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Asymmetric Systemic Risk

by Radoslav Raykov[1] and Consuelo Silva-Buston[2]

[1] Financial Stability Department
Bank of Canada

[2] School of Management
Pontificia Universidad Católica de Chile

rraykov@bankofcanada.ca, consuelosilva@uc.cl

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Abstract

Bank regulation is based on the premise that risks spill over more easily from large banks to the banking system than vice versa. On the contrary, we document that risk transmission is stronger in the system-to-bank direction. We term this asymmetric systemic risk, measure it with net exposure metrics, and explore the consequences and channels behind it. We show that banks with positive net exposure to the system had higher default risk during the 2008 crisis, and that bank size and trading activities were the main determinants of this net exposure, which increased default risk through trading income volatility and overall profit volatility. We argue that the current bank supervision objectives can be achieved more efficiently if regulation focuses on reducing such net exposures, rather than buffering the default risks arising from them.

Topics: Financial institutions; Financial stability; Financial system regulation and policies
JEL codes: G10, G20

> *"...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 make large banks face more complex regulations, meet higher capital requirements, and face more regulatory scrutiny than smaller banks to reduce this transmission.[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 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

[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.

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. Interestingly, 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), especially during the crisis. In addition, Figures 2 and 3 reveal that banks that experienced high insolvency risk during the crisis[3] (colored in red) had consistently larger exposures than contributions, therefore appearing to the right of each chart's 45º line.

Motivated by these facts, we hypothesize systemic risk *directionality* matters for banks' individual stability. The variety of activities that banks can perform is likely to impact a bank's contribution differently compared to its exposure, and more importantly, activities affecting exposure versus contribution may have opposite effects on bank soundness, sometimes offsetting each other. For instance, significant involvement in traditional lending (e.g., real estate, household, and C&I loans), which is known to increase a bank's contribution to systemic risk, may still benefit bank stability due to a better risk-return trade-off than alternative non-traditional activities, which are likely to increase a bank's exposure through counterparty risk. In other words, banks with high systemic exposure may not necessarily face higher insolvency risk if this exposure is accompanied by a high systemic contribution driven by activities that improve bank soundness. The balance between these types of activities strongly depends on the bank's business model (traditional versus modern).

We confirm our hypothesis and document that this asymmetry matters in practice. 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 the net

[2]Systemic risk measures in this figure are computed using Adrian and Brunnermeier's (2016) ΔCoVaR and Exposure ΔCoVaR, defined rigorously in Section 3.

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

exposure of large banks before the global financial crisis meaningfully correlates with their 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. To this end, we decompose a bank's net exposure into two components: (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. We show that the effect on bank default risk is driven by the net transmission factor rather than the net losses, and that the link between this factor and insolvency runs through asset risk, increasing the volatility of trading income and profits.

Next, we analyze the balance sheet determinants of a bank's net exposure. 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 find that the use of credit default swaps and trading activities increase a bank's net exposure. However, this exposure decreases if banks offload more risk than they gain by maintaining larger positions on net protection bought on credit derivatives. 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.

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 contained 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 as the net transmission factor increases, which is positively related to size and the use of credit derivatives. We argue that current bank supervision objectives can be achieved more efficiently if regulation focuses on reducing such net exposures, 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 the data and our risk measures. Section 4 shows the empirical strategy and lays out results from the regression analysis. Section 5 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.[4] As the figure shows, large banks' exposure (the blue line) is consistently higher than their systemic risk contribution (the red line).[5] 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 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.

[4] All systemic risk measures are defined and discussed in Section 3.

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

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[6] (colored in red) appear to the right of the diagonal line. However, high contribution alone appears uncorrelated with default risk, as some of the safest among the top 200 banks feature contributions higher than those of the riskier ones. Net exposure, by contrast, correlates well with both size and risk.

These preliminary facts highlight a source of heterogeneity in the banking system that could be important for better understanding systemic risk. The rest of the paper explores the reasons behind it and its implications.

3 Data and Risk Measures

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 default risk and bank-specific covariates, 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

[6]See Section 3.3 for how we define banks with high insolvency risk.

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.[7] 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.[8]

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.[9] The summary statistics for the sample are provided in Table 1.

3.1 Systemic risk measures

3.1.1 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

[7] 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.

[8] 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.

[9] 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.

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 (e.g. $q = 5$), R_i the stock market return of financial institution i, and R_s that of the system, 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 median state to its q-percent quantile. More formally,

$$\Delta CoVaR^C_{i,q} = CoVaR_q^{s|R^i=VaR^i_q} - CoVaR_q^{s|R^i=VaR^i_{50}}, \tag{1}$$

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).[10] 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 (1) to obtain:

$$\Delta CoVaR^E_{i,q} = CoVaR_q^{i|R^s=VaR^s_q} - CoVaR_q^{i|R^s=VaR^s_{50}}. \tag{2}$$

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:

$$\Delta CoVaR^C_{i,q} = \beta^C_i(VaR^i_q - VaR^i_{50}) \tag{3}$$

$$\Delta CoVaR^E_{i,q} = \beta^E_i(VaR^s_q - VaR^s_{50}), \tag{4}$$

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

[10] 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.

each respective entity to make it equally worse off (at its 5% VaR).[11] More importantly, the risk transmission 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's (2016) approach in estimating equations (3) and (4) with quantile regressions using q set to 5.[12] For ease of interpretation, we take the negatives of CoVaR and Exposure CoVaR, so higher values indicate larger systemic risk.

Table 1 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.

3.1.2 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.[13] 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 distri-

[11]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 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.

[12]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.

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

bution ($R_s < -VaR_q^s$). This regression can be expressed as:

$$R_{i,t} = \beta_{T,i}^E R_{s,t} + \varepsilon_{i,t} \quad \text{for} \quad R_{s,t} < -VaR_q^s. \tag{5}$$

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

$$\beta_{T,i}^E = \tau_i(k/n)^{1/\xi_s} \frac{VaR_{k/n}^i}{VaR_{k/n}^s}, \tag{6}$$

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

$$\tau_i(q) = \Pr\left(R_i < -VaR_q^i \mid R_s < -VaR_q^s\right), \tag{7}$$

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),[14] and the estimation period at two years (about 500 daily observations) following Davydov et al. (2021).[15] 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

$$R_{s,t} = \beta_{T,i}^C R_{i,t} + \epsilon_{i,t} \quad \text{for} \quad R_{i,t} < -VaR_q^i, \tag{8}$$

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

[15]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.

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:

$$\beta_{T,i}^C = \tau_i (k/n)^{1/\xi_i} \frac{VaR_{k/n}^s}{VaR_{k/n}^i}, \tag{9}$$

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 1 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.

3.1.3 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 remaining banks' 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

$$MES_{i,t}^E = \frac{1}{|I|} \sum_{d \in I} R_{i,d}, \quad \text{where} \quad I = \{\text{worst 5\% of days for the system return } R_{s,d}\}, \tag{10}$$

where $R_{s,d}$ is the return of the S&P Banking Index. This measure has been shown to be a powerful tool to identify systemically important banks (Acharya et al., 2017). 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:

$$MES_{i,t}^{C} = \frac{1}{|I|} \sum_{d \in I} R_{s,d}, \quad \text{where} \quad I = \{\text{worst 5\% of days for } i\text{'s return } R_{i,d}\}. \tag{11}$$

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 1 shows that the exposures of large banks to shocks from the system exceeded their systemic risk contributions. Table 1 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.

3.2 Net systemic risk measures

We have hypothesized that banks' contributions and exposures have offsetting effects on bank soundness. Hence, a natural metric to capture whether a bank's linkage to the system is stronger in the system-to-bank direction is its 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:

$$Net\ Measure_{i,t} = Measure_{i,t}^{E} - Measure_{i,t}^{C}, \tag{12}$$

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

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 similar, but not identical results.

Table 2 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 3 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.

Banks with large net exposures differ systematically from the rest. Table 4 presents the standardized differences of bank characteristics for banks with above- and below-median values of Net ΔCoVaR 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 4 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; they also featured different loan portfolio composition. High net exposure banks also featured a larger involvement in trading activities and CDS markets, 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 loans. We therefore hypothesize, and subsequently verify, that these banks feature higher net exposures because of undertaking activities that affect exposure and contribution differently.

Table 1 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.

3.3 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 based on the Merton bond pricing model (Merton, 1974). 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:

$$DD = \frac{\ln(V/F) + (\mu - 0.5\sigma_V^2)T}{\sigma_V \sqrt{T}}, \tag{13}$$

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 (13). We refer the reader to Merton (1974) and Bharath and Shumway (2008) for further details.

The distance to default is a measure of distance to insolvency; a higher value of this variable indicates better bank soundness. Table 1 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., Demirguc-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

$$\text{Z-Score}_{i,t} = \frac{\text{ROA}_{i,t} + (\text{Total equity capital}_{i,t}/\text{Total Assets}_{i,t})}{\sigma_{\text{ROA}_{i,t}}}, \tag{14}$$

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 called *Insolvency*, flagging the banks with high risk of insolvency during the crisis. We manually compile data 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. 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.[16] The purpose of a cease-and-desist order is "to remedy unsafe or unsound practices or violations and to correct conditions resulting from such practices or violations" (FDIC, 2019). Such an order can be 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. Thus, this is a regulatory enforcement action meant to bring an institution identified by the FDIC as risky back into compliance with the supervisory standard. Table 1 shows that 11% of the banks in the sample faced such insolvency risk during the crisis.

[16] 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.

4 Empirical Strategy and Results

4.1 Systemic risk exposure versus contribution and default risk

We first examine the relation between a bank's systemic risk exposure or contribution versus its default risk. To this end, we estimate the following cross-section model at the bank level:

$$y_{i,crisis} = \beta_1 Systemic\ risk_{i,pre} + \beta_2 X_{i,pre} + \epsilon_i, \tag{15}$$

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 5. 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 shows to be 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. Thus, we test whether it is the variation in the *difference* between both measures that affects stability. Results confirm this is the case; the net systemic risk measure now enters significantly in all three models. 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.[17] 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 levels. 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

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

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 5 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. 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 suggests 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.[18] 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.

[18]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.

We present the results of these models in Panel A of Table 6. The first stage of these models shown in 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.[19] 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 2.1. The results in Panel B of Table 6 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.

4.2 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 $(VaR^s_q - VaR^s_{50}) - (VaR^i_q - VaR^i_{50})$, from equations (4) and (3). 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 $\beta^E_i - \beta^C_i = \text{Net } \beta_i$.

The results of this study are shown in Table 7. 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

[19] 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.

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. We investigate these dimensions in Table 8 and study the numerator and the denominator of the Z-Score separately.[20] We split the Z-score into the capital equity ratio plus ROA (numerator) and the standard deviation of ROA over the relevant period (the denominator). The evidence in this table suggests 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-

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

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 those high net exposure banks. Hence, Table 8 shows a positive relationship between net betas and the volatility of profits, and a negative relationship between net betas and Z-scores. This result further reinforces the view that non-interest income activities are a source of increased risk (Stiroh, 2004; Demirgüç-Kunt and Huizinga, 2010).

4.3 Determinants of net systemic risk exposure

We argue 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 examine in this section 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.

We first investigate banks' business models. For this purpose, we split non-interest income into three components: securitization revenue, fiduciary income and trading income. We include all three variables measured as a fraction of total income. We also include loan loss provisions over total loans, and ROA. 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 9. 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 intuition, trading increases exposure, and might reduce contribution, but the effect's significance on the individual exposure and contribution measures is harder to detect than on the net measure. 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 during the crisis, 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 significant in column (15). Moreover, this effect in column (15) equals almost exactly the net difference of the separate exposure and contribution coefficients in columns (5) and (10), suggesting that both play a role.

Second, we study the relationship between banks' systemic risk and funding structure, which has also been pointed out as a source of systemic risk. 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 (2) and (7) 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 (12) 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).

Third, we consider loan portfolio composition. To this end, we include loans over total assets and the share of real estate loans, commercial loans, and household loans over total loans. This allows us to examine a bank's exposure to traditional activities, which has been shown to reduce systemic risk exposure and contribution (Brunnermeier et al., 2020), and its portfolio mix, which has been identified as a key driver of systemic risk during the crisis (in particular, the share of real estate loans). Column (3) suggests no significant relationship between a bank's loan portfolio composition and its systemic exposure, whereas, when we study a bank's contribution (column (8)), we find a higher proportion of real estate, commercial and household loans to be related to higher contribution to systemic risk. 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 (13), 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, which may increase a bank's contribution to systemic risk, may still benefit bank stability due to a better risk-return trade-off compared to alternative non-traditional activities, which are likely to increase a bank's exposure through counterparty risk.

Fourth, we consider derivatives usage to proxy for interconnectedness and complexity. For this, we study gross and net CDS positions over total assets,[21] 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. Results remain similar when including all controls in columns (5) and (10). When we study net systemic exposure in column (14), we find the opposite result: 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

[21] 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.

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 9, 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 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 10, 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 idea that banks with different business models undertake activities that affect their systemic contributions and exposures differently. It shows that even though some balance sheet variables, such as non-interest income and 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, which is what matters for bank stability (as shown in the previous section). At the same time, size, which has also been identified as a key determinant of both exposure and contribution, increases net systemic exposure and hence the default risk of large banks. Furthermore, the use of credit default swaps and trading activities also increase net systemic exposure, but this exposure is reduced if banks offload more risk than they gain, thus having larger net positions on protection bought. The analysis suggests that the effect of size, trading activities, and credit default swaps 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.

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.

5 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. This systemic impact has typically been considered excessive, as evidenced by the "too big to fail" label so frequently applied to them. 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. 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.

To understand the underpinnings of this phenomenon, we examine the determinants of a bank's net exposure to the financial system, that is, its exposure net of its impact. We find that bank size and derivatives trading increase a bank's net exposure; however, this exposure decreases if banks offload more risk than they gain by maintaining larger positions on net protection bought on CDS. 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 these derivatives, banks suffered increased income volatility during the crisis, increasing default risk. Banks carried out these activities at the cost of investing in other assets that would have increased their contribution but also contained default risk, such as traditional lending activities.

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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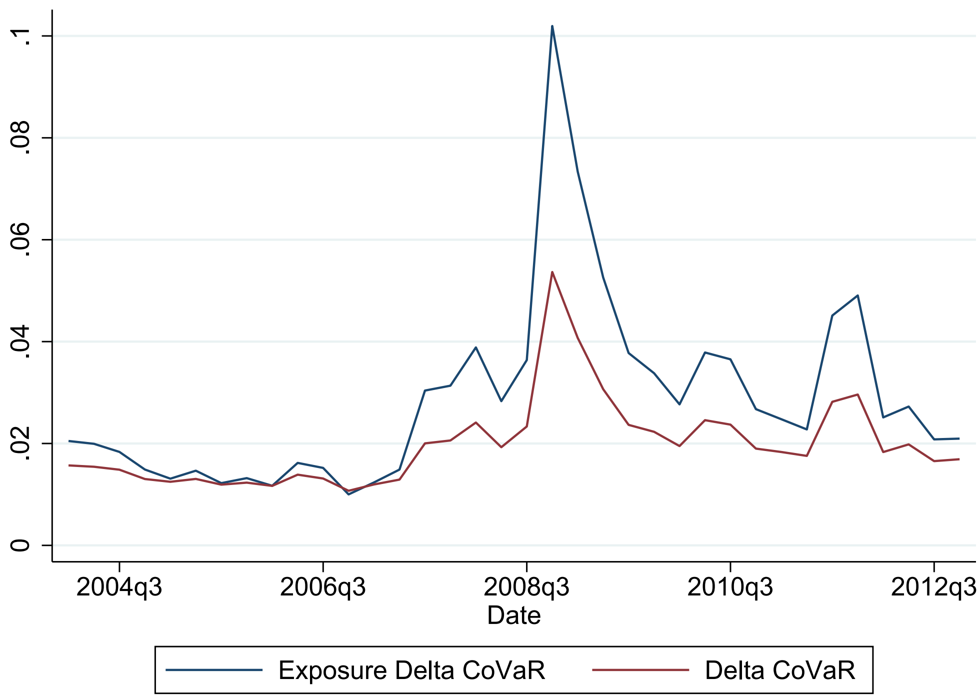
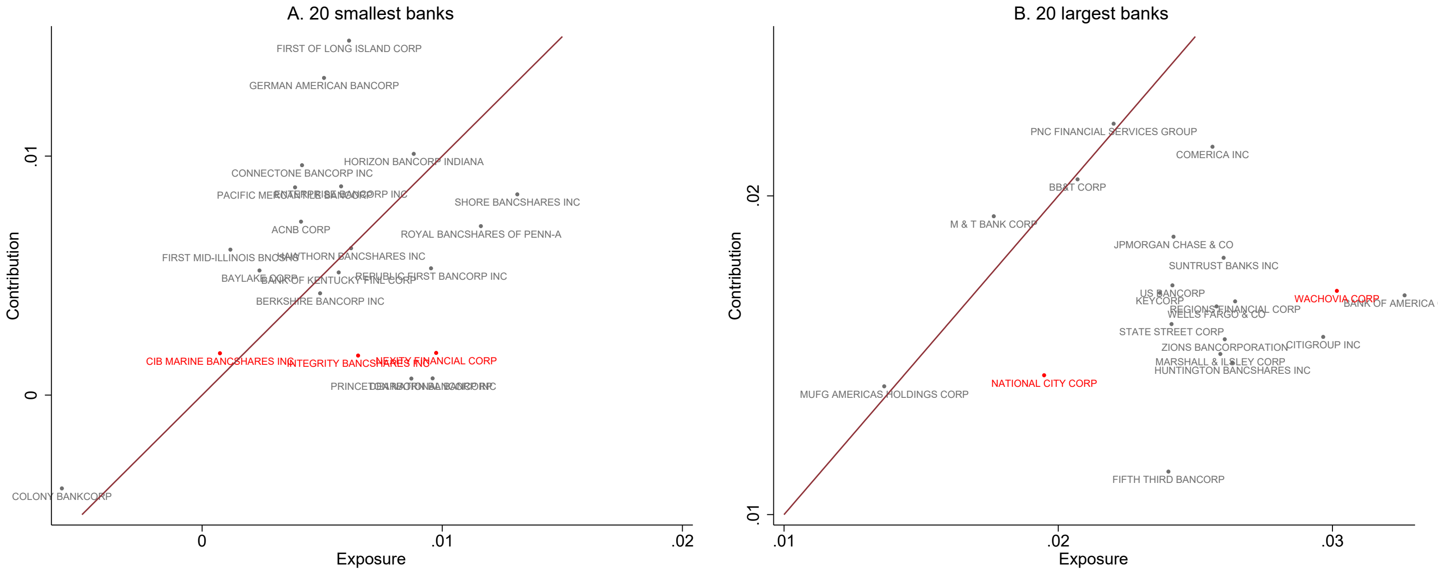
6 Figures

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



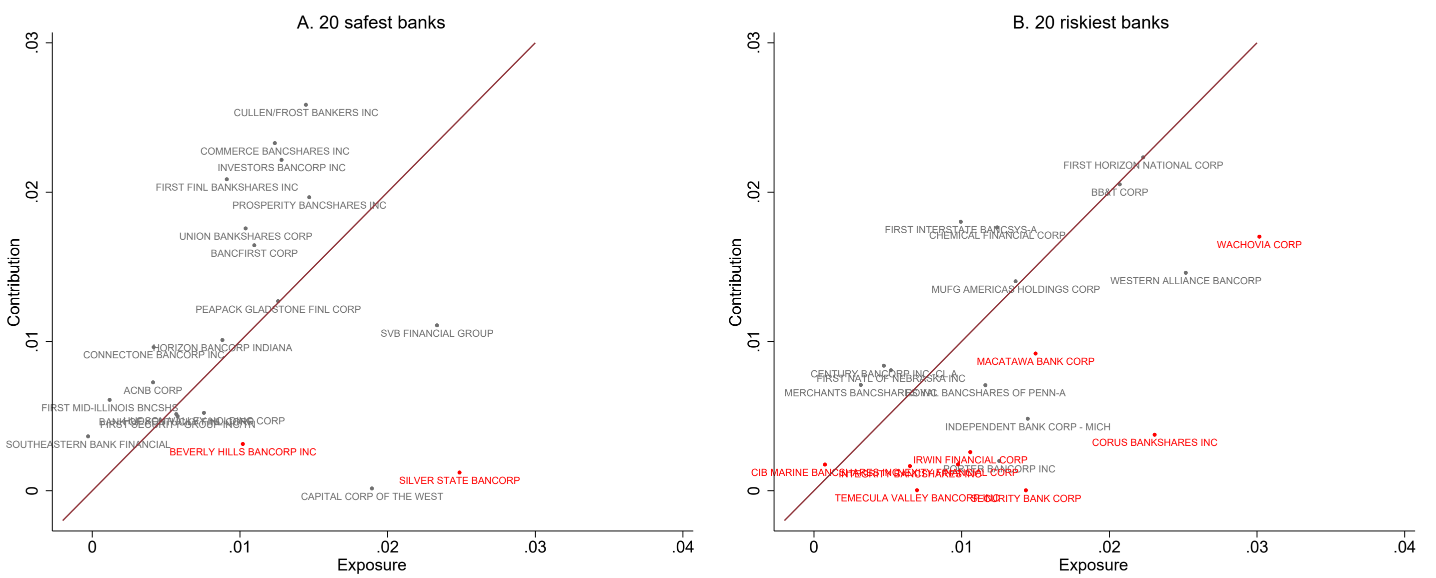
The figure shows the evolution of banks' average systemic risk exposure and contribution as measured by Adrian and Brunnermeier's (2016) Exposure ΔCoVaR and ΔCoVaR metrics, respectively. The graph displays the cross-sectional average across the top 200 US bank holding companies by assets as measured 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.

7 Tables

Table 1: 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 Appendix A.

Table 2: Correlations of Systemic Risk Metrics

Panel A: Exposure measures

	ΔCoVaR^E	$\text{Log}(\beta_T^E)$	MES^E
ΔCoVaR^E	1		
$\text{Log}(\beta_T^E)$	0.04	1	
MES^E	0.55	0.30	1

Panel B: Contribution measures

	ΔCoVaR^C	$\text{Log}(\beta_T^C)$	MES^C
ΔCoVaR^C	1		
$\text{Log}(\beta_T^C)$	0.47	1	
MES^C	0.59	0.33	1

Panel C: Net exposure measures

	Net ΔCoVaR	Net $\text{Log}(\beta_T)$	Net MES
Net ΔCoVaR	1		
Net $\text{Log}(\beta_T)$	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 Appendix A.

Table 3: 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 4: 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 Appendix A.

Table 5: 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 Appendix A. All models are estimated using robust standard errors (in parentheses). ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Table 6: 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$(\beta_T)_{t-1}$	-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 Appendix A. 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 Components

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	DD	Log(Z-Score)	Insolvency	DD	Log(Z-Score)	Insolvency	DD	Log(Z-Score)	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 (3) and (4). *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 Appendix A. All models are estimated using robust standard errors (in parentheses). ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 8: Default Risk and Net Transmission Channels

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Log(ROA+Equity/TA)	Log(SD(ROA))	Log(SD(Interest))	Log(SD(Non-interest))	Log(SD(Trading))	Log(SD(Securitization))	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 (3) and (4). *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 Appendix A. All models are estimated using robust standard errors (in parentheses). ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 9: 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***	0.0112***	0.0109***	0.0121***	0.0123***	0.00871***	0.00826***	0.00757***	0.00968***	0.00811***	0.00112	0.00190**	0.00280***	0.00145*	0.00250**
	(0.00136)	(0.00123)	(0.000874)	(0.00116)	(0.00189)	(0.000841)	(0.000726)	(0.000679)	(0.000640)	(0.000828)	(0.000803)	(0.000763)	(0.000705)	(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)
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)
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)
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	0.357	0.360	0.365	0.388	0.626	0.568	0.598	0.601	0.681	0.081	0.048	0.130	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) to (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 Appendix A. All models are estimated using robust standard errors (in parentheses). ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 10: 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**	0.0394***	0.0638***	0.0266*	0.0513***	0.00310	0.00501	-0.00271	0.00559**	0.000805
	(0.0152)	(0.0140)	(0.0141)	(0.0144)	(0.0196)	(0.00234)	(0.00312)	(0.00189)	(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)
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)
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)
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	0.067	0.194	0.101	0.279	0.131	0.036	0.171	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 Appendix A. All models are estimated using robust standard errors (in parentheses). ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Appendix A: 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	$(VaR^i_q - VaR^i_{50})$ from equation (3)	Authors' calculation with Bloomberg price data
Shock CoVaR^E	$(VaR^s_q - VaR^s_{50})$ 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
$\beta^E_{T,i}$	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
$\beta^C_{T,i}$	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 (3) and (4)	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)	$\log(\beta^E_T) - \log(\beta^C_T)$	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
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

Appendix A: Variable Definitions (cont'd)

Variable	Definition	Source
Bank controls (cont'd)		
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