# Systemic Risk in Commercial Bank Lending

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**Abstract**

This paper develops a bank model for financial systemic risk in bank lending. The model analyzes the impact of a financial institution failure on the distribution of losses in the financial system. The fundamental idea is that bank loss rates may be decomposed into a level, momentum, systematic and systemic component. Financial institutions fail when unexpected losses exceed the capital buffer and the release of capital allocated to credits. Failed financial institutions pass these loss exceedances on to creditors, deposit insurance schemes or the general public. The benefits of the presented model framework are (i) the identification of systemically relevant financial institutions, and (ii) the measurement of the size of safety nets in terms of attachment likelihood and expected losses given attachment. The model is generally applicable as it does not rely on financial market data. The empirical evidence presented is based on information collected by US prudential regulators from 1997 to 2012. The parameter estimation is based on a novel maximum likelihood technique to derive the parameters in a non-linear mixed model with multiple random effects.

*JEL classification:* G20; G28; C51

*Keywords:* Asset correlation; Bank capital buffer; Basel Committee on Banking Supervision; Credit portfolio risk; Commercial banks; Regulation; Systemic risk.

# 1 Introduction

## *1.1 Motivation*

Failures of financial institutions are capable of destabilizing financial systems. Financial system stability and the associated risk has been an area of increased research effort after the Global Financial Crisis (GFC). This process has in part been driven by the attention of regulators and the general public. Systemically important financial institutions are often classified as 'too big to fail' or 'too interconnected to fail'. [2]

Cerutti et al. (2012) stress the need for information about how banks are connected in order to analyze systemic risk. Many forms of interconnectedness exist, such as counterparties in over-the-counter (OTC) transactions, borrower/lender relationships, or client/supplier relationships. Going forward, financial institutions may be asked to disclose material direct and indirect evidence of such relationships. In addition, counterparty credit risk in OTC transactions will be mitigated through centralized clearing systems. The systematic and systemic nature of bank lending is difficult to mitigate directly through regulation as it relates to the basic functions financial institutions provide in economies. Banks are exposed to systematic risk through similar asset portfolio characteristics such as geographic concentrations. This paper focuses on the systematic risk in relation to commercial bank lending and its contribution to systemic risk.

Public statements by regulators underline the need for systemic risk measures. For example, The Office of the Special Inspector General for the Troubled Asset Relief Program (2011) commented on the bail-out of Citibank through the Troubled Asset Relief Program (TARP)/Capital Purchase Program (CPP) and other guarantees on 13 January 2011:

[2] Compare Property Casualty Insurers Association of America: www.pciaa.net.

"[...] The conclusion of the various Government actors that Citigroup had to be saved was strikingly ad hoc. While there was consensus that Citigroup was too systemically significant to be allowed to fail, that consensus appeared to be based as much on gut instinct and fear of the unknown as on objective criteria. [...]"

This paper analyzes the impact of financial institution failure on the distribution of losses in the financial system. The fundamental idea is that bank loss rates may be decomposed into a level, momentum, systematic and systemic component. Financial institutions fail when unexpected losses exceed the capital buffer and release of capital allocated to credits. Failed financial institutions pass these loss exceedances on to creditors, deposit insurance schemes or the general public. The benefits of the presented models are (i) the identification of systemically relevant financial institutions, and (ii) the measurement of the size of safety nets in terms of attachment likelihood and expected losses given attachment. The research is able to define minimum adequacy levels for existing protection schemes for creditors. Figure 1 shows the Federal Deposit Insurance Corporation (FDIC) fund balance over time and an optimal fund balance in 2007 and 2012 for a scheme that protects depositors and other liability holders based on the unconditional systemic risk measure expected shortfall.[3] Note that the fund size may be pro-rated by the deposits (red bar) and other liabilities (blue bar) of the financial system (2007: 0.4983 to 0.5017; 2012: 0.3935 to 0.6065). In summary, the advent of the GFC has decreased the size of the FDIC fund, increased the systemic risk and increased the dominance of deposit funding of financial institutions.

*[Figure 1 about here.]*

The model is generally applicable as it does not rely on financial market data. The empirical evidence presented is based on information collected by US prudential regulators from 1997 to 2012. The model is innovative as it is based on a maximum likelihood technique

[3] An alternative term is conditional Value-at-Risk (i.e., CVaR) or Mean Excess Loss (i.e., MEL); the reference likelihood is 90% in the following.

to derive the parameters in a non-linear mixed model with multiple random effects, which measures the level, momentum, systematic and systemic risk in credit portfolios exposures of commercial lending.

Previous literature has focused predominantly on market prices for equity, debt or credit derivatives. Figure 2 shows a resulting measure DeltaCoVaR from Figure 5 in Adrian & Brunnermeier (2011).

*[Figure 2 about here.]*

In this contribution, tail events of market equity returns given tail events of bank equity returns are analyzed. It is striking that the systemic risk of every financial institution increases during the GFC and in particular around the date of the bankruptcy of Lehman Brothers. The levels appear to be closely related to the volatility of financial markets. Following this metric, one may argue that the financial institutions had a lower systemic importance on the day before the bankruptcy of Lehman Brothers than on the day after. It is challenging to explain such a dramatic increase in share prices within a day and consequently, systemic risk. Financial markets may underprice risk prior to the event and overprice risk after the event. For example, Borio & Drehmann (2009) and Cerutti et al. (2012) argue that financial markets may be exposed to systematic under and/or over pricing which implies a higher degree of systemic risk than actuarial losses may suggest. An application of market-based systemic risk measures may require the efficiency of financial markets, which is controversial given the literature in important areas including ambiguity, uncertainty or behavioral finance. Market efficiency is also most controversial in economic downturns.

It is the aim of this paper to develop systemic risk measures based on information that is available to regulators, build a structural model, and collect and start a discussion on financial system risk and protection including the coverage, level of confidence, past and future reference periods, layering and funding. We include some thoughts at the end of this paper.

### 1.2 Literature Review

Bisias et al. (2012) categorize systemic risk measures into macroeconomic measures [4], network measures [5], forward-looking risk measure [6], illiquidity and insolvency measures [7]

[4] Macroeconomic measures of systemic risk analyze macroeconomic variables such as equity price, real estate indices, GDP growth rates or public debt as proxies for financial (in)stability. Reinhart & Rogoff (2008) examine macroeconomic aggregates. Borio (2011) defines a macro prudential framework to limit system-wide financial distress events. Procyclicality is identified as the main driver behind the occurrence of system-wide financial distress. Alessi & Detken (2011) propose a signaling methodology to predict costly aggregate asset price boom/bust cycles. Caruana (2010) argues that the building of countercyclical buffers for banks should be adopted explicitly into the Basel III framework.

[5] Granulated foundations and network measures analyze how systemic events unfold. Billio et al. (2011) propose a systemic risk measure based on principal-components analysis and Granger-causality networks and analyze equity return data for financial institutions. For both measures they find that banks, brokers, insurance companies and hedge funds have become highly correlated within the last 10 years. Giesecke & Kim (2011) propose the default intensity model which focuses on both direct and indirect linkages in the financial system. Chan-Lau et al. (2009) present network models of banking instability using financial institutions data. Upper (2007) presents further contributions in literature.

[6] Forward-looking risk measures provide insight into the evolution of a portfolio, an individual institution or an entire financial system. Gray & Jobst (2010) develop a model that generates estimates of implicit probability of failure/default using observed equity prices as inputs. Capuano (2008) presents the option implied probability of default as a forward looking risk measure. Basurto & Goodhart (2009) propose four forward-looking indicators of systemic risk: the joint probability of default, the banking stability index, the distress dependence matrix, and the probability of cascade effects as a measure of systemic risk. Kritzman et al. (2010) use principal components analysis to define an Absorption Ratio measure that effectively captures the extent to which markets are unified or tightly coupled. Drehman & Tarashev (2011*b*) analyze the systemic risk given default probabilities, asset correlations and interbank exposures. Schwaab et al. (2011) analyze a dynamic latent factor model for financial institutions and other firms based on historic defaults. Stress-testing models are often expansions from forward-looking measures used to determine the stability of a given system. Alfaro & Drehmann (2009) propose a macroeconomic stress test, in which they utilize a simple autoregressive model of GDP growth. Duffie (2011) analyzes the exposures of a given number of systemically important institutions to a set of defined stress scenarios.

[7] Measures of illiquidity and insolvency are used to predict systemic crises. Brunnermeier et al. (2011) propose a 'risk topography' of the entire financial system. Hu et al. (2010) develop a daily liquidity 'noise' measure from bond prices and yields on U.S. Treasury securities. Geanakoplos (2010) proposes the existence of a 'leverage cycle', referring to the fact that at times the leverage in the financial system is sufficiently high that individuals and institutions can buy assets with limited down payment. Getmansky et al. (2004) investigate serial correlation and illiquidity in hedge

and cross-sectional measures. This paper aims to advance the literature on cross-sectional measures, and looks at how financial institutions affect each other in a situation of distress. Two streams exist which are comparatively analyzed by Benoit et al. (2011):

The first stream looks at the the impact of **individual institutions' failure on the financial system failure**. Adrian & Brunnermeier (2011) suggest the measurement of systemic risk by the conditional value at risk (CoVaR), which is defined as an institution's contribution to systemic risk as the difference between (i) CoVaR of the financial system conditional on the institution being under distress and (ii) the CoVaR of the financial system conditional on the median state of the institution. The empirical application of this concept is based on equity prices of financial institutions. The idea was applied by other authors using various categories of market price information and/or analyzing different geographic regions. For instance, Wong & Fong (2010) estimate CoVaR using CDS quotes for Asian banks. Adams et al. (2010) study risk spillovers among financial institutions using quantile regressions. Gauthier et al. (2009) estimate systemic risk exposures for the Canadian banking system. In another novel contribution, Puzanova & Düllmann (2013) apply the asymptotic single risk factor framework based on MoodysKMV EDF measures to calculate the portfolio value-at-risk as well as expected shortfall and marginal bank-specific contributions as a measure for systemic risk.

The second stream analyzes the impact of **the financial system failure on individual financial institutions' failure**. The argument is that financial institutions' failure are prevented by mergers, capital issuance or regular bankruptcy filing. Solution mechanisms fail when the financial system is in distress. Therefore, systemic risk is defined as the loss of a financial institution given a stress on the financial system. Huang et al. (2010) develop a systemic risk indicator which is based on CDS prices. Acharya et al. (2010) analyze the systemic

fund returns. Chan et al. (2005) and Chan et al. (2006) discuss autocorrelation based measures of illiquidity, hedge fund liquidation probabilities and so called regime-switching-based systemic risk measures.

expected shortfall, which is based on a financial institution's propensity to be undercapitalized conditional on the financial system being undercapitalized. The empirical analysis is based on book value of equity and assets as well as market value of equity. Brownlees & Engle (2012) build on this work and propose the marginal expected shortfall as a systemic risk measure. Drehman & Tarashev (2011*a*) develop a measure for systemic risk based on Shapley values to capture the contribution of interconnected banks to systemic risk. Giglio (2011) applies a nonparametric approach to derive bounds of systemic risk from CDS prices.

## 2 Contributions

This paper analyzes the interaction between financial institution risk and systemic risk in a contemporary fashion which effectively enables us to address both streams. The models can be extended to contagion considerations. Analyzing such a contagion structure would require the formulation of a causality structure and the restriction of the analysis to either the first stream or the second stream. We would like to highlight the contributions of this paper relative to three important papers in this literature: Adrian & Brunnermeier (2011), Acharya et al. (2010) and Brownlees & Engle (2012). The model is able to address both streams within this category and applies the framework to the first stream in Section 4.3.

The first contribution of the proposed framework relative to the existing literature is that the framework is completely independent from the efficiency of financial markets and the critique by Borio & Drehmann (2009) and Cerutti et al. (2012). Adrian & Brunnermeier (2011), Acharya et al. (2010) and Brownlees & Engle (2012) use equity and CDS prices. The framework does not require the observation of financial crises – Acharya et al. (2010) base their measure for systemic risk on marginal expected shortfall and leverage which requires post-crises market information and in parts motivates the contribution by Brownlees & Engle (2012). Both contributions rely on market prices for capital which are only available for a small number of financial institutions.

The second contribution of the proposed framework is the presentation of an economic model, where bank default occurs if losses exceed capital buffers and regulatory capital releases due to losses. Capital buffers are calculated as the difference between the book value of capital and the Cooke ratio times risk-weighted assets and asset equivalents (i.e., generally off-balance sheet activities). Adrian & Brunnermeier (2011) limit their considerations to VaR of market variables and are agnostic of the asset risk of the bank. Acharya et al. (2010) and Brownlees & Engle (2012) acknowledge the role of leverage but do not control for the asset risk either. Note that empirical capital buffers deviate significantly from this definition. Our empirical analysis supports a more granular framework. For example, we find that banks with negative capital buffer are subject to intense regulatory supervision (e.g., Capitol Bancorp), forced merger and deregistrations (e.g., Taunus Corporation). The model develops a loan level default model and aggregates loss rates to the bank portfolio level which in turn are aggregated to the financial system level. In summary, the model is closer to the default process and addresses the distribution of loan level losses, bank level losses and financial system losses based on empirical evidence. The resulting distributions of bank losses in excess of capital mitigation are heavily right skewed.

The third contribution is the extension of literature by a decomposition of the dependence structure into systematic (which may trigger bank failure and are diversifiable in the financial system) and systemic risk factors (which may trigger bank failure and are non-diversifiable in the financial system).

The fourth contribution is that the proposed framework controls for the banks' concentration risk with regard to borrowers, geographic regions or financial products in inefficient financial markets. In such an environment, bank portfolios are bank specific in nature. We assume that the decomposition of a bank portfolio is in large time-constant and estimate four parameters per bank for (i) the average level of loss rates, (ii) the loss rates in the prior period, (iii) the exposure to systematic risk and (iv) the exposure of systematic risk to systemic risk. Brownlees & Engle (2012) who rely on the CAPM framework estimate three parameters: volatility, covariance and tail risk. This approach assumes is agnostioc about the bank level of risk which is not diversified and the degree of systematic risk which is systemic.

The fifth contribution of the model is the parameter estimation based on a maximum likelihood technique to derive the parameters in a non-linear mixed model with multiple random effects. This is important as most commercial banks are not publicly traded and credit portfolio risk is the predominant risk exposure in commercial banking and difficult to hedge in a system. Credit portfolio risk is also a heavy-tailed risk which is why we build on the approaches common in credit portfolio risk modeling (rather than market risk) to control for this risk.

Lastly, the paper provides a comparison of a variety of systemic risk measures for the financial system. Value-at-Risk (VaR [8]) and Conditional Value-at-Risk (CVaR, also known as expected shortfall) are examined. In addition, VaR and CVaR conditional on institutions under distress (CoVaR, CoCVar) as well as differentials between conditional and unconditional systemic risk measures are analyzed (DeltaCoVaR and DeltaCoCVar). The analysis includes bank control variables such as asset allocation, funding and off-balance sheet items. Note that Adrian & Brunnermeier (2011) focus on VaR-based measures, while Acharya et al. (2010) and Brownlees & Engle (2012) focus on Expected Shortfall-based measures.

The paper proceeds as follows: Section 3 presents the model framework and introduces a number of measures for systemic risk. Section 4 presents the empirical results and includes data description, the model estimation, the analysis of the impact of financial institutions on the system and the impact of the financial system on financial institutions. Section 5 concludes.

[8] Note the capitalization to distinguish from two other statistical concepts: var - variance and VAR and vector autoregression.

## 3 A model for bank failure and financial system loss

Based on the theory of Merton (1974), a bank borrower defaults on a loan when the latent asset value falls below the nominal amount of debt at maturity (the threshold). We follow the recent contributions by Gordy & Howells (2006), Pykhtin & Dev (2002) and Gordy & Jones (2004) and assume that asset returns are normally distributed and driven by an idiosyncratic risk factor, an independent systematic factor common to all borrowers in a bank portfolio and an independent systemic factor common to all borrowers in all bank portfolios. Further, it is assumed that the banks' asset portfolios are infinitely granular (see Gordy 2000, 2003, Vasicek 1987, 1991) which implies that idiosyncratic risk is fully diversified in a bank portfolio.[9]

The asset return of **borrower** $i$ of **bank** $j$ in period $t$ ($i = 1, ..., I_j; j = 1, ..., J; t = 1, ..., T$) is driven by a common time-specific systematic risk factor $X_{jt}$ and an idiosyncratic (i.e., diversifiable) factor $S_{ijt}$:

$$R_{ijt} = \sqrt{\rho_j} X_{jt} + \sqrt{1 - \rho_j} S_{ijt} \tag{1}$$

Without loss of generality, $X_{jt}$ and $S_{ijt}$ are standard normally distributed and independent from each other, with standardized weights $\rho_j$ and $\sqrt{1 - \rho_j}$.[10]

We decompose the systematic risk factor $X_{jt}$ further into a systematic factor $U_{jt}$ and a systemic factor $X_t^*$ (compare Gordy & Howells 2006):

[9] This model and some variants are common in literature and practice. The Gaussian factor model can also be interpreted in terms of a Gaussian copula for the borrowers' asset returns or their default times (see Li 2000). These models have also found recognition in the supervisory rules for determining regulatory capital of banks (i.e., Basel II and Basel III).

[10] Please note that a non-linear transformation ensures that distributions of risk measures such as probability of default, default rate or loss rate are highly skewed. In other words, the propensity of large losses is higher than a normal distribution would suggest. Figure 3 shows that the portfolio default rate has a positive skew for positive correlation parameters.

$$X_{jt} = \sqrt{\delta_j} X_t^* + \sqrt{1 - \delta_j} U_{jt} \tag{2}$$

The asset return process is then:

$$R_{ijt} = \sqrt{\rho_j \delta_j} X_t^* + \sqrt{\rho_j - \rho_j \delta_j} U_{jt} + \sqrt{1 - \rho_j} S_{ijt} \tag{3}$$

The borrower default is modeled by the indicator

$$D_{ijt} = \begin{cases} 1 & \text{borrower } i \text{ of bank } j \text{ defaults in period } t \\ 0 & \text{otherwise} \end{cases} \tag{4}$$

A default event occurs when and if the asset return $R_{ijt}$ on assets falls below threshold $c_{jt-1}$:

$$R_{ijt} < c_{jt-1} = \tilde{\beta}_{0,j} + \tilde{\beta}_{1,j} z_{1,jt-1} \tag{5}$$

which is a summary of all observable information on the borrower, the bank or the financial system. As we collect information on the bank level, we assume borrowers to be homogeneous for a given bank and heterogeneous for different banks. Note that bank regulators may collect borrower specific information (e.g., FICO scores and LTV ratios for mortgage borrowers or financial ratios for corporate borrowers) and extend these models.

$\tilde{\beta}_0$ is an intercept. In our empirical analysis, $z_{1,jt-1}$ represents time-lagged information for the level of loss rates (i.e., the Probit transformed lagged loss rate for pools of borrowers in the empirical application) and $\tilde{\beta}_{1,j}$ the respective sensitivity. [11]

The conditional default probability, conditional on the systematic factor and systemic factor is given by:

$$
\begin{aligned}
P(D_{ijt}=1|X_t^*) &= P(R_{ijt} < c_{jt-1}|X_t^*, U_{jt}) \\
&= P(\sqrt{1-\rho_j}S_{ijt} < c_{jt-1} - \sqrt{\rho_j\delta_j}X_t^* - \sqrt{\rho_j - \rho_j\delta_j}U_{jt}|X_t^*, U_{jt}) \\
&= \Phi\left(\frac{c_{jt-1} - \sqrt{\rho_j\delta_j}X_t^* - \sqrt{\rho_j - \rho_j\delta_j}U_{jt}}{\sqrt{1-\rho_j}}\right)
\end{aligned} \tag{6}
$$

$\Phi(\cdot)$ is the cumulative density function (CDF) of the standard normal distribution.

The unconditional probability of default for this borrower is:

$$
P(D_{ijt}=1) = P(R_{ijt} < c_{jt-1}) = \Phi(c_{jt-1}) \tag{7}
$$

A bank generally holds larger borrower portfolios and the pool default rate $P_{jt}$, which measures the ratio of defaulting borrowers divided by the total number of borrowers in a bank, converges in probability to the conditional default probability. In other words, given a granular credit portfolio, the default rate of bank $j$ (as proportion of market value) in time period $t$ is: [12]

[11] Note that we chose the transformations to extend the theoretical range of explanatory variables to a range from minus infinity to plus infinity.
[12] In the empirical analysis we model losses in relation to credit and trading portfolios (both asset and derivatives). We have confirmed that all exposures have a skewed (i.e., heavy tailed) distribution.

$$P_{jt} = \frac{\sum_{i=1}^{I_j} D_{ijt}}{I_j} \quad \xrightarrow{p} \quad \Phi\left(\frac{c_{jt-1} - \sqrt{\rho_j \delta_j} X_t^* - \sqrt{\rho_j - \rho_j \delta_j} U_{jt}}{\sqrt{1-\rho_j}}\right) \text{ as } I_j \to \infty \tag{8}$$

$$\text{as } I_j \to \infty \tag{9}$$

see e.g., Kupiec (2009).[13] The right hand side of Equation (9) is the asymptotic default rate of bank $j$ in period $t$. $P_{jt}$ can be interpreted as the loss rate rather than the default rate of the portfolio if loss rates given default are deterministic and equal to unity.

The asymptotic cumulative density function conditional on the systemic factor is given by (see e.g., Bluhm et al. 2003):

$$\begin{aligned}
L(p_{jt}) &= P(P_{jt} < p_{jt}) \\
&= P(\Phi\left(\frac{c_{jt-1} - \sqrt{\rho_j \delta_j} X_t^* - \sqrt{\rho_j - \rho_j \delta_j} U_{jt}}{\sqrt{1-\rho_j}}\right) < p_{jt}) \\
&= P(\frac{\sqrt{\rho_j - \rho_j \delta_j}}{\sqrt{1-\rho_j}} U_{jt} > \frac{c_{jt-1} - \sqrt{\rho_j \delta_j} X_t^*}{\sqrt{1-\rho_j}} - \Phi^{-1}(p_{jt})) \\
&= 1 - \Phi\left(\frac{c_{jt-1} - \sqrt{\rho_j \delta_j} X_t^* - \sqrt{1-\rho_j}\Phi^{-1}(p_{jt})}{\sqrt{\rho_j - \rho_j \delta_j}}\right) \\
&= \Phi\left(\frac{\sqrt{1-\rho_j}\Phi^{-1}(p_{jt}) + \sqrt{\rho_j \delta_j} X_t^* - c_{jt-1}}{\sqrt{\rho_j - \rho_j \delta_j}}\right)
\end{aligned} \tag{10}$$

The marginal density function follows:

[13] In the empirical analysis we model losses in relation to credit and trading portfolios (both asset and derivatives). We have confirmed that all exposures have a skewed (i.e., heavy tailed) distribution.

$$
\begin{aligned}
l(p_{jt}) = \frac{dL(p_{jt})}{dp_{jt}} &= \frac{dL(p_{jt})}{d\Phi^{-1}(L(p_{jt}))}\frac{d\Phi^{-1}(L(p_{jt}))}{dp_{jt}} \\
&= \phi\left(\frac{\sqrt{1-\rho_j}\Phi^{-1}(p_{jt}) + \sqrt{\rho_j\delta_j}X_t^* - c_{jt-1}}{\sqrt{\rho_j - \rho_j\delta_j}}\right)\frac{\sqrt{1-\rho_j}}{\sqrt{\rho_j - \rho_j\delta_j}}\frac{1}{\phi\left(\Phi^{-1}(p_{jt})\right)} \\
&= \frac{\sqrt{1-\rho_j}}{\sqrt{\rho_j - \rho_j\delta_j}} \cdot exp\left(0.5\Phi^{-1}(p_{jt})^2 - \frac{0.5\left(\sqrt{1-\rho_j}\Phi^{-1}(p_{jt}) + \sqrt{\rho_j\delta_j}X_t^* - c_{jt-1}\right)^2}{\rho_j - \rho_j\delta_j}\right)
\end{aligned} \tag{11}
$$

$\phi(\cdot)$ is the probability density function (PDF) of the standard normal distribution.

In literature, a discussion on the selection of the appropriate distribution exists. Note that the resulting density for the default rate or the losses is skewed if the correlation is greater than zero although the systematic factor is standard normally distributed. In other words, the default rate is not normally distributed and the applied distribution assigns a higher density to the right tail than a normal distribution would do. Please also note that time-varying independent variables imply shifts of the distributions given economic changes. This increases the ability to explain the historic observed economic downturns.

Figure 3 shows two exemplary densities with correlations $\rho = 0.2$ and $\rho = 0.5$ (and $\delta = 0$ in both instances). The densities are more positively skewed for higher correlation. This confirms that the chosen model framework and distributional assumptions are able to model heavy tailed empirical distributions (with a positive skew).[14]

*[insert Figure 3 here]*

We estimate the model parameters by maximizing the logarithm of the uncondi-

[14] Schloegl & O'Kane (2005) show that the percentiles, such as a Value-at-Risk, obtained from a Gaussian copula credit model and a student-T copula credit model are comparable, provided that the parameters are estimated for the same empirical data.

tional likelihood $L(p_{jt}|\beta_{0j}, \beta_{1j}, \delta_j, \rho_j)$ with regard to $x_t^*$ using the adaptive Gauss-Hermite-quadrature method. This likelihood is:

$$l(p_{jt}|\beta_{0,j}, \beta_{1,j}, \delta_j, \rho_j) = \prod_{t=1}^{T} \int_{-\infty}^{\infty} l(p_{jt}|\beta_{0,j}, \beta_{1,j}, \delta_j, \rho_j, x_t^*) \cdot \phi(x_t^*) dx_t^* \tag{12}$$

Four parameters are estimated per bank: the sensitivities for (i) the average level of loss rates, (ii) the loss rates in the prior period, (iii) the exposure to systematic risk and (iv) the exposure of systematic risk to systemic risk. In year 2007, we estimate 965 parameter sets (i.e., 4,825 parameters in total) and in year 2012, we estimate 1,021 parameter sets (i.e., 5,105 parameters in total).[15]

The individual bank is required to hold capital in relation to the relative Credit Value-at-Risk based (CrVaR, i.e., Value-at-Risk less expected losses in relation to the asset base) on a regulatory confidence level $\alpha_r$.[16] In other words, the bank capital is based on the percentile of its loss distribution. However, all banks hold capital in excess of this level, i.e., based on the bank-subjective confidence level $\alpha_s$ with $\alpha_s > \alpha_r$. The difference between these two relative Value-at-Risks is the relative capital buffer: $CrVaR_{it}^{\alpha_s} - CrVaR_{it}^{\alpha_r}$

$$D_{jt} = 1 \Leftrightarrow \underbrace{P_{jt} - E(P_{jt})}_{\text{unexpected loss rate}} > \underbrace{CrVaR_{jt}^{\alpha_s} - CrVaR_{jt}^{\alpha_r}}_{\text{capital buffer}} + \underbrace{CrVaR_{jt}^{\alpha_r} * (P_{jt} - E(P_{jt}))}_{\text{capital release for loss exposures}} \tag{13}$$

with the expected loss $E(P_{jt}) = \Phi(\beta_0 + \beta_1 z_{kt-1})$ under the assumption of a loss rate given default equal to unity.[17]

[15] We observe a maximum of 64 quarters (i.e., 16 years) which limits the number of parameters which can be included to the model. We chose this model to acknowledge that banks are diversified but face concentration risk with regard to borrowers, geographic regions or financial products that financial markets are inefficient. In such an environment, bank portfolios are bank specific in nature.
[16] For example, 99.9% in credit risk and 99% in market risk exposures.
[17] The assumption lower loss rates given default does not materially impact the results as it would

where $D_{it}$ is an indicator variable with

$$D_{jt} = \begin{cases} 1 & \text{bank } j \text{ gets into financial distress in } t \\ 0 & \text{otherwise} \end{cases} \tag{14}$$

Note that the capital release to total capital matches the unexpected loss rate to unity.[18] The relative loss exceedance $M_{jt}$ is:

$$M_{jt} = max(P_{jt} - E(P_{jt}) - CrVaR_{jt}^{\alpha_s} + CrVaR_{jt}^{\alpha_r} - CrVaR_{jt}^{\alpha_r} * (P_{jt} - E(P_{jt})), 0) \tag{15}$$

The **financial system** is characterized by the sum of loss exceedance amounts in the system

$$L_t = \sum_{j=1}^{J} w_{jt} \cdot m_{jt}$$

with weight $w_{jt}$ (e.g., total assets), realized relative loss exceedance $m_{jt}$, and distribution function $G(.)$.

The financial system gets into distress if its $VaR_t^{\gamma}$ given by

increase the level of default probabilities when estimating the parameters based on realized loss rates.

[18] Variations in this assumption do not have larger impacts on the results as this capital release is less influential than the loss buffers.

$$G(VaR_t^\gamma) = P(L_t < VaR_t^\gamma) \tag{16}$$
$$= \gamma \tag{17}$$

is exceeded. The threshold $\gamma$ or the expectation of exceedances of $\gamma$ may be linked to the size of a protection mechanism such as a deposit insurance scheme or taxpayers' funds or willingness to fund.

Following Adrian & Brunnermeier (2011), we use the following abbreviations for the tail risk of the financial system in the analysis:

- Unconditional Value-at-Risk: VaR;
- Unconditional expected shortfall, i.e., conditional Value-at-Risk: CVaR;
- Value-at-Risk conditional on the failure of BHC $j$: CoVaR(j);
- Conditional expected shortfall conditional on the failure of BHC $j$: CoCVaR(j);
- Difference between Value-at-Risk conditional on the failure of BHC $j$ and unconditional Value-at-Risk: DeltaCoVaR(j);
- Conditional expected shortfall conditional on the failure of BHC $j$: CoCVaR(j) and unconditional expected shortfall: DeltaCoCVaR(j).

Given the parameter estimates for the individual banks, the loss of the system is simulated. All results are based on an estimation of the parameters and a simulation with one million iterations of the risk factors $X_t^*$ and $U_{jt}$.[19] Conditional values compute the values for the subsets of iterations which meet the respective condition. The steps of the simulation

[19] Note that conditional systemic risk considerations are computationally extensive as the tail of the financial system loss given the loss exceedance of an individual bank is analyzed. This implies that a large number of iterations is required to assess this conditional risk. We analyze the tail of the financial system by the 90th percentile to ensure that a sufficient number of loss exceedances are recorded. Note that no standards with regard to reasonable confidence levels exist.

are as follows:

(1) Estimate parameters $b_0$, $b_1$, $\rho$ and $\delta$ per bank;
(2) Simulate the system-systematic and bank-systematic factor: independent and standard normally distributed;
(3) Calculate loss per bank and iteration;
(4) Calculate loss of the financial system;
(5) Calculate unconditional VaR and CVaR of the financial system;
(6) Identify and collect iterations with losses exceeding the capital buffer and capital release per bank (importance sampling);
(7) Calculate the loss of the financial system for these bank-specific loss exceedance scenarios;
(8) Calculate conditional CoVaR and CoCVaR of the financial system per bank;
(9) Calculate DeltaCoVaR and DeltaCoCVaR of the financial system per bank.

Figure 4 shows various measures for systemic risk. The left curve in the following chart displays the system VaR at the left vertical line and the combination of area A and B the expected shortfall (i.e., conditional VaR, CVaR) of the financial system and the right curve the displays the system VaR at the right vertical line and the combination of area B and C the expected shortfall (i.e., conditional VaR, CVaR) of the financial system conditional on the shortfall of a financial institution (here JP Morgan Chase). These moments are called CoVaR and CoCVaR. In addition, we define the DeltaCoVaR as the difference between CoVaR and VaR (i.e., the distance between teh two vertical lines) and and DeltaCVaR as the difference between CoCVaR and CVaR (i.e., the difference between area C and area A). [20]

*[Figure 4 about here.]*

[20] Adrian & Brunnermeier (2011) propose the CoVaR given the median state of a financial institution. We follow this approach but assume that CoVaR given the median state of a financial institution is equal to the unconditional VaR of the financial system.

## 4 Empirical Results

### *4.1 Data*

We analyze consolidated financial statements for Bank Holding Companies (BHCs) collected and published by the Federal Reserve Bank from 1997 (third quarter) to 2012 (third quarter), i.e., 16 years (64 quarters) in total. We eliminated 40 BHCs which were domiciled in Cayman, Guam, Netherland Antilles and Puerto Rico.

We analyze the data on a BHC level rather than the individual bank level due to the cross-guarantee provision of the Financial Institutions Reform, Recovery, and Enforcement Act of 1989. The act gives the FDIC the authority to charge off losses in relation to a failing banking subsidiary from a non-failing banking subsidiary. Ashcraft (2004) shows that this rule increases the probability of future financial distress and capital injections of subsidiaries. These findings support the use of consolidated (i.e., BHC) information.[21]

With regard to bank mergers we generate a dummy variable which is equal to one in the year prior to a merger for the acquiring BHC (see Stolz & Wedow 2011) as these firms generally have higher capital buffers prior to an acquisition. Note that we restrict our analysis predominantly to the two years 2007 (Q3) and 2012 (Q3) and collect merger information (survivor and non-survivor) from the Federal Reserve Bank Chicago. We assume that the surviving BHC is the acquirer.[22] 35 merger cases are recorded in 2007 and 32 merger cases in 2012.

Table 1 describes the financial system per year and reports the number of banks as

[21] Note that it is also common in commercial bank lending to analyze the financial strength of the parent instead of a borrowing subsidiary. The analysis is also consistent with the current literature on market-implied systemic risk measures, as equity and CDS prices are generally available for the BHC level but not the individual bank subsidiaries.

[22] We have confirmed this for a random selection manually through a search in various databases and are able to collect this information for all mergers (i.e., Bloomberg, Reuters and the internet).

well as the empirical distribution of total assets.

*[Table 1 about here.]*

Total assets are reported in million USD and relate to the Q3 filings in a given year. Q3 was chosen as a reference point as the number of reference variables increases in Q3 in 1997, the GFC started in Q3 of 2007 and the latest quarter of data available at the time of writing this paper was Q3 2012. Note that these numbers are consistent with Avraham et al. (2012). In the US, domestic bank holding companies are required to file a consolidated basis report FR Y-9C if total assets exceed $500 million. The reporting threshold was $150 million before March 31, 2006. As a result, the total assets in the sample drop by $3.8 trillion and the total BHCs drops by 1,333 from 2005 to 2006. BHCs below these thresholds may file their financial data. Note that the empirical analysis focuses on BHCs which are active and included in the sample in the reference periods 2007 (Q3) and 2012 (Q3).

We divide the data into a period excluding (1997:3 to 2007:3) and a period including the Global Financial Crisis (1997:3-2012:3).

Using the data we collect loss histories of credit portfolios, trading portfolios and off-balance sheet activities (in particular financial letters of credit and interest rate, credit and other derivatives). We define:

- **Loss for credit portfolios** as the provision for loan and lease losses (Variable 4230 in Schedule HI-Consolidated Income Statement, item 4) [23] plus net gains (losses) on sales of loans and leases (Variable 8560 in Schedule HI-Consolidated Income Statement, item 5i) plus the net gains (losses) on sales of other real estate owned (Variable 8561 in Schedule HI-Consolidated Income Statement, item 5j).
- **Loss for trading portfolios** (cash instruments and derivative instruments) as the nega-

[23] We assume that the provisions are a reasonable proxy for the expected present value of future losses which includes write-offs due to loan modifications and work-outs as well as associated costs.

tive trading revenue (Variable A220 in Schedule HI-Consolidated Income Statement, item 5c) plus the realized gains (losses) on held-to-maturity securities (Variable 3521 in Schedule HI-Consolidated Income Statement, item 6a) plus the realized gains (losses) on available-for-sale securities (Variable 3196 in Schedule HI-Consolidated Income Statement, item 6b) plus net gains (losses) recognized in earnings on credit derivatives that economically hedge credit exposures held outside the trading account (Variable C889 plus C890 in Schedule HI-Consolidated Income Statement, memoranda items 10a and 10b) plus credit losses on derivatives (Variable A251 in Schedule HI-Consolidated Income Statement, memoranda item 11).

The combined loss rate is the sum of loss for credit portfolios and the loss for trading portfolios divided by total assets. The credit loss rate is the loss for credit portfolios divided by total assets. The trading loss rate is the trading portfolios divided by total assets. We calculate annualized loss rates by the ratio of the sum of losses in relation to the past four quarters and the average of total assets in relation to the past four quarters. We analyze level effects by conditioning loss rates on one year lagged loss rates (i.e., lagged by four quarters).

Figure 5 shows in the upper chart the average loss rate per quarter (combined, credit and trading) over time and the grey bars indicate years which include a period of economic downturn as indicated by the National Bureau of Economic Research (NBER). The lower chart shows the average combined loss rate per quarter and 1st and 99th percentile over time.

*[Figure 5 about here.]*

The upper chart shows that loss rates increase with economic downturns. Losses in relation to credit portfolio exposures are generally a multiple of losses in relation to trading portfolios. Losses during the GFC have been significantly larger than losses in prior economic downturns. The lower chart shows that the impact of economic downturns is much more severe for some banks than others.

Table 2 shows descriptive statistics for two sets of control variables: (i) the various endogenous variables that generated the systemic risk measure to analyze the direction of their impact and their relative importance, (ii) financial ratios and other bank characteristics for the period in which the systemic risk measures are calculated.

*[Table 2 about here.]*

Note that in our empirical data, negative capital buffers are possible for the following reasons: (i) we measure risk on a BHC level while capital regulation may relate to the bank subsidiaries only, (ii) banks are currently facing regulatory attention. [24] , or (iii) banks may be capital exempt [25]

The number of such banks is limited: in 2007 four BHC were undercapitalized (total negative capital buffer: $3.01 billion; positive capital buffer of adequately capitalized BHCs: $760.95 billion) and in 2012 (i.e., after the GFC) 38 BHCs were undercapitalized (total negative capital buffer: $16.00 billion; positive capital buffer of adequately capitalized BHCs: $334.39 billion).

Two important issues need to be noted with regard to the following analysis: capital

[24] Note that BHCs with negative capital buffer are categorized as 'undercapitalized' or 'significantly undercapitalized' by the FDIC and are subject to regulatory actions such as oversight, intervention, requirements and limitations. This does not necessarily mean a failure of the institution. For example, Capital Bankcorp has a negative capital position of $-142 million in 2012 Q3, has filed for Chapter 11 protection but is not considered a failed institution by FDIC standards. The bank is required to (i) comply to a number of restrictions on dividends and increase of debt and guarantees, (ii) submit a sufficient capital maintenance plan, and (iii) individual bank subsidiaries have entered into formal enforcement actions with their regulators.

[25] Taunus Corporation (parent company: Deutsche Bank, Germany) is such an example in 2007. This was permissable until the implementation of the Dodd-Frank act under exemption SR 01-01, effectively allowing foreign-owned BHCs to avoid minimum capital requirements. Note that Deutsche Bank deregistered its US BHC on February 1, 2012. Note that Deutsche Bank deregistered its US BHC on February 1, 2012. FDIC Vice Chairman Thomas Hoenig confirmed in an interview with Reuters on 14 June 2013 that Deutsche Bank is 'horribly undercapitalzed'.

buffers have been significantly reduced from 2007 to 2012 as a result of the GFC and to a smaller degree to the reduction of regulatory capital requirements (as a result of reduction in risk weighted assets).[26] In summary, undercapitalized BHCs are of a relatively small size and the implication for our analysis is that the financial system loss is (i) larger than zero in most scenarios, and (ii) mainly driven by adequately capitalized BHC as large losses are either due to large institution losses, or due to systematic losses in a large number of BHCs.

The financial ratios cover various aspects of the BHCs and include state ratio (fraction of state bank assets), state recourse (indicator whether BHC is headquartered in a recourse state), the natural logarithm of total assets as a proxy for size[27], net interest income ratio, lending ratio (loans to total assets), interbank lending ratio, trading ratio, loan commitment ratio, letter of credit ratio, and derivatives ratio (interest, foreign exchange, equity and commodity). All financial ratios are subject to a floor at the 1st percentile and a cap at the 99th percentile of the respective financial ratio. the financial ratios analyzed in Adrian & Brunnermeier (2011) are extended for return, asset and off-balance sheet ratios.

### *4.2 Model estimation*

The loss rates are then be used to describe the outcome of risk. In addition, we perform the following model specifications:

- Model 1: Model based on data from 1997 Q3 to 2007 Q3;
- Model 2: Model based on data from 1997 Q3 to 2012 Q3;

[26] Note that this relates to assets and asset equivalents for off-balance sheet items.
[27] Note that total assets are adjusted for inflation by using the consumer price index for size considerations.

Table 3 shows moments of the distributions of parameter estimates. Note that four parameters are estimated per bank. [28]

*[Table 3 about here.]*

### *4.3 Analysis of measures for systemic risk*

This section follows the definition of systemic risk presented by Adrian & Brunnermeier (2011). We simulate a sufficient number of iterations of the risk factors $X_t^*$ and $U_{jt}$. Conditional on the simulated values compute the values for loss per bank and the loss of the financial system as the sum of all losses. We then compute the various measures for systemic risk by analyzing moments of the complete distributions or conditional distributions.

The systematic risk measures are computed for various confidence levels but only reported for the 90th percentile and one million iterations. [29]

Table 4 describes the empirical distribution for the exceedance ratio and the systemic risk measures in 2007 and 2012 for all BHCs.

*[Table 4 about here.]*

The exceedance ratio is the number of loss exceedances over the number of iterations. All risk measures relate to the system. Note that VaR is the value-at-risk, CVaR is the expected shortfall, VaR and CVaR are unconditional measures. CoVaR and CoCVaR are conditional measures, conditional on the loss exceedance of the respective bank. DeltaCoVaR and DeltaCoCVaR is the difference between the conditional and unconditional risk measure.

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[28] Parameters can not be estimated in a few instances where banks have short time series. We assume average parameters for such banks. We have tested various limiting assumptions (i.e., minimum and maximum values) and these do not impact our empirical findings.

[29] Note that the VaR of the financial system increases with the confidence level but relative results, interpretations and conclusions are maintained.

Note that systemic risk measures after the GFC (2012) are higher than prior to the GFC (2007). Note that systemic risk measures are calculated if the number of loss exceedences is greater than five.

Furthermore, we are interested in analyzing the drivers for systemic risk and regress in a first step, the natural logarithm of the systemic risk measures DeltaCoVaR and DeltaCoCVaR on the input factors to analyze the direction and relative importance of their impact. The input factors are the various endogenous variables that generated the systemic risk measure. Table 5 shows the results of this analysis:

*[Table 5 about here.]*

The level of loss rate has a negative impact on systematic risk as default is likely to occur in all periods and not only the periods of systemic distress. $c$ has a negative impact on systemic risk. $\rho$ has a negative impact on systematic risk. $\delta$ has a positive impact on systematic risk and the capital buffer has a positive impact as it makes the bank default in periods of systemic distress.

In a second step, we regress the natural logarithm of the systemic risk measures DeltaCoVaR and DeltaCoCVaR on financial ratios representing BHC characteristics such as leverage, liquidity, profitability, as well as the distributions of assets, derivatives and derivatives relative to assets.[30] Table 6 shows the results of this analysis:

*[Table 6 about here.]*

Variables with a significant impact on the input factors of the systemic risk measures in particular are the recourse, the size (i.e., the natural logarithm of total assets), the net interest income, the credit ratio, the trading ratio and the derivatives ratio.

[30] Note that in unreported results, we have confirmed the robustness of this model specification by alternatively regressing the CoVaR and CoCVaR and mean financial ratios as well as time lagged financial ratios (we analyzed lags of 1 - 4 quarters). The results are qualitatively the same.

### *4.4 TARP funding - CPP program*

We now analyze how the TARP funding relates to systemic risk measures and other bank characteristics in 2007 (Q3). Note that total TARP funding under the CPP program was $204,943,831,320 and that we were able to match 204,738,036,320. The difference of 0.1% in TARP funding for banks could not be matched with BHC data despite a manual search for the BHC of the receiving bank subsidiary. Table 7 shows the results of this analysis:

*[Table 7 about here.]*

Note that size is a dominant factor explaining TARP funding allocation. Brownlees & Engle (2012) show that the SRISK measure places a heavy weight on the size of financial institutions, which explains that the ten institutions with the largest SRISK score were TARP recipients.

## 5 Conclusion

This paper develops a bank model for systemic risk in bank lending. The model analyzes the impact of a financial institution failure on the distribution of losses in the financial system. The fundamental idea is that bank loss rates may be decomposed into a level, momentum, systematic and systemic component. Financial institutions fail when unexpected losses exceed the capital buffer and the release of capital allocated to credits. Failed financial institutions pass these loss exceedances on to creditors, deposit insurance schemes or the general public. The benefits of the presented model framework are (i) the identification of systemically relevant financial institutions, and (ii) the measurement of the size of safety nets in terms of attachment likelihood and expected losses given attachment. The model is generally applicable as it does not rely on financial market data. The empirical evidence presented is based on information collected by US prudential regulators from 1997 to 2012.

The parameter estimation is based on a novel maximum likelihood technique to derive the parameters in a non-linear mixed model with multiple random effects.

The key findings of this paper are that the systemic risk of a financial institution (i) decreases with the level of loss rates, (ii) increases with its asset portfolio exposure to systemic risk, (iii) declines with its exposure to portfolio specific systematic risk, and (iv) increases with the size of the capital buffer. Additional findings are that the current FDIC fund level may be insufficient as the fund balance is relatively low, was insufficient in the past and deposit funding as well as systemic risk have increased in recent years. The credit ratio, trading ratio and derivatives ratio have a positive impact on systemic risk. In addition size was the predominant consideration by the US government when making an allocation decision of TARP funds while our systemic risk measures did not provide a significant explanation.

The findings of the paper have important implications. Firstly, regulators who are interested in the resilience of the financial system may use the proposed models and model outputs to allocate supervisory resources, i.e. systemic banks may receive a higher regulatory attention than non-systemic banks.

Secondly, deposit insurers (e.g., the Federal Deposit Insurance Corporation in the US) may base deposit insurance premiums on such models and model outputs. Traditionally, deposits are insured in the US by the Federal Deposit Insurance Corporation (FDIC). The insurance premiums averaged approximately 11.1 cents per $100 of the assessment base for the last three quarters of 2011. The assessment base was changed from insured deposits to the average total consolidated assets less average tangible equity in the second quarter of 2011, following the Dodd-Frank Act. The fund size was $11.8 billion at the end of 2011 and the fund size plus labilities (stemming from prepayments and GFC resolutions) is $75.9 billion. The proposed models are able to estimate the appropriate fund size (e.g., by the unconditional system VaR or CVaR) and allocate premiums according to size and systemic risk contribution.

Cerutti et al. (2012) and others point out that systemic risk may be driven by many institutional characteristics. As a result, the systemic risk measures derived in this paper should be interpreted in conjunction with other systemic relevant information.

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## Tables

Table 1

Descriptive statistics of the US financial system

Total assets are reported in million USD and relate to the Q3 filings in a given year. Q3 was chosen as a reference point as the number of reference variables increases in Q3 in 1997, the GFC started in Q3 of 2007 and the latest quarter of data available at the time of writing this paper was Q3 2012. Note that financial system in 2009 is consistent with numbers presented by Avraham et al. (2012). In the US domestic bank holding companies are required to file on a consolidated basis report FR Y-9C if total assets exceed $500 million. Before March 31, 2006 this threshold was $150 million. As a result, the total assets in the sample drop by $3.8 trillion and the total BHCs drops by 1,333 from 2005 to 2006. BHCs below these thresholds may file their financial data. Note that the empirical analysis focuses BHCs which are active and included in the sample in the reference periods 2007 (Q3) and 2012 (Q3).

| **Year** | **Mean** | **P1** | **P25** | **P50** | **P75** | **P99** | **Total** | **N** |
|---|---|---|---|---|---|---|---|---|
| 1997 | 3,771,761,297 | 123,086,000 | 211,878,000 | 321,799,000 | 819,620,000 | 71,729,206,000 | 5,593,522,000,000 | 1,483 |
| 1998 | 3,848,736,349 | 143,372,000 | 209,080,000 | 318,644,000 | 722,366,000 | 74,379,508,000 | 6,007,877,400,000 | 1,561 |
| 1999 | 4,571,040,133 | 148,322,000 | 207,238,000 | 326,512,500 | 712,372,000 | 76,914,149,000 | 7,615,352,900,000 | 1,666 |
| 2000 | 5,074,869,118 | 150,999,000 | 210,466,000 | 324,935,000 | 694,935,000 | 87,064,425,000 | 8,957,144,000,000 | 1,765 |
| 2001 | 5,543,260,138 | 151,987,000 | 214,022,000 | 324,609,000 | 685,581,000 | 97,215,024,000 | 10,404,699,000,000 | 1,877 |
| 2002 | 5,432,276,638 | 151,254,000 | 220,147,000 | 330,938,000 | 691,604,000 | 106,299,844,000 | 10,783,069,000,000 | 1,985 |
| 2003 | 5,690,165,169 | 148,207,000 | 217,415,000 | 329,622,000 | 684,458,000 | 95,361,560,000 | 12,285,067,000,000 | 2,159 |
| 2004 | 6,385,029,521 | 149,593,000 | 219,509,000 | 337,472,000 | 669,893,000 | 118,712,487,000 | 14,513,172,000,000 | 2,273 |
| 2005 | 6,820,279,927 | 147,248,000 | 229,897,000 | 359,752,500 | 724,213,000 | 146,576,344,000 | 15,809,409,000,000 | 2,318 |
| 2006 | 12,150,992,491 | 205,987,000 | 575,726,000 | 862,651,000 | 1,878,107,000 | 216,855,000,000 | 11,968,728,000,000 | 985 |
| 2007 | 14,008,593,598 | 221,771,000 | 603,227,000 | 910,358,000 | 1,953,523,000 | 227,628,000,000 | 13,518,293,000,000 | 965 |
| 2008 | 15,227,838,615 | 234,309,000 | 639,642,000 | 937,516,500 | 1,968,912,000 | 286,712,268,000 | 14,710,092,000,000 | 966 |
| 2009 | 15,819,139,577 | 271,273,000 | 642,675,000 | 931,056,000 | 1,914,372,000 | 271,449,905,000 | 15,977,331,000,000 | 1,010 |
| 2010 | 16,274,657,750 | 224,085,000 | 627,095,000 | 929,029,000 | 1,862,912,000 | 290,654,000,000 | 16,551,327,000,000 | 1,017 |
| 2011 | 16,609,433,097 | 277,854,000 | 624,156,000 | 928,171,000 | 1,925,625,000 | 322,980,000,000 | 16,725,699,000,000 | 1,007 |
| 2012 | 16,366,544,365 | 267,095,000 | 631,795,000 | 938,004,000 | 1,965,329,000 | 302,114,103,000 | 16,710,242,000,000 | 1,021 |

Table 2
Descriptive statistics of analyzed banks

This table shows descriptive statistics for financial ratios and other bank characteristics for the period to which the systemic risk measures were calculated.

| **2007** | | | | | | | |
|---|---|---|---|---|---|---|---|
| **Variable** | **Mean** | **P1** | **P25** | **P50** | **P75** | **P99** | **N** |
| Loss rate | 0.0034 | 0.0000 | 0.0009 | 0.0020 | 0.0036 | 0.0287 | 965.0 |
| Loss rate lagged | 0.0027 | 0.0000 | 0.0007 | 0.0018 | 0.0033 | 0.0179 | 965.0 |
| Reg. capital | 0.0622 | 0.0379 | 0.0568 | 0.0629 | 0.0680 | 0.0815 | 965.0 |
| Capital buffer | 0.6852 | 0.1509 | 0.4052 | 0.5476 | 0.8063 | 2.9236 | 965.0 |
| State ratio | 0.0131 | 0.0001 | 0.0008 | 0.0026 | 0.0082 | 0.2007 | 965.0 |
| Recourse | 0.7637 | 0.0000 | 1.0000 | 1.0000 | 1.0000 | 1.0000 | 965.0 |
| Log assets | 21.1368 | 19.3272 | 20.3278 | 20.7394 | 21.5029 | 26.2610 | 965.0 |
| NII | 0.0363 | 0.0205 | 0.0303 | 0.0346 | 0.0405 | 0.0720 | 965.0 |
| Credit ratio | 0.7084 | 0.2709 | 0.6532 | 0.7298 | 0.7877 | 0.8854 | 965.0 |
| Interbank ratio | 0.0006 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0200 | 965.0 |
| Trading ratio | 0.0017 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0330 | 965.0 |
| Commitment ratio | 0.0885 | 0.0044 | 0.0526 | 0.0819 | 0.1192 | 0.2033 | 965.0 |
| LOC ratio | 0.0110 | 0.0000 | 0.0035 | 0.0074 | 0.0142 | 0.0524 | 965.0 |
| Derivatives ratio | 0.0224 | 0.0000 | 0.0000 | 0.0000 | 0.0144 | 0.2928 | 965.0 |
| **2012** | | | | | | | |
| **Variable** | **Mean** | **P1** | **P25** | **P50** | **P75** | **P99** | **N** |
| Loss rate | 0.0070 | 0.0000 | 0.0019 | 0.0044 | 0.0081 | 0.0548 | 1,021.0 |
| Loss rate lagged | 0.0080 | 0.0000 | 0.0026 | 0.0053 | 0.0101 | 0.0425 | 1,021.0 |
| Reg. capital | 0.0544 | 0.0293 | 0.0489 | 0.0552 | 0.0607 | 0.0765 | 1,021.0 |
| Capital buffer | 1.0327 | -1.2591 | 0.6647 | 0.9068 | 1.2269 | 4.2027 | 1,020.0 |
| State ratio | 0.0162 | 0.0000 | 0.0008 | 0.0031 | 0.0095 | 0.2789 | 1,021.0 |
| Recourse | 0.7571 | 0.0000 | 1.0000 | 1.0000 | 1.0000 | 1.0000 | 1,021.0 |
| Log assets | 21.0736 | 19.4163 | 20.2772 | 20.6724 | 21.4121 | 26.4472 | 1,021.0 |
| NII | 0.0403 | 0.0200 | 0.0340 | 0.0384 | 0.0442 | 0.0817 | 1,020.0 |
| Credit ratio | 0.6284 | 0.2332 | 0.5528 | 0.6408 | 0.7170 | 0.8780 | 1,021.0 |
| Interbank ratio | 0.0007 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0200 | 1,020.0 |
| Trading ratio | 0.0010 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0330 | 1,021.0 |
| Commitment ratio | 0.0458 | 0.0000 | 0.0235 | 0.0404 | 0.0622 | 0.1481 | 1,021.0 |
| LOC ratio | 0.0068 | 0.0000 | 0.0017 | 0.0036 | 0.0082 | 0.0524 | 1,021.0 |
| Derivatives ratio | 0.0316 | 0.0000 | 0.0000 | 0.0014 | 0.0261 | 0.2928 | 1,021.0 |

Table 3
Distributions for parameter estimates

This table shows the distributions of parameter estimates. Note that four parameters are estimated per bank. Parameters can not be estimated for banks with short time series and we assume average parameters for such banks.

| **Parameter** | **Mean** | **P1** | **P25** | **P50** | **P75** | **P99** | **N** |
|---|---|---|---|---|---|---|---|
| | | | Model 1: 2007 | | | | |
| b0 | -2.0618 | -4.2430 | -2.2825 | -2.0618 | -1.7004 | -0.3385 | 965 |
| b1 | 0.2276 | -0.4834 | 0.1465 | 0.2276 | 0.3537 | 0.8688 | 965 |
| delta | 0.2313 | 0.0014 | 0.1207 | 0.2313 | 0.2686 | 0.7676 | 965 |
| rho | 0.0989 | 0.0043 | 0.0447 | 0.0989 | 0.1197 | 0.3972 | 965 |
| | | | Model 2: 2012 | | | | |
| b0 | -2.0001 | -3.6697 | -2.3590 | -2.0001 | -1.5948 | -0.7484 | 1,021 |
| b1 | 0.2263 | -0.3030 | 0.1169 | 0.2263 | 0.3583 | 0.6594 | 1,021 |
| delta | 0.3375 | 0.0014 | 0.1591 | 0.3375 | 0.4870 | 0.8505 | 1,021 |
| rho | 0.1410 | 0.0119 | 0.0816 | 0.1410 | 0.1675 | 0.4983 | 1,021 |

Table 4
Descriptive statistics of systemic risk measures

The systematic risk measures are computed for the 90th percentile and 1,000,000 iterations. The exceedance ratio is the number of loss exceedances over the number of iterations. All risk measures relate to the system. VaR is the value-at-risk, CVaR is the expected shortfall, VaR and CVaR are unconditional measures. CoVaR and CoCVaR are conditional measures, conditional on the loss exceedance of the respective bank. DeltaCoVaR and DeltaCoCVaR is the difference between the conditional and unconditional risk measure. Note that systemic risk measures after the GFC (2012) are higher than prior to the GFC (2007). Note that systemic risk measures were calculated if the number of loss exceedences is greater than five.

| 2007 | | | | | | | |
|---|---|---|---|---|---|---|---|
| **Variable** | **Mean** | **P1** | **P25** | **P50** | **P75** | **P99** | **N** |
| Exceedance ratio | 0.0248 | 0.0000 | 0.0001 | 0.0009 | 0.0046 | 0.6787 | 685 |
| VaR | 30,404,011,458 | 30,404,011,458 | 30,404,011,458 | 30,404,011,458 | 30,404,011,458 | 30,404,011,458 | 685 |
| CVaR | 42,011,125,003 | 42,011,125,003 | 42,011,125,003 | 42,011,125,003 | 42,011,125,003 | 42,011,125,003 | 685 |
| CoVaR | 54,295,375,778 | 27,098,636,395 | 40,623,485,148 | 50,046,722,720 | 60,574,270,530 | 145,512,120,607 | 685 |
| CoCVaR | 73,162,316,348 | 27,192,890,085 | 57,095,268,258 | 71,637,565,323 | 83,239,815,863 | 174,256,465,627 | 685 |
| DeltaCoVaR | 23,891,364,321 | (3,305,375,063) | 10,219,473,691 | 19,642,711,262 | 30,170,259,072 | 115,108,109,149 | 685 |
| DeltaCoCVaR | 31,151,191,344 | (14,818,234,918) | 15,084,143,255 | 29,626,440,320 | 41,228,690,859 | 132,245,340,624 | 685 |

| 2012 | | | | | | | |
|---|---|---|---|---|---|---|---|
| **Variable** | **Mean** | **P1** | **P25** | **P50** | **P75** | **P99** | **N** |
| Exceedance ratio | 0.0596 | 0.0000 | 0.0001 | 0.0016 | 0.0095 | 1.0000 | 870 |
| VaR | 31,441,461,060 | 31,441,461,060 | 31,441,461,060 | 31,441,461,060 | 31,441,461,060 | 31,441,461,060 | 870 |
| CVaR | 107,719,257,372 | 107,719,257,372 | 107,719,257,372 | 107,719,257,372 | 107,719,257,372 | 107,719,257,372 | 870 |
| CoVaR | 394,239,894,031 | 19,319,048,954 | 144,793,500,186 | 330,166,862,936 | 550,637,170,483 | 1,381,962,200,000 | 870 |
| CoCVaR | 564,504,817,942 | 19,319,048,954 | 298,627,907,557 | 533,259,173,501 | 759,404,330,815 | 1,460,169,200,000 | 870 |
| DeltaCoVaR | 362,798,432,971 | (12,122,412,105) | 113,352,039,126 | 298,725,401,876 | 519,195,709,424 | 1,350,520,700,000 | 870 |
| DeltaCoCVaR | 456,785,560,570 | (88,400,208,417) | 190,908,650,185 | 425,539,916,129 | 651,685,073,443 | 1,352,450,000,000 | 870 |

Table 5
Regression analysis for input factors on systemic risk measures

This table shows the impact of the input factors on systemic risk. The systematic risk measures are computed for the 90th percentile and 1,000,000 iterations.

| | 2007 | | 2012 | |
|---|---|---|---|---|
| **Variable** | **log(DeltaCoVaR)** | **log(DeltaCoCVaR)** | **log(DeltaCoVaR)** | **log(DeltaCoCVaR)** |
| Intercept | 19.1929*** | 20.8165*** | 19.8521*** | 21.6331*** |
| Std. Err. | 0.4356 | 0.4193 | 0.3522 | 0.3109 |
| c | -1.0577*** | -0.7632*** | -1.4199*** | -1.1022*** |
| Std. Err. | 0.0954 | 0.0921 | 0.085 | 0.0753 |
| rho | -4.1889*** | -3.9121*** | -4.6116*** | -3.7292*** |
| Std. Err. | 0.3807 | 0.3678 | 0.2905 | 0.2562 |
| delta | 4.7558*** | 4.1156*** | 3.9323*** | 3.2155*** |
| Std. Err. | 0.1995 | 0.1934 | 0.118 | 0.1046 |
| log(buffer) | 0.057*** | 0.0372** | 0.1188*** | 0.0912*** |
| Std. Err. | 0.0181 | 0.0175 | 0.0156 | 0.0137 |
| Adj. R-sq. | 0.5533 | 0.4872 | 0.6554 | 0.6152 |
| Obs. | 642 | 628 | 793 | 785 |

Table 6
Regression analysis for bank characteristics on input factors on systemic risk measures

The systematic risk measures are computed for the 90th percentile and 1,000,000 iterations.

| | 2007 | | | | 2012 | | | |
|---|---|---|---|---|---|---|---|---|
| **Dependent variable** | **c** | **rho** | **delta** | **log(buffer)** | **c** | **rho** | **delta** | **log(buffer)** |
| Intercept | -3.2932*** | 0.4597*** | 0.2536 | -1.2588*** | -2.1725*** | 0.2156*** | 0.1776 | -2.6935*** |
| Std. Err. | 0.3075 | 0.0858 | 0.1564 | 0.4229 | 0.219 | 0.0764 | 0.1851 | 0.4441 |
| State ratio | 0.0646 | -0.0036 | -0.3107 | -0.7344 | 0.1449 | -0.0978 | -0.0776 | 0.4441 |
| Std. Err. | 0.3943 | 0.11 | 0.2006 | 0.5524 | 0.2499 | 0.0872 | 0.2113 | 0.5058 |
| Recourse | -0.0256 | -0.0162** | 0.0048 | 0.0017 | 0.0122 | -0.01 | 0.0101 | -0.1222*** |
| Std. Err. | 0.0258 | 0.0072 | 0.0131 | 0.0354 | 0.02 | 0.007 | 0.0169 | 0.0402 |
| Log assets | -0.0022 | -0.0133*** | 0.0057 | 0.8937*** | -0.0297*** | -0.0016 | 0.0068 | 0.98*** |
| Std. Err. | 0.0126 | 0.0035 | 0.0064 | 0.0174 | 0.0099 | 0.0035 | 0.0084 | 0.02 |
| NII | 2.834** | -0.8335** | -1.4281** | 14.4971*** | -0.539 | -0.4053 | 0.1916 | 10.1252*** |
| Std. Err. | 1.1714 | 0.3268 | 0.5959 | 1.626 | 0.8891 | 0.3102 | 0.7517 | 1.8165 |
| Credit ratio | 0.6733*** | -0.0925*** | -0.1478** | -0.7017*** | 0.3167*** | -0.0127 | 0.0016 | -0.3816** |
| Std. Err. | 0.1146 | 0.032 | 0.0583 | 0.1583 | 0.0812 | 0.0283 | 0.0686 | 0.1646 |
| Interbank ratio | -0.1116 | -0.2883 | -4.2674** | 7.2225 | 3.8016 | 1.9481* | 1.1106 | 4.381 |
| Std. Err. | 3.9516 | 1.1025 | 2.0101 | 5.5804 | 3.1638 | 1.1036 | 2.675 | 6.2703 |
| Trading ratio | 5.0123*** | 0.7839 | -1.4971 | 0.8626 | -1.1904 | 1.3527 | 0.7925 | 7.9428 |
| Std. Err. | 1.9031 | 0.531 | 0.9681 | 2.622 | 2.4255 | 0.8461 | 2.0507 | 4.8572 |
| Commitment ratio | 0.2501 | 0.2493*** | 0.0757 | 0.0731 | -0.4766 | -0.1909* | 0.0328 | 0.1178 |
| Std. Err. | 0.2408 | 0.0672 | 0.1225 | 0.331 | 0.2965 | 0.1034 | 0.2507 | 0.5982 |
| LOC ratio | -0.2844 | 0.0295 | 0.8828 | 1.2455 | 0.5799 | -0.5528 | -0.0262 | 0.1366 |
| Std. Err. | 1.0683 | 0.2981 | 0.5434 | 1.4832 | 1.0704 | 0.3734 | 0.9051 | 2.1305 |
| Derivatives ratio | 0.9293*** | 0.2238*** | 0.0897 | 0.8767*** | 1.291*** | 0.1083** | -0.0344 | -0.2726 |
| Std. Err. | 0.2308 | 0.0644 | 0.1174 | 0.3196 | 0.1477 | 0.0515 | 0.1249 | 0.2967 |
| Adj. R-sq. | 0.0701 | 0.0327 | 0.0119 | 0.8846 | 0.099 | 0.0211 | -0.0074 | 0.8692 |
| Obs. | 930 | 930 | 930 | 924 | 988 | 988 | 988 | 950 |

Table 7
Regression analysis for bank characteristics of TARP funding amounts

The systematic risk measures are computed for the 90th percentile and 1,000,000 iterations.

| | 2007 | 2012 |
|---|---|---|
| **Dependent variable** | **log(TARP amount)** | **log(TARP amount)** |
| Intercept | -4.8001*** | -1.3609 |
| Std. Err. | 1.8204 | 1.3473 |
| log(DeltaCoVaR) | 0.0159 | -0.0312 |
| Std. Err. | 0.0445 | 0.0363 |
| State ratio | -0.1985 | 1.0318 |
| Std. Err. | 1.3358 | 0.9879 |
| Recourse | -0.1102 | -0.1627* |
| Std. Err. | 0.1052 | 0.0968 |
| log(total assets) | 0.9644*** | 0.9279*** |
| Std. Err. | 0.0509 | 0.0435 |
| NII | 15.4107** | -8.1524 |
| Std. Err. | 6.5911 | 5.2658 |
| Credit ratio | 1.1668** | 0.2388 |
| Std. Err. | 0.5236 | 0.4395 |
| Interbank ratio | -0.3791 | 0.7694 |
| Std. Err. | 16.2878 | 15.7022 |
| Trading ratio | 12.8434* | -0.0219 |
| Std. Err. | 6.8641 | 12.4399 |
| Commitment ratio | -0.1022 | -0.1914 |
| Std. Err. | 1.022 | 1.3838 |
| LOC ratio | 2.2096 | -1.4031 |
| Std. Err. | 4.4195 | 4.8253 |
| Derivatives ratio | 0.2235 | 0.242 |
| Std. Err. | 0.9517 | 0.6525 |
| Adj. R-sq. | 0.8945 | 0.8697 |
| Obs. | 187 | 250 |

## Figures

Fig. 1. FDIC fund size and fund size for deposits and other liabilities based on CVaR

This chart shows the FDIC fund size and optimal fund size based on the unconditional CVaR criterion. Note that the fund size is pro rated by the deposits and other liabilities of the financial system (2007: 0.4983 to 0.5017; 2012: 0.3935 to 0.6065).

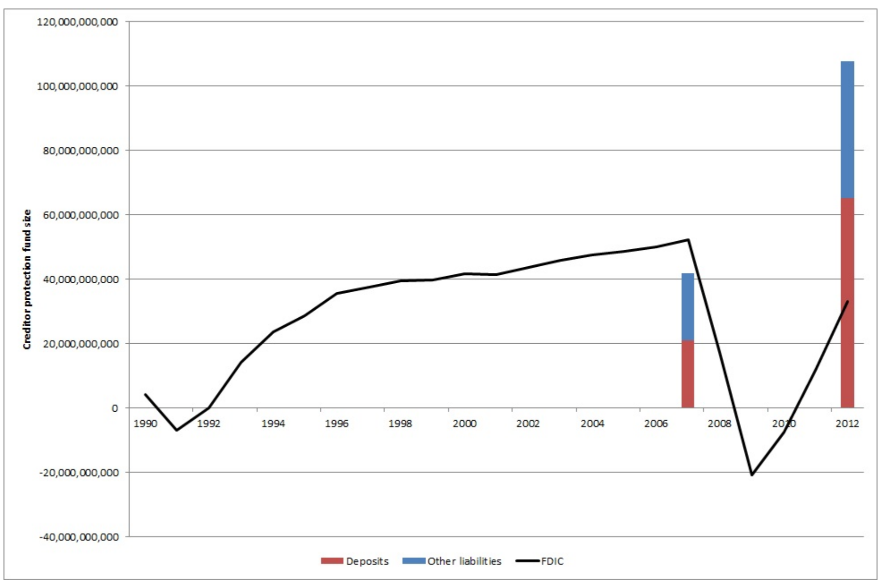

Fig. 2. DeltaCoVaR from Figure 5 in Adrian & Brunnermeier (2011)

This chart shows the 5% DeltaCoVaR based on share returns for four financial institutions shown in Figure 5 in Adrian & Brunnermeier (2011).

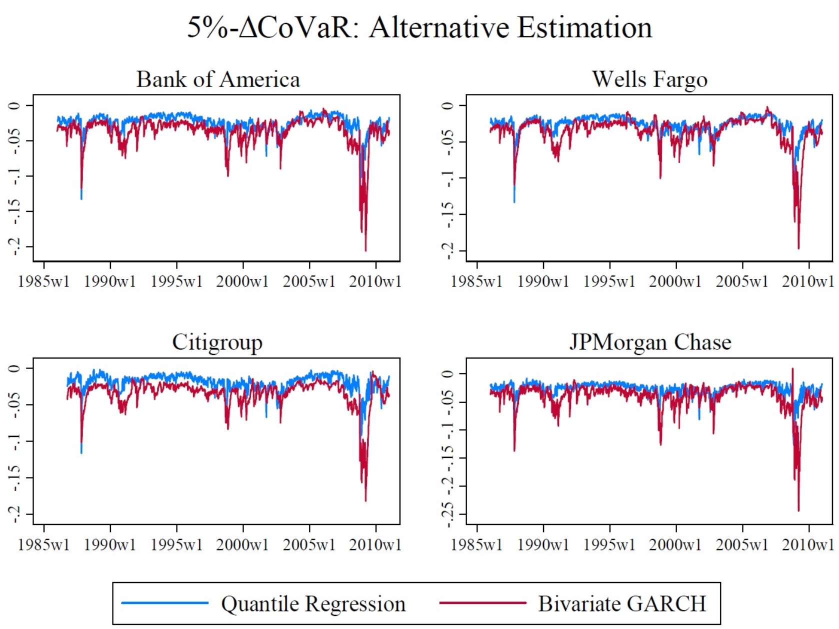

Fig. 3. Portfolio default rate distribution resulting from the Gaussian Copula model

This figure shows the densities of the portfolio default rates for a default probability of 5% and asset correlations $\rho = 0.2$ and $\rho = 0.5$. The densities are more skewed for higher correlation. This confirms that the chosen model framework and distributional assumptions are able to model heavy tailed empirical distributions (here with positive skew).

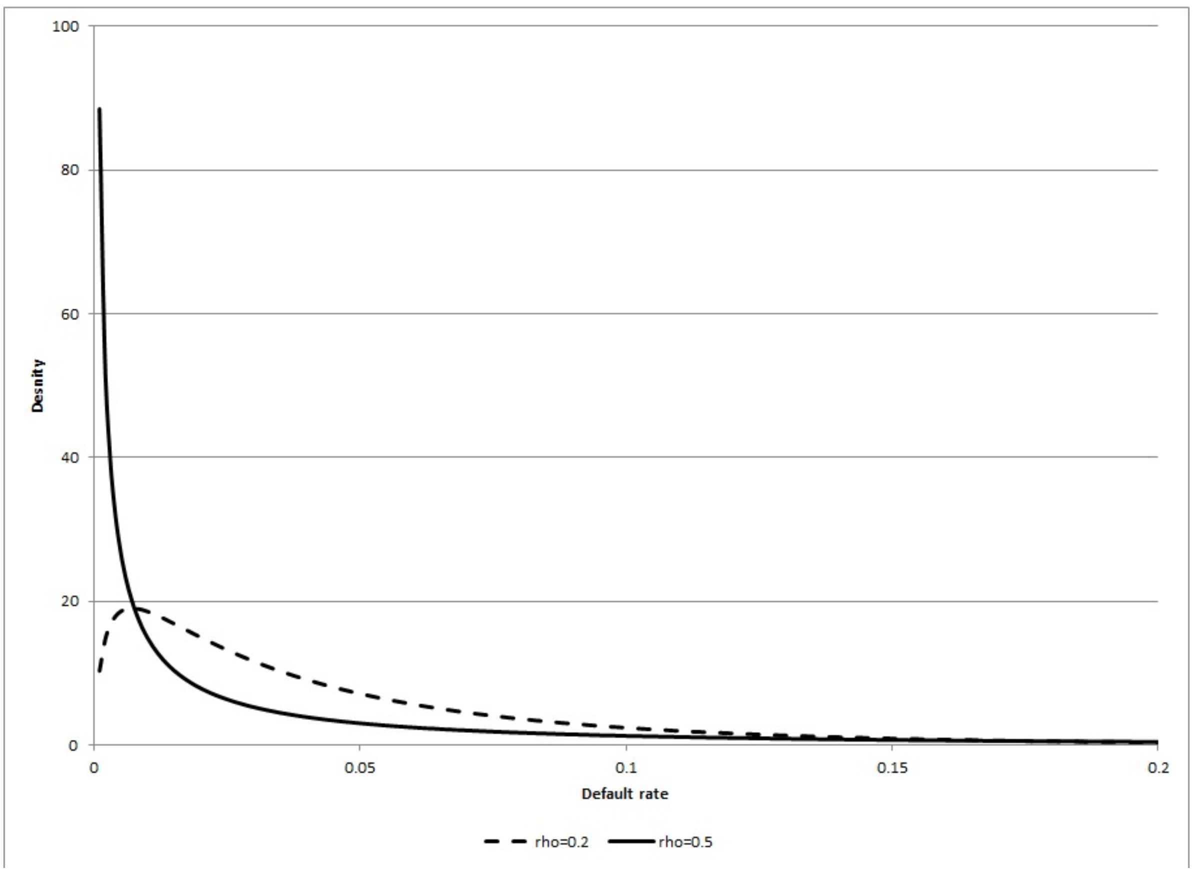

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Fig. 4. Explanation of VaR, CVaR, CoVaR, CoCVaR and DeltaCoVaR and DeltaCoCVaR, Example: JPMorgan Chase
The left curve represents the unconditional cumulative loss distribution of the financial system and the $\alpha$ percentile the VaR. The right curve represents the conditional cumulative loss distribution of the financial system conditional on a failure of Bank of America and the $\alpha$ percentile the CoVaR. The Area A represents the CVaR and area B represents CoCVaR. The difference between area B and A represents DeltaCoCVaR.

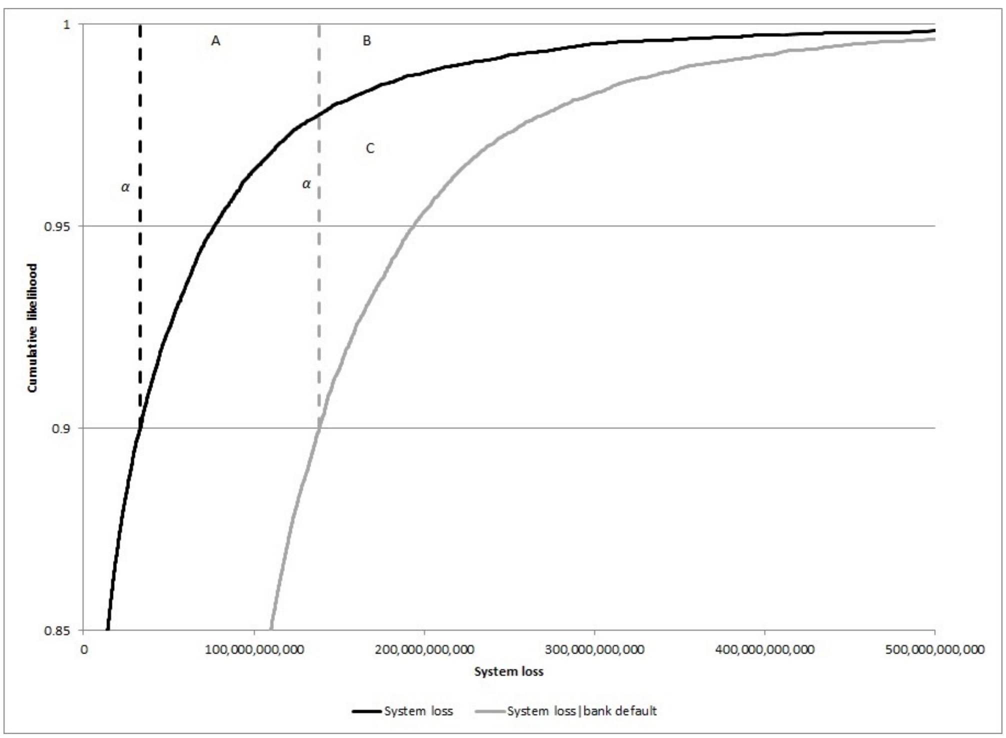

Fig. 5. Loss rates for credit portfolios, trading portfolios and their combinations, per quarter

The upper chart shows the average loss rate per quarter (combined, credit and trading) over time and the grey bars indicate years which include a period of economic downturn as indicated by the National Bureau of Economic Research (NBER). The Loss rate is defined as the loss relative to total assets. The loss for credit portfolios is the sum of the provision for loan and lease losses plus net gains (losses) on sales of loans and leases plus the net gains (losses) on sales of other real estate owned. The loss for trading portfolios (cash instruments and derivative instruments) is the sum of the trading revenue plus the realized gains (losses) on held-to-maturity securities plus the realized gains (losses) on available-for-sale securities plus net gains (losses) recognized in earnings on credit derivatives that economically hedge credit exposures held outside the trading account plus credit losses on derivatives. Losses rate increase with economic downturns. Losses in relation to credit portfolio exposures are generally a multiple of losses in relation to trading portfolios. Losses during the GFC have been significantly larger than losses in prior economic downturns. The chart also shows that while we use both the combined loss rate and the loss rate of credit portfolios to analyze systemic risk it is the credit portfolio risk which predominantly explains our findings.

The lower chart shows the average combined loss rate per quarter and 1st and 99th percentile over time. The impact of economic downturns is much more severe for some bank than others. Regulatory action (such requirement to recapitalize or merge) are generally imposed when the loss rate exceeds the regulatory capital buffer (which is generally between 1% and 2%).