Concentrating on Bailouts: Government Guarantees and Bank Asset Composition*

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June 2023

Abstract

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.

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Eufinger gratefully acknowledges the financial support of the State Research Agency (AEI) of the Spanish Ministry of Science, Innovation and Universities (MCIU) and the European Regional Development Fund (FEDER) - REF PROYECTO PGC2018-097335-A-I00 (MCIU/AEI/FEDER, UE)

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 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 and 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 and 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.

[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, faced the default of its largest borrower Nordwolle, with the exposure amounting to 80% of Danatbank's capital (Doerr et al., 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 et al. (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.

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 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

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

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 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 and 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 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 and 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),

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

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 and Dybvig, 1983) and to avoid the social cost of bank failures (e.g., Gorton and Huang, 2004). Early papers showed that government guarantees create moral hazard problems (e.g., Kareken and Wallace, 1978 and Merton, 1977; see Allen et al., 2011 for a review), while more recent literature links government guarantees and systemic risk (Farhi and Tirole, 2012; Bianchi, 2016; Keister, 2016; and Dávila and Walther, 2020).[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 and Koetter, 2012, Brandao-Marques et al., 2013, and Gropp et al., 2014). Gropp et al. (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

[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. Dávila and Walther (2020) shows that large banks anticipate that their actions affect bailout decisions and thus leverage more than smaller banks.

[6] Burietz and Ureche-Rangau (2020) shows that banks lend more to domestic borrowers and familiar industries. Duquerroy et al. (2022) shows that banks specialize locally by industry. Paravisini et al. (2015) find that firms take bank specialization into account when selecting their lenders. Acharya et al.

bank risk.[7] Most closely related to our paper, there is evidence showing that distressed banks increase their asset concentration. De Jonghe et al. (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 et al. (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.

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.

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

(2006) and Tabak et al. (2011) find a positive link between portfolio concentration and bank performance.

[7] Goetz et al. (2016) shows that lower geographic concentration reduces bank risk. Galaasen et al. (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 et al. (2010) shows that specialization can have opposing effects on portfolio risk, negative through improved monitoring and positive due to concentration risk. Beck et al. (2022) finds that systemic risk exposure decreases with specialization. De Jonghe et al. (2021) finds that bank specialization is associated with less zombie lending.

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 when the legacy asset is successful.

[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.

Table 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	$\lambda_L - \rho_{\underline{A}}$	$1 - \lambda_L - \lambda_{\underline{A}} + \rho_{\underline{A}}$

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 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

[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.

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.

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 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.

2.2.1 Low-exposure case.

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

$$\begin{aligned} \Pi_{A,lo} &= \Delta_A + \rho_A \left[lR_L + xR_A - dD \right] + (\lambda_L - \rho_A) \left[lR_L - dD \right] \\ &+ (\lambda_A - \rho_A) \left[xR_A - dD \right] - e, \end{aligned} \tag{1}$$

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

$$\rho_A dD + (\lambda_L - \rho_A)\, dD + (\lambda_A - \rho_A)\, dD + (1 - \lambda_L - \lambda_A + \rho_A)\alpha dD \geq d. \tag{2}$$

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 (2) for D:

$$D_{A,lo} = \frac{1}{\rho_A + (\lambda_L - \rho_A) + (\lambda_A - \rho_A) + (1 - \lambda_L - \lambda_A + \rho_A)\alpha}. \tag{3}$$

Plugging the binding creditor's participation constraint from Eq. (2) and $D_{A,lo}$ from Eq. (3) into Eq. (1) and simplifying yields for the bank's expected return:

$$\begin{aligned} \Pi^{*}_{A,lo} = {} & \Delta_A + \underbrace{(\lambda_L l R_L + \lambda_A x R_A)}_{=PV_{A,lo}} \\ & + \underbrace{(1 - \lambda_L - \lambda_A + \rho_A)\alpha \frac{d}{\rho + (\lambda_L - \rho_A) + (\lambda_A - \rho_A) + (1 - \lambda_L - \lambda_A + \rho_A)\alpha}}_{=G_{A,lo}} - 1, \end{aligned} \tag{4}$$

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

Eq. (4) consists of the following parts: The investments in assets L and A yield in expectations $\lambda_L l R_L$ and $\lambda_A x R_A$, respectively (first term), denoted $PV_{A,lo}$. The second term in Eq. (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. (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*

$$\begin{aligned} \Delta \leq \Delta^*_{lo} \quad &\equiv \quad \frac{(1-\lambda_L-\lambda_{\overline{A}}+\rho_{\overline{A}})\alpha d}{\rho_{\overline{A}}+(\lambda_L-\rho_{\overline{A}})+(\lambda_{\overline{A}}-\rho_{\overline{A}})+(1-\lambda_L-\lambda_{\overline{A}}+\rho_{\overline{A}})\alpha} \\ &- \quad \frac{(1-\lambda_L-\lambda_{\underline{A}}+\rho_{\underline{A}})\alpha d}{\rho_{\underline{A}}+(\lambda_L-\rho_{\underline{A}})+(\lambda_{\underline{A}}-\rho_{\underline{A}})+(1-\lambda_L-\lambda_{\underline{A}}+\rho_{\underline{A}})\alpha}, \end{aligned} \tag{5}$$

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

$$\begin{aligned} E[\Delta^*_{lo}] \quad &= \quad \frac{(1-\lambda_L-\lambda+\rho_{\overline{A}})\alpha d}{\rho_{\overline{A}}+(\lambda_L-\rho_{\overline{A}})+(\lambda-\rho_{\overline{A}})+(1-\lambda_L-\lambda+\rho_{\overline{A}})\alpha} \\ &- \quad \frac{(1-\lambda_L-\lambda+\rho_{\underline{A}})\alpha d}{\rho_{\underline{A}}+(\lambda_L-\rho_{\underline{A}})+(\lambda-\rho_{\underline{A}})+(1-\lambda_L-\lambda+\rho_{\underline{A}})\alpha} > 0. \end{aligned} \tag{6}$$

Proof. See Appendix A.

From Eqs. (5) and (6), it follows that the ex-ante probability that the bank invests in asset $\overline{A}$ and $\underline{A}$ is given by

$$F_{\overline{A},lo} \quad \equiv \quad P(\Delta \leq \Delta^*_{lo}) = \frac{E[\Delta^*_{lo}]}{2\delta}, \tag{7}$$

$$F_{\underline{A},lo} \quad \equiv \quad P(\Delta > \Delta^*_{lo}) = 1 - \frac{E[\Delta^*_{lo}]}{2\delta}, \tag{8}$$

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*

$$\begin{aligned}\frac{\partial F_{\overline{A},lo}}{\partial \alpha} &= \frac{1}{2\delta}\frac{d(\lambda_L+\lambda-\rho_{\overline{A}})(1-\lambda_L-\lambda+\rho_{\overline{A}})}{(\rho_{\overline{A}}+(\lambda_L-\rho_{\overline{A}})+(\lambda-\rho_{\overline{A}})+(1-\lambda_L-\lambda+\rho_{\overline{A}})\alpha)^2} \\ &- \frac{1}{2\delta}\frac{d(\lambda_L+\lambda-\rho_{\underline{A}})(1-\lambda_L-\lambda+\rho_{\underline{A}})}{(\rho_{\underline{A}}+(\lambda_L-\rho_{\underline{A}})+(\lambda-\rho_{\underline{A}})+(1-\lambda_L-\lambda+\rho_{\underline{A}})\alpha)^2},\end{aligned} \tag{9}$$

which can be positive or negative.

Proof. See Appendix A.

2.2.2 High-exposure case.

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

$$\Pi_{A,hi} = \Delta_A + \rho_A\,[lR_L + xR_A - dD] + (\lambda_L - \rho_A)\,[lR_L - dD] - e. \tag{10}$$

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. (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

$$\rho_A dD + (\lambda_L - \rho_A)\, dD + (\lambda_A - \rho_A)\, [\alpha dD + (1-\alpha)xR_A] \\ + (1 - \lambda_L - \lambda_A + \rho_A)\alpha dD \geq d. \tag{11}$$

The creditor receives full repayment in all states in which either asset L is successful (first two terms of Eq. 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 (11) for D yields the creditor's interest rate for the high-exposure case:

$$D_{A,hi} = \frac{1 - \frac{1}{d}\,(\lambda_A - \rho_A)\,(1-\alpha)xR_A}{\lambda_L + (1-\lambda_L)\alpha}. \tag{12}$$

Moreover, Eq. (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. (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) and (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. (11) and $D_{A,hi}$ from Eq. (12) into Eq. (10) and simplifying yields for the bank's expected return at $t = 1$ in the high-exposure case

$$\begin{aligned}\Pi^{\star}_{A,hi} &= \Delta_A + \underbrace{(\lambda_L l R_L + \lambda_A x R_A)}_{=PV_{A,hi}} \\ &+ \underbrace{(1-\lambda_L)\alpha \frac{d - (\lambda_A - \rho_A)(1-\alpha)xR_A}{\lambda_L + (1-\lambda_L)\alpha} - (\lambda_A - \rho_A)\,\alpha x R_A}_{=G_{A,hi}} - 1. \end{aligned} \tag{13}$$

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

$$\frac{\partial \Pi^{\star}_{A,hi}}{\partial \rho_A} = \frac{\alpha x R_A}{\lambda_L + (1-\lambda_L)\alpha} > 0. \tag{14}$$

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. 10); on the other hand, it leads to higher financing costs, as the bank's creditor demands a higher interest rate (see Eq. 12). Without government guarantees, these two channels exactly offset each other (i.e., $\partial \Pi^{\star}_{A,hi}/\partial \rho_A(\alpha = 0) = 0$), as shown by Eq. (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 $\Pi^{\star}_{A,hi}$ 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. (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. 13). As a result, the bank's expected return increases with the return correlation between the marginal and the legacy asset.

Finally, comparing Eq. (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 su ciently* *low, that is,*

$$\Delta \leq \Delta_{hi}^{*} \equiv \alpha \frac{(\lambda_{\underline{A}} \rho_{\overline{A}} - \lambda_{\overline{A}} \rho_{\underline{A}}) x R}{\lambda_{\overline{A}} \lambda_{\underline{A}} (\alpha + (1-\alpha)\lambda_L)}. \tag{15}$$

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

$$E[\Delta_{hi}^{*}] = \alpha \frac{(\rho_{\overline{A}} - \rho_{\underline{A}}) x R}{\lambda (\alpha + (1-\alpha)\lambda_L)}. \tag{16}$$

From Eq. (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

$$F_{\overline{A},hi} \equiv P(\Delta \leq \Delta_{hi}^{*}) = \frac{E[\Delta_{hi}^{*}]}{2\delta}. \tag{17}$$

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

$$\frac{\partial F_{\overline{A},hi}}{\partial \alpha} = \frac{1}{2\delta} \frac{\lambda_L (\rho_{\overline{A}} - \rho_{\underline{A}}) x R}{\lambda (\lambda_L + (1-\lambda_L)\alpha)^2} > 0. \tag{18}$$

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.

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 1. *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*

$$\frac{\partial F_{\overline{A},hi}}{\partial \alpha} > \frac{\partial F_{\overline{A},low}}{\partial \alpha}. \tag{19}$$

Proof. See Appendix A.

The result summarized in Proposition 1 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 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.

3.1 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 and 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.

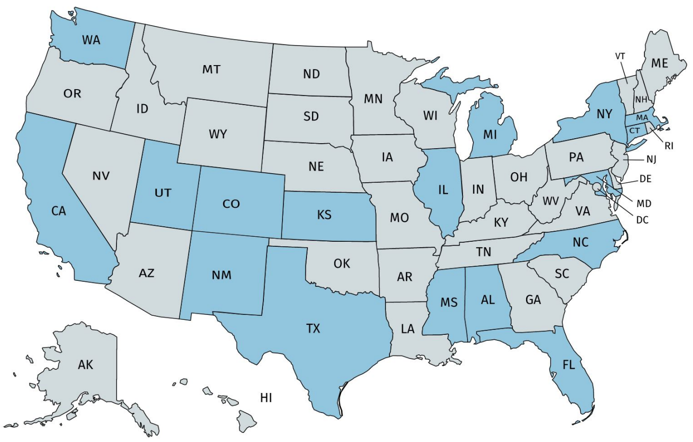
We build on the geography-based political connection measure from Kostovetsky (2015) to identify variation in banks' expected government guarantee values. The results therein are consistent with the conjecture that having a senator from its state of incorporation in the BHUA Senate committee significantly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

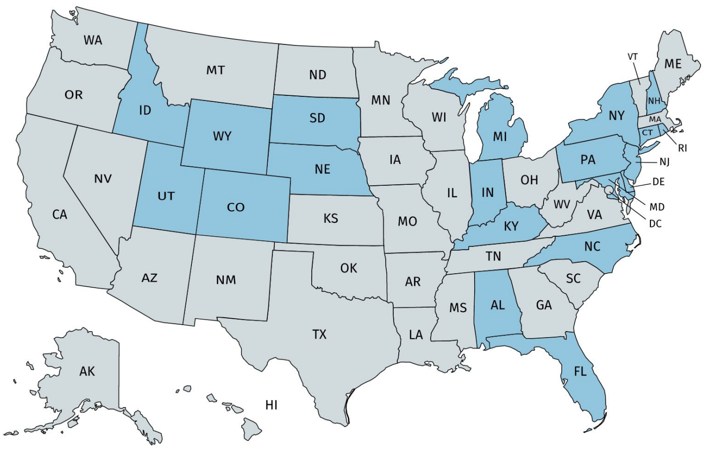
Although senators are formally elected to standing committees by the entire membership of the Senate, in practice each party conference is largely responsible for determining which of its members will sit on each committee. Party conferences appoint a "committee on committees" or a "steering committee" 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.

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

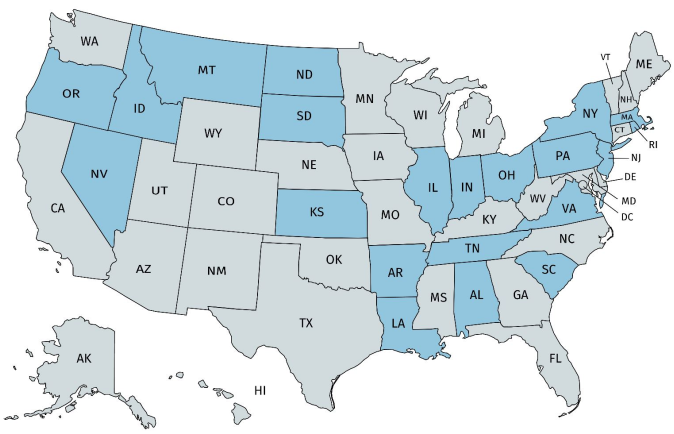
Figure 1: States with a senator in the BHUA Senate committee (in light blue) in 1996, 2006, and 2016.



(a) As of 1996



(b) As of 2006



(c) As of 2016

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 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 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 $\mathit{GG}_{b,t}$ (for Government Guarantee) 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 $\triangle \mathit{GG}_{b,t}$, which can take the values $\{-1, 0, 1\}$: 0 when there was no change in $\mathit{GG}_{b,t}$ in year t, 1 if $\mathit{GG}_{b,t}$ changed from zero to one, and -1 if $\mathit{GG}_{b,t}$ 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 $\mathit{GG}_{b,t}$ during our sample period.

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

Table 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.

lender's portfolio, the class weight (CW) at time t, calculated as

$$CW_{b,c,t} = \frac{Lending\ Volume\ to\ Class_{b,c,t}}{Total\ Lending\ Volume_{b,t}}. \tag{20}$$

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

Table 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

class c times its logarithm:

$$Portfolio\ HHI_{b,t} = \sum[CW^2_{b,c,t}] \times 100 \tag{21}$$

$$Portfolio\ EDM_{b,t} = \sum[CW_{b,c,t} * Log(CW_{b,c,t})] \times 100. \tag{22}$$

A higher HHI and EDM both correspond to a higher asset concentration in the bank's loan portfolio. Table 2 provides an overview over the definitions of our dependent, independent, and control variables and Table 3 presents summary statistics for portfolio 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]

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.

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:

$$y_{b,t+1} = \alpha_t + \alpha_b + \beta_1 GG_{b,t} + \delta X_{b,t} + \epsilon_{b,t}, \tag{23}$$

where $y_{b,t+1}$ is either $\mathit{HHI}_{b,t+1}$ or $\mathit{EDM}_{b,t+1}$. 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 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.

[13] For example, Hansen et al. (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 et al. (2003) and Carazo Hitos et al. (2010) find a default correlation within mortgages 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%.

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:

$$\begin{aligned} y_{b,t+1} &= \alpha_t + \alpha_b + \beta_1 GG_{b,t} + \beta_2 Lending\ Exposure_{b,t} \\ &+ \beta_3 GG_{b,t} \times Lending\ Exposure_{b,t} + \delta X_{b,t} + \epsilon_{b,t}, \end{aligned} \tag{24}$$

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 (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:

$$\begin{aligned} y_{b,t+1} &= State_s \times \alpha_t + \alpha_b + \beta_1 Lending\ Exposure_{b,t} \\ &+ \beta_2 GG_{b,t} \times Lending\ Exposure_{b,t} + \delta X_{b,t} + \epsilon_{b,t}. \end{aligned} \tag{25}$$

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.

4.2 Results

Table 4 shows the regression results for Specification (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 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 (24), we further investigate whether the outcome differences between banks with high vs. low lending exposures are statistically different (see Panel A of Table 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

[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 4.3.

Table 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 (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. (21). The dependent variable in columns (4)-(6) is the entropy measure of bank b's lending portfolio in $(t+1)$ from Eq. (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 4.3.

with very high lending exposures. Accordingly, we employ dummies indicating a very 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 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 5 shows that the results on the moderating effect of banks' lending

Table 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 (24) (Panel A) and Specification (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. (21). The dependent variables in columns (4)-(6) is the entropy measure of bank b's lending portfolio in $(t+1)$ from Eq. (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: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

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.

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 and Pischke, 2009). Specifically, we perform an additional DiD estimation "treating" banks three years before the actual treatment.[15]

Table B.1 presents the placebo test results for the effect on banks' portfolio concentration from Table 4 and Table B.2 for the effects conditional on banks' lending exposure from Table 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 and d'Haultfoeuille, 2020; Callaway and Sant'Anna, 2021; Goodman-Bacon, 2021; Imai and Kim, 2021; Sun and Abraham, 2021; Athey and 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 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

[15] Our results from Section 5 suggest that the effects take three years to build up.

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 (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 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 and 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 and d'Haultfoeuille, 2020), suggesting that $T2$ would imply implausibly large treatment effect heterogeneity.

Hence, our full sample results in Table 4 pass both diagnostic tests. Note that the interaction specifications in Table 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 4, respectively, which closely resemble the tests from Table 5. Again, our results pass both diagnostic tests.

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.

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:

$$\begin{aligned} y_{b,c,t+h} &= \alpha_b + Class_c \times \alpha_t + \beta_1 \triangle GG_{b,t} + \beta_2 Exposure\ Ratio_{b,c,t} \\ &+ \beta_3 \triangle GG_{b,t} \times Exposure\ Ratio_{b,c,t} + \delta X_{b,t} + \epsilon_{b,c,t}. \end{aligned} \tag{26}$$

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 $\textit{Exposure Ratio}_{b,c,t}$ 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 (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 (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:

$$\begin{aligned} y_{b,c,t+h} &= \alpha_b + Class_c \times \alpha_t + State_s \times \alpha_t + \beta_1 Exposure\ Ratio_{b,c,t} \\ &+ \beta_2 \triangle GG_{b,t} \times Exposure\ Ratio_{b,c,t} + \delta X_{b,t} + \epsilon_{b,c,t}. \end{aligned} \tag{27}$$

5.2 Results

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

5.2.1 Portfolio weights

Table 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 (26) and Panel B for Specification (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 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 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 (26) (Panel A) and Specification (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. *4GG* can take the values $f{-1}, 0, 1g$: 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 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 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.

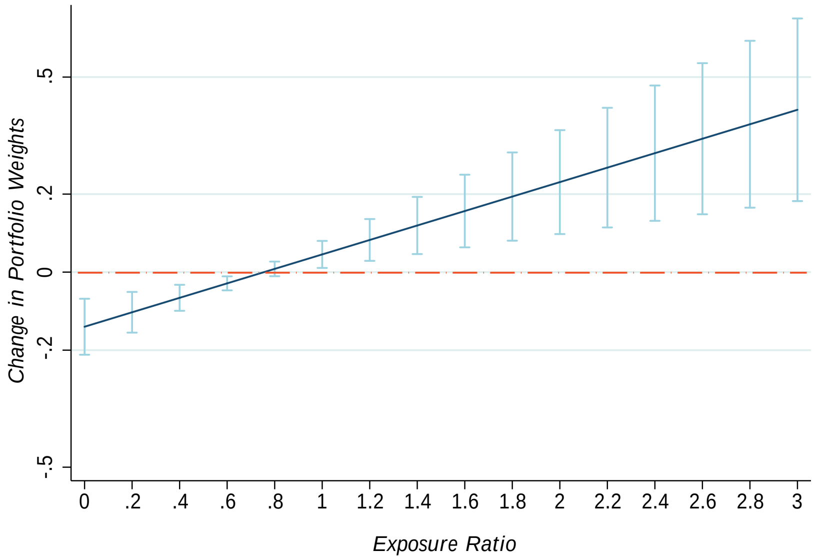
5.2.2 Loan volumes

We find corresponding evidence for shifts in banks' lending volume across loan classes. Specifically, the results in Table 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 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 7, Panel A suggest that three years after a positive change in *GG*, banks increase their loan volume to high-exposure loan classes

Figure 2: Change in Portfolio Weights at $t = 3$



This figure presents post-estimation results derived from Specification (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., $|\Delta GG| = 1$), 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. ΔGG 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.

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).

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 B.3 and B.4 show that the results from Tables 6 and 7 are robust to this restriction.

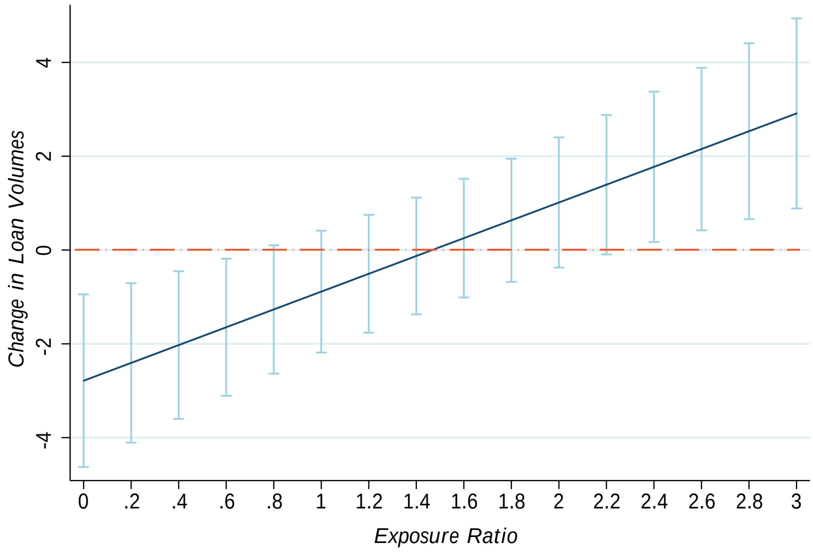
Next, we confirm that our results are not driven by certain years. Table B.5 shows the estimation results for the analyses from Table 6 and 7 but excluding one year at a

Table 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)
△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)
△GG x Exposure Ratio	0.132	1.131**	1.903***			
	(0.617)	(0.018)	(0.002)			
△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)
△GG x Exposure Ratio	0.044	0.956*	1.761***			
	(0.873)	(0.062)	(0.009)			
△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 (26) (Panel A) and Specification (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. *4 GG* can take the values $f-1, 0, 1g$: 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: Change in Lending Behavior at $t = 3$



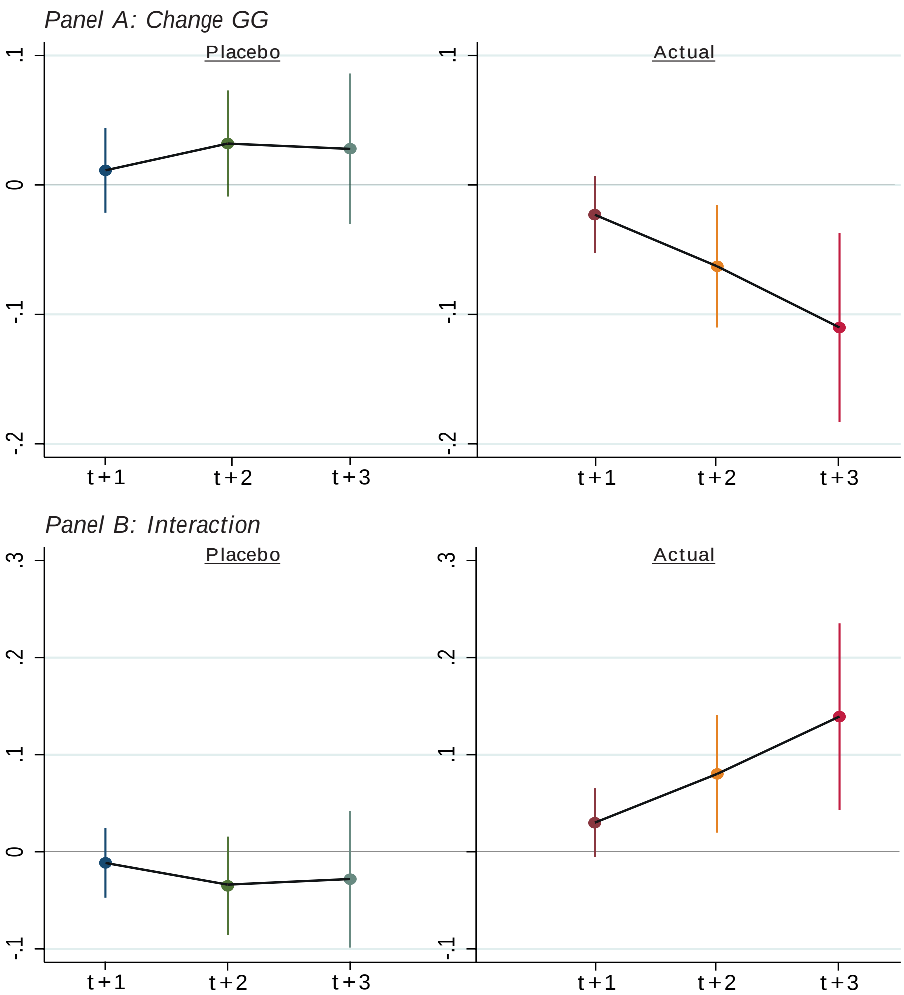
This figure presents post-estimation results derived from Specification (26) for the period 1996-2016. The dependent variable is the change in the log of one plus the weight of loan class *c* over total lending of bank *b* from year t to $t + 3$ ($\Delta Log(1 + LCV)_{b,c,t+3}$). The blue line represents the predicted additional change in the dependent variable when bank *b* experiences a change in $GG_{b,t}$ in t, (i.e., $j4GGj = 1$), 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. $4GG$ can take the values $f-1, 0, 1g$: 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.

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 B.6 presents the placebo test results for the change in portfolio weights and Table B.7 for the change in loan volumes. All DiD estimates in the pre-treatment period are again statistically indistinguishable from zero. Figures 4 and 5 visualize the placebo test results together with the DiD results from Tables 6 and 7, respectively.

The staggered DiD design that we employ for the analysis in Section 5 could, in general, be affected by the "negative weighting" problem discussed in Section 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

Figure 4: Visualization of the Portfolio Weights Results

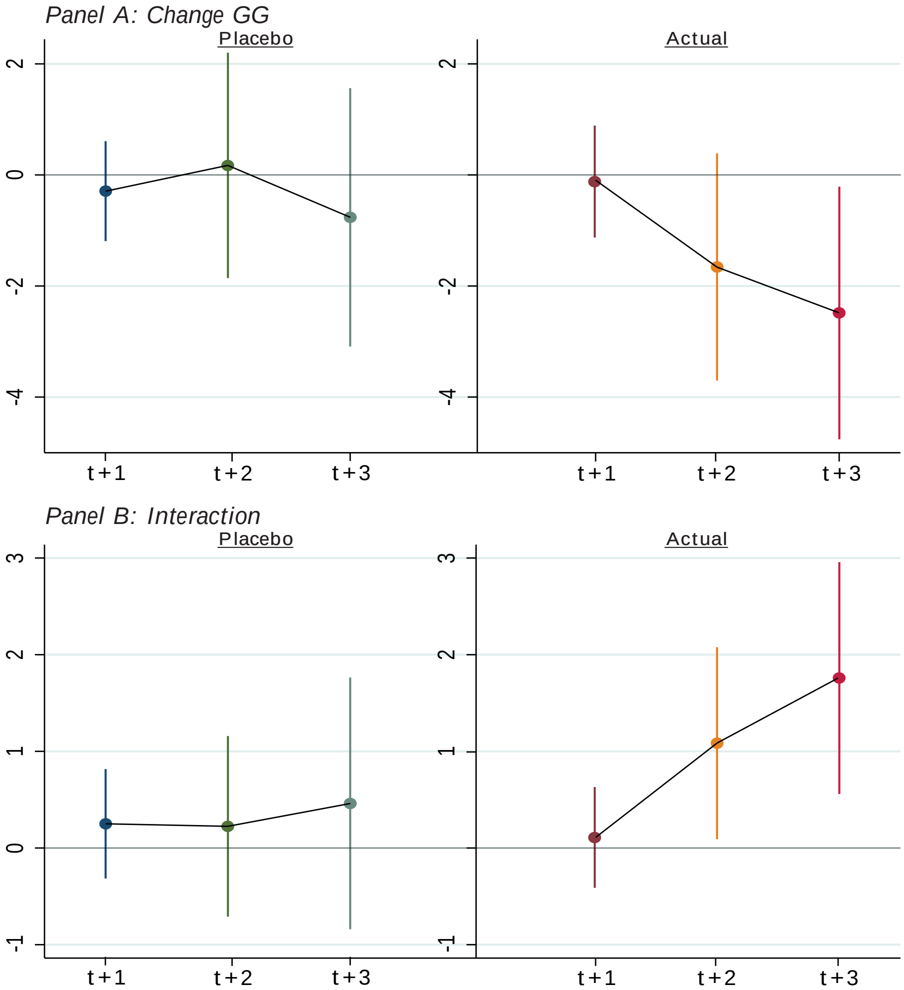


This figure visualizes the results from Table 6 (the two panels on the right) and the corresponding placebo test three years before the actual treatment from Table B.6 (the two panels on the left). The dots indicate the estimated coe□cients, Panel A for β_1 in Specification (26) and Panel B for β_3, respectively. We plot the 95% confidence interval for each coe□cient.

(26), however, do not allow us to implement the weight decomposition from De Chaisemartin and d'Haultfoeuille (2020), which we apply in Section 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 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

Figure 5: Visualization of the Loan Volume Results



This figure visualizes the results from Table 7 (the two panels on the right) and the corresponding placebo test three years before the actual treatment from Table B.7 (the two panels on the left). The dots indicate the estimated coefficients, Panel A for β_1 in Specification (26) and Panel B for β_3, respectively. We plot the 95% confidence interval for each coefficient.

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 B.8 and 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. The fact that our results are even stronger for our binary treatment in columns (4)-(6) of Tables 6 and 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.

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., Borusyak et al., 2021; Goodman-Bacon, 2021; De Chaisemartin and 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").

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:

$$\begin{aligned} y_{b,c,t+1} = {} & \alpha_b + Class_c \times \alpha_t + \beta_1 Treated_b + \beta_2 Post_t + \beta_3 Exposure\ Ratio_{b,c,t} \\ & + \beta_4 Treated_b \times Post_t + \beta_5 Treated_b \times Exposure\ Ratio_{b,c,t} \\ & + \beta_6 Post_t \times Exposure\ Ratio_{b,c,t} \\ & + \beta_7 Treated_b \times Post_t \times Exposure\ Ratio_{b,c,t} + \delta X_{b,t} + \epsilon_{b,c,t}, \end{aligned} \tag{28}$$

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

[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 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	-0.125**		0.128**	
x Exposure Ratio	(0.029)		(0.022)	
Treated x Post		-0.261**		0.289**
x Top 25% Exposure		(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	-1.874**		2.548**	
x Exposure Ratio	(0.043)		(0.021)	
Treated x Post		-3.902**		5.964***
x Top 25% Exposure		(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 (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: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

variables are the one-year change in bank b's portfolio weights and loan volumes for the different loan classes.

The variable $\textit{Treated}_b$ 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 $\textit{Post}_{b,t}$ 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 $\textit{Exposure Ratio}_{b,c,t}$ 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 (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.

6.2 Results

Table 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 $\textit{Treated}_b$ 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 $\textit{Treated}_b$ 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 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 $\mathit{Treated}_b$ as follows: $\mathit{Treated}_b$ 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 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.

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 B.11 and B.12 suggest that the parallel trends assumption also holds for the modified DiD design.

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 et al., 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 and 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.

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Internet Appendix

"Concentrating on Bailouts: Government Guarantees and Bank Asset Composition"

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October 2022

Structure

This online appendix is structured as follows. Section Appendix A presents the proofs for our theoretical model. Section Appendix B presents additional tables.

Appendix A Proofs

Proof of Lemma 1

Setting $\Pi^{\star}_{\overline{A},lo}$ equal to $\Pi^{\star}_{\underline{A},lo}$ (see Eq. 4) and solving for Δ yields

$$\begin{aligned}\Delta^{\star}_{lo} &= \frac{(1-\lambda_L-\lambda_{\overline{A}}+\rho_{\overline{A}})\alpha d}{\rho_{\overline{A}}+(\lambda_L-\rho_{\overline{A}})+(\lambda_{\overline{A}}-\rho_{\overline{A}})+(1-\lambda_L-\lambda_{\overline{A}}+\rho_{\overline{A}})\alpha} \\ &- \frac{(1-\lambda_L-\lambda_{\underline{A}}+\rho_{\underline{A}})\alpha d}{\rho_{\underline{A}}+(\lambda_L-\rho_{\underline{A}})+(\lambda_{\underline{A}}-\rho_{\underline{A}})+(1-\lambda_L-\lambda_{\underline{A}}+\rho_{\underline{A}})\alpha}. \end{aligned} \tag{A1}$$

Eq. (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. (9) can switch sign, depending on α. First, note that for $\alpha=0$, $\partial F_{\overline{A},lo}/\partial\alpha$ becomes

$$\frac{\partial F_{\overline{A},lo}}{\partial\alpha}(\alpha=0) = \frac{1}{2\delta}\frac{d(\rho_{\overline{A}}-\rho_{\underline{A}})}{(\lambda_L+\lambda-\rho_{\overline{A}})(\lambda_L+\lambda-\rho_{\underline{A}})} > 0, \tag{A2}$$

which is always positive as $\rho_{\overline{A}}>\rho_{\underline{A}}$. Moreover, for $\alpha=1$, $\partial F_{\overline{A},lo}/\partial\alpha$ becomes

$$\begin{aligned}\frac{\partial F_{\overline{A},lo}}{\partial\alpha}(\alpha=1) &= -\frac{1}{2\delta}d(\rho_{\overline{A}}-\rho_{\underline{A}})(1-\lambda_L-\lambda+\rho_{\overline{A}})(1-\lambda_L-\lambda+\rho_{\underline{A}}) \\ &+ \frac{1}{2\delta}d(\rho_{\overline{A}}-\rho_{\underline{A}})(\lambda_L+\lambda-\rho_{\overline{A}})(\lambda_L+\lambda-\rho_{\underline{A}}). \end{aligned} \tag{A3}$$

Hence, if

$$(1-\lambda_L-\lambda+\rho_{\overline{A}})(1-\lambda_L-\lambda+\rho_{\underline{A}}) > (\lambda_L+\lambda-\rho_{\overline{A}})(\lambda_L+\lambda-\rho_{\underline{A}}), \tag{A4}$$

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. (9) is a continuous function of α. Hence, if Condition (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 (A4) is not satisfied, it always holds that $\partial F_{\overline{A},lo}/\partial\alpha \geq 0$.

Proof of Proposition 1

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,

$$\begin{aligned}\overline{Z} \equiv \frac{\partial F_{\overline{A},hi}}{\partial\alpha} - \frac{\partial F_{\overline{A},lo}}{\partial\alpha} = {} & \frac{1}{2\delta}\frac{\lambda_L(\lambda-\rho_{\underline{A}})}{\lambda(\lambda_L+(1-\lambda_L)\alpha)^2}xR \\ & -\frac{1}{2\delta}\frac{(\lambda_L+\lambda-\rho_{\overline{A}})(1-\lambda_L-\lambda+\rho_{\overline{A}})}{(\rho_{\overline{A}}+(\lambda_L-\rho_{\overline{A}})+(\lambda-\rho_{\overline{A}})+(1-\lambda_L-\lambda+\rho_{\overline{A}})\alpha)^2}d \\ & -\frac{1}{2\delta}\frac{\lambda_L(\lambda-\rho_{\overline{A}})}{\lambda(\lambda_L+(1-\lambda_L)\alpha)^2}xR \\ & +\frac{1}{2\delta}\frac{(\lambda_L+\lambda-\rho_{\underline{A}})(1-\lambda_L-\lambda+\rho_{\underline{A}})}{(\rho_{\underline{A}}+(\lambda_L-\rho_{\underline{A}})+(\lambda-\rho_{\underline{A}})+(1-\lambda_L-\lambda+\rho_{\underline{A}})\alpha)^2}d > 0.\end{aligned} \tag{A5}$$

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

$$\begin{aligned}
\underline{Z} &\equiv \frac{1}{2\delta}\frac{\lambda_L(\lambda-\rho_{\underline{A}})}{\lambda(\lambda_L+(1-\lambda_L)\alpha)^2} \\
&- \frac{1}{2\delta}\frac{(\lambda_L+\lambda-\rho_{\overline{A}})(1-\lambda_L-\lambda+\rho_{\overline{A}})}{(\rho_{\overline{A}}+(\lambda_L-\rho_{\overline{A}})+(\lambda-\rho_{\overline{A}})+(1-\lambda_L-\lambda+\rho_{\overline{A}})\alpha)^2} \\
&- \frac{1}{2\delta}\frac{\lambda_L(\lambda-\rho_{\overline{A}})}{\lambda(\lambda_L+(1-\lambda_L)\alpha)^2} \\
&+ \frac{1}{2\delta}\frac{(\lambda_L+\lambda-\rho_{\underline{A}})(1-\lambda_L-\lambda+\rho_{\underline{A}})}{(\rho_{\underline{A}}+(\lambda_L-\rho_{\underline{A}})+(\lambda-\rho_{\underline{A}})+(1-\lambda_L-\lambda+\rho_{\underline{A}})\alpha)^2} \geq 0, \qquad \text{(A6)}
\end{aligned}$$

to prove that Eq. (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. (A6) yields

$$\begin{aligned}
\underline{Z} &= \frac{1}{2\delta}\frac{\lambda_L\underline{X}}{\lambda(\lambda_L+(1-\lambda_L)\alpha)^2} - \frac{1}{2\delta}\frac{(\lambda_L+\overline{X})(1-\lambda_L-\overline{X})}{\left(\lambda_L+\overline{X}+(1-\lambda_L-\overline{X})\alpha\right)^2} \\
&- \frac{1}{2\delta}\frac{\lambda_L\overline{X}}{\lambda(\lambda_L+(1-\lambda_L)\alpha)^2} + \frac{1}{2\delta}\frac{(\lambda_L+\underline{X})(1-\lambda_L-\underline{X})}{\left(\lambda_L+\underline{X}+(1-\lambda_L-\underline{X})\alpha\right)^2}. \qquad \text{(A7)}
\end{aligned}$$

Next, we show that $\underline{Z}$ in Eq. (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

$$\begin{aligned}
\frac{\partial \underline{Z}}{\partial \overline{X}} &= \frac{1}{2\delta}\left[\frac{1}{1-\alpha}\left(1-\frac{\alpha}{\alpha+(1-\alpha)\left(\lambda_L+\overline{X}\right)}\right) - \frac{\lambda_L}{\lambda(\lambda_L+(1-\lambda_L)\alpha)^2}\right] \qquad \text{(A8)} \\
\frac{\partial \underline{Z}}{\partial \underline{X}} &= -\frac{1}{2\delta}\left[\frac{1}{1-\alpha}\left(1-\frac{\alpha}{\alpha+(1-\alpha)\left(\lambda_L+\underline{X}\right)}\right) - \frac{\lambda_L}{\lambda(\lambda_L+(1-\lambda_L)\alpha)^2}\right], \qquad \text{(A9)}
\end{aligned}$$

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. (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 $\rho_{\underline{A}} = 0$:

$$\underline{Z}(\overline{X} = \lambda - \underline{\lambda}, \underline{X} = \lambda) = \frac{1}{2\delta}\left[\frac{\lambda_L}{\lambda_L + (1-\lambda_L)\alpha)^2}\right] - \frac{1}{2\delta}\left[\frac{(\lambda_L + \overline{X})(1-\lambda_L - \overline{X})}{\left(\lambda_L + \overline{X} + (1-\lambda_L - \overline{X})\alpha\right)^2}\right] - \frac{1}{2\delta}\left[\frac{\lambda_L \overline{X}}{\lambda(\lambda_L + (1-\lambda_L)\alpha)^2}\right] + \frac{1}{2\delta}\left[\frac{(\lambda_L + \lambda)(1-\lambda_L - \lambda)}{\left(\lambda_L + \lambda + (1-\lambda_L - \lambda)\alpha\right)^2}\right]. \quad \text{(A10)}$$

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. (A7) becomes

$$Z(\overline{X} = 0, \underline{X} = \lambda) = \frac{1}{2\delta}\left[\frac{\lambda_L}{(\lambda_L + (1-\lambda_L)\alpha)^2}\right] - \frac{1}{2\delta}\left[\frac{\lambda_L(1-\lambda_L)}{\left(\lambda_L + (1-\lambda_L)\alpha\right)^2}\right] + \frac{1}{2\delta}\left[\frac{(\lambda_L + \lambda)(1-\lambda_L - \lambda)}{\left(\lambda_L + \lambda + (1-\lambda_L - \lambda)\alpha\right)^2}\right] > 0, \quad \text{(A11)}$$

which is positive since the first term in Eq. (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. (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 $\rho_{\underline{A}} = 0$:

$$\underline{Z}(\overline{X} = \lambda, \underline{X} = \lambda) = \frac{1}{2\delta}\left[\frac{\lambda_L \underline{X}}{\lambda(\lambda_L + (1-\lambda_L)\alpha)^2}\right] - \frac{1}{2\delta}\left[\frac{(\lambda_L + \overline{X})(1-\lambda_L - \overline{X})}{\left(\lambda_L + \overline{X} + (1-\lambda_L - \overline{X})\alpha\right)^2}\right] - \frac{1}{2\delta}\left[\frac{\lambda_L \overline{X}}{\lambda(\lambda_L + (1-\lambda_L)\alpha)^2}\right] + \frac{1}{2\delta}\left[\frac{(\lambda_L + \underline{X})(1-\lambda_L - \underline{X})}{\left(\lambda_L + \underline{X} + (1-\lambda_L - \underline{X})\alpha\right)^2}\right] = 0, \quad \text{(A12)}$$

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. (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. (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 $\partial F_{\overline{A},hi}/\partial \alpha > \partial F_{\overline{A},low}/\partial \alpha$.

Appendix B Additional Tables

Table 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 (23), where we redo the estimations from Table 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 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 (24) (Panel A) and Specification (25) (Panel B), where we redo the estimations from Table 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 B.3: Change in Portfolio Weights on Loan Class Level – Non-Missing Outcome Leads

	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	-0.030*	-0.073***	-0.111***	-0.015	-0.051**	-0.073**
	(0.097)	(0.006)	(0.004)	(0.315)	(0.019)	(0.010)
△GG x Exposure Ratio	0.044**	0.096***	0.140***			
	(0.017)	(0.003)	(0.004)			
△GG x Top 25% Exposure				0.079	0.227**	0.298**
				(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: Intra-State	ΔPW (t+1)	ΔPW (t+2)	ΔPW (t+3)	ΔPW (t+1)	ΔPW (t+2)	ΔPW (t+3)
△GG x Exposure Ratio	0.042**	0.093***	0.138***			
	(0.020)	(0.003)	(0.004)			
△GG x Top 25% Exposure				0.076	0.227**	0.297**
				(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 (26) (Panel A) and Specification (27) (Panel B), where we redo the estimations from Table 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 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 (26) (Panel A) and Specification (27) (Panel B), where we redo the estimations from Table 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 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 6 and 7 (the coe□cient β_3 from Specification 26), but excluding one year at a time. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 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)
$\triangle$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)
$\triangle$GG x Exposure Ratio	-0.010	-0.032	-0.025			
	(0.581)	(0.198)	(0.480)			
$\triangle$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)
$\triangle$GG x Exposure Ratio	-0.010	-0.034	-0.027			
	(0.567)	(0.172)	(0.450)			
$\triangle$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 (26) (Panel A) and Specification (27) (Panel B), where we redo the estimations from Table 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 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)
△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)
△GG x Exposure Ratio	0.229	0.186	0.411			
	(0.440)	(0.678)	(0.508)			
△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)
△GG x Exposure Ratio	0.124	0.119	0.310			
	(0.693)	(0.814)	(0.647)			
△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 (26) (Panel A) and Specification (27) (Panel B), where we redo the estimations from Table 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 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 (26) (Panel A) and Specification (27) (Panel B), where we redo the estimations from Table 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 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)
△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)
△GG x Exposure Ratio	0.106	1.109**	1.909***			
	(0.698)	(0.022)	(0.002)			
△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)
△GG x Exposure Ratio	0.018	0.920*	1.750**			
	(0.950)	(0.080)	(0.010)			
△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 (26) (Panel A) and Specification (27) (Panel B), where we redo the estimations from Table 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 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 (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 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 x Exposure Ratio	0.016		0.029	
	(0.892)		(0.711)	
Treated x Post x Top 25% Exposure		0.244		0.172
		(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 x Exposure Ratio	2.191		-0.210	
	(0.371)		(0.896)	
Treated x Post x Top 25% Exposure		5.587		-0.475
		(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 (28), where we redo the estimations from Table 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 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 (28), where we redo the estimations from Table 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: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.