank b's total syndicated lending (i.e., $\triangle Log(SL)_{b,i,t+1}$ and $\triangle Log(SL)_{b,f,t+1}$), winsorized at 3%. Alternatively, we create a dummy variable for each case, equal to one when the change in the bank's lending is above the median change in that year and zero otherwise.

Finally, we track bank-firm credit relationships to provide evidence of the indirect

[17] Total lending is estimated using variable BHCK2122, and loans for commercial and industrial purposes to business enterprises are computed as the sum between BHCK1763 and BHCK1764.

[18] Authors develop a ranking hierarchy. For each loan package, the lender(s) with the highest ranking is (are) considered the lead arranger(s). The ranking is the following: 1) lender is denoted as "Admin Agent", 2) lender is denoted as "Lead bank", 3) lender is denoted as "Lead arranger", 4) lender is denoted as "Mandated lead arranger", 5) lender is denoted as "Mandated arranger", 6) lender is denoted as either "Arranger" or"Agent" and has a "yes" for the lead arranger credit, 7) lender is denoted as either "Arranger" or "Agent" and has a "no" for the lead arranger credit, 8) lender has a "yes" for the lead arranger credit but has a role other than those previously listed ("Participant" and "Secondary investor" are also excluded), 9) lender has a "no" for the lead arranger credit but has a role other than those previously listed ("Participant" and "Secondary investor" are also excluded), and 10) lender is denoted as a "Participant" or "Secondary investor"". Similarly to the authors finding, approximately 90% of the loans in the sample have a lender ranked six or higher. We exclude any loan without at least one lead arranger. We consider loans when first originated, and assume exposure matters until end of maturity. To approximate the time lag between the effective moment banks and firms commit to loan contract terms and the reported start date, we follow Murfin (2012), and consider the origination date of a package 90 days prior to the one reported in DealScan.

effect of banks' government guarantees on borrowers' real and financial outcomes. We employ financial and general information from Compustat to measure borrower behavior, condensing information at the year level using year-end values, and dropping observations with missing or negative assets and/or equity.

Based on this firm-level information, we test our model prediction that firms with *Indirect GG* will have the incentive to increase their debt-based leverage and channel this into more investment. We expect bank risk-shifting at the intensive margin will lead indirectly protected borrowers into increasing their debt-taking.

We rely on three measures to identify changes in borrowers' debt-taking. First, we measure it as the change in firm f's total debt, computed as the sum of long-term debt and debt in current liabilities, scaled by assets (i.e., $\triangle Debt_{f,t+1}$). Complementary to this, we look at the change in the logarithm of the firm f's total debt (i.e., $\triangle Log(Debt)_{f,t+1}$) and the probability of the borrower obtaining a new loan during the following five years (i.e. $NewLoan_{f,t+5}$).

We then estimate the change in borrower investment outcomes by looking at the change in firm f's capital expenditures scaled by assets (i.e., $\triangle Capex_{f,t+1}$) and the change in firm f's investment scaled by assets (i.e., $\triangle Investment_{f,t+1}$), where investment ($I_{f,t}$) is defined as:

$$I_{f,t} = Capex_{f,t} + R\&D_{f,t} + Acquisitions_{f,t} - Sales\,of\,PP\&E_{f,t} - Dep\&Am_{f,t} \quad (4.40)$$

All change variables are computed year-over-year and winsorized at 1%. Additionally, we control for the overall regional economic situation and account for industry conditions using Fama-French 48 industry classification.[19]

A subsequent prediction of our model is that bank risk-shifting behavior leads borrowers to overinvest and take over inferior projects. To measure firm f's overinvestment and test for investment quality, we follow Richardson (2006) and Anton and Lin (2020) and estimate the divergence between its actual and predicted investment levels.

[19]Firm f's sector is identified based on Fama-French 48 industry classification. Consistent with the literature, we exclude those sectors identified as part of the financial or utilities sector. We account for economic conditions at the regional level using economic region classification from the Bureau of Economic Activity (BEA) for U.S. firms, and classify non-U.S. firms as foreign. U.S. economic regions include Far West, Great Lakes, Mideast, New England, Plains, Rocky Mountain, Southeast, and Southwest. Our results are also robust to control economic conditions at the state level.

We first define new investment expenditures net of maintenance expenditures (I_{NEW}) as follows:

$$I_{NEW,t} = \frac{I_{f,t}}{Total\ Assets_{f,t-1}} \tag{4.41}$$

Where $I_{f,t}$ follows the definition in Specification (4.40). I_{NEW} can also be represented as a function of expected investment in new projects ($I^{*}_{NEW,t}$) and overinvesting ($I^{\varepsilon}_{NEW,t}$):

$$I_{NEW,t} = I^{*}_{NEW,t} + I^{\varepsilon}_{NEW,t} \tag{4.42}$$

We then estimate firm f's overinvesting based on the residuals of regressing a set of relevant predictors on its expected investment (I^{*}_{NEW}) on the actual new investment expenditures net of maintenance expenditures (I_{NEW}):

$$I_{NEW,f,t+1} = \delta X_{f,t} + \alpha_t + Industry_i + Region_r + I^{\varepsilon}_{NEW,f,t} \tag{4.43}$$

Where the vector $X_{f,t}$ represents the relevant predictors of investment, which are: firm size (log of total assets), growth opportunities (book-to-market ratio), leverage, cash holdings, annual stock returns, and years since being public. We also include year, industry, and economic region fixed effects. The variable of interest is $I^{\varepsilon}_{NEW,f,t}$, which captures investment distortion as the difference between actual and predicted investment.

To test if indirect *GG* coverage leads to a higher overinvestment, we identify the magnitude of the investment distortion defining overinvestment equal to $I^{\varepsilon}_{NEW,f,t}$ when positive and zero otherwise (*OI*). Based on the approach in Anton and Lin (2020), we winsorize $I^{\varepsilon}_{NEW,f,t}$ at 5%.[20]

$$OI_{f,t} = \begin{cases} I^{\varepsilon}_{NEW,f,t}, & \text{if } I^{\varepsilon}_{NEW,f,t} > 0 \\ 0, & \text{otherwise} \end{cases} \tag{4.44}$$

Where a higher $OI_{f,t}$ corresponds to a higher overinvestment by the borrower.

Ultimately, if borrowers overinvest in low-quality projects due to indirect *GG* coverage should lead to a decrease in borrower productivity and a deterioration of credit ratings. We define productivity based on borrower's headcount and physical capital endowment,

[20]Our results remain robust to winsorizing at the 1%.

as follows:

$$Productivity_{f,t} = log(Sales_{f,t}) - \frac{2}{3} * log(Employees_{f,t}) - \frac{1}{3} * log(PP\&E_{f,t}) \quad (4.45)$$

and subsequently estimate our variable of interest as the change in firm f's productivity (i.e., $\triangle Productivity_{f,t}$) and winsorize it at 1%.

Complementing the tests on firm productivity, we analyze if *Indirect GG* coverage is linked to a deterioration in credit quality. Specifically, for these tests, we use the probability that the borrower experiences a downgrade in its credit rating. Using S&P long-term ratings available in Compustat, we estimate credit deterioration (i.e., $Downgrade_{f,t}$) as a dummy variable equal to one when the borrower experiences a downgrade in its credit rating three years ahead, and zero otherwise.

Tables 4.1 and 4.2 provide an overview of the definitions of dependent, independent, and control variables at the bank and firm level, respectively, and Table 3.3 presents summary statistics for these variables.

Table 4.1: Variable definitions (bank-level)

Variable	Description
Panel A: Lender Controls (Non-log variables winsorized at 1%)	
$GG_{b,t}$	Bank b's headquarters are in state represented in BHUA Senate committee
$Size_{g,t}$	Logarithm of total assets
$Leverage_{g,t}$	Total liabilities scaled by total assets
$Liquidity_{b,t}$	Cash and short-term investments over total assets
$ROA_{b,t}$	Income before interests and taxes over total assets
$Dividends_{b,t}$	Dividends over total assets
$Non\ Performing_{b,t}$	Allowance for loan losses over total assets
Panel B: Lender Outcomes (winsorized at 3%)	
$\Delta Log(WF_{b,t})$	Change in log of bank b's wholesale funding, multiplied by 100
$\Delta Log(TL_{b,t})$	Change in log of bank b's total lending, multiplied by 100
$\Delta Log(CI_{b,t})$	Change in log of bank b's commercial and industrial lending, multiplied by 100
$\Delta Log(SL_{b,f,t})$	Change in log of bank b's syndicated lending to firm f, multiplied by 100

Table 4.2: Variable definitions (firm-level)

Panel A: Borrower Controls (Non-log variables winsorized at 1%)	
$Indirect\ GG_{f,t}$	Firm f's weighted sum of creditors' GG
$Size_{f,t}$	Logarithm of total assets
$Leverage_{f,t}$	Total liabilities scaled by total assets
$Z\text{-}score_{f,t}$	$1.2 \times \frac{WK}{Assets} + 1.4 \times \frac{Ret.\ Earnings}{Assets} + 3.3 \times \frac{EBIT}{Assets} + \frac{Sales}{Assets} + 0.6 \times \frac{MV}{Liabilities}$
$ROA_{f,t}$	Net income, scaled by total assets
$Tang.\ Net\ Worth_{f,t}$	Total assets minus liabilities and intangible assets, scaled by total assets
$EBITDA\ coverage_{f,t}$	EBITDA over short-term debt and interest expenses
$Dividends_{f,t}$	Total dividends, scaled by total assets
$Book\text{-}to\text{-}Market_{f,t}$	Total assets over market value of equity and debt
Panel B: Borrower Real and Financial Outcomes (winsorized at 1%)	
$\triangle Debt_{f,t}$	Change in firm f's total debt, scaled by total assets, multiplied by 100
$\triangle Log(Debt_{f,t})$	Change in firm f's log of total debt, multiplied by 100
$\triangle Capex_{f,t}$	Change in firm f's capital expenditures scaled by total assets, multiplied by 100
$\triangle Investment_{f,t}$	Change in firm f's investment scaled by total assets, multiplied by 100
$\triangle Productivity_{f,t}$	Change in firm f's log(sales) - 2/3*log(employment) - 1/3*log(PP&E), multiplied by 100
$New\ Loan_{f,t}$	Dummy variable equal to one if firm f obtains a new loan on the next five years, and zero otherwise
$Downgrade_{f,t}$	Dummy variable equal to one if firm f's rating is downgraded in the next three years, and zero otherwise

Table 4.3: Descriptive Statistics

Panel A: Lenders						
	Observations	Mean	Std. Dev.	10 %	50 %	90 %
Control Variables						
GG	731	0.518	0.500	0.000	1.000	1.000
Size	741	17.579	1.697	15.340	17.543	19.791
Leverage	741	0.911	0.020	0.879	0.913	0.935
ROA	741	0.041	0.023	0.020	0.045	0.065
Liquidity	741	0.234	0.113	0.086	0.222	0.401
Non-Performing	741	0.017	0.007	0.010	0.015	0.025
Dividends	741	0.113	0.070	0.006	0.114	0.204
$\triangle GG$	43,156	-0.019	0.325	0.000	0.000	0.000
Dependent Variables						
△ log(WF)	623	8.091	21.904	-18.572	7.897	35.322
△ log(TL)	623	7.376	10.766	-4.335	5.862	23.103
△ log(CI)	623	7.348	14.885	-12.128	7.534	26.698
△ log(SL)	36,870	2.971	35.836	-30.560	0.000	47.136

Panel B: Borrowers						
	Observations	Mean	Std. Dev.	10 %	50 %	90 %
Control Variables						
Indirect *GG*	37,187	0.714	0.441	0.000	1.000	1.000
Size	35,086	6.775	1.919	4.256	6.720	9.279
Leverage	35,011	0.551	0.199	0.274	0.557	0.816
Return on Assets	35,054	0.023	0.111	-0.072	0.039	0.115
Z-score	31,565	3.754	3.292	1.205	2.883	6.872
Tang. Net Worth	35,011	0.257	0.296	-0.143	0.274	0.635
EBITDA coverage	32,676	2.857	13.223	0.104	0.436	2.468
Dividends	34,873	0.011	0.022	0.000	0.000	0.031
Book-to-Market	33,009	0.964	0.537	0.379	0.876	1.619
Dependent Variables						
△ Debt	27,141	11.004	42.181	-14.111	0.000	40.675
△ log(Debt)	25,838	9.902	69.774	-39.977	0.028	73.945
New Loan	37,187	0.498	0.500	0.000	0.000	1.000
△ Capex	27,782	0.735	4.706	-2.684	0.196	4.388
△ Investment	27,782	1.903	16.682	-10.688	0.197	13.977
OI	25,442	2.823	6.042	0.000	0.000	10.748
△ Productivity	26,501	1.379	18.688	-17.192	1.557	19.884
Downgrade	16,094	0.231	0.422	0.000	0.000	1.000

4.6 Bank level Analysis

We start our empirical analysis by testing how banks' funding and lending behavior is affected by our government guarantee proxy.

4.6.1 Empirical Setup

Based on our model predictions, we expect that enjoying from government guarantees (i.e., *GG*=1) coverage is associated with banks increasing their wholesale funding and channeling it into more lending. We use the following staggered DiD specification to test this prediction:

$$y_{b,t+1} = \alpha_t + \alpha_b + \beta_1 GG_{b,t} + \delta X_{b,t} + \varepsilon_{b,t}, \tag{4.46}$$

where $y_{b,t+1}$ is the change in the logarithm of either bank *b*'s wholesale funding (i.e., $\Delta Log(WF)_{b,t+1}$), total lending (i.e., $\Delta Log(TL)_{b,t+1}$), or lending to commercial and industrial business enterprises (i.e., $\Delta Log(CI)_{b,t+1}$), all winsorized at the 3%. Alternatively, each variable is represented by a dummy equal to one if the change in the outcome of interest is higher than the median change across all banks in year *t*, and zero otherwise. Accordingly, our coefficient of interest is β_1, which captures the effect of *GG* on the banks' funding policy and lending behavior.

The vector $X_{b,t}$ includes the control variables size (logarithm of assets), ROA (earnings before interest and taxes, scaled by assets), liquidity (cash holdings and short-term investments, scaled by assets), leverage (liabilities over assets), dividends (dividends over assets) and non-performing loans (allowance for loan losses over assets). All continuous non-log control variables are winsorized at 1%. Moreover, we include time and bank fixed effects to absorb time-invariant bank characteristics and common shocks.

Conservatively, we cluster standard errors at the treatment level (i.e., at the state level) in all regression specifications, whilst our results are also robust to clustering at the bank level.

4.6.2 Results

Table 4.4 shows the regression results for Specification (4.46). In line with our model predictions, we find that government guarantees are associated with banks leveraging more by increasing their wholesale funding. The table shows that banks with government guarantees coverage (i.e., *GG* equal to one) increase their wholesale funding by an additional 6.2pp (column 1) when compared to non-protected banks. This change represents 31.4% of the average within-bank SD of wholesale funding growth. Consistently, protected banks are 17.2% more likely to experience an above-median growth in their wholesale funding.

Next, we test whether the increase in funding is channeled into more lending by performing similar tests on banks' lending behavior. Indeed, we find that government guarantees are associated with an increase in total lending and lending to business enterprises, with a *GG* equal to one leading to an additional 2.2pp growth in total lending (column 3) and an additional 3.0pp increase in lending to business enterprises (column 5). These changes represent 26.0% and 26.7% of the average within-bank SD of total lending growth and loan growth to business enterprises, respectively. Consistently, a protected bank is 11.4% more likely to increase its total lending above the median and 14.6% more likely to increase its lending to business enterprises in a similar way.

4.6.3 Validity

We conduct a set of validity tests to assess further the identification assumptions of our DiD specification and the robustness of our results.

Recent advances in econometric theory suggest that, under certain conditions, staggered DiD designs might not provide valid estimates of the causal estimands of interest even if the equal trends assumption holds (e.g., De Chaisemartin & d'Haultfoeuille, 2020; Callaway & Sant'Anna, 2021; Goodman-Bacon, 2021; Imai & Kim, 2021; Sun & Abraham, 2021; Athey & Imbens, 2022). The intuition is that already treated units can act as effective comparison units, and changes in their outcomes over time are subtracted from the changes of later-treated units. As a result, staggered DiD estimates could obtain the opposite sign compared to the true effect.

Table 4.4: Bank *GG* coverage on funding and lending

	Wholesale Funding		Total Lending		Business Lending	
	△ log	>p50% (1/0)	△ log	>p50% (1/0)	△ log	>p50% (1/0)
GG	6.238**	0.172**	2.151**	0.114**	3.039*	0.146**
	(0.025)	(0.024)	(0.025)	(0.035)	(0.086)	(0.047)
Fixed Effects						
Bank	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
N	612	612	612	612	612	612
adj. R^2	0.230	0.001	0.377	0.116	0.431	0.114
$T1$	4.551	0.125	1.569	0.083	2.217	0.107
$T2$	25.033	0.690	8.633	0.457	12.197	0.588
Weight (+)	75.5%	75.5%	75.5%	75.5%	75.5%	75.5%
Sum (+)	1.088	1.088	1.088	1.088	1.088	1.088
Sum (−)	-0.088	-0.088	-0.088	-0.088	-0.088	-0.088

This table presents estimation results from Specification (4.46) for 1996-2016. The dependent variables are the change in wholesale funding (total assets minus total equity and deposits), total lending (all loans and leases extended by the bank), and lending to business enterprises. In columns 1, 3 and 5, the dependent variables are presented as the change in the log of the total dollar amount and winsorized at 3%. In columns 2, 4 and 6, the dependent variables are a dummy equal to one when the change in the respective variable is higher than the median change for all banks in year t, and zero otherwise. The variable GG is a dummy variable equal to one when at least one senator from the bank's state of incorporation is a member of the BHUA Senate committee in year t. The regressions include banks and year fixed effects (column 3), plus a set of one-period lagged control variables: size, leverage, liquidity, non-performing loans over assets, dividend over assets, and return on assets. All control variables are winsorized at 1%. Standard errors are clustered at the state level. t-statistics are reported in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

In general, staggered DiD designs produce estimates of weighted averages of many different treatment effects (Baker et al., 2022). De Chaisemartin and D'Haultfoeuille (2022) demonstrates that the phenomenon of estimating opposite signs compared to the true effect can only arise when some of these weights are negative. We employ the diagnostic tests suggested by De Chaisemartin and d'Haultfoeuille (2020) to assess the extent of this issue in our setting.

We start our diagnosis with estimating the weights attached to our full sample regressions in Table 4.4 (reported at the end of the table). We find that 75.5% of the weights are strictly positive and the negative weights sum to only -0.088, alleviating the negative weights concern. Next, we derive the two diagnostic measures suggested by De Chaisemartin and d'Haultfoeuille (2020).

The first measure corresponds to the minimal value of the standard deviation of the treatment effect across treated units and time periods under which beta and the average treatment effect on the treated (ATT) could be of opposite signs. In the following, we denote this measure $T1$. When $T1$ is large, the likelihood that beta and ATT are of opposite sign is rather small. Specifically, when $T1$ is large, beta and ATT can only be of opposite sign under a very large treatment effect heterogeneity. For all coefficients it holds that $|\beta| < \sqrt{3} \times T1$ (the threshold suggested by De Chaisemartin & d'Haultfoeuille, 2020), suggesting that $T1$ is in both cases an implausibly high amount of treatment effect heterogeneity.

The second measure corresponds to the minimal value of the standard deviation of the treatment effect across treated units and time periods under which beta could be of a different sign than the treatment effect in all treated units and time periods. In the following, we denote this measure $T2$. For all coefficients, it holds that $|\beta| < 2\sqrt{3} \times T2$ (the threshold suggested by De Chaisemartin & d'Haultfoeuille, 2020), suggesting that $T2$ would imply implausibly large treatment effect heterogeneity.

Hence, our results in Table 4.4 pass both diagnostic tests.

4.7 Granular Analysis

Given the evidence that government guarantee coverage incentivizes banks to increase their wholesale funding and to lend more, we exploit the granularity of syndicated loan data to verify that protected banks expand their corporate lending while controlling for demand factors.

4.7.1 Empirical setup

To this end, we study the changes in lending volumes at the industry and firm level for banks that experience a change in the government guarantee proxy ($\triangle GG$). Specifically, our model predicts that banks will increase their supply of credit in response to an increase in expected government guarantee value.

We first test this at the bank-industry level, employing the following staggered DiD specification for this analysis:

$$y_{b,i,t+1} = \alpha_b + Industry_i \times \alpha_t + \beta_1 \triangle GG_{b,t} + \delta X_{b,t} + \gamma Z_{b,i,t} + \varepsilon_{b,i,t}. \quad (4.47)$$

Here, the dependent variable is the change in the logarithm of bank b's lending volume to industry i, from year t to year $t+1$ (i.e., $\Delta Log(SL)_{b,i,t+1}$). Alternatively, the dependent variable can be represented by a dummy equal to one if the change in the lending volume at the industry level is higher than the median change across all bank-industry pairs in year t, and zero otherwise. The interval variable ΔGG can take the values $\{-1,0,1\}$: equal to 0 when there was no change in $GG_{b,t}$ in year t; equal to 1 if $GG_{b,t}$ changed from zero to one; and equal to -1 if $GG_{b,t}$ changed from one to zero.

We include bank and industry-year fixed effects in this regression. This stringent fixed effects setting absorbs time-invariant bank characteristics and industry-specific shocks, most importantly, demand shocks. Specifically, this fixed effects setting allows us to compare the changes in bank lending to a particular industry between banks that gain/lose government guarantee coverage relative to banks that do not experience any change in their expected government guarantee value, holding constant the time-varying demand at the industry level. In addition, we include the same set of control variables from Specification (4.46), plus the average size, leverage, Altman's Z-score, and return on assets of bank's borrowers in the industry ($Z_{b,i,t}$). The coefficient of interest in Specification (4.47) is β_1, which captures the effect of a change in GG on the loan volume extended to industry i by bank b.

Similarly, we repeat our test at the bank-firm level, employing the following staggered DiD specification for this analysis:

$$y_{b,f,t+1} = \alpha_b + Firm_f \times \alpha_t + \beta_1 \triangle GG_{b,t} + \delta X_{b,t} + \varepsilon_{b,f,t}. \tag{4.48}$$

Analogously to Specification (4.47), the dependent variable is the change in the logarithm of bank b's lending volume to firm f, from year t to year $t+1$ (i.e., $\Delta Log(SL)_{b,f,t+1}$). Alternatively, the dependent variable can be represented by a dummy equal to one if the change in the lending volume at the firm level is higher than the median change across all bank-firm pairs in year t, and zero otherwise.

Here, we include bank and firm-year fixed effects, which absorb time-invariant bank characteristics and firm-specific shocks. Specifically, this fixed effects setting allows us to compare the changes in bank lending to a particular firm between banks that gain/lose government guarantee coverage relative to banks that do not experience any change in their expected government guarantee value, holding constant the time-varying credit demand at the firm level. In addition, we include the same set of control variables from Specification (4.46). The coefficient of interest in Specification (4.48) is β_1, which captures the effect of a change in *GG* on the loan volume extended to firm f by bank b.

4.7.2 Results

Table 4.5 presents the results for the effect of a change in *GG* on banks' lending behavior. As predicted by our model, banks that experience an increase in their government guarantee coverage increase their lending, while the opposite occurs with banks that experience a decrease in their government guarantee coverage.

Based on data at the bank-industry-time level, columns 1 and 2 of Table 4.5 show results for specification (4.47). These results suggest that gaining (losing) government guarantee coverage is associated with an additional (lessened) 2.9pp loan volume growth and a 5.0% higher (lower) likelihood that their lending volume to the industry is above the median among all bank-industry pairs at year t, both conditional on demand shocks at the industry level. This change represents an 8.1% of the average within-bank SD of loan volume growth.

Similarly, columns 3 and 4 of Table 4.5 show results for Specification (4.48) with data at the bank-firm-time level. Results indicate that gaining (losing) government guarantee coverage is associated with an additional (lessened) 2.1pp loan volume growth and a 1.7% higher (lower) likelihood that their lending volume to the firm is above the median among all bank-firm pairs at year t, both conditional on demand shocks at the firm level. This change represents an 8.2% of the average within-bank SD of loan volume growth.

4.8 Financial and Real Outcomes from Indirect *GG*

Given the evidence that government guarantees coverage incentivizes banks to grow their corporate lending, we next investigate the indirect effect of government guarantees on their borrowers' financial and real outcomes.

Table 4.5: $\triangle GG$ on syndicated lending

	Corporate Lending in the Syndicated Loan Market			
	Bank-Industry level		*Bank-Firm level*	
	$\triangle$ log	>p50% (1/0)	$\triangle$ log	>p50% (1/0)
$\triangle GG$	2.904*	0.050***	2.110**	0.017**
	(0.085)	(0.003)	(0.024)	(0.030)
Fixed Effects				
Bank	Yes	Yes	Yes	Yes
Industry-Year	Yes	Yes	No	No
Firm-Year	No	No	Yes	Yes
N	6053	6053	8231	8231
adj. R^2	0.055	0.122	0.049	0.061

This table presents estimation results from Specification 4.47 (columns 1 and 2) and Specification 4.48 (columns 3 and 4) for 1996-2016. In columns 1 and 3, the dependent variable is the change in the logarithm of syndicated lending volume where bank b acted as a lead arranger, winsorized at 3%. In columns 2 and 4, the dependent variables is a dummy equal to one when the change in the lending volume is higher than the median change for all banks in year t, and zero otherwise. The variable $\triangle$ GG is equal to one when bank b has gained GG protection in year t, equal to minus ones when bank b has lost GG protection in year t, and zero otherwise. The dummy GG is equal to one when at least one senator from bank b's state of incorporation is a member in the BHUA Senate committee in year t. The regressions include bank plus industry-year (columns 1 and 2) or firm-year (columns 3 and 4) fixed effects, and a set of one-period lagged control variables: size, leverage, liquidity, non-performing loans over assets, dividend over assets, and return on assets. Columns 1 and 2 also include controls for the size, leverage, Z-score, and return on assets of borrowers averaged at the bank-industry level. All control variables are winsorized at 1%. Standard errors are clustered at the state level. t-statistics are reported in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

4.8.1 Empirical setup

To this end, we study the changes in debt-based leverage and investment behavior for borrowers that experience an incidental advantage of government guarantees through their bank relationships (*Indirect GG*). Specifically, our model predicts that risk-shifting incentives arising from *GG* motivate banks to lend more to their borrowers, which translates into indirectly protected borrowers increasing their debt-taking. At the same time, we expect borrowers to direct these additional resources by increasing their capital expenditures and overall investment. Particularly, these borrowers will overinvest in low-quality projects, which should be reflected in higher-than-expected investment levels (Richardson, 2006). Ultimately, their increased leverage and low-quality overinvestment will lead borrowers to have a lower firm productivity and a higher likelihood of experiencing a downgrade in their credit rating.

We first employ the following staggered DiD specification to test if indirectly protected firms increase their debt leverage:

$$y_{f,t+t} = \beta Indirect\ GG_{f,t} + \delta X_{f,t} + \alpha_f + \alpha_t * Industry_i + \varepsilon_{f,t} \tag{4.49}$$

where $y_{f,t+T}$ is either the change in the firm f's total debt scaled by assets (i.e., $\triangle Debt_{f,t+1}$) or the change in the logarithm of its total debt (i.e., $\triangle log(Debt)_{f,t+1}$). Alternatively, we define the dependent variable as the probability that firm f obtains a new loan in the upcoming five years (i.e., $NewLoan_{f,t+5}$). Accordingly, our coefficient of interest is β, which captures the average effect of *Indirect GG* coverage on the firm f's debt-taking measures.

The vector $X_{f,t}$ includes the control variables on the firm's characteristics, including size (log of total assets), leverage (total liabilities over total assets), tangible net worth (assets minus equity and intangible assets, over total assets), Altman's Z-score, return on assets (net income over total assets), EBITDA coverage (EBITDA over short term debt and interest expenses), dividends over assets, and book-to-market ratio (total assets over market value of equity plus total debt). We first include firm fixed effects to absorb time-invariant firm characteristics and the interaction between year and industry fixed effects to control for economic conditions. Additionally, we include region-year and industry-region-year fixed effects to further account for overall economic conditions.

Next, we verify if the resources obtained through additional debt-taking is indeed channeled into more investment. Following an equivalent approach to Specification 4.49, we test if indirectly protected firms tend to increase relatively more their capital expenditures (i.e., $\triangle CAPEX_{f,t+1}$) and total new investment (i.e., $\triangle Investment_{f,t+1}$), both scaled by assets.

Furthermore, we test if the increase in investment from indirectly protected firms can indeed be characterized as overinvestment. For this, we regress our overinvestment measure on firm f's indirect *GG* protection plus a set of alternative determinants on investment levels not included in the first stage regression:

$$OI_{f,t+1} = \beta Indirect\ GG_{f,t} + \gamma W_{f,t} + \alpha_f + \alpha_t * Industry_i + \varepsilon_{f,t} \tag{4.50}$$

Where the vector $W_{f,t}$ includes alternative predictors of investment not included in Specification (4.43): tangible net worth, change in sales, Altman's Z-score, operating cash flow over assets, fixed assets, dividends over assets, and return on assets. Our coefficient of interest is β, which captures the average effect of indirect *GG* coverage on the firm's f overinvestment. We rely on linear and Poisson regression models as *OI* has a highly right-skewed distribution with a mass of values at zero (Cohn, Liu, & Wardlaw, 2022), using the same sequence of fixed effects as in Specification (4.49).

Finally, to provide complementary evidence consistent with borrowers overinvesting in low-quality projects, we follow Specification 4.49 test if firms' indirect coverage is associated with a relative reduction in firms overall productivity (i.e., $\triangle Productivity_{f,t+1}$) and a higher likelihood of experiencing a downgrade in their credit rating in the upcoming three years (i.e., $Downgrade_{f,t+3}$).

4.8.2 Results

Debt

Table 4.6 presents the main results for the effect of *indirect GG* on the firms' debt growth. In Panel A, the table shows that firms with indirect protection increase their leverage by 2.0-2.2 points, which represents between 5.9-6.5% of a standard deviation of the within-firm distribution. Consistently, we find that indirectly protected firms experience an additional growth in their debt-based funding of approximately 4.1-4.3pp, as shown in Panel B, which represents between 7.3-7.7% of a standard deviation of the within-firm distribution. Additionally, in column 1 of Table 4.7 we show that indirect protection is associated with a 13.8% (i.e., $exp(0.130) - 1$) increase in the odds of getting a loan in the following five years. We find consistent results using linear probability (column 2) and poisson (column 3) models with high-dimensional fixed effects.

Capex and Investment

Table 4.8 presents the results for the effect of *Indirect GG* on the firms' capital expenditures and investment growth. The table shows that firms with indirect protection increase their capital expenditures over assets by an additional 0.19-0.26 points, which represents between 5.3-7.2% of a standard deviation of the within-firm distribution. Similarly, indirectly protected firms increase their investment over assets by an additional 0.69-1.02

Table 4.6: Indirect *GG* on Firm Debt-based Leverage

Panel A: △ Total Debt over Assets			
Indirect GG	2.040**	2.093**	2.152**
	(0.022)	(0.020)	(0.031)
N	23,056	23,056	21,426
adj. R^2	0.238	0.238	0.233
Panel B: △ log of Total Debt			
Indirect GG	4.040**	4.268**	4.220**
	(0.018)	(0.013)	(0.027)
N	22,601	22,601	20,979
adj. R^2	0.207	0.207	0.199
Fixed Effects			
Firm	Yes	Yes	Yes
Industry-Year	Yes	Yes	No
Region-Year	No	Yes	No
Ind-Reg-Year	No	No	Yes

This table presents estimation results from Specification (4.49) for 1996-2016. The dependent variables are the change in total debt (long-term debt plus debt in current liabilities), scaled by total assets (Panel A) and the change in the log of total debt (Panel B), defined as the sum of capital expenditures and R&D, plus acquisitions minus sales of PP&E. Both variables are scaled by total assets. The variable *Indirect GG* is the weighted sum of the coverage obtained by the firm f through its borrowing relationships, where bank b's government guarantees are equal to one when at least one senator from its state of incorporation is a member in the BHUA Senate committee in year t. The regressions include firm, industry-year (column 1-2), region-year (column 2), and industry-region-year fixed effects (column 3), plus a set of one-period lagged control variables: size (logarithm of assets), leverage (liabilities over assets), tangible net worth (assets minus liabilities and intangible assets, scaled by assets), Altman's Z-score, return on assets, EBITDA coverage (EBITDA over short term debt and interest expenses), dividends over assets, and book-to-market ratio. All control variables are winsorized at 1%. Standard errors are clustered at the firm level. t-statistics are reported in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 4.7: Indirect *GG* on New Loan Probability

	New loan in following 5 years		
	Logit(1/0)	LPM(1/0)	Poisson(1/0)
Indirect GG	0.130**	0.020*	0.046**
	(0.041)	(0.055)	(0.021)
Fixed Effects			
Firm	Yes	Yes	Yes
Year	Yes	No	No
Industry-Year	No	Yes	Yes
N	23,178	28,677	23,401
adj. R^2	-	0.494	-
p. R^2	0.391	-	0.088

This table presents estimation results from Specification (4.49) for 1996-2016. The dependent variable is a dummy variable equal to one if the firm gets at least one new loan in the following five years. The variable *Indirect GG* is the weighted sum of the coverage obtained by the firm f through its borrowing relationships, where bank b's government guarantees are equal to one when at least one senator from its state of incorporation is a member in the BHUA Senate committee in year t. In column 1, we present the results of a logit model with firm and year fixed effects. In column 2, we present the results of a linear probability model with firm and industry-year fixed effects. In column 3, we present the results of a poisson regression with firm and industry-year fixed effects. All regressions include a set of one-period lagged control variables: size (logarithm of assets), leverage (liabilities over assets), tangible net worth (assets minus liabilities and intangible assets, scaled by assets), Altman's Z-score, return on assets, EBITDA coverage (EBITDA over short term debt and interest expenses), dividends over assets, and book-to-market ratio. All control variables are winsorized at 1%. Standard errors are clustered at the firm level. t-statistics are reported in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, ***

points, which represents between 5.1-7.5% of a standard deviation of the within-firm distribution.

Overinvestment

Table 4.9 presents the results for the effect of Indirect *GG* on firms' overinvestment. The table shows that indirect protection is associated with a higher excess investments over assets by an additional 0.25-0.33 points, which represents between 6.1-8.0% of a standard deviation of the within-firm distribution. Consistently, results in column 4-6 show that firms overinvest 9.5-9.9% more than unprotected firms.

Productivity

Here, we present the results for the effect of *indirect GG* on the firms' productivity and the probability that the firm experiences a downgrade in its credit rating on the following three years. Table 4.10 shows that firms with indirect protection experience a reduction in their productivity by approximately 0.8-1.2pp, which represents between 4.8-7.2% of a standard deviation of the within-firm distribution.

Table 4.8: Indirect *GG* on Firm Real Outcomes

Panel A: △ Capital Expenditures over Assets			
Indirect GG	0.188*	0.208**	0.255**
	(0.051)	(0.036)	(0.027)
N	22,915	22,915	21,295
adj. R^2	0.180	0.180	0.145
Panel B: △ New investments over Assets			
Indirect GG	0.697**	0.756**	1.023***
	(0.035)	(0.025)	(0.008)
N	22,915	22,915	21,295
adj. R^2	0.109	0.110	0.087
Fixed Effects			
Firm	Yes	Yes	Yes
Industry-Year	Yes	Yes	No
Region-Year	No	Yes	No
Ind-Reg-Year	No	No	Yes

This table presents estimation results from Specification (4.49) for 1996-2016. The dependent variables are the change in capital expenditures (Panel A) and the change in new investments (Panel B), defined as the sum of capital expenditures and R&D, plus acquisitions minus sales of PP&E. Both variables are scaled by total assets. The variable *Indirect GG* is the weighted sum of the coverage obtained by the firm f through its borrowing relationships, where bank b's government guarantees are equal to one when at least one senator from its state of incorporation is a member in the BHUA Senate committee in year t. The regressions include firm, industry-year (column 1-2), region-year (column 2), and industry-region-year fixed effects (column 3), plus a set of one-period lagged control variables: size (logarithm of assets), leverage (liabilities over assets), tangible net worth (assets minus liabilities and intangible assets, scaled by assets), Altman's Z-score, return on assets, EBITDA coverage (EBITDA over short term debt and interest expenses), dividends over assets, and book-to-market ratio. All control variables are winsorized at 1%. Standard errors are clustered at the firm level. t-statistics are reported in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 4.9: Indirect *GG* and Firm Overinvestment

	Linear regression			*Poisson*		
Indirect GG	0.246*	0.258*	0.330**	0.091*	0.091*	0.095*
	(0.061)	(0.057)	(0.028)	(0.061)	(0.068)	(0.098)
Fixed Effects						
Firm	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year	Yes	Yes	No	Yes	Yes	No
Region-Year	No	Yes	No	No	Yes	No
Ind-Reg-Year	No	No	Yes	No	No	Yes
N	23,460	23,460	21,834	19,884	19,884	16,301
adj. R^2	0.218	0.217	0.210	-	-	-
pseudo R^2	-	-	-	0.363	0.371	0.450

This table presents estimation results from Specification (4.50) for 1996-2016. The dependent variable is *OI*, equal to the residuals I^{ε}_{new} defined in (4.44) are positive and zero otherwise, where residuals are winsorized at 5%. Model specifications are linear probability (columns 1-3) and Poisson models (columns 4-6). The variable *Indirect GG* is the weighted sum of the coverage obtained by the firm *f* through its borrowing relationships, where bank *b*'s government guarantees are equal to one when at least one senator from its state of incorporation is a member in the BHUA Senate committee in year *t*. The regressions include firm, year (column 1), industry-year (columns 2 and 5), region-year (columns 3 and 6), industry-region-year (columns 4 and 7), plus a set of one-period lagged control variables: change in total sales, tangible net worth (assets minus liabilities and intangible assets, scaled by assets), fixed assets (PP&E scaled by assets), Altman's Z-score, operating cash flow over assets, dividend over assets, and return on assets. All control variables are winsorized at 1%. Standard errors are clustered at the firm level. *t*-statistics are reported in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, ***

Table 4.10: Indirect *GG* on Firm Productivity

	△ Productivity		
Indirect GG	-0.836**	-0.943**	-1.173**
	(0.034)	(0.019)	(0.012)
Fixed Effects			
Firm	Yes	Yes	Yes
Industry-Year	Yes	Yes	No
Region-Year	No	Yes	No
Ind-Reg-Year	No	No	Yes
N	22,258	22,258	20,602
adj. R^2	0.127	0.129	0.112

This table presents estimation results from Specification (4.49) for 1996-2016. The dependent variable is the change in Productivity, defined in Equation (4.45) as the difference between the log of sales and the weighted sum of log of employment (2/3) and the log of fixed assets (1/3). The variable *Indirect GG* is the weighted sum of the coverage obtained by the firm *f* through its borrowing relationships, where bank *b*'s government guarantees are equal to one when at least one senator from its state of incorporation is a member in the BHUA Senate committee in year *t*. The regressions include firm, industry-year (column 1-2), region-year (column 2), and industry-region-year fixed effects (column 3), plus a set of one-period lagged control variables: size (logarithm of assets), leverage (liabilities over assets), tangible net worth (assets minus liabilities and intangible assets, scaled by assets), Altman's Z-score, return on assets, EBITDA coverage (EBITDA over short term debt and interest expenses), dividends over assets, and book-to-market ratio. All control variables are winsorized at 1%. Standard errors are clustered at the firm level. *t*-statistics are reported in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** Consistent with indirectly protected borrowers becoming relatively more leveraged and being overinvesting in low-quality projects that reduce their productivity, we observe that these firms have a higher likelihood of experiencing a downgrade in their credit rating during the following three years. As shown in columns 1 and 2 of Table 4.11, indirect protection is associated with a 29.4% (i.e., $exp(0.258)-1$) increase in the odds of experiencing a downgrade, and is considerably higher (67.1%) if the borrower has an investment grade rating in year t. We find consistent results using linear probability (columns 3 and 4) and poisson (column 5 and 6) models with high-dimensional fixed effects.

Table 4.11: Indirect *GG* on Firm Rating: Downgrade

	Rating downgrade in following 3 years					
	Logit(1/0)		LPM(1/0)		Poisson(1/0)	
Indirect GG	0.258***	0.010	0.034*	-0.001	0.199**	0.021
	(0.007)	(0.937)	(0.058)	(0.949)	(0.020)	(0.844)
IG		1.446***		0.217***		0.657***
		(0.000)		(0.000)		(0.000)
Indirect GG		0.514***		0.068**		0.304**
		(0.003)		(0.012)		(0.027)
Fixed Effects						
Firm	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	No	No	No	No
Industry-Year	No	No	Yes	Yes	Yes	Yes
N	9,602	9,602	13,318	13,318	8,523	8,523
adj. R^2	-	-	0.230	0.250	-	-
p-R^2	0.126	0.156	-	-	0.120	0.129

This table presents estimation results from Specification (4.49) for 1996-2016. The dependent variable is a dummy variable equal to one if the firm's rating is downgraded at least once in the following three years. The variable *Indirect GG* is the weighted sum of the coverage obtained by the firm f through its borrowing relationships, where bank b's government guarantees are equal to one when at least one senator from its state of incorporation is a member in the BHUA Senate committee in year t. The variable *IG* is a dummy variable equal to one if the firm f has a rating equal or above "BBB-" at year t. In columns 1 and 2, we present the results of a logit model with firm and year fixed effects. In columns 3 and 4, we present the results of a linear probability model with firm and industry-year fixed effects. In columns 5 and 6, we present the results of a poisson regression with firm and industry-year fixed effects. All regressions include a set of one-period lagged control variables: size (logarithm of assets), leverage (liabilities over assets), tangible net worth (assets minus liabilities and intangible assets, scaled by assets), Altman's Z-score, return on assets, EBITDA coverage (EBITDA over short term debt and interest expenses), dividends over assets, and book-to-market ratio. All control variables are winsorized at 1%. Standard errors are clustered at the firm level. t-statistics are reported in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, ***

4.9 Conclusions

The public outrage over the massive taxpayer-funded rescue packages during the course of the recent banking crises sparked a debate about the general desirability of implicit and explicit government guarantees for banks. Proponents of government guarantees claim that rescue measures are justified to avoid the systemic threat posed by bank failures. Critics, however, argue that government guarantees undermine market discipline and are a source of moral hazard.

Our paper adds to this debate by highlighting that the moral hazard problems caused by government guarantees not only negatively affect the banks' credit allocation at the extensive margin (i.e., riskier and worse firms are financed), but that these guarantees also have negative real effects for existing borrowers at the intensive margin.

We show theoretically that banks can exploit their government guarantees strategically by just intermediating funds between investors and ultimate borrowers. Because the government guarantees substantially lower the banks' funding costs, they allow banks to earn the spread between their reduced funding rate and the competitive market rate on each unit of intermediated funds. This mechanism gives banks an incentive to crowd out direct market finance. We confirm these predictions empirically in the context of the U.S. syndicated loan market and show it has real effects on the banks' borrowers. That is, it can give banks an incentive to induce their borrowers to leverage excessively, to overinvest, and to conduct inferior high-risk projects.

These findings emphasize the importance of policymakers' efforts on both sides of the Atlantic to limit bailout guarantees by lowering bailout expectations. In the U.S., the Dodd-Frank Act has introduced stricter limits on the government's ability to conduct bailouts by, for example, implementing a bail-in regime for distressed banks in which shareholders lose their shares and debtholders potentially have their debt claims turned into equity. The EU adopted the Bank Recovery and Resolution Directive and agreed on a Single Resolution Mechanism, which also subscribes to the bail-in philosophy.

Further policies to remedy the negative effects of government guarantees include the implementation of internationally agreed capital and liquidity standards, the tightening of supervision both in micro and macro prudential terms, and efforts to make resolution more effective.

Chapter 5

Conclusions

The disturbing reminiscence of the global financial crisis has revived with the recent crisis led by the failure of Silicon Valley Bank and First Republic Bank's coordinated takeover. This has prompted new scrutiny of banks' propensity for excessive risk-taking and the unwanted consequences of government interventions to mitigate the adverse effects of bank crises. Consequently, the recent events also put our understanding of bank risk-taking under the spotlight and call for further comprehension of the factors that drive banks to take risks.

In this dissertation, I contribute to the existing knowledge by highlighting the critical role of pre-existing exposure in shaping banks' risk management incentives and connecting it to two key issues: bank concentration and government guarantees coverage. Over the course of the chapters, I elaborate on three different aspects of this idea.

In the first chapter, I provide empirical evidence exhibiting that banks with high exposure internalize the potential competition spillovers from their own lending decisions, extending loans with stricter non-monetary terms to curtail borrowers' growth strategies and reduce the overall risk of their industry exposure. This contributes to the literature by proposing a portfolio view of loan contracting, as optimal contract design is not solely determined by the individual risk of the firm.

In the second chapter, I show that the government guarantees, in combination with high leverage, incentivize banks to concentrate their loan portfolios and further load up on the same type of assets to which they were already exposed. This finding contrasts the focus on idiosyncratic risks prevailing in the government guarantees literature.

In the third chapter, I show that under certain conditions, government guarantees incentivize banks to exploit their funding cost advantage, crowding-out direct investors, and hence, inducing their borrowers to increase their debt-based leverage excessively and overinvest in bad projects that reduce their overall productivity. Overall, these findings highlight that the moral hazard problems caused by government guarantees not only affects the banks' credit allocation at the extensive margin (i.e., riskier and worse firms are financed) but also have negative welfare effects on the behavior of existing borrowers at the intensive margin (i.e., overinvestment and inferior project choice within existing lending relationships).

By delving into these three facets of bank risk-taking from a portfolio perspective, this research deepens our understanding of the intricate dynamics at play. The findings not only shed light on banks' behavior and lending practices but also provide valuable insights into the implications for borrowers' corporate policies. As a result, policymakers and industry practitioners can benefit from the knowledge gained, allowing for informed decision-making and strategic actions. Moreover, it calls for continued research and examination to further explore the complexities involved and uncover additional insights that can shape the future of banking practices and policies.

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Chapter 6

Structure

The appendix is structured as follows. For Chapter 2, section 2.A presents additional tables. For Chapter 3, section 3.A presents the proofs for our theoretical model, and section 3.B presents additional tables. For Chapter 4, section 4.A presents additional proofs.

2.A Appendix - Additional Tables

Table 2.A.1: Bank industry exposure on covenant strictness - Robustness

	Covenant Strictness			
	Alternative Controls	Single Lead Arrangers	Alternative Clustering	
Lending Share	2.07**	3.36**	2.94*	2.94**
	(0.019)	(0.012)	(0.055)	(0.048)
Fixed Effects:				
Bank-Quarter	Yes	Yes	Yes	Yes
Industry-Quarter	Yes	Yes	Yes	Yes
N	4,412	3,580	4,373	4,373
R^2	0.660	0.679	0.691	0.691
SE Clustering	*Bank*	*Bank*	*Industry*	*Bank Industry*

This table presents a robustness check on the results from Specification (2.2), for the period 1990-2018 at the bank-loan level. The dependent variable is the loan covenant strictness as reported in Demerjian and Owens (2016). The variable *Lending Share* represents the importance of the lender in the industry (zero to one), averaged across the previous 20 quarters $[t-4, t-23]$ and standardized. I include Bank-Time and Industry-Time fixed effects. In column 1, I also include additional control variables: current ratio, loan purpose, and debt over tangible net worth. In column 2, I exclude loans extended by more than one lead arranger. In columns 3 and 4, I cluster standard errors at the industry and bank-industry levels, respectively. In columns 2 and 4, I only incorporate the main set of lagged control variables: firm risk measures as size, leverage, tangibility, debt-to-cash-flow ratio, debt service ratio, profitability (all winsorized at 1%), and rating, plus controls on loan characteristics, including loan type, log maturity, log amount, and total leaders. Standard errors clustered at the bank level in Columns 1 and 2. p-values are reported in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 2.A.2: Bank industry exposure on covenant strictness - Time frame robustness

	Covenant Strictness		
Lending Share	2.57^{***}		
(2 Years)	(0.001)		
Lending Share		3.02^{***}	
(3 Years)		(0.002)	
Lending Share			3.19^{***}
(4 Years)			(0.001)
Fixed Effects:			
Bank-Quarter	Yes	Yes	Yes
Industry-Quarter	Yes	Yes	Yes
N	4,269	4,324	4,355
R^2	0.691	0.691	0.691

This table presents a robustness check on the results from Specification 2, for the period 1990-2018 at the bank-loan level. I include Bank-Time and Industry-Time fixed effects. The dependent variable is the loan covenant strictness as reported in Demerjian and Owens (2016). The variable *Lending Share* represents the importance of the lender in the industry (zero to one), averaged across the previous 8 quarters $[t-4, t-11]$ (Column 1), 12 quarters $[t-4, t-15]$ (Column 2), and 16 quarters $[t-4, t-19]$ (Column 3). and standardized. I incorporate the main set of lagged control variables: firm risk measures as size, leverage, tangibility, debt-to-cash-flow ratio, debt service ratio, profitability (all winsorized at 1%), and rating, plus controls on loan characteristics, including loan type, log maturity, log amount, and total leaders. Standard errors clustered at the bank level. p-values are reported in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 2.A.3: Bank industry exposure on covenant strictness at mature industries: Mature industry split - Alternative measures.

	Covenant Strictness			
	Sales Growth		$\triangle\, log(M/B)$	
Lending Share	3.96***	1.71*	3.49***	1.89*
	(0.000)	(0.036)	(0.001)	(0.036)
Lending Share x Mature Industry (Continous)	-24.57**		-21.07*	
	(0.021)		(0.058)	
Lending Share x Mature Industry (Bottom 25%)		7.45**		6.08**
		(0.010)		(0.032)
Fixed Effects:				
Bank-Quarter	Yes	Yes	Yes	Yes
Industry-Quarter	Yes	Yes	Yes	Yes
N	4,362	4,362	4,368	4,368
R^2	0.692	0.692	0.691	0.691

This table presents estimation results from Specifications 5 for the period 1990-2018. The dependent variable is the general covenant strictness of the deal, as estimated by Demerjian and Owens (2016). The variable *Lending Share* represents the importance of the lender in the industry (zero to one), averaged across the previous 20 quarters $[t-4, t-23]$ and standardized. The variable *Mature Industry* is a continuous variable identifying the change in industry average sales (columns 1 and 2) and the change in the logarithm of industry market-to-book ratio (columns 3 and 4) at $t-4$, both to proxy for growth opportunities at the industry level, and also represented as a dummy variable equal to one for industries with relatively lower growth prospects (Comparing across industries, the dummy is equal to one when the industry is below the 25^{th} percentile, i.e., *Bottom 25%*, in columns 2 and 4). I include Bank-Time and Industry-Time fixed effects. Additionally, I incorporate a set of lagged control variables, including firm risk measures as size, leverage, tangibility, debt-to-cash-flow ratio, debt service ratio, profitability (all winsorized at 1%), and rating, plus controls on loan characteristics: type, log maturity, log amount, and total leaders. Standard errors are clustered at the bank level, and p-values are reported in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 2.A.4: Bank industry exposure on covenant strictness: Controlling for bank specialization

	Covenant Strictness			
Lending Share	4.32***	4.91***	5.35***	4.86***
	(0.004)	(0.001)	(0.000)	(0.001)
Specialization (2 Years)	-6.17**			
	(0.029)			
Specialization (3 Years)		-6.75**		
		(0.021)		
Specialization (4 Years)			-7.72***	
			(0.007)	
Specialization (5 Years)				-12.39***
				(0.007)
Fixed Effects:				
Bank-Quarter	Yes	Yes	Yes	Yes
Industry-Quarter	Yes	Yes	Yes	Yes
N	4,269	4,324	4,355	4,373
R^2	0.691	0.691	0.692	0.692

This table presents estimation results from Specification 2 for the period 1990-2018. I include Bank-Time and Industry-Time fixed effects. The dependent variable is the general covenant strictness of the deal, as estimated by Demerjian and Owens (2016). The variable *Lending Share* represents the importance of the lender in the industry (zero to one), averaged across the previous 20 quarters $[t-4, t-23]$ and standardised. Bank *Specialization* is a dummy variable that identifies a bank as specialized if its lending share has been higher than the 75^{th} percentile plus 1.5 times the inter-quantile range of the lending shares at some quarter during the previous 2, 3, 4 and 5 years (Col. 1, 2, 3 and 4, respectively) (Giometti & Pietrosanti, 2022; Paravisini et al., 2020). Additionally, I incorporate a set of lagged control variables, including firm risk measures as size, leverage, tangibility, debt-to-cash-flow ratio, debt service ratio, profitability (all winsorised at 1%), and rating, plus controls on loan characteristics: type, log maturity, log amount, and total leaders. Standard errors are clustered at bank level and p-values are reported in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 2.A.5: Bank industry exposure (1-year IV est.) on loan covenant strictness

	Covenant Strictness	
	1-year	Subsequent Mergers
Lending Share	6.87^{***}	5.17^{**}
(IV Estimate)	(0.039)	(0.027)
Fixed Effects:		
Bank-Quarter	Yes	Yes
Industry-Quarter	Yes	Yes
N	4,377	4,377
R^2	0.056	0.058

This table presents the second stage estimation results from Specification (2.7) for the period 1990-2018. The dependent variable is covenant strictness as estimated in Demerjian and Owens (2016).*Lending Share - IV Estimate* represents the importance of the lender in the industry (zero to one), averaged across the previous 20 quarters $[t-4, t-23]$ and instrumented by the incremental share of bank mergers. I instrument *Lending Share* only for those loans extended over the first year after the bank merger. In column 2, I also include subsequent mergers in the IV, which had been excluded from the original Specification (2.7) given the concerns on the effect of overlapping mergers being less than three years apart. I include Bank-Time and Industry-Time fixed effects. Additionally, I incorporate a set of lagged control variables, including firm risk measures as size, leverage, tangibility, debt-to-cash-flow ratio, debt service ratio, profitability (all winsorised at 1%), and rating, plus controls on loan characteristics: type, log maturity, log amount, and total leaders. Standard errors are clustered at the bank level, and p-values are reported in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 2.A.6: Bank industry exposure (IV Estimates) on other loan contract terms

	Capital Strictness	Capital Intensity	Interest Spreads	Loan Maturity	Spread-to-Strictness	Spread-to-Capital Str.
Lending Share	2.73**	0.09*	-0.07***	-0.05**	-0.12**	-0.23**
(IV Estimate)	(0.021)	(0.071)	(0.002)	(0.030)	(0.025)	(0.011)
Fixed Effects:						
Bank-Qtr.	Yes	Yes	Yes	Yes	Yes	Yes
Ind.-Qtr.	Yes	Yes	Yes	Yes	Yes	Yes
N	4,377	6,040	12,345	13,664	4,210	5,852
R^2	0.010	0.035	0.112	0.038	0.029	0.043

This table presents the second stage estimation results from Specification (2.7) for the period 1990-2018. I include Bank-Time and Industry-Time fixed effects. The dependent variables are the capital-based covenant strictness (Demerjian & Owens, 2016) (column 1), the capital-based covenant intensity (count measure) (column 2), the logarithm of the average interest rate spread of the loan (column 3), the logarithm of the loan maturity measured in months (column 4), the ratio between the logarithm of the loan average interest rate spread over loan covenant strictness (column 5) and over loan capital-based loan strictness (column 6) as estimated in Demerjian and Owens (2016). *Lending Share - IV Estimate* represents the importance of the lender in the industry (zero to one), averaged across the previous 20 quarters $[t-4, t-23]$ and instrumented by the incremental share of bank mergers. For robustness, I exclude years 2008-2009 and winsorize the top 10% of lending shares. Additionally, I incorporate a set of lagged control variables, including firm risk measures as size, leverage, tangibility, debt-to-cash-flow ratio, debt service ratio, profitability (all winsorised at 1%), and rating, plus controls on loan characteristics: type, log maturity, log amount, and total leaders. Standard errors are clustered at bank level and p-values are reported in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 2.A.7: Bank industry exposure on capital covenants: Poisson

	Capital Intensity	Net Worth Covenants	Tangible N.W.	Unspecified N.W.
Lending Share	0.11***	0.08***	0.23**	-0.06
	(0.000)	(0.005)	(0.011)	(0.432)
Fixed Effects:				
Bank-Quarter	Yes	Yes	Yes	Yes
Industry-Quarter	Yes	Yes	Yes	Yes
N	4172	4128	2066	2087
$pseudo-R^2$	0.157	0.163	0.219	0.154

This table presents estimation results with Poisson regression models based on Specifications (2.8) (column 1), and Specification (2.9) (columns 2 to 5) for the period 1990-2018. I include Bank-Time and Industry-Time fixed effects. The dependent variables are: the strictness of capital covenants as defined in Demerjian and Owens (2016) (column 1), and count variables on the total number of capital-based covenants ("Capital Intensity") (column 2), covenants requiring net worth (N.W.), either as a Min. N.W. or a Max. Debt over N.W. (column 3), and covenants explicitly requiring tangible N.W. (column 4) or not specified N.W. (column 5). All dependent variables are standardized. The variable *Lending Share* represents the importance of the lender in the industry (zero to one), averaged across the previous 20 quarters $[t-4, t-23]$ and standardized. Additionally, I incorporate a set of lagged control variables, including firm risk measures such as size, leverage, tangibility, debt-to-cash-flow ratio, debt service ratio, profitability (all winsorized at 1%), and rating, plus controls on loan characteristics: type, log maturity, log amount, and total leaders. Standard errors are clustered at bank level and p-values are reported in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 2.A.8: Bank industry exposure on negative covenants: Non-linear probability models

	Payout Restriction		Capex Restriction	
	Probit	Poisson	Probit	Poisson
Lending Share	-0.02*	-0.04***	0.08**	0.07***
	(0.083)	(0.003)	(0.026)	(0.001)
Fixed Effects:				
Bank-Year		Yes		Yes
Industry-Year		Yes		
N	1,981	1,762	20,335	15,657
$pseudo-R^2$	0.253	0.194	0.121	0.112

This table presents the results of both Probit (columns 1 and 3) and Poisson (columns 2 and 4) regressions at the bank-loan level for loans extended during the period 1990-2018. I include Bank-Year fixed effects in Poisson models, plus Industry-Time fixed effects when looking at Payout restrictions (column 2). Due to limitations in sample size, I do not saturate the regression further for capital expenditures (columns 3 and 4). The *dependent variables* is a binary variable equal to one if the deal has a dividend payout (columns 1 and 2) restriction or capital expenditure (columns 3 and 4). The variable *Lending Share* represents the importance of the lender in the industry (zero to one), averaged across the previous 20 quarters $[t-4, t-23]$ and standardised. Additionally, I incorporate a set of lagged control variables, including firm risk measures as size, leverage, tangibility, debt-to-cash-flow ratio, market-to-book ratio (Columns 3-4), debt service ratio, profitability (all winsorized at 1%), and rating, plus controls on loan characteristics: type, log maturity, log amount, and total leaders. Standard errors are clustered at the bank level, and *p*-values are reported in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

3.A Appendix - Proofs

Proof of Lemma 1

Setting $\Pi^*_{\overline{A},lo}$ equal to $\Pi^*_{\underline{A},lo}$ (see Eq. 3.4) and solving for Δ yields

$$\begin{aligned}\Delta^*_{lo} &= \frac{(1-\lambda_L-\lambda_{\overline{A}}+\rho_{\overline{A}})\alpha d}{\rho_{\overline{A}}+\left(\lambda_L-\rho_{\overline{A}}\right)+\left(\lambda_{\overline{A}}-\rho_{\overline{A}}\right)+(1-\lambda_L-\lambda_{\overline{A}}+\rho_{\overline{A}})\alpha} \\ &- \frac{(1-\lambda_L-\lambda_{\underline{A}}+\rho_{\underline{A}})\alpha d}{\rho_{\underline{A}}+\left(\lambda_L-\rho_{\underline{A}}\right)+\left(\lambda_{\underline{A}}-\rho_{\underline{A}}\right)+(1-\lambda_L-\lambda_{\underline{A}}+\rho_{\underline{A}})\alpha}.\end{aligned} \tag{3.A1}$$

Eq. (3.6) follows from the fact that λ_A is a random variable with $E[\lambda_A]=\lambda$. ■

Proof of Lemma 2

In the following, we show that $\partial F_{\overline{A},lo}/\partial\alpha$ from Eq. (3.9) can switch sign, depending on α. First, note that for $\alpha=0$, $\partial F_{\overline{A},lo}/\partial\alpha$ becomes

$$\frac{\partial F_{\overline{A},lo}}{\partial\alpha}(\alpha=0) = \frac{1}{2\delta}\frac{d(\rho_{\overline{A}}-\rho_{\underline{A}})}{(\lambda_L+\lambda-\rho_{\overline{A}})(\lambda_L+\lambda-\rho_{\underline{A}})} > 0, \tag{3.A2}$$

which is always positive as $\rho_{\overline{A}} > \rho_{\underline{A}}$. Moreover, for $\alpha=1$, $\partial F_{\overline{A},lo}/\partial\alpha$ becomes

$$\begin{aligned}\frac{\partial F_{\overline{A},lo}}{\partial\alpha}(\alpha=1) &= -\frac{1}{2\delta}d(\rho_{\overline{A}}-\rho_{\underline{A}})(1-\lambda_L-\lambda+\rho_{\overline{A}})(1-\lambda_L-\lambda+\rho_{\underline{A}}) \\ &+ \frac{1}{2\delta}d(\rho_{\overline{A}}-\rho_{\underline{A}})(\lambda_L+\lambda-\rho_{\overline{A}})(\lambda_L+\lambda-\rho_{\underline{A}}).\end{aligned} \tag{3.A3}$$

Hence, if

$$(1-\lambda_L-\lambda+\rho_{\overline{A}})(1-\lambda_L-\lambda+\rho_{\underline{A}}) > (\lambda_L+\lambda-\rho_{\overline{A}})(\lambda_L+\lambda-\rho_{\underline{A}}), \tag{3.A4}$$

it holds that $\partial F_{\overline{A},lo}/\partial\alpha(\alpha=1) < 0$ and vice versa. Furthermore, note that $\partial F_{\overline{A},lo}/\partial\alpha$ from Eq. (3.9) is a continuous function of α. Hence, if Condition (3.A4) holds, the intermediate value theorem implies that $\partial F_{\overline{A},lo}/\partial\alpha$ changes its sign for some $\alpha^*_{lo}=(0,1)$ and can thus be positive or negative depending on the value of α. If Condition (3.A4) is not satisfied, it always holds that $\partial F_{\overline{A},lo}/\partial\alpha \geq 0$. ■

Proof of Proposition 4

In the following, we compare the marginal change in $F_{\overline{A}}$ for a marginal change in α for both exposure cases and show that $\partial F_{\overline{A},hi}/\partial\alpha > \partial F_{\overline{A},low}/\partial\alpha$, that is,

$$\begin{aligned}\overline{Z} \equiv \frac{\partial F_{\overline{A},hi}}{\partial\alpha} - \frac{\partial F_{\overline{A},lo}}{\partial\alpha} = &\frac{1}{2\delta}\frac{\lambda_L(\lambda-\rho_{\underline{A}})}{\lambda(\lambda_L+(1-\lambda_L)\alpha)^2}xR \\ &- \frac{1}{2\delta}\frac{(\lambda_L+\lambda-\rho_{\overline{A}})(1-\lambda_L-\lambda+\rho_{\overline{A}})}{(\rho_{\overline{A}}+\left(\lambda_L-\rho_{\overline{A}}\right)+\left(\lambda-\rho_{\overline{A}}\right)+(1-\lambda_L-\lambda+\rho_{\overline{A}})\alpha)^2}d \\ &- \frac{1}{2\delta}\frac{\lambda_L(\lambda-\rho_{\overline{A}})}{\lambda(\lambda_L+(1-\lambda_L)\alpha)^2}xR \\ &+ \frac{1}{2\delta}\frac{(\lambda_L+\lambda-\rho_{\underline{A}})(1-\lambda_L-\lambda+\rho_{\underline{A}})}{(\rho_{\underline{A}}+\left(\lambda_L-\rho_{\underline{A}}\right)+\left(\lambda-\rho_{\underline{A}}\right)+(1-\lambda_L-\lambda+\rho_{\underline{A}})\alpha)^2}d > 0.\end{aligned} \tag{3.A5}$$

In the low-exposure case it holds that $dD \leq xR_A$, which implies $xR > d$. Since $xR > d$, it is sufficient to show that

$$\begin{aligned}\underline{Z} \equiv\ &\frac{1}{2\delta}\frac{\lambda_L(\lambda-\rho_{\underline{A}})}{\lambda(\lambda_L+(1-\lambda_L)\alpha)^2} \\ -\ &\frac{1}{2\delta}\frac{(\lambda_L+\lambda-\rho_{\overline{A}})(1-\lambda_L-\lambda+\rho_{\overline{A}})}{(\rho_{\overline{A}}+\left(\lambda_L-\rho_{\overline{A}}\right)+\left(\lambda-\rho_{\overline{A}}\right)+(1-\lambda_L-\lambda+\rho_{\overline{A}})\alpha)^2} \\ -\ &\frac{1}{2\delta}\frac{\lambda_L(\lambda-\rho_{\overline{A}})}{\lambda(\lambda_L+(1-\lambda_L)\alpha)^2} \\ +\ &\frac{1}{2\delta}\frac{(\lambda_L+\lambda-\rho_{\underline{A}})(1-\lambda_L-\lambda+\rho_{\underline{A}})}{(\rho_{\underline{A}}+\left(\lambda_L-\rho_{\underline{A}}\right)+\left(\lambda-\rho_{\underline{A}}\right)+(1-\lambda_L-\lambda+\rho_{\underline{A}})\alpha)^2} \geq 0,\end{aligned} \tag{3.A6}$$

to prove that Eq. (3.A5) is non-negative since it always holds that $\overline{Z} > \underline{Z}$. Substituting $\overline{X} = \lambda - \rho_{\overline{A}}$ and $\underline{X} = \lambda - \rho_{\underline{A}}$ in Eq. (3.A6) yields

$$\begin{aligned}\underline{Z} =\ &\frac{1}{2\delta}\frac{\lambda_L\underline{X}}{\lambda(\lambda_L+(1-\lambda_L)\alpha)^2} - \frac{1}{2\delta}\frac{(\lambda_L+\overline{X})(1-\lambda_L-\overline{X})}{\left(\lambda_L+\overline{X}+(1-\lambda_L-\overline{X})\alpha\right)^2} \\ -\ &\frac{1}{2\delta}\frac{\lambda_L\overline{X}}{\lambda(\lambda_L+(1-\lambda_L)\alpha)^2} + \frac{1}{2\delta}\frac{(\lambda_L+\underline{X})(1-\lambda_L-\underline{X})}{\left(\lambda_L+\underline{X}+(1-\lambda_L-\underline{X})\alpha\right)^2}.\end{aligned} \tag{3.A7}$$

Next, we show that $\underline{Z}$ in Eq. (3.A7) is always non-negative by showing the non-negativity of $\underline{Z}$ for the $\overline{X}$ and $\underline{X}$ that minimize $\underline{Z}$. Taking the derivatives of $\underline{Z}$ with respect to $\overline{X}$ and $\underline{X}$

yields

$$\frac{\partial \underline{Z}}{\partial \overline{X}} = \frac{1}{2\delta}\left[\frac{1}{1-\alpha}\left(1-\frac{\alpha}{\alpha+(1-\alpha)\left(\lambda_L+\overline{X}\right)}\right)-\frac{\lambda_L}{\lambda(\lambda_L+(1-\lambda_L)\alpha)^2}\right] \tag{3.A8}$$

$$\frac{\partial \underline{Z}}{\partial \underline{X}} = -\frac{1}{2\delta}\left[\frac{1}{1-\alpha}\left(1-\frac{\alpha}{\alpha+(1-\alpha)\left(\lambda_L+\underline{X}\right)}\right)-\frac{\lambda_L}{\lambda(\lambda_L+(1-\lambda_L)\alpha)^2}\right] \tag{3.A9}$$

respectively. Note that $\mid \partial\underline{Z}/\partial\underline{X} \mid \geq \partial\underline{Z}/\partial\overline{X}$ because $\underline{X} > \overline{X}$. Therefore, we have to consider three possible cases:

1. $\partial\underline{Z}/\partial\overline{X} > 0 \wedge \partial\underline{Z}/\partial\underline{X} < 0$
2. $\partial\underline{Z}/\partial\overline{X} < 0 \wedge \partial\underline{Z}/\partial\underline{X} < 0$
3. $\partial\underline{Z}/\partial\overline{X} < 0 \wedge \partial\underline{Z}/\partial\underline{X} > 0$

Case 1. $\underline{Z}(\overline{X},\underline{X})$ from Eq. (3.A7) has its minimum in this case when minimizing $\overline{X}$ (i.e., when $\overline{X} = \lambda - \underline{\lambda}$) and maximizing $\underline{X}$ (i.e., when $\underline{X} = \lambda$), which implies $\rho_{\overline{A}} = \underline{\lambda}$ and $\rho_{\underline{A}} = 0$:

$$\underline{Z}(\overline{X} = \lambda-\underline{\lambda}, \underline{X} = \lambda) = \frac{1}{2\delta}\left[\frac{\lambda_L}{\lambda_L+(1-\lambda_L)\alpha)^2}\right] - \frac{1}{2\delta}\left[\frac{(\lambda_L+\overline{X})(1-\lambda_L-\overline{X})}{\left(\lambda_L+\overline{X}+(1-\lambda_L-\overline{X})\alpha\right)^2}\right] - \frac{1}{2\delta}\left[\frac{\lambda_L\overline{X}}{\lambda(\lambda_L+(1-\lambda_L)\alpha)^2}\right] + \frac{1}{2\delta}\left[\frac{(\lambda_L+\lambda)(1-\lambda_L-\lambda)}{\left(\lambda_L+\lambda+(1-\lambda_L-\lambda)\alpha\right)^2}\right]. \tag{3.A10}$$

Next, we show that $\underline{Z}(\overline{X} = \lambda - \underline{\lambda}, \underline{X} = \lambda)$ is always non-negative by showing the non-negativity for $\overline{X} = 0 < \lambda - \underline{\lambda}$ (recall that in Case 1, $\underline{Z}$ increases with $\overline{X}$). With $\overline{X} = 0$, $\underline{Z}$ from from Eq. (3.A7) becomes

$$Z(\overline{X} = 0, \underline{X} = \lambda) = \frac{1}{2\delta}\left[\frac{\lambda_L}{(\lambda_L+(1-\lambda_L)\alpha)^2}\right] - \frac{1}{2\delta}\left[\frac{\lambda_L(1-\lambda_L)}{\left(\lambda_L+(1-\lambda_L)\alpha\right)^2}\right] + \frac{1}{2\delta}\left[\frac{(\lambda_L+\lambda)(1-\lambda_L-\lambda)}{\left(\lambda_L+\lambda+(1-\lambda_L-\lambda)\alpha\right)^2}\right] > 0, \tag{3.A11}$$

which is positive since the first term in Eq. (3.A11) is larger than the second term since $\lambda_L < 1$. Hence, $\underline{Z}$ is always positive for Case 1.

Case 2. $\underline{Z}(\overline{X},\underline{X})$ from Eq. (3.A7) has its minimum in this case when maximizing both

$\overline{X}$ (i.e., $\overline{X} = \lambda$) and $\underline{X}$ (i.e., $\underline{X} = \lambda$), which implies $\rho_{\overline{A}} = 0$ and $\rho_{\underline{A}} = 0$:

$$\underline{Z}(\overline{X} = \lambda, \underline{X} = \lambda) = \frac{1}{2\delta}\left[\frac{\lambda_L \underline{X}}{\lambda(\lambda_L + (1-\lambda_L)\alpha)^2}\right] - \frac{1}{2\delta}\left[\frac{(\lambda_L + \overline{X})(1-\lambda_L - \overline{X})}{\left(\lambda_L + \overline{X} + (1-\lambda_L - \overline{X})\alpha\right)^2}\right]$$
$$- \frac{1}{2\delta}\left[\frac{\lambda_L \overline{X}}{\lambda(\lambda_L + (1-\lambda_L)\alpha)^2}\right] + \frac{1}{2\delta}\left[\frac{(\lambda_L + \underline{X})(1-\lambda_L - \underline{X})}{(\lambda_L + \underline{X} + (1-\lambda_L - \underline{X})\alpha)^2}\right] = 0, \tag{3.A12}$$

which is equal to zero. Hence, $\underline{Z}$ is always non-negative for Case 2.

Case 3. $\underline{Z}(\overline{X}, \underline{X})$ from Eq. (3.A7) has its minimum in this case when maximizing $\overline{X}$ and minimizing $\underline{X}$. Since it holds that $\underline{X} > \overline{X}$, we can show that $\underline{Z}$ from Eq. (3.A7) is non-negative by showing the non-negativity for $\underline{X} = \overline{X}$, which is straightforward as $Z(\underline{X} = \overline{X}) = 0$.

Therefore, $\underline{Z}$ is always non-negative, and thus $\partial F_{\overline{A},hi}/\partial\alpha > \partial F_{\overline{A},low}/\partial\alpha$. ■

3.B Appendix - Additional Tables

Table 3.B.1: Portfolio Concentration – Placebo Test

	Portfolio HHI			Portfolio EDM		
	Full Sample	High Ex.	Low Ex.	Full Sample	High Ex.	Low Ex.
GG	-0.035	0.078	-0.044	-0.120	0.361	-0.184
	(0.841)	(0.780)	(0.799)	(0.831)	(0.687)	(0.752)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
N	14,882	2,761	12,121	14,882	2,761	12,121
R^2	0.843	0.907	0.830	0.873	0.924	0.860

This table presents estimation results from Specification (3.23), where we redo the estimations from Table 3.4, but moving the treatment year for each bank three years before the actual treatment. Standard errors are clustered at the state level, p-values are reported in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 3.B.2: Portfolio Concentration Conditional on Lending Exposure – Placebo Test

Panel A: Inter-State	Portfolio HHI			Portfolio EDM		
GG	-0.383	-0.081	-0.033	-1.375	-0.303	-0.148
	(0.389)	(0.661)	(0.856)	(0.330)	(0.617)	(0.803)
GG x Lending Exposure	0.046			0.166		
(Continuous)	(0.392)			(0.336)		
GG x Lending Exposure		0.204			0.801	
(Top 25%)		(0.421)			(0.313)	
GG x Lending Exposure			-0.063			0.248
(Top 10%)			(0.873)			(0.850)
$\hat{\beta}_1 + \hat{\beta}_3$		0.122	-0.095		-0.497	-0.099
		(0.632)	(0.791)		(0.534)	(0.934)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
N	14,882	14,882	14,882	14,882	14,882	14,882
R^2	0.843	0.842	0.842	0.873	0.872	0.872

Panel B: Intra-State	Portfolio HHI			Portfolio EDM		
GG x Lending Exposure	0.070			0.201		
(Continuous)	(0.169)			(0.191)		
GG x Lending Exposure		0.286			0.896	
(Top 25%)		(0.262)			(0.268)	
GG x Lending Exposure			0.043			0.392
(Top 10%)			(0.916)			(0.765)
State-Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
N	14,811	14,811	14,811	14,811	14,811	14,811
R^2	0.858	0.858	0.858	0.886	0.885	0.885

This table presents estimation results from Specification (3.24) (Panel A) and Specification (3.25) (Panel B), where we redo the estimations from Table 3.5, but moving the treatment year for each bank three years before the actual treatment. Standard errors are clustered at the state level, p-values are reported in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 3.B.3: Change in Portfolio Weights on Loan Class Level – Non-Missing Outcome Leads

	Continuous Exposure			Top 25% Exposure		
Panel A:	ΔPW	ΔPW	ΔPW	ΔPW	ΔPW	ΔPW
Inter-State	(t+1)	(t+2)	(t+3)	(t+1)	(t+2)	(t+3)
△GG	-0.030*	-0.073***	-0.111***	-0.015	-0.051**	-0.073**
	(0.097)	(0.006)	(0.004)	(0.315)	(0.019)	(0.010)
△GG x	0.044**	0.096***	0.140***			
Exposure Ratio	(0.017)	(0.003)	(0.004)			
△GG x				0.079	0.227**	0.298**
Top 25% Exposure				(0.153)	(0.015)	(0.021)
$\hat{\beta}_1 + \hat{\beta}_3$				0.065	0.176**	0.225**
				(0.115)	(0.013)	(0.023)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Class-Time FE	Yes	Yes	Yes	Yes	Yes	Yes
N	128,019	128,019	128,019	128,019	128,019	128,019
R^2	0.094	0.146	0.187	0.092	0.140	0.176
Panel B:	ΔPW	ΔPW	ΔPW	ΔPW	ΔPW	ΔPW
Intra-State	(t+1)	(t+2)	(t+3)	(t+1)	(t+2)	(t+3)
△GG x	0.042**	0.093***	0.138***			
Exposure Ratio	(0.020)	(0.003)	(0.004)			
△GG x				0.076	0.227**	0.297**
Top 25% Exposure				(0.162)	(0.014)	(0.019)
State-Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Class-Time FE	Yes	Yes	Yes	Yes	Yes	Yes
N	128,019	128,019	128,019	128,019	128,019	128,019
R^2	0.093	0.143	0.182	0.091	0.138	0.174

This table presents estimation results from Specification (3.26) (Panel A) and Specification (3.27) (Panel B), where we redo the estimations from Table 3.6, but restricting the sample to banks for which all three leads of the outcome variable are non-missing (i.e., $t+1, t+2, t+3$). Standard errors are clustered at the state level, p-values are reported in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 3.B.4: Change in Loan Volumes on Loan Class Level – Non-Missing Outcome Leads

	Continuous Exposure			Top 25% Exposure		
Panel A: Inter-State	ΔLCV (t+1)	ΔLCV (t+2)	ΔLCV (t+3)	ΔLCV (t+1)	ΔLCV (t+2)	ΔLCV (t+3)
△GG	-0.895	-2.152*	-1.999	-0.778	-1.781**	-1.393
	(0.155)	(0.050)	(0.109)	(0.181)	(0.046)	(0.173)
△GG x Exposure Ratio	0.343	1.287**	1.886***			
	(0.270)	(0.025)	(0.007)			
△GG x Top 25% Exposure				0.539	2.702***	3.619***
				(0.473)	(0.003)	(0.000)
$\hat{\beta}_1 + \hat{\beta}_3$				-0.239	0.920	2.226**
				(0.624)	(0.181)	(0.015)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Class-Time FE	Yes	Yes	Yes	Yes	Yes	Yes
N	128,019	128,019	128,019	128,019	128,019	128,019
R^2	0.082	0.139	0.184	0.080	0.136	0.179
Panel B: Intra-State	ΔLCV (t+1)	ΔLCV (t+2)	ΔLCV (t+3)	ΔLCV (t+1)	ΔLCV (t+2)	ΔLCV (t+3)
△GG x Exposure Ratio	0.302	1.272**	1.689**			
	(0.323)	(0.042)	(0.023)			
△GG x Top 25 Exposure				0.340	2.315***	3.074***
				(0.628)	(0.008)	(0.001)
State-Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Class-Time FE	Yes	Yes	Yes	Yes	Yes	Yes
N	128,019	128,019	128,019	128,019	128,019	128,019
R^2	0.061	0.101	0.130	0.060	0.098	0.126

This table presents estimation results from Specification (3.26) (Panel A) and Specification (3.27) (Panel B), where we redo the estimations from Table 3.7, but restricting the sample to banks for which all three leads of the outcome variable are non-missing (i.e., $t+1, t+2, t+3$). Standard errors are clustered at the state level, p-values are reported in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 3.B.5: Change in Portfolio Weights and Loan Volumes – Robustness

	△PW (t+3) Continuous	△LCV (t+3) Continuous		△PW (t+3) Continuous	△LCV (t+3) Continuous
exc. 1996	0.144***	1.903***	*exc*. 2007	0.135***	1.781***
	(0.003)	(0.002)		(0.006)	(0.004)
exc. 1997	0.158***	2.062***	*exc*. 2008	0.155***	1.905***
	(0.001)	(0.000)		(0.003)	(0.007)
exc. 1998	0.144***	1.898***	*exc*. 2009	0.144***	1.890***
	(0.003)	(0.002)		(0.003)	(0.002)
exc. 1999	0.074**	1.596***	*exc*. 2010	0.133**	1.942***
	(0.017)	(0.010)		(0.014)	(0.002)
exc. 2000	0.141***	1.851***	*exc*. 2011	0.129**	1.817***
	(0.004)	(0.004)		(0.019)	(0.005)
exc. 2001	0.170***	2.520***	*exc*. 2012	0.144***	1.906***
	(0.009)	(0.001)		(0.003)	(0.002)
exc. 2002	0.144***	1.907***	*exc*. 2013	0.147***	1.840***
	(0.003)	(0.002)		(0.003)	(0.004)
exc. 2003	0.154***	1.784***	*exc*. 2014	0.144***	1.903***
	(0.002)	(0.006)		(0.005)	(0.005)
exc. 2004	0.144***	1.910***	*exc*. 2015	0.144***	1.903***
	(0.003)	(0.002)		(0.003)	(0.002)
exc. 2005	0.154***	1.732***	*exc*. 2016	0.144***	1.903***
	(0.003)	(0.009)		(0.003)	(0.002)
exc. 2006	0.143***	1.899***			
	(0.004)	(0.002)			

This table shows estimation results for the analyses from Tables 3.6 and 3.7 (the coefficient β_3 from Specification 3.26), but excluding one year at a time. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 3.B.6: Change in Portfolio Weights on Loan Class Level – Placebo Tests

	Continuous Exposure			Top 25% Exposure		
Panel A: Inter-State	ΔPW (t+1)	ΔPW (t+2)	ΔPW (t+3)	ΔPW (t+1)	ΔPW (t+2)	ΔPW (t+3)
△GG	0.010	0.030	0.026	0.002	0.015	0.018
	(0.521)	(0.141)	(0.375)	(0.831)	(0.193)	(0.336)
△GG x Exposure Ratio	-0.010	-0.032	-0.025			
	(0.581)	(0.198)	(0.480)			
△GG x Top 25% Exposure				-0.007	-0.080	-0.111
				(0.899)	(0.356)	(0.400)
$\hat{\beta}_1 + \hat{\beta}_3$				-0.004	-0.065	-0.092
				(0.919)	(0.397)	(0.416)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Class-Time FE	Yes	Yes	Yes	Yes	Yes	Yes
N	154,316	155,946	155,372	154,387	156,017	155,443
R^2	0.089	0.140	0.179	0.086	0.131	0.165
Panel B: Intra-State	ΔPW (t+1)	ΔPW (t+2)	ΔPW (t+3)	ΔPW (t+1)	ΔPW (t+2)	ΔPW (t+3)
△GG x Exposure Ratio	-0.010	-0.034	-0.027			
	(0.567)	(0.172)	(0.450)			
△GG x Top 25% Exposure				-0.014	-0.094	-0.127
				(0.814)	(0.307)	(0.353)
State-Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Class-Time FE	Yes	Yes	Yes	Yes	Yes	Yes
N	154,316	155,946	155,372	154,387	156,017	155,443
R^2	0.088	0.137	0.175	0.084	0.129	0.162

This table presents estimation results from Specification (3.26) (Panel A) and Specification (3.27) (Panel B), where we redo the estimations from Table 3.6, but moving the treatment year for each bank three years before the actual treatment. Standard errors are clustered at the state level, p-values are reported in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 3.B.7: Change in Loan Volumes on Loan Class Level – Placebo Tests

	Continuous Exposure			Top 25% Exposure		
Panel A: Inter-State	ΔLCV (t+1)	ΔLCV (t+2)	ΔLCV (t+3)	ΔLCV (t+1)	ΔLCV (t+2)	ΔLCV (t+3)
$\triangle$GG	-0.194	0.353	-0.544	-0.136	0.433	-0.306
	(0.682)	(0.707)	(0.618)	(0.734)	(0.599)	(0.743)
$\triangle$GG x Exposure Ratio	0.229	0.186	0.411			
	(0.440)	(0.678)	(0.508)			
$\triangle$GG x Top 25% Exposure				0.739	0.053	-0.116
				(0.362)	(0.963)	(0.934)
$\hat{\beta}_1 + \hat{\beta}_3$				0.602	0.485	-0.423
				(0.374)	(0.608)	(0.701)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Class-Time FE	Yes	Yes	Yes	Yes	Yes	Yes
N	154,316	155,946	155,372	154,387	156,017	155,443
R^2	0.077	0.136	0.179	0.075	0.132	0.174
Panel B: Intra-State	ΔLCV (t+1)	ΔLCV (t+2)	ΔLCV (t+3)	ΔLCV (t+1)	ΔLCV (t+2)	ΔLCV (t+3)
$\triangle$GG x Exposure Ratio	0.124	0.119	0.310			
	(0.693)	(0.814)	(0.647)			
$\triangle$GG x Top 25% Exposure				0.773	0.400	-0.037
				(0.277)	(0.720)	(0.984)
State-Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Class-Time FE	Yes	Yes	Yes	Yes	Yes	Yes
N	154,316	155,946	155,372	154,387	156,017	155,443
R^2	0.055	0.092	0.121	0.054	0.089	0.117

This table presents estimation results from Specification (3.26) (Panel A) and Specification (3.27) (Panel B), where we redo the estimations from Table 3.7, but moving the treatment year for each bank three years before the actual treatment. Standard errors are clustered at the state level, p-values are reported in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 3.B.8: Change in Portfolio Weights on Loan Class Level – Excluding Mostly Represented States

	Continuous Exposure			Top 25% Exposure		
Panel A: Inter-State	ΔPW (t+1)	ΔPW (t+2)	ΔPW (t+3)	ΔPW (t+1)	ΔPW (t+2)	ΔPW (t+3)
$\triangle$GG	-0.025	-0.063***	-0.116***	-0.010	-0.038*	-0.075***
	(0.102)	(0.009)	(0.002)	(0.375)	(0.068)	(0.005)
$\triangle$GG x Exposure Ratio	0.033*	0.084***	0.147***			
	(0.065)	(0.005)	(0.002)			
$\triangle$GG x Top 25% Exposure				0.041	0.167*	0.302**
				(0.429)	(0.075)	(0.013)
$\hat{\beta}_1 + \hat{\beta}_3$				0.030	0.129*	0.227**
				(0.452)	(0.076)	(0.016)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Class-Time FE	Yes	Yes	Yes	Yes	Yes	Yes
N	169,467	143,718	122,214	169,467	143,718	122,214
R^2	0.093	0.149	0.195	0.091	0.143	0.183
Panel B: Intra-State	ΔPW (t+1)	ΔPW (t+2)	ΔPW (t+3)	ΔPW (t+1)	ΔPW (t+2)	ΔPW (t+3)
$\triangle$GG x Exposure Ratio	0.032*	0.082***	0.143***			
	(0.070)	(0.006)	(0.002)			
$\triangle$GG x Top 25% Exposure				0.038	0.163*	0.297**
				(0.450)	(0.080)	(0.012)
State-Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Class-Time FE	Yes	Yes	Yes	Yes	Yes	Yes
N	169,467	143,718	122,214	169,467	143,718	122,214
R^2	0.091	0.146	0.191	0.090	0.141	0.181

This table presents estimation results from Specification (3.26) (Panel A) and Specification (3.27) (Panel B), where we redo the estimations from Table 3.6, but excluding banks that are headquartered in the following states: New York, Alabama, Rhode Island, Nebraska, or South Dakota. Standard errors are clustered at the state level, p-values are reported in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 3.B.9: Change in Loan Volumes on Loan Class Level – Excluding Mostly Represented States

	Continuous Exposure			Top 25% Exposure		
Panel A: Inter-State	ΔLCV (t+1)	ΔLCV (t+2)	ΔLCV (t+3)	ΔLCV (t+1)	ΔLCV (t+2)	ΔLCV (t+3)
$\triangle$GG	-0.160	-1.577	-2.560**	-0.104	-1.230	-2.032**
	(0.745)	(0.122)	(0.034)	(0.818)	(0.164)	(0.039)
$\triangle$GG x Exposure Ratio	0.106	1.109**	1.909***			
	(0.698)	(0.022)	(0.002)			
$\triangle$GG x Top 25% Exposure				-0.022	2.140**	3.994***
				(0.974)	(0.020)	(0.000)
$\hat{\beta}_1 + \hat{\beta}_3$				-0.125	0.910	1.962**
				(0.801)	(0.242)	(0.41)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Class-Time FE	Yes	Yes	Yes	Yes	Yes	Yes
N	169,467	143,718	122,214	169,467	143,718	122,214
R^2	0.077	0.137	0.190	0.075	0.134	0.184
Panel B: Intra-State	ΔLCV (t+1)	ΔLCV (t+2)	ΔLCV (t+3)	ΔLCV (t+1)	ΔLCV (t+2)	ΔLCV (t+3)
$\triangle$GG x Exposure Ratio	0.018	0.920*	1.750**			
	(0.950)	(0.080)	(0.010)			
$\triangle$GG x Top 25 Exposure				-0.348	1.342	3.359***
				(0.606)	(0.154)	(0.000)
State-Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Class-Time FE	Yes	Yes	Yes	Yes	Yes	Yes
N	169,467	143,718	122,214	169,467	143,718	122,214
R^2	0.056	0.095	0.130	0.055	0.093	0.126

This table presents estimation results from Specification (3.26) (Panel A) and Specification (3.27) (Panel B), where we redo the estimations from Table 3.7, but excluding banks that are headquartered in the following states: New York, Alabama, Rhode Island, Nebraska, or South Dakota. Standard errors are clustered at the state level, p-values are reported in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 3.B.10: Joint Modified DiD Design

	ΔPW	ΔPW	ΔLCV	ΔLCV
Treated x Post	-0.114***	-0.070***	-2.303	-1.827
	(0.004)	(0.009)	(0.164)	(0.216)
Treated x Post	0.146***		2.077***	
x Exposure Ratio	(0.001)		(0.004)	
Treated x Post		0.275***		4.155***
x Top 25% Exposure		(0.001)		(0.001)
N	57,544	57,572	57,544	57,572
R^2	0.242	0.240	0.236	0.234
Bank FE	Yes	Yes	Yes	Yes
Class-Time FE	Yes	Yes	Yes	Yes

This table presents estimation results from Specification (3.28) for the period 1996-2016. The dependent variables are the annual change in the log of one plus the weight of loan class c over total lending of bank b ($\Delta Log(1+PW)_{b,c,t+1}$) (columns 1 and 2) and the annual change in the log one plus the loan volume of loan class c ($\Delta\, Log(1+LCV)_{b,c,t+1}$) (columns 3 and 4). We include observations that lie within a window of three years before and three years after bank b's treatment. The variable $Treated_b$ is equal to minus one if bank b loses representation in the BHUA Senate committee during our sample period, equal to zero if the bank is non-treated, and equal to one if bank b gains representation in the BHUA Senate committee. Treated bank b is matched with comparable non-treated banks based on size (proxied as the logarithm of assets), wholesale debt (assets minus equity and deposits, divided by assets), liquidity (measured as cash holdings and short-term investments, scaled by assets), and the number of loan classes to which the bank is exposed, all measured in the year of the treatment. The variable $Post_{b,t}$ is a dummy that takes unity in the three years after bank b's treatment and zero for the years before treatment. *Exposure Ratio* is the ratio between bank b's holdings of loan class c and its Tier-1 equity capital. The variable *Top 25% Exposure* is a dummy variable identifying bank-class pairs above the 25% percentile of the *Exposure Ratio* distribution in the previous year. The regressions include a set of one-period lagged control variables: log of state GDP, size (proxied as the logarithm of assets), ROA (return on assets, measured as earnings before interest and taxes, scaled by assets), liquidity (measured as cash holdings and short-term investments, scaled by assets), dividends (dummy variable identifying dividend payers), number of loan classes, and wholesale debt (assets minus equity and deposits, divided by assets). Standard errors are clustered at the state level, p-values are reported in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 3.B.11: "Losers" and "Gainers" – Placebo Test

	Losers		Gainers	
Panel A	ΔPW	ΔPW	ΔPW	ΔPW
Treated x Post	0.071	0.004	-0.044	-0.060
	(0.331)	(0.942)	(0.447)	(0.219)
Treated x Post	0.016		0.029	
x Exposure Ratio	(0.892)		(0.711)	
Treated x Post		0.244		0.172
x Top 25% Exposure		(0.144)		(0.344)
N	9,797	9,797	18,373	18,373
R^2	0.251	0.247	0.329	0.326
Panel B:	ΔLCV	ΔLCV	ΔLCV	ΔLCV
Treated x Post	-2.250	-2.433	0.433	0.471
	(0.664)	(0.602)	(0.864)	(0.833)
Treated x Post	2.191		-0.210	
x Exposure Ratio	(0.371)		(0.896)	
Treated x Post		5.587		-0.475
x Top 25% Exposure		(0.248)		(0.898)
N	9,797	9,797	18,373	18,373
R^2	0.228	0.227	0.295	0.293
Bank FE	Yes	Yes	Yes	Yes
Class-Time FE	Yes	Yes	Yes	Yes

This table presents estimation results from Specification (3.28), where we redo the estimations from Table 3.8, but moving the treatment year for each bank three years before the actual treatment. Standard errors are clustered at the state level, p-values are reported in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 3.B.12: Joint Modified DiD Design – Placebo Test

	ΔPW	ΔPW	ΔLCV	ΔLCV
Treated x Post	-0.040	-0.042	0.274	0.103
	(0.384)	(0.354)	(0.899)	(0.959)
Treated x Post	-0.000		-0.556	
x Exposure Ratio	(0.997)		(0.628)	
Treated x Post		0.033		-0.470
x Top 25% Exposure		(0.824)		(0.848)
N	28,170	28,170	28,170	28,170
R^2	0.296	0.292	0.265	0.264
Bank FE	Yes	Yes	Yes	Yes
Class-Time FE	Yes	Yes	Yes	Yes

This table presents estimation results from Specification (3.28), where we redo the estimations from Table 3.B.10, but moving the treatment year for each bank three years before the actual treatment. Standard errors are clustered at the state level, p-values are reported in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

4.A Appendix - Proofs I

Proof of Proposition 1

Constraint (4.14) is a non-negative constraint for the bank's objective function. We thus first omit this constraint and, after the maximization, check whether the constraint is satisfied. Therefore, we solve:

$$\pi_b^{ng} = \max_{R_B, L \geq 0} p_H \left[R_B - L(1 + r_d) \right] - L\beta \tag{4.A1}$$

$$s.t.\ (4.13),\ (4.15),\ \text{and}\ (4.17)$$

If $L > 0$, Constraint (4.13) must be binding because, given an arbitrary feasible contract $\{R_B, L\}$, the bank's expected return decreases with r_d and, meanwhile, a lower r_d does not make any other constraint tighter.

If $L = 0$, r_d can be arbitrary since the bank does not borrow from investors. Therefore, we can simply let Constraint (4.13) be binding and solve for the bank's optimal constract. If the resulting optimal loan amount is 0, r_d can be arbitrary.

Next, we show that Constraint (4.17) must also be binding in the optimum. If $\{R'_B, L'\}$ is an optimal contract but Constraint (4.17) is not binding for $\{R'_B, L'\}$, the bank can increase R'_B to R''_B while fixing $L = L'$ until the constraint is binding. The new contract $\{R''_B, L'\}$ satisfies all constraints if $\{R'_B, L'\}$ does, and dominates $\{R'_B, L'\}$ because the bank's objective function increases with R_B. Therefore, $\{R'_B, L'\}$ cannot be an optimal contract and Constraint (4.17) must be binding.

Substituting the binding Constraints (4.13) and (4.17) into Eq. (4.A1) allows us to simplify the bank's optimization problem to

$$\pi_b^{ng} = \max_{R_B} \left(1 + \frac{\beta}{1+r}\right) \Delta NR - \frac{p_H R_B \beta}{1+r}, \tag{4.A2}$$

$$s.t.\ R_B \geq \frac{\gamma}{\triangle p}\ \text{and}\ R_B \geq \frac{\Delta NR}{p_H}, \tag{4.A3}$$

where the second constraint results from the binding Constraint (4.17) and $L \geq 0$.

Since the objective function (4.A2) decreases with R_B, the bank's optimal loan contract is a pair of contract elements $\{R_B^{ng}, L^{ng}\}$ that satisfies:

$$R_B^{ng} = \max\left\{\frac{\gamma}{\triangle p}, \frac{\Delta NR}{p_H}\right\}, \tag{4.A4}$$

$$L^{ng} = \max\left\{\frac{1}{1+r}\left[\frac{p_H\gamma}{\triangle p} - \Delta NR\right], 0\right\}. \tag{4.A5}$$

Assumption 4 guarantees $L^{ng} + E \leq I^*$, so indeed the firm will choose an investment level I^*.

Furthermore, any investment level $I \neq I^*$ would make the bank worse-off, since it would reduce the incremental project net return and thus the bank's expected return (see Eq. 4.A2). Therefore, $\{R_B^{ng}, L^{ng}\}$ is the optimal contract for the bank.

Finally, we need to check whether the bank's PC (4.14) is satisfied. If $\Delta NR \geq p_H\gamma/\triangle p$, the expected profit of the bank is

$$\pi_b^{ng} = \Delta NR, \tag{4.A6}$$

and Constraint (4.14) is satisfied. If $\Delta NR < p_H\gamma/\triangle p$, the bank's expected return is

$$\pi_b^{ng} = \left(1 + \frac{\beta}{1+r}\right)\Delta NR - \frac{p_H\gamma}{(1+r)\triangle p}\beta. \tag{4.A7}$$

Therefore, the bank will participate if and only if $\pi_b^* \geq 0$. Note that this condition is always satisfied when $\Delta NR \geq p_H\gamma/\triangle p$.

Proof of Proposition 2

We first ignore the bank's PC (4.14) and then check later, after solving the bank's maximization problem subject to the other constraints, whether this constraint holds. Leaving Constraint (4.14) aside, the bank solves

$$\pi_b^{gmH} = \max_{R_B, L\geq 0} p_H\left[R_B - L(1+r_d)\right] - L\beta, \tag{4.A8}$$

$$s.t.\ (4.15),\ (4.17),\ \text{and}\ (4.22).$$

As in the proof of Proposition 1, Constraints (4.17) and (4.22) have to be binding in the optimum and, again, r_d is arbitrary if the optimal amount of loans is equal to zero.

Inserting the investor's binding PC (4.22) into the objective function, the bank's optimization problem reduces to

$$\pi_b^{gmH} = \max_{R_B, L \geq 0} p_H R_B - L \cdot MLC^H, \tag{4.A9}$$

$$s.t. \; R_B \geq \frac{\gamma}{\triangle p},$$

$$\max_{I \geq L+E} p_H \left[f(I) - \frac{(I-L-E)(1+r)}{p_H} - R_B \right] - E(1+r) \geq p_H f(\bar{I}) - \bar{I}(1+r). \tag{4.A10}$$

So far it is not clear whether constraint $I \geq L+E$ for the firm is binding, so we need to discuss both possible cases.

If $I > L+E$, Constraint (4.A10) reduces to $p_H R_B - L(1+r) = \Delta NR$. Substituting $L = p_H R_B - \Delta NR$ into the contracting problem, it becomes

$$\pi_b^{gmH} = \max_{R_B} p_H R_B \left[1 + r - MLC^H \right] + MLC^H \cdot \Delta NR \tag{4.A11}$$

$$s.t. \; R_B \geq \frac{\gamma}{\triangle p} \text{ and } p_H R_B \geq \Delta NR,$$

where the second constraint is implied by $L > 0$.

Optimization problem (4.A11) has a solution only when $1 + r - MLC^H \leq 0$. Specifically, if $1 + r - MLC^H \leq 0$, the optimal contract, given the firm's investment level I^*, is a pair of contract elements $\{R_B^{gm\overline{H}}, L^{gm\overline{H}}\}$ that satisfies:

$$R_B^{gm\overline{H}} = \max \left\{ \frac{\gamma}{\triangle p}, \frac{\Delta NR}{p_H} \right\} = R_B^{ng},$$

$$L^{gm\overline{H}} = \max \left\{ \frac{p_H \gamma}{\triangle p} - \Delta NR, 0 \right\} = L^{ng},$$

since Eq. (4.A11) decreases with R_B. Assumption 4 guarantees $L^{gm\overline{H}} + E \leq I^*$, so the constraint $I \geq L+E$ is not binding for the firm under the contract. Furthermore, any investment level different from I^* makes the bank worse off, because for $I \neq I^*$ the left hand side of Constraint (4.A10) decreases, which tightens the constraint for the bank. As a result, $\{R_B^{gm\overline{H}}, L^{gm\overline{H}}\}$ is the bank's optimal contract in this case.

Next, we need to check the bank's PC (4.14). If $\Delta NR/p_H \geq \gamma/\triangle p$, the bank's expected profit is ΔNR, so the bank always participates; if $\Delta NR/p_H < \gamma/\triangle p$, the bank's expected profit is

$$\pi_b = \Delta NR \frac{p_H}{p_H + (1-p_H)\alpha} + \frac{p_H \gamma}{\triangle p} \frac{(1-p_H)\alpha}{p_H + (1-p_H)\alpha} - \beta \left(\frac{p_H \gamma}{\triangle p} - \Delta NR \right), \qquad (4.A12)$$

so the bank participates only if Eq. (4.A12) is non-negative.

Next, we consider the case where $1 + r - MLC^H > 0$. In this case, optimization problem (4.A11) has no solution, which implies $I \geq L + E$ must be binding for the firm. Therefore, Constraint (4.A10), which also must be binding, reduces to

$$p_H f(L+E) - E(1+r) - \left(p_H f(\bar{I}) - \bar{I}(1+r)\right) = p_H R_B. \qquad (4.A13)$$

Inserting Eq. (4.A13) back to the bank's optimization problem (4.A11) yields

$$\pi_b^{gm\underline{H}} = \max_L p_H f(L+E) - E(1+r) - \left(p_H f(\bar{I}) - \bar{I}(1+r)\right) - L \cdot MLC^H, \qquad (4.A14)$$

$$s.t. \ \frac{p_H f(L+E)}{1+r} - E(1+r) - \left(\frac{p_H f(\bar{I})}{1+r} - \bar{I}(1+r) \right) \geq \frac{p_H \gamma}{\triangle p} \text{ and } L \geq 0.$$

Let $\lambda_1 \geq 0$ and $\lambda_2 \geq 0$ be the Lagrangian multipliers for the first and the second constraint of the optimization problem (4.A14), respectively. The first order condition is

$$p_H f'(L+E) - MLC^H + \lambda_1 p_H f'(L+E) + \lambda_2 = 0, \qquad (4.A15)$$

where λ_2 must be equal to zero. Otherwise, we have $L = 0$, which is impossible since I must be higher than I^* to make $I \geq L + E$ binding. λ_1 is also 0, because

$$\begin{aligned} & p_H f(L+E) - E(1+r) - \left(p_H f(\bar{I}) - \bar{I}(1+r)\right) \\ \geq \ & p_H f(I^*) - E(1+r) - \left(p_H f(\bar{I}) - \bar{I}(1+r)\right) \geq \frac{p_H \gamma}{\triangle p}. \end{aligned} \qquad (4.A16)$$

The first inequality of (4.A16) holds because $L + E$ is equal or greater than I^*, while the second inequality is just a transformation of Assumption 4. Therefore, Eq. (4.A15) reduces to

$$p_H f'(L+E) = MLC^H. \qquad (4.A17)$$

Denoting the optimal contract in this case as $\{R_B^{gm\underline{H}}, L^{gm\underline{H}}\}$, obviously $L^{gm\underline{H}}$ is the solution of Eq. (4.A17), while $R_B^{gm\underline{H}}$ is implied by Eq. (4.A13) given that $L = L^{gm\underline{H}}$. Since, in this case, it holds that $MLC^H < 1+r$, it must hold that $L^{gm\underline{H}} + E > I^*$ according to Eq. (4.A17) and the definition of I^*. Therefore, we verify that the constraint $I \geq L+E$ is indeed binding in the case.

Finally, we verify that the bank's PC (4.14) is satisfied in this case, which is the case because

$$
\begin{aligned}
\pi_b^{gm\underline{H}} &= p_H f(L^{gm\underline{H}} + E) - E(1+r) - \big(p_H f(\bar{I}) - \bar{I}(1+r)\big) - L^{gm\underline{H}} \cdot MLC^H \\
&> p_H f(I^*) - E(1+r) - \big(p_H f(\bar{I}) - \bar{I}(1+r)\big) - (I^* - E) \cdot MLC^H \\
&= \Delta NR + \underbrace{\big[(1+r) - MLC^H\big]}_{>0 \text{ in this case}} (I^* - E) > 0, \qquad (4.A18)
\end{aligned}
$$

where the first inequality holds because $I^* - E$ is not the optimal loan amount ($L^{gm\underline{H}}$) in this case. As a result, the bank always participates in this case.

Proof of Lemma 5

(i) If the bank wants the firm to implement the good project, but does not monitor the firm, a necessary (but not sufficient) condition is

$$p_H \frac{R_B}{L} \leq 1+r, \qquad (4.A19)$$

otherwise the firm purely borrows from investors because market-based finance is cheaper, and the bank makes zero profit. Given that Condition (4.A19) is satisfied, the bank can have a positive expected return only if

$$MLC^H < 1+r, \qquad (4.A20)$$

because otherwise the lowest possible expected marginal lending cost, MLC^H, would be above the expected income for each unit of loaned funds, $p_H R_B / L$. Therefore, we only need to consider the case where Condition (4.A20) holds.

With Condition (4.A20), we can show that it is optimal for the bank to completely crowd out market-based finance, that is, to provide $I = L+E$. If the firm accepts the contract $\{R_B', L'\}$ and borrows additional K units of funds from investors with the lowest possible bond interest rate $(1+r)/p_H$, the bank can offer a new contract $\{R_B' + K(1+r)/p_H, L'+K\}$, which is also acceptable for the firm, and which increases the bank's expected return by $K\left(1+r-MLC^H\right)$. Taking this constraint into consideration, the bank solves the following contracting problem:

$$\pi_b^{gw\underline{H}} = \max_{R_B, L\geq 0} p_H\left[R_B - L(1+r_d)\right] - L\beta, \tag{4.A21}$$

$$s.t.\ (4.14),\ (4.22),\ R_B \leq \overline{R}, \text{ and}$$

$$p_H[f(L+E) - R_B] - E(1+r) \geq p_H f(\bar{I}) - \bar{I}(1+r). \tag{4.A22}$$

Note that we do not include Condition (4.A19) in the optimization problem because Condition (4.A22) is already the sufficient and necessary PC for the firm.

As in the proof of Proposition 2, we proceed by first neglecting the bank's PC (4.14) and then check this condition after the optimization. As in the proof of Proposition 1, the investor's PC (4.22) and the firm's PC (4.A22) have to be binding in the optimum. Inserting these two binding constraints into the optimization problem, reduces Eq. (4.A21) to

$$\pi_b^{gw\underline{H}} = \max_{L\geq 0} p_H\left[f(L+E) - f(\bar{I})\right] + (1+r)\left(\bar{I} - E\right) - L\cdot MLC^H, \tag{4.A23}$$

$$s.t.$$

$$f(L+E) - f(\bar{I}) + \frac{(1+r)\left(\bar{I}-E\right)}{p_H} \leq \frac{p_H - p_L\delta}{\triangle p} f(L+E), \tag{4.A24}$$

where Constraint (4.A24) is implied by $R_B \leq \overline{R}$. It is easy to show that Condition (4.A24) is equivalent to

$$L \leq \bar{I} - E, \tag{4.A25}$$

according to the definition of $\bar{I}$. Without Constraint (4.A25), the first order condition of Eq. (4.A23) is exactly the same as Eq. (4.A17), which implies $L = L^{gm\underline{H}} > I^* - E > \bar{I} - E$ due to Condition (4.A20). Therefore, Constraint (4.A24) must be binding. Denoting the optimal contract in this case as $\left\{R_B^{gw\underline{H}}, L^{gw\underline{H}}\right\}$, we have

$$R_B^{gw\underline{H}} = \frac{(1+r)\left(\bar{I}-E\right)}{p_H} \text{ and } L^{gw\underline{H}} = \bar{I} - E. \tag{4.A26}$$

Under $\left\{R_B^{gw\underline{H}}, L^{gw\underline{H}}\right\}$, the firm cannot get more funds from investors since its investment level is already $\bar{I}$ and there is no monitoring. Hence, bank finance completely crowds out market-based finance. The bank's expected return, $\pi^{gw\underline{H}}$, in the case is given by

$$\pi_b^{gw\underline{H}} = \left[1 + r - MLC^H\right] \left(\bar{I} - E\right), \tag{4.A27}$$

which is positive under Condition (4.A20).

(ii) If the firm implements the bad project, the bank's expected marginal lending cost for each loan unit is

$$MLC^L = p_L \frac{1+r}{p_L + (1-p_L)\alpha} + \beta. \tag{4.A28}$$

Therefore, a necessary condition for the bank to make a positive profit is

$$MLC^L < 1 + r. \tag{4.A29}$$

Otherwise, bank finance would be more expensive than market-based finance and thus there would be no contract that is acceptable for both, the bank and the firm, because $p_L \delta f(I) < (1+r)$ according to Assumption 2.

As in the proof of Item (i), we can show that under Condition (4.A29) it is optimal for the bank to completely crowd out market-based finance. Therefore, the bank's contracting problem is

$$\pi_b^{gwL} = \max_{R_B, L \geq 0} p_L \left[R_B - L(1+r_d)\right] - L\beta, \tag{4.A30}$$

$$s.t.$$

$$p_L L(1+r_d) + (1-p_L)\alpha L(1+r_d) \geq L(1+r) \tag{4.A31}$$

$$p_L \left[R_B - L(1+r_d)\right] - L\beta \geq 0 \tag{4.A32}$$

$$p_L \left[\delta f(L+E) - R_B\right] - E(1+r) \geq p_H f(\bar{I}) - \bar{I}(1+r). \tag{4.A33}$$

As before, we first neglect the bank's PC (4.A32) and then check later, after solving the maximization problem, whether the condition holds. It is again straightforward to show that Conditions (4.A31) and (4.A33) must be binding in the optimum, so the maximization problem can be reduced to

$$\pi_b^{gwL} = \max_{L \geq 0} p_L \delta f(L+E) - p_H f(\bar{I}) + (1+r)\left(\bar{I} - E\right) - L \cdot MLC^L, \tag{4.A34}$$

Without considering Constraint $L \geq 0$, the first order condition is therefore

$$p_L \delta f'(L+E) = MLC^L. \tag{4.A35}$$

Denoting the solution of Eq. (4.A35) as L^{gwL}, the optimal loan amount in this case is $\max\left\{L^{gwL}, 0\right\}$. Because of Condition (4.A29), the firm does not have an incentive to borrow from investors after taking the contract, since the marginal benefit of a unit of additional investment, $p_L \delta f'(\max\left\{L^{gwL}, 0\right\} + E)$, is lower than the marginal cost of market finance, $1+r$.

Inserting $\max\left\{L^{gwL}, 0\right\}$ back into the objective function (4.A34), we obtain for the bank's expected return:

$$\begin{aligned} \pi_b^{gwL}\left(\max\left\{L^{gwL}, 0\right\}\right) &= p_L \delta f(\max\left\{L^{gwL}, 0\right\} + E) - p_H f(\bar{I}) + \left(\bar{I} - E\right)(1+r) \\ &- \max\left\{L^{gwL}, 0\right\} \cdot MLC^L. \end{aligned} \tag{4.A36}$$

Assumption 2 implies that $\pi_b^{gwL}(0) < 0$. Therefore, whenever the bank makes a positive expected profit, the optimal loan volume must be positive, which implies $L^{gwL} > 0$. When the bank's expected return is positive, the optimal loan repayment R_B^{gwL} can be obtained using the binding Constraint (4.A33), which is:

$$p_L[\delta f(L^{gwL} + E) - R_B^{gwL}] - E(1+r) = p_H f(\bar{I}) - \bar{I}(1+r).$$

Hence, the optimal contract when the bank can make a positive expected profit is given by $\{R_B^{gwL}, L^{gwL}\}$.

Proof of Proposition 3

(i) Since $\pi_b^{gw\underline{H}} < \left[1 + r - MLC^H\right](I^* - E)$ when $MLC^H < 1+r$, $\pi_b^{gw\underline{H}} < \pi_b^{gm\underline{H}}$ is a natural result of Inequality (4.A18).

(ii.1)/(ii.2) There are two possible cases when Condition (4.A29) holds: $MLC^H < 1+r$ and $MLC^H \geq 1+r$.

If $MLC^H < 1+r$, we need to compare $\pi_b^{gwL}\left(\max\left\{L^{gwL},0\right\}\right)$ with $\pi_b^{gm\underline{H}}$. If $\pi_b^{gwL}\left(\max\left\{L^{gwL},0\right\}\right) > \pi_b^{gm\underline{H}}$, implementing the bad project yields a higher expected return for the bank than implementing the good project. Since $\pi_b^{gm\underline{H}}$ is always positive, $\pi_b^{gwL}\left(\max\left\{L^{gwL},0\right\}\right)$ must also be positive when $\pi_b^{gwL}\left(\max\left\{L^{gwL},0\right\}\right) > \pi_b^{gm\underline{H}}$ holds. Therefore, $\pi_b^{gwL}\left(\max\left\{L^{gwL},0\right\}\right) > \pi_b^{gm\underline{H}}$ is the sufficient and necessary condition under which the bank prefers the bad project. According to Lemma 5, the bank's best strategy is to offer $\left\{R_B^{gwL},L^{gwL}\right\}$ if the firm implements the bad project. Item (iii) of Proposition 3 states that the firm will implement the bad project if the bank offers $\left\{R_B^{gwL},L^{gwL}\right\}$. Therefore, the bank will offer $\left\{R_B^{gwL},L^{gwL}\right\}$ whenever it prefers the bad project.

If $MLC^H \geq 1+r$, we need to compare $\pi_b^{gwL}\left(\max\left\{L^{gwL},0\right\}\right)$ with $\pi_b^{gm\overline{H}}$. Since $\pi_b^{gm\overline{H}}$ can be negative, the sufficient and necessary condition under which the bank prefers implementing the bad project is that both $\pi_b^{gwL}\left(\max\left\{L^{gwL},0\right\}\right) > \pi_b^{gm\overline{H}}$ and $\pi_b^{gwL}\left(\max\left\{L^{gwL},0\right\}\right) \geq 0$ hold. As in the case $MLC^H < 1+r$, the bank optimally offers $\left\{R_B^{gwL},L^{gwL}\right\}$ whenever it prefers implementing the bad project.

(iii) We prove the result by contradiction. Assume that the optimal contract that implements the good project is $\{R'_B,L'\}$, and the corresponding expected bank return is π'_b. If $\pi_b^{gwL}\left(\max\left\{L^{gwL},0\right\}\right) > \max\left(\pi'_b,0\right)$, but the firm has an incentive to implement the good project after taking $\left\{R_B^{gwL},L^{gwL}\right\}$, we must have $f(I) > R_B^{gwL}$; otherwise, there is no residual positive income for the firm after paying R_B^{gwL} if the good project is implemented. Given that $f(I) > R_B^{gwL}$ holds and the firm implements the good project, the bank's expected return is actually higher than $\pi_b^{gwL}\left(\max\left\{L^{gwL},0\right\}\right)$ because the probability of receiving R_B^{gwL} increases from p_L to p_H. However, this implies that $\left\{R_B^{gwL},L^{gwL}\right\}$ implements the good project and is a strictly better contract than $\{R'_B,L'\}$, since we have $\pi_b^{gwL}\left(\max\left\{L^{gwL},0\right\}\right) > \max\left(\pi'_b,0\right)$. This contradicts the assumption that $\{R'_B,L'\}$ is the optimal contract implementing the good project. Therefore, the firm has no incentive to implement the good project after taking $\left\{R_B^{gwL},L^{gwL}\right\}$.