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ABSTRACT

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Short-term Wholesale Funding and Systemic Risk: A Global CoVaR Approach*

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Abstract

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1. Introduction

The fact that financial markets move more closely together during times of crisis is well documented. Conditional correlations between assets are much higher when market returns are low in periods of financial stress (see 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 (SIFIs) in order to ensure global financial stability and prevent, or at least mitigate, future episodes of systemic contagion.[1]

In this paper, 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 examine a sample of large international banks that are the target of current regulatory efforts and that would likely be considered too-big-to-fail by central banks. These banks are characterized by their large capitalization, global activity, cross-border exposures and/or representative size in the local industry. Using data spanning 2001–2009, we explicitly

[1] 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.

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.

Our study builds on the novel procedure put forward by Adrian and Brunnermeier (2011), the so-called CoVaR methodology, and generalizes it in several ways in order to deal with the characteristics of a sample of 54 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 reliable balance sheet determinant of a bank's contribution to global systemic risk. Financial institutions use short-term 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 deposit, 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 high degree of maturity mismatch, and more vulnerable to market conditions and liquidity risk. These features can critically increase the vulnerability not only of interbank markets and money market mutual funds, which act as wholesale providers of liquidity, but eventually of the whole financial system.

According to our analysis, an increase of one percentage point in short-term wholesale funding leads to an increase in the contribution to systemic risk of 16 basis points for quarterly asset returns at the 1-quarter horizon and 43 basis points at the 1-year horizon. These results support current 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 recently laid out by the Basel Committee on Banking Supervision under the new Basel III regulatory framework.[2] This paper shows that these initiatives may also help to reduce the likelihood of systemic contagion. In contrast to the role played by short-term wholesale funding, we find weaker evidence that either size or leverage is helpful in predicting future systemic risk within our set of large international banks. Consequently, the empirical analysis in this paper provides clear evidence of the major role played by short-term wholesale funding in the spreading of systemic risk in global markets.

Second, our analysis reveals a strong degree of asymmetric response that has not been discussed in the existing literature on systemic risk. We examine the asymmetric sensitivity of the system to an individual bank based on the sign of bank returns. A distressed systemic institution is likely to have greater spillover effects on the rest of the financial system when its balance sheet is contracting, and therefore an empirical analysis of tail risk-dependence within a financial system should distinguish between episodes of expanding and contracting balance sheets. Our results show that individual balance sheet contraction produces a significant negative spillover on the

[2] 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.

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 more than two times larger. Therefore, controlling for balance sheet contraction is crucial in order to rank financial institutions by their contribution to systemic risk.

Third, we find evidence that the banks that received prompt recapitalization in Q4 2008 were able to improve their relative position during the crisis period. In contrast, the banks that were rescued by public authorities later in Q4 2009 became relatively more systemic during the crisis period. In other words, the ripple effects from their individual distress were more widespread throughout the financial system. This conclusion is based on the results showing that the credit crisis added 0.1 percentage points to the co-movement between individual and global asset returns, while recapitalization during the crisis period dampened co-movement by 0.14 percentage points. Consequently, the timing of recapitalization is also important for systemic risk.

Finally, our paper highlights the relevance of crisis episodes in measuring systemic risk and of the response policy actions. Our results show that the marginal contribution of an individual bank's financial distress to the 1st percentile of the system returns increases from 1 percent in an average quarter between 2001 and 2009 to 1.4 percent in a quarter characterized by money market turbulence at the height of the global financial crisis during Q3 2007–Q1 2009.

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 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.

2. Related literature and choice of methodology

Our study builds on the CoVaR methodology proposed by Adrian and Brunnermeier (2011), which allows us to generate time-varying estimates of the systemic risk contribution for each bank in our sample. This methodology has been applied in a number of recent studies (e.g. Van Oordt and Zhou, 2010; Roengiptya and Rungcharoenkitkul, 2011). Our study provides two main contributions with respect to these studies. First, we focus on an international sample of large banks. These banks are particularly important from a regulatory perspective. Second, we extend the basic CoVaR methodology to account for a number of econometric issues related to asymmetric responses, recapitalization effects and structural changes that 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 asset 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 swap 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) they construct short- and long-run MES forecasts propose the SRISK index, which captures the expected capital shortage of a firm given its degree of leverage and Marginal Expected Shortfall (MES). Alternatively, De Nicolo and Lucchetta (2010) use a dynamic factor 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 the 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). A very comprehensive survey of the main systemic risk measures and analytical frameworks developed over the past several years is contained in Bisias et al. (2012). All of these procedures have both methodological advantages and shortcomings relative to other methods, so there is no such a thing as an optimal procedure in the literature with which to measure systemic risk.

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 procedure 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 can easily control for relevant features of the data, such as the occurrence of a crisis or a bank recapitalization, and allows us to use both historical-based and forward-looking state variables to improve downside risk forecasts. Finally, this setting can be generalized straightforwardly 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 the marginal effects of individual banks on the global system are both economically and statistically very different in good and bad times.

3. 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 regulatory 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 Sections 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.[3] The resulting sample is formed by a total of 54 large firms from 18 countries, starting in July 2001 and ending in December 2009.[4] All the variables used in the paper are measured in United States dollars (USD).[5] Appendix A lists these banks.

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[3] The initial sample consisted of the 200 largest banks as of 2008. We then restricted our sample to listed consolidated banks, yielding a total of 93 banks. Qualitative information about the financial markets where they operate, together with data limitations, namely the lack of quarterly or semi-annual balance sheet data during the sample period, constrained our final sample to 54 banks. The average size of the representative bank is USD 862 billion and accounts for 54.6 percent of domestic GDP.

[4] Among others, the final sample includes 22 out of the 29 banks identified as global SIFIs by the Financial Stability Board in November, 2011.

[5] 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 robustness checks.) Results remain unaltered and are available upon request to the authors.

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 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 Volatility Index (VIX) of the Chicago Board Options Exchange (CBOE); 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 10-year bonds 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 data have been obtained from the CBOE, the Federal Reserve Board's H.15 Release, and the Datastream databases. Table 1 reports the summary statistics for the U.S. predictive variables.

[Insert Table 1 around here]

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 or semi-annual data (depending on the reporting frequency in 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). Since several banks were recapitalized over the sample period, 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.

4. Modelling and forecasting global CoVaR dynamics

In the following subsections, we describe the features involved in the first stage involved in the CoVaR analysis and discuss the main estimation results.

4.1. Estimation methodology

VaR is the most common procedure to measure portfolio downside risk in practice. For a certain 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.[6] 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 set capital requirements. Because the main interest in systemic risk derives from regulatory considerations, it seems natural to consider risk measures that attempt to capture the extent of systemic risk using the same methodological approach.

[6] 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 through the following subsections: VaR, CoVaR and ΔCoVaR.

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 a specific confidence level and time horizon. More formally, the $\lambda\%$ CoVaR of portfolio *j* given the conditioning event $\Phi\left(X_t^i\right)$ of portfolio *i*, is defined as the λ quantile of the conditional loss function:

$$\Pr\left(X_t^j \leq CoVaR_{\lambda,t}^{j|\Phi\left(X_t^i\right)} \middle| \Phi\left(X_t^i\right) \right) \tag{1}$$

where X_t^j and X_t^i denote the respective portfolio returns.[7] Given this measure, Adrian and Brunnermeier (2011) propose to approach the portfolio *i*'s contribution to *j*'s systemic risk as:

$$\Delta CoVaR_{\lambda,t}^{i} = CoVaR_{\lambda,t}^{j|X_t^i=VaR_\lambda^i} - CoVaR_{\lambda,t}^{j|X_t^i=Median^i} \tag{2}$$

This captures the amount of additional risk that a certain firm inflicts upon the financial system when this firm is in distress (when it reaches its VaR) rather than conditional on its median level of returns. In our baseline analysis, we shall consider portfolio returns over a weekly horizon and focus on the 1% 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 outlined in the following subsections.

[7] 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.

4.1.1. Individual banks

For each bank, we consider weekly returns from a portfolio formed by the market-valued total assets of the firm. Our interest in this particular portfolio is entirely 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 are 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 report on a semi-annual basis).

We adopt two different strategies to circumvent the sampling frequency mismatch problem involved. As in Adrian and Brunnermeier (2011), we assume that the leverage ratio remains (approximately) constant throughout 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 the authors upon request.

4.1.2. 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:

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

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 $0 \leq \omega_{j,t} \leq 1$. 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 that allows us to study how a shock in a stressed bank spills over in the class of financial assets that poses the highest risk to the global financial system. We shall now refer to the resulting portfolios as global system portfolios.

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 not only when the total number of institutions n in the sample is not particularly large, but also when a single institution has a significant weight in relation to the whole system even if n is fairly large.[8] Because the bank under analysis is not included, the

[8] 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 the Bank Regulatory Database and CRSP.

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 weighting variables to define the global system portfolios in (3). Following Adrian and Brunnermeier (2011), we use the lagged value of the total assets variable. Alternatively, we use (the lagged book value of a bank's liabilities. Whereas 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 between financial institutions under certain circumstances.[9] We report the results using total assets as the weighting variable.[10]

4.1.3. 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 1% quantile conforms to a standard measure of market risk used by financial institutions and regulatory authorities to compute capital requirements.

Among the 277 firms involved, the largest bank in terms of total assets in this period was Bank of America. 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.

[9] 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. 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 counterparts, would remain unaltered.

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

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 let D_t be 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 1% 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 $Q(u_{\lambda,t} | Z_{t-1}) = 0,$ where $Q(u_{\lambda,t} | Z_{t-1})$ is the conditional quantile of the error term. 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. The quantile regression in VaR modelling specification has been used by Engle and Manganelli (2004), among others.

Although we do not report here the estimates from the QR estimation of the VaR processes (results are available upon request), some features are worth commenting upon. First, the market volatility index has a strong and negative effect on the size of the expected VaR, with increases in volatility levels triggering larger than expected losses. Not surprisingly, among all the predictive variables analyzed, market volatility turns out to be the best predictor. Second, 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. Third, the dummy variable related to the financial crisis shows a structural impact on the unconditional level of the inferred VaR dynamics, and helps to improve the overall fit 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.

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

The key step in the CoVaR methodology is to estimate the measure of conditional co-movement. This is readily achieved by augmenting the quantile regression model (4) with the returns of the *i*-th bank and by setting $Y_t^i = X_t^{S,i}$. Building on this approach, in this paper we consider several econometric specifications of increasing complexity, which extend the basic CoVaR model. More specifically, our baseline specification is the same model used by Adrian and Brunnermeier (2011), 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

$$\Delta CoVaR_{\lambda,t}^{i} = \hat{\delta}_{\lambda,i}\left(VaR_i^t(\lambda) - VaR_i^t(50\%)\right) \tag{6}$$

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 behavior of the left tail, for which 1% 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 significantly underestimate the impact on 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 (henceforth referred to as Asymmetric CoVaR),

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

where $I_{(\bullet)}$ is an indicator function taking a value equal to one if the condition in the subscript is true and zero otherwise (see López-Espinosa et al. (2012) 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

$$\Delta CoVaR_{\lambda,t}^{i} = \hat{\delta}^-_{\lambda,i} VaR_i^t\left(\lambda\right) - \hat{\delta}^+_{\lambda,i} VaR_i^t\left(50\%\right) \tag{8}$$

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 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:

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

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

4.2. 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 datasets. We consider all 54 banks and use U.S. state variables as predictors of expected return. This is termed as “1-Region” in our analysis. Table 2 displays median results for equations (5), (7) and (9) under the “1-Region” specification. The table shows 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. We also considered a “2-Region” specification with U.S. + Canada as one region and Europe as the second. While we do not report the results here, they are robust. Complete results for both the “2-Region” specification and banks at the individual level are available upon request.

[Insert Table 2 around here]

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 among 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 considerable enhancement in the overall fit of the model as measured by the pseudo-R^2. Interestingly, the predictive power of the liquidity spread becomes insignificant, which implies that this variable was 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 more than two times larger than the coefficient under the symmetric model.

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 it difficult to draw a clear conclusion. In general terms, global returns become more sensitive to negative bank returns during global financial crises. Similarly, on average, the impact of negative bank returns on system returns tends to decrease after a capital injection, indicating the success of recapitalization programs in containing systemic risk.

[Insert Table 3a around here]

Table 3a 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 Bank of America, HSBC and Lloyds were among the most systemic under the lens of our asymmetric beta coefficient. Asymmetries are also very noticeable. For instance, for Bank of America the coefficient on negative returns is more than 5 times larger than the coefficient on positive returns, whereas for HSBC, it is more than10 times larger. Interestingly, the higher the coefficient on bank negative returns, the more asymmetric is its contribution to overall systemic risk. 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 listed in Table 3a. The figure reveals a strong relation between the position in this ranking and the size of the asymmetry: the higher the sensitivity of system returns to the negative returns of a bank, the more asymmetric is this bank. This again reinforces the need to account for asymmetries when performing systemic risk regressions. Table 3a also shows that some banks tend to impact global returns more during crises, while for other banks the opposite is true. For instance, two specific Canadian banks – Bank of Montreal and Toronto-Dominion Bank – impacted system returns heavily during the crisis.

Finally, we see that recapitalizations had a very positive effect for three US banks – PNC, Wells Fargo, and Citibank – and for several European institutions, such as BNP, Unicredit, BMPS, Barclays, and Lloyds. This suggests that early government intervention helped mitigate systemic risk.

[Insert Figure 1 and Table 3b around here]

Table 3b 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. On average across banks, contributions are almost 0.9 percentage points higher during the crisis period, relative to the pre-crisis period. Interestingly, the ranking of an institution in the crisis period is influenced by the timing of public intervention in that bank. For instance, some banks that received prompt recapitalization in Q4 2008, such as Citigroup, Bank of America and ING, improved their relative position during the crisis period.

[Insert Tables 3c and 3d around here]

In order to draw cross-country comparisons of systemic risk contributions, Table 3c shows the sensitivity parameter estimates of the first-stage regressions across countries, whereas Table 3d 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. Interestingly, Table 3c shows that recapitalizations engineered by governments of major countries reduced systemic risk in their banking system, especially in Italy, the US and the UK.

5. Determinants of systemic risk

5.1 Regression analysis

In this section, we discuss the main drivers of systemic risk in global banking. We aggregate the estimates of the weekly $\Delta CoVaR_{it}$ processes obtained in Section 4 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:

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

with $\Delta CoVaR_{it}$ computed from the first stage as described above and VaR_{it} denoting 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:

- $Leverage_{it-k}$ is the total assets to equity ratio of bank *i* at quarter *t-k* (where *k* can be 1, 4 or 8 quarters). This ratio is a usual a proxy for the level of solvency of the bank, and so the higher the leverage the lower the solvency. Therefore, we expect a negative relation with the dependent variable.

- WSF_{it-k} 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-k* (*k*=1, 4, 8 quarters). 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, discounted bills, purchased federal funds and securities sold but 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 $\Delta CoVaR_{it}$.

- $Size_{it-k}$ is the total assets of bank *i* at quarter *t-k* (*k*=1, 4, 8 quarters) over the total assets of all banks in the sample at quarter *t-k*. We expect that the larger the relative size of a bank, the higher its contribution to systemic risk.

- MTB_{it-k} is the market-to-book ratio of bank *i* at quarter *t-k* (*k*=1, 4, 8 quarters). 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-k* (*k*=1, 4, 8 quarters). It is a proxy for the proportion of financial instruments that account 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*$_j$ are bank and time dummies to control for individual fixed bank and time effects, respectively.

Table 4 reports the estimates from equation (10) for asset-weighted global systems, after controlling for bank and time fixed effects and, additionally, allowing for bank clustered errors. We show three specifications depending on the forecast horizon of systemic risk predictors: 1 quarter, 1 and 2 years. Across forecast horizons, wholesale funding appears as the most robust determinant of systemic risk, suggesting that banks that are heavily dependent on short-term borrowing contribute decisively to higher systemic risk, thus generating negative externalities. Similar results have been found in Acharya et al. (2010) and Adrian and Brunnermeier (2011). Size also appears significant at the 1-year horizon across econometric specifications, whereas marketable securities appear significant in the 2-year specification at the 10% significance level in the panel data specification. In contrast to these papers, we find that leverage and book to market are never 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 it is the excessive risk-taking behavior of “too big to fail” institutions, which may be triggered by the anticipation of future bail-out policies. Our paper suggests that riskier funding is a key contributor to systemic risk.

[Insert Table 4 around here]

There are, at least, two interrelated reasons that explain why short-term wholesale funding plays such a fundamental role in contributing to systemic risk in the global banking industry. First, banks usually raise short-term 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 pointed out early on as being a key determinant of systemic importance.

Second, 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.

Our analysis employs the CoVaR methodology developed by Adrian and Brunnermeier (2011) but our empirical application departs importantly from theirs, as it focuses on a sample of large global banks, whereas they focus on a wider set of U.S. institutions, including also other types of companies, such as broker-dealers, real estate institutions and insurance companies. Given that our sample is international, we can assess the differential features of the systemic risk channels between banks in the two largest monetary areas in our sample, U.S. / E.M.U. (United States / European Monetary Union), and in the rest of the world. To do so, we enlarge our set of explanatory variables of the previous table and include the dummy variable for U.S./E.M.U. bank, and interact it with the most relevant state variables of the literature (size, leverage and wholesale funding). This new regression setting can be expressed as:

$$\begin{aligned}\Delta CoVaR_{it} = \beta_0 + \beta_1 \Delta CoVaR_{it-1} + \beta_2 VaR_{it-1} + \beta_3 Leverage_{it-1} + \beta_4 WSF_{it-k} + \beta_5 Size_{it-1} + \\ \beta_6 MTB_{it-1} + \beta_7 Mktb_{it-1} + \beta_8 C_i + \beta_9 C_i x Leverage_{it-1} + \\ \beta_{10} C_i x WSF_{it-1} + \beta_{11} C_i x Size_{it-1} + \sum_{j=1}^{m-1} Time_j + \varepsilon_{it}\end{aligned} \tag{11}$$

where C_i is the U.S./E.M.U. dummy.

[Insert Table 5 around here]

Table 5 shows results for the 1-quarter forecast horizon. Regressions with U.S. dummies show that short-term wholesale funding is still the most reliable systemic risk predictor for all except U.S. banks, as it appears statistically significant under both econometric specifications. However, for U.S. banks, it does not appear significant and it even has the opposite sign. Thus, U.S. banks behave differently to the remaining banks in our sample. In the case of the E.M.U. regressions, the opposite is the case, and both short-term wholesale funding and size are significant drivers of systemic risk only for E.M.U. banks. As a result, and within the set of banks in our sample, a relevant difference emerges between U.S. and E.M.U. banks, with these latter banks exhibiting a strong systemic risk channel stemming from the level of short-term wholesale funding. As our sample spans the early years after the creation of the euro currency, the reduction in transaction costs may have spurred the growth of the pool of short-term wholesale funding in the European interbank system, with the associated effects on systemic risk.

5.2 Robustness checks

We performed a battery of 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 the authors upon request.

5.2.1. Two-Regions v/s One-Region State Variables

In the first stage of our analysis, we use the U.S. state variables as the relevant market state variables for all international banks. As an alternative, we also grouped most banks in our sample (48 out of the 54, given the exclusion of 6 banks in Asia, Africa and Australia) into two different economic regions, namely U.S. + Canada and Europe, for which we observe two sets of local predictive variables (e.g., the VIX for American banks and the Euronext Volatility Index for European banks).[11] As a result, in the first stage, we have alternative state variables for U.S. and European banks. Results under the "Two-Region" specification are very similar to those reported above, under the U.S. (One-Region) state variables.

[11] In particular, the European counterparts 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.

5.2.2. 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.

5.2.3. 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 $E(r_{it} \le r_{it}^* \mid R_t \le R_t^*)$, where r_{it} and R_t denote the returns of an individual bank and the stock market, respectively, and r_{it}^* and R_t^* are the (unobservable) target values of these variables. By interchanging $r_{it} \le r_{it}^*$ 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 1% 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% level).

5.2.4. Definition of ΔCoVaR

In a previous version of their work, Adrian and Brunnermeier define the measure of contribution to systemic risk as $\Delta CoVaR_{\lambda,t}^{i} = CoVaR_{\lambda,t}^{S|i} - VaR_{\lambda,t}^{S}$, that is, a bank's systemic risk is measured by its marginal impact on system returns conditional on the bank reaching its VaR relative to the unconditional system returns. This measure has been used in other papers, such as Van Oordt and Zhou (2010). We repeated the determinants analysis of Section 5 with estimates of quarterly *ΔCoVaR* based on this definition and the main conclusions remained unaltered.

5.2.5. 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 clustering with bank and country dummies separately. Finally, we also performed Generalized Method of Moments (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. We also 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 Adrian and Brunnermeier

(2011). 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.

6. 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 international institutions that would, in principle, be deemed "too big to fail" by financial regulators and are therefore of major interest for policy makers. For this class of firms, the evidence based on the CoVaR methodology indicates 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, seem to provide little incremental information about systemic risk. This suggests that short-term wholesale funding subsumes most of the relevant information on systemic risk conveyed by other characteristics of the firm. The fact that systemic risk can be predicted by balance sheet variables – short-term wholesale funding, in particular – with a sufficiently large forecast horizon has important policy implications, as it prompts the regulator to take pre-emptive action against banks with riskier positions.

We also compare the relative influence of balance sheet variables on systemic risk for E.M.U. and U.S. banks. Our findings suggest that the short-term wholesale funding channel has been operating mainly through non-U.S. banks, especially via E.M.U. banks. One possible explanation for this fact is that banks in the newly created monetary area had an increased pool of funding available due to the emergence of the euro interbank market. As a result, higher short-term borrowing by these institutions may have triggered an increased level of systemic risk. In future research, we intend to further examine these underlying international differences.

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 SIFIs. 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, makes a significant contribution 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 short-term wholesale funding can generate large systemic risk externalities (see, for instance, Perotti and Suarez, 2011).

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. In non-tabulated results, our study also points to the role of large trading books as a source of systemic risk for those banks that 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 help to mitigate systemic risk.

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Appendix A. List of Financial Institutions

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

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; 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 governmetnt under the TARP

Source: Bloomberg, authorities' websites, and IMF

Table 1. 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
1^{st} 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 2. 1st-stage regressions: 1 Region

	Baseline	Asym.	Asym. Ext.
Constant	0.002	-0.002	-0.002
	(0.56)	(-0.40)	(-0.24)
Volatility	-0.001	-0.001	-0.001
	(-8.55)	(-4.99)	(-5.82)
Liquidity Spread	-0.026	-0.007	-0.002
	(-2.57)	(-0.69)	(-0.24)
ΔTbill	-0.114	-0.006	0.002
	(-0.56)	(-0.30)	(-1.41)
ΔSlope	0.013	0.009	0.013
	(0.71)	(0.62)	(1.57)
ΔCredit Spread	-0.041	-0.030	-0.029
	(-1.95)	(-1.44)	(-3.65)
Market Return	0.003	0.001	0.001
	(4.69)	(2.50)	(3.37)
Crisis Dummy	-0.011	-0.006	-0.005
	(-1.83)	(-1.18)	(1.65)
X_{t-1}^{i}	0.313	-	-
	(5.73)		
$X_{t-1}^{i}\, I_{\left(X_{t-1}^{i}<0\right)}$	-	0.673	0.684
		(12.73)	(6.41)
$X_{t-1}^{i}\, I_{\left(X_{t-1}^{i}\geq 0\right)}$	-	0.148	0.156
		(2.35)	(2.68)
$X_{t-1}^{i}\, I_{\left(X_{t-1}^{i}<0, Crisis\right)}$	-	-	0.082
			(2.01)
$X_{t-1}^{i}\, I_{\left(X_{t-1}^{i}<0, \mathrm{Recap}\right)}$	-	-	-0.143
			(0.53)
Pseudo-R^2	0.406	0.477	0.489

The table shows the median of estimated coefficients, *t*-statistics and pseudo-R^2 in 1% 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 3a: Systemic Risk Sensitivity of each Bank

Bank	$X_t<0$	$X_t\geq0$	$(X_t<0)$*Crisis	$(X_t<0)$*Recap	Pseudo-R^2
BNS	1,199	0,298	0,083		0,448
BAC	1,132	0,219	-0,641	-0,122	0,543
HSBC	1,087	0,095	0,742		0,472
WFC	1,058	0,030	-0,092	-0,540	0,513
LLOY	1,058	0,011	-0,461	-0,329	0,489
BBT	0,883	0,216	0,076		0,455
SVK	0,861	0,269	0,044		0,523
STI	0,858	0,166	-0,354		0,523
CM	0,845	0,191	0,450		0,438
USB	0,819	0,324	-0,053		0,480
SCH	0,813	0,065	0,045		0,589
TD	0,811	0,189	0,799		0,432
UC	0,796	0,026	0,228	-0,594	0,558
STT	0,795	0,019	-0,193		0,460
C	0,791	0,066	0,082	-0,524	0,475
ING	0,788	0,221	-0,036	-0,121	0,612
UBS	0,774	-0,155	-0,174		0,497
SWED	0,772	0,300	-0,183		0,557
NDA	0,763	0,393	-0,010		0,575
RF	0,757	0,069	-0,246		0,490
DAB	0,756	0,242	-0,159		0,503
BMPS	0,730	0,096	0,650	-0,726	0,529
BBVA	0,711	0,086	0,191		0,588
KBC	0,710	0,238	-0,232	-0,060	0,607
DBK	0,707	0,016	0,039		0,606
BNP	0,697	0,200	0,594	-0,375	0,625
DEA	0,696	0,258	-0,053		0,552
CSGN	0,671	0,257	-0,207		0,531
SLM	0,668	0,120	-0,062		0,375
POP	0,662	0,197	0,124		0,546
BK	0,640	0,065	0,197		0,445
BTO	0,634	0,309	0,195		0,456
RBS	0,609	-0,004	-0,097	0,100	0,521
CBK	0,599	0,050	0,216	-0,132	0,538
BARC	0,569	0,108	-0,128	-0,338	0,490
SGE	0,554	0,158	0,138	0,360	0,607
CBAX	0,553	0,283	0,629		0,398
WBCX	0,549	0,177	0,541		0,349
ALBK	0,539	0,131	-0,140	-0,120	0,493
RY	0,525	0,275	0,622		0,455
PNC	0,513	0,072	1,404	-1,412	0,478
STAN	0,508	0,161	0,499		0,492
DNB	0,505	0,151	0,056		0,474
MS	0,500	0,154	0,051		0,453
BIN	0,441	0,037	0,582	0,286	0,488
BMO	0,433	0,305	0,863		0,405
JPM	0,410	0,100	-2,005		0,346
SBKJ	0,404	0,123	0,602		0,440
ERS	0,388	0,237	0,186	0,055	0,455
GS	0,383	0,321	0,147		0,467
COF	0,327	0,135	0,453	-0,154	0,478
DS	0,250	0,097	0,472		0,352
NM	0,219	0,087	0,496		0,322
NABX	0,191	0,251	0,477		0,382

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).

Table 3b: Systemic Risk Contribution to Quarterly Asset Returns

Overall Period		Pre-crisis Period		Crisis Period	
Bank	**ΔCoVaR**	**Bank**	**ΔCoVaR**	**Bank**	**ΔCoVaR**
LLOY	-1.022	LLOY	-0,930	PNC	-2,173
ING	-0.937	ING	-0,820	BMPS	-1,906
CBK	-0.927	BAC	-0,800	STAN	-1,867
BMPS	-0.910	CSGN	-0,674	CBK	-1,866
SLM	-0.883	STT	-0,647	UC	-1,801
HSBC	-0.856	SCH	-0,622	BIN	-1,728
UC	-0.848	DBK	-0,622	SLM	-1,656
BNP	-0.848	NDA	-0,621	HSBC	-1,654
BAC	-0.823	KBC	-0,616	CM	-1,631
BNS	-0.822	SLM	-0,608	TD	-1,600
BBVA	-0.801	BMPS	-0,608	BNP	-1,596
BBT	-0.796	C	-0,599	BBT	-1,527
CM	-0.796	SVK	-0,597	WFC	-1,526
PNC	-0.794	BNP	-0,592	BNS	-1,525
SVK	-0.794	USB	-0,591	BBVA	-1,505
STT	-0.792	CBK	-0,591	WBCX	-1,486
DBK	-0.783	STI	-0,576	SGE	-1,475
SCH	-0.777	UC	-0,569	CBAX	-1,450
C	-0.776	DEA	-0,566	C	-1,422
SWED	-0,769	SWED	-0,566	LLOY	-1,371
BIN	-0,768	BNS	-0,565	SWED	-1,365
WFC	-0,768	HSBC	-0,559	SVK	-1,361
SGE	-0,755	BBVA	-0,557	RY	-1,338
KBC	-0,755	WFC	-0,546	MS	-1,318
TD	-0,752	BK	-0,533	COF	-1,302
STAN	-0,747	BBT	-0,526	ING	-1,297
STI	-0,744	UBS	-0,524	BMO	-1,284
NDA	-0,743	BARC	-0,507	ALBK	-1,283
DEA	-0,729	CM	-0,493	DBK	-1,261
USB	-0,723	SGE	-0,487	RF	-1,251
UBS	-0,701	RF	-0,471	SCH	-1,241
BK	-0,684	ALBK	-0,462	UBS	-1,227
RF	-0,682	TD	-0,455	STT	-1,221
CSGN	-0,672	MS	-0,445	STI	-1,221
ALBK	-0,661	DAB	-0,441	POP	-1,217
MS	-0,655	DNB	-0,427	DEA	-1,212
BARC	-0,634	RBS	-0,419	SBKJ	-1,197
RBS	-0,615	BIN	-0,399	KBC	-1,175
WBCX	-0,613	PNC	-0,389	ERS	-1,163
COF	-0,609	STAN	-0,380	RBS	-1,136
CBAX	-0,596	POP	-0,370	NDA	-1,135
POP	-0,589	COF	-0,355	BK	-1,058
DAB	-0,572	BTO	-0,345	USB	-1,030
DNB	-0,569	GS	-0,343	BARC	-1,026
RY	-0,546	ERS	-0,322	DNB	-0,993
ERS	-0,544	WBCX	-0,306	BTO	-0,987
BMO	-0,542	SBKJ	-0,297	BAC	-0,987
SBKJ	-0,536	JPM	-0,293	NM	-0,934
BTO	-0,508	DS	-0,283	DAB	-0,934
GS	-0,474	CBAX	-0,276	DS	-0,925
DS	-0,469	RY	-0,260	GS	-0,872
NM	-0,421	BMO	-0,247	NABX	-0,776
NABX	-0,282	NM	-0,212	CSGN	-0,741
JPM	-0,006	NABX	-0,103	JPM	0,792

This table ranks the quarterly contribution to systemic risk of each individual bank. 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 3c: Systemic Risk Contribution (Sensitivity) by Country

Country	X_t<0	X_t≥0	(X_t<0)*Crisis	(X_t<0)*Recap	Pseudo-R^2
Netherlands	0.788	0.220	-0.036	0.121	0.612
Sweden	0.773	0.305	-0.050		0.552
United Kingdom	0.766	0.074	0.111	-0.113	0.493
Canada	0.763	0.252	0.564		0.435
Denmark	0.756	0.242	-0.159		0.503
Switzerland	0.723	0.051	-0.190		0.513
Belgium	0.710	0.238	-0.232	-0.060	0.607
Spain	0.705	0.164	0.139		0.544
United States	0.702	0.138	-0.082	-0.183	0.466
Italy	0.655	0.053	0.487	-0.345	0.525
Germany	0.653	0.033	0.128	-0.066	0.572
France	0.625	0.178	0.366	-0.007	0.616
Ireland	0.539	0.131	-0.140	0.120	0.493
Norway	0505	0.151	0.056		0.474
Australia	0.430	0.237	0.549		0.376
South Africa	0.404	0.123	0.602		0.440
Austria	0.388	0.237	0.186	0.055	0.455
Japan	0.234	0.092	0.484		0.337

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).

Table 3d: Systemic Risk Contribution to Quarterly Asset Returns

Overall Period		Pre-crisis Period		Crisis Period	
Country	**ΔCoVaR**	**Country**	**ΔCoVaR**	**Country**	**ΔCoVaR**
Netherlands	-0.937	Netherlands	-0.820	Italy	-1.812
Germany	-0.918	Switzerland	-0.660	Germany	-1.563
Italy	-0.883	United States	-0.624	France	-1.536
France	-0.836	Belgium	-0.616	Canada	-1.476
Spain	-0.797	Sweden	-0.613	United Kingdom	-1.411
United States	-0.788	Italy	-0.601	Netherlands	-1.297
Belgium	-0.755	France	-0.591	Ireland	-1.283
Sweden	-0.724	Germany	-0.584	Sweden	-1.268
Switzerland	-0.666	Spain	-0.541	Australia	-1.237
Ireland	-0.661	United Kingdom	-0.484	Spain	-1.237
United Kingdom	-0.613	Ireland	-0.462	South Africa	-1.197
Australia	-0.586	Denmark	-0.441	United States	-1.185
Denmark	-0.572	Norway	-0.427	Belgium	-1.175
Norway	-0.569	Austria	-0.322	Austria	-1.163
Austria	-0.544	South Africa	-0.297	Norway	-0.993
South Africa	-0.536	Japan	-0.280	Switzerland	-0.984
Canada	-0.506	Australia	-0.261	Denmark	-0.934
Japan	-0.444	Canada	0.187	Japan	-0.929

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 4: Forecasting Systemic Risk

	1-quarter		1-year		2-year	
	Estimation Method		Estimation Method		Estimation Method	
Independent Variables	Panel	One-way	Panel	One-way	Panel	One-way
Constant	-0.315***	-0.315***	-0.261***	-0.261	-0.784***	-0.784***
ΔCoVaR$_{it-k}$	0.724***	0.724***	0.620***	0.620***	0.009	0.009
VaR$_{it-k}$	-0.139***	-0.139***	-0.197***	-0.197***	-0.051	-0.051
Leverage$_{it-k}$	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001
WSF$_{it-k}$	-0.159**	-0.159**	-0.432***	-0.432**	-0.432***	-0.432
Size$_{it-k}$	-0.148	-0.148	-5.131***	-5.131**	-3.198*	-3.198
MTB$_{it-k}$	0.019*	0.019	0.014	0.014	0.009	0.009
Mktb$_{it-k}$	0.090	0.090	-0.030	-0.030	-0.262*	-0.262
Bank Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Time Dummies	Yes	Yes	Yes	Yes	Yes	Yes
R^2 (%)	0.880	0.880	0.822	0.822	0.801	0.801
Number of observations	1,378	1,378	1,229	1,229	1,031	1,031

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

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

where ΔCoVaR$_{it}$ is the ΔCoVaR of bank *i* at quarter *t*; ΔCoVaR$_{it-1}$is the ΔCoVaR of bank *i* at quarter *t-k*; VaR$_{it-k}$ is the VaR of bank *i* at quarter *t-k*; Leverage$_{it-k}$ is the total assets to equity ratio of bank *i* at quarter *t-k*; WSF$_{it-k}$ is the short-term borrowings to total assets ratio of bank *i* at quarter *t-k*; Size$_{it-k}$ is the total assets of bank *i* at quarter *t-k* over the total assets of all banks in the sample at quarter *t-k*; MTB$_{it-k}$ is the Market-to-Book ratio of bank *i* at quarter *t-k*; Mktb$_{it-k}$ is the marketable securities to total assets ratio of bank *i* at quarter *t-k*; all right-hand-side variables are included with a lag of k=1 quarter, 1,2 years. Bank$_j$ are the *n-1* bank dummies; Time$_j$ 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. In the Panel column, the equation is estimated via firm and time fixed-effects panel data methodology. In the One-way column, the equation is estimated via Firm and Time fixed-effects one-way cluster methodology using banks as clusters. All ΔCoVaRs are estimated using 1% percentile. * Significant at 10%, ** Significant at 5%, *** Significant at 1%.

Table 5: Forecasting Systemic Risk with an Extended Model

	US		EMU	
	Estimation Method		Estimation Method	
Independent Variables	**Panel**	**One-way**	**Panel**	**One-way**
Constant	-0.134***	-0.134***	0.119*	0.119
Δ CoVaR$_{it-1}$	0.793***	0.793***	0.787***	0.787***
VaR$_{it-1}$	-0.107***	-0.107***	-0.085***	-0.085***
Leverage$_{it-1}$	-0.001	-0.001	-0.001	-0.001*
WSF$_{it-1}$	-0.092**	-0.092*	0.011	0.011
Size$_{it-1}$	-0.659	-0.659**	0.544	0.544
MTB$_{it-1}$	0.009	0.009	-0.003	-0.003
Mktb$_{it-1}$	0.072*	0.072*	0.016	0.016
US	-0.028**	-0.028		
US *Leverage$_{it-1}$	-0.659	-0.659		
US *WSF$_{it-1}$	0.097	0.097		
US *Size$_{it-1}$	1.840***	1.840		
EMU			0.037	0.037
EMU *Leverage$_{it-1}$			0.001	0.001
EMU *WSF$_{it-1}$			-0.169**	-0.169**
EMU *Size$_{it-1}$			-1.482**	-1.482*
Bank Dummies$_j$	No	No	No	No
Time Dummies$_k$	Yes	Yes	Yes	Yes
R^2 (%)	0.872	0.872	0.871	0.871
Number of observations	1,378	1,378	1,378	1,378

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

$$\Delta CoVaR_{it} = \beta_0 + \beta_1 \Delta CoVaR_{it-k} + \beta_2 VaR_{it-k} + \beta_3 Leverage_{it-k} + \beta_4 WSF_{it-k} + \beta_5 Size_{it-k} + \beta_6 MTB_{it-k} + \beta_7 Mktb_{it-k} + \beta_8 C_i + \beta_9 C_i xLeverage_{it-k} + \beta_{10} C_i xWSF_{it-k} + \beta_{11} C_i xSize_{it-k} + \sum_{j=1}^{m-1} Time_j + \varepsilon_{it}$$

where the right hand side variables are defined analogously to the table 4a and the C_i variable stands for the US_i / EMU_i, taking the value 1 if the bank is from the U.S. / European Monetary Union in each regression. In the Panel column, the equation is estimated via firm and time fixed-effects panel data methodology. In the One-way column, the equation is estimated via Firm and Time fixed-effects one-way cluster methodology using banks as clusters. All ΔCoVaRs are estimated using percentile 1%. * Significant at 10%, ** Significant at 5%, *** Significant at 1%.

Figure 1: Difference between the estimates of the δ^- and δ^+ parameters in 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 3a. The numbers in the x-axis are associated with the ranking in that table (for instance 1 is BNS –with the highest δ^- coefficient, and 10 is HSBC) whereas the y-axis shows the difference between the δ^- and δ^+ estimates (asymmetry).