Asymmetric Systemic Risk

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August 16, 2022

Abstract

Bank regulation presumes risks spill over more easily from large banks to the banking system than vice versa. Yet, we document that risk transmission is stronger in the system-to-bank direction, because different bank activities affect the flow of risk differently in each direction. We term this phenomenon asymmetric systemic risk, measure it with net exposure metrics, and explore the consequences and channels behind it. We show that high-net-exposure banks faced higher default risk during the 2008 crisis, and that trading activities and bank size were the main determinants of this net exposure, which increased default risk through trading income volatility.

Keywords: systemic risk, financial stability.

JEL codes: G10, G20.

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"...Supervision of large financial institutions is designed to: (i) enhance the resiliency of these firms, in order to lower probability of failure or inability to serve as a financial intermediary, and (ii) to reduce the impact on the financial system and the broader economy in the event of a firm's failure or material weakness." Board of Governors of the Federal Reserve System (2020)

1 Introduction

Large US banks are regulated with the explicit intention to limit their risk impact on the rest of the banking system. This impact is often termed *systemic risk contribution* (Adrian and Brunnermeier, 2016), reflecting the systemic risk transmission from the bank to the system. Regulations implemented through the Dodd-Frank Act and the Basel III standard explicitly seek to reduce this transmission by making large banks subject to more complex regulations, higher capital requirements, and more regulatory scrutiny than smaller banks.[1] At the same time, interconnectedness in the modern financial system also exposes large banks to shocks emanating from the rest of the banking system, creating *systemic risk exposures* in the system-to-bank direction. This paper investigates what these directional risk linkages mean when interconnectedness is stronger in one direction than in the other, and what the effect of this asymmetry is on bank soundness. Furthermore, we explore the mechanisms behind this relation. We hypothesize that banks with different business models can undertake activities that affect their systemic contributions and exposures differently, thereby creating asymmetric (directional) linkages with the rest of the system that matter for individual bank stability.

The recent literature has developed systemic exposure and contribution metrics, permitting researchers to quantify the flow of systemic risk between the bank and the system in each direction. For example, one common metric of systemic risk contribution is Adrian and Brunnermeier's ΔCoVaR, while Acharya et al.'s (2017) marginal expected shortfall (MES) and Adrian and Brunnermeier's Exposure ΔCoVaR are examples of metrics of systemic risk exposure. However, the literature has not yet considered what the directionality

[1] The Dodd-Frank Act of 2012 strengthened existing measures and introduced new ones aimed at large banks, such as countercyclical capital buffers, DSIB capital surcharges, and annual stress tests, in order to increase solvency and prevent default risks from spilling over to the rest of the system.

of such systemic risk linkages implies if the linkage in one direction is stronger than in the other one. To find this out, we compare banks' systemic exposures and contributions with a net exposure metric, and study the effect of asymmetric systemic risk transmission on bank stability.

The importance of examining banks' systemic exposures versus contributions can be illustrated with simple, but telling facts. Based on how large US banks are regulated, one would expect that their systemic risk contributions ought to exceed their systemic risk exposures, i.e., that their risks ought to spill over to other banks more easily rather than vice versa. More importantly, one would also expect that risk externalities generated by important banks are more detrimental to financial stability than their exposure to such risks. Surprisingly, however, we observe this is not the case. Figure 1 shows the average exposure and contribution for the 200 largest publicly traded US bank holding companies around the 2007–09 financial crisis.[2] The figure shows that the average systemic exposure (the blue line) is consistently higher than the average contribution (the red line), resulting in positive net exposure (the difference between banks' exposure and contribution). In addition, Figures 2 and 3 reveal that banks that experienced insolvency during the crisis[3] (colored in red) had consistently larger exposures than contributions, therefore appearing to the right of each chart's 45^{o} line. These figures show this pattern holds for banks with different sizes (Figure 2) and individual default risk (Figure 3).

Motivated by these facts and a toy model to build intuition, we hypothesize that banks' net exposures result from business models that affect exposure and contribution differently, and more precisely, from the balance between traditional lending and non-traditional trading activities. Since this balance also impacts a bank's risk-return profile, we hypothesize systemic risk *directionality* matters for banks' individual stability.

We predict that banks optimally choose involvement in trading activities because they provide a hedge against idiosyncratic shocks, thereby reducing banks' systemic contributions, but at the cost of exposing the

[2]Systemic risk measures in this figure are computed using Adrian and Brunnermeier's (2016) ΔCoVaR and Exposure ΔCoVaR, defined in Section 4.

[3]These are banks that failed, had a direct subsidiary fail, received an enforcement action by the FDIC, or were acquired to prevent failure.

banks to common shocks, which increase their systemic exposure. Thus, an optimally diversified portfolio consists of contribution-increasing traditional activities (e.g., real estate, household, and C&I loans) as well as exposure-increasing trading activities, which move exposure and contribution metrics in opposite directions. The net balance between these activities determines the bank's overall net exposure. Since trading increases exposure and reduces contribution, the model predicts higher diversification towards trading increases a bank's *net* exposure to systemic risk. Conditional on a crisis increasing cross-asset return covariances, the model predicts that high net exposure banks may face higher default risk through increasing the volatility of profits.

We first test whether a bank's business model is correlated with its systemic net exposure. For this, we relate balance sheet variables with a bank's net exposure computed using Adrian and Brunnermeier's (2016) ΔCoVaR and Exposure ΔCoVaR.[4] Interestingly, we find that some variables that have been identified as a source of systemic risk (such as some non-interest income activities and the share of real estate loans) do not matter much for banks' *net* exposures, whereas size, which has also been identified as a source of systemic risk, shows to be positively related to it. We also confirm our predictions and find that banks' business models strongly correlate to banks' net exposures. In particular, non-traditional activities proxied by the use of credit default swaps and trading activities increase a bank's net exposure, whereas traditional household and C&I lending negatively affect a bank's net exposure. To further understand though which channel bank characteristics affect banks' net exposure, we decompose a bank's net exposure into (1) the net simulated shock to the bank, that is, the difference between the losses to be transmitted to the bank when the system is in distress and the losses to be transmitted to the system when the bank is in distress, and (2) the net transmission factor, that is, the difference between the fraction of the simulated shock transmitted from the system to the bank and the fraction transmitted from the bank to the system. The analysis suggests that the effect of size, trading activities, and the use of credit default swaps on net exposure is due to their

[4] We also test the robustness of our results using Acharya et al.'s (2017) MES (marginal expected shortfall) and Oordt and Zhou's (2019a) tail beta.

impact on the net transmission factor and not on the net simulated shock to the bank, thus increasing the net fraction of losses transmitted in the system-to-bank direction. This is also the case for traditional lending, which decreases the net fraction of losses transmitted from the system to the bank.

We confirm this asymmetry matters for banks' stability. We use a variety of default risk measures (distance to default, Z-scores, and an indicator for insolvency based on banks' default or cease-and-desist orders) to establish that net exposure before the global financial crisis meaningfully correlates with banks' default risk during the crisis. This effect is economically significant. For example, one standard deviation increase in net exposure deteriorates a bank's distance to default by 0.11 standard deviations, its log(Z-Score) by 0.34 standard deviations, and increases its probability of insolvency by 3 percentage points.

Furthermore, we examine the channels behind this relation. We show that the effect on bank default risk is also driven by the net transmission factor rather than the net losses. In addition, in line with the model intuition, we find the link between the net transmission factor and insolvency runs through asset risk, increasing the volatility of trading income and profits.

Taken together, the evidence in this paper suggests high-net exposure banks engaged in activities that increased systemic exposure and, in particular, the transmission linkages with the rest of the system, such as derivatives trading, leaving banks exposed to the soundness of other counterparties. With the extensive involvement in these activities, banks suffered from increased income volatility during the crisis, increasing default risk. Trading activities were carried out at the cost of performing other activities that would have increased banks' systemic contribution but would have featured lower default risk, such as traditional lending activities.

Our findings offer two important policy implications. First, interconnectedness in the financial system is directional, and future bank regulation will increasingly need to reflect this. Regulation should focus on containing and imposing buffers on high-net exposure banks, rather than just large banks or banks displaying high systemic contributions. Second, default risk increases with the net transmission factor, which is positively related to size and trading activities. We argue that current bank supervision objectives can be achieved more efficiently if regulation focuses on reducing such net transmission factors, rather than buffering the default risks arising from them. Therefore, regulators should focus on monitoring banks' size and further reducing banks' interconnectedness through the derivatives market.

Our paper contributes to three distinct strands of literature. First, it contributes to the literature studying systemic risk measurement. Most of these papers have focused on measuring systemic risk exposure. Acharya et al. (2017) propose to measure systemic risk through the marginal expected shortfall (MES), which is the expected loss of a financial institution conditional on the banking sector performing poorly. The *SRISK* (Brownlees and Engle, 2017) calculates the expected capital shortfall of a financial institution conditional on a severe market decline. Finally, van Oordt and Zhou's (2019a) tail beta is an exposure metric estimating the sensitivity of a bank's stock return to extremely adverse shocks in the financial system based on a few tail observations. There are also a few measures proposed to capture a bank's contribution to systemic risk. Huang, Zhou, and Zhu (2011) combine default probabilities from CDS with stock returns correlations to calculate a *Distressed Insurance Premium* (DIP), which is the insurance premium required to cover distressed losses in the banking system. Thus, a bank's systemic contribution corresponds to its marginal contribution to the hypothetical distress insurance premium of the whole banking system. Some measures are defined to capture both a bank's systemic risk exposure and its contribution. Billio et al. (2012) characterize systemic risk by studying comovement through principal component analysis, thus capturing both a bank's contribution and its exposure. Diebold and Yilmaz (2014) develop directional connectedness measures based on variance decompositions. Adrian and Brunnermeier (2016) also propose a measure that can be adapted to measure systemic risk in both directions. The Exposure ΔCoVaR and ΔCoVaR estimate the change in value at risk of a bank (or the banking sector, respectively) conditional on the banking sector (or the bank) experiencing a tail event. The results in our paper suggest that one must distinguish between systemic risk measures of exposure, contribution, and the difference between the two, as net exposure is what matters for individual bank stability.

A few papers have distinguished between banks' systemic exposure and contribution when studying aspects of systemic risk. For instance, Pagano and Sedunov (2016) investigate systemic risk exposure and sovereign debt; Bostandzic and Weiss (2018) compare systemic risk contributions and exposures of US versus European banks; and Sedunov (2016) studies the determinants of banks' exposure and performance for high-exposure banks during the crisis. However, despite distinguishing exposures from contributions, these papers neither measure them in comparable units nor study the implications of their difference and, hence, of the asymmetry in the directionality of systemic risk. One exception is Diebold and Yilmaz (2014), who measure the net systemic contribution for US financial firms. They perform a descriptive univariate analysis of the net contribution of six troubled banks during the global financial crisis and find inconclusive results about the relationship between banks' solvency and net contribution. To the best of our knowledge, ours is the first paper to comprehensively study the relation between net systemic risk and bank soundness.

Second, our paper also contributes to the literature studying the relationship between banks' default risk and pre-crisis systemic risk. These papers have found mixed or insignificant results about this relationship when using a bank's exposure (e.g., Acharya et al., 2017; Fahlenbrach et al., 2012) or contribution (e.g., Sedunov, 2016). We extend this literature by showing that a bank's *net* exposure predicts the bank's insolvency during the crisis better than its pre-crisis exposure or contribution.

Third, our paper also relates to the extant work on the determinants of systemic risk. This literature has focused on the effects of bank characteristics (e.g., Davydov et al., 2021; Brunnermeier et al., 2020; Bostandzic and Weiss, 2018; Laeven et al., 2016), banking sector competition levels (e.g., Anginer et al., 2014; Silva-Buston, 2019), and country-level characteristics (De Jonghe et al., 2015; Anginer et al., 2014). Our study extends this work by taking into account the directionality of systemic risk when studying its determinants and thus, examining the determinants of a bank's net exposure. Furthermore, we also investigate the determinants of its components, of the net transmission factor, and of the net losses.

The rest of the paper is organized as follows. Section 2 describes some stylized facts. Section 3 describes a toy model to build up the intuition of our hypothesis. Section 4 describes the data and our risk measures. Section 5 shows the empirical strategy and lays out results from the regression analysis. Section 6 concludes.

2 Stylized Facts

Based on how large US banks are regulated, one would expect that their systemic contribution is larger and more important for systemic stability than the exposure they face from remaining banks. The Federal Reserve explicitly states that the supervision of large financial institutions has two goals: to "enhance the resiliency of these firms" and "reduce the impact on the financial system and the broader economy in the event of a firm's failure or material weakness." (Board of Governors of the Federal Reserve System, 2020). In line with this, the Dodd-Frank Act and Basel III regulations introduced additional capital surcharges for globally systemically important banks, a new capital conservation buffer (CCB), countercyclical capital buffers (CCyB), and annual stress testing exercises (DFAST and CCAR) targeting banks and bank holding companies with assets above $ 1 billion (Haubrich, 2020). The intention of these regulations is to shield the system from these large, "too big to fail" banks by making them more resilient.

It is therefore surprising to find that large US banks consistently face larger exposures from the rest of the system than they pose to it, resulting in positive net exposures. Figure 1 shows the average exposure and contribution of the top 200 US bank holding companies around the 2007–08 financial crisis, as measured by Adrian and Brunnermeier's (2016) Exposure ΔCoVaR and ΔCoVaR.[5] As the figure shows, large banks' exposure (the blue line) is consistently higher than their systemic risk contribution (the red line).[6] This is especially pronounced from 2007:Q3 on. Thus, the notion that large banks pose higher systemic risk than they face is not borne out by the data.

Moreover, banks with high net exposures appear to systematically differ from the rest on a number of

[5] All systemic risk measures are defined and discussed in Section 4.

[6] A similar pattern is found in Diebold and Yilmaz (2014) when measuring banks' exposure, contribution and net contribution based on variance decompositions.

dimensions. One such dimension is size. The left and right panels of Figure 2 plot contribution versus exposure for the 20 smallest and 20 largest banks in our sample, with the diagonal line indicating the locus where contribution equals exposure. While the small banks are evenly split by the diagonal in a 10:10 ratio, 17 out of the 20 top banks appear below the diagonal with a positive net exposure. As evidenced by the dispersion of points in the figure, contribution alone or exposure alone are not very good correlates of bank size; net exposure, however, is.

Figure 3 shows that banks with high net exposure performed worse during the crisis. Figure 3's two panels show contribution versus exposure for the 20 safest and 20 riskiest banks in our sample, ranked according to their distance to default. While the safe banks in the left panel overwhelmingly feature negative net exposure, the risky banks to the right are mostly to the right of the main diagonal, featuring positive net exposure. In both Figures 2 and 3, banks with high insolvency risk[7] (colored in red) appear to the right of the diagonal line, suggesting a positive correlation between insolvency risk and net exposure.

To further understand the underlying differences between high and low-net exposure banks we inspect heterogeneities in several bank characteristics. Table 1 presents the standardized differences of bank characteristics for banks with above- and below-median values of net exposure, before and during the crisis. High net exposure banks differ from the rest on a number of dimensions, the most important of which are higher involvement in trading and the CDS market, combined with high risk on the asset side through the extension of risky loans.

For instance, Table 1 shows that pre-crisis, banks with high net exposures gave out more loans relative to assets and generated higher loan loss provisions than the rest, despite being larger and less leveraged. However, they also featured different loan portfolio compositions. In particular, when examining the various loan types, we observe high net exposure banks display a lower share of household loans and C&I loans. High net exposure banks also featured a more extensive involvement in trading activities and CDS markets,

[7] See Section 4.3 for how we define banks with high insolvency risk.

offloading risk via larger net purchases of CDS protection, and lower involvement in mortgage back securities held for hedging. These differences, taken together, point to a departure from the traditional business model that generates substantial linkages with the rest of the system through trading and the CDS market, combined with high risk on the assets side through the extension of risky real estate loans. We, therefore, hypothesize and subsequently verify that these banks feature higher net exposures because of undertaking activities that affect exposure and contribution differently.

3 Toy model

Since it is not obvious why the same activity could affect exposure and contribution differently, we first build a toy model to inform intuition. We hypothesize that banks' positive net exposures may be related to their business models and, more precisely, to the balance between traditional lending and non-traditional trading activities.

We explore this hypothesis with a simple short-run, partial equilibrium portfolio choice model. There is a continuum of competitive, risk-neutral, profit-maximizing banks uniformly distributed over an interval $[0, K]$ on the real axis. Each representative bank receives a deposit endowment of 1 and faces a portfolio choice problem of having to invest the endowment into an optimal mix of a low-risk, low-return asset (traditional lending) and a risky, high-return asset (trading), whose returns are exogenous (that is, the banks are price-takers).[8]

Because we model systemic risk, we cannot assume the two assets' returns are uncorrelated; thus we orient the model towards a structure where asset covariance can be modeled tractably and explicitly. Such a structure is offered by modeling the joint asset returns as two correlated binary variables. Each bank optimally invests a share α of its deposits in trading (Y), and $1 - \alpha$ in traditional lending (X). In the event of a good outcome, lending gives a return of 1 (net of interest and principal paid to depositors), but with a

[8] Previous literature shows non-traditional activities feature higher risk than traditional lending activities (see, e.g., DeYoung and Roland, 2001). Furthermore, among the different non-traditional activities, trading activities show to be riskier than other non-interest income sources (Chen et al., 2017; Stiroh and Rumble, 2006).

small probability $p > 0$, the borrower defaults and the net return becomes 0. Likewise, in the event of a good outcome, trading produces a return $R > 1$, but with a probability $q > p$, a bad outcome occurs and the net return is also 0.[9] The two assets comove with an exogenously determined covariance $Cov(X, Y)$. Consistent with the risk/return trade-off, trading offers higher expected return in compensation for its higher risk, so $\mathbb{E}Y > \mathbb{E}X$. The joint asset returns are shown in Matrix 1.

Matrix 1: Joint Model Asset Returns

	Trading gain	Trading loss
Lending gain	$(1, R),\ p_1$	$(1, 0),\ p_2$
Lending loss	$(0, R),\ p_3$	$(0, 0),\ p_4$

Matrix 1 shows the joint asset returns for the two assets (X, Y) for each possible combination of joint gains and losses, together with the associated probability of each outcome p_τ.

Since the joint outcomes are not independent, we assign to them probabilities p_1 to p_4 as shown in Matrix 1. The binary structure of these random variables allows us to neatly express the above probabilities in terms of the two assets' individual loss probabilities and their covariance:

Lemma 1 *The probabilities p_1 to p_4 can be expressed in terms of p, q and $Cov(X, Y)$ as:*

$$p_1 = 1 - p - q + pq + R^{-1}Cov(X, Y) \tag{1}$$

$$p_2 = q(1 - p) - R^{-1}Cov(X, Y) \tag{2}$$

$$p_3 = p(1 - q) - R^{-1}Cov(X, Y) \tag{3}$$

$$p_4 = pq + R^{-1}Cov(X, Y) \tag{4}$$

Proof: See Internet Appendix A.

Based on the outcomes in Matrix 1, the representative bank maximizes the expected profit function

$$\mathbb{E}(\pi) = p_1 [1 + \alpha(R - 1)] + p_2(1 - \alpha) + p_3\alpha R - TC(\alpha), \tag{5}$$

[9] These numbers can be linearly scaled or made negative as needed, but at the cost of significantly complicating the computation of the covariance term. They do not change the model's outcome.

where TC denotes total costs. To allow for an interior solution, costs are assumed convex (quadratic) in each activity:

$$TC(\alpha) = \alpha^2 + (1-\alpha)^2 = 1 - 2\alpha + 2\alpha^2. \tag{6}$$

The convex costs imply a strictly concave profit function, and therefore the optimal asset mix α^* is given by the first-order condition

$$\frac{\partial \mathbb{E}(\pi)}{\partial \alpha} = p_1(R-1) - p_2 + p_3 R + 2 - 4\alpha = 0 \tag{7}$$

producing an optimal solution

$$\alpha^* = \frac{1}{2} + \frac{1}{4}\Big[(1-q)R - (1-p)\Big] = \frac{1}{2} + \frac{1}{4}\left[\mathbb{E}Y - \mathbb{E}X\right], \tag{8}$$

where we used the equations from Lemma 1 to simplify the expression. Thus, the optimal asset mix α^* depends on the difference between the expected returns of the two assets and on the slope of the cost function.[10]

We are interested on how trading (α) and lending ($1-\alpha$) affect a bank i's systemic exposure from and contribution to the rest of the system. The system in this setting is modeled as the sum of remaining banks on the interval $[0, K]\backslash\{i\}$, which we interpret as a single aggregate agent. Since this is a representative agent model, the aggregate bank's profit $\mathbb{E}\pi_{sys}$ is the integration over the remaining banks' profits

$$\mathbb{E}\pi_{sys} = \int_{[0,K]\backslash\{i\}} \mathbb{E}\pi_j dj. \tag{9}$$

Since in reality the system's profit is always larger than that of the individual bank, the empirical literature uses size-invariant units (such as percent or quantiles of the return distribution) to compare system and bank profits. In the model, we implement this by calibrating the continuum of banks $[0, K]$ representing

[10] The model should not be interpreted literally as predicting that banks invest half or more of their deposits in trading. The free term 1/2 in equation (8) is produced by the squared term in the quadratic cost function (6), chosen because it produces a tractable linear solution. This term can be made smaller by choosing a steeper cost function, but at the cost of sacrificing tractability. This does not change the direction of the effects in the model.

the full system to the unit interval $[0, 1]$. This is equivalent to positing that if i is an individual bank, then the rest of the system is represented by another bank with an analogous profit function, interpreted as an aggregate agent. The system and the individual bank interact through two stylized, reduced-form channels transferring the risk in the system-to-bank and bank-to-system direction.

System-to-bank channel. Consistent with the empirics of the 2008 crisis, we assume that system-to-bank contagion occurs through common exposures to the risky asset Y. For exposition purposes, it is helpful to think of trading losses from Y as occurring contemporaneously across all banks, and of lending losses from X as not necessarily coincident with the trading shock, depending on $Cov(X, Y)$. Thus, the trading shock can be thought of as a systemic one (common to all banks), while the lending shock can be idiosyncratic, especially if $Cov(X, Y)$ is low or zero. A bank's exposure to the system will therefore be a function of this common negative trading shock. To make model concepts consistent with the empirical analysis that follows, we closely follow the spirit of Adrian and Brunnermeier (2016) in defining a model analog of a bank i's systemic exposure. Thus, we define i's exposure to the system as the drop in i's individual bank profits relative to their unconditional mean,[11] conditional on a common systemic (trading) shock corresponding to the bad realization of the risky asset $Y = 0$:

$$E = \mathbb{E}\pi_i^* - \mathbb{E}(\pi_i|Y = 0). \tag{10}$$

This definition emulates Adrian and Brunnermeier's (2016) empirical exposure metric Exposure ΔCoVaR used in Figures (1) to (3).[12]

The trading shock $Y = 0$ occurs in the two events associated with probabilities p_2 and p_4 in Matrix 1,

[11] Adrian and Brunnermeier (2016) use the median of the return distribution.

[12] The model definition is a conceptual analog of the Exposure CoVaR measure, but should not be interpreted as being literally identical, since the model's main purpose is to build intuition. For tractability reasons, we use means rather than medians, the profit distribution rather than stock return distribution, etc. For the same reasons, certain decompositions that can be done with the empirical CoVaR's are not straightforward with the model ones (e.g. decomposition into a transmission factor and a return shock).

resulting in an associated conditional profit function

$$\mathbb{E}(\pi_i|Y=0) \;=\; \frac{p_2(1-\alpha)+p_4\cdot 0}{1-p_1-p_3} - TC(\alpha) \;=\; \frac{p_2(1-\alpha)}{q} - TC(\alpha), \tag{11}$$

where we used the identity $(1-p_1-p_3) = p_2+p_4 = q$ to simplify the expression. Thus, a bank's systemic exposure is the difference between the equilibrium profit $\mathbb{E}\pi^*$ and the conditional profit (11).

Bank-to-system channel. The individual bank i can also transmit risk to the system if i's profits deteriorate. This transmission happens through the counterparty risk channel. Real-world banks use their revenues to settle end-of-day payments and repay intraday loans on the interbank loan market; a deterioration in revenues (profits) increases this counterparty risk commensurate with the drop in i's profits. For model purposes, we therefore define i's systemic risk contribution as the drop in system profits conditional on a bad shock or a combination of shocks $s_i = \{X_i = 0 \cup Y = 0\}$ to bank i:

$$C = \mathbb{E}\pi^*_{sys} - \mathbb{E}(\pi_{sys}|s_i). \tag{12}$$

This definition emulates Adrian and Brunnermeier's (2016) metric ΔCoVaR. In the model, i's profit drop relative to the mean affects the second (aggregate) bank in a one-to-one fashion, because the aggregate bank has the same profit function; the interpretation is that shocks making one bank unstable transfer over to the second (aggregate) bank. Such negative shocks to profits occur in the events associated with probabilities p_2, p_3 and p_4 at or below the main diagonal of Matrix 1. The associated conditional profit function is

$$\mathbb{E}(\pi_{sys}|s_i) = \int_{[0,1]\setminus\{i\}} \mathbb{E}(\pi_j|s_i)dj \;=\; \frac{p_2(1-\alpha)+p_3\alpha R+p_4\cdot 0}{1-p_1} - TC(\alpha), \tag{13}$$

where we used the fact the excluded bank i is small relative to the market and has a measure of zero. Using this setup, one can obtain the following results:

Proposition 1 *Near the optimal asset mix α^*, a bank's systemic exposure E increases in α and its systemic* *contribution C falls in α:*

$$\left.\frac{\partial E}{\partial \alpha}\right|_{\alpha^*} > 0, \quad \left.\frac{\partial C}{\partial \alpha}\right|_{\alpha^*} < 0, \tag{14}$$

provided that the riskier asset has a higher return ($\mathbb{E}Y > \mathbb{E}X$), but not so high as to be incomparable: $R < \kappa + \sqrt{\kappa^2 - 2p}$, where $\kappa = q^{-1}[2(1-q(1-p))-p]$. Moreover, net exposure $E(\alpha) - C(\alpha)$ strictly increases in α.

Proof: See Internet Appendix A.

The intuition behind this result is based on the costs and benefits of diversification. Investing a positive amount α in a trading asset Y increases both the bank's exposure to common trading shocks *and* its resilience to negative lending shocks because of hedging. The former effect increases the risk of the individual bank scoring a trading loss together with all other banks. The latter effect reduces the drop in bank profits conditional on a lending shock through the trading asset's use as a hedge at least some of the time, which reduces the bank's systemic contribution C. As it turns out, the effect of hedging can be quite significant even if the two assets' returns are positively correlated. The main reason for this is the fact that Y has a higher loss probability, which puts an upper bound on cross-asset covariance. Using equations (2) and (4), this covariance bound can be shown to be $-pqR \leq Cov(X,Y) \leq Rp(1-q)$. Using this, one can show that the minimum fraction of cases where, given a loss on any one asset, the other one scores a profit, is $(q-p)/(p+q)$. For example, when $p = 0.05$ and $q = 0.20$, the realized loss is hedged at least 60% of the time. For $p = 0.05$ and $q = 0.25$, this fraction is 67%. Thus, diversification increases profits both because hedging improves the average profit and because the riskier asset Y has a higher return. This suggests that moving away from a strictly one-asset model (e.g. traditional lending) towards some trading is not only profit-maximizing, but also helpful for risk management, since hedging, as an active risk-management technique, increases a bank's resilience to shocks from its lending business, thereby reducing its systemic risk contribution. Empirical evidence already suggests that banks use derivatives for this purpose (Silva-Buston, 2016). This, however, occurs at the cost of increasing exposure to trading shocks common to all banks, which increases risk flow in the system-to-bank direction (i.e. exposure), as shown by the first part of Proposition 1.

Therefore, the model suggests trading involvement can have opposite effects on different systemic risk measures: it *increases* systemic risk when measured by an exposure measure, and *reduces* systemic risk when measured by a contribution measure. Traditional activities, as a substitute, exert the opposite effects. This provides plausible insight into the empirical facts in Table 1. Moreover, based on the same logic, it can be shown that at the optimal asset mix α^*, exposure exceeds contribution: $E(\alpha^*) > C(\alpha^*)$. Therefore, the observed positive net exposures in Figure 1 and Table 1 could be the outcome of optimal diversification behavior by large banks.

Diversification, however, could have negative implications during a crisis if the covariance of assets goes up. For example, the 2008 financial crisis was characterized both by a jump in mortgage defaults *and* a simultaneous derivatives market decline. Table 1 shows banks with above-median net exposures exhibited higher default risk during the crisis, measured by metrics such as Z-Scores. To explore the effect of diversification on default risk, we therefore create a corresponding "model Z-Score" variable and explore its behavior conditional on a crisis, modeled as an increase in $Cov(X, Y)$. A Z-Score is constructed as the ratio of banks' buffers, measured by their returns, and their risks, measured by their returns' standard deviations (Roy, 1952). Thus, a higher Z-Score indicates better bank stability, and a lower Z-Score, higher default risk. In the model context, we analogously define

$$Z - Score_{model} = \frac{1 + \mathbb{E}\pi}{\sqrt{Var(\pi)}} \tag{15}$$

and explore what happens to bank stability conditional on an increase in $Cov(X, Y)$.[13]

Proposition 2 *Recalling that a lower Z-Score implies higher default risk,*

(i) At the optimal diversification point α^*, default risk is increasing in net exposure defined as $NE \equiv E(\alpha) - C(\alpha)$:

$$\frac{\partial(Z - Score_{model})}{\partial NE}(\alpha^*) < 0. \tag{16}$$

[13]This Z-Score definition closely follows Lepetit et al. (2008).

(ii) Conditional on a crisis that increases $Cov(X,Y)$, diversified banks face higher default risk compared to non-diversified banks and compared to the pre-crisis period.

$$\frac{\partial(Z-Score_{model})}{\partial Cov(X,Y)} \begin{cases} <0 & \textit{if } \alpha \in (0,1) \textit{ and} \\ =0 & \textit{if } \alpha = 0 \textit{ or } \alpha = 1. \end{cases} \tag{17}$$

(iii) $Cov(X,Y)$ increases default risk through increasing the volatility of profits $Var(\pi)$.

Proof: See Internet Appendix A.

This result shows three related phenomena. Firstly, since trading increases exposure and reduces contribution, more trading means a higher net exposure, but such higher exposures increase default risk because the possibility of two coincident bad shocks means higher profit variance (part (i)). Secondly, while diversification helps hedge bank-specific shocks, when cross-asset covariance goes up, the volatility of profits goes up because the two negative profit shocks occur together more often, increasing the probability mass associated with this tail outcome. As a consequence, any stability metric using profit volatility as an input (such as a Z-Score or distance to default) ought to register heightened default risk, all else equal (parts (ii) and (iii)). This suggests that diversification may result not only in asymmetrical risk linkages between the bank and the system, but also in heightened default risk during a crisis.

The model thus provides a number of testable implications: (1) That trading activity resulting from optimal diversification can affect exposure and contribution measures of systemic risk in opposite ways. This occurs because trading helps hedge bank-specific risks, but at the cost of increasing banks' exposure to common shocks to which they would not otherwise be exposed; (2) That traditional lending, being a substitute to trading, moves the above systemic risk measures in directions opposite to that of trading activity; and (3) That high net exposure, which arises naturally from these opposite effects, correlates with higher crisis default risk. In the next sections, we subject our toy model to a formal empirical test of these implications.

4 Data and Risk Measures

In this section, we present the data and risk measures used to test our empirical predictions. To measure both systemic risk exposures and contributions, we rely on the observation of Adrian and Brunnermeier (2016) that one can compute both the comovement of an individual bank against a system-wide shock as well as the comovement of the system in response to a bank-specific shock using different conditioning on the same data. The interchangeability of the individual bank and the system in the ΔCoVaR and Exposure ΔCoVaR calculations ensures these two systemic risk metrics measure systemic risk contribution and exposure in a methodologically consistent way. We extend this approach by creating consistent exposure and contribution risk metrics from other market-based systemic and systematic risk measures, such as Acharya et al.'s (2017) MES and van Oordt and Zhou's (2019a) tail beta.

To compute systemic risk measures and study their relationship to bank-specific covariates and default risk, we combine data from several sources. We obtain quarterly bank-level data from the Federal Reserve's Form FR-Y9C, containing the balance sheets of US bank holding companies. Since systemic risk asymmetries are surprising only for large banks, we focus our analysis on the top 200 US commercial bank holding companies as of Q4:2006. We combine this data with daily share-price information from Bloomberg. This database provides daily stock price information and stock market indices for listed companies, which are some of the inputs for the calculation of the individual and systemic risk measures. To match the frequency of the balance sheets, our bank-level risk measures are computed quarterly from the daily Bloomberg data over the relevant time window for each measure. We also compute discrete default risk measures from FDIC enforcement actions, known as cease-and-desist orders, sourced from the FDIC's enforcement decisions and orders (ED&O) database, as well as from public information on bank defaults (see the Insolvency dummy subsection below). To control for government aid received, we identify banks aided by the Troubled Assets Relief Program (TARP) using the TARP recipient list from the US Department of the Treasury. The latter two discrete measures are time-invariant.

Following Bertrand et al. (2004), we collapse the time series information in the data and convert it to a panel with two periods: pre-crisis and crisis, containing the period's average for each bank.[14] As in Fahlenbrach et al. (2012), we define the crisis as Q3:2007–Q4:2008, and the pre-crisis period, symmetrically, as Q1:2006–Q2:2007, including the endpoints. However, our results are robust to the choice of period length.[15]

The data we thus assemble, therefore, contains a cross-section of the top 200 US bank holding companies observed during the crisis, with lagged controls from the pre-crisis period.[16] The summary statistics for the sample are provided in Table 2. Variable definitions and data sources are listed in Internet Appendix B.

4.1 Systemic risk measures

4.1.1 ΔCoVaR and exposure ΔCoVaR

As our main systemic risk measures, we adopt Adrian and Brunnermeier's (2016) ΔCoVaR and Exposure ΔCoVaR. These two measures evaluate the extent to which a shock to a bank's return (system's return, respectively) moves the system's (bank's) return. The shock is simulated as a drop from the median to the bottom $q\%$ quantile of the relevant return distribution. The regular (i.e., contribution) ΔCoVaR shocks the bank's return to determine its effect on the system, while Exposure CoVaR shocks the financial system's return to determine the effect on the bank.

Adrian and Brunnermeier (2016) define a bank i's contribution ΔCoVaR^C as follows. If q is a specific quantile of the stock return distribution, R_i the stock market return of financial institution i, and R_s that of the system (empirically proxied by the S&P Banking index return), then the impact of institution i on the system equals the change of the system's value at risk conditional on a shock moving bank i from its

[14]Bertrand et al. (2002) show that collapsing the times series information into pre-crisis and crisis periods corrects standard errors that are otherwise inconsistent when running difference in difference estimations with serially correlated outcomes.

[15]We also explore other definitions. For example, Cornett et al. (2011) define the crisis as Q3:2007–Q2:2009, and Huang et al. (2012), as Q3:2007–Q4:2009. Our results remain qualitatively very similar using these alternative periodizations.

[16]Not every bank has a valid value for every balance sheet variable, thus some robustness regressions feature slightly fewer than 200 banks. For our baseline regressions, we select the sample as the top 200 US BHCs with nonmissing CoVaR and Exposure CoVaR as of the last quarter before the crisis (2007:Q2), so these regressions always have 200 banks.

median state to its q-percent quantile. More formally,

$$\Delta CoVaR^{C}_{i,q} = CoVaR_q^{s|R^i=VaR^i_q} - CoVaR_q^{s|R^i=VaR^i_{50}}, \tag{18}$$

where CoVaR is the value at risk of the system's return conditional on the state of bank i (corresponding to the bank's q-th percentile in the first term and its median state in the second one).[17] Exposure ΔCoVaR, which captures the system's influence on the bank, is defined by interchanging the place of the bank and the system in equation (18) to obtain:

$$\Delta CoVaR^{E}_{i,q} = CoVaR_q^{i|R^s=VaR^s_q} - CoVaR_q^{i|R^s=VaR^s_{50}}. \tag{19}$$

Adrian and Brunnermeier (2016) show that ΔCoVaR and Exposure ΔCoVaR can be equivalently expressed as the product of a risk transmission factor β times a shock to the relevant entity's return from the median to the q-th percentile:

$$\Delta CoVaR^{C}_{i,q} = \beta^C_i (VaR^i_q - VaR^i_{50}) \tag{20}$$

$$\Delta CoVaR^{E}_{i,q} = \beta^E_i (VaR^s_q - VaR^s_{50}), \tag{21}$$

where $\Delta CoVaR^{C}_{i,q}$ and $\Delta CoVaR^{E}_{i,q}$ respectively denote Contribution and Exposure ΔCoVaR for bank i, calculated at q%; VaR_q and VaR_{50} are the q% and median value at risk, indexed with i for the individual bank and with s for the system, and the β coefficients capture what fraction of the simulated shock transmits from the bank to the system (β^C) and vice versa (β^E). The CoVaR is the first mainstream, market-based family of measures evaluating the flow of risk in either direction. This is done in a methodologically consistent way because the place of the bank and the system is interchangeable in the risk calculation, shocking each respective entity to make it equally worse off (at its 5% VaR).[18] More importantly, the risk transmission

[17] The conditional value at risk for the system, $CoVaR^s_q$, is implicitly defined by the equation $\Pr\left(R_s|C(R_i) \leq CoVaR_q^{s|C(R_i)}\right) = q\%$, where $C(R_i)$ is some event affecting bank i's return R_i.

[18] It is reasonable to ask whether the system shock (the 5% VaR of the banking index) is comparable to the 5% VaR shocks of the individual banks. The summary statistics show no evidence that the two shocks operate on a different scale, but nonetheless, we explicitly test for this in a series of unreported robustness tests. In them, we construct the system shock for

factors β are inherently comparable by design: β's simply measure the *rate* of risk transmission in the relevant direction (system-to-bank and vice versa) completely independent of the shock component. CoVaR betas thus consistently measure the individual bank's and the system's sensitivity to each other. We follow Adrian and Brunnermeier (2016, Section II.B) in estimating the VaR and β components in equations (20) and (21) with the quantile regression approach using q set to 5.[19] For ease of interpretation, we take the negatives of CoVaR and Exposure CoVaR, so higher values indicate larger systemic risk.

Table 2 shows that Exposure ΔCoVaR consistently exceeds ΔCoVaR both before and during the crisis, resulting in a positive NetΔCoVaR (this is also shown graphically in Figure 1). This indicates that as a whole, the large US banks forming our sample were more exposed to spillovers from the system than vice versa. Before the crisis, the average exposure and contribution were 0.013 and 0.012, respectively. Both figures increase during the crisis, rising to 0.044 and 0.027, respectively, and maintaining the positive difference. The standard deviations of both measures also increase during the crisis, rising from 0.008 and 0.007 before the crisis (for the exposure and the contribution, respectively), to 0.027 and 0.016 during the crisis.

4.1.2 Other systemic risk measures

Since systemic risk metrics differ in the extent to which they capture comovements under extreme stress, we robustify our analysis with two additional systemic risk measures suitably modified to measure systemic risk in both directions: tail beta and MES.

Exposure tail beta and contribution tail beta. Firstly, we use van Oordt and Zhou's (2019a) exposure metric tail beta β_T^E, which captures the sensitivity of a bank's stock market return to extremely adverse shocks to the financial system, based on just a few tail observations. It is interpreted as the regression coefficient from a regression of the bank's return $R_{i,t}$ on the system's return $R_{s,t}$, restricted to the tail of

Exposure CoVaR as the cross-sectional average of the sampled banks' individual shocks. This did not change our results, which remained quantitatively and qualitatively similar.

[19] Following Adrian and Brunnermeier (2016), we require banks to have at least 260 weeks of equity return data to be included in the sample, and estimate this model over a long time period, from 1999 to 2016, thus allowing reasonable inference.

the system's return where the latter is smaller than a pre-specified quantile VaR_q^s. The regression is

$$R_{i,t} = \beta^E_{T,i} R_{s,t} + \varepsilon_{i,t} \quad \text{for} \quad R_{s,t} < -VaR_q^s. \tag{22}$$

By analogy, we create a contribution tail beta $\beta^C_{T,i}$ by running the regression in the opposite direction

$$R_{s,t} = \beta^C_{T,i} R_{i,t} + \epsilon_{i,t} \quad \text{for} \quad R_{i,t} < -VaR_q^i. \tag{23}$$

This type of regression is estimated with extreme value theory (EVT) methods, detailed in Internet Appendix C.

Exposure MES and contribution MES. Acharya et al.'s (2017) MES (marginal expected shortfall) is a reduced-form exposure metric aiming to capture the expected capital shortfall of individual bank i, conditional on stress in the rest of the system. These authors have shown that MES is a powerful predictor of the institutions affected by the 2008 crisis. This exposure measure, which we label MES^E, is constructed as the average of bank i's daily returns, taken over the days where the system's returns are within their worst 5% for each quarter. We create a contribution analog of this measure, MES^C, by averaging the system's daily returns, taken over the days where bank i's returns are within their worst 5% for the quarter. This construction is detailed in Internet Appendix C.

4.2 Net systemic risk measures

We have hypothesized that banks' business models have opposite effects on banks' exposure and contribution, and that default risk during the crisis is positively related to banks' net exposure (the difference between its exposure and contribution). Banks with positive net exposures feature a stronger system-to-bank risk transmission, whereas banks with negative net exposures feature a stronger bank-to-system transmission. Since we can measure the risk in each direction for each of the three bidirectional measures ΔCoVaR, β_T, or MES discussed above, we define the corresponding net measure as follows:

$$Net\ Measure_{i,t} = Measure_{i,t}^{E} - Measure_{i,t}^{C}, \tag{24}$$

where $Measure$ equals ΔCoVaR, β_T, or MES, and the superscripts E and C index the exposure and contribution version of the metric, respectively.

Table 2 shows the descriptive statistics for the net exposure measures. Our main net measure, Net ΔCoVaR, has an average value of 0.001 before the crisis, which increases to 0.018 after the crisis. The table also shows that there is significant variation in this variable: the 25th and 75th percentiles, respectively, are -0.003 and 0.006 before the crisis, and 0.009 and 0.027 during the crisis.

The three systemic risk measures complement each other by capturing different systemic risk aspects. For example, ΔCoVaR's components give a 100% weighting to the bottom q% quantile; MES, on the contrary, gives equal weight to all quantiles below the q% quantile and zero weight to remaining quantiles (Hull, 2006); and tail beta uses all observations below the q% quantile. Therefore, they produce non-identical, but similar results.

Table 3 shows that ΔCoVaR, MES, and tail beta are positively correlated in all of their versions – exposure, contribution, and net. Being equally weighted below the cutoff, MES correlates strongly with both tail beta and ΔCoVaR (28%–59% with ΔCoVaR, and 30–38% with tail beta). Regardless of their different construction, ΔCoVaR and tail beta are also positively correlated everywhere, only less consistently across different versions (4%–47%). This is likely because ΔCoVaR focuses solely on the location of the q% quantile, while tail beta uses information from all observations within the q% tail. However, when applied to the data, all three measures paint a similar picture; as before, we use Net ΔCoVaR as our principal measure and the other two for robustness.

Table 4 shows the top 50 banks with the largest net systemic exposure in the pre-crisis period acording to Net ΔCoVaR. The table reveals the presence of large important banks, such as Bank of America and

Citigroup, as well as banks that later faced insolvency problems, such as Wachovia, Irwin Financial, and Nexity Financial.

4.3 Individual risk metrics

To study the relation between systemic risk asymmetries and bank default risk, we measure individual bank risk with metrics such as distance to default, accounting Z-scores, and a dummy variable for insolvent or risky banks.

Distance to default. As a default risk metric, we use the classic distance to default (DD) based on the Merton bond pricing model (Merton, 1974).[20] Its calculation is detailed in Internet Appendix C. The distance to default is a measure of distance to insolvency; a higher value of this variable indicates better bank soundness. Table 2 shows this measure substantially decreases during the crisis, indicating higher default risk, as expected. The pre-crisis average equals 8 and decreases to 2.9 in the crisis period.

Z-Scores. As an alternative measure of individual default risk, we compute each bank's pre-crisis and crisis accounting Z-Score (Roy, 1952). Z-Score is widely used in the literature examining banks' stability (e.g., Demirgüç-Kunt and Huizinga, 2010; Houston et al., 2010, and many others). This measure captures banks' buffers, measured by their returns, and their risks, measured by the returns' standard deviations. It is calculated as

$$\text{Z-Score}_{i,t} = \frac{\text{ROA}_{i,t} + (\text{Total equity capital}_{i,t}/\text{Total Assets}_{i,t})}{\sigma_{\text{ROA}_{i,t}}}, \tag{25}$$

where ROA is a bank's return on assets (ROA) and σ_{ROA} is the standard deviation of ROA, calculated over the relevant period (pre-crisis and crisis). In separate regressions, we also split this measure into its numerator and its denominator.

As the distance to default, the Z-Score is also a measure of distance to insolvency; thus, higher values indicate lower default risk. The average Z-Score decreases from 3.4 to 3.1 during the crisis.

Insolvency dummy. As a third measure of individual default risk, we construct a dummy variable

[20] This data was calculated and provided courtesy of the Bank of Canada's Financial Institutions division.

called *Insolvency*, flagging the banks with high risk of insolvency during the crisis. We set the *Insolvency* dummy equal to 1 for banks that failed, were acquired to prevent failure, had a direct subsidiary fail, or had an enforcement action known as a cease-and-desist order issued by the FDIC during the crisis.[21] Such an order is issued if a bank engages in unsafe and unsound practices or violates a law, rule, or regulation, a condition imposed in writing by the FDIC, or a written agreement with the FDIC (Federal Deposit Insurance Corporation, 2019). The information comes from the FDIC's list of failed banks, the FDIC's enforcement decisions and orders (ED&O) database, and publicly available information on banks acquired as a result of financial trouble. Table 2 shows that 11% of the banks in the sample faced such insolvency risk during the crisis.

5 Empirical Strategy and Results

5.1 Determinants of net systemic risk exposure

Proposition 1 in our model suggests that banks with different business models can undertake activities that affect their systemic contributions and exposures differently, thereby creating asymmetric (directional) linkages with the rest of the system. We test this hypothesis in this section and examine the balance sheet determinants of a bank's systemic risk exposure, contribution and net exposure. For this, we relate the systemic risk measures averaged in the crisis period to lagged bank balance sheet variables averaged in the pre-crisis period, using a cross-section model. Besides examining business models, we also follow the literature and investigate banks' funding structure and derivatives usage.

We start by investigating our model's primary net exposure determinant: a bank's business model. For this purpose, we examine banks' non-interest income. The bank risk literature shows that different non-interest income sources have a different relationship with bank risk (Stiroh and Rumble, 2006; Chen et al., 2017). Therefore, we split non-interest income into securitization revenue, fiduciary income, and trading

[21] To reduce the results' sensitivity to the specific definition of the crisis period in this risk measure we include banks that failed all the way up to Q4:2010.

income. We include all three variables measured as a fraction of total income. We also include loan loss provisions over total loans and ROA to study banks' risk-return profiles.

Non-interest income activities have been shown to be more volatile than traditional sources of income (DeYoung and Roland, 2001), and banks would earn income in the same correlated non-interest income activities, thus increasing banks' systemic risk exposure and contribution (Brunnermeier et al., 2020). At the same time, lower portfolio quality has been documented to positively relate to banks' systemic exposure and contribution (see, e.g., Brunnermeier et al., 2020). On the other hand, as documented in the previous literature (e.g., Davydov et al., 2021; van Oordt and Zhou, 2019a), profitability is associated with lower levels of systemic risk exposure and contribution. The results of this analysis are displayed in Table 5. The model in column (1) shows higher securitization income is related to higher systemic risk exposure, but only weakly; whereas it is not significantly related to a bank's systemic risk contribution, as shown in column (6). In line with the previous literature, fiduciary activities also enter with a positive and significant sign in this model, suggesting a higher share of this particular non-traditional activity is related to a higher bank contribution to systemic risk. In line with the intuition in our toy model, trading increases exposure, and might reduce contribution, but the effect's significance on the individual exposure and contribution measures is weak. Lower loan loss provisions and higher ROA do not enter significantly in column (1), whereas they show to be positively related to systemic contribution in column (6). By contrast, when we investigate the *net* systemic risk exposure in column (11), we find trading activities in the pre-crisis period to be related to higher net systemic risk exposure, whereas securitization revenue is negatively related to net exposure. Loan loss provisions and profitability are insignificant in this model. Results remain similar when including all controls in columns (5), (10), and (15). However, among the non-interest income variables, only trading activities remain positive and highly significantly related to net exposure, consistent with model predictions.

Second, we consider a bank's loan portfolio. This allows us to examine a bank's exposure to traditional activities. To this end, we follow Brunnermeier et al. (2020) and include loans over total assets and the share of real estate loans, commercial loans, and household loans over total loans. The literature shows mixed results about the relation between systemic risk and the share of loans (see e.g., Bostandzic and Weiss, 2018). A bank's portfolio mix has been identified as a key driver of systemic risk during the crisis, and in particular, the share of real estate loans (Herring and Wachter, 1999; Crowe et al., 2011). Column (2) suggests no significant relationship between a bank's loan portfolio composition and its systemic exposure, whereas, when we study a bank's contribution (column (7)), we find a higher proportion of real estate, commercial and household loans to be related to higher contribution to systemic risk, consistent with model predictions. Results remain similar when including all controls in columns (5) and (10). On the other hand, when we look at the relationship between loan portfolio composition and *net* exposure in column (12), we find a higher proportion of commercial and household loans to be related to lower net exposure. The proportion of real estate loans also enters with a negative sign but is not significant. Results are similar when we include all controls in column (15). Thus, significant involvement in traditional loan types decrease a bank's net exposure to systemic risk, as predicted by the model.

In the next columns, we follow the systemic risk literature and study how various other balance sheet variables relate to net systemic risk. Thus, in a third set of regressions, we study the relationship between banks' systemic risk and funding structure. To this end, we include leverage and deposits over loans in our regressions. The previous literature, however, shows mixed results on the relationship between funding structure and systemic risk – both exposure and contribution (see, e.g., Brunnermeier et al., 2020; Bostandzic and Weiss, 2018; Beltratti and Stulz, 2012). In line with these mixed results, columns (3) and (8) suggest no significant relationship between a bank's funding structure and a bank's systemic exposure or contribution. This remains unchanged when we look at a bank's net exposure. Column (13) suggests no relationship between a bank's funding structure and its net systemic exposure, as shown by the insignificant coefficients in this model. Results remain similar when including all controls in columns (5), (10), and (15).

Fourth, we consider derivatives usage to proxy for interconnectedness and complexity. For this, we study gross and net CDS positions over total assets,[22] and mortgage back securities (MBS) held until maturity over total assets. Derivatives can be used for risk management purposes, thus containing losses in crisis periods (Silva-Buston, 2016). However, they also increase interbank linkages as banks act as counterparts of each other. Therefore, the effect on systemic risk is ambiguous. Column (4) suggests no significant relationship between a bank's interconnectedness and systemic exposure, while the model for bank contribution shows that higher MBS held to maturity are related to higher systemic contribution. By contrast, higher gross CDS positions are related to a lower systemic risk contribution, probably due to hedging benefits, as predicted by our toy model. Results remain similar when including all controls in columns (5) and (10). Since high contribution reduces net exposure, we find the opposite result when we study net systemic exposure in column (14): a higher MBS held until maturity is related to a lower net systemic exposure. The net CDS protection bought also enters with a (weakly) significant and negative sign when we include all controls in column (15), while the gross CDS position turns significant and positively related to the net exposure in this model. The MBS are not significant in this model.

Finally, we include bank size, measured by the logarithm of assets, in all models since bank size is documented to be one of the main drivers of systemic risk exposure and contribution (e.g., Brunnermeier et al., 2020; Bostandzic and Weiss, 2018). In line with this literature, the logarithm of assets enters with a positive and significant sign in all models, including the net systemic exposure models, suggesting that large banks display not only high exposure and contribution, but also high *net* systemic exposure. This confirms the intuition conveyed by Figure 2.

The effects on net systemic exposure are also economically significant. Considering the coefficients in the last column of Table 5, a one standard deviation increase in size (1.52) is related to a rise of 0.29 standard deviations in net exposure CoVaR. By contrast, a one standard deviation increase in commercial loans (0.1) and household loans (0.07) is related to a reduction by 0.31 and 0.38 standard deviations in net exposure

[22] Unfortunately, FR-Y9C data does not report the amount of credit derivatives held for risk management purposes versus trading. Thus, we include in our models the aggregate amount of credit derivatives.

CoVaR, respectively. In addition, a one standard deviation increase in derivatives trading income (0.01) and gross CDS positions (0.006) is related to a respective rise of 0.20 and 0.18 standard deviations in net CoVaR during the crisis. We obtain similar results in unreported robustness tests using the alternative systemic risk measures MES and tail beta.

In Table 6, we investigate the determinants of the components of the net CoVar exposure. Columns (1) to (5) examine the net transmission component (net β CoVaR), and columns (6) to (10) examine the net losses component (net shock CoVaR). We find that the proportion of commercial loans and household loans are strongly negatively related to the net fraction transmitted from the system to the bank. Taking the coefficients in column (5), a one standard deviation increase in commercial loans and household loans is related to a reduction of 0.30 and 0.44 standard deviations in the net β, respectively. Conversely, bank size, trading activities, and gross CDS positions are positively related to the transmission component. A one standard deviation increase in size, trading income, and gross CDS positions is related to an increase of 0.32, 0.17 and 0.20 standard deviations, respectively, in net β during the crisis.

When we examine the net losses in the next five columns, we find that trading activities reduce the net losses to be transmitted to the bank when the system is in distress. In contrast, fiduciary income, leverage, and the proportion of commercial loans and household loans, are related to higher net losses to be transmitted to the bank, as shown by the models in columns (6) to (10). When considering the coefficients in column (10), a one standard deviation increase in fiduciary income, leverage, commercial loans, and household loans is associated with a respective increase of 0.18, 0.19, 0.35, and 0.40 standard deviations in the net shock. By contrast, a one standard deviation increase in trading income is related to a reduction of 0.18 standard deviations in the net shock.

The analysis in this section offers several lessons. It confirms the model's predictions that banks with different business models undertake activities that affect their systemic contributions and exposures differently. In particular, trading activities increase net exposure, whereas higher involvement in C&I and household loans decrease net exposure. Furthermore, the results show that even though some balance sheet variables, such as the share of real estate loans, have been previously identified as a source of systemic risk, they do not significantly increase and can even decrease net systemic exposure. At the same time, size, which has also been identified as a key determinant of both exposure and contribution, increases net systemic exposure. The analysis suggests that the effect of size and trading activities on net exposure is due to their effect on the net transmission factor, thereby increasing the net fraction of losses transmitted from the system to the bank.

5.2 Net exposure and default risk

We now turn to test Proposition 2 in our toy model. It predicts that higher net exposure increases profit volatility and default risk. To test this prediction, we examine the relation between a bank's pre-crisis net systemic exposure, its components (exposure and contribution) and its default risk during the crisis. We test this hypothesis with the following cross-section model at the bank level:

$$y_{i,crisis} = \beta_1 Systemic\ risk_{i,pre} + \beta_2 X_{i,pre} + \epsilon_i, \tag{26}$$

where $y_{i,crisis}$ is a measure of default risk measured in the crisis period, proxied by distance to default, the Log(Z-Score), and a dummy variable indicating whether the bank faced insolvency risk during that time. $Systemic\ risk_{i,pre}$ is a bank's systemic risk exposure, systemic risk contribution, or its systemic net exposure (the difference between the two). $X_{i,pre}$ is a set of bank controls. All systemic risk measures and controls reflect the pre-crisis period. As bank controls, we include a bank's log assets as an indicator of size, deposits over total assets as a proxy for the funding structure, non-interest income over total income and loans over total assets to proxy for the bank business model, and loan loss provisions over total loans as indicator of lending quality and asset growth. This follows the literature exploring the relationship between bank characteristics and bank stability (see, e.g., Beck et al., 2013). Furthermore, since banks' insolvency during the crisis was affected by government interventions, we also control for whether the bank received TARP aid by including a dummy variable flagging such banks.

The results of these models are shown in Table 7. We examine the relationship between a bank's pre-crisis systemic risk exposure and its crisis default risk in the first three columns of this table. All three models show no significant relationship between systemic risk exposure and insolvency risk. This result is in line with the previous literature, which has documented mixed results about the relationship between pre-crisis systemic exposure and bank performance during the crisis (see, e.g., Acharya et al., 2017; Fahlenbrach et al., 2012). We then examine the relationship between a bank's systemic contribution and default risk. In these models, the coefficients for distance to default and the Z-Score enter with a positive sign, but only the Z-Score is significant. This evidence is again in line with the previous literature, which finds a mixed or an insignificant relationship between a bank's pre-crisis contribution CoVaR and its performance during the crisis (Sedunov, 2016). The model in column (6), which studies the probability of failure, shows a negative and significant marginal effect indicating that a higher systemic risk contribution before the crisis reduces the probability of default in the crisis period. This might be the result of some banks undertaking activities with a better risk-return trade-off, but a higher systemic risk contribution, such as traditional activities.

We allow for the possibility that both measures may be correlated and, at the same time, affect bank soundness independently. Hence, we include exposure and contribution measures together in the next three columns, (7) to (9). The results remain similar to those in previous regressions. Systemic exposure enters with an insignificant coefficient in all three models, and systemic contribution coefficients suggest a positive relationship with bank soundness in the Z-Score and insolvency models. However, the coefficient is insignificant in the distance to default model.

Finally, we investigate the *net* systemic risk exposure in the last three columns of this table in accordance with the model predictions. According to the model, a bank's net difference $E - C$ is positively related to default risk. Thus, we test whether the variation in this net difference affects bank stability. Results confirm this is the case; the net systemic risk measure now enters significantly in all three regression models, confirming our toy model predictions. Furthermore, the adjusted R-squared in the distance to default and Z-Score models in columns (10) and (11) (not reported) are higher when the net measure, rather than both measures independently, are included in columns (7) and (8) (0.07 versus 0.06 and 0.23 versus 0.20, respectively), suggesting net measure variation better predicts default risk. Both the distance to default and the Z-Score models display a negative and significant coefficient, and the insolvency probability model shows a positive and significant marginal effect. This evidence suggests higher systemic net exposure pre-crisis is related to higher default risk in the crisis period. The coefficients in these models indicate economic significance. One standard deviation increase in the net exposure (0.007) reduces a bank's distance to default by 0.11 standard deviations, the Log(Z-Score) by 0.34 standard deviations, and increases the probability of default by 3 percentage points. Among the control variables, we find that larger banks (as measured pre-crisis) experienced higher insolvency risk during the crisis.[23] Banks with higher non-interest income as a share of total income in the pre-crisis period had lower default risk in the crisis, which could be explained by their higher diversification towards non-traditional activities with less volatile income streams, such as fiduciary and securitization activities (Chen et al., 2017; Stiroh and Rumble, 2006). Finally, receiving TARP aid is related to lower default risk during the crisis, as measured by the Z-Score and the insolvency dummy, consistent with Berger et al. (2020), but related to higher default risk when measured by distance to default. This latter result could be explained by the market's negative expectations regarding these banks.

The results in Table 7 confirm our hypothesis and suggest that it is not high systemic exposures or high contributions alone that increase banks' default risk, but rather, it is the *net* systemic risk exposure that matters. Moreover, it is important to note this measure independently relates to a bank's default risk when controlling for other bank covariates, as suggested by its robust and significant coefficient. This evidence indicates that net exposure better captures a bank's overall risk-return profile caused by its business

[23] This has also been documented in e.g., Fahlenbrach et al. (2012).

activities. As in Figure 3, banks with both high exposure and high contribution pre-crisis were not the ones that experienced heightened default risk during the crisis; the riskiest banks were those with the largest systemic risk asymmetry. This strongly suggests that not just systemic risk, but also its *directionality* matter for financial stability. To our knowledge, this paper is the first to demonstrate this result. Thus, high systemic exposure alone may not be detrimental for individual bank stability if also accompanied by high systemic contribution. This confirms that high-contribution banks might engage in activities that mitigate individual default risk.

We confirm our results with a couple of additional tests. First, we run an instrumental variable model to address potential endogeneity concerns. In our baseline regressions, we lag net systemic risk measures, which reduces reverse causality concerns. However, unobserved confounding factors affecting both systemic risk in the pre-crisis period and default risk during the crisis could still bias our results. To address this concern, we instrument for Net ΔCoVaR in a series of instrumental variable regressions. The instrument is a dummy variable indicating whether the bank is located in a reserve city as established by the National Banking Acts (NBAs) of 1863 and 1864. The NBAs designated specific reserve cities where all country banks had to deposit their reserve requirements.[24] Anderson et al. (2019) show the NBAs changed the banking network structure, transforming these cities (and their banks) into important nodes. We argue these cities have remained important nodes in the banking network, and banks in these cities display higher net exposures, as they are more exposed to shocks from the rest of the banking system. At the same time, the NBAs established these cities more than 140 years before the 2008 crisis. Thus, the characteristics that influenced this decision are unlikely to correlate with bank-level soundness during the crisis. Moreover, any threat to instrument exogeneity would need to coincide in these 18 cities to invalidate our instrument. A threat that satisfies this criterion is unlikely to exist.

We present the results of these models in Panel A of Table 8. The first stage of these models shown in

[24] These reserve cities were: Albany, Baltimore, Boston, Chicago, Cincinnati, Cleveland, Detroit, Leavenworth, Louisville, Milwaukee, New Orleans, New York City, Philadelphia, Pittsburgh, Providence, San Francisco, St. Louis, and Washington.

columns (1), (3), and (5) show a positive and significant relationship between the reserve city dummy and net exposure, confirming banks in these cities display higher net exposure to systemic risk. The F-statistics in these models are close to 10, which suggests the instrument is relevant.[25] The second stage of these models presented in columns (2), (4), and (6) confirm our previous results. The coefficients in the distance to default and the Z-Score models remain statistically significant and are larger in absolute terms, which suggests the presence of bias in the previous OLS estimation. The estimate for the insolvency model displays a positive coefficient and is marginally significant (p-value 11%). Hence, higher net exposure before the crisis increases default risk during the crisis.

Second, we confirm our findings using two alternative net systemic risk exposure measures: the net tail beta (after van Oordt and Zhou, 2019a) and the net marginal expected shortfall (after Acharya et al., 2017), computed as described in section 4.1. The results in Panel B of Table 8 confirm the findings obtained from the CoVaR, showing negative and significant coefficients for distance to default, and positive and significant marginal effects for the failure model for the net exposure as measured by net tail beta and net MES. The coefficient for the Z-Score is not significant in either model. This evidence suggests that insolvency risk during the crisis increased with net pre-crisis exposure.

5.3 Systemic risk components and default risk

Next, we examine which component of net exposure drives default risk – the net shock or the net transmission factor. The net shock is the difference between the losses transmitted to the bank when the system is in distress and the losses to be transmitted to the system when the bank is in distress. It is defined as $(VaR_q^s - VaR_{50}^s) - (VaR_q^i - VaR_{50}^i)$, from equations (21) and (20). The net transmission is the difference between the fraction of the simulated shock transmitted from the system to the bank (β^E) and the fraction transmitted from the bank to the system (β^C). Thus, we define net transmission as $\beta_i^E - \beta_i^C = \text{Net } \beta_i$.

[25] Because the F-statistics are slightly smaller than 10, we confirm our results using the Anderson Rubin Wald test, which allows for robust inference in the case of weak instruments. Overall, the results suggest we can reject the null that the net systemic risk coefficients are equal to zero in these models.

The results of this study are shown in Table 9. Columns (1) to (3) in this table show the effect of the net transmission factor (Net β), and columns (4) to (6) show the effects of the net shock. Since these two components could be correlated (banks with higher net losses might also display a larger net transmission factor), we include both components together in columns (7) to (9). This table suggests the effect is driven by the transmission component, as shown by the positive and significant relationship between the net β and all the three insolvency measures in the first three columns of this table. The evidence in these models then suggests a higher net fraction transmitted from the system to the bank pre-crisis is related to increased insolvency risk during the crisis period. Thus, banks face higher insolvency risk when the fraction of shock transmitted in the system-to-bank direction is larger than the fraction of shock transmitted in the bank-to-system direction. In contrast, the results for the shock component suggest a negative and significant relation with insolvency risk, as shown by the next three columns in this table.

These results remain unchanged when including both risk components in the default risk models in columns (7) to (9). The net β is significant and positively related, and the net losses are negatively related to insolvency risk. The effect is also economically relevant. Taking the coefficients in the last three columns of this table, a one standard deviation increase in the net β (0.24) decreases a bank's distance to default and the Log(Z-Score) by 0.17 and 0.31 standard deviations, respectively, and increases the probability of failure by 2 percentage points.

The results in the previous tables do not answer the question through which channel net systemic exposure increases bank default risk. Banks can become riskier in two non-mutually exclusive dimensions: (1) by taking riskier activities or reducing risk management, thus increasing the variance of returns, or (2) by increasing leverage or taking up less profitable activities, thus reducing the buffer to avoid default. Our model suggests net systemic risk increases default risk though the first channel. We investigate these dimensions in Table 10 and study the numerator and the denominator of the Z-Score separately.[26] We split the Z-score into the

[26] We focus on the Z-Score for this study since our sample is reduced when calculating distance to default.

capital equity ratio plus ROA (numerator) and the standard deviation of ROA over the relevant period (the denominator). The evidence in this table confirms the net transmission effect operates through increasing the volatility of profits, rather than by reducing leverage or profit levels (columns (1) and (2)). Further disaggregating profits into interest income and non-interest income, columns (3) and (4) show that the main channel through which net systemic exposure affects default risk is the volatility of non-interest income, and of derivatives trading income in particular (column 5). Other sources of non-interest income, such as securitization or fiduciary income, do not enter the model with significant coefficients (columns (6) and (7)). We interpret this as banks undertaking trading activities pre-crisis that increased their net linkages to the system (net betas). Once the crisis began, volatility in financial markets increased significantly, resulting in more volatile trading income, and therefore lower Z-scores for high net exposure banks. These results confirm the default risk mechanism predicted in Proposition 2 of the toy model. Hence, Table 10 shows a positive relationship between net betas and the volatility of profits, and a negative relationship between net betas and Z-scores, reinforcing the view that non-interest income activities can be a source of increased risk (Stiroh, 2004; Demirgüç-Kunt and Huizinga, 2010).

Taken together, the evidence in this paper suggests high-net exposure banks engaged in activities that increased systemic exposure, such as derivatives trading, leaving banks exposed to the soundness of other counterparties. With the extensive involvement in these activities, banks suffered from increased income volatility during the crisis, increasing default risk. Trading activities were carried out at the cost of performing other activities that would have increased banks' systemic contribution but would have also contained default risk, such as traditional lending activities.

6 Conclusion

The regulatory treatment of large banks poses unique challenges to regulators. Existing regulatory regimes, such as the Dodd-Frank Act of 2012 and the Basel III framework, have focused on reinforcing the capital buffers of large banks to improve systemic stability through reducing these banks' default risk and their impact on the rest of the system. The apparent intention behind these regulations is to shield the system from the "too big to fail" banks by making them more resilient.

In contrast to the philosophy behind these regulations, we extensively document that the largest US bank holding companies are consistently more vulnerable to shocks originating from the rest of the banking system than vice versa. To understand the underpinnings of this phenomenon, we examine the determinants of a bank's net exposure to the financial system (its exposure net of its impact) first theoretically and then empirically. We discover theoretically that optimally diversified banks undertake trading activities which increase their net exposure and default risk, and we confirm the prediction empirically. In addition to derivatives trading, we also find that bank size and involvement in CDS markets also increase a bank's net exposure. The analysis suggests that the effect of size, trading activities, and the use of credit default swaps on net exposure is due to their impact on the net transmission factor, increasing the net fraction of losses transmitted in the system-to-bank direction. Overall, the evidence shows that high-net exposure banks engaged in activities that increased the transmission of adverse shocks to the banks, such as derivatives trading, which exposed banks to the healthiness of other bank counterparties. With an extensive portfolio invested in derivatives, banks suffered increased income volatility during the crisis, increasing default risk. Banks carried out these activities at the cost of not investing in other assets that would have increased their contribution but also contained default risk, such as traditional lending activities.

Moreover, we show that the larger this asymmetry, i.e., the more exposed a large bank is to the system relative to its impact on it, the riskier it becomes. Examining the channels behind this relation, we find that the effect on bank default risk is driven by the net transmission factor of shocks rather than the size of net shocks, and that the link between this factor and insolvency risk runs through activities such as trading, increasing the volatility of profits.

Our findings offer two important policy implications. First, interconnectedness in the financial system can be directional, and bank regulation will increasingly need to reflect this to stay ahead of future risks to systemic stability. It might be beneficial for regulation to focus on containing and imposing buffers on high net exposure banks, rather than just large banks or banks displaying a high systemic contribution. Second, default risk increases with the net system-to-bank shock transmission factor, which in turn is positively related to bank size and the use of credit derivatives. An efficient regulation should therefore focus first on reducing such net exposures, rather than subsequently buffering the default risks arising from them. Therefore, regulators should put their efforts on containing banks' size, and monitoring banks' connections through the CDS market. Such regulation would help address more efficiently not only the challenges of size and complexity, but also of directional interconnectedness making some banks more vulnerable than others.

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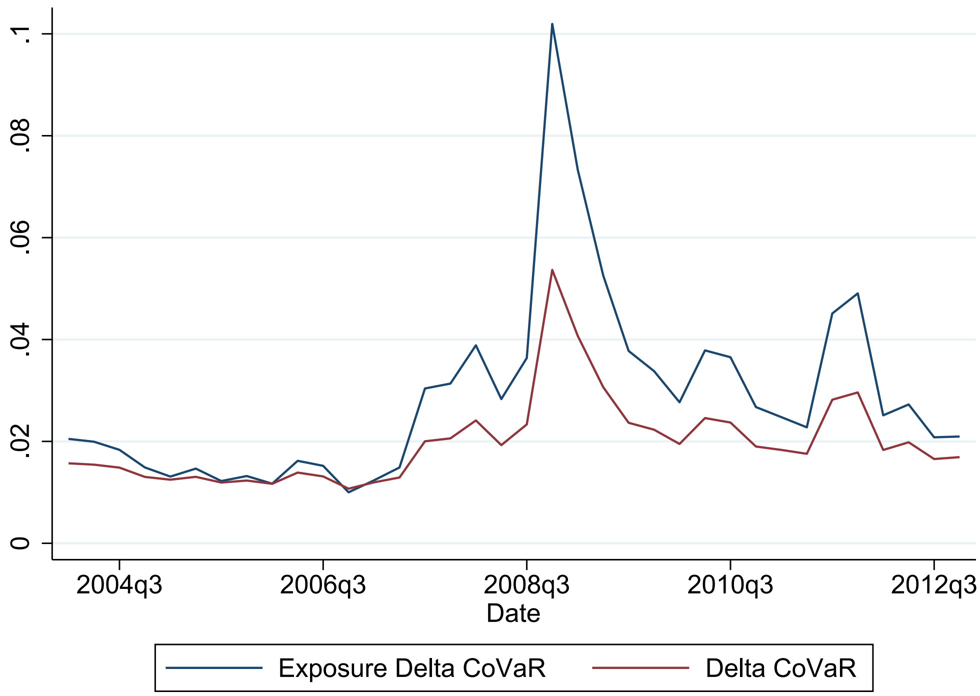
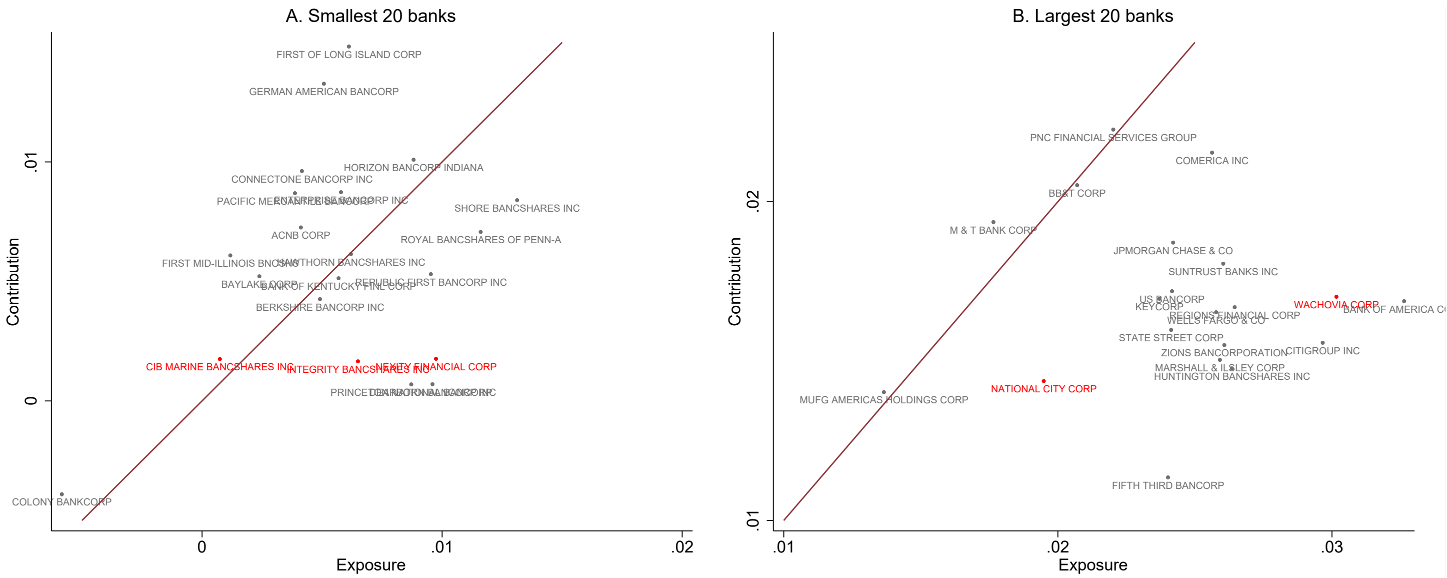
7 Figures

Figure 1. Evolution of banks' average systemic risk exposure and contribution



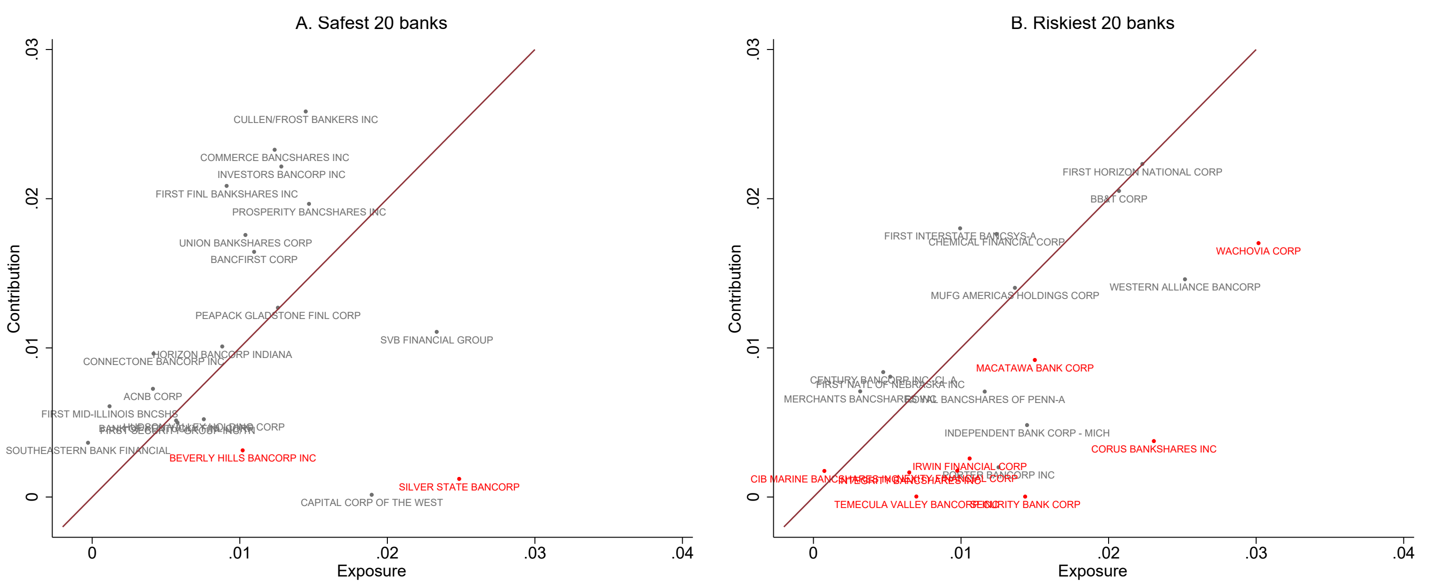
The figure shows the evolution of banks' average systemic risk exposure and contribution as measured by Adrian and Brunnermeier's (2016) Exposure ΔCoVaR and ΔCoVaR metrics, respectively. The graph displays the cross-sectional average across the top 200 US bank holding companies by assets as measured at Q4:2006. The time frame shown is from Q1:2004 to Q4:2012.

Figure 2. Banks' net exposure and size



The figure shows a plot of the systemic risk exposures versus systemic risk contributions for two sets of banks, as measured by Adrian and Brunnermeier's (2016) Exposure ΔCoVaR and ΔCoVaR metrics. Panel A shows the 20 smallest banks in the sample, and Panel B – the 20 largest banks. Banks with an *Insolvency* dummy equal to 1 are flagged in red. The full sample consists of the 200 top US bank holding companies by assets as measured at Q4:2006.

Figure 3. Banks' net exposure and risk



The figure shows a plot of the systemic risk exposures versus systemic risk contributions for two sets of banks, as measured by Adrian and Brunnermeier's (2016) Exposure ΔCoVaR and ΔCoVaR metrics. Panel A shows the 20 safest banks in the sample, and Panel B, the 20 riskiest banks, as ranked by their distance to default (DD). Banks with an *Insolvency* dummy equal to 1 are flagged in red. The full sample consists of the 200 top US bank holding companies by assets as measured at Q4:2006.

8 Tables

Table 1: Selected Summary Statistics by Net ΔCoVaR Exposure and Period

	Pre-Crisis					Crisis				
	Above-median		Below-Median			Above-median		Below-Median		
	Mean	Std. Dev.	Mean	Std. Dev.	Std. Diff	Mean	Std. Dev.	Mean	Std. Dev.	Std. Diff
Net ΔCoVaR	0.007	0.005	-0.004	0.003	2.492***	0.031	0.017	0.004	0.006	2.168***
Log(Z-Score)	3.416	0.380	3.400	0.354	0.045	2.809	0.908	3.292	0.702	-0.596***
DD	8.07	2.222	7.842	2.900	0.088	2.583	1.115	3.217	1.917	-0.404***
Log(assets)	15.470	1.919	14.950	0.894	0.351***	15.500	1.768	15.200	1.201	0.196*
Fiduciary/TI	.020	.0416	.0243	.0356	-0.117	.0195	.041	.025	.037	-0.150
Securitization/TI	0.001	0.005	0.0004	0.003	0.165	.0195	.041	.025	.037	-0.150
Trading/TI	0.005	0.015	0.001	0.004	0.390***	0.003	0.014	0.001	0.005	0.210*
LLP/TL	0.0014	0.0015	0.0009	0.0007	0.429***	0.0083	0.0064	0.0047	0.0046	0.653***
ROA	0.0061	0.0021	0.0058	0.0022	0.122	0.0009	0.0075	0.0047	0.0061	-0.569***
Leverage	0.904	0.021	0.912	0.019	-0.379***	0.908	0.018	0.910	0.019	-0.083
Deposits/TL	0.826	0.102	0.836	0.070	-0.107	0.801	0.104	0.804	0.074	-0.033
Loans/TA	0.713	0.119	0.681	0.099	0.294**	0.731	0.113	0.698	0.095	0.318**
RE/TL	0.736	0.159	0.715	0.129	0.145	0.741	0.154	0.714	0.136	0.186*
C&I/TL	0.163	0.095	0.168	0.097	-0.062	0.163	0.093	0.174	0.099	-0.111
HH/TL	0.053	0.067	0.077	0.068	-0.346***	0.050	0.063	0.070	0.069	-0.297**
GrossCDS/TA	0.002	0.009	0	0	0.398	0.002	0.008	0.001	0.004	0.240**
NetCDS/TA	0.0002	0.001	0	0	0.442***	1.28e-04	4.86e-04	4.32e-04	2.90e-04	0.213*
MBSheld/TA	0.003	0.009	0.012	0.033	-0.399***	0.004	0.013	0.008	0.027	-0.223*

Summary statistics for banks with different Net ΔCoVaR exposures over two time periods. The table displays covariate means and standard deviations for banks with above-median and below-median Net CoVaR exposures before and during the crisis. The left panel shows statistics for the pre-crisis period (2006:Q1-2007:Q2), and the right panel – for the crisis period (2007:Q3-2008:Q4). The normalized differences in means are also displayed, with asterisks (*) showing the significance level of the one-sided t-test for the corresponding non-normalized difference. Definitions and sources of control variables are listed in Internet Appendix B.

Table 2: Descriptive Statistics

	N	mean	sd	p25	p50	p75	N	mean	sd	p25	p50	p75
	Pre-crisis period						Crisis period					
ΔCoVaR^E	200	0.013	0.008	0.010	0.013	0.017	200	0.044	0.027	0.034	0.044	0.057
ΔCoVaR^C	200	0.012	0.007	0.007	0.014	0.018	200	0.027	0.016	0.013	0.028	0.037
Net ΔCoVaR	200	0.001	0.007	-0.003	-0.000	0.006	200	0.018	0.013	0.009	0.017	0.027
β^E	200	0.537	0.326	0.405	0.534	0.689	200	0.537	0.326	0.405	0.534	0.689
β^C	200	0.336	0.209	0.176	0.344	0.487	200	0.336	0.209	0.176	0.344	0.487
Net β CoVaR	200	0.210	0.243	0.044	0.186	0.377	200	0.210	0.243	0.044	0.186	0.377
Shock^E	200	0.025	0.000	0.025	0.025	0.025	200	0.083	0.003	0.083	0.083	0.083
Shock^C	200	0.050	0.038	0.034	0.040	0.046	200	0.093	0.041	0.070	0.081	0.105
Net shock CoVaR	200	-0.025	0.036	-0.022	-0.015	-0.009	200	-0.013	0.044	-0.022	0.002	0.013
Log(β_T^E)	172	0.332	0.522	0.111	0.507	0.634	176	0.221	0.379	0.129	0.327	0.443
Log(β_T^C)	172	-1.274	0.376	-1.502	-1.268	-1.052	176	-1.081	0.323	-1.262	-1.051	-0.858
Net Log(β_T)	172	1.611	0.607	1.224	1.738	2.040	176	1.305	0.427	1.031	1.299	1.581
MES^E	197	0.012	0.007	0.009	0.013	0.016	199	0.043	0.022	0.031	0.047	0.056
MES^C	198	0.006	0.004	0.004	0.008	0.009	199	0.039	0.022	0.027	0.043	0.055
Net MES	197	0.005	0.005	0.003	0.005	0.008	199	0.004	0.013	-0.004	0.002	0.011
DD	190	7.956	2.579	5.965	7.532	9.235	190	2.890	1.584	2.174	2.590	3.128
Log(Z-Score)	200	3.408	0.366	3.184	3.352	3.585	199	3.052	0.845	2.708	3.324	3.588
Log(ROA+Equity/TA)	200	-2.349	0.211	-2.490	-2.350	-2.229	200	-2.396	0.235	-2.520	-2.382	-2.224
Log(SD(ROA))	200	-5.756	0.376	-5.915	-5.709	-5.499	199	-5.450	0.749	-5.924	-5.672	-5.203
Log(SD(Interest))	200	-4.693	0.215	-4.831	-4.692	-4.548	199	-4.597	0.202	-4.699	-4.602	-4.473
Log(SD(Non-interest))	200	-5.480	0.416	-5.637	-5.412	-5.219	199	-5.197	0.492	-5.426	-5.227	-4.961
Log(SD(Trading))	200	0.00007	0.0002	0	0	0	199	0.0001	0.0003	0	0	0.00002
Log(SD(Securitization))	200	0.00002	0.0001	0	0	0	199	0.00002	0.00009	0	0	0
Log(SD(Fiduciary))	200	0.0005	0.0008	0	0.0002	0.0006	199	0.0005	0.0009	0	0.0003	0.0006
Insolvency							200	0.110	0.314	0	0	0
Log(Assets)	200	15.210	1.516	14.113	14.714	15.682	200	15.352	1.515	14.281	14.861	15.874
Deposits/TA	200	0.754	0.079	0.709	0.771	0.812	200	0.728	0.081	0.682	0.742	0.785
Non-IntInc/TI	200	0.167	0.094	0.105	0.154	0.215	200	0.167	0.092	0.109	0.155	0.222
Fiduciary/TI	200	0.022	0.039	0	0.010	0.029	200	0.022	0.039	0	0.011	0.029
Securitization/TI	200	0.001	0.004	0	0	0	200	0.001	0.003	0	0	0
Trading/TI	200	0.003	0.011	0	0	0	200	0.002	0.011	0	0	0
Loans/TA	200	0.697	0.110	0.656	0.714	0.767	200	0.714	0.105	0.670	0.731	0.782
LLP/TL	200	0.001	0.001	0.001	0.001	0.001	200	0.007	0.006	0.003	0.004	0.008
Asset growth	200	0.025	0.026	0.009	0.021	0.035	200	0.023	0.024	0.008	0.021	0.036
TARP							200	0.425	0.496	0	0	1
ROA	200	0.006	0.002	0.005	0.006	0.007	200	0.003	0.007	0.001	0.005	0.007
Leverage	200	0.908	0.020	0.898	0.911	0.922	200	0.909	0.019	0.895	0.911	0.921
Deposits/TL	200	0.831	0.087	0.787	0.853	0.892	200	0.802	0.090	0.754	0.816	0.867
RE/TL	200	0.726	0.145	0.647	0.747	0.818	200	0.727	0.145	0.640	0.747	0.832
C&I/TL	200	0.165	0.096	0.099	0.158	0.215	200	0.168	0.096	0.097	0.155	0.221
HH/TL	200	0.065	0.068	0.014	0.041	0.094	200	0.060	0.067	0.012	0.033	0.079
GrossCDS/TA	200	0.001	0.006	0	0	0	200	0.001	0.006	0	0	0
NetCDS/TA	200	0.00008	0.0004	0	0	0	200	0.00009	0.0004	0	0	0
MBSheld/TA	200	0.008	0.025	0	0	0	200	0.006	0.022	0	0	0

This table reports summary statistics of the main regression variables. The statistics are based on averaged data for the pre-crisis and crisis periods. The pre-crisis period spans from Q1:2006 to Q2:2007, and the crisis period spans from Q3:2007 to Q4:2008. Definitions and sources of variables are listed in Internet Appendix B.

Table 3: Correlations of Systemic Risk Metrics

Panel A: Exposure measures			
	ΔCoVaR^E	Log(β_T^E)	MES^E
ΔCoVaR^E	1		
Log(β_T^E)	0.04	1	
MES^E	0.55	0.30	1
Panel B: Contribution measures			
	ΔCoVaR^C	Log(β_T^C)	MES^C
ΔCoVaR^C	1		
Log(β_T^C)	0.47	1	
MES^C	0.59	0.33	1
Panel C: Net exposure measures			
	Net ΔCoVaR	Net Log(β_T)	Net MES
Net ΔCoVaR	1		
Net Log(β_T)	0.07	1	
Net MES	0.28	0.38	1

This table reports correlations between the systemic risk variables. The statistics are based on quarterly data for the pre-crisis period which spans from Q1:2006 to Q2:2007. Definitions and sources of variables are listed in Internet Appendix B.

Table 4: BHCs Ranked According to Net CoVaR Exposure (Pre-Crisis)

Name	Total Assets	Net CoVaR exposure
1 SILVER STATE BANCORP	1,180	0.02365
2 RELIANCE BANCSHARES, INC.	869	0.02024
3 UCBH HOLDINGS, INC.	9,322	0.02015
4 CORUS BANKSHARES, INC.	9,688	0.01932
5 CAPITAL CORP OF THE WEST	1,870	0.01879
6 BANNER CORPORATION	3,551	0.01600
7 BANK OF AMERICA CORPORATION	1,464,009	0.01575
8 CENTRAL PACIFIC FINANCIAL CORP.	5,413	0.01523
9 SECURITY BANK CORPORATION	2,320	0.01432
10 UNITED COMMUNITY BANKS, INC.	6,872	0.01409
11 CITIGROUP INC.	1,847,525	0.01409
12 WACHOVIA CORPORATION	631,471	0.01314
13 FIFTH THIRD BANCORP	103,144	0.01267
14 SVB FINANCIAL GROUP	5,700	0.01227
15 HUNTINGTON BANCSHARES INCORPORATED	35,739	0.01158
16 PAB BANKSHARES, INC.	1,113	0.01110
17 OLD SECOND BANCORP, INC.	2,443	0.01105
18 MARSHALL & ILSLEY CORPORATION	54,781	0.01087
19 HORIZON FINANCIAL CORP.	1,228	0.01067
20 MBT FINANCIAL CORP.	1,572	0.01061
21 WESTERN ALLIANCE BANCORPORATION	4,186	0.01058
22 ZIONS BANCORPORATION	46,411	0.01057
23 PORTER BANCORP, INC.	1,061	0.01055
24 FNB CORP.	1,713	0.01050
25 CASCADE BANCORP	2,107	0.01008
26 REGIONS FINANCIAL CORPORATION	112,784	0.00976
27 INDEPENDENT BANK CORPORATION	3,395	0.00965
28 WELLS FARGO & COMPANY	497,191	0.00924
29 FIDELITY SOUTHERN CORPORATION	1,565	0.00913
30 DEARBORN BANCORP, INC.	876	0.00890
31 BANCTRUST FINANCIAL GROUP, INC.	1,350	0.00838
32 STATE STREET CORPORATION	108,156	0.00815
33 INTERVEST BANCSHARES CORPORATION	1,936	0.00809
34 PRINCETON NATIONAL BANCORP, INC.	992	0.00802
35 IRWIN FINANCIAL CORPORATION	6,291	0.00800
36 NEXITY FINANCIAL CORPORATION	864	0.00798
37 SUNTRUST BANKS, INC.	181,998	0.00797
38 EAST WEST BANCORP, INC.	10,405	0.00789
39 CENTERSTATE BANKS OF FLORIDA, INC.	1,077	0.00773
40 HERITAGE COMMERCE CORP	1,122	0.00772
41 BEVERLY HILLS BANCORP INC.	1,535	0.00707
42 GREENE COUNTY BANCSHARES, INC.	1,921	0.00701
43 U.S. BANCORP	217,230	0.00697
44 TEMECULA VALLEY BANCORP INC.	1,159	0.00694
45 KEYCORP	93,660	0.00675
46 BOSTON PRIVATE FINANCIAL HOLDINGS, INC.	5,595	0.00670
47 WEST COAST BANCORP	2,372	0.00633
48 SYNOVUS FINANCIAL CORP.	31,502	0.00630
49 PINNACLE FINANCIAL PARTNERS, INC.	2,091	0.00587
50 MACATAWA BANK CORPORATION	2,043	0.00581

This table shows the 50 US banks with highest net CoVaR exposure in our sample, ranked in descending order as of the pre-crisis period (Q1:2006-Q2:2007). Average assets are shown in millions of US dollars.

Table 5: ΔCoVaR Determinants

VARIABLES	(1) ΔCoVaR^E	(2) ΔCoVaR^E	(3) ΔCoVaR^E	(4) ΔCoVaR^E	(5) ΔCoVaR^E	(6) ΔCoVaR^C	(7) ΔCoVaR^C	(8) ΔCoVaR^C	(9) ΔCoVaR^C	(10) ΔCoVaR^C	(11) Net ΔCoVaR	(12) Net ΔCoVaR	(13) Net ΔCoVaR	(14) Net ΔCoVaR	(15) Net ΔCoVaR
Log(assets)$_{t-1}$	0.0107***	0.0109***	0.0112***	0.0121***	0.0123***	0.00871***	0.00757***	0.00826***	0.00968***	0.00811***	0.00112	0.00280***	0.00190**	0.00145*	0.00250**
	(0.00136)	(0.000874)	(0.00123)	(0.00116)	(0.00189)	(0.000841)	(0.000679)	(0.000726)	(0.000640)	(0.000828)	(0.000803)	(0.000705)	(0.000763)	(0.000781)	(0.00105)
Fiduciary/TI$_{t-1}$	-0.0246				-0.0199	0.0317**				0.0269**	-0.0552*				-0.0394*
	(0.0303)				(0.0314)	(0.0152)				(0.0131)	(0.0288)				(0.0238)
Securitization/TI$_{t-1}$	-0.665*				-0.575	-0.129				-0.192	-0.444**				-0.281
	(0.373)				(0.432)	(0.254)				(0.318)	(0.216)				(0.200)
Trading/TI$_{t-1}$	0.101				0.166	-0.173*				-0.0857	0.255***				0.258**
	(0.145)				(0.169)	(0.0939)				(0.105)	(0.0903)				(0.101)
LLP/TL$_{t-1}$	-1.582				-1.581	-1.802***				-1.558**	0.774				0.447
	(1.077)				(1.115)	(0.676)				(0.777)	(0.827)				(1.012)
ROA$_{t-1}$	1.087				0.944	0.883**				0.936**	0.512				0.236
	(0.708)				(0.678)	(0.423)				(0.393)	(0.538)				(0.559)
Loans/TA$_{t-1}$		0.00661			0.00621		-0.00660			-0.00135		0.0183*			0.0140
		(0.0131)			(0.0146)		(0.00780)			(0.00918)		(0.00986)			(0.0127)
RE/TL$_{t-1}$		-0.00138			-0.00311		0.0185**			0.0228*		-0.0145			-0.0197
		(0.0135)			(0.0184)		(0.00862)			(0.0122)		(0.0119)			(0.0150)
C&I/TL$_{t-1}$		0.00772			-0.00209		0.0434***			0.0481***		-0.0301***			-0.0420***
		(0.0149)			(0.0195)		(0.0104)			(0.0132)		(0.0115)			(0.0153)
HH/TL$_{t-1}$		-0.0267			-0.0227		0.0441***			0.0581***		-0.0653***			-0.0715***
		(0.0173)			(0.0211)		(0.0126)			(0.0154)		(0.0147)			(0.0178)
Leverage$_{t-1}$			-0.0195		0.0227			-0.0333		-0.00483			-0.0600		-0.0475
			(0.115)		(0.118)			(0.0439)		(0.0409)			(0.0555)		(0.0553)
Deposits/TL$_{t-1}$			0.0206		0.00980			0.00354		-0.0204			0.00845		0.0187
			(0.0163)		(0.0177)			(0.0125)		(0.0125)			(0.0136)		(0.0141)
GrossCDS/TA$_{t-1}$				-0.326	0.0125				-0.467**	-0.437**				0.167	0.403**
				(0.231)	(0.237)				(0.221)	(0.185)				(0.211)	(0.160)
NetCDS/TA$_{t-1}$				-5.220	-8.251*				-2.100	0.869				-1.544	-6.187*
				(3.785)	(4.671)				(4.473)	(3.358)				(3.899)	(3.147)
MBSheld/TA$_{t-1}$				-0.00295	0.00738				0.0579**	0.0687**				-0.0687**	-0.0567
				(0.0276)	(0.0312)				(0.0237)	(0.0319)				(0.0302)	(0.0441)
Observations	200	200	200	200	200	200	200	200	200	200	200	200	200	200	200
R-squared	0.378	0.360	0.357	0.365	0.388	0.626	0.598	0.568	0.601	0.681	0.081	0.130	0.048	0.055	0.196

This table presents the results of cross-section regressions of net systemic risk exposure measures on balance-sheet variables. The dependent variable is a bank's $\Delta CoVaR^E$ in columns (1) to (5), $\Delta CoVaR^E$ in columns (6)-(10), and *Net* $\Delta CoVaR$ in columns (11) to (15). All regressions contain the sample of the 200 largest banks in Q4:2006. The data is averaged within each period (pre-crisis and crisis), where the pre-crisis period spans from Q1:2006 to Q2:2007, and the crisis period spans from Q3:2007 to Q4:2008. Definitions and sources of control variables are listed in Internet Appendix B. All models are estimated using robust standard errors (in parentheses). ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 6: Net Systemic Risk Components' Determinants

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
VARIABLES	Net β CoVaR	Net β CoVaR	Net β CoVaR	Net β CoVaR	Net β CoVaR	Net shock CoVaR	Net shock CoVaR	Net shock CoVaR	Net shock CoVaR	Net shock CoVaR
Log(assets)$_{t-1}$	0.0315**	0.0638***	0.0394***	0.0266*	0.0513***	0.00310	-0.00271	0.00501	0.00559**	0.000805
	(0.0152)	(0.0141)	(0.0140)	(0.0144)	(0.0196)	(0.00234)	(0.00189)	(0.00312)	(0.00227)	(0.00328)
Fiduciary/TI$_{t-1}$	-1.253**				-0.883*	0.245**				0.175**
	(0.610)				(0.509)	(0.100)				(0.0841)
Securitization/TI$_{t-1}$	-7.893				-4.045	1.418**				0.709
	(4.944)				(4.392)	(0.637)				(0.461)
Trading/TI$_{t-1}$	4.595**				4.148**	-0.610**				-0.688**
	(1.981)				(2.090)	(0.285)				(0.279)
LLP/TL$_{t-1}$	22.72*				14.97	-9.543**				-8.122*
	(12.52)				(15.11)	(4.203)				(4.176)
ROA$_{t-1}$	3.917				-1.242	1.142				2.008
	(8.787)				(8.515)	(2.631)				(2.489)
Loans/TA$_{t-1}$		0.418**			0.313		-0.0810**			-0.0613*
		(0.173)			(0.223)		(0.0316)			(0.0363)
RE/TL$_{t-1}$		-0.242			-0.355		0.0149			0.0409
		(0.223)			(0.269)		(0.0458)			(0.0506)
C&I/TL$_{t-1}$		-0.513**			-0.714***		0.117**			0.141**
		(0.210)			(0.272)		(0.0532)			(0.0547)
HH/TL$_{t-1}$		-1.361***			-1.506***		0.207***			0.231***
		(0.274)			(0.304)		(0.0603)			(0.0621)
Leverage$_{t-1}$			-1.037		-0.849			0.357*		0.368**
			(1.007)		(0.936)			(0.192)		(0.164)
Deposits/TL$_{t-1}$			0.0540		0.267			0.0467		-0.00458
			(0.245)		(0.242)			(0.0662)		(0.0678)
GrossCDS/TA$_{t-1}$				4.274	7.920**				-0.708*	-0.686
				(4.400)	(3.636)				(0.384)	(0.453)
NetCDS/TA$_{t-1}$				3.981	-75.56				-4.410	3.673
				(76.24)	(66.87)				(6.075)	(6.489)
MBSheld/TA$_{t-1}$				-1.791***	-1.477*				0.275***	0.223*
				(0.527)	(0.785)				(0.0599)	(0.117)
Observations	200	200	200	200	200	200	200	200	200	200
R-squared	0.117	0.194	0.067	0.101	0.279	0.131	0.171	0.036	0.046	0.311

This table presents the results of cross-section regressions of net systemic risk exposure components on balance-sheet variables. The dependent variable is a bank's *Net β CoVaR* in columns (1) to (5) and *Net shock CoVaR* in columns (6) to (10). All regressions contain the sample of the 200 largest banks in Q4:2006. The data is averaged within each period (pre-crisis and crisis), where the pre-crisis period spans from Q1:2006 to Q2:2007, and the crisis period spans from Q3:2007 to Q4:2008. Definitions and sources of control variables are listed in Internet Appendix B. All models are estimated using robust standard errors (in parentheses). ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 7: Default Risk and Systemic Risk

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
VARIABLES	DD	Log(Z-Score)	Insolvency	DD	Log(Z-Score)	Insolvency	DD	Log(Z-Score)	Insolvency	DD	Log(Z-Score)	Insolvency
ΔCoVaR$^E_{t-1}$	-21.25	-7.593	-1.309				-23.11	-14.10	0.133			
	(14.21)	(13.10)	(2.090)				(14.38)	(15.05)	(1.705)			
ΔCoVaR$^C_{t-1}$				9.015	39.18***	-11.51***	13.68	42.29***	-11.55***			
				(22.23)	(13.08)	(2.929)	(22.09)	(13.46)	(2.994)			
Net Δ CoVaR$_{t-1}$										-26.32*	-41.53***	6.469**
										(15.54)	(11.25)	(2.614)
Log(assets)$_{t-1}$	-0.0886	-0.106	0.0449**	-0.181**	-0.193***	0.0528***	-0.105	-0.149*	0.0523***	-0.117	-0.0531	0.0222
	(0.0930)	(0.0746)	(0.0194)	(0.0899)	(0.0615)	(0.0158)	(0.0978)	(0.0758)	(0.0164)	(0.0889)	(0.0580)	(0.0172)
Deposits/TA$_{t-1}$	2.859	0.772	-0.296	2.678	0.576	-0.323	2.805	0.635	-0.324	2.716	0.688	-0.362
	(1.990)	(1.054)	(0.292)	(2.020)	(1.011)	(0.262)	(2.018)	(0.976)	(0.265)	(1.983)	(0.921)	(0.271)
Non-IntInc/TI$_{t-1}$	3.062**	2.773**	-1.033***	2.999**	2.160**	-0.687***	2.821**	2.013**	-0.685***	2.525**	1.746*	-0.762***
	(1.337)	(1.067)	(0.303)	(1.335)	(0.989)	(0.237)	(1.292)	(0.981)	(0.234)	(1.236)	(0.950)	(0.268)
Loans/TA$_{t-1}$	-1.558	-0.720	0.247	-1.604	-0.665	0.219	-1.522	-0.616	0.219	-1.491	-0.538	0.220
	(1.035)	(0.728)	(0.199)	(1.047)	(0.676)	(0.193)	(1.036)	(0.670)	(0.193)	(1.028)	(0.664)	(0.197)
LLP/TL$_{t-1}$	-168.4*	-118.8**	7.756	-135.3	-60.34	-4.320	-143.8	-64.16	-4.280	-118.7	-80.17	4.303
	(96.32)	(55.71)	(9.252)	(90.86)	(63.92)	(10.49)	(94.93)	(64.69)	(10.43)	(87.24)	(64.13)	(9.522)
Asset growth$_{t-1}$	0.468	-3.661	1.126*	1.069	-2.181	0.730	0.995	-2.184	0.731	2.075	-1.534	0.847
	(3.851)	(3.027)	(0.680)	(3.942)	(2.939)	(0.575)	(4.100)	(2.967)	(0.577)	(3.745)	(2.998)	(0.708)
TARP	-0.401**	0.281**	-0.190***	-0.478**	0.179	-0.166***	-0.420**	0.218*	-0.166***	-0.441**	0.295***	-0.205***
	(0.200)	(0.119)	(0.0565)	(0.208)	(0.118)	(0.0613)	(0.204)	(0.120)	(0.0591)	(0.204)	(0.108)	(0.0585)
Observations	190	199	200	190	199	200	190	199	200	190	199	200
(*pseudo*) R-squared	0.11	0.18	0.33	0.10	0.23	0.41	0.11	0.24	0.40	0.11	0.26	0.37

This table presents the results of cross-section regressions of default risk indicators on systemic risk measures. The dependent variable is a bank's Merton *DD* in columns (1), (4), (7), and (10) *Log(Z-Score)* in columns (2), (5), (8), and (11) and *Insolvency* in columns (3), (6), (9), and (12). $\Delta CoVaR^E$ is the difference between the value at risk of the bank conditional on the stressed and the median state of the financial system. $\Delta CoVaR^C$ is the difference between the value at risk of the financial system conditional on the stressed and the median state of the bank. *Net* $\Delta CoVaR$ is the difference between the $\Delta CoVaR^E$ and the $\Delta CoVaR^C$. All regressions contain the sample of the 200 largest banks in Q4:2006. The data is averaged within each period (pre-crisis and crisis), where the pre-crisis period spans from Q1:2006 to Q2:2007 and the crisis period spans from Q3:2007 to Q4:2008. Columns (3), (6), (9) and (12) report marginal effects. Definitions and sources of control variables are listed in Internet Appendix B. All models are estimated using robust standard errors (in parentheses). ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Table 8: Additional Tests

Panel A: Instrumental Variables						
	(1)	(2)	(3)	(4)	(5)	(6)
	DD		Log(Z-Score)		Insolvency	
	1st stage	2nd stage	1st stage	2nd stage	1st stage	2nd stage
Reserve city	0.004***		0.005***		0.004**	
	(0.0017)		(0.0015)		(0.0015)	
Net Δ CoVaR$_{t-1}$		-103.6**		-95.67*		32.63
		(45.88)		(54.81)		(20.72)
F - test	6.33		9.01		8.10	
Controls	Y	Y	Y	Y	Y	Y
Observations	190	190	199	199	200	200
R-squared		0.023		0.11		0.02

Panel B: Alternative Net Systemic Risk Measures						
	(1)	(2)	(3)	(4)	(5)	(6)
	DD	Log(Z-Score)	Insolvency	DD	Log(Z-Score)	Insolvency
Net Log(β_T)$_{t-1}$	-0.370**	0.0323	0.107***			
	(0.182)	(0.106)	(0.0406)			
Net MES$_{t-1}$				-80.73***	-6.867	11.68***
				(27.09)	(12.73)	(4.057)
Controls	Y	Y	Y	Y	Y	Y
Observations	165	171	172	188	196	197
(*Pseudo*) R-squared	0.18	0.22	0.39	0.18	0.20	0.42

This table presents the results of cross-section regressions of default risk indicators on systemic risk measures. Panel A shows the results of IV regressions using as an instrument the dummy variable *Reserve city*, which indicates whether the bank is located in a reserve city as defined by the National Banking Acts of 1863–1864. Panel B shows the results of default risk models using as alternative net systemic risk measures the *Net Log(β_T)* that corresponds to the difference between $log(\beta_T^E)$ and $log(\beta_T^C)$, and the *Net MES* that corresponds to the difference between MES^E and MES^C. Columns (1) and (4) report marginal effects. All regressions contain the sample of the 200 largest banks in Q4:2006. The data is averaged within each period (pre-crisis and crisis), where the pre-crisis period spans from Q1:2006 to Q2:2007, and the crisis period spans from Q3:2007 to Q4:2008. Definitions and sources of control variables are listed in Internet Appendix B. All models are estimated using robust standard errors (in parentheses). ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 9: Default Risk and Systemic Risk Components

VARIABLES	(1) DD	(2) Log(Z-Score)	(3) Insolvency	(4) DD	(5) Log(Z-Score)	(6) Insolvency	(7) DD	(8) Log(Z-Score)	(9) Insolvency
Net β CoVaR_{t-1}	-1.187***	-1.196***	0.156**				-1.131***	-1.068***	0.137*
	(0.400)	(0.299)	(0.0792)				(0.376)	(0.284)	(0.0728)
Net shock CoVaR_{t-1}				3.591	6.410***	-1.188***	2.261	5.098**	-1.077***
				(3.963)	(1.972)	(0.400)	(3.965)	(2.209)	(0.394)
Log(assets)$_{t-1}$	-0.0878	-0.0531	0.0247	-0.178**	-0.155***	0.0408**	-0.0992	-0.0797	0.0275
	(0.0826)	(0.0553)	(0.0184)	(0.0871)	(0.0580)	(0.0169)	(0.0825)	(0.0546)	(0.0170)
Deposits/TA_{t-1}	2.773	0.711	-0.351	2.446	0.237	-0.162	2.597	0.318	-0.200
	(1.968)	(0.904)	(0.271)	(1.974)	(0.946)	(0.277)	(1.912)	(0.837)	(0.277)
Non-IntInc/TI_{t-1}	2.287*	1.825*	-0.820***	2.768**	2.141**	-0.654**	2.086**	1.388	-0.484**
	(1.178)	(0.947)	(0.280)	(1.188)	(1.020)	(0.256)	(1.055)	(0.908)	(0.230)
Loans/TA_{t-1}	-1.416	-0.532	0.224	-1.525	-0.551	0.161	-1.364	-0.402	0.156
	(1.007)	(0.663)	(0.197)	(1.062)	(0.706)	(0.185)	(1.027)	(0.656)	(0.187)
LLP/TL_{t-1}	-118.5	-97.34	6.826	-150.3	-108.6**	6.977	-118.8	-94.52	6.308
	(92.30)	(62.53)	(9.207)	(92.34)	(52.34)	(8.672)	(92.30)	(59.74)	(8.622)
Asset growth$_{t-1}$	3.019	-1.314	0.877	1.907	-1.424	0.623	3.665	0.173	0.395
	(3.756)	(3.061)	(0.721)	(4.066)	(2.959)	(0.660)	(4.062)	(2.853)	(0.661)
TARP	-0.374*	0.353***	-0.212***	-0.509**	0.175	-0.155***	-0.408*	0.278**	-0.171***
	(0.197)	(0.108)	(0.0583)	(0.222)	(0.118)	(0.0566)	(0.211)	(0.115)	(0.0549)
Observations	190	199	200	190	199	200	190	199	200
(*Pseudo*) R-squared	0.125	0.262	0.357	0.105	0.225	0.385	0.127	0.294	0.409

This table presents the results of cross-section regressions of default risk indicators on systemic risk measures. The dependent variable is a bank's Merton *DD* in columns (1), (4), and (7), *Log(Z-Score)* in columns (2), (5), and (8), and *Insolvency* in columns (3), (6), and (9). *Net β CoVaR* is the difference between $\beta^E - \beta^C$ from equations (21) and (20). *Net shock CoVaR* is Shock CoVaR^E − Shock CoVaR^C. All regressions contain the sample of the 200 largest banks in Q4:2006. The data is averaged within each period (pre-crisis and crisis), where the pre-crisis period spans from Q1:2006 to Q2:2007 and the crisis period spans from Q3:2007 to Q4:2008. Columns (3), (6), and (9) report marginal effects. Definitions and sources of control variables are listed in Internet Appendix B. All models are estimated using robust standard errors (in parentheses). ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 10: Default Risk and Net Transmission Channels

	(1) Log(ROA+Equity/TA)	(2) Log(SD(ROA))	(3) Log(SD(Interest))	(4) Log(SD(Non-interest))	(5) Log(SD(Trading))	(6) Log(SD(Securitization))	(7) Log(SD(Fiduciary))
Net β CoVaR$_{t-1}$	-0.0674	0.986***	0.00568	0.427**	0.000218**	3.64e-06	2.03e-05
	(0.0826)	(0.264)	(0.0739)	(0.188)	(0.000103)	(2.49e-05)	(0.000247)
Net shock CoVaR$_{t-1}$	1.013**	-4.053*	0.601	-0.178	-0.00150*	-9.13e-05	-0.00108
	(0.510)	(2.214)	(0.491)	(1.264)	(0.000855)	(8.24e-05)	(0.00101)
Log(assets)$_{t-1}$	0.0178	0.0999*	-0.00531	-0.0475	6.80e-05***	1.68e-05***	-0.000104
	(0.0159)	(0.0514)	(0.0135)	(0.0390)	(2.08e-05)	(5.56e-06)	(7.08e-05)
Deposits/TA$_{t-1}$	0.0790	-0.173	0.718***	0.660	-0.000206	-7.80e-05	4.93e-05
	(0.258)	(0.804)	(0.251)	(0.598)	(0.000309)	(0.000102)	(0.000817)
Non-IntInc/TI$_{t-1}$	0.338	-0.993	0.0680	-0.649	0.000768**	8.74e-05	0.00625***
	(0.210)	(0.834)	(0.261)	(0.681)	(0.000347)	(0.000121)	(0.00172)
Loans/TA$_{t-1}$	0.242	0.629	0.512***	0.857**	-0.000628***	-0.000161**	-5.83e-05
	(0.172)	(0.602)	(0.152)	(0.389)	(0.000224)	(6.55e-05)	(0.000662)
LLP/TL$_{t-1}$	-69.16***	20.30	3.169	10.34	0.0392*	0.0227**	-0.0349
	(17.69)	(41.50)	(11.82)	(40.09)	(0.0212)	(0.0106)	(0.0431)
Asset growth$_{t-1}$	1.207	1.084	-0.950	-0.404	1.29e-05	0.000384*	-0.00276*
	(0.864)	(2.415)	(0.662)	(1.676)	(0.000804)	(0.000196)	(0.00142)
TARP	0.0130	-0.265**	-0.0733***	-0.115	3.62e-05	-4.45e-07	-2.74e-05
	(0.0320)	(0.103)	(0.0273)	(0.0717)	(3.40e-05)	(7.71e-06)	(0.000103)
Observations	200	199	199	199	199	199	199
R-squared	0.201	0.279	0.252	0.242	0.445	0.383	0.345

This table presents the results of cross-section regressions of Log(Z-Score) components on systemic risk measures. The dependent variable is a bank's Log(ROA+Equity/TA)) in column (1), *Log(SD(ROA)* in column (2), and components of non-interest income in columns (4) to (6). *Net β CoVaR* is the difference between $\beta^E - \beta^C$ from equations (21) and (20). *Net shock CoVaR* is Shock CoVaR^E − Shock CoVaR^C. All regressions contain the sample of the 200 largest banks in Q4:2006. The data is averaged within each period (pre-crisis and crisis), where the pre-crisis period spans from Q1:2006 to Q2:2007, and the crisis period spans from Q3:2007 to Q4:2008. Definitions and sources of control variables are listed in Internet Appendix B. All models are estimated using robust standard errors (in parentheses). ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Internet Appendix

A Model Proofs

Proof of Lemma 1. Consider two correlated Bernoulli variables X and Z, where X is 0 with probability p and Z is 0 with probability q, and observe that the risky asset Y is simply the transformation $Y = RZ$. Therefore, $Cov(X, Y) = Cov(X, RZ) = RCov(X, Z)$. Next, recall that

$$\mathbb{E}(XZ) = \mathbb{E}X\mathbb{E}Z + Cov(X, Z) \tag{27}$$

and observe that $\mathbb{E}X = 1 - p$ and $\mathbb{E}Z = 1 - q$. Therefore, the probability of joint success p_1 from Matrix 1 equals

$$p_1 = (1 - p)(1 - q) + Cov(X, Z) = (1 - p)(1 - q) + R^{-1}Cov(X, Y). \tag{28}$$

Knowing this we set up the equation system

$$p_1 = (1 - p)(1 - q) + R^{-1}Cov(X, Y) \tag{29}$$

$$p_1 + p_2 = 1 - p \tag{30}$$

$$p_1 + p_3 = 1 - q \tag{31}$$

$$\sum_i p_i = 1 \tag{32}$$

which produces the solution

$$p_1 = 1 - p - q + pq + R^{-1}Cov(X, Y) \tag{33}$$

$$p_2 = q(1 - p) - R^{-1}Cov(X, Y) \tag{34}$$

$$p_3 = p(1 - q) - R^{-1}Cov(X, Y) \tag{35}$$

$$p_4 = pq + R^{-1}Cov(X, Y). \tag{36}$$

as claimed. ■

Proof of Proposition 1. We will show that, at the optimal α^*, $\frac{\partial C}{\partial \alpha}(\alpha^*) > 0$ and $\frac{\partial E}{\partial \alpha}(\alpha^*) < 0$. Recall from the definition of contribution (11) and exposure (12) that

$$\frac{\partial C}{\partial \alpha} = \frac{d\mathbb{E}\pi}{d\alpha}(\alpha^*) - \frac{d\mathbb{E}(\pi_{sys}|s_i)}{d\alpha}(\alpha^*) = -\frac{d\mathbb{E}(\pi_{sys}|s_i)}{d\alpha}(\alpha^*) \tag{37}$$

$$\frac{\partial E}{\partial \alpha} = \frac{d\mathbb{E}\pi}{d\alpha}(\alpha^*) - \frac{d\mathbb{E}(\pi_i \mid Y=0)}{d\alpha}(\alpha^*) = -\frac{d\mathbb{E}(\pi_i \mid Y=0)}{d\alpha}(\alpha^*), \tag{38}$$

since the profit derivative is zero at the maximizer α^*. Hence, we need to focus on the above derivatives of conditional profits.

Effect of trading on Contribution. The expected profits conditional on a negative shock are

$$\mathbb{E}(\pi_{sys}|s_i) = \int_{[0,1]\setminus\{i\}} \mathbb{E}\pi_j dj \;=\; \frac{p_2(1-\alpha) + p_3\alpha R + p_4 \cdot 0}{1-p_1} - 1 + 2\alpha - 2\alpha^2, \tag{39}$$

This conditional profit is maximized when

$$\frac{\partial \mathbb{E}(\pi \mid s_i)}{\partial \alpha} = -\frac{p_2}{1-p_1} + \frac{p_3}{1-p_1}R + 2 - 4\alpha = 0 \tag{40}$$

whose maximizer is the root α_0 defined as

$$\alpha_0 = \frac{1}{2} + \frac{1}{4}\left[\frac{p_3 R - p_2}{1-p_1}\right] \tag{41}$$

To find whether trading increases or reduces contribution near the optimum α^*, we must evaluate the sign of the derivative $\frac{\partial \mathbb{E}(\pi|s_i)}{\partial \alpha}$ at α^*. Since the conditional profit function is concave,[27] we know that it increases for $\alpha < \alpha_0$ and decreases for $\alpha > \alpha_0$. Thus, we must find whether α^* is greater or smaller than α_0. If $\alpha^* < \alpha_0$, then trading increases conditional expected profit, thereby reducing contribution C.

We next verify under what conditions $\alpha^* < \alpha_0$. Substituting the values of α^* and α_0, we get

$$(p_1 + p_3)R - p_1 - p_2 < \frac{p_3 R - p_2}{1-p_1}. \tag{42}$$

[27] This is easily provable by taking the second derivative of the function (39).

This simplifies down to

$$R(1-p_1-p_3) < 1-p_1+p_2. \tag{43}$$

Substituting the definitions of p_i in terms of p and q, this inequality reduces down to

$$Rq+p < 2[1-q(1-p)+R^{-1}Cov(X,Y)], \tag{44}$$

or equivalently, to the quadratic inequality in R

$$R^2 - \left(\underbrace{\frac{2[1-q(1-p)]-p}{q}}_{\kappa}\right) R + 2p < 0. \tag{45}$$

This expression has two roots, $R = \kappa \pm \sqrt{\kappa^2-2p}$, where κ is the expression defined by the horizontal brace above. The inequality holds for any R between these two roots. Since the smaller root is easily shown to be less than 1, while $R > 1$ is required, the binding condition is $R < \kappa + \sqrt{\kappa^2-2p}$. However, this upper bound is so large that it likely does not matter in practice. For example, for $p = 0.05$ and $q = 0.10$, the upper bound $\kappa + \sqrt{\kappa^2-2p} > 35$; thus, the return R of the risky asset has to exceed the return of the safe asset by a factor of 35 for this condition to start to matter. Nonetheless, for completeness we list this as a required condition.

As a result, we can conclude that $\frac{\partial \mathbb{E}(\pi|s_i)}{\partial \alpha}|_{\alpha^*} > 0$, whenever $1 < R < \kappa + \sqrt{\kappa^2-2p}$. Hence, according to equation (42), $\partial C/\partial \alpha < 0$ at and near α^*. (The "near" part follows since any continuous function preserves its sign in a sufficiently small neighborhood of a point at which the function's value is non-zero.) Hence, trading reduces contribution C when the upper bound condition on R is met.

Effect of trading on Exposure. The expected profits conditional on a trading shock are

$$\begin{aligned}\mathbb{E}(\pi \mid Y=0) =& \frac{p_2(1-\alpha)+p_4\cdot 0}{(1-p_1-p_3)} - 1 + 2\alpha - 2\alpha^2 \\ =& \frac{p_2}{q}(1-\alpha) - 1 + 2\alpha - 2\alpha^2\end{aligned} \tag{46}$$

This concave conditional profit function is maximized when

$$\frac{\partial \mathbb{E}(\pi \mid Y=0)}{\partial \alpha} = -\frac{p_2}{q} + 2 - 4\alpha = 0 \tag{47}$$

producing the maximizer

$$\alpha_1 = \frac{1}{2} - \frac{p_2}{4q}. \tag{48}$$

Profits conditional on a trading shock (46) will be decreasing in trading at α^* if we find that $\alpha_1 < \alpha^*$, because this conditional profit function is concave. Next we verify under what conditions $\alpha_1 < \alpha^*$. By substituting the expressions for the two roots α^* and α_1 in the last inequality and simplifying, we obtain the necessary condition

$$-p_2/q < \underbrace{(1-q)R}_{\mathbb{E}Y} - \underbrace{(1-p)}_{\mathbb{E}X}. \tag{49}$$

But this always holds if $\mathbb{E}Y - \mathbb{E}X > 0$, as already assumed in the model setup. Therefore, $\frac{\partial \mathbb{E}(\pi|Y=0)}{\partial \alpha}|_{\alpha^*} < 0$, and by equation (43), $\partial E/\partial \alpha > 0$ at and near the optimal asset mix α^*. (The "near" part follows since any continuous function preserves its sign in a sufficiently small neighborhood of a point at which the function's value is non-zero.) Hence, trading increases exposure E.

Net exposure is strictly increasing in trading α. Recalling the definitions of exposure and contribution from equations (10) and (12),

$$E = \pi^* - (1-\alpha)\frac{p_2}{q} + TC(\alpha) \tag{50}$$

$$C = \pi^* - (1-\alpha)\frac{p_2}{1-p_1} - \alpha R \frac{p_3}{1-p_1} + TC(\alpha), \tag{51}$$

we can express net exposure $NE(\alpha)$ as

$$\begin{aligned} NE = E - C = & -(1-\alpha)\frac{p_2}{q} + (1-\alpha)\frac{p_2}{1-p_1} + \alpha R\frac{p_3}{1-p_1} \\ =&(1-\alpha)p_2\left[\frac{q-1+p_1}{(1-p_1)q}\right] + \frac{\alpha p_3}{1-p_1}R \\ =&\frac{1}{1-p_1}\left[(1-\alpha)\frac{p_2}{q}\left[q-1+p_1\right] + \alpha p_3 R\right] \\ =&\frac{1}{1-p_1}\left[-(1-\alpha)\frac{p_2 p_3}{q} + \alpha p_3 R\right] \end{aligned} \tag{52}$$

The derivative of net exposure with respect to trading α is

$$\frac{\partial(E-C)}{\partial\alpha} = \frac{1}{(1-p_1)}\left[\frac{p_2 p_3}{q} + p_3 R\right] > 0 \tag{53}$$

which is positive. Hence, net exposure increases with trading α.

Proof of Proposition 2. (i). *Default risk increases with net exposure.*

We are going to prove that profit variance is increasing in α at the optimal α^*, i.e., $\frac{dVar(\pi)}{d\alpha}(\alpha^*) > 0$, and use this fact jointly with $d(E-C)/d\alpha > 0$ to prove that profit variance and default risk are both increasing in net exposure $E - C$.

The first derivative of the profit variance with respect to α is

$$\begin{aligned} \frac{dVar(\pi)}{d\alpha} = & \alpha\Big\{2p_1(R-1)(qR-p) + 2p_2[R(1-q)+p] + 2p_3 R[Rq + (1-p)]\Big\} + \\ & +2p_1[qR-p] - 2p_2[R(1-q)+p] \end{aligned} \tag{54}$$

and the second derivative is positive

$$\frac{d^2Var(\pi)}{d\alpha^2} = 2p_1(R-1)(qR-p) + 2p_2[R(1-q)+p] + 2p_3 R[Rq + (1-p)] > 0 \tag{55}$$

because

$$qR - p > 0, \quad R(1-q) + p > 0, \quad \text{and} \quad Rq + (1-p) > 0 \tag{56}$$

(all of these follow from the assumptions $R > 1$ and $q > p$). This demonstrates that the profit variance is strictly convex in α, and therefore has a minimum at a variance minimizer α_v obtained by setting the first derivative (54) equal to zero (we verify α_v is not a corner solution below). The question is therefore whether $\alpha_v < \alpha^*$, in which case α^* would be on the increasing portion of the $Var\big(\pi(\alpha)\big)$ curve as claimed in the result.

The variance minimizer

$$\alpha_v = \frac{p_1[qR-p] - p_2[R(1-q)+p]}{p_1(R-1)(qR-p) + p_2[R(1-q)+p] + p_3R[Rq+1-p]} > 0 \tag{57}$$

is clearly positive due to the inequalities in (56), but is smaller than or equal to 1/2, from which it follows that $\alpha_v < \alpha^*$. Hence, $\frac{dVar(\pi)}{d\alpha}(\alpha^*) > 0$. To ascertain this, we verify the inequality $\alpha_v \leq 1/2$, which (after some algebra) reduces down to

$$p_1(qR-p)[3-R] - 3p_2[R(1-q)+p] \leq p_3R[Rq+(1-p)]. \tag{58}$$

This is a quadratic inequality in R with a solution of $R \in [R_1, R_2]$, where the roots R_1 and R_2 (when existent) are given by

$$R_{1,2} = \frac{\gamma \mp \sqrt{\gamma^2 - 12pq(1-p)(1-q)}}{2q(1-q)}, \tag{59}$$

and where $\gamma = 2p(1-p)(1-q) + R^{-1}Cov(X,Y)(3+4p-p^2)$.

Since γ contains the covariance term, the inequality's solution range $R \in [R_1, R_2]$ depends on the numerical value of $Cov(X,Y)$ and cannot be checked analytically for all possible values. (For example, for $Cov(X,Y) = 0$, the inequality always holds, but for $Cov(X,Y) > 0$ the roots also depend on p and q). Instead we verify numerically that the inequality (58) holds for the full range of covariances $-pqR \leq Cov(X,Y) \leq Rp(1-q)$ and for a wide set of plausible loss probabilities $p < q$ on the interval [0.01, 0.25]. Thus, for the plausible parameter range for the model, it is true that $\alpha_v < \alpha^*$, and given the convexity of $Var\ \pi(\alpha)\big)$ and its continuity, it follows that $\frac{dVar(\pi)}{d\alpha}(\alpha^*) > 0$. We use this fact jointly with the fact $d(E-C)/d\alpha > 0$ to prove default risk is increasing in net exposure $E - C$.

Recall from the previous discussion that net exposure $NE(\alpha) \equiv E(\alpha) - C(\alpha)$ is a differentiable and strictly increasing function of α, for which the inverse function $\alpha(NE)$ exists and is also strictly increasing in net exposure, i.e. $\frac{d\alpha}{d(NE)} > 0$. Now define the nested function $Var\ \pi(\alpha(NE))\big)$ and observe that, by the chain rule, the derivative

$$\frac{dVar(\pi)}{d\alpha}\frac{d\alpha}{d(NE)} = \frac{dVar(\pi)}{d(NE)} > 0 \tag{60}$$

when evaluated at α^*. Hence, the profit variance $Var(\pi)$ is strictly increasing in net exposure at α^*.

Now consider the model Z-Score,

$$Z - Score_{model} = \frac{1 + \pi(\alpha)}{\sqrt{Var(\pi(\alpha))}}. \tag{61}$$

We will show that the Z-Score is decreasing in net exposure and in α at the optimal α^*. Observe that

$$\frac{dZ - Score_{model}}{d\alpha}\bigg|_{\alpha^*} = \frac{\pi'(\alpha^*)\sqrt{Var(\pi)} - 0.5(1+\pi(\alpha^*))Var^{-1/2}(\pi)\frac{dVar(\pi)}{d\alpha}}{Var(\pi(\alpha^*))}. \tag{62}$$

Since $\pi'(\alpha^*) = 0$, $Var(\pi) \geq 0$, $1 + \pi(\alpha^*) \geq 0$, and $\frac{dVar(\pi)}{d\alpha}\Big|_{\alpha^*} > 0$, we have

$$\frac{dZ - Score_{model}}{d\alpha}\bigg|_{\alpha^*} < 0. \tag{63}$$

At the same time, we also know that $d\alpha/d(NE) > 0$. Combining these two facts,

$$\frac{dZ - Score_{model}}{d\alpha}\frac{d\alpha}{d(NE)} = \frac{dZ - Score_{model}}{d(NE)} < 0, \tag{64}$$

therefore the model predicts that higher net exposure reduces the Z-Score and hence increases default risk at and near the optimal diversification point α^*.

(ii) *An increase in $Cov(X, Y)$ reduces the Z-Score.*

We are interested in the effect of an increase in $Cov(X,Y)$ on the model Z-Score.

$$\frac{dZ - Score_{model}}{dCov(X,Y)} = \frac{[\mathbb{E}\pi]'\sqrt{Var(\pi)} - 0.5(1+\mathbb{E}\pi)(Var(\pi))^{1/2}[Var(\pi)]'}{Var(\pi)}. \tag{65}$$

Observe that $[\mathbb{E}\pi]' = 0$, because differentiating the expected profit

$$\begin{aligned}\mathbb{E}\pi =& [1-(p+q)+pq+R^{-1}Cov(X,Y)](1-\alpha+\alpha R)+\\ &+[q(1-p)-R^{-1}Cov(X,Y)](1-\alpha)+\\ &+[p(1-q)-R^{-1}Cov(X,Y)]\alpha R - TC(\alpha)\end{aligned} \tag{66}$$

with respect to $Cov(X,Y)$ yields the derivative

$$[\mathbb{E}\pi]' = [1-\alpha+\alpha R-(1-\alpha)-\alpha R]R^{-1} = 0. \tag{67}$$

Therefore, from equation (65) it follows that

$$\text{sgn}\left\{\frac{dZ - Score_{model}}{dCov(X,Y)}\right\} = -\text{sgn}\left\{\frac{dVar(\pi)}{dCov(X,Y)}\right\}, \tag{68}$$

which implies that the effect on the model Z-Score operates through the profit variance channel: an increase in covariance results in more variable profits, but does not change their average value.

Since costs are deterministic, the variance of profit is the same as that of total revenue. Therefore,

$$\begin{aligned}Var(\pi) =& p_1[1+\alpha(R-1)-\overline{TR}]^2 + p_2[(1-\alpha)-\overline{TR}]^2+\\ &+p_3[\alpha R-\overline{TR}]^2+p_4[-\overline{TR}]^2 =\\ &= -\overline{TR}^2 + p_1(1+\alpha(R-1))^2 + p_2(1-\alpha)^2 + p_3(\alpha R)^2,\end{aligned} \tag{69}$$

where $\overline{TR}$ is the mean total revenue. Substituting p_1 to p_4 from equations (34) to (36) and the mean revenue value yields

$$
\begin{aligned}
&Var(\pi) = \\
&\qquad -\Big([1-(p+q)+pq+R^{-1}Cov(X,Y)](1+\alpha(R-1))+ \\
&\qquad (1-\alpha)\left[q(1-p)-R^{-1}Cov(X,Y)\right]+\alpha R\left[p(1-q)-R^{-1}Cov(X,Y)\right]\Big)^2+ \\
&\qquad [1-(p+q)+pq+R^{-1}Cov(X,Y)][1+\alpha(R-1)]^2+ \\
&\qquad [q(1-p)-R^{-1}Cov(X,Y)](1-\alpha)^2+(\alpha R)^2[p(1-q)-R^{-1}Cov(X,Y)].
\end{aligned}
\tag{70}
$$

The derivative of $Var(\pi)$, however, simplifies down to the simple expression

$$
\begin{aligned}
\frac{dVar(\pi)}{dCov(X,Y)} &= R^{-1}\Big([(1-\alpha)+\alpha R]^2-(1-\alpha)^2-(\alpha R)^2\Big) = \\
&= 2\alpha(1-\alpha),
\end{aligned}
\tag{71}
$$

which is positive for $\alpha \in (0,1)$ and zero when $\alpha = 0$ or $\alpha = 1$.

Putting everything together, we obtain

$$
\text{sgn}\left\{\frac{dZ-Score_{model}}{dCov(X,Y)}\right\} = -\text{sgn}\left\{2\alpha(1-\alpha)\right\} = \begin{cases} <0 & \text{for } \alpha \in (0,1) \\ 0 & \text{for } \alpha = 0 \text{ or } 1. \end{cases}
\tag{72}
$$

Hence an increase in covariance reduces bank stability by lowering the bank's Z-Score for any interior α. This implies that, conditional on a crisis (increase in covariance), default risk should increase for diversified banks (which feature an interior α^*). Non-diversified banks, by contrast, are not affected by covariance changes, because they hold only one asset.

(iii). *Default risk operates through the profit variance channel.*

Substituting $\alpha = \alpha^*$ in equation (71), we see that at and near the optimal diversification point α^*, $\frac{dVar(TR)}{dCov(X,Y)}(\alpha^*) > 0$.

B Variable Definitions

Variable Definitions

Variable	Definition	Source
Systemic Risk Measures and Components		
ΔCoVaR^C	ΔCoVaR as defined in equation (1)	Authors' calculation with Bloomberg price data
ΔCoVaR^E	Exposure ΔCoVaR defined in equation (2)	Authors' calculation with Bloomberg price data
β CoVaR^C	Estimated β_C from equation (3)	Authors' calculation with Bloomberg price data
β CoVaR^E	Estimated β_E from equation (4)	Authors' calculation with Bloomberg price data
Shock CoVaR^C	$(VaR_q^i - VaR_{50}^i)$ from equation (3)	Authors' calculation with Bloomberg price data
Shock CoVaR^E	$(VaR_q^s - VaR_{50}^s)$ from equation (4)	Authors' calculation with Bloomberg price data
MES^E	A bank's average return taken over the days scoring the 5% worst daily returns of the S&P Banks Index for each quarter	Authors' calculation with Bloomberg price data
MES^C	The banking sector's S&P Banks Index average return taken over the days scoring the 5% worst daily returns of the individual bank for each quarter	Authors' calculation with Bloomberg price data
$\beta_{T,i}^E$	Bank i's tail exposure to the rest of the system as in van Oordt and Zhou (2019a), estimated by EVT	Authors' calculation with Bloomberg price data
$\beta_{T,i}^C$	The system's tail exposure to bank i obtained by inverting the conditioning in van Oordt and Zhou (2019a), estimated by EVT	Authors' calculation with Bloomberg price data
Net Exposure Measures		
Net ΔCoVaR	ΔCoVaR^E − ΔCoVaR^C	Authors' calculation
Net β CoVaR	$\beta^E - \beta^C$ from equations (21) and (20)	Authors' calculation
Net shock CoVaR	Shock CoVaR^E − Shock CoVaR^C	Authors' calculation
Net MES	MES^E − MES^C	Authors' calculation
Net Log(β_T)	$\log(\beta_T^E) - \log(\beta_T^C)$	Authors' calculation
Individual Risk measures		
Z-Score	[ROA + (Total equity capital/Total assets)]/sd(ROA)	Authors' calculation with Form FR-Y9C data
DD	Merton distance to default as in Merton (1974)	Authors' calculation with Bloomberg price data and Form FR-Y9C
Insolvency	A dummy equal to 1 if the bank failed, was acquired due to insolvency risk, had a direct subsidiary fail, or had a cease-and-desist order from the FDIC during the crisis up to Q4:2010.	FDIC ED&O database and FDIC Failed Banks List

Variable Definitions (cont'd)

Variable	Definition	Source
Bank controls		
Log(assets)	Logarithm of assets	Federal Reserve Form FR-Y9C
Fiduciary/TI	Fiduciary income over total income	Federal Reserve Form FR-Y9C
Securitization/TI	Securitization income over total income	Federal Reserve Form FR-Y9C
Trading/TI	Trading income over total income	Federal Reserve Form FR-Y9C
Loans/TA	Total loans as a fraction of total assets	Federal Reserve Form FR-Y9C
LLP/TL	Loan loss provisions over total loans	Federal Reserve Form FR-Y9C
Asset growth	Quarterly asset growth	Federal Reserve Form FR-Y9C
TARP	Equals 1 if bank received TARP government aid, 0 otherwise.	US Dept. of the Treasury
ROA	Net income over assets	Federal Reserve Form FR-Y9C
Leverage	Debt over assets	Federal Reserve Form FR-Y9C
Deposits/TL	Deposits as fraction of total loans	Federal Reserve Form FR-Y9C
RE/TL	Real estate loans over total loans	Federal Reserve Form FR-Y9C
C&I/TL	C&I loans over total loans	Federal Reserve Form FR-Y9C
HH/TL	Household loans over total loans	Federal Reserve Form FR-Y9C
GrossCDS/TA	$ of CDS held over total assets	Federal Reserve Form FR-Y9C
NetCDS/TA	$ of CDS protection bought minus $ of CDS protection sold over total assets	Federal Reserve Form FR-Y9C
MBSheld/TA	MBS securities held over total assets	Federal Reserve Form FR-Y9C

C Risk Measures Details

C.1 Exposure tail beta and contribution tail beta

Systemic risk metrics differ in their ability to capture comovements under extreme stress. To robustify our analysis, we use the systemic risk measure of van Oordt and Zhou (2019a), known as tail beta, which captures the sensitivity of a bank's stock market return to extremely adverse shocks to the financial system, based on just a few observations. In its original form, the tail beta is an exposure metric.[28] It is based on a regression of bank returns R_i on system-wide returns R_s, restricted to the $q\%$-tail of the system's return distribution ($R_s < -VaR_q^s$). This regression can be expressed as:

$$R_{i,t} = \beta_{T,i}^E R_{s,t} + \varepsilon_{i,t} \quad \text{for} \quad R_{s,t} < -VaR_q^s, \tag{73}$$

where the system return is empirically proxied by that of the S&P Banking index. This regression cannot be estimated with OLS due to the low number of tail observations, and is instead estimated with extreme value theory methods (EVT) as in van Oordt and Zhou (2019a). These authors show that for a tail of k observations in a moving window totaling n observations, β_T^E can be estimated as

$$\beta_{T,i}^E = \tau_i(k/n)^{1/\xi_s} \frac{VaR_{k/n}^i}{VaR_{k/n}^s}, \tag{74}$$

where $k/n = q\%$ is the size of the tail, ξ_s is a tail index estimated separately with the Hill (1975) EVT estimator, and the $q\%$ values at risk for the bank and the system ($VaR_{k/n}^i$ and $VaR_{k/n}^s$) are estimated from the lowest k daily returns of the relevant return distribution. The parameter τ is a measure of the tail dependence between the bank and the market, defined as

$$\tau_i(q) = \Pr\left(R_i < -VaR_q^i \mid R_s < -VaR_q^s \right), \tag{75}$$

[28] Hence we superscript it with an "E."

and is estimated non-parametrically as in Embrechts, De Haan and Huang (2000). The estimation approach and its applications are developed in van Oordt and Zhou (2016) and van Oordt and Zhou (2019b), based on EVT methods as in De Haan and Ferreira (2006). We set the size of the tail at 4% as in van Oordt and Zhou (2016),[29] and the estimation period at two years (about 500 daily observations) following Davydov et al. (2021).[30] Based on the reasoning in van Oordt and Zhou (2019a), we also construct a contribution tail beta (β_T^C), capturing the effect of the bank on the system in the tail regression

$$R_{s,t} = \beta_{T,i}^C R_{i,t} + \epsilon_{i,t} \quad \text{for} \quad R_{i,t} < -VaR_q^i, \tag{76}$$

restricted to observations when individual bank i's returns drop within the worst q% of the return distribution. The contribution tail beta β_T^C is similarly estimated by EVT as:

$$\beta_{T,i}^C = \tau_i (k/n)^{1/\xi_i} \frac{VaR_{k/n}^s}{VaR_{k/n}^i}, \tag{77}$$

where ξ_i is the tail index of individual bank i's return distribution, estimated with the Hill (1975) estimator. For convenience, we transform β_T^E and β_T^C in log form, denoting them as Log(β_T^E) and Log(β_T^C), noting that since the estimated β_T^C is between 0 and 1, its logarithm is negative. This does not indicate a negative contribution to systemic risk.

Table 2 shows that, in line with our remaining measures, contribution consistently exceeded exposure both before and during the crisis, resulting in a large positive net beta averaging at 1.61 before and 1.31 during the crisis. The average log exposure tail beta remained similar before and during the crisis, averaging at 0.33 and 0.22, respectively, with the change being statistically insignificant. The log contribution tail beta increased from -1.27 to -1.08. The variance of these measures did not change significantly, since they are slow-moving by construction. This family of metrics confirms our earlier CoVaR findings.

[29] However, our results are robust to tail sizes anywhere from 2.5% to 5%.

[30] The intention is to provide a time window closer to the one used by ΔCoVaR while still meeting the minimum sample requirement for EVT estimation.

C.2 Exposure MES and contribution MES

Acharya et al.'s (2017) MES (marginal expected shortfall) is a reduced-form exposure metric aiming to capture the expected capital shortfall of individual bank i, conditional on stress in the rest of the system. By definition, this is an exposure metric, so we superscript it as MES^E. The MES^E for a bank i is constructed quarterly (the standard frequency in the literature) as the average of i's daily returns, taken over the days where the system's returns are within their worst 5% for each quarter. If $R_{i,d}$ is the return of bank i on day d, then this bank's exposure MES for quarter t is defined as

$$MES_{i,t}^{E} = \frac{1}{|I|} \sum_{d \in I} R_{i,d}, \quad \text{where} \quad I = \{\text{worst 5\% of days for the system return } R_{s,d}\}, \tag{78}$$

where $R_{s,d}$ is the return of the S&P Banking Index. We create the contribution version of this metric, MES^C, by interchanging the place of the bank versus the system while conditioning on the stress event. Thus, MES^C is the average of the system's returns conditional on bank i experiencing tail returns within their worst 5% for the quarter:

$$MES_{i,t}^{C} = \frac{1}{|I|} \sum_{d \in I} R_{s,d}, \quad \text{where} \quad I = \{\text{worst 5\% of days for } i\text{'s return } R_{i,d}\}. \tag{79}$$

Since stressed returns are negative, we take the negative values of MES^E and MES^C for ease of interpretation. Thus, higher exposure MES values indicate a higher exposure, and higher contribution MES values indicate a higher impact on the system by bank i.

Consistent with ΔCoVaR and tail beta, Table 2 shows that the exposures of large banks to shocks from the system exceeded their systemic risk contributions. Table 2 shows that both the average exposure and contribution MES increase after the crisis, from 0.012 to 0.043 and from 0.006 to 0.039, respectively, with a positive Net MES both before and during the crisis. The standard deviations of both measures also increase after the crisis, rising from 0.007 to 0.022 and from 0.004 to 0.022.

C.3 Merton distance to default

The Merton model uses two nonlinear equations to translate the value and volatility of a firm's equity into a Z-score-like metric often dubbed distance to default (DD), calculated as:

$$DD = \frac{\ln(V/F) + (\mu - 0.5\sigma_V^2)T}{\sigma_V \sqrt{T}}, \tag{80}$$

where V is the firm's total value, F is the face value of the firm's debt, μ is an estimate of the expected annual return of the firm's assets, σ_V^2 is the variance of firm value, and T is the forecast horizon, usually taken as 1 year. The main idea behind this calculation is to subtract the face value of the firm's debt from an estimate of the firm's market value and then divide this difference by an estimate of the firm's volatility, scaled to the forecast horizon. The more market value exceeds debt given the volatility, the more stable the firm is.

Since the volatility of firm value V is unknown, Merton's (1974) bond pricing model is usually invoked to represent firm equity as a call option on the underlying firm value with a strike price equal to the face value of the firm's debt and a time-to-maturity of T. Merton's model links observed firm equity E, the face value of debt F, and firm value V in a nonlinear equation that can be solved numerically conditional on a few distributional assumptions, making it possible to calculate the distance in equation (80). We refer the reader to Merton (1974) and Bharath and Shumway (2008) for further details.