WP/12/46

IMF Working Paper

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INTERNATIONAL MONETARY FUND

 WP/12/46

IMF Working Paper

IMF Institute

Short-term Wholesale Funding and Systemic Risk: A Global CoVaR Approach [1]

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Authorized for distribution by Marc Quintyn
February 2012

Abstract

In this paper we identify some of the main factors behind systemic risk in a set of international large-scale complex banks using the novel CoVaR approach. We find that short-term wholesale funding is a key determinant in triggering systemic risk episodes. In contrast, we find no evidence that a larger size increases systemic risk within the class of large global banks. We also show that the sensitivity of system-wide risk to an individual bank is asymmetric across episodes of positive and negative asset returns. Since short-term wholesale funding emerges as the most relevant systemic factor, our results support the Basel Committee's proposal to introduce a net stable funding ratio, penalizing excessive exposure to liquidity risk.

JEL Classification Numbers: C30; G01; G20
Keywords: Systemic Risk, Wholesale Funding, Liquidity Risk, Macroprudential Regulation

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[1] We thank María Abascal, Tobias Berg, Saifeddine Chaibi, Reyes Calderón, José Luis Escrivá, Iván Guerra, Maite Ledo, Fernando Pérez de Gracia, Victoria Santillana, Javier Suárez, Francesco Vallascas, Jérôme Vandenbussche, Chen Zhou and an anonymous referee for helpful comments and suggestions. An earlier version of this paper was presented at 2011 FMA Conference (Porto), the "Systemic Risk, Basel III, Financial Stability and Regulation" Conference (Sidney), the "Systemic Risk" Conference (London), and a research seminar in BBVA (Madrid). Financial support from the Spanish Department of Education and Innovation (projects ECO2008-02599 and ECO 2009-11151) and Navarra Government (Jerónimo de Ayanz program) is gratefully acknowledged. Antonio Moreno also thanks the IMF for hospitality during his research visit.

Contents

I. Introduction

That financial markets move more closely together during times of crisis is a well-documented fact. Conditional correlations among assets are much higher when market returns are low in periods of financial stress; see, among others, King and Wadhwani (1990) and Ang, Chen and Xing (2006). Co-movements typically arise from common exposures to shocks, but also from the propagation of distress associated with a decline in the market value of assets held by individual institutions, a phenomenon we dub balance sheet contraction and which is of particular concern in the financial industry. The recent crisis has shown how the failure of large individual credit institutions can have dramatic effects on the overall financial system and, eventually, spread to the real economy. As a result, international financial policy institutions are currently designing a new regulatory framework for the so-called systemically important financial institutions in order to ensure global financial stability and prevent, or at least mitigate, future episodes of systemic contagion.[2]

In this paper, building on a global system of international financial institutions that comprises the largest banks in a sample of 18 countries, we analyze the main determinants of systemic contagion from an individual institution to the international financial system, i.e., the empirical drivers of tail-risk interdependence. We restrict our attention to a set of large-scale, complex institutions that are the target of current regulation efforts and that would likely be considered too-big-to-fail by central banks. These firms are characterized by their large capitalization, global activity, cross-border exposures and/or representative size in the local industry. Using data spanning the 2001-2009 period, we explicitly measure the contribution of the balance-sheet contraction of these institutions to international financial distress. As regulators seek for meaningful measures of interconnectedness (Walter 2011), this paper contributes to the current debate on prudential regulatory requirements by showing formal evidence that short-term wholesale funding is a major driver of systemic risk in global banking.

Financial institutions use wholesale funding to supplement retail deposits and expand their balance sheets. These funds are typically raised on a short-term rollover basis with instruments such as large-denomination certificates of deposits, brokered deposits, central bank funds, commercial paper and repurchase agreements. Whereas it is agreed that wholesale funding provides certain managerial advantages (see Huang and Ratnovski, 2011, for a discussion), the effects on systemic risk of an overreliance on these liabilities were under-recognized prior to the recent financial crisis. Banks with excessive short-term funding ratios are typically more interconnected to other banks, exposed to a large degree of maturity mismatch and more vulnerable to market conditions and liquidity risk. These

[2] A rapidly growing literature discusses how contagion can occur through spikes in counterparty risk within a network of credit-interdependent institutions or through fire sales of securities (Adrian and Shin, 2010; IMF 2010). Section 2 in this paper offers a survey of the literature in this field.

features can critically increase the vulnerability of interbank markets and money market mutual funds which act as wholesale providers of liquidity and, eventually, of the whole financial system. The empirical analysis on this paper provides clear evidence on the major role played by short-term wholesale funding to spread systemic risk in global markets.

Additionally, we explore the possibility that the contribution to systemic risk may be asymmetric, i.e. that it depends on whether the market value of a bank's balance sheet is increasing or decreasing. Because a distressed institution is likely to generate larger externalities on the rest of the financial system when its balance sheet is contracting, an empirical analysis of tail risk-dependence within a financial system should distinguish between episodes of expanding and contracting balance sheets. We deal with this previously unaddressed but key issue, finding strong evidence supporting the existence of asymmetric patterns. Finally, we also analyze the effects of the 2008-2009 global financial crisis on systemic risk and assess the impact of public recapitalizations directly targeted at individual banks.

Our study builds on the novel procedure put forward by Adrian and Brunnermeier (2009), the so-called CoVaR methodology, and generalizes it in several ways in order to deal with the characteristics of a sample of international banks and to address the asymmetric patterns that may underlie tail dependence. The main empirical findings of our analysis can be summarized as follows. First, we find that short-term wholesale funding is the most significant balance sheet determinant of individual contributions to global systemic risk. An increase of one percentage point in this variable leads to an increase in the contribution to systemic risk of 40 basis points of quarterly asset returns. These results support regulatory initiatives aimed at increasing bank liquidity buffers to lessen asset-liability maturity mismatches as a mechanism to mitigate individual liquidity risk, such as the liquidity coverage ratio standard recently laid out by the Basel Committee on Banking Supervision under the new Basel III regulatory framework.[3] This paper shows that these provisions may also help to reduce the likelihood of systemic contagion. By contrast, we find little evidence that, within the class of large-scale banks, either relative size or leverage is helpful in predicting future systemic risk after accounting for short-term wholesale funding.

Second, our analysis shows that individual balance sheet contraction produces a significant negative spillover on the Value-at-Risk (VaR) threshold of the global index. Whereas the sensitivity of left tail global returns to a shock in an institution's market valued asset returns is on average about 0.3, the elasticity conditional on an institution having a shrinking balance sheet is almost three times larger. This result reveals a strong degree of asymmetric response that has not been discussed in the extant literature and which turns out to be larger

[3] This ratio will require banks to maintain sufficient liquid assets to contain a 100% run-off of unsecured wholesale funding provided by financial institutions during a 30-day stress scenario, which contrasts with the 5 to 10% run-off assumed for retail deposits during a significant liquidity stress episode.

the more systemic the bank is when its balance sheet is contracting. Therefore, controlling for balance sheet contraction is crucial to rank financial institutions by their contribution to systemic risk.

Third, restricting attention to balance sheet contraction episodes, the credit crisis added up 0.1 percentage points to the co-movement between individual and global asset returns while recapitalization during the crisis period dampened co-movement by 0.2 percentage points. Furthermore, the timing of recapitalization also matters for systemic risk. Banks that received prompt recapitalization in Q4 2008 proved able to improve their relative position during the crisis period, whereas banks that were rescued by public authorities later in Q4 2009 became relatively more systemic during the crisis period. Finally, the marginal contribution of an individual bank to overall systemic risk increases from 0.76 quarterly percent returns in an average quarter to 0.92 in a quarter characterized by money market turbulence. These results highlight the relevance of crisis episodes in measuring systemic risk and of policy actions in controlling it.

The remainder of the paper is organized as follows. Section 2 surveys the most representative literature on systemic risk, highlighting the differential features of the CoVaR approach. Section 3 discusses the data employed in the two stages of our analysis. Section 4 lays out our CoVaR framework and estimation framework and shows the estimates of individual contributions to systemic risk. Section 5 analyzes the determinants of systemic risk and reports the results of several robustness checks. Finally, Section 6 summarizes our main findings and concludes with policy recommendations.

II. Related literature

Our study builds on the CoVaR methodology proposed by Adrian and Brunnermeier (2009), which allows us to generate time-varying estimates of systemic risk contribution for each bank in our sample. This methodology has been applied in a number of recent studies; see, for instance, Van Oordt and Zhou (2010) and Roengiptya and Rungcharoenkitkul (2011). There are several key differences with respect to our study and that in Adrian and Brunnermeier (2009). We focus not only on an international sample of large banks, but we also extend the basic CoVaR methodology to account for a number of econometric issues related to asymmetric responses, recapitalization effects and structural changes originated during the global financial crisis.

There exists a growing literature that has suggested several alternative approaches to address the existence of systemic interrelations using different procedures and variables. Lehar (2005) characterizes the conditional correlations between banks and assets portfolios using default probabilities of financial institutions as a measure of systemic risk. Goodhart and Segoviano (2009) construct a banking stability index to estimate interbank dependence for tail events using credit default swaps data. Huang, Zhou and Zhu (2009) propose a measure of systemic risk based on the price of insuring a pool of banks against financial distress based on ex ante measures of default probabilities of individual banks and forecasts of asset return correlations. More recently, Acharya et al. (2010) define the systemic expected shortfall as the propensity of a financial institution to be undercapitalized when the system as a whole is undercapitalized. This is a measure of the *exposure* of banks to systemic tail events, which nevertheless can easily be reverted to capture risk contribution (see Section 5 for more details). Brownlees and Engle (2011) suggest multivariate GARCH-type volatility modeling to measure marginal expected-shortfall measures in a similar spirit. Alternatively, De Nicolo and Lucchetta (2010) use a dynamic factor model to model quarterly time series of macroeconomic indicators of financial and real activity and obtain forecasts of systemic real risk and systemic financial risk. Gray and Jobst (2010) examine contagion across markets and institutions using extreme value theory, while Kritzman et al. (2010) introduce the so-called absorption ratio measure to assess systemic risk using a principal components approach; see also Billio, et al. (2010) for a related analysis.

As an alternative to systemic risk measures based on marginal risk contributions of individual institutions, network analysis is concerned with the joint distribution of losses of all market participants. Cont et al. (2009) and Martinez-Jaramillo et al. (2010) have analyzed the Brazilian and Mexican interbank markets, respectively, using this approach. Cao (2010) shows how to use Shapley values to decompose the system-wide risk among the individual institutions in a CoVaR setting; see also Tarashev et al. (2010).

Any of these procedures have both methodological advantages and shortcomings relative to alternative methods, so there is not such a thing as an optimal procedure to measure systemic risk in the literature. The particular choice of the CoVaR methodology as a tool to characterize systemic risk in this paper is largely motivated by three considerations. First, this methodology is particularly appealing because it allows us to characterize contagion under balance sheet deleveraging, which is a main regulatory concern and a key driver of this paper. In contrast, most of the alternative measures omit balance sheet data as they are naturally intended for stock market return data and/or default-related data, as surveyed previously. Second, the CoVaR methodology is extremely informative about the dynamics followed by the systemic contribution of a particular bank to the system, which allows us to characterize the effects of different observable variables on the time-series dynamics of this latent process. In particular, the CoVaR methodology can easily control for relevant features of the data, such as the occurrence of a crisis or bank recapitalizations, and allows us to resort to both historical-based and forward-looking state variables aiming at improving downside risk forecasts. Finally, the CoVaR setting can be generalized straightforward to accommodate non-linear patterns and other relevant effects that likely characterize the contribution of a large bank to the global system and which have not been discussed in the existing literature. Indeed, an additional contribution of our study to the literature is to show that marginal effects of individual banks on the global system are both economically and statistically very different in good and bad times.

III. DATA

Given the adverse effect on global financial stability from the failure of a large financial institution, with the recent crisis providing ample evidence of cross-country ripple effects, we define the financial system as a network of large, internationally active banking institutions that are the target of current regulation efforts and that may be considered too-big-to-fail by central banks. Concerning the perimeter of the financial system, we restrict the analysis to the regulated banking sector to exclude the unobservable impact of different regulatory frameworks across financial industries.

These features configure the total population universe in our analysis. In order to construct a representative sample, we focus on banks characterized by their large capitalization, global activity, cross-border exposures and/or representative size in the local industry. Since our methodological approach is based on a two-stage procedure that requires both stock market data and firm-specific balance sheet variables (see Section 4 and 5 for details), the ultimate criterion to configure our sample of potentially systemic banks is the availability of comparable data over a long enough period of time.[4] The resulting sample is formed by a total of 54 large firms from 18 countries, starting in July 2001 and ending in December 2009.[5] All the variables used in the paper are measured in USD.[6]

In the first stage of our analysis, we characterize the time-varying conditional VaR dynamics of both individual banks and the global system (see Section 4.1 for details.) The time-series parametric estimation of these processes is enhanced by using a set of macro-financial state variables that are acknowledged to capture the expected return in financial markets. We adopt two alternative approaches in relation to these predictors. On the one hand, we group most banks in our sample (48 out of the 54) into two different economic

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[4] The initial sample consisted of 93 banks selected on the basis of their total size denominated in USD as well as in percent of domestic GDP. Qualitative information about the financial markets where they operate together with data limitations, namely the lack of reported balance sheet data during the sample period, constrained our final sample to 54 banks. The average size of the representative bank is USD 830 billion and accounts for 57.7 percent of domestic GDP.

[5] Among others, the final sample includes 21 out of the 24 banks that Financial Times reported in a list of 30 systemic risk institutions in November 2009 allegedly compiled by regulators under the guidance of the FSB: http://www.ft.com/intl/cms/s/0/df7c3f24-dd19-11de-ad60-00144feabdc0.html#axzz1aViQQS1z

[6] The shortage of USD liquidity in global markets during the financial crisis triggered sharp depreciations of most currencies against the U.S. dollar in Q3 2008. To exclude the impact of exchange rate fluctuations from bank performance we conduct a robustness check of the results in USD by applying the CoVaR methodology on market valued asset returns denominated in local currency (see Section 5.2 for further robust checks.) Results remain unaltered and are available upon request to the authors.

regions, namely U.S. + Canada and Europe, for which we observe local predictive variables (e.g., VIX index for American banks and Euronext Volatility Index for European banks). Although these predictors are strongly correlated, they may help capturing idiosyncratic risk patterns. Under this first approach we focus the analysis on two economic regions, excluding 6 banks in Asia, Africa and Australia from the sample due to data limitations in the latter regions over the whole period. On the other hand, since it is desirable to carry out the analysis including all the available banks in the sample, we use the set of state variables sampled from the U.S. market as common conditioning variables. This approach also seems reasonable because of the strong degree of globalization in the financial industry and the predominance of the U.S. economy.

The U.S. state variables used in this analysis are the VIX index (CBOE option implied volatility); liquidity spread (difference between the 3-month U.S. repo rate and the 3-month U.S. T-bill yield); the change in the U.S. Treasury bill secondary market 3-month rate; the change in the slope of the yield curve (yield spread between the U.S. Treasury benchmark bond 10-year and the U.S. 3-month T bill); the change in the credit spread between the 10-year Moody's seasoned Baa corporate bond and the 10-year U.S. Treasury bond; and the S&P 500 Composite Index return. All these variables are sampled weekly. The European counterpart of these variables are, respectively, the Euronext volatility index, the difference between the 3-month U.K. repo rate and the 3-month U.K. T-bill yield, the first difference of the French 3-month interest rate, the first difference of the French yield slope (5-year minus 3-month) on government bonds, the difference between Baa corporate bonds and the 10-year German government bond, and the FTSE European stock index. The data have been obtained from the Chicago Board Options Exchange, the Federal Reserve Board's H.15 Release, and the Datastream databases. Tables 1a and 1b report the summary statistics for the U.S. and European predictive variables, respectively.

In the second stage of our analysis, we identify the empirical drivers of our estimates of systemic risk using bank-specific balance-sheet data. We gather quarterly/semi-annual data (depending on the reporting frequency of each country) from Bloomberg to construct meaningful measures of leverage, market-to-book ratio, short-term wholesale funding, relative size, and marketable securities; see Section 5 for further details. In addition, and since several banks in our sample were recapitalized at least once during the crisis, we included dummy variables to capture the specific timing of these events. Appendix B provides detailed information on the extent and timing of these recapitalizations.

IV. MODELLING AND FORECASTING GLOBAL COVAR DYNAMICS

In order to quantify the risk contribution of each bank to the system and conduct an analysis of its determinants, we follow a two-stage procedure as explained above. In the first stage, we measure the contribution of each bank to the reference portfolio over the sample. In the second stage, the resulting estimates are treated as feasible proxies of the unobservable level of systemic risk and their determinants analyzed through both panel-data and pooled cross-sectional regression techniques. Throughout the following subsections, we describe the features involved in the first stage and discuss the main estimation results. Section 5 will describe the methodology and the main conclusions involved in the second stage.

A. Estimation methodology

VaR is the most common procedure to measure portfolio downside risk in practice. For a certain level of probability $\lambda \in (0,1)$, the $\lambda\%$ VaR of a portfolio is defined as the maximum loss over a horizon of *h* days which is expected at the $(1-\lambda)\%$ confidence level given the set of observable information, *i.e.*, the λ-quantile of the conditional loss distribution.[7] This statistical measure has been largely popularized by the present regulatory risk-management framework, as it allows sophisticated banks and other financial institutions to use internal VaR models to meet capital requirements. Because the main interest in systemic risk builds on regulatory considerations, it seems natural to consider risk measures that attempt to capture the extent of systemic risk using the same methodological approach.

Paralleling the VaR definition, the CoVaR is defined as the maximum loss to be expected in a certain portfolio (e.g., an individual bank or, more generally, a portfolio representative of the whole financial system) for a given confidence level and time horizon given the maximum loss expected in another portfolio at such confidence level and time horizon. More formally, the $\lambda\%$ CoVaR of portfolio *i* given the $\lambda\%$ VaR of portfolio *j*, denoted $CoVaR^{j|i}_{\lambda,t}$, is defined as the λ quantile of the conditional loss function

$$\Pr\left(X^j_t \leq CoVaR^{j|i}_{\lambda,t} \mid X^i_t = VaR^i_{\lambda,t}\right) = \lambda \qquad (1)$$

where X^j_t and X^i_t denote the respective portfolio returns.[8] Given this measure, AB propose to approach the portfolio *i*'s contribution to *j* as:

$$\Delta CoVaR^i_{\lambda,t} = CoVaR^{j|i}_{\lambda,t} - VaR^j_{\lambda,t} \qquad (2)$$

[7] When reporting downside risk statistics, such as VaR, it is customary to present the outcomes in positive values (i.e., -VaR) since it is implicitly understood that these refer to a loss. In this paper, we maintain the original sign of the conditional quantile in all the downside risk measures described thorough the following subsections: VaR, CoVaR and ΔCoVaR.

[8] In a recent study, Girardi and Ergun (2011) propose a multivariate GARCH model to estimate the dynamics of CoVaR under the conditioning event $X_t \leq VaR_t$. Their analysis shows that the effect of individual institution characteristics (e.g., VaR, size, leverage, etc.) on the resulting ΔCoVaR does not differ significantly from that reported under the "standard" CoVaR analysis conditioned on X=VaR. This suggests that conditioning the CoVaR measure on X=VaR rather than on X<VaR may not imply a drastic loss of generality, yet it considerably simplifies the methodolocial analysis and, more importantly, makes it robust to distributional assumptions.

as it captures how much risk a certain institution adds to overall systemic risk when it reaches its VaR. In our analysis, we shall consider portfolio returns over a weekly horizon and focus on the 5% quantile of the conditional loss distribution.

Our main interest is to capture the contribution of an individual bank to a portfolio representative of the surrounding system, formed by the remaining banks. The details of the main steps involved in the application of this analysis are sketched in the sequel.

Individual banks

For each bank, we consider weekly simple returns from a portfolio formed by the market-valued total assets of the firm. Our interest in this particular portfolio is completely motivated by a regulatory perspective, since balance sheet contraction is associated with negative spillovers that may trigger financial sector instability. In order to construct weekly returns, it should be noted that whereas market equity data are available at weekly frequency, balance sheet data is usually reported on a quarterly basis, and even on a lower frequency for several banks in our sample (e.g., banks in Australia, Belgium, France, Ireland, UK and South Africa.)

We adopt two different strategies to circumvent the sampling frequency mismatch problem involved. As in AB, we assume that the leverage ratio remains (approximately) constant along the successive weeks within any given quarter/semester, thereby approaching the unobservable weekly value with the low-frequency data available in the period. Alternatively, to avoid the seasonal discontinuities that this method may create, we "smooth" weekly the quarterly/biannual leverage ratio through cubic spline interpolation, a well-known technique in applied finance (e.g., it is routinely used to construct the term structure) and other disciplines. Because the final results are not sensitive to this consideration, we present and discuss the main outcomes from the constant approach, noting that complete results are available from authors upon request.

Global System Portfolio(s)

For each bank in the sample, we construct a (different) global system portfolio as a weighted average of the returns of the remaining banks in the sample. Thus, the returns of the representative global system portfolio for institution *i,* are characterized according to:

$$X_t^{S,i} = \sum_{j=1, j\neq i}^{n} \omega_{t,j} X_t^j \,, \quad \omega_{t,j} = W_t^j \left(\sum_{j=1, j\neq i}^{n} W_t^j \right)^{-1} \tag{3}$$

where X_t^j refers to the simple returns of the *j*-th institution and W_t^j is some (strictly positive) variable used in the weighting scheme such that the resultant weights satisfy the restriction $0 \leq \omega_{t,l} \leq 1$. Some comments on this approach follow.

First, each of the resulting indices is a portfolio of large-scale complex banks and, consequently, represents a systemic portfolio which allows us to study how a shock in a stressed bank spills over in the class of financial assets which poses the highest risk to the global financial system. We shall refer to the resulting portfolios as global system portfolios in what follows.

Second, the most distinctive feature of this approach is that global system portfolios are computed after excluding the bank under analysis. This procedure ensures a small-sample adjustment that prevents a mechanical correlation effect (i.e., a spurious interdependence) between the bank and the system when the total number of institutions *n* in the sample is not particularly large, but also when a single institution may have a significant weight in relation to the whole system even if *n* is fairly large.[9] Because the bank under analysis is not included, the subsequent analysis of tail co-movements between this bank and the resulting system is much more rigorous and necessarily rules out the possibility of spurious interrelations stemming from the simultaneous presence of the same firm in both portfolios.

Finally, we consider two different variables as weighting variables to define the global system portfolios in (3). Following AB, we use the lagged value of the total assets variable as a weighting variable and, additionally, the lagged book value of bank's liabilities. Whereas the interest in the former is motivated by the belief that relatively larger banks may impose larger shocks to the supply of credit, the latter may capture more accurately the extent of interconnectedness among financial institutions under certain circumstances.[10] We report the results using total assets as the weighting variable.[11]

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[9] In our particular case, the sample is formed by 54 banks, which makes the returns of a common global system formed by all banks fairly sensitive to the largest firms. More generally, the refinement proposed may still be advisable even in large samples because a single bank (or a small set of banks) may still drive the dynamics of a common system portfolio. To illustrate this point we have computed the total assets of all listed bank holding companies and commercial banks in the U.S. at Q4 2010 using data from Bank Regulatory and CRSP. Among the 277 firms involved, the largest bank attending to total assets in this period was Bank of America Corporation. With a value of $167 billion over a total market value of $841 billion, this bank represents approximately 19.9% of the banking sector. Obviously, if we analyze dependences between this particular bank and a portfolio formed by the 277 banks, the results would likely support the existence of interdependences because of the massive presence of Bank of America in both portfolios. Our simple adjustment rules out the possibility of overstating tail dependence.

[10] To underline why liabilities may be better intended as weighting variables than total assets, consider the following example. Assume that a systemic bank has financed most of its assets by issuing debt. Suppose that, following an episode of financial distress, total assets are marked down in value. Note that using total assets as a weighting variable would underestimate the importance of the bank in the financial system. While the size of the firm may have declined, the initial value of its outstanding claims and thus, its potential for spillover effects on its financial counterparties, would remain unaltered.

[11] Results using book value of liabilities remain the same and are available upon request.

Estimating VaR of individual banks and system portfolios

The CoVaR methodology requires the estimation of the VaR for any individual bank and any system portfolio in our sample. To this end, we consider the Quantile Regression methodology (QR henceforth). The focus on the 5% quantile provides a fair balance between our goal of characterizing extreme movements in the left-tail of the conditional loss distribution and the statistical difficulties related to parameter identification that arise in the QR approach in finite samples when the target probability is close to the boundary limits (see Chernozhukov, 2005, for a technical discussion on this issue).[12] Furthermore, this quantile is a usual choice in the related literature; see, for instance, Acharya et al. (2010).

Let $(Z_{1t},...,Z_{kt})'$ be a vector with the observations at time t of the macroeconomic and financial state variables described in Section 3, and denote by D_t a dummy variable taking the value of one in the crisis period (after September 2008) and zero otherwise. Then, given the set of variables $Z_t = (1, D_t, Z_{1t},...,Z_{kt})'$ we run a predictive QR model to capture the 5% VaR dynamics,

$$Y_t^i = Z_{t-1}^{'}\beta_\lambda + u_{\lambda,t}; \quad t = 1,...,T \tag{4}$$

with $Y_t^i \in \{X_t^{S,i}, X_t^i\}$ and the error term $u_{\lambda,t}$ satisfying the usual restriction $E(u_{\lambda,t} \mid Z_{t-1}) = 0$. This general specification does not impose any particular restriction on the distribution of the data, and parameters can be estimated consistently upon mild regularity conditions.

Although we do not report the estimates from the QR estimation of the VaR processes in order to save space (results are available upon request), some features are worth commenting. The market volatility index has a strong and negative effect on the size of the expected VaR, with increases in volatility levels triggering larger expected losses. Not surprisingly, among all the predictive variables analyzed, market volatility turns out to be the best predictor. In addition, changes in the T-bill rate, a widening of liquidity spreads, and spikes in credit spreads are generally found to be significantly associated with a larger one-period ahead VaR and, hence, could be used to anticipate higher levels of downside risk. The dummy variable related to the financial crisis shows a structural impact in the unconditional level of the inferred VaR dynamics, and largely contributes to improve the overall fitting of the model. Generally speaking, the goodness of fit as measured by the pseudo-R^2 shows a strong degree of predictability in terms of the conditioning variables used in the analysis, particularly, of the volatility index.

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[12] Applied papers typically avoid extreme percentiles routinely in their QR analysis even with larger samples than ours; see, for instance, Pesaran et al (2011), who focus on quantiles in the range 5%-95%.

Computing $CoVaR_{\lambda,t}^{S|i}$ and $CoVaR_{\lambda,t}^{i}$

The key step in the CoVaR methodology is to estimate the measure of conditional comovement. This is readily achieved by augmenting the quantile regression model (4) with the returns of the *i*-th bank and by setting $Y_t^i = X_t^{S,i}$. Together with this approach, in this paper we consider several econometric specifications growing in complexity which extend the basic CoVaR model.

More specifically, our baseline specification is the same model used by AB, namely:

$$X_t^{S,i} = Z_{t-1}^{'}\beta_\lambda + \delta_{\lambda,i} X_t^i + u_{\lambda,t} \tag{5}$$

for which the contribution of institution *i* to its portfolio system can be approached as

$$\Delta CoVaR_{\lambda,t}^{i} = Z_{t-1}^{'}\hat{\beta}_\lambda + \hat{\delta}_{\lambda,i} VaR_{\lambda,t}^{i} - VaR_{\lambda,t}^{S,i} \tag{6}$$

with $Z_{t-1}^{'}\hat{\beta}_\lambda + \hat{\delta}_{\lambda,i} VaR_{\lambda,t}^{i}$ capturing the VaR forecast of the system conditional on the distress of a particular bank. In this expression, the existence of risk spillovers is captured through the estimates of the $\delta_{\lambda,i}$ parameter: for non-zero values of this parameter, the left tail of the system distribution can be predicted by observing the predetermined distribution of a bank's returns.

Because the CoVaR is essentially a measure of downside risk, there are certain caveats in the basic specification of model (5) and its resulting predictions, given by (6). In particular, the estimates of $\delta_{\lambda,i}$ reflect the average response of the conditional distribution of the global system returns to the whole distribution of the returns of a bank. Since the interest of our analysis is clearly on the behaviour of the left tail for which 5% VaR is expected to be a negative value, the basic specification (5) neglects an important feature of the conditioning: the final prediction is constructed on a negative value. If we factor in the reinforcing effects from credit constraints in a downward market, the model is likely to yield parameter estimates of $\delta_{\lambda,i}$ which can largely underestimate the impact in the system of a negative shock in the balance sheet of a bank. We therefore propose a simple, yet meaningful extension that accounts for the possible asymmetries in the specification (referred to as Asymmetric CoVaR hereafter),

$$X_t^{S,i} = Z_{t-1}^{'}\beta_\lambda + \delta^{-}_{\lambda,i} X_t^i I_{\left(X_t^i<0\right)} + \delta^{+}_{\lambda,i} X_t^i I_{\left(X_t^i\geq 0\right)} + u_{\lambda,t} \tag{7}$$

where $I_{(\bullet)}$ is an indicator function taking value equal to one if the condition in the subscript is true and zero otherwise; see López-Espinosa et al. (2011) for further details. The baseline model trivially arises as a particular case under the restriction $\delta^{-}_{\lambda,i} = \delta^{+}_{\lambda,i} = \delta_{\lambda,i}$. In turn, the asymmetric model delivers one-period ahead forecasts of the contribution to the CoVaR given by

$$\Delta CoVaR^{i}_{\lambda,t} = Z'_{t-1}\hat{\beta}_{\lambda} + \hat{\delta}^{-}_{\lambda,i} VaR^{i}_{\lambda,t} - VaR^{S,i}_{\lambda,t} \tag{8}$$

and should generally be expected to generate more precise estimates of systemic risk than those based on the restricted model (6), at least if $\delta^{-}_{\lambda,i} \neq \delta^{+}_{\lambda,i}$ holds true.

In addition, since most banks in our sample underwent a recapitalization process as a an endogenous policy response to large losses incurred during the financial crisis, we account for the impact on returns from the crisis period as well as from the recapitalization process as follows:

$$X^{S,i}_{t} = Z'_{t-1}\beta_{\lambda} + \delta^{-}_{\lambda,i} X^{i}_{t} I_{\left(X^{i}_{t}<0\right)} + \delta^{+}_{\lambda,i} X^{i}_{t} I_{\left(X^{i}_{t}\geq 0\right)} + \zeta_{\lambda,i} X^{i}_{t} I_{\left(X^{i}_{t}<0,Crisis\right)} + \tau_{\lambda,i} X^{i}_{t} I_{\left(X^{i}_{t}<0,\mathrm{Re}\right)} + u_{\lambda,t} \tag{9}$$

where $I_{\left(X^{i}_{t}<0,Crisis\right)}$ and $I_{\left(X^{i}_{t}<0,\mathrm{Re}\right)}$ take value equal to one, for negative returns observed in the crisis period and on the bank recapitalization date, respectively.

B. Estimation Results

The main results from the QR estimation of models (5), (7) and (9) are discussed in this subsection. Recall that estimations are carried out for two different types of samples. On the one hand, we consider all the 54 banks and use U.S. state variables as predictors of expected return. This is termed as “1-Region” in our analysis. On the other hand, we consider U.S. + Canada and Europe and use regional predictors for each bank in this area, which implies excluding Asian, African and Australian banks from the analysis. This is termed “2-Regions” in our analysis. Tables 2 and 3 display average results for equations (5), (7) and (9) under the “1-Region” and the “2-Regions” specifications, respectively. These tables show the median of the coefficient estimates, the median of the *t*-statistics for the individual significance of the estimated coefficients, and the median of the pseudo-R^2. Complete results at the individual level are available upon request.

A remarkably robust picture emerges from the analysis across different estimations. Among the different state variables used as controlling variables, market volatility and market return exhibit the strongest predictive power in statistical terms. The significance of the remaining variables is much more sensitive to the specification of the model. The coefficient related to the dynamics of the lagged returns of a potentially systemic bank is always significant in our analysis and enhances the ability of the model to forecast the tail performance of the global system portfolio.

The overall evidence reveals the importance of globalization in the banking industry as it shows strong evidence of interconnectedness between large-scale banks even if they belong to different countries and different economic regions.

Allowing for asymmetric effects in the characteristic response of the VaR of the system portfolio to the returns of a particular bank leads to a considerable enhancement in the overall fitting of the model as measured by the pseudo-R^2. Interestingly, the predictive power of several financial predictors (e.g., the spread of interest rates) becomes insignificant, which implies that these variables were essentially required to explain non-linear patterns. More importantly, we observe the dramatic effect that neglecting asymmetric responses has on the estimated value of the CoVaR coefficient. A model that assumes a symmetric response tends to largely underestimate the size of the link between the bank and its system portfolio and, hence, leads to conservative predictions of the extent of systemic risk. Note that, according to our estimates, the median of the estimates of the coefficient $\delta^{-}_{\lambda,i}$ is almost three times larger than $\delta^{+}_{\lambda,i}$.

On average, allowing for time-effects related to the crisis seems to lead to moderate incremental gains over the asymmetric specification, although we note that there exist considerable degrees of heterogeneity in the results that make difficult to draw a clear conclusion. In general terms, most banks in our sample have become more systemic in the aftermath of the global financial crisis. Similarly, on average, the systemic risk of a financial institution tends to decrease after a capital injection pointing at the success of recapitalization programs in containing systemic risk.

Table 4a displays the systemic risk contribution of each bank, ranking banks based on the size of the asymmetric sensitivity of the system to negative bank returns. We also show the other sensitivity coefficients, including dummy variables multiplied by negative returns. The table shows that banks such as ING, HSBC, Lloyds and Royal Bank of Scotland were among the most systemic under the lens of our asymmetric beta coefficient. Asymmetries are also very noticeable. For instance, for ING, the coefficient on negative returns is around 8 times larger than the coefficient on positive returns. Interestingly, the more systemic the bank is, the more asymmetric its contribution to overall systemic risk is. Figure 1 plots the difference between the median estimates of the coefficient on negative returns and that on positive returns as a function of the ranking of each bank in Table 4a. The figure reveals a strong relation between the position in this ranking and the size of the asymmetry: the higher is the sensitivity of system returns to the negative returns of a bank, the more asymmetric this bank is. This again reinforces the need to account for asymmetries when performing systemic risk regressions. Table 4a also shows that some banks tend to be more systemic during crises, while for other banks the opposite is true. There are two specific Canadian banks -Bank of Montreal and Toronto-Dom Bank- which became very systemic during the crisis. Finally, we see that recapitalizations had a very positive effect for several

European institutions, particularly, for Italian banks. This suggests that government intervention helped mitigate systemic risk.

Table 4b shows the ranking of banks based on their contribution to overall systemic risk based directly on the average ΔCoVaR measure. It does so for the whole period as well as for the pre-crisis and crisis periods. It is noticeable that some large institutions, such as Citigroup, appear very systemic during the whole period. On average across banks, contributions are 0.2 percentage points higher during the crisis period. Interestingly, the ranking of an institution in the crisis period is influenced by the timing of public intervention in that bank. Whereas banks that received prompt recapitalization in Q4 2008 such as Citigroup, Bank of America, ING and Commerzbank, improved their relative position during the crisis period, banks that were rescued by public authorities later in Q4 2009, i.e. RBS and Lloyds, became relatively more systemic during the crisis period.

In order to draw cross-country comparisons of systemic risk contributions, Table 4c shows the sensitivity parameter estimates of the first-stage regressions across countries, whereas Table 4d shows the implied cross-country ΔCoVaR metric before the crisis, during the crisis and for the whole period. Both tables reveal that the system is most sensitive to Dutch banks in distress. This is essentially due to the large effect of ING on the system, especially before the crisis.

V. DETERMINANTS OF SYSTEMIC RISK

A. Regression Analysis

In this section, we discuss the main drivers of systemic risk in global banking. Since the best overall fitting in the first stage CoVaR estimation was provided by a specification accounting for asymmetric responses, crisis and recapitalization effects under a "2-Region" approach, we use this specification for the second stage of the analysis. We aggregate the estimates of the weekly $\Delta CoVaR_{it}$ processes obtained in the first stage to quarterly frequency and relate them to a set of bank-specific variables in panel-data and pooled regressions. In particular, we consider the following baseline predictive regression model with fixed effects:

$$\Delta CoVaR_{it} = \beta_0 + \beta_1 \Delta CoVaR_{it-1} + \beta_2 VaR_{it-1} + \beta_3 Leverage_{it-1} + \beta_4 WSF_{it-1} + \beta_5 Size_{it-1} + \beta_6 MTB_{it-1} + \beta_7 Mktb_{it-1} + \sum_{j=1}^{n-1} Bank_j + \sum_{k=1}^{m-1} Time_k + \varepsilon_{it} \tag{10}$$

where $\Delta CoVaR_{it}$ is computed in the first stage as described above and VaR_{it} denotes the quarterly estimates of VaR. We include lags of these variables to correct for endogenous risk persistence. In addition, the right-hand side of (10) includes the following predictive variables:

- $Leverage_{it-1}$ is the total assets to equity ratio of bank i at quarter $t-1$. This ratio is a usual proxy for the level of solvency of the bank, so the higher the leverage the lower the solvency. Therefore, we expect a negative relation with the dependent variable.
- WSF_{it-1} approaches the relative level of short-term wholesale funding as the total short-term borrowings to total assets ratio of bank i at quarter $t-1$. Short-term borrowings include bank overdrafts, short-term debt and borrowing, repo, short-term portion of long-term borrowing due to other banks (including to the central bank) or any other financial institutions, call money, bills discounted, federal funds purchased and securities sold not yet purchased. This ratio is a proxy for interconnectivity among financial institutions and captures liquidity risk exposures. Hence, we expect a negative relation with $\Delta CoVaR_{it}$.
- $Size_{it-1}$ is the total assets of bank i at quarter $t-1$ over the total assets of all banks in the sample at quarter $t-1$. We expect that the larger the relative size of a bank, the higher its contribution to systemic risk.
- MTB_{it-1} is the market-to-book ratio of bank i at quarter $t-1$. This ratio may proxy growth opportunities, but under potential mispricing, it could also capture systemic risk due to expected market value realignment. Thus a higher value of this ratio would imply a negative relationship with $\Delta CoVaR_{it}$.
- $Mktb_{it-1}$ is the marketable securities to total assets ratio of bank i at quarter $t-1$. It is a proxy for the proportion of financial instruments available-for-sale or financial instruments accounted for fair value. Similarly to wholesale funding, we expect a negative relation with the dependent variable due to reinforcing effects from the fire sale of distressed assets.
- $Bank_j$ and $Time_k$ are bank and time dummies to control for individual fixed bank and time effects, respectively.

Table 5 reports the estimates from equation (10) for asset-weighted global systems, after controlling for bank and time fixed effects and allowing for bank clustered errors. Across specifications, wholesale funding appears as a robust determinant of systemic risk, suggesting that banks heavily dependent on short-term borrowing decisively contribute to higher systemic risk thus generating negative externalities. Similar results have been found in Adrian and Brunnermeier (2009) and Acharya et al. (2010). By contrast to these papers, we find that relative size, leverage and marketable assets are not significant at any of the standard confidence levels, implying that these firm characteristics do not add additional information over short-term wholesale funding. This evidence supports the theoretical claims in Zhou (2010), who argues that being too big is not necessarily a systemic driver, but rather having a balance sheet exposed to riskier projects. Our paper suggests that riskier funding is a key contributor to systemic risk.

There are, at least, two interrelated reasons that explain why short-term wholesale funding plays such a fundamental role on systemic risk contributions in the global banking industry. First, banks usually raise wholesale funding in the interbank unsecured market, where banks can handle liquidity needs by borrowing and lending money from their peers in over-the-counter operations. This market provides a direct channel for financial contagion, because a bank that intensively operates in this segment interconnects its balance sheet with those of other financial intermediaries around the world, thereby increasing the likelihood of a global domino fall in the industry. The extent of wholesale funding is, therefore, a natural proxy for interconnectedness, a factor that the Financial Stability Board early pointed out as key determinant of systemic importance.

In addition, a bank that relies excessively on short-term funding has greater maturity mismatch between assets and liabilities and becomes more vulnerable to liquidity risk. This feature makes the possibility of fire sales more likely and causes risk externalities to other intermediaries holding the same asset classes; see, among others, Brunnermeier (2009), Ratnovski (2009), Acharya and Merrouche (2010), and Allen et al. (2010). Consequently, short-term wholesale funding is also strongly related to liquidity risk, a major source of systemic disruption during the financial crisis. The confluence of these two channels makes short-term wholesale funding a critical variable in understanding the degree of systemic importance of a bank.

In addition, we find that bank recapitalizations have had an important influence in modifying systemic risk inter-dependences. Therefore, model (10) can be suitably extended to address this issue.[13] In particular, let $Recap_{it}$ be an impulse dummy taking value equal to one if bank *i* is recapitalized at time *t* and zero otherwise (see Appendix B for the timing of recapitalization of each bank in our sample). Then, equation (10) can be extended to capture interactions of the form $Recap_{it}\ x\ V_{it}$, with V_{it} denoting any of the bank characteristics $\{Leverage_{it}, WSF_{it}, Size_{it}, MTB_{it}, Mktb_{it}\}$ described previously. The resulting variables attempt to capture cross-effects and act as a proxy for the need of fresh capital as a function of the financial position before the recapitalization takes place. The main results from the estimation of equation (10) extended with all these cross-effects are reported in Table 6.

Again, wholesale funding appears as a robust predictor of systemic risk, while the other firm characteristics do not seem to add incremental information. Regarding the

[13] King (2009) shows in an event study framework that rescue packages announcements for banks benefited creditors at the expense of shareholders.

recapitalization cross-effects, only the size of marketable securities seems to increase significantly systemic risk to the extent that the bank has been recapitalized, although the statistical evidence is weaker (the estimate is significant at the 10% nominal size). This result lends some support to the fire sales channel as a key transmitter of financial distress from recapitalized institutions.

B. Robustness Checks

We performed a number of robustness checks to gauge the robustness of the main conclusions in the previous subsection. In order to save space, these checks and their results are briefly discussed below, but a complete analysis is available from authors upon request.

Characterization of individual VaR dynamics

In the first stage, we use the QR to characterize and estimate the dynamics of VaR in individual banks and global system portfolios. We also consider alternative estimation procedures, namely, the popular parametric GARCH (1,1) applied on conditionally demeaned returns. Given the quasi-maximum likelihood estimates of the GARCH parameters, the VaR for each bank is then determined as $\hat{\sigma}_t Q_\lambda(\hat{\eta})$, where $Q_\lambda(\hat{\eta})$ is the empirical λ-quantile of the distribution of the empirical innovations $\hat{\eta}_t = X_t^i / \hat{\sigma}_t$ and $\hat{\sigma}_t$ is the empirical conditional volatility process according to the GARCH equation. Under this estimation method, no predetermined information is used to capture individual VaR dynamics apart from the statistical information conveyed by the time-series variability of X_t^i which offers an alternative representation. The results based on this approach were remarkably similar to those obtained under the QR approach.

Measuring systemic risk

As an alternative to *ΔCoVaR*, we use a measure of contribution to systemic risk in the spirit of the so-called Systemic Expected Shortfall (SES) proposed by Acharya et al. (2010). These authors measure the *exposure* to systemic risk of bank *i* as $E(r_{ti} \le r_{ti}^* \mid R_t \le R_t^*)$, where r_{ti} and R_t denote the returns of an individual bank and the stock market, respectively, and r_{ti}^* and R_t^* are the (unobservable) target values of these variables. By interchanging $r_{ti} \le r_{ti}^*$ and $R_t \le R_t^*$, the *contribution* of a bank to the market risk can be defined analogously. Thus, following Acharya et al. (2010), we use daily stock and market returns to approximate the unobservable SES with the so-called Marginal Expected Shortfall (MES_{it}), defined as the average of global market returns during the 5% worst days of bank *i* for each bank *i* and each quarter *t*. The resulting estimates were regressed on lagged values of the accounting ratios defined in equation (10), finding that short-term wholesale funding appears to be a significant predictor of this measure, although its significance is somewhat weaker in this analysis (significant at the 10% benchmark).

Definition of ΔCoVaR

Adrian and Brunnermeir (2009) define the measure of contribution to systemic risk as $\Delta CoVaR^{i}_{\lambda,t} = CoVaR^{S|i}_{\lambda,t} - VaR^{S}_{\lambda,t}$. This measure has been used in other papers, such as Van Oordt and Zhou (2010). The contribution to systemic risk may be defined as $\Delta CoVaR^{i}_{\lambda,t} = CoVaR^{S|i}_{\lambda,t} - CoVaR^{S|i}_{50\%,t}$ where a bank's systemic risk is measured by its marginal impact on system returns from reaching its VaR relative to when it exhibits median returns. We repeated the determinants analysis of Section 5 with estimates of quarterly *ΔCoVaR* based on this definition and the main conclusions remained unaltered.

Estimation techniques and other considerations in the determinants analysis

In terms of estimation techniques, we also corrected standard errors in the panel data framework with time effects. Additionally, we estimated equation (10) and the recapitalization-extended model applying two-way cluster with bank and country dummies separately. Finally, we also performed both GMM estimation –with all the independent variables as instruments- and the results remained unaltered.

We also checked the model specification of equation (10) and included macroeconomic variables related to the business cycle, namely, unemployment and interest rates time series. The results are robust to these considerations. Alternatively, we checked the robustness of the results to the model specification used to estimate CoVaR dynamics and the main variables involved. First, we computed CoVaR dynamics using a symmetric specification as that in AB. Second, we estimated the smoothed series by implementing a cubic spline on the balance sheet data. Third, we estimated marginal CoVaR on a global system constructed by using the accounting value of liabilities to compute the weights of each bank in the system. The results are similar, with short-term wholesale funding being the main driver of systemic risk.

VI. CONCLUDING REMARKS AND POLICY RECOMMENDATIONS

In this paper we examine some of the main factors driving systemic risk in a global framework. We focus on a set of large-scale, international complex institutions which would in principle be deemed too-big-to-fail by national regulators and which are therefore of mayor interest for policy makers. For this class of firms, the evidence based on the CoVaR methodology suggests that short-term wholesale funding –a variable strongly related to interconnectedness and liquidity risk exposure-, is positively and significantly related to systemic risk, whereas other features of the firm, such as leverage or relative size, do not seem to provide incremental information over wholesale funding. This suggests that this latter variable subsumes to a large extent most of the relevant information on systemic risk conveyed by other firm characteristics. We also uncover the relevant role played by asymmetric responses when assessing the impact of individual institutions on system-wide risk, as we find that the sensitivity of system returns to individual bank returns is much higher in periods of balance sheet deleveraging.

Regulators are currently developing a methodological framework within the context of Basel III that attempts to embody the main factors of systemic importance; see Walter (2011). These factors are categorized as size, interconnectedness, substitutability, global activity and complexity, and will serve as a major reference to determine the amount of additional capital requirements and funding ratios for systemically important financial institutions. Our analysis provides formal empirical support to the Basel Committee's proposal to penalize excessive exposures to liquidity risk by showing that short-term wholesale funding, a variable capturing interconnectedness, largely contributes to systemic risk. Furthermore, since our findings suggest that some factors are much more important than others in determining systemic risk contributions, an optimal capital buffer structure on systemic banks could in principle be designed by suitably weighting the different driving factors as a function of their relative importance. This is an interesting topic for further research. Similarly, the evidence in this paper also offers empirical support to justify the theoretical models that acknowledge the premise that wholesale funding can generate large systemic risk externalities; see, for instance, Perotti and Suarez (2011) for a recent analysis and references therein.

Given the relevance of liquidity strains as a contributing factor to systemic risk, the regulation of systemic risk could be strengthened by giving incentives to disclose contingent short-term liabilities, in particular those related to possible margin calls under credit default swap contracts and repo funding. Our study also points at the role of large trading books as a source of systemic risk –for those banks which were recapitalized during the crisis. As a result, the 2010 revamp of the Basel II capital framework to cover market risk associated with banks' trading book positions will not only decrease individual risk but will also contribute to mitigate systemic risk.

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Appendix A. List of Financial Institutions

Country	Bank	Abbreviation
AUSTRIA	ERSTE GROUP BANK	EBS AV
AUSTRALIA	COMMONW BK AUSTR	CBA AU
	NATL AUST BANK	NAB AU
	WESTPAC BANKING	WBC AU
BELGIUM	KBC GROEP	KBCB PZ
BRITAIN	BARCLAYS PLC	BARC LN
	HSBC HOLDINGS	HSBC LN
	LLOYDS BANKING	LLOY LN
	ROYAL BK SCOTLAND	RBS LN
	STANDARD CHARTER	STAN LN
CANADA	BANK OF MONTREAL	BMO CN
	BANK OF NOVA SCO	BNS CT
	CAN IMPL BK COMM	CM CT
	ROYAL BANK OF CA	RY CT
	TORONTO-DOM BANK	TD CT
DENMARK	DANSKE BANK A/S	DANSKE DC
FRANCE	BNP PARIBAS	BNP FP
	SOC GENERALE	GLE FP
GERMANY	COMMERZBANK	CBK GR
	DEUTSCHE BANK-RG	DBK GR
IRELAND	ALLIED IRISH BK	ALBK ID
ITALY	BANCA MONTE DEI	BMPS IM
	INTESA SANPAOLO	ISP IM
	UNICREDIT SPA	UCG IM
JAPAN	DAIWA SECS GRP	8601 JT
	NOMURA HOLDINGS	8604 JT
NETHERLANDS	ING GROEP NV-CVA	INGA NA
NORWAY	DNB NOR ASA	DNBNOR NO
SOUTH AFRICA	STANDARD BANK GR	SBK SJ
SPAIN	BBVA	BBVA SM
	BANESTO SA	BTO SM
	BANCO POPULAR	POP SM
	BANCO SANTANDER	SAN SM
SWEDEN	NORDEA BANK AB	NDA SS
	SEB AB-A	SEBA SS
	SVENSKA HAN-A	SHBA SS
	SWEDBANK AB-A	SWEDA SS
SWITZERLAND	CREDIT SUISS-REG	CSGN VX
	UBS AG-REG	UBSN VX
UNITED STATES	BANK OF AMERICA	BAC UN
	BB&T CORP	BBT UN
	BANK NY MELLON	BK UN
	CITIGROUP INC	C US
	CAPITAL ONE FINA	COF UN
	GOLDMAN SACHS GP	GS UN
	JPMORGAN CHASE	JPM US
	MORGAN STANLEY	MS UN
	PNC FINANCIAL SE	PNC UN
	REGIONS FINANCIA	RF UN
	SLM CORP	SLM UN
	SUNTRUST BANKS	STI UN
	STATE ST CORP	STT UN
	US BANCORP	USB US
	WELLS FARGO & CO	WFC UN

Appendix B: List of recapitalizations

Bank	Date	Recapitalization Policy
ERS	Oct 30 2008	Injection of €2.7 bn of non-listed, non-voting, non-transferable capital
KBC	Oct 27 2008	Injection of €3.5 bn from the government, and €2.7 bn from the Flemish Regional Government
BARC	Sept 16 2009	Sale of $12 bn of risky credit assets to a special purpose vehicle
Lloyds	Sep 18 2008	Competition rules waived to allow the merger with HBOS
	Oct 19 2008	The government injected £4 bn of preference shares
RBS	Jan 19 2009	The government swapped preferred shares for ordinary shares worth £5 bn
	Feb 26 2009	The bank received £13 bn in additional capital for a participation fee of £6.5 bn
	Nov 3 2009	The authorities announced an additional injection of £25.5 bn shoring up the gov stake to 84 %
BNP	Oct 22 2008	The bank issued hybrid subordinated debt for €2.55 bn
	March 1 2009	The French banking plan purchased €5.1 bn of non-voting shares; the hybrid debt was redeemed
SGE	Oct 22 2008	The bank issued hybrid subordinated debt for €1.7 bn
CBK	Nov 4 2008	The government announced an injection of €8.2 bn with a further injection of €10 bn
ALBK	Feb 11 2009	Injection of €3.5 bn of tier I capital
UC	March 18 2009	The bank issued €4.0 bn of government capital instruments
BIN	March 20 2009	The bank announced the issuance of €4 bn of subordinated debt subscribed by the government
BMPS	March 27 2009	The bank announced the issuance of €1.9 bn of special bonds subscribed by the government
ING	Oct 21 2008	Government capital injection of €10 bn
BAC	Jan 16 2009	Capital injection of $20 bn from the TARP in exchange for preferred stock with 8% dividend
C	Nov 23 2008	Capital injection of $20 bn from the TARP in exchange for preferred stock with 8% dividend
		Further issuance of $7 bn of preferred stock to the Treasury and the FDCI
COF	Oct 30 2008	Capital injection of $3.55 bn from the TARP in exchange for preferred stock with 8% dividend
PNC	Oct 30 2009	Capital injection of $7.6 bn from the TARP in exchange for preferred stock with 8% dividend
WFC	Oct 30 2010	Redemption of $25 bn issued to the government under the TARP

Source: Bloomberg, authorities' websites, and IMF

Table 1a. U.S. State Variables

	CREDIT SPREAD	CHANGE TBILL	LIQ SPREAD	S&P	VIX	YIELD SPREAD
Mean	0.004	-0.008	0.246	-0.020	21.827	0.004
Median	-0.020	0.000	0.170	0.147	19.400	-0.010
Maximum	0.830	0.690	1.140	16.889	72.916	0.710
Minimum	-0.580	-0.790	-0.040	-26.537	10.185	-0.554
Std. Dev.	0.154	0.118	0.223	2.964	10.579	0.161
Skewness	1.475	-1.212	1.731	-1.763	1.772	0.640
Kurtosis	9.200	15.083	5.984	22.104	7.008	5.331
1st order autocorrelation	0.284	0.084	0.874	-0.150	0.972	-0.010

Summary statistics of the U.S. weekly market variables: the credit spread is the difference between BAA rated bonds and the Treasury rate (with same maturity of 10 years). The change in TBILL is the change in the 3 month T-Bill rate. The liquidity spread is the difference between the 3-month repo rate and the 3-month T-Bill rate. The return variable is the weekly market equity return. The VIX is the CBOE option implied volatility. The yield spread is the change in the yield slope between the 10-year and the 3-month T-Bill rate.

Table 1b. European State Variables

	CREDIT SPREAD	CHANGE TBILL	LIQ SPREAD	FTSE	VOLAT INDEX	YIELD SPREAD
Mean	0.000	0.010	0.037	0.078	25.890	0.002
Median	0.001	0.000	0.016	0.232	22.870	-0.001
Maximum	0.793	0.299	0.831	13.592	81.030	0.316
Minimum	-0.461	-0.948	-0.041	-25.130	11.600	-0.294
Std. Dev.	0.099	0.089	0.074	3.417	12.228	0.079
Skewness	1.309	-4.963	4.873	-1.036	1.421	0.594
Kurtosis	12.667	41.238	36.567	7.504	2.209	3.038
1st order autocorrelation	0.296	0.254	0.863	-0.070	0.949	0.011

This table contains the descriptive statistics for the European state variables. The credit spread is constructed as the difference between the Moody's seasoned BAA corporate bond yield and the 10 year German government bond. The change in the T-Bill rate is the first difference in the 3 month interest rates on French government bonds. The liquidity spread is the difference between the UK 3-month repo rate and the UK 3-month T-bill yield. Stock returns are constructed with the FSTE European index, the volatility index corresponds to the Euronext index and the yield spread is the change in the yield slope between the French 5 year and 3 month interest rates on government securities.

Table 2. 1st-stage regressions: 1 Region

1 REGION: 438 weekly observations, 54 banks			
	Baseline	Asym.	Asym. Ext.
Constant	-0.023 (-2.41)	-0.020 (-2.50)	-0.019 (-2.26)
Volatility	-0.001 (-3.55)	-0.001 (-3.08)	-0.001 (-2.89)
Liquidity Spread	-0.056 (-2.72)	-0.003 (-0.40)	-0.004 (-0.25)
ΔTbill	-0.087 (-1.59)	-0.007 (-0.13)	0.002 (0.09)
ΔSlope	0.029 (0.77)	0.034 (1.34)	0.020 (0.97)
ΔCredit Spread	-0.102 (-1.92)	-0.035 (-1.00)	-0.028 (-0.82)
Market Return	0.005 (4.32)	0.002 (2.18)	0.002 (2.56)
Crisis Dummy	-0.011 (-1.20)	-0.006 (-0.88)	-0.003 (-0.44)
X_{t-1}^{i}	0.270 (2.40)	-	-
$X_{t-1}^{i}\, I_{\left(X_{t-1}^{i}<0\right)}$	-	0.804 (10.05)	0.683 (7.98)
$X_{t-1}^{i}\, I_{\left(X_{t-1}^{i}\geq 0\right)}$	-	0.167 (1.67)	0.182 (1.82)
$X_{t-1}^{i}\, I_{\left(X_{t-1}^{i}<0, Crisis\right)}$	-	-	0.086 (0.38)
$X_{t-1}^{i}\, I_{\left(X_{t-1}^{i}<0, \mathrm{Re}\right)}$	-	-	-0.24 (-0.96)
Pseudo-R^2	0.551	0.635	0.641

The table shows the median of estimated coefficients, *t*-statistics and pseudo-R^2 in 5% quantile regressions on global system returns on a set of state variables (credit spread, change in the Treasury Bill, liquidity spread, volatility index, stock market return, yield spread and a dummy for the subsequent periods to the August 2007 credit crisis) and the returns of each bank. The baseline specification corresponds to the symmetric model presented in equation (5), whereas the asymmetric model is described in equation (7) and the asymmetric extended model is in equation (9). This table shows results for the model using U.S. state variables for all countries. These results are based on weekly data from the week of July 20, 2001 to the week of December 11, 2009.

Table 3. 1st-stage regressions: 2 Regions

2 REGIONS: 438 weekly observations, 48 banks (Europe, and US+Canada)			
	Baseline	Asym.	Asym. Ext.
Constant	-0.041 (-3.51)	-0.022 (-2.67)	-0.020 (-2.73)
Volatility	-0.001 (-2.02)	-0.001 (-2.49)	-0.001 (-3.22)
Liquidity Spread	-0.075 (-1.02)	-0.025 (-071)	-0.027 (-1.05)
ΔTbill	0.054 (0.91)	-0.009 (-0.19)	0.012 (0.39)
ΔSlope	-0.061 (-1.28)	0.008 (0.28)	0.001 (0.06)
ΔCredit Spread	0.034 (0.79)	0.017 (0.67)	0.025 (0.56)
Market Return	0.003 (2.26)	0.001 (1.64)	0.001 (0.94)
Crisis Dummy	-0.015 (-1.39)	-0.007 (-0.66)	-0.009 (-1.04)
X_{t-1}^{i}	0.321 (2.38)	-	-
$X_{t-1}^{i} I_{\left(X_{t-1}^{i}<0\right)}$	-	0.785 (8.65)	0.636 (6.07)
$X_{t-1}^{i} I_{\left(X_{t-1}^{i}\geq 0\right)}$	-	0.153 (1.76)	0.159 (2.10)
$X_{t-1}^{i} I_{\left(X_{t-1}^{i}<0,Crisis\right)}$	-	-	0.059 (0.23)
$X_{t-1}^{i} I_{\left(X_{t-1}^{i}<0,\mathrm{Re}\right)}$	-	-	-0.200 (-0.40)
Pseudo-R^2	0.570	0.639	0.644

The table shows the median of the estimated coefficients, *t*-statistics and pseudo-R^2 in the 5% quantile regressions of global system returns on a set of state variables (credit spread, change in the Treasury Bill, liquidity spread, volatility index, stock market return, yield spread and a dummy for the subsequent periods to the August 2007 credit crisis) and the returns of each bank. The baseline specification corresponds to the symmetric model presented in equation (5), whereas the asymmetric model is described in equation (7) and the asymmetric extended model is in equation (9). This table shows results for the model using alternative state variables across regions (U.S. and European) in the first stage. These results are based on weekly data from the week of July 20, 2001 to the week of December 11, 2009

Table 4a: Systemic Risk Contribution (Sensitivity) of each Bank

Banks	X_t<0	X_t≥0	(X_t<0)*Crisis	(X_t<0)*Recap	Pseudo-R^2
ING	1.677	0.223	-1.129	0.047	0.737
HSBC	1.575	0.349	0.619		0.667
SVK	1.306	0.160	-0.511		0.673
POP	1.113	0.208	-0.056		0.699
DBK	1.097	0.024	0.070		0.735
LLOY	1.083	0.034	-0.427	-0.611	0.579
RBS	1.072	0.020	-0.421	-0.010	0.657
CSGN	1.025	0.187	-0.532		0.648
NDA	1.042	0.126	-0.254		0.696
CBK	1.040	0.141	-0.387	0.195	0.697
DEA	1.039	0.208	-0.167		0.717
BMPS	0.983	-0.037	0.047	-0.321	0.696
RY	0.947	0.424	0.446		0.642
BNP	0.921	0.157	0.563	-0.325	0.761
STI	0.886	0.136	-0.333		0.637
UBS	0.879	-0.226	-0.452		0.669
SCH	0.868	0.081	-0.000		0.750
STAN	0.842	-0.511	-0.387		0.645
BTO	0.838	0.402	-0.459		0.637
KBC	0.832	0.319	-0.160	-0.156	0.737
SWED	0.824	0.381	-0.301		0.724
C	0.743	0.026	-0.247	-0.154	0.604
UC	0.727	0.026	0.497	-0.971	0.730
BBVA	0.649	0.278	0.488		0.653
TD	0.622	0.415	1.629		0.599
BARC	0.618	0.128	-0.137	-0.580	0.559
CM	0.616	-0.340	0.860		0.598
BIN	0.606	0.039	0.798	-0.994	0.623
DNB	0.606	0.083	0.008		0.684
BK	0.584	0.237	0.552		0.610
PNC	0.554	0.027	0.323	-0.306	0.645
ALBK	0.551	0.253	-0.365	0.003	0.625
SGE	0.540	0.220	0.234	0.310	0.722
USB	0.509	0.288	0.015		0.641
WFC	0.504	0.033	0.140	-0.241	0.612
STT	0.484	0.099	0.089		0.624
DAB	0.450	0.347	0.378		0.708
BAC	0.438	0.232	0.134	-0.295	0.639
RF	0.436	0.098	0.260		0.620
ERS	0.372	0.420	0.148	-0.158	0.610
BMO	0.292	0.213	3.324		0.547
COF	0.287	0.161	0.173	0.497	0.646
MS	0.245	-0.052	0.424		0.584
BNS	0.221	0.511	0.805		0.588
GS	0.193	0.088	0.771		0.578
BBT	0.150	0.439	0.447		0.585
SLM	0.106	0.065	-0.301		0.486
JPM	-0.032	0.277	-1.578		0.556

This table shows the contribution to systemic risk of each bank in our sample. Banks are sorted by the asymmetric coefficient on negative bank returns in the most general model estimated (asset weighted system returns and two regions).

Table 4b: Systemic Risk Contribution to Quarterly Asset Returns

Overall Period		Pre-crisis Period		Crisis Period	
Bank	**ΔCoVaR**	**Bank**	**ΔCoVaR**	**Bank**	**ΔCoVaR**
STT	-2.224	BBT	-1.957	STT	-3.249
C	-1.667	C	-1.911	BIN	-3.180
BBT	-1.521	STT	-1.805	PNC	-2.483
BIN	-1.421	BK	-1.523	TD	-2.033
BK	-1.348	BNS	-1.308	KBC	-2.004
LLOY	-1.277	SLM	-1.255	LLOY	-1.824
BNS	-1.162	CBK	-1.132	CM	-1.658
TD	-1.113	ING	-1.128	BMO	-1.576
PNC	-1.096	LLOY	-1.014	COF	-1.544
ING	-1.042	SVK	-0.948	SBKJ	-1.509
CBK	-1.018	NDA	-0.925	DAB	-1.316
CM	-1.000	RF	-0.915	RBS	-1.264
BMO	-0.982	STI	-0.872	CSGN	-1.237
CSGN	-0.956	USB	-0.870	BMPS	-1.161
SLM	-0.956	CSGN	-0.870	HSBC	-1.157
RF	-0.923	SCH	-0.862	C	-1.048
HSBC	-0.920	BAC	-0.814	DBK	-1.038
USB	-0.874	TD	-0.803	WFC	-1.032
SVK	-0.841	UC	-0.802	GS	-1.020
RBS	-0.831	DEA	-0.795	BTO	-1.014
DBK	-0.820	HSBC	-0.789	MS	-1.001
BAC	-0.817	CM	-0.781	RF	-0.899
BTO	-0.809	BIN	-0.746	DNB	-0.876
WFC	-0.805	DBK	-0.733	UC	-0.876
COF	-0.791	WFC	-0.721	USB	-0.838
KBC	-0.789	RY	-0.719	BAC	-0.818
NDA	-0.786	PNC	-0.679	BARC	-0.814
UC	-0.781	BTO	-0.678	BK	-0.802
STI	-0.772	RBS	-0.664	BNP	-0.774
GS	-0.765	GS	-0.638	RY	-0.757
SCH	-0.763	BMO	-0.631	BNS	-0.691
RY	-0.755	POP	-0.598	CBAX	-0.690
DEA	-0.731	STAN	-0.596	WBCX	-0.678
SBKJ	-0.607	COF	-0.570	NABX	-0.653
STAN	-0.597	ALBK	-0.508	CBK	-0.637
BMPS	-0.594	ERS	-0.476	NM	-0.613
DNB	-0.574	BMPS	-0.473	ING	-0.610
ERS	-0.546	DNB	-0.459	ERS	-0.606
BNP	-0.540	BNP	-0.440	SWED	-0.602
POP	-0.532	BBVA	-0.352	BBVA	-0.552
DAB	-0.525	SWED	-0.344	STAN	-0.514
BARC	-0.480	KBC	-0.343	SVK	-0.501
SWED	-0.457	UBS	-0.316	SCH	-0.487
ALBK	-0.445	JPM	-0.309	DEA	-0.450
BBVA	-0.419	BARC	-0.304	STI	-0.441
UBS	-0.324	SBKJ	-0.292	DS	-0.421
DS	-0.316	SGE	-0.234	NDA	-0.343
MS	-0.299	DS	-0.225	ALBK	-0.324
CBAX	-0.257	DAB	-0.212	POP	-0.273
SGE	-0.254	CBAX	-0.036	BBT	-0.273
WBCX	-0.214	MS	-0.031	SGE	-0.225
NM	-0.166	WBCX	-0.015	UBS	-0.195
NABX	-0.099	NM	-0.003	SLM	-0.148
JPM	0.285	NABX	0.129	JPM	1.996

This table ranks the quarterly contribution to systemic risk of each individual bank to the most inclusive liability-weighted global index. The overall period includes Q4-2001 to Q3-2009, the pre-crisis period covers Q4-2001 to Q2-2007, and the crisis period spans from Q3-2007 to Q1-2009.

Table 4c: Systemic Risk Contribution by Country

Country	X_t<0	X_t≥0	(X_t<0)*Crisis	(X_t<0)*Recap	Pseudo-R^2
Netherlands	1.677	0.223	-1.129	0.047	0.737
Germany	1.069	0.083	-0.158	0.195	0.716
Sweden	1.053	0.219	-0.308		0.702
Britain	1.038	0.004	-0.150	-0.400	0.621
Switzerland	0.952	-0.019	-0.492		0.658
Spain	0.867	0.242	-0.006		0.685
Belgium	0.832	0.319	-0.160	-0.156	0.737
Italy	0.772	0.009	0.447	-0.762	0.683
France	0.731	0.188	0.398	-0.007	0.741
Norway	0.606	0.083	0.008		0.684
Ireland	0.551	0.253	-0.365	0.003	0.625
Canada	0.540	0.244	1.413		0.595
Denmark	0.450	0.347	0.378		0.708
US	0.406	0.143	0.058	-0.100	0.604
Austria	0.372	0.420	0.148	-0.158	0.610

This table shows the average contribution to systemic risk of each country in our sample. Banks are sorted by the asymmetric coefficient on negative bank returns in the most general model estimated (asset weighted system returns and two regions).

Table 4d: Systemic Risk Contribution by Period

Overall Period		Pre-crisis Period		Crisis Period	
Country	**ΔCoVaR**	**Country**	**ΔCoVaR**	**Country**	**ΔCoVaR**
Netherlands	-1.042	Netherlands	-1.128	Belgium	-2.004
Canada	-1.002	US	-0.991	Italy	-1.739
US	-0.972	Germany	-0.933	South Africa	-1.509
Italy	-0.932	Canada	-0.848	Canada	-1.343
Germany	-0.919	Sweden	-0.753	Denmark	-1.316
Britain	-0.821	Italy	-0.673	Britain	-1.115
Belgium	-0.789	Britain	-0.673	US	-0.907
Sweden	-0.703	Spain	-0.622	Norway	-0.876
Switzerland	-0.640	Switzerland	-0.593	Germany	-0.838
Spain	-0.631	Ireland	-0.508	Switzerland	-0.716
South Africa	-0.607	Austria	-0.476	Australia	-0.674
Norway	-0.574	Norway	-0.459	Netherlands	-0.610
Austria	-0.546	Belgium	-0.343	Austria	-0.606
Denmark	-0.525	France	-0.337	Spain	-0.582
Ireland	-0.445	South Africa	-0.292	Japan	-0.517
France	-0.397	Denmark	-0.212	France	-0.500
Japan	-0.241	Japan	-0.114	Sweden	-0.474
Australia	-0.190	Australia	0.026	Ireland	-0.324

This table ranks the average quarterly contribution to systemic risk by country measured by the implied ΔCoVaR. The overall period includes Q4 2001 to Q3 2009, the pre-crisis period covers Q4 2001 to Q2 2007, and the crisis period spans from Q3 2007 to Q1 2009.

Table 5: Systemic Risk Factors: Asymmetric Model

Estimation Method	**Panel**	**One-way**
Independent Variables		
Constant	-0.058	-0.058
Δ CoVaR$_{it-1}$	0.843***	0.843***
VaR$_{it-1}$	-0.095***	-0.095**
Leverage$_{it-1}$	-0.002	-0.002
WSF$_{it-1}$	-0.410**	-0.410***
Size$_{it-1}$	2.440	2.440
MTB$_{it-1}$	-0.000	-0.000
Mktb$_{it-1}$	-0.048	-0.048
Bank Dummies$_j$	Yes	Yes
Time Dummies$_k$	Yes	Yes
R^2 (%)	78.98	78.98
Number of observations	1,280	1,280

The table is based on all banks (firm-quarter observations) with data about marketable securities from 2001:Q4 until 2009:Q3 from Bloomberg database. The following equation is estimated:

$$\Delta CoVaR_{it} = \beta_0 + \beta_1 \Delta CoVaR_{it-1} + \beta_2 VaR_{it-1} + \beta_3 Leverage_{it-1} + \beta_4 WSF_{it-1} + \\ + \beta_5 Size_{it-1} + \beta_6 MTB_{it-1} + \beta_7 Mktb_{it-1} + \sum_{j=1}^{n-1} Bank_j + \sum_{k=1}^{m-1} Time_k + \varepsilon_{it}$$

where Δ CoVaR$_{it}$ is the Δ CoVaR of bank *i* at quarter *t*; Δ CoVaR$_{it-1}$ is the Δ CoVaR of bank *i* at quarter *t-1*; VaR$_{it-1}$ is the VaR of bank *i* at quarter *t-1*; Leverage$_{it-1}$ is the total assets to equity ratio of bank *i* at quarter *t-1*; WSF$_{it-1}$is the short-term borrowings to total assets ratio of bank *i* at quarter *t-1*; Size$_{it-1}$ is the total assets of bank *i* at quarter *t-1* over the total assets of all banks in the sample at quarter *t-1*; MTB$_{it-1}$ is the Market-to-Book ratio of bank *i* at quarter *t-1*; Mktb$_{it-1}$ is the marketable securities to total assets ratio of bank *i* at quarter *t-1*; Bank$_j$ are the *n-1* bank dummies; Time$_k$ are the m-*1* time dummies taking into account the year and quarter. The system is constructed using assets to compute the weights of each bank in the system. Panel: The equation is estimated via firm and time fixed-effects panel data methodology; One-way: The equation is estimated via Firm and Time fixed-effects one-way cluster methodology using banks as clusters. All Δ CoVaRs are estimated using percentile 5. * Significant at 10%, ** Significant at 5%, *** Significant at 1%.

Table 6: Systemic Risk Factors: Asymmetric Model Controlling for Recapitalization

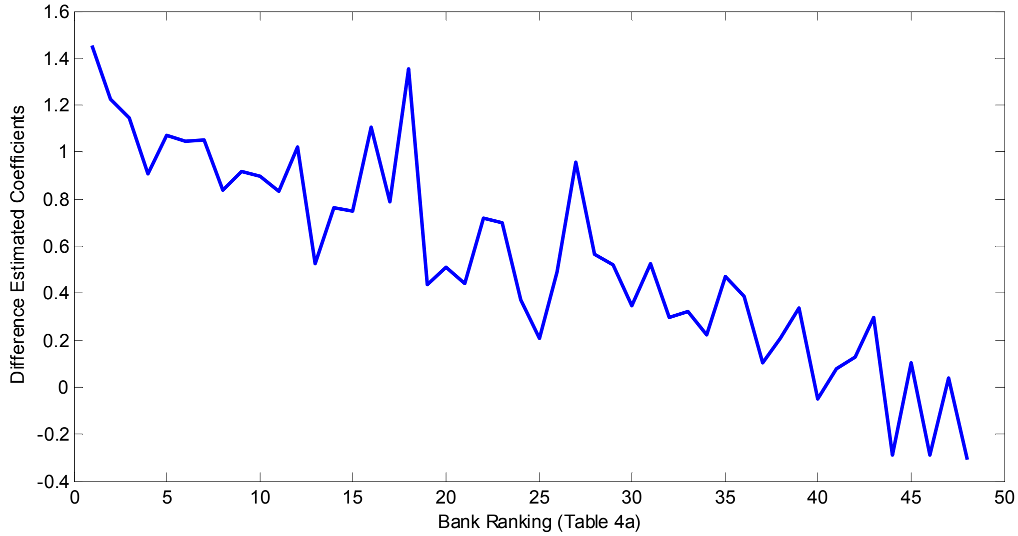
Estimation Method	**Panel**	**One-way**
Independent Variables		
Constant	-0.081	-0.081
Δ CoVaR$_{it-1}$	0.845***	0.845***
VaR$_{it-1}$	-0.097***	-0.097**
Leverage$_{it-1}$	-0.002	-0.002
WSF$_{it-1}$	-0.416**	-0.416***
Size$_{it-1}$	2.433	2.433
MTB$_{it-1}$	-0.002	-0.002
Mktb$_{it-1}$	-0.033	-0.033
Recap$_{it}$	0.383	0.383
Recap$_{it}$ x Leverage$_{it-1}$	-0.002	-0.002
Recap$_{it}$ x WSF$_{it-1}$	2.508	2.508
Recap$_{it}$ x Size$_{it-1}$	0.854	0.854
Recap$_{it}$ x MTB$_{it-1}$	0.180	0.180
Recap$_{it}$ x Mktb$_{it-1}$	-2.543*	-2.543*
Bank Dummies$_j$	Yes	Yes
Time Dummies$_k$	Yes	Yes
R^2 (%)	79.10	79.10
Number of observations	1,280	1,280

The table is based on all banks (firm-quarter observations) with data about marketable securities from 2001:Q4 until 2009:Q3 from Bloomberg database. The following equation is estimated:

$$\Delta CoVaR_{it} = \beta_0 + \beta_1 \Delta CoVaR_{it-1} + \beta_2 VaR_{it-1} + \beta_3 Leverage_{it-1} + \beta_4 WSF_{it-1} + \beta_5 Size_{it-1} + \beta_6 MTB_{it-1} + \beta_7 Mktb_{it-1} + \beta_8 Recap_{it} + \beta_9 Recap_{it} x Leverage_{it-1} + \beta_{10} Recap_{it} x WSF_{it-1} + \beta_{11} Recap_{it} x Size_{it-1} + \beta_{12} Recap_{it} x MTB_{it-1} + \beta_{13} Recap_{it} x Mktb_{it-1} + \sum_{j=1}^{n-1} Bank_j + \sum_{k=1}^{m-1} Time_k + \varepsilon_{it}$$

where Recap$_{it}$ is a dummy that takes value one when the bank is recapitalized and zero for the quarters the bank is not recapitalized; see Table 5 for details.

Figure 1: The asymmetric systemic risk model



This Figure plots the difference between δ– and δ+ in the 1st stage systemic risk model (equation 9) as a function of the coefficient size on individual banks negative returns reported in Table 4a. The numbers in the x-axis are associated with the ranking in that table (for instance 1 is ING –with the highest δ– coefficient, and 10 is CBK) whereas the y-axis shows the difference between the δ– and δ+ estimates (asymmetry).