The Impact of Policy Interventions on Systemic Risk across Banks

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Abstract

This paper investigates the impact of policy interventions on systemic risk across banks by analyzing a comprehensive sample of European banks and bank-specific bailout events between 2008 and 2014. We find that *guarantees* have a limited effect in reducing the systemic risk contribution made by small, lowly-capitalized or -liquid banks in the long run and of liquid banks in the short run. *Recapitalizations* immediately decrease in banks' systemic importance, but the effect seems short-lived. *Liquidity injections* can provide immediate beneficial effects for risky or lowly-profitable banks, but in the long run increase these banks` contribution to systemic risk. (98 words)

Key words: systemic risk, policy interventions, risk strategies, systemically important banks

JEL classification: E58, G01, G21, G28, H81

1. Introduction

The 2008 financial events lead to coordinated efforts by governments and central banks to avoid a major systemic crisis. Public interventions such as capital injections, state loans, acquisitions of impaired assets, and/or nationalizations were implemented on an unprecedented scale by most countries. At the European Union (EU) level, policy actions adopted by member states immediately after the Lehman Brothers collapse were coordinated in a massive bailout of financial institutions estimated at 3.65 trillion euro (European Commission, 2009). Since then several additional financial support programs were set up, especially after the European sovereign debt crisis and the Greek bailout in 2010.[1] These types of emergency assistance programs play an important role in restoring public confidence in the banking sector. But how effective are these tools in controlling systemic risk and how heterogonous is their impact across banks' risk models?

Policy intervention programs can have a mixed effect on the stability of the financial system. On the one hand, deposit insurance schemes for example likely prevent bank runs (Diamond and Dybvig, 1983), liquidity injections can temper the risk incentives of insolvent institutions (Cordella and Yeyati, 2003), while recapitalizations reduce the systemic contribution of banks (López-Espinosa et al., 2012). On the other hand, liquidity injections administered by central banks and other methods to avoid the spread of contagion may not always be adequate to control systemic risk and may even induce moral hazard (Acharya and Yorulmazer, 2007; Farhi and Tirole, 2012). Financial help in general may deteriorate the liquidity situation of banks when regulators can and/or do not distinguish between illiquid and insolvent financial institutions (Freixas et al., 1999; Repullo, 2005).

In addition, the efficiency of the policy interventions may vary with respect to bank strategies, as the contribution of financial institutions to systemic risk may be influenced by their incentives to take risk. Large banks for example are (maybe not surprisingly) associated with a larger contribution to systemic risk (Girardi and Ergun, 2013; Anginer, Demirgüç-Kunt and Zhu, 2014a; Laeven, Ratnovski and Tong, 2016), while better capitalized banks have a lower systemic importance (Tarashev, Borio and Tsatsaronis, 2010; Acharya, Engle and Richardson, 2012). The deterioration of loan portfolio quality enhances systemic risk (Mayordomo, Rodriguez-Moreno and Peña, 2014), as so do unstable funding (López-Espinosa et al., 2012) and low levels of profitability (Demirgüç-Kunt and Huizinga, 2011).

Our paper contributes to this existing literature by investigating the interplay between systemic risk, policy interventions and banks' risk profiles. First, we provide a framework that allows us to identify banks with a significant contribution to systemic risk (these banks will be henceforth labeled SIBs - Systemically Important Banks). Second, we examine the relationship between systemic risk, policy interventions and risk profiles in the long and short run. The main research questions we aim to answer therefore are: *How do banks' risk profiles determine the impact of policy interventions on their contribution to systemic risk? How does this relationship evolve in time?*

[1] On May 2010, the European Union member states set up the European Financial Stability Facility (EFSF) that has a maximum lending capacity of 440 billion euro and the European Financial Stabilization Mechanism (EFSM) with a lending capacity of 60 billion euro. Funds are raised through borrowing from financial markets which are guaranteed by the European Commission using as collateral the European Union budget. On 27 September 2012 these two funds were replaced by the European Stability Mechanism (ESM) with the aim of providing instant financial assistance to Eurozone members with a limit of 500 billion euro (ESM Annual Report, 2013).

Our study analyses 110 local and global financial institutions from 22 European countries during the 2005-2014 period (see Appendix 1). We rely on bank and country level data, as well as market indices representative for both local and global financial markets. We employ a bottom-up approach to measure the negative spillovers from each bank to the system (which will be defined as contribution to systemic risk or systemic importance).[2]

In the first stage of our analysis, we estimate systemic risk indicators using the *Conditional Value at Risk* framework *(CoVaR)* developed by Adrian and Brunnermeier (2016). This approach estimates the loss of the system's market assets conditioned on the event that each bank faces the most severe loss of its market assets at a given confidence level.[3] Additionally, we apply an asymmetric extension of *CoVaR* developed by López-Espinosa et al. (2012) which starts from the premise that negative returns pose greater contagion effects to the system than the positive ones. We employ both *Quantile Regression (QR)* and *DCC-GJR GARCH models (DCC)* in the empirical estimations.

Further, we explore the effect of interventions on banks' systemic exposure (top-down approach) measured by the *Marginal Expected Shortfall (MES)* of Acharya et al. (2017) and the *Systemic Risk Index (SRISK)* proposed by Acharya et al. (2012) and Brownlees and Engle (2017).

The empirical findings suggest that both the banks` contribution and exposure to systemic risk intensify, especially after the 2008 financial crisis. Also, we identify a large number of domestic systemically important banks (D-SIBs) that are not included in the FSB's (Financial Stability Board) list of global systemically important banks (G-SIBs).

In the second stage, we estimate (in a panel) the impact on systemic risk of policy interventions by national governments and their interplay with banks' risk profiles both in the long and short term. Although during the last years a number of financial assistance programs have been set up to combat the Eurozone crisis,[4] we focus on the emergency rescue measures implemented by member states immediately after Lehman collapse in September 2008. These public interventions, supported by governments or central banks at the national level and agreed to by the European Commission, consisted of single instruments that were to limit systemic risk and the spread of contagion at the onset of the crisis in Europe. Our interest resides in assessing the effectiveness of these most flexible policy interventions in controlling systemic risk. To perform this evaluation we employ a unique dataset of bank level interventions by national authorities (state guarantees, recapitalizations and liquidity injections) collected from banks' annual reports, financial statements, websites and the State Aid Register of European Commission (see Appendix 2 and Appendix 3).

Our empirical findings establish that bailouts have different effects on banks' contribution to systemic risk in the long versus short run. We find strong evidence that in the long run banks that receive *liquidity injections* increase their systemic importance *(sic)*. The economic effect is substantial. Given that the mean contribution to systemic risk equals 12%

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[2] We use as synonyms: contribution to systemic risk, systemic contribution and systemic importance.

[3] The banks' market assets are determined by adjusting the total assets from the balance sheet with the ratio between the market value of equity and the book value of equity on a weekly basis. The system's market assets are the sum of all banks' market assets. Table 1 provides computational details.

[4] The EFSF, EFSM and ESM funds, EU's Balance of Payments programme (BoP), bilateral loans from International Monetary Fund (IMF), Worldbank, European Investment Bank (EIB) and European Bank for Reconstruction and Development (EBRD).

(i.e., the quarterly percent loss of the system's market assets during 2008-2014) our estimates imply an associated semi-elasticity of 93%. In the short run only *recapitalizations* significantly decrease banks' systemic importance. The associated semi-elasticity is -34%. Unfortunately, the strong influence of these capital injections disappears in the long run.

We further provide empirical evidence that policy interventions have a different impact on systemic risk across banks with various risk strategies. In sum, the picture that arises is one in which in the long run, guarantees have a limited effect in reducing the contribution to systemic risk for small, lowly-capitalized or -liquid banks, recapitalizations have a beneficial impact on lowly-capitalized banks, while liquidity injections by providing only temporary relief end up significantly increasing banks` systemic importance especially for less profitable banks. In the short run, guarantees are useful for banks with low liquidity and liquidity injections have a narrow effect in reducing the systemic importance of banks with a higher share of non-performing loans or low profitability.

On the basis of our estimates a number of important policy conclusions can be made. First, our findings support the current regulatory initiatives to include D-SIBs in the SIFIs classification (Systemically Important Financial Institutions), as we have identified a significant number of small local banks that are systemically important. Second, emergency policy interventions should be adequately implemented because they may have adverse effects on systemic risk in the long versus short run (i.e., recapitalizations have a positive effect only in the short run). Nonetheless, special importance should be given to banks' risk profiles. Characteristics like size, leverage, liquidity and profitability can significantly shape the impact of bailouts on banks' systemic importance in the long run, and the immediate impact of governmental assistance programs on systemic risk is heterogeneous among banks with different levels of credit risk and profitability.

The remainder of the paper is organized as follows. Section 2 provides the literature review. Section 3 describes the methodology. Section 4 introduces the sample and the data. Section 5 presents the empirical results. Finally, section 6 concludes.

2. Literature Review

2.1. General

This paper connects several strands of literature. First, our research is related to a number of recent contributions on systemic risk that have challenged the existing prudential supervision framework (see Bisias et al. (2012) for a survey). Considering banks' undercapitalization as one of the most important sources of systemic risk, Acharya, Engle and Richardson (2012) propose two risk measures, i.e., the *Systemic Expected Shortfall* and the *Marginal Expected Shortfall,* that combine the leverage of a bank with the evolution of credit default swaps (CDSs). The need for countercyclical prudential regulation is further highlighted by Adrian and Brunnermeier (2016) who develop a supervisory framework based on the *Conditional Value at Risk* (*CoVaR),* a measure that reflects the *Value at Risk (VaR)* of the entire system conditioned on an institution being in distress. Pagano and Sedunov (2016) propose an *Adapted Exposure CoVaR* that estimates the exposures to systemic risk for each financial institution within a country and then aggregates them at the country level. Adams, Füss and Gropp (2014) develop the *SDSVaR* method *(State-Dependent Sensitivity Value at Risk)*, which reflects the contagion effects within different states of the economy: tranquil, normal and stressed. Chan-Lau (2010) suggests capital adequacy regulations based on *CoRisk*, an indicator that captures changes in the credit risk level of a bank in response to changes in the credit risk level of another bank.

Second, our paper fits well with recent studies that highlight the systemic importance of domestic banks. Recognizing their role, in 2012 the Basel Committee on Banking Supervision (BCBS) extended the G-SIBs framework to include the D-SIBs. This is important especially in the European zone, as a run on a local bank can not only affect the financial stability from that country, but also from the bank-holding company's country. Using a sample of 44 European banks belonging to 10 countries, Benoit (2014) for example highlights the importance of identifying the systemically important financial institutions at the national level, as a domestic shock can have a larger impact than a global one. Black et al. (2016) find that the systemic risk contribution of U.K. and German banks declined after 2011, while smaller Italian and Spanish banks increased their systemic importance. Analyzing 22 European Union countries, Pagano and Sedunov (2016) find a simultaneous relation between systemic exposure and sovereign debt yields. Moreover, an increased systemic risk exposure of financially stronger countries such as Germany, U.K, and France in financially troubled European countries, is associated with lower sovereign debt yields in the former ones. Moenninghoff, Ongena and Wieandt (2015) examine the stock price reaction of a panel of 300 large banks from 52 countries and find that the new G-SIBs regulation influence negatively the stock returns of G-SIBs compared with the other banks, but that revealing the identities of G-SIBs have a positive impact on G-SIBs value by eliminating ambiguity regarding the investors' too big to fail perception.

And thirdly, our paper is linked to research on policy interventions. A number of studies analyze how regulatory policies can help in controlling systemic risk. Considering several international financial crisis, Weiβ, Bostandzic and Neumann (2014) for example find that global systemic risk is significantly influenced by the characteristics of the regulatory regimes and explicit deposit insurance schemes. Anginer, Demirgüç-Kunt and Zhu (2014b) point to the stabilizing role played by deposit insurance arrangements during stress periods, but also criticize their destabilizing role in normal times. The removal of guarantees for German Landesbanken after 2001 following a lawsuit was associated with lower credit ratings and higher funding costs (Fischer et al., 2014). The same natural experiment reveal that banks with government guarantees removed cut off the riskiest borrowers from credit, while savings banks adjusted their liabilities away from risk-sensitive debt instruments (Gropp, Gruendl and Guettler, 2014). Buch, Krause and Tonzer (2015) show that European banks that received state aid during the crisis are associated with increased systemic importance. On the other hand, the U.S. Troubled Assets Relief Program (TARP) based on injections of preferred equity, significantly reduced contributions to systemic risk, particularly for larger and safer banks (Berger, Roman and Sedunov (2016). Homar (2016) highlights the importance of the amount of interventions, presenting empirical evidence that banks that receive large enough capital injections boost the supply of credit, access supplementary funding and improve their balance sheets. In the same line, Giannetti and Simonov (2013) show that a reasonable level of capital injections helped banks to increase lending and stimulate investments during the Japanese banking crisis of the 1990s. Also, interventions may increase banks' profitability and the liquidity within the banking system (Hoelscher and Quintyn, 2003).

There is of course an extensive literature that investigates moral hazard embedded in deposit insurance schemes (Demirgüç-Kunt and Detragiache, 2002; Demirgüç-Kunt and

Huizinga, 2004; Gropp, Gruendl and Guettler, 2014) or recapitalizations (Kane, 1995). The bail out of large systemically important banks can be too expensive (Demirgüç-Kunt and Huizinga, 2013) and finally the rescue cost may be very high for the taxpayers (Engle, Jondeau and Rockinger, 2015). Moreover, rescue packages provided to large banks may incentivize them to engage in highly risky operations (Mishkin, 2006), invest in illiquid assets (Cao and Illing, 2008) and take on excessive credit risk (Gropp, Gruendl and Guettler, 2014). Also, state guarantees provided to efficient banks enhance their exposure to systemic events (Myerson, 2012). On the other hand, the adverse impact of a deposit insurance scheme on systemic risk may diminish if banks hold higher levels of Tier 1 capital (Bostandzic, Pelster and Weiß, 2014).

2.2. Contributions

We contribute to the extant literature in several ways. First, our foremost contribution is to assess to what extent emergency policy interventions implemented by governments in response to the 2008 financial events are efficient in controlling systemic risk. A large spectrum of the most important policy interventions taken by European member states and implemented at bank level is examined: state guarantees, recapitalizations (capital injections) and liquidity injections. The dataset is collected manually from banks' annual reports, financial statements, websites, and, the State Aid Register of European Commission. Albeit, the isolate impact of bailout mechanism has been addressed in a number of theoretical and empirical studies, our specifications include different forms of interventions as several banks received more than one type of package. We distinguish ourselves from other studies by assessing the interaction between policy interventions and a broad range of risk profile indicators (i.e., size, tier 1 ratio, credit risk, liquidity and profitability). The differentiation among various risk profiles may be crucial not only for policy makers in designing proper bailout mechanisms, but also for the banks' risk management when developing Early Warning System frameworks (EWSs).

Second, we contribute to the literature on systemic risk determinants exploring a unique set of market variables. Similar to other studies we estimate systemic risk measures conditioned on a set of indices that characterize financial markets, but our approach is different as we consider indices specific for European banking sector, i.e., we account for shocks to funding conditions on interbank markets, shocks to foreign exchange markets, the evolution of yields on long term government bonds and the evolution of real estate market on a weekly basis.

Third, we add to the literature on systemically important financial institutions (SIFIs) by using a unique sample that consists of 110 banking institutions from 22 European countries. The group includes both small domestic banks, as well as global systemically important banks. A number of them were included in the FSB's list of G-SIBs, in the European Banking Association (EBA) stress testing exercise and in the European Central Bank (ECB) Single Supervisory Mechanism. However, our results highlight a large number of small systemically important banks that are not included in the FSB's list of G-SIBs.

3. Methodology

This section presents in the first part the framework used for estimating banks' contribution to systemic risk, and, in the second part, the regression specifications used to assess the impact of policy interventions and risk profiles on these estimated systemic risk indicators.

3.1. Systemic risk estimation

3.1.1. Identifying SIBs

The dominant criterion to identify systemically important financial institutions is the negative externalities they transmit to other banks in the case of bankruptcy. In our framework, we assume that the reduction of a bank's market value of total assets below a target level generates an increased contribution of the bank to systemic risk. This hypothesis has been studied in a number of theoretical models (Kelly and LeRoy, 2005; Acharya and Yorulmazer, 2007; Allen and Gale, 2007; Adrian and Shin, 2010; Shleifer and Vishny, 2010). One motivation for using this approach is that banks' total assets reflect the credit supply shocks within an economy (Adrian and Brunnermeier, 2016), while their assessment at market value accounts for the market conditions and all possible channels of risk transmission. Also, this indicator provides an instantaneous image on risks affecting banks' portfolios, as it can be computed at a higher frequency than balance sheet reporting for example which is done at a quarterly frequency.

In this context, we focus on the loss generated by the reduction of the banks' market assets under extreme events in the spirit of Adrian and Brunnermeier (2016). The market value of total assets $\left(Market\ Assets_t^i\right)$ for bank i at moment t is determined by adjusting the book value of total assets with the ratio between the market value of equity (market capitalization) and the book value of equity. Based on this ratio we determine on a weekly base the return of bank i's market assets $\left(R^i_{Market\ Assets,t}\right)$ and the return of the system's market assets $\left(R^{sys}_{Market\ Assets,t}\right)$.[5] Detailed formulae are given in Table 1.

The reason for focusing on weekly instead of daily data is that the estimates are more robust in the presence of noise in market capitalization returns. Weekly data on market capitalization are extracted from Datastream. Quarterly values of banks' total assets and equity are extracted from Worldscope and transformed into weekly frequencies through linear interpolation between two consecutive quarters.[6]

3.1.2. Idiosyncratic risk and systemic risk

According to our hypothesis, the risk we assess is the reduction of each bank's market value of total assets. For quantifying this idiosyncratic risk we determine the *Value at Risk* $\left(VaR^i_{q,t}\right)$ which expresses the maximum possible loss (as percent of the total market assets) that bank i could register for a given confidence level α (usually 99%), over a specific period of time.[7] Technically, this loss "is found in the left tail" corresponding to a given confidence level α (or a significance level $q=1-\alpha$) of the returns distribution function of the market assets. It involves the estimation of each bank's q^{th} quantile of the following loss function:

[5] In an alternative exercise we define the system by the Euro Stoxx Financial Services Index. Empirical findings remain robust.

[6] Our approach is in line with Adrian and Brunnermeier (2011) who assume a constant growth rate of the assets returns within a quarter. Hautsch, Schaumburg and Schienle (2014) use cubic spline interpolations to compute *CoVaR*. Using both linear interpolation and cubic splines to perform the transformations, López-Espinosa et al. (2012) find that the systemic risk estimates are not sensitive to the type of transformation.

[7] This theoretical research of the widely used *Value at Risk* indicator was initiated by Jorion (1997), Dowd (1998) and Saunders (1999).

$$q = Prob(R^i_{Market\ Assets,t} \le VaR^i_{q,t}) \tag{1}$$

VaR reflects the idiosyncratic risk of a particular bank and it is mainly used in the context of micro-prudential regulation, as it fails to capture the system's risk. In order to assess the contagion spillovers from a bank to the whole system in case of a severe reduction of the market assets, there is a large strand of literature that follows the *Conditional Value at Risk (CoVaR)* framework. The method treats each bank as part of the system. The contagion effects from a particular bank to the whole system can be determined through the *VaR* of the system conditioned on the event that each bank is at its own *VaR* level. *CoVaR* involves the estimation of the q^{th} quantile of the system's returns distribution over a given period of time $\left(R^{sys}_{Market\ Assets,t}\right)$ conditioned on the event that each bank registers the maximum possible loss of its returns for the same significance level q:

$$q = Prob\Big(R^{sys}_{Market\ Assets,t} \le CoVaR^{sys|R^i_{Market\ Assets,t}=VaR^i_{q,t}}_{q,t} \big| R^i_{Market\ Assets,t} = VaR^i_{q,t}\Big) \tag{2}$$

3.1.3. Estimating the systemic importance of banks

The successful implementation of *CoVaR* depends on the accuracy of the distribution estimation. Using the normal distribution can lead to the underestimation of risk due to fat tails corresponding with extreme movements in markets that are then not captured. In order to fix this problem a number of papers propose the *Quantile Regression (QR)* method developed by Koenker and Bassett (1978).[8] In comparison with the *Ordinary Least Squares* method, the *QR* permits the estimation of the dependent variable's quantiles conditioned on the explanatory variables, being more robust in the presence of extreme market variations.[9] We will use the *QR* method to estimate each bank's individual risk, as well as the contribution to systemic risk.[10] In order to correct for heteroskedasticity we apply the *QR* method with robust standard errors.[11]

Due to continuous changes in the market environment, both idiosyncratic and systemic risks vary over time, depending on different factors that affect the banking system. To capture this time variation of banks' risk we estimate *VaR* and *CoVaR* on a weekly basis, conditioned on several market indices $\boldsymbol{MI}'_t=(MI_{1,t},\dots,MI_{k,t})$ that incorporate information representative for European financial markets. A detailed description of these indices is given in Section 4.2.

Each bank's idiosyncratic risk is estimated using a linear model that captures the dependence of bank's asset returns on market indices lagged one period:

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[8] Its usage in *VaR* estimations was initiated by Engle and Manganelli (1999), followed by Chernozhukov and Umantsev (2001).

[9] The mean of the dependent variable conditioned on the regressors does not capture all the information necessary to analyze the behavior of the regressand distribution. Therefore, the *OLS* method is not adequate when the series present extreme values, as it fails to account for the different levels of asymmetry and kurtosis.

[10] The estimation is done by minimizing the asymmetrically weighted sum of absolute errors with the number of observations corresponding to the quantile of interest. This can efficiently be solved through the algorithm proposed by Portnoy and Koenker (1997), which proved to be robust both in large and in small samples.

[11] This approach permits the standard errors to be asymptotically valid in the presence of heteroskedasticity and misspecification (Machado and Santos Silva, 2013).

$$R^{i}_{Market\ Assets,t} = \alpha^{i} + \boldsymbol{MI}'_{t-1} \times \boldsymbol{\beta}^{i} + \gamma^{i} \times Crisis_{t} + \varepsilon^{i} \tag{3}$$

Unobserved characteristics of bank i are captured by α^i. $\boldsymbol{MI}'_{t-1}$ is a (1×k) vector of market indices with observations at t-1. $\boldsymbol{\beta}^{i}$ is a (k×1) vector of coefficients that captures the bank i's return dependence relationship with the market indices. $Crisis_t$ is a dummy variable that takes the value one after the Lehman collapse and zero otherwise. ε^{i}_{t} is an *iid* error term. The measure is estimated on a weekly basis for each bank individually. We use one lag of the market indices to control for the speed of adjustment of the banks' returns to the financial markets risks.

The return of the system's market assets can change with each bank's return and also with the lagged market indices, following the linear relationship:

$$R^{sys}_{Market\ Assets,t} = \alpha^{sys|i} + \delta^{sys|i} \times R^{i}_{Market\ Assets,t} + \boldsymbol{MI}'_{t-1} \times \boldsymbol{\beta}^{sys|i} + \gamma^{sys|i} \times Crisis_{t} + \varepsilon^{sys|i}_{t} \tag{4}$$

$\alpha^{sys|i}$ captures the banking system characteristics conditioned on bank i. $\boldsymbol{\beta}^{sys|i}$ is a (k×1) vector of coefficients that capture the system's return dependence relationship with the one week lagged market indices $\boldsymbol{MI}'_{t-1}$ conditioned on bank i. $\delta^{sys|i}$ reflects the conditional dependence of the system's return on bank i's return, a large coefficient being associated with an enhanced contribution of that bank to systemic risk. $\varepsilon^{sys|i}_{t}$ is an *iid* error term.

Running the *QR* technique on Eq. (3) and (4) for the 1% quantile and for the median we obtain the values of the regressors that will be used to calculate each bank's *VaR* and *Contribution CoVaR* in stressed periods (1% quantile) and in normal periods (median):

$$\widehat{VaR}^{i}_{q,t} = \hat{\alpha}^{i}_{q} + \boldsymbol{MI}'_{t-1} \times \hat{\boldsymbol{\beta}}^{i}_{q} + \hat{\gamma}^{i}_{q} \times Crisis_{t} \tag{5}$$

$$c\widehat{CoVaR}^{sys|i}_{q,t} = \hat{\alpha}^{sys|i}_{q} + \hat{\delta}^{sys|i}_{q} \times \widehat{VaR}^{i}_{q,t} + \boldsymbol{MI}'_{t-1} \times \hat{\boldsymbol{\beta}}^{sys|i}_{q} + \hat{\gamma}^{sys|i}_{q} \times D_{Crisis_{t}} \tag{6}$$

Following Adrian and Brunnermeier (2016), each bank's *Contribution to Systemic Risk (cCoVaR)* is determined as the difference between *VaR* of the whole system conditioned on the event that the bank registers the lowest return at a given confidence level and *VaR* of the whole system conditioned on the event that the bank faces the median return:

$$cCoVaR^{sys|i}_{q,t} = CoVaR^{sys|R^{i}_{Market\ Assets,t}=VaR^{i}_{q,t}}_{q,t} - CoVaR^{sys|R^{i}_{Market\ Assets,t}=VaR^{i}_{50\%,t}}_{q,t} \tag{7}$$

The one-period forward forecast of an individual bank's systemic contribution would be:

$$cCoVaR^{sys|i}_{q,t} = \hat{\delta}^{sys|i}_{q} \times \left(\widehat{VaR}^{i}_{q,t} - \widehat{VaR}^{i}_{50\%,t}\right) \tag{8}$$

To sum up, using *QR* we have managed to express the whole system risk conditioned on the event that a particular bank will register low returns on the market assets at a given probability (bottom-up approach). If applied in the original form the *CoVaR* measure presents several caveats. If it is negatively associated with *VaR*, it could create incentives for banks to increase their idiosyncratic risk in order to lower the estimated contribution to systemic risk (Löffler and Raupach, 2013). There may also be situations where the implementation of *CoVaR* fails to capture the non-linear contagion tail effect, therefore underestimating systemic risk (Jiang, 2012).

A rapidly growing literature proposed several refinements to the original *CoVaR* measure. Among them, López-Espinosa et al. (2012) found that systemic risk presents a strong degree of asymmetric response, since negative returns pose greater contagion effects to the system compared with the positive ones. They suggest the *Asymmetric CoVaR* which is a modified version of the original *CoVaR* model that accounts for asymmetries in the initial specification. As this method provides more robust results in the presence of extreme events, parallel with estimating *CoVaR* in its original form, we apply the *Asymmetric CoVaR* model for banks' *Systemic contribution (cACoVaR)*.

The approach involves expressing the system's returns as a function of each bank's returns and of the lagged market indices, following the next asymmetric relationship:

$$\begin{aligned} R_{Market\ Assets,t}^{sys} = \alpha^{sys|i} &+ \delta^{sys|i\,(-)} \times R_{Market\ Assets,t}^{i} \times I_{(R_{Market\ Assets,t}^{i}<0)} \\ &+ \delta^{sys|i\,(+)} \times R_{Market\ Assets,t}^{i} \times I_{(R_{Market\ Assets,t}^{i}\geq 0)} + \boldsymbol{MI}_{t-1}' \times \boldsymbol{\beta}^{sys|i} + \gamma^{sys|i} \times Crisis_t + \varepsilon_t^{sys|i} \end{aligned} \tag{9}$$

$\delta^{sys|i\,(-)}$ and $\delta^{sys|i\,(+)}$ reflect the conditional dependence of the system's returns on each bank's returns when they are negative ($I_{.<0}$) and, respectively, positive ($I_{.\geq 0}$). Large coefficients are associated with an enhanced contribution to systemic risk. Under the restriction $\delta^{sys|i\,(-)} = \delta^{sys|i\,(+)} = \delta^{sys|i}$ the initial *CoVaR* model of Adrian and Brunnermeier (2016) is a particular case of Eq. (9). Running the *quantile regression* for the 1% quantile and for the median we can estimate each bank's *Asymmetric Contribution CoVaR* in stressed and normal periods as in Eq. (10):

$$c\widehat{ACoVaR}_{q,t}^{sys|i} = \hat{\alpha}_q^{sys|i} + \left(\hat{\delta}_q^{sys|i\,(-)} I_{(VaR_{q,t}^{i}<0)} + \hat{\delta}_q^{sys|i\,(+)} I_{(VaR_{q,t}^{i}\geq 0)}\right) \times \widehat{VaR}_{q,t}^{i} + \boldsymbol{MI}_{t-1}' \times \hat{\boldsymbol{\beta}}_q^{sys|i} + \hat{\gamma}_q^{sys|i} \times Crisis_t \tag{10}$$

Finally banks' asymmetric contribution to systemic risk is determined using Eq. (11):

$$cACoVaR_{q,t}^{sys|i} = ACoVaR_{q,t}^{sys|R_{Market\ Assets,t}^{i}=VaR_{q,t}^{i}} - ACoVaR_{q,t}^{sys|R_{Market\ Assets,t}^{i}=VaR_{50\%,t}^{i}} \tag{11}$$

As an alternative for *QR* we employ *DCC-GJR GARCH models (DCC)* to estimate VaR and CoVaR indicators to test the robustness of results.[12] Further, we also explore the effects for the exposure of banks to systemic risk (top down approach) using *Marginal Expected Shortfall (MES)* of Acharya et al. (2017) and *Systemic Risk Index (SRISK)* proposed by Acharya, Engle

[12] When using DCC models we consider the dependence between system's market assets returns and banks' market assets return, omitting the impact of market indices.

and Richardson (2012) and Brownlees and Engle (2017). A summary description of the methods is given in Table 1. The results obtained given these measures are discussed in Section 5.2.1.2.

The accuracy of systemic risk models is assessed through two backtesting procedures that compare the losses estimated by *VaR* and *CoVa*R models with the real losses during the testing interval. First, we apply the Kupiec (1995) likelihood ratio test of unconditional coverage that assesses if the model's failure rate is compatible with the chosen confidence level. Second, we apply the Christoffersen (1998) likelihood ratio test of conditional coverage that examines the frequency of exceptions and their independence in time. A detailed description is provided in Appendix 4. Our approach is in line with other studies that use these tests to assess the performance of *VaR* and *CoVaR* models (Jiang, 2012; Girardi and Ergün, 2013).

3.2. Panel regression estimation

In the second stage of our empirical framework we analyze the impact of the emergency policy interventions taken by national supervisory authorities in the banking sector to limit the negative spillovers of the 2008 financial crisis. Their influence on systemic risk is assessed using the *Ordinary Least Squares with Fixed Effects (OLS FE)* method. First, we examine how bank level policy interventions affect banks' contribution to systemic risk after controlling for a variety of bank, market and macro characteristics. Second, we explore how banks' risk profiles exacerbate or mitigate the relationship between rescue actions and systemic risk. For both approaches we run different models to account for the long run impact (one year) and short run impact (one quarter).

3.2.1. Baseline model. Long run and short run effect

We start our analysis considering the *long run* impact of emergency policy interventions on systemic risk that is examined through the following baseline model specification:

$$\begin{gathered} SystemicRisk_{ij,t} = \beta_0 + \boldsymbol{\beta_1 \times Policy\ interventions\ after\ event_{ij,t}} + \Phi \times Bank\ controls_{ij,t-1} + \\ \Psi \times Market\ \&\ Macro\ controls_{j,t-1} + \varphi_i + \mu_j + \upsilon_t + \varepsilon_{ij,t} \end{gathered} \tag{12}$$

The sample includes 110 banks from 22 European countries and the period accounts for 28 quarters during 2008-2014. We detail our choice of banks in the next section; this period we chose because the emergency assistance programs of our main interest were provided by European member states after the Lehman Brothers collapse.

The dependent variable is represented by bank i's from country j contribution to systemic risk in quarter t. The data stand for the values of bank level systemic risk indicators estimated on a weekly base as presented in Section 3.1. In order to be merged with the quarterly balance sheet and macroeconomic variables, we transform the weekly values of the systemic risk indicators into quarterly frequency by summing them up for each bank within each quarter.

The main regressors of interest are represented by the emergency rescue measures *(Policy interventions after event$_{ij,t}$)* received by bank i from government j to mitigate the negative effects of the crisis under the form of state guarantees, recapitalizations and liquidity injections. We employ an event window approach starting one quarter after the intervention offered by government j has been implemented by bank i and ending one year after the event. Using this framework policy interventions are allowed to be different from zero four quarters after the event.[13] A negative β_1 coefficient is associated with a decrease in systemic importance for the intervened banks after receiving the assistance package from government.

Bank controls$_{ij,t-1}$ represent differences in risk profiles among banks (size, leverage, credit risk, liquidity and profitability). To account for heterogeneity among different banking systems and economies we include banking market controls *(Market controls*$_{j,t-1}$*)* and macroeconomic controls *(Macro controls*$_{j,t-1}$*)* which are country-level. Specifications include bank fixed effects (φ_i) and/or year fixed effects (υ_t) to control for unobserved heterogeneity. $\varepsilon_{ij,t}$ is an *iid* error term specific to bank i from country j in quarter t. The bank level explanatory variables are lagged by one period in order to control for the speed of adjustment of the systemic risk indicators. The country level variables (market and macro controls) are lagged by four quarters because they have an annual frequency. Several alternative models that include for example country fixed effects (μ_j) or other proxies for bank level risk profiles are estimated to test the robustness of the results. Variables are winsorized within the 1% and 99% percentiles. Results are corrected for heteroskedasticity and correlation using bank level clustered standard errors,[14] especially in the context that the dependent variables are pre-estimated.

In the next step we analyze the *short run* impact of bailouts on systemic risk. The main regressors of interest are represented by the emergency rescue measures taken by national authorities of country j and implemented by bank i during quarter t-1 *(Policy interventions*$_{ij,t-1}$*)* to mitigate the negative effects of the crisis. The following model specification is estimated via *OLS FE*:

$$\begin{aligned} SystemicRisk_{ij,t} = \beta_0 + \boldsymbol{\beta_1 \times Policy\ interventions_{ij,t-1}} + \Phi \times Bank\ controls_{ij,t-1} + \\ \Psi \times Market\ \&\ Macro\ controls_{j,t-1} + \varphi_i + \mu_j + \upsilon_t + \varepsilon_{ij,t} \end{aligned} \tag{13}$$

The description of regressors is similar to Eq. (12), but instead of an event window approach we employ bank-quarter policy interventions offered by government j to bank i in a specific quarter. A negative β_1 indicates a decrease in systemic importance of affected banks immediately after the interventions received from government.

3.2.2. Further analysis

The actions taken by the supervisory authorities may have a different impact across banks with various risk profiles, and also, systemic risk can be mitigated or exacerbated by risk strategies. To further explore the effects of emergency policy interventions on systemic risk we examine the

[13] Alternatively we use an event window of two years (i.e., policy interventions are allowed to be different from zero eight quarters after the event). Unreported results show that the significance and size of the regressors are unaffected.

[14] In different exercises we use standard errors clustered at country level, bank×year level, bank×quarter level and two-way clustering by bank and quarter. Unreported results confirm that the significance of the main regressors is unaffected.

impact of banks' risk profiles on the relationship between emergency rescue actions and systemic risk. The following regression model extends the baseline specification regarding the *long run* impact:

$$SystemicRisk_{ij,t} = \beta_0 + \boldsymbol{\beta_1 \times Policy\ interventions\ after\ event_{ij,t}} + \boldsymbol{\beta_2 \times Policy\ interventions\ after\ event_{ij,t} \times Bank\ risk_{ij,t-1}} + \Phi \times Bank\ controls_{ij,t-1} + \Psi \times Market\ \&\ Macro\ controls_{j,t-1} + \varphi_i + \mu_j + \upsilon_t + \varepsilon_{ij,t} \quad (14)$$

The dependent variable is represented by bank i's from country j contribution to systemic risk in quarter t. The policy interventions are allowed to be different from zero four quarters (one year) after their implementation by banks. In addition to Eq. (12) we include the interaction term of policy interventions with the bank level risk profile indicators (size, tier 1 ratio, credit risk, liquidity and profitability). The coefficient β_2 should be positive and significant if banks' risk strategies enhance the systemic importance of banks that receive bailouts, and negative otherwise. As in the baseline specification we use the same bank level, market and macro controls. The strategy resides in estimating the empirical models separately for each interaction of policy interventions with the risk profile indicators using *OLS FE* with bank level clustered standard errors.

For assessing the *short term* impact of emergency rescue measures on banks' systemic importance Eq. (14) is re-estimated as below:

$$SystemicRisk_{ij,t} = \beta_0 + \boldsymbol{\beta_1 \times Policy\ interventions_{ij,t-1}} + \boldsymbol{\beta_2 \times Policy\ interventions_{ij,t-1} \times Bank\ risk_{ij,t-1}} + \Phi \times Bank\ controls_{ij,t-1} + \Psi \times Market\ \&\ Macro\ controls_{j,t-1} + \varphi_i + \mu_j + \upsilon_t + \varepsilon_{ij,t} \quad (15)$$

Under this approach emergency rescue measures *(Policy interventions$_{ij,t-1}$)* implemented by bank i are different from zero just during the quarter they were implemented, which enable us to assess their relationship with banks' risk profiles and systemic risk on short term.

4. Sample and data

This section presents the sample of banks, the data used for estimating systemic risk measures and the variables employed in the panel regression specifications.

4.1. Sample

Our sample consists of 110 publicly listed European banks which assets total more than 20 trillion euro at the end of 2014 (Table 2). They are international active and represent 22 European states. The interest in this portfolio is motivated by a regulatory perspective as the group includes large banks identified as G-SIBs by Financial Supervisory Board, but also small local banks that present systemic importance (D-SIBs). Among them 40% are included in the EBA's stress testing exercise, while 29% are included in the ECB's Single Supervisory Mechanism framework (Appendix 1).

We focus just on banks because they are the most important financial intermediaries in Europe. Size variation is considerable within the sample, as total assets at the end of 2014 range from 178 million euro to about 2 trillion euro. The average coverage in total banking system assets of analyzed countries is about 49% (Table 2). We use consolidated statements in order to capture all cross-border business transactions of the international banks. Initially, we started from a sample of 351 active and publicly listed financial institutions from the EU28 area, which are included in the Thomson Reuters Financial Datastream within the sector “Banks”. Due to methodology constraints (i.e., systemic risk estimations), we excluded banks that do not have the weekly market capitalization Datastream data available for the whole period and banks with more than 25% of the quarterly balance sheet Worldscope data missing.

Table 2 here

Data required for systemic risk estimations span 2005 to 2014, allowing us to track the evolution of systemic risk before and after the 2008 global financial crisis. The pre-crisis period covers 2005Q1 to 2008Q2. The crisis period starts in 2008Q3 and ends in 2011Q4 and consists of two phases. The first phase of the crisis begins after the Lehman Brothers collapse in 2008Q3 and continues through 2009Q4, corresponding with the intensification of global financial crisis effects in Europe (Brei, Gambacorta and von Peter, 2013). The second phase of the crisis runs from 2010Q1 to 2011Q4 and coincides with the European sovereign debt crisis of Greece, Ireland, Italy, Portugal and Spain (De Santis, 2011). Following Brunnermeier and Oehmke (2013) we estimate systemic risk during the whole period (2005-2014) in order to account for the build-up phase in the pre-crisis and the propagation phase during the crisis. The impact of policy interventions on systemic risk is analyzed during the period 2008-2014 as a number of European countries received support through various programs in the aftermath of 2008 financial crisis and 2010 European sovereign debt crisis (Petrovic and Tutsch, 2009).

4.2. Market variables

The tail risk measures *VaR* and *CoVaR* are estimated separately for each bank using weekly returns of the market assets. The measures are based on weekly market capitalization data extracted from Datastream and quarterly book values of total assets and equity retrieved from Worldscope (see Table 1 for computation details). The missing quarterly values of total assets and equity are inputted through linear interpolation between two consecutive quarters like in Adrian and Brunnermeier (2016). We eliminate banks with missing total assets or equity data for two consecutive quarters or more.

Figure 1 presents the evolution of our sample’s market assets and market capitalization. This corresponds to the 110 banks analyzed over 521 weeks (2005-2014). Due to deteriorating economic conditions in international financial markets, both market assets and market equity show a downturn during the first phase of the crisis (2008-2009). The market assets return decrease with more than 75% in comparison with the maximum value that is reached in the middle of 2007. There are signs of recovery during 2009-2010, but the market assets and equity start declining again at the end of 2011 since the European sovereign debt crisis took off.

Figure 1 here

The downward trend of the European banking market assets is closely linked to the evolution of financial market indices. They control for common exposure of banks to credit risk, short term liquidity risk and shocks to funding conditions. The choice of these explanatory variables is in consensus with the evidence provided by the empirical literature (Acharya, Engle and Richardson, 2012; Gauthier, Lehar and Souissi, 2012; Adrian and Brunnermeier, 2016). But, in comparison with these studies, our dataset focuses on a unique set of factors that significantly impact the European banking market. Due to increased counterparty risk, the European interbank markets experienced large interest spreads and jumps of term interest rates after Lehman collapse. Even banks with a good quality of loans portfolio had to borrow at high spreads in the term market due to precautionary liquidity incentives (Acharya and Skeie, 2011). To account for the impact of interbank market, we employ the change in the interest rates Eonia and Euribor. The long term government bond yields reached high levels especially in the aftermath of the 2008 financial crisis. Considering their evolution, we use the change in the Government bonds (Euro area triple A) yield curve instantaneous forward rate 10-years against 1-month residual maturity. In addition we employ the real estate price index for Europe and the realized volatility of the euro exchange rate vis-a-vis other currencies (CISS foreign exchange market index).[15] The choice of region specific variables is motivated by Lo Duca and Peltonen (2013), Popescu and Turcu (2014) and Pagano and Sedunov (2016) who show that the combination of domestic and global factors significantly improve the forecasting of systemic events.

The summary statistics of systemic risk indicators are reported in Table 3 (Panel A). Data corresponding to the *Asymmetric CoVaR* model reveal that during 2008-2014, the quarterly average contribution to systemic risk of all banks translates to about 12% loss of the system's market assets. The values correspond to the output detailed in Section 5.1. Statistics resulting from the other systemic risk measures *(Delta CoVaR DCC, Delta CoVaR QR)* show that banks' marginal contribution to systemic risk represents around a 3% loss of the system's market capitalization within a quarter.[16] On the other hand, MES and SRISK highlight that the exposure of banks to the risk that the system would register a downturn is about 5% quarterly loss of the banks' market equity (MES), and, respectively, 12.55 billion quarterly loss (SRISK).

Table 3 here

The main features are compared over the non-intervened banks and banks affected by rescue packages (Table 3 Panel B). Overall, the difference in means analysis shows that banks' contribution and exposure to systemic risk are larger for banks that received state guarantees, capital injections or liquidity injections in comparison with the non-affected banks.

Figure 2 presents the weekly average individual risk and contribution to systemic risk of all banks from our sample during 2005-2014. Both risk indicators reveal a progressive increase

[15] The market variables are transformed into log differences or percentage differences in order to assure their stationary behavior, as indicated by the unit root tests. Table 1 gives the transformation formulae.

[16] Considering that the average systems' market equity during 2008-2014 is about 731 billion euro, the average marginal contribution of banks to systemic risk translates into about 22 billion euro quarterly loss of market equity.

of losses in the period immediately after the Lehman collapse in September 2008. Similar to us, Black et al. (2016) find that the systemic risk of the European banking system increased during the crisis reaching one peak in March 2009 and another one in November 2011 during the sovereign debt crisis in Europe.

Figure 2 here

4.3. Emergency policy interventions

The impact on systemic risk of the emergency measures taken by European member states after Lehman collapse is analyzed through a series of policy interventions. In order to limit the negative spillovers in the banking system and to ensure financial stability, supervisory authorities used a broad range of mechanisms represented by: (1) state loans; (2) recapitalizations (capital injections); and (3) liquidity injections. These are broadly described in Appendix 2. Banks from our sample received state guarantees for bond issues, senior notes or other form of debt; recapitalizations in the form of hybrid capital, participation capital, preferred shares, deeply subordinated perpetual notes or contingent convertible subordinated bonds (CoCos); and, liquidity injections consisting of loan facilities, swap facilities, illiquid assets back-up facilities or asset protection schemes. We hand-collect the dataset from banks' annual reports, financial statements, websites and the State Aid Register of the European Commission.

Although during the last years a number of financial assistance programs have been set up to combat the Eurozone crisis, we focus on the emergency policy interventions implemented by member states immediately after the Lehman collapse. These public interventions supported by governments or central banks at the national level and agreed by the European Commission were about the single instruments available to limit systemic risk and the spread of contagion at the debut of the crisis in Europe. We expect the implementation of the rescue measures to be associated with a reduction in systemic risk.

Among the most popular emergency interventions received by banks from our sample are state guarantee schemes and capital injections (Appendix 3). In terms of value, liquidity injections lead with an average size of about 14% reported to total assets, followed by state guarantees (6 % of total assets) and recapitalizations (3 % of total assets). The aim of guarantee schemes is to ensure the supply of liquidity in the interbank market or to prevent bank runs. Recapitalizations are intended to strengthen the capital base of banks in order to comply with the regulatory requirements. Among liquidity injections, state loans are given under certain conditions. Usually, the remuneration for management is limited, bonuses are prohibited and dividends may be distributed only to government (Petrovic and Tutsch, 2009). Acquisitions of impaired assets are adopted to avoid future drops in asset prices and are expected to generate higher liquidity and greater transparency, increasing the confidence in the banking sector.

Descriptive statistics are provided in Table 4. In sum, our sample was exposed to 72 policy intervention events: 36 events corresponding to state guarantees, 36 events related to recapitalizations, and, 15 events linked with liquidity injections. Out of 110 banks, 31 implemented these types of policies: 6 banks received all three types of interventions, 10 banks applied two types of interventions, while 15 banks relied on a single intervention measure. The intervened banks represent 15 countries (out of 22 included in our sample), among which in seven countries more than two banks were affected.

Table 4 here

Figure 3 presents the average quarterly contribution to systemic risk of affected banks eight quarters (two years) before and after the event (i.e., the implementation of policy rescue measures offered by government). Banks that received state guarantees present a lower systemic importance before interventions, but their weekly contribution to systemic risk increase close to banks unaffected by state guarantees after the intervention. Banks provided with liquidity injections represent a higher contribution to systemic risk than non-affected banks that becomes larger after the interventions. Among all rescue measure, recapitalizations appear to have an immediate beneficial effect on reducing the systemic importance of affected banks.

Figure 3 here

4.4. Bank level controls

In order to account for different risk strategies we control for the risk profiles of banks. Prior studies suggest that bank characteristics like size, leverage, profitability, along with the credit and liquidity risk are key drivers of systemic risk during the most recent financial crisis (Tarashev, Borio and Tsatsaronis, 2010; Acharya, Engle and Richardson, 2012; Mayordomo, Rodriguez-Moreno and Peña, 2014). In line with the literature, the following risk profile indicators are used: (1) size (logarithm of Total assets); (2) leverage (Common equity to Total assets ratio, as well as Tier 1 regulatory capital ratio); (3) the quality of the loans portfolio (Provisions for loan losses to Gross loans); (4) liquidity ratio (Liquid assets to Deposits and short term funding); and (5) profitability represented by ROAA ratio (Net profit to Average assets). Our presumption is that size and credit risk will be associated with a high level of systemic risk, while capitalization, liquidity and profitability with a low level. Additionally, we capture the orientation of banks' business towards traditional and non-traditional activities by including the share of lending activity (Gross loans to Total assets) and Net non-interest margin (Net non-interest income to Gross revenues). Previous studies show that systemic risk is associated with a high share of non-traditional activity (Brunnermeier et al. 2016, Demirgüç-Kunt and Huizinga 2010). Variables are extracted from Worldscope and their definition is given in Table 1.[17] The descriptive statistics presented in Table 4 show that on average during 2008-2012 banks from our sample have Tier 1 ratio of 12.2%, Liquidity ratio of 30.1%, Credit risk ratio of 1.2% and Gross loans shares of 63.2%. These statistics suggest that on average the institutions are well capitalized, have a good liquidity situation and a high quality loan portfolio. Also, they are more oriented towards traditional banking business.

4.5. Macro controls

Following previous studies (Girardi and Ergün, 2013; Anginer, Demirgüç-Kunt and Zhu, 2014a;

[17] In the regression analysis several of these variables are transformed in order to assure the stationary behavior, as indicated by Panel unit root tests. Table 1 gives the transformation formulae.

Weiβ, Bostandzic and Neumann, 2014), we control for the banking market and macroeconomic environment. Accounting for the particularities of each banking sector we consider the intensity of competition − or lack thereof − expressed by the Boone indicator,[18] that was previously associated with a reduced contribution to systemic risk (Anginer, Demirgüç-Kunt and Zhu, 2014a). Next, we account for the strictness of prudential regulations regarding initial and overall capital held by banks and the tightness of supervisory power in preventing and correcting problems in the local banking sectors. As proxies we use the Capital regulatory index and Supervisory power index provided by Bank Regulation and Supervision Database of World Bank and calculated as in Barth et al. (2013).[19] Finally, we employ the inflation rate and the GDP growth as macro controls. We expect systemic risk to be negatively influenced by the deterioration of macro conditions. Variables are extracted from World Development Indicators, Global Financial Development and Bank for International Settlements databases. Their definition is given in Table 1 and the descriptive statistics in Table 4.

5. Empirical results

5.1. Individual contribution and SIB-s

Table 5 reports the output of the weekly 1% *QR* run for the *VaR* and *CoVaR* models. *Normal* stands for the original *CoVaR* model of Adrian and Brunnermeier (2016), while *Asymmetric* represents the extension of López-Espinosa et al. (2012). The *QR* estimations are carried out separately for each of the 110 banks from the sample during 2005-2014. Therefore, the table displays the median for the individual estimated coefficients, median standard errors and median Pseudo-R^2. Panel 1 shows the output for the *VaR* regressions, while Panel 2 for the *Contribution CoVaR*. A positive coefficient is related to an improvement of the systemic risk situation (the increase of the returns on the market value of total assets), while a negative coefficient is linked to a deteriorating situation (the decrease of the returns on the market assets).[20]

Table 5 here

Empirical results shows that higher yields on long term government bonds forward rates reduce banks' individual risk as well as their contribution to systemic risk. Among the interbank market indices, increased overnight interest rates enhance banks' systemic importance while an upward trend of the three-month interest rates has and opposite effect. Finally, a reduction of the European real estate price index has a negative impact on all risk measures as so does an increase in the realized volatility of the euro exchange rate vis-a-vis other currencies.

[18] Boone indicator is a measure of competition in the banking market calculated as the elasticity of profits to marginal costs. The lower the Boone indicator is, the higher the level of competition.

[19] These data are available for years 2007 and 2012. Capital regulatory index takes values from 0 (relaxed regulations) to 10 (tight regulations). Supervisory power index takes values from 0 (relaxed supervision) to 14 (tight supervision).

[20] The dependent variables are expressed in units of weekly percentage change of the system's market value of total assets in case of *Contribution CoVaR* and, respectively, weekly percentage change of the banks' market value of total assets in case of *VaR*. Therefore, the interpretation of the coefficients is directly.

Banks with high *VaR* levels contribute more to the loss of the whole banking system (Panel 2). A reduction of the banks' market assets with 1% leads to a fall of the system's market assets with a weekly median size of 0.01%. When considering the asymmetric *CoVaR* model the effects are larger. The median value of the coefficient associated with negative returns jumps to 0.07%. The specifications clearly indicate that systemic risk is higher when the asymmetric effect is present. Our results are in line with López-Espinosa et al. (2012) who find strong asymmetric responses of *CoVaR* to changes in individual *VaR* levels.

The accuracy of *VaR* and *CoVaR* specifications is confirmed by the in-sample backtesting procedures (Appendix 4). Table 5 reports the number of violations and the mean statistics for Kupiec's test of unconditional coverage (LR_{ucr}), Christoffersen's likelihood ratio test of independence (LR_{ind}) and Christoffersen's likelihood ratio test of conditional coverage (LR_{ccr}). The statistics validate the models for almost all banks in our sample.

Lastly, this methodology permits us to identify a large number of small domestic banks with an important contribution to systemic risk (D-SIBs) that are not included in the FSB's list of G-SIBs (Appendix 1). Our results are in line with other papers that find systemic importance of quite a few small European banks (Benoit, 2014; Castro and Ferrari, 2014; Black et al., 2016).

5.2. The impact of policy interventions on systemic risk

This section presents the results of the regressions between systemic risk measures as dependent variables and policy interventions as main determinants. First, we discuss the influence of policy interventions on banks' systemic importance. Both long and short term effects are assessed. Second, we examine how banks' risk strategies affect the impact of emergency rescue actions on systemic risk. Usually these measures require a long term horizon to produce their effects due to legislative and political constraints. Therefore, we star our analysis by assessing the implications on long run.

5.2.1. Emergency policy interventions and systemic risk: baseline results

5.2.1.1. Long run and short run effects

Long run effects. Table 6 shows the estimation results for the *OLS Fixed Effects* regression presented in Eq. (12). The dependent variable is represented by banks' contribution to systemic risk, estimated using the asymmetric CoVaR methodology *(cACoVaR)*. The main regressors of interest include the emergency rescue measures received by bank i from government j and are allowed to be different from zero to one year (four quarters) after the event, in order to assess their long term impact on systemic risk.[21]

Model (1) provides a baseline specification that includes all policy interventions, bank characteristics, bank fixed effects and year fixed effects.[22] Models (2) to (8) present several

[21] Unreported results based on a two years event window show that the significance, sign and size of the regressors are unaffected.

[22] We included also separately the policy intervention variables in the empirical specifications. Unreported results show that the sign and significance of coefficients remain unchanged. Out of 36 intervened banks from our sample, six of them received all three types of interventions, while 10 banks applied two types of interventions.

alternative regressions to test the robustness of results, by adding country fixed effects, country×year fixed effects and/or bank, market and macro controls.

Table 6 here

We consider column (8) that includes bank and macro characteristics, as well country fixed effects and year fixed effects, to be our benchmark specification. In what follows the interpretation of empirical results is detailed for this model. A negative coefficient is related to a lower systemic importance, while a positive coefficient is linked to an increased contribution of banks to systemic risk.[23]

The findings show strong evidence that long term *liquidity injections* provided by governments under the form of loans or acquisitions of impaired assets have a significant adverse impact on systemic risk. Indeed the positive and significant coefficient suggests that banks that receive emergency liquidity assistance during the crisiss are associated with an enhanced systemic importance *(sic)*. A one standard deviation increase in liquidity injections reported to total assets enhances banks' marginal contribution to systemic risk by about 14% its standard deviation (as measured by *cACoVaR*). The economic effect is substantial. Given that the mean contribution to systemic risk equals 12% (i.e., the quarterly percent loss of the system's market assets during 2008-2014) our estimates imply an associated semi-elasticity of more than 90%! Regarding state guarantees and recapitalizations results reveal no significant impact in the long run.

Among bank characteristics, the findings suggest that banks' leverage is a key driver of systemic risk. As expected, leverage, measured through the shareholders' equity to total assets ratio, enters the regressions with a negative significant coefficient, showing that better capitalized banks contribute to the reduction of systemic importance. The result is in line with Tarashev, Borio and Tsatsaronis (2010) and Acharya, Engle and Richardson (2012), among others. The effects of a one standard deviation increase in the equity to total assets ratio is associated with a reduction of banks' contribution to systemic risk by about 18% (the equivalent of 18% quarterly decrease of the system's market assets). In contrast with previous studies (Girardi and Ergun, 2013; Anginer, Demirgüç-Kunt and Zhu, 2014a; Adrian and Brunnermeier, 2016)[24] size is negatively associated with systemic risk indicators, showing that smaller banks pose a greater contribution to systemic risk. However, the coefficients are insignificant.

As for the banking market characteristics the Capital regulatory index enters the specifications with a negative and significant size, suggesting that tight prudential regulations regarding initial and overall capital held by banks actually help them to decrease their systemic importance. The impact of supervisory power is also negative yet insignificant.

Short run effects. Analyzing further the short run impact of policy interventions, empirical results presented in our benchmark model (Table 7, column (8)) reflect that only *recapitalizations* can actually significantly decrease banks' systemic importance. A one standard deviation increase in equity injected by government reported to total assets reduces banks'

[23] The dependent variable is expressed in units of percentage loss of the system's market assets within a quarter.

[24] These studies are conducted on samples of U.S. financial institutions that are exposed to different regulations than European banks.

contribution to systemic risk by about 2% its standard deviation (as measured by *cACoVaR*). The economic effect is also meaningful. Given that the mean contribution to systemic risk equals 12% (i.e., the quarterly percent loss of the system's market assets during 2008-2014) the associated semi-elasticity is about -34%. Different empirical specifications that control for heterogeneity across banking markets or countries, as well as macroeconomic shocks yield similar results (Table 7, models (1)-(7)).

Table 7 here

These findings can be linked with the evidence provided by Homar (2016) who documented that European banks injected with a reasonably amount of capital during 2000-2013 boosted lending, accessed supplementary funding and restructured their balance sheets. The stabilizing effect of recapitalizations on lending growth is also documented for the Japanese banking market by Peek and Rosengren (2005) and Caballero, Hoshi and Kashyap (2008). In contrast, for the US market recapitalizations are found to have an opposite effect. Duchin and Sosyura (2014) show that banks that received TARP capital infusions improved their capitalization level, but approved riskier loans. This could be a possible explanation for the fact that the strong influence of capital injections disappears on longer term periods as shown in Table 6, suggesting that their efficiency in reducing banks' contribution to systemic risk is limited to short periods after the implementation.

Robustness. The robustness of our results is checked by employing several alternative specifications, in addition to the output presented in Tables 6 and 7. First, we re-estimate the benchmark model (column (8) from Table 6 and 7) employing alternative variables for funding risk and profitability. We replace the Liquidity ratio with the Loans to Deposits ratio (computed as Net loans to Total deposits and borrowings) and the Interbank liquidity ratio (Interbank assets to Interbank liabilities), and, the Return on assets ratio with the Operating profit margin (Operating profit to Average total assets). Second, for long term effects we use a two years event window (i.e., emergency rescue measures received by bank i from government j are allowed to be different from zero eight quarters after the event). Third, we change the level of clustering of the standard errors from bank level to bank and quarter level (two-way clustering). Fourth, instead of dividing the policy interventions received by bank i in quarter t by total assets of the bank in the same quarter, we compute their weight in total assets in the previous quarter before implementation (t-1). Finally, we include separately the policy intervention variables in the empirical specifications. Unreported results show that there are no important differences in comparison with the benchmark regression specification and the impact of the policy interventions on systemic risk in terms of sign, size and significance remains unaltered.

5.2.1.2. Implications for alternative systemic risk measures

In this section we analyze our benchmark specification re-estimated using alternative systemic risk measures. Table 8 Panel A provides the output for long run effects, while Panel B for the immediate effects of policy interventions on banks' systemic importance. This has important policy implications as in the aftermath of the crisis a significant number of systemic risk measures have been developed and attracted the attention of supervisory authorities as an alternative to classical balance sheet indicators or idiosyncratic risk measures that asses banks' risk separately not as part of a system. In this context, we explore the effects of interventions on one of the most cited methods of systemic risk in the literature: *CoVaR*, *MES* and *SRISK*.

Table 8 here

Empirical findings related to **long term effects** (Table 8, Panel A) show that the significant association of recapitalizations with banks' systemic importance is validated by all systemic risk indicators. In the same time, there are several differences regarding the magnitude of the impact that could come from the method of computation of systemic risk indicators. *Asymmetric CoVaR (cACoVaR)* predicts the marginal impact of a bank in distress on the loss of the system in terms of market assets returns, while *CoVaR DCC* and *CoVaR QR* predict the system's loss based on market equity returns. On the other hand we also explore the rescue measures effects on banks' exposures to systemic risk captured by *MES* and *SRISK*. They estimate the average return on bank's market capitalization on the days the total market capitalization of the system experience its 1% worst outcomes (i.e., the returns of banks' market equity conditioned on the left tail of the system's market equity returns).

The *Asymmetric CoVaR* model (Panel A column (1)) reveals that the impact of recapitalizations on bank's contribution to systemic risk implies a semi-elasticity of 93% (in the context that the mean contribution to systemic risk in terms of market assets loss equals 12%). The next two columns present the output for *Delta CoVaR DCC* and *Delta CoVaR QR* as dependent variables. The impact of recapitalizations on bank's contribution to systemic risk (measured by *Delta CoVaR DCC*, column (2)) implies a semi-elasticity of 575% (considering that the mean contribution to systemic risk in terms of quarterly market equity loss equals 3.01%), while the associated semi-elasticity for *Delta CoVaR QR* measure is 1,105% (given that the mean contribution to systemic risk equals about 3.13% loss of quarterly market equity). The approach used to estimate these models is close to *cACoVaR* framework, but we consider just the dependence between system's market assets returns and banks' market assets return, omitting the impact of market indices (i.e., global and local market variables). Also, while *Delta CoVaR DCC* is based on *DCC-GJR GARCH* models to estimate dynamic conditional correlation between system's market equity returns and bank returns, *Delta CoVaR QR* captures the dependence between returns using *Quantile Regression* models.

The long term effects of liquidity infusions on banks' systemic exposure are even larger when considering the *Marginal Expected Shortfall (MES)* and *Systemic Risk Index (SRISK)*, as suggested by columns (4) and (5). For MES the associated semi-elasticity of recapitalizations is 1,445% (corresponding to a mean exposure to systemic risk of about 5% of the banks' market capitalization), while for SRISK is 1,390% (given a mean exposure of banks' to the loss of the system's market equity of about 13 billion euro quarterly).

Results linked with the **short term** empirical specifications (Table 8, Panel B) highlight the beneficial effect of *recapitalizations* on reducing banks' systemic importance. The negative sign is maintained for almost all alternatives and the significant impact is confirmed by *Delta CoVaR DCC* models. The semi-elasticity jumps from -34% (when expressing systemic contribution by *cACoVaR*, column (6)) to -1,960% (when using the dynamic conditional volatility model, column (7)).

Finally, exploring the immediate effect of policy interventions on banks' exposure to systemic risk we find no significant impact of recapitalization or liquidity injections. Column (10) indicates a slightly significant impact for state guarantees, suggesting that banks which receive state guarantees from government indeed present an immediate significant exposure to the risk that the whole system experiences a capital shortfall. However the impact on long term disappears, as suggested by models (4) and (5).

In our models system is defined as the total return of market assets (in case of *cACoVaR*) or market capitalization (in case of the other systemic risk measures) of the banks from our sample. In an alternative exercise we define the system by the Euro Stoxx Financial Services Index return. Unreported results confirm that our empirical findings remain robust.

5.2.2. Risk profiles, policy interventions and systemic risk

This section presents the impact of banks' risk profiles on the relationship between emergency rescue actions and systemic risk. The model specification was introduced in sub-section 3.2.2. We discuss the empirical results for the next risk profile indices: size, tier 1 ratio, credit risk, liquidity and profitability. The dependent variable is capturing the bank i's contribution to systemic risk ($cACoVaR_{ij,t}$) in quarter t. Table 9 Panel A shows the empirical estimates for the long run benchmark model (column (8), Table 6), while Panel B for the short run benchmark specification (column (8),Table 7).[25]

Table 9 here

The findings presented in Table 9 column (1) show that the influence of guarantee schemes in the long run become significant when interacting with size, as suggested by the coefficient on the interaction term *Guarantees* × *Size* (i.e., 0.046**). This highlights that state guarantees provided to large banks increase their contribution to systemic risk. The result is consistent with the views regarding moral hazard embedded in government support programs for TBTF banks. Rescue packages provided to large banks may incentivize them to engage in riskier operations (Mishkin, 2006), invest in illiquid assets (Cao and Illing, 2008) or take on excessive credit risk (Gropp, Gruendl and Guettler, 2014). Also, the increased contribution of large banks to systemic risk could occur when banks have a lower capital ratio and unstable funding (Laeven, Ratnovski and Tong, 2016). Nevertheless, large banks are usually more focused on investment activities that are riskier in comparison with the traditional lending activities. In terms of policy implications, the findings support the incentives of the European Commission which requested the downsizing of several large European banks that received public assistance during the crisis.

[25] Unreported results confirm that models (1)-(5) from Table 6 (long run effects) and Table 7 (short run effects) yield similar results. Therefore, our main findings on the interaction between policy interventions and risk profiles are robust in the presence of alternative bank characteristics, macro controls and/or country and year fixed effects.

The impact of regulatory capital proxied by Tier 1 ratio on the link between interventions and systemic risk is reflected in model (2) Panel A and model (7) Panel B. Long run estimates show that the interaction of Tier 1 ratio with state guarantees and recapitalizations enters the specifications with a significantly positive sign (i.e., 0.081***, and respectively 0.054***).[26] The results highlight that guarantees and capital injections provided by state to less capitalized banks help them reduce their contribution to systemic risk. On the other side state guarantees and recapitalizations enhance the systemic importance of banks with a high level of regulatory capital. A possible explanation for this adverse effect can be attributed to the fact that better capitalized banks, above the regulatory requirements, may engage in risky operations like securitizations, carry trade strategies based on short term wholesale funding or undiversified exposures to real estate market (Perotti et al., 2011). Bichsel and Blum (2004) also provide empirical evidence of a positive association between the level of capital and bank risk-taking. In an alternative exercise we replace Tier 1 ratio with Excess Tier 1 ratio (computed as the surplus Tier 1 ratio above the Basel minimum requirements of 6% Tier 1 ratio), attaining similar results. Our findings suggest that the amount of guarantees and capital injections as well as the period during which they are offered to banks should be optimally established. If banks will end up exceeding their regulatory capital in time an unintended effect is possible to appear.

Credit risk can shape the impact of bailouts on systemic risk on short run.[27] The coefficients corresponding with the impact of non-performing loans share on the relationship between emergency rescue actions and systemic risk are in Panel B model (3)). Banks with higher ratios of non-performing loans on their balance sheet manage to reduce their systemic importance if they are provided with liquidities as suggested by the coefficient on the interaction term *Liquidity injections* × *Credit risk* (i.e., - 0.680***).

Further, we provide evidence that the short term effect of state guarantees on banks' systemic importance is beneficial for institutions with high liquidity levels, as shown by the coefficient linked with the interaction term *Guarantees* × *Liquidity* (i.e., -0.008**, Panel B model (9)). In contrast, on long term the effect become adverse (i.e., 0.006**, Panel A model (4)). This finding is consistent with the theory that high liquid banks increase moral hazard incentives and take on additional risks.

Finally, performance can significantly influence the impact of liquidity injections on banks' contribution to systemic risk. On short run, banks with high ROAA levels that receive liquidity assistance are associated with higher systemic importance (Panel B, column (10)). The findings can be linked to studies documenting that liquidity injections administered by central banks to avoid the spread of contagion may induce moral hazard (Acharya and Yorulmazer, 2007; Farhi and Tirole, 2012). Myerson (2012) found a similar effect for state guarantees showing that they enhance banks` exposure to systemic events when provided to efficient banks. Fortunately enough the effect is reversed for longer time horizons as highlighted by the interaction term *Liquidity injections* × *Profitability* (i.e., -0.027***, Panel A column (6)),

[26] We also interact leverage (the ratio of Total equity to Total assets) with bank level interventions. Unreported results yield to similar conclusions.

[27] We also assessed the interaction with lending activity. Unreported results show that specialization of banks in traditional activities (expressed by Gross loans share in Total assets) enhances contribution to systemic risk on short run of banks that receive state guarantees (the coefficient on the interaction term *Guarantees* × *Credit share* is 0.044**). In the long run the significance of the credit share disappears, but the impact of credit growth becomes important. Banks with higher credit growth ratios and injected with liquidities manage to reduce their systemic importance (the coefficient on the interaction term *Liquidity injections* × *Credit growth* is - 0.017**).

suggesting that liquidity provided to performant banks help them reduce the contribution to systemic risk. This could be the result of a reduced portfolio risk as banks that receive this type of assistance are usually more scrutinized. Also they are required to limit executive remunerations and distribute dividends to government.

Figure 4 summarizes our estimates along each bank risk characteristic. We highlight the resultant estimate of the contribution to systemic risk in the long run and in the short run as a consequence of the indicated policy intervention for the range between the mean minus one standard deviation and the mean plus one standard deviation of the specified bank risk characteristic.

Figure 4 here

Overall, the results suggest that the risk profiles of banks have a significant influence on the relationship between policy interventions and systemic contribution during the crisis. Characteristics like size, leverage, liquidity and profitability can significantly shape the impact of bailouts on banks' systemic importance in the long run. On the other side the immediate impact of governmental assistance programs on systemic risk is heterogeneous among banks with different levels of credit risk and profitability. Most important, from the supervisors' perspective, the efficiency of emergency rescue measures can be mitigated or exacerbated by banks' risk strategies.

6. Conclusion

In this paper we investigate how bank risk profiles determine the impact of crisis policy interventions on systemic risk. Using a unique bank-level dataset that consists of 110 banking institutions from 22 European countries, the estimation of systemic risk is based on the loss generated by the reduction of the banks' market assets under extreme events. We employ a bottom-up approach to analyze the negative spillovers from a bank to the system (contribution to systemic risk). The estimations are performed over the 2005-2011 period using the *CoVaR* framework of Adrian and Brunnermeier (2016) and its asymmetric extension of López-Espinosa et al. (2012). We identify a fairly large number of domestic systemically important banks (D-SIBs) that are not included in the Financial Stability Board's list of global systemically important banks. The empirical results show that there is a progressive increase of banks` contribution and exposure to systemic risk in the period immediately after the September 2008 financial events.

Analyzing a large and original bank-level dataset of policy interventions within a *OLS Fixed Effects* empirical setting, we then show that the impact of emergency rescue measures provided by national authorities to the banking sector immediately after the Lehman Brothers collapse have different effects on systemic risk in the long versus short run. We find strong evidence that in the long run banks that receive *liquidity injections* from governments are associated with an enhanced systemic importance. The economic effect is substantial, implying an associated semi-elasticity of more than 90%. In the short run only *recapitalizations* can actually significantly decrease banks' systemic importance, with an associated semi-elasticity of -34%. Guarantees have no significant impact. Moreover, we provide evidence that the impact of policy interventions on systemic risk is strongly influenced by banks' risk strategies: in the long run, *guarantees* at best have a limited effect in reducing the contribution to systemic risk for small, less capitalized or less liquid banks, *recapitalizations* have a beneficial effect for less capitalized banks, while *liquidity injections* by providing only temporary relief end up significantly increasing banks` systemic importance especially for less profitable banks. In the short run, *guarantees* are useful for banks with lower liquidity and *liquidity injections* have a narrow effect in reducing the systemic importance of banks with a higher share of non-performing loans.

In sum, banks' risk profiles should play a key role when designing optimal financial assistance programs, because systemic risk is concentrated among financial institutions with similar risk incentives and the effectiveness of policy interventions can be significantly altered by the banks' risk strategies.

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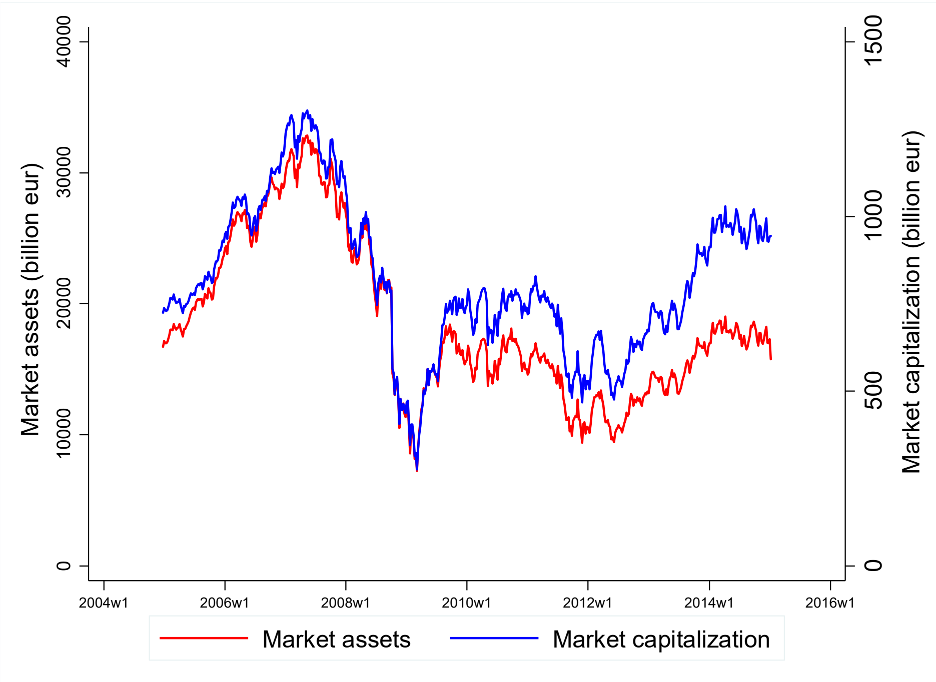
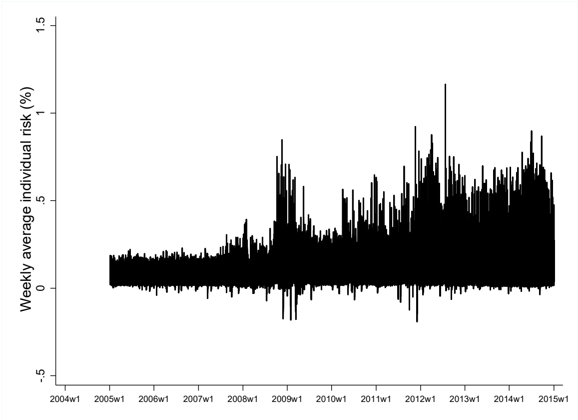
Figure 1. Evolution of the sample's market assets and market capitalization

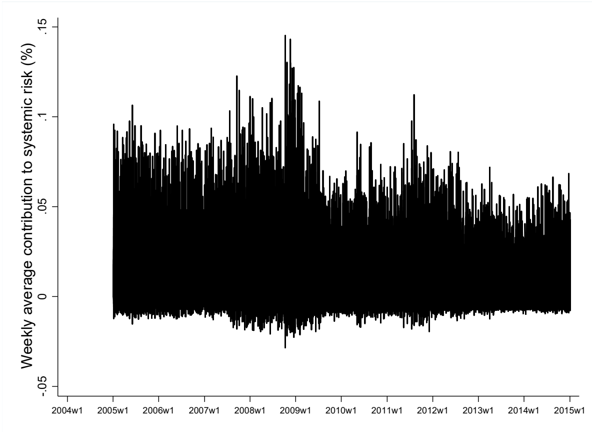


Note: The figure presents the evolution of the market value of total assets and market capitalization for 110 European banks from 2005 to 2014. The market value of total assets for each bank is determined by adjusting the total assets from the balance sheet with the ratio between the market value of equity (market capitalization) and the book value of equity. The values are expressed in billion euros.

Figure 2. Weekly individual risk and contribution to systemic risk of banks



Individual risk (VaR)

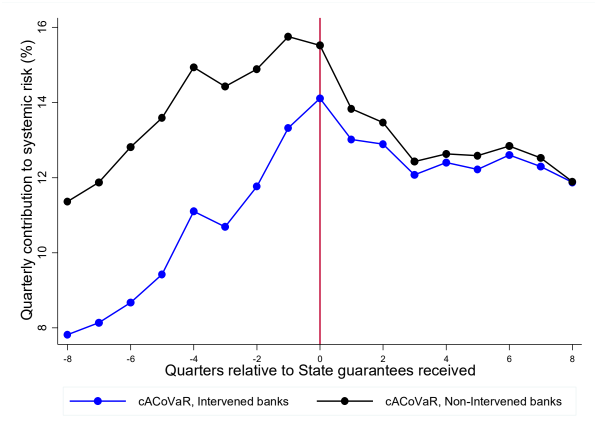


Contribution to systemic risk (cACoVaR)

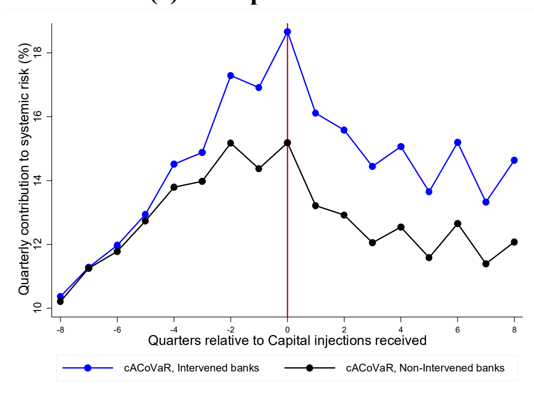
Note: The figures present the weekly evolution of *Individual risk (VaR*) and *Contribution to systemic risk (cACoVaR)* for all 110 banks in our sample during 2005-2014. Values obtained for each bank are averaged on a weekly base for the whole sample. The output corresponds to the asymmetric systemic risk models based on the *1% Quantile Regression* with heteroskedasticity robust standard errors. *Value at Risk (VaR)* is determined as in Eq. (5), whereas *Asymmetric Contribution to Systemic Risk (cACoVaR)* is determined as in Eq. (11). The values are expressed in weekly percentage loss of the banks' market assets for *VaR*, and weekly percentage loss of the system's market assets for *cACoVaR*.

Figure 3. Contribution to systemic risk of affected and non-affected banks before and after interventions

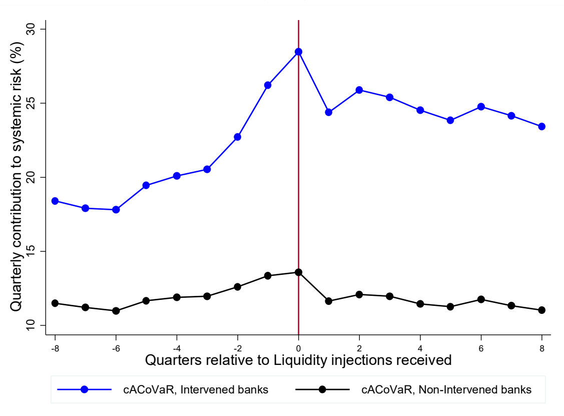
(1) State guarantees



(2) Recapitalizations

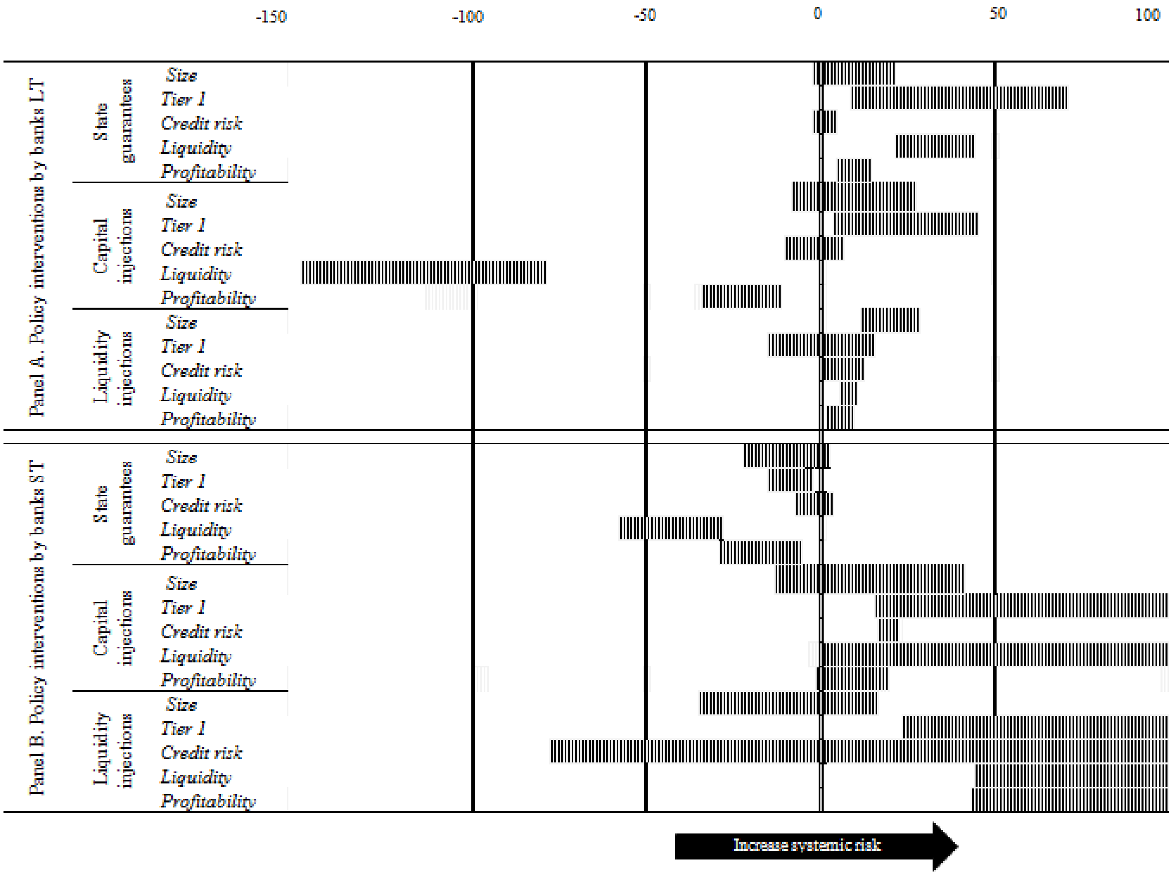


(3) Liquidity injections



Note: The figures present the average quarterly contribution to systemic risk of banks that received policy interventions during the crisis (intervened banks) and non-intervened banks eight quarters (two years) before and after the events. Values obtained for each bank using *cACoVaR* (determined as in Eq. (11) and expressed in percentage loss of the system's market assets within a quarter) are summed on a quarterly base and averaged for the intervened and, respectively non-intervened banks samples. Panel (1) presents the evolution of contributions to systemic risk for banks affected versus banks unaffected by state guarantees, Panel (2) for banks affected versus banks unaffected by capital injections, and, Panel (3) for banks affected versus banks unaffected by liquidity injections from government. The peak of interventions implemented by banks was recorded during 2008q4-2009q4.

Figure 4. Summary of systemic risk estimates along policy interventions and bank risk



Note: The figure summarizes the estimate of *Contribution to systemic risk* with respect with the indicated policy interventions (State guarantees, Recapitalizations and Liquidity injections) for the range between the mean minus one standard deviation and the mean plus one standard deviation of the bank risk characteristics (Size, Tier 1, Credit risk, Liquidity and Profitability). Panel A provides the output for long run effects, while Panel B for short run effects.

Table 1. Description of variables

Variable name	Description and calculation	Frequency	Source
Dependent variables (bank level)			
Delta CoVaR Asymmetric (cACoVaR)	Asymmetric contribution to systemic risk expressed in units of percentage loss of the system's market value of total assets within a quarter. The measure is determined using *Quantile Regression* method as in Eq. (11), based on market capitalization and a set of market indices specific to domestic and global financial markets. cACoVaR is an adjusted version of Delta CoVaR defined in Adrian and Brunnermeier (2016), i.e. the difference of the Value-at-Risk (VaR) of the system's market value of assets conditional on the distress of a particular bank (1% worst outcomes) and the VaR of the system's market value of assets conditional on the median state of the bank. cACoVaR accounts for the asymmetry of market value assets as in López-Espinosa et al. (2012). System is defined by the Market value of total assets of the sample.	Q	Own C[a]
Delta CoVaR DCC	Contribution to systemic risk expressed in units of percentage loss of the system's market value of equity within a quarter. The measure is determined using *DCC - GJR GARCH* method, based on market capitalization. System is defined by the Market capitalization of the sample.	Q	Own C[a]
Delta CoVaR QR	Contribution to systemic risk expressed in units of percentage loss of the system's market value of equity within a quarter. The measure is determined using *Quantile Regression* method, based on market capitalization. System is defined by the Market capitalization of the sample.	Q	Own C[a]
MES	Marginal expected shortfall expressed in units of percentage loss of the banks' market value of equity within a quarter. The measure is determined using *DCC - GJR GARCH* method. MES is defined as in Acharya et al. (2017) as the average return on bank's market capitalization on the days the total market capitalization of the sample experienced its 1% worst outcomes. System is defined by the Market capitalization of the sample.	Q	Own C[a]
SRISK	The loss of the banks expressed in billion EUR within a quarter conditioned by the whole system being in distress (1% worst outcomes). Systemic Risk Index is determined using *DCC - GJR GARCH* method. The measure is proposed by Acharya et al. (2012) and Brownlees and Engle (2017), based on banks' MES (Marginal Expected Shortfall) and market value of equity. System is defined by the Market capitalization of the sample.	Q	Own C[a]
Data used for estimating systemic			
Balance sheet data (bank level)			
Market equity	Market capitalization (bil eur)	W	Datastream
Total assets	The book value of Total Assets (bil eur)	Q	Worldscope
Book equity	The book value of Common Equity (bil eur)	Q	Worldscope
Market assets	$\text{Market Assets}_t^i = \text{Total Assets}_t^i \times \frac{\text{Market Equity}_t^i}{\text{Book Equity}_t^i}$ (%)	W	Worldscope
Returns on bank i's market assets in week t	$R^i_{\text{Market Asset (t)}} = \frac{\text{Market Assets}_t^i}{\text{Market Assets}_{t-1}^i} - 1$ (%)	W	Worldscope
Returns on system's market assets in week t	$R^{sys}_{\text{Market Assets (t)}} = \sum_i \frac{\text{Market Assets}_t^i}{\sum_i \text{Market Assets}_t^i} \times R^i_{\text{Market Assets,t}}$, i takes values from 1 to the sample's number of banks (%)	W	Worldscope
Value at Risk (VaR) in week t	Individual risk of bank i expressed in units of percentage loss of the bank's market value of total assets in week t. The measure is determined using *Quantile Regression* method as in Eq. (5)	W	Own C[a]
Financial market indices			
Government bonds yield	Change in the Government bonds (Euro triple A) yield curve instantaneous forward rate 10-years against 1-month residual maturity	W	ECB
Eonia rate	Change in the Eonia overnight interbank rate	W	Bundesbank
Euribor three-month rate	Change in the Euribor three-month interbank rate	W	Bundesbank

Real estate price index	Change in the Real estate price index for Europe	W	Datastream
Foreign exchange market index	Realized volatility of the euro exchange rate vis-a-vis the USD, JPY ans GBP (CISS stress subindex)	W	ECB
Data used for panel regressions			
Policy interventions (bank level)			
State guarantees	Guarantees provided by state j to bank i in quarter t (as % of Total assets)	Q	Own C[b]
Recapitalizations	Capital injections provided by state j to bank i in quarter t (as % of Total assets)	Q	Own C[b]
Liquidity injections	Liquidity injections provided by state j to bank i in quarter t (as % of Total assets)	Q	Own C[b]
State guarantees after event$_{1y(2y)}$	Indicates that the level of guarantees provided by state j to bank i in quarter t (as % of Total assets) is maintained at the same level 4 quarters (1 year) after event and 8 quarters (2 years) after event	Q	Own C[b]
Recapitalizations after event$_{1y(2y)}$	Indicates that the level of capital injections provided by state j to bank i in quarter t (as % of Total assets) is maintained at the same level 4 quarters (1 year) after event and 8 quarters (2 years) after event	Q	Own C[b]
Liquidity injections after event$_{1y(2y)}$	Indicates that the level of liquidity injections provided by state j to bank i in quarter t (as % of Total assets) is maintained at the same level 4 quarters (1 year) after event and 8 quarters (2 years) after event	Q	Own C[b]
Bank characteristics (bank level)			
Size	log(Total Assets)	Q	Worldscope
Leverage	Common Equity/Total Assets (%)	Q	Worldscope
Tier 1	Tier 1 Capital/Risk Weighted Assets (%)	Q	Worldscope
Credit risk ratio	Provisions for Loan Losses/Gross Loans (%)	Q	Worldscope
Liquidity ratio	Liquid Assets/Deposits and Short Term Funding (%)	Q	Worldscope
Return on Average Assets (ROAA)	Net Profit/Average Assets (%)	Q	Worldscope
Gross loans share	Gross Loans/Total Assets (%)	Q	Worldscope
Net non-interest margin	Net Non-Interest Income/Gross Revenues (%)	Q	Worldscope
Market & Macro controls (country level)			
Competition	Boone indicator, a measure of competition in the banking market calculated as the elasticity of profits to marginal costs. The lower the Boone indicator is, the higher the level of competition.	A	GFDB
Capital regulatory index	A composite index that measures the amount of regulatory capital banks must hold and the stringency of regulations on the quality capital. The index takes values from 0 (relaxed regulations) to 10 (tight regulations).	A	SBRS
Supervisory power index	A composite index that measures the strictness of prudential supervisory framework within the banking sector. The index takes values from 0 (relaxed supervision) to 14 (tight supervision).	A	SBRS
Inflation	Inflation measured by the consumer price index, reflecting the annual percentage change in the cost to the average consumer of acquiring a basket of goods and services that may be fixed or changed at specified intervals.	A	WDI
GDP growth	Gross domestic product at market prices, calculated as % change on previous period, based on 2005=100.	A	WDI
Other controls			
Crisis	Dummy variable that takes the value 1 after the Lehman Brothers collapse and 0 otherwise.	0/1	

Note: Y represents yearly frequency, Q is quarterly frequency, and, W is weekly frequency. Own C[a] represents own calculations using data from Worldscope, Datastream and FITCH, while Own C[b] are calculations based on data from banks' financial statements, websites and State Aid Register of European Commission. EC stands for European Commission, GFDB for Global Financial Development Database, SBRS for World Bank Survey of Bank Regulation and Supervision (2003, 2007 and 2011), BIS for Bank for International Settlements and WDI for World Development Indicators.

Table 2. The distribution of banks

Country	Number of banks	Total assets sample (billion €)	Total assets country (billion €)	Total assets sample / Total assets banking system (%)
Austria	6	354.00	915.11	38.68%
Belgium	1	245.00	1,021.57	23.98%
Bulgaria	2	4.94	47.41	10.41%
Cyprus	3	35.02	90.20	38.82%
Czech Republic	1	34.39	190.87	18.02%
Denmark	18	580.00	1,048.30	55.33%
Finland	1	4.29	525.31	0.82%
France	16	5,990.00	7,881.63	76.00%
Germany	6	2,280.00	7,528.95	30.28%
Hungary	1	34.87	116.06	30.05%
Ireland	2	237.00	1,016.95	23.30%
Italy	12	1,880.00	4,047.89	46.44%
Lithuania	1	1.64	24.04	6.82%
Malta	3	16.66	50.33	33.09%
Netherlands	2	1,010.00	2,250.13	44.89%
Poland	11	233.00	361.63	64.43%
Portugal	3	119.00	515.33	23.09%
Romania	3	19.04	91.40	20.83%
Slovakia	4	24.76	61.13	40.50%
Spain	6	2,620.00	3,150.74	83.16%
Sweden	4	1,480.00	1,514.50	97.72%
United Kingdom	4	3,050.00	8,895.35	34.29%
Total	**110**	**20,200.00**	**41,344.80**	**48.86%**
EU-28			**42,520.53**	**47.51%**

Source: The calculations are based on Worldscope data for Total assets of our sample and European Banking Federation data for Total assets of the banking system in each country at year end 2014.

Table 3. Summary statistics of systemic risk indicators

Panel A. All sample

	Variables	Unit	Mean	Std. dev.	Min	p25	p50	p75	Max	No. obs.
Contribution to systemic risk	cACoVaR	% loss of system's Market assets	12.42	16.38	-24.02	0.69	8.82	20.97	121.85	3080
	Delta CoVaR DCC	% loss of system's Market equity	3.01	2.79	-0.56	1.10	2.41	4.05	19.93	3080
	Delta CoVaR QR	% loss of system's Market equity	3.13	2.59	-1.21	1.42	2.81	4.27	21.27	3080
Exposure to systemic risk	MES	% loss of banks' Market equity	5.42	4.87	-0.47	2.13	4.59	7.51	53.24	3080
	SRISK	bil. Eur loss of banks' Market equity	12.55	30.26	-17.75	0.04	0.59	6.39	196.13	3060
Raw data	Market assets	bil. eur	15590.39	3674.84	13059.90	15430.20	17328.71	7223.16	26820.36	3080
	Market equity	bil. eur	731.28	165.54	616.88	737.81	838.82	276.64	1075.08	3080

Panel B. Intervened versus non-intervened banks

		Non-intervened bank								Intervened banks								Difference	
Variables	Unit	Mean	Std. dev.	Min	p25	p50	p75	Max	No. obs.	Mean	Std. dev.	Min	p25	p50	p75	Max	No. obs.		
State guarantees																			
cACoVaR	%	12.59	16.89	-24.02	0.69	8.41	20.91	121.85	2520	11.68	13.86	-17.36	0.78	9.43	21.11	84.28	560	-0.91	
Delta CoVaR DCC	%	2.71	2.65	-0.56	0.97	2.00	3.65	19.93	2520	4.40	2.98	0.02	2.75	3.75	5.15	17.50	560	1.70	***
Delta CoVaR QR	%	2.93	2.49	-1.02	1.21	2.51	4.00	21.27	2520	4.00	2.83	-1.21	2.50	3.63	5.24	20.38	560	1.07	***
MES	%	4.61	4.22	-0.47	1.88	3.65	6.27	48.43	2520	9.06	5.85	-0.09	6.35	8.11	10.04	53.24	560	4.46	***
SRISK	bil. eur	9.37	27.90	-3.25	0.02	0.35	1.53	171.26	2500	26.78	35.82	-17.75	4.61	10.72	39.45	196.13	560	17.42	***
Recapitalizations																			
cACoVaR	%	11.99	16.66	-24.02	0.58	6.47	19.67	121.85	2436	14.07	15.19	-12.49	2.45	12.06	23.06	84.28	644	2.08	***
Delta CoVaR DCC	%	2.57	2.52	-0.56	0.93	1.88	3.46	19.93	2436	4.69	3.11	0.02	2.90	4.00	5.55	18.80	644	2.12	***
Delta CoVaR QR	%	2.85	2.39	-1.02	1.15	2.44	4.00	19.12	2436	4.15	3.03	-1.21	2.54	3.57	5.15	21.27	644	1.29	***
MES	%	4.51	3.84	-0.47	1.86	3.63	6.45	32.73	2436	8.86	6.55	-0.09	5.58	7.52	10.17	53.24	644	4.36	***
SRISK	bil. eur	6.09	19.54	-2.38	0.02	0.35	1.59	170.82	2416	36.82	46.64	-17.75	2.97	13.54	64.63	196.13	644	30.74	***
Liquidity injections																			
cACoVaR	%	11.34	16.31	-24.02	0.11	6.66	18.53	121.85	2800	23.25	12.79	1.42	15.30	22.94	28.75	84.28	280	11.91	***
Delta CoVaR DCC	%	2.87	2.72	-0.56	1.01	2.24	3.88	19.93	2800	4.45	3.10	0.74	2.43	3.79	5.40	18.01	280	1.58	***
Delta CoVaR QR	%	3.05	2.49	-1.21	1.34	2.76	4.24	21.27	2800	3.89	3.34	0.22	1.74	3.13	4.49	20.38	280	0.84	***
MES	%	4.89	4.10	-0.47	1.99	4.17	6.96	34.54	2800	10.67	7.91	3.64	6.50	8.65	11.24	53.24	280	5.78	***
SRISK	bil. eur	9.98	26.90	-3.25	0.03	0.52	3.66	171.26	2780	38.12	45.95	-17.75	2.10	14.38	66.92	196.13	280	28.14	***

Note: The table reports the summary statistics of the dependent variables during 2008-2014. Panel A reports the output for the whole sample. Panel B provides the difference in means analysis between non-intervened banks and banks affected by policy interventions. Definition of variables is provided in Table 1. Values are expressed in units of percentage loss of the system's market assets within a quarter (cACoVaR), units of percentage loss of the system's market equity within a quarter (Delta CoVaR DCC, Delta CoVaR QR, MES) or billion EUR loss of market equity within a quarter (SRISK).

Table 4. Descriptive statistics of explanatory variables

Variables	Unit	Mean	Std. dev.	Min	p25	p50	p75	Max	No. obs.
Policy interventions (bank level)									
State guarantees (% of Total assets)	%	6.057	15.173	1.402	2.191	3.787	0.150	85.081	36
Recapitalizations (% of Total assets)	%	3.037	7.022	0.473	1.061	2.729	0.123	41.365	36
Liquidity injections (% of Total assets)	%	13.835	19.303	1.789	5.807	17.828	0.400	68.310	15
Risk profile indicators (bank level)									
Size	Log(bil. €)	23.845	2.496	18.986	21.946	23.754	25.854	28.554	2290
Leverage	%	8.714	5.857	1.080	5.530	7.620	10.640	90.390	2290
Tier 1 ratio	%	12.144	3.816	9.460	11.400	14.100	0.600	27.130	1738
Credit risk ratio	%	1.181	1.536	-8.889	0.426	0.814	1.432	29.907	2263
Liquidity ratio	%	30.719	41.116	11.610	20.250	38.250	2.470	812.310	2289
ROAA	%	0.447	1.131	0.170	0.460	0.820	-10.460	10.640	2299
Market & Macro conditions (country level)									
Competition (Boone indicator)	-	-0.038	0.046	-0.130	-0.064	-0.036	-0.024	0.223	2640
Capital regulatory index	-	6.159	2.039	4.000	6.000	8.000	3.000	11.000	3080
Supervisory power index	-	10.405	1.749	9.000	11.000	11.670	5.000	14.000	3080
Inflation	%	2.032	1.602	-4.480	0.864	2.000	2.961	12.349	3080
GDP growth	%	0.000	2.797	-13.863	-1.300	0.332	1.635	9.674	3068

Note: The definition of variables is provided in Table 1. Statistics are based on data spanning from 2008 to 2014.

Table 5. Estimations of banks' individual risk and contribution to systemic risk

Variable	Panel 1.VaR^{i} Y: $R^{i}_{Market\ Assets,t}$	Panel 2. Contribution CoVaR$^{sys\|i}$ Y: $R^{sys}_{Market\ Assets,t}$	
		Normal	Asymmetric
Banks' returns: $R^{i}_{Market\ Assets,t}$	-	0.012	-
		(0.03)	
Banks' returns: $R^{i}_{Market\ Assets,t} I_{(R^{i}_{Market\ Assets,t}<0)}$	-	-	0.073
			(0.06)
Banks' returns: $R^{i}_{Market\ Assets,t} I_{(R^{i}_{Market\ Assets,t}\geq 0)}$	-	-	0.006
			(0.04)
Government bonds yield (-1)	0.022	0.022	0.017
	(0.06)	(0.01)	(0.07)
Eonia rate (-1)	0.020	-0.007	-0.005
	(0.07)	(0.01)	(0.01)
Euribor three-month rate (-1)	0.095	0.041	0.042
	(0.17)	(0.03)	(0.03)
Real estate price index (-1)	0.521	1.071	1.060
	(0.17)	(0.03)	(0.04)
Foreign exchange market index (-1)	-0.505	-0.192	-0.163
	(0.26)	(0.05)	(0.04)
Pseudo R^2	0.33	0.68	0.78
Number of observations per bank	520	520	520
LR_{UC} test (no. of violations)[1]	2	1	3
LR_{UC} statistic (mean)	(1.66)	(1.42)	(2.02)
LR_{IND} test (no. of violations)[2]	0	0	0
LR_{IND} statistic (mean)	(-118.73)	(-120.49)	(-130.01)
LR_{CC} test (no. of violations)[3]	0	0	1
LR_{CC} statistic (mean)	(1.66)	(1.42)	(2.02)

Note: This table represents the output of a *1% Quantile Regression* with heteroskedasticity robust standard errors and t-statistics, estimated separately for each of the 110 banks from our sample analyzed during 2005-2014. *Normal* stands for the original *CoVaR* model proposed by Adrian and Brunnermeier (2016), while *Asymmetric* represents its asymmetric extension developed by López-Espinosa et al. (2012). The table reports the median of the estimated coefficients, median robust standard errors in parentheses and Pseudo-R^2. All models include a Crisis dummy and a constant.

The dependent variable is represented by the return on the market value of total assets of bank i in week t (% change) in the *VaR* specifications, and respectively by the return on the market value of total assets of the system in week t (% change) for the *Contribution CoVaR* specifications. The *VaR* model is described by Eq. (3), the *Contribution CoVaR* model by Eq. (4) and its asymmetric extension by Eq. (9). All explanatory variables are one week lagged.

[1] *The Kupiec test* is based on the likelihood ratio test of unconditional coverage (LR_{UC}) which statistic follows a $\lambda^2(1)$ distribution. The critical value for a 99% confidence interval is 6.635. Under the null hypothesis H_0: $LR^{i}_{UC} = q$, with the alternative H_1: $LR^{i}_{UC} > q$ where the model is not correctly specified (see Appendix 4 Eq. (A1.4)). The table reports the number of violations and the mean statistic in parentheses.

[2] *The Christoffersen test* of independence is based on the likelihood ratio test of independence (LR_{IND}) which statistic follows a $\lambda^2(1)$ distribution. The critical value for a 99% confidence interval is 6.635. Under the null hypothesis the exception occurred in week t is not conditional on the exception occurred in the previous week and the model is correctly specified (see Appendix 4 Eq. (A1.6)). The table reports the number of violations and the mean statistic in parentheses.

[3] *The Christoffersen* test for conditional coverage is based on the likelihood ratio test of conditional coverage (LR_{CC}) which statistic follows a $\lambda^2(2)$ distribution. The critical value for a 99% confidence interval is 9.210. Under the null hypothesis the model is correctly specified (see Appendix 4 Eq. (A1.9)). The table reports the number of violations and the mean statistic in parentheses.

Table 6. Long run impact of policy interventions by banks on systemic risk

								benchmark model
Dependent variable	cACoVaR (1)	cACoVaR (2)	cACoVaR (3)	cACoVaR (4)	cACoVaR (5)	cACoVaR (6)	cACoVaR (7)	cACoVaR (8)
Policy interventions								
Guarantees after event 1 year	-0.010	-0.006	-0.009	-0.009	0.017	0.014	0.015	0.015
	(0.026)	(0.025)	(0.026)	(0.026)	(0.029)	(0.030)	(0.031)	(0.031)
Recapitalizations after event 1	0.010	-0.006	0.008	0.008	-0.051	-0.040	-0.039	-0.039
	(0.061)	(0.051)	(0.058)	(0.058)	(0.059)	(0.062)	(0.064)	(0.064)
Liquidity injections after event 1	**0.148*** **	**0.154*** **	**0.146*** **	**0.146*** **	**0.076** **	**0.114*** **	**0.116*** **	**0.116*** **
	(0.026)	**(0.023)**	**(0.025)**	**(0.025)**	**(0.038)**	**(0.038)**	**(0.038)**	**(0.038)**
Bank characteristics								
Size	-2.479		-2.482	-2.482	-1.946	-2.525	-2.475	-2.475
	(1.689)		(1.722)	(1.722)	(1.586)	(1.644)	(1.643)	(1.643)
Leverage	-0.471**		-0.493***	-0.493***	-0.468***	-0.487***	-0.490***	-0.490***
	(0.191)		(0.182)	(0.182)	(0.170)	(0.175)	(0.175)	(0.175)
Credit risk ratio	0.113		0.136	0.136	-0.330*	0.102	0.089	0.089
	(0.261)		(0.235)	(0.235)	(0.169)	(0.221)	(0.217)	(0.217)
Liquidity ratio	-0.012		-0.007	-0.007	-0.006	-0.006	-0.005	-0.005
	(0.015)		(0.016)	(0.016)	(0.012)	(0.015)	(0.015)	(0.015)
ROAA	0.010		0.073	0.073	-0.030	0.172	0.191	0.191
	(0.323)		(0.268)	(0.268)	(0.215)	(0.262)	(0.241)	(0.241)
Gross loans share		0.000	0.016	0.016	-0.013	0.023	0.019	0.019
		(0.039)	(0.040)	(0.040)	(0.031)	(0.038)	(0.038)	(0.038)
Net non-interest margin		-0.004	-0.005	-0.005	-0.015*	-0.004	-0.006	-0.006
		(0.011)	(0.009)	(0.009)	(0.008)	(0.009)	(0.009)	(0.009)
Market and macro controls								
Competition						-3.574	-4.297	-4.297
						(8.554)	(8.353)	(8.353)
Capital regulatory index						-0.480**	-0.475**	-0.475**
						(0.188)	(0.185)	(0.185)
Supervisory power index						-0.132	-0.132	-0.132
						(0.149)	(0.146)	(0.146)
Inflation							0.197	0.197
							(0.189)	(0.189)
GDP growth							-0.103	-0.103
							(0.142)	(0.142)
Bank FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	NO	YES	YES	YES
Country FE	NO	NO	NO	YES	NO	NO	NO	YES
Country*Year FE	NO	NO	NO	NO	YES	NO	NO	NO
Cluster	Banks	Banks	Banks	Banks	Banks	Banks	Banks	Banks
Observations	2,265	2,257	2,238	2,238	2,238	2,238	2,238	2,238
Number of banks	110	110	110	110	110	110	110	110
No of countries	22	22	22	22	22	22	22	22
R-squared	0.177	0.158	0.175	0.175	0.349	0.197	0.198	0.198

Note: This table reports the estimation results of the following regression:

$$SystemicRisk_{ij,t} = \beta_0 + \beta_1 \times Policy\ interventions\ after\ event_{ij,t} + \Phi \times Bank\ controls_{ij,t-1} + \Psi \times\ Market\ \&\ Macro\ controls_{j\,j,t-1} + \varphi_i + \mu_j + \upsilon_t + \varepsilon_{ij,t}$$

Method used is *OLS Fixed Effects*. The sample includes 110 banks from 22 European countries and the period accounts for 28 quarters during 2008-2014. The dependent variable is represented by Delta CoVaR Asymmetric (cACoVaR) estimated using Eq. (12) and reflects bank i's from country j contribution to systemic risk in quarter t. Policy interventions received by bank i from government j in quarter t-1 are allowed to be different from zero for one year (four quarters) after the event. Bank level variables are one quarter lagged; market and macro controls are four quarters lagged. All models include an unreported constant. Variables are winsorized within the 1% and 99% percentiles. Their definition is given in Table 1. Different specifications include year fixed effects, country fixed effects or country*year fixed effects. Standard errors clustered at the bank level in models (1)-(5) and at the bank level and quarter level in model (6) are reported in brackets.*, ** and *** denote significance levels of 10%, 5% and 1%.

Table 7. Short run impact of policy interventions by banks on systemic risk

								benchmark model
Dependent variable	cACoVaR (1)	cACoVaR (2)	cACoVaR (3)	cACoVaR (4)	cACoVaR (5)	cACoVaR (6)	cACoVaR (7)	cACoVaR (8)
Policy interventions								
Guarantees	0.067	0.140	0.063	0.063	0.048	0.066	0.066	0.066
	(0.150)	(0.151)	(0.149)	(0.149)	(0.128)	(0.130)	(0.127)	(0.127)
Recapitalizations	**-0.048*****	**-0.049*****	**-0.045*****	**-0.045*****	0.010	**-0.044*****	**-0.042****	**-0.042****
	(0.015)	**(0.018)**	**(0.015)**	**(0.015)**	(0.020)	**(0.016)**	**(0.018)**	**(0.018)**
Liquidity injections	-0.019	0.003	-0.025	-0.025	-0.039	-0.056	-0.054	-0.054
	(0.096)	(0.083)	(0.096)	(0.096)	(0.076)	(0.113)	(0.113)	(0.113)
Bank characteristics								
Size	-2.494		-2.494	-2.494	-1.988	-2.531	-2.489	-2.489
	(1.703)		(1.736)	(1.736)	(1.594)	(1.643)	(1.645)	(1.645)
Leverage	-0.463**		-0.492***	-0.492***	-0.466***	-0.482***	-0.487***	-0.487***
	(0.195)		(0.185)	(0.185)	(0.172)	(0.177)	(0.177)	(0.177)
Credit risk ratio	0.172		0.203	0.203	-0.321*	0.149	0.134	0.134
	(0.265)		(0.243)	(0.243)	(0.170)	(0.222)	(0.219)	(0.219)
Liquidity ratio	-0.013		-0.007	-0.007	-0.006	-0.006	-0.005	-0.005
	(0.015)		(0.016)	(0.016)	(0.012)	(0.015)	(0.015)	(0.015)
ROAA	0.010		0.094	0.094	-0.023	0.186	0.215	0.215
	(0.337)		(0.294)	(0.294)	(0.216)	(0.284)	(0.268)	(0.268)
Gross loans share		0.006	0.021	0.021	-0.011	0.028	0.025	0.025
		(0.041)	(0.041)	(0.041)	(0.031)	(0.039)	(0.039)	(0.039)
Net non-interest margin		-0.005	-0.007	-0.007	-0.015*	-0.006	-0.007	-0.007
		(0.011)	(0.009)	(0.009)	(0.008)	(0.009)	(0.009)	(0.009)
Market and macro controls								
Competition						-4.408	-4.911	-4.911
						(8.675)	(8.551)	(8.551)
Capital regulatory index						-0.524***	-0.524***	-0.524***
						(0.198)	(0.196)	(0.196)
Supervisory power index						-0.116	-0.113	-0.113
						(0.151)	(0.148)	(0.148)
Inflation							0.152	0.152
							(0.195)	(0.195)
GDP growth							-0.119	-0.119
							(0.146)	(0.146)
Bank FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	NO	YES	YES	YES
Country FE	NO	NO	NO	YES	NO	NO	NO	YES
Country*Year FE	NO	NO	NO	NO	YES	NO	NO	NO
Cluster	Banks	Banks	Banks	Banks	Banks	Banks	Banks	Banks
Observations	2,265	2,257	2,238	2,238	2,238	2,238	2,238	2,238
Number of banks	110	110	110	110	110	110	110	110
No of countries	22	22	22	22	22	22	22	22
R-squared	0.168	0.148	0.166	0.166	0.347	0.192	0.193	0.193

Note: This table reports the estimation results of the following regression:

$$SystemicRisk_{ij,t}=\beta_0 + \boldsymbol{\beta_1 \times Policy\ interventions_{ij,t-1}} + \Phi \times Bank\ controls_{ij,t-1} + \Psi \times\ Market\ \&\ Macro\ controls_{j\,j,t-1} + \varphi_i + \mu_j + \upsilon_t + \varepsilon_{ij,t}$$

Method used is *OLS Fixed Effects*. The sample includes 110 banks from 22 European countries and the period accounts for 28 quarters during 2008- 2014. The dependent variable is represented by Delta CoVaR Asymmetric (cACoVaR) estimated using Eq. (13) and reflects bank i's from country j contribution to systemic risk in quarter t. Policy interventions are received by bank i from government j in quarter t-1. Bank level variables are one quarter lagged; market and macro controls are four quarters lagged. All models include an unreported constant. Variables are winsorized within the 1% and 99% percentiles. Their definition is given in Table 1. Different specifications include year fixed effects, country fixed effects or country*year fixed effects. Standard errors clustered at the bank level in models (1)-(5) and at the bank level and quarter level in model (6) are reported in brackets.*, ** and *** denote significance levels of 10%, 5% and 1%.

Table 8. The impact of policy interventions. The effect for different systemic risk measures

		Panel A: Long term impact					Panel B: Short term impact				
		Contribution			Exposure		Contribution			Exposure	
Dependent variable		cACoVaR (1)	Delta CoVaR DCC (2)	Delta CoVaR QR (3)	MES (4)	SRISK (5)	cACoVaR (6)	Delta CoVaR DCC (7)	Delta CoVaR QR (8)	MES (9)	SRISK (10)
Policy interventions											
Guarantees	Coeff.	0.015	-0.077	-0.123	-0.198	-0.049	0.066	2.014	1.555	2.824	**6.734***
	S.E.	(0.031)	(0.073)	(0.170)	(0.263)	(0.503)	(0.127)	(1.452)	(1.193)	(2.266)	**(3.745)**
	Effect	*0.12*	*-2.56*	*-3.93*	*-3.65*	*-0.39*	*0.53*	*66.91*	*49.68*	*52.10*	***53.66***
Recapitalizations	Coeff.	-0.039	-0.193	0.284	0.490	0.191	**-0.042****	**-0.590*****	-0.096	-0.282	0.072
	S.E.	(0.064)	(0.226)	(0.449)	(0.699)	(1.418)	**(0.018)**	**(0.144)**	(0.202)	(0.357)	(0.691)
	Effect	*-0.31*	*-6.41*	*9.07*	*9.04*	*1.52*	***-0.34***	***-19.60***	*-3.07*	*-5.20*	*0.57*
Liquidity injections	Coeff.	**0.116*****	**0.173****	**0.346*****	**0.783*****	**1.745*****	-0.054	0.037	0.089	0.154	-3.767
	S.E.	**(0.038)**	**(0.085)**	**(0.107)**	**(0.248)**	**(0.577)**	(0.113)	(0.218)	(0.301)	(0.446)	(3.182)
	Effect	***0.93***	***5.75***	***11.05***	***14.45***	***13.90***	*-0.43*	*1.23*	*2.84*	*2.84*	*-30.02*
Bank characteristics		YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Market and macro controls		YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Bank FE		YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE		YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Country FE		YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Cluster		Banks	Banks	Banks	Banks	Banks	Banks	Banks	Banks	Banks	Banks
Observations		2,238	2,238	2,238	2,238	2,238	2,238	2,238	2,238	2,238	2,238
Number of banks		110	110	110	110	110	110	110	110	110	110
No of countries		22	22	22	22	22	22	22	22	22	22
R-squared		0.198	0.350	0.245	0.225	0.222	0.193	0.351	0.243	0.222	0.224

Note: Panel A shows the output for the long term impact of policy interventions corresponding to Eq. (12) (i.e., interventions received by bank i from government j in quarter t-1 are allowed to be different from zero for one year after the event. Panel B shows the output for the short term impact of policy interventions received by bank i from government j in quarter t-1, corresponding to Eq. (13). We report the results for the benchmark models (i.e., Column (8) Table 5 for long run effects, and, respectively, Column (8) Table 6 for short run effects.

Method used is *OLS Fixed Effects*. The sample includes 110 banks from 22 European countries and the period accounts for 28 quarters during 2008-2014. The dependent variable is the Delta CoVaR Asymmetric (cACoVaR) in models 1 and 6, Delta CoVaR DCC in models 2 and 7, Delta CoVaR QR in models 3 and 8, Marginal Expected Shortfall (MES) in models 4 and 9, and, Systemic risk indicator (SRISK) in models 5 and 10. The coefficients for bank characteristics, market and macro control variables are suppressed for brevity. Bank level variables are one quarter lagged; market and macro controls are four quarters lagged. All models include an unreported constant, year fixed effects and country fixed effects. Variables are winsorized within the 1% and 99% percentiles. Their definition is given in Table 1. Standard errors (S.E.) clustered at bank level are reported in brackets.*, ** and *** denote significance levels of 10%, 5% and 1%. Effect reflects the associated semi-elasticity.

Table 9. Policy interventions by banks. Interactions with bank risk

	Panel A: Long term impact					Panel B: Short term impact				
Dependent variable	cACoVaR	cACoVaR	cACoVaR	cACoVaR	cACoVaR	cACoVaR	cACoVaR	cACoVaR	cACoVaR	cACoVaR
Bank risk measure	***Size***	***Tier 1***	***Credit risk***	***Liquidity***	***Profitability***	***Size***	***Tier 1***	***Credit risk***	***Liquidity***	***Profitability***
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Policy interventions										
Guarantees	-1.005***	-0.584***	0.030	-0.102***	0.010	1.040	0.108	0.018	0.135**	0.036
	(0.359)	(0.156)	(0.048)	(0.034)	(0.029)	(0.719)	(0.186)	(0.039)	(0.064)	(0.054)
Recapitalizations	-0.255	-0.408***	-0.081	0.316*	-0.025	-2.458	-3.656	0.215	-0.224	0.266
	(1.109)	(0.155)	(0.066)	(0.177)	(0.066)	(2.175)	(2.515)	(0.315)	(0.432)	(0.338)
Liquidity injections	0.986	0.487**	0.021	0.154	0.119***	-2.549	1.656	1.065***	-0.454	0.176**
	(0.616)	(0.192)	(0.088)	(0.104)	(0.025)	(1.939)	(1.701)	(0.263)	(0.696)	(0.068)
Interventions × Bank risk										
Guarantees × *Bank risk*	**0.046*** **	**0.081*** **	-0.017	**0.006*** **	0.034	-0.048	-0.016	-0.032	**-0.008** **	-0.085
	(0.017)	**(0.021)**	(0.063)	**(0.001)**	(0.067)	(0.033)	(0.028)	(0.089)	**(0.004)**	(0.125)
Recapitalizations × *Bank risk*	0.012	**0.054*** **	0.048	**-0.021* **	-0.082	0.109	0.457	-0.017	0.028	-0.072
	(0.051)	**(0.020)**	(0.053)	**(0.011)**	(0.112)	(0.098)	(0.306)	(0.056)	(0.034)	(0.135)
Liquidity injections × *Bank risk*	-0.033	**-0.040* **	0.038	-0.001	**-0.027*** **	0.103	-0.170	**-0.680*** **	0.017	**0.234** **
	(0.023)	**(0.023)**	(0.037)	(0.003)	**(0.008)**	(0.073)	(0.212)	**(0.220)**	(0.019)	**(0.106)**
Bank characteristics	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Market and macro controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Bank FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Country FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Cluster	Banks	Banks	Banks	Banks	Banks	Banks	Banks	Banks	Banks	Banks
Observations	2,238	1,702	2,238	2,238	2,238	2,238	1,702	2,238	2,238	2,238
Number of banks	110	110	110	110	110	110	110	110	110	110
No of countries	22	22	22	22	22	22	22	22	22	22
R-squared	0.200	0.182	0.199	0.200	0.199	0.202	0.187	0.203	0.201	0.201

Note: This table reports the estimation results of the following regression:

$$SystemicRisk_{ij,t} = \beta_0 + \boldsymbol{\beta_1 \times Policy\ interventions_{ij,t-1}} + \boldsymbol{\beta_2 \times Policy\ interventions_{ij,t-1} \times Bank\ risk_{ij,t-1}} + \Phi \times Bank\ controls_{ij,t-1} + \Psi \times Market\ \&\ Macro\ controls_{j,t-1} + \varphi_i + \mu_j + \upsilon_t + \varepsilon_{ij,t}$$

Method used is *OLS Fixed Effects*. The sample includes 110 banks from 22 European countries and the period accounts for 28 quarters during 2008-2014. The dependent variable is represented by Delta CoVaR Asymmetric (cACoVaR) estimated using Eq. (11) and reflects bank i's from country j contribution to systemic risk in quarter t.

Panel A shows the output for the long term impact of rescue measures interacted with bank risk profiles (i.e., interventions received by bank i from government j in quarter t-1 are allowed to be different from zero for one year after the event), corresponding to Eq. (14). Panel B shows the output for the short term impact of policy interventions (i.e., received by bank i from government j in quarter t-1) interacted with bank risk profiles, corresponding to Eq. (15). We report the results for the benchmark models (i.e., Column (8) Table 5 for long run effects and Column (8) Table 6 for short run effects that includes bank level controls (Size, Leverage, Credit risk, Liquidity, Profitability) and banking market and macro controls (Competition, Capital regulatory index, Supervisory power index, Inflation, GDP growth). The coefficients for bank characteristics, market and macro control variables are suppressed for brevity.

Bank level variables are one quarter lagged; market and macro controls are four quarters lagged. All models include an unreported constant, year fixed effects and country fixed effects. Variables are winsorized within the 1% and 99% percentiles. Their definition is given in Table 1. Standard errors clustered at bank level are reported in brackets.*, ** and *** denote significance levels of 10%, 5% and 1%.

APPENDICES

Appendix 1. List of banks and their SIB status

Country	Bank	FSB list (G-SIBs)	EBA list	ECB List	Own calculations (SIBs)
Austria	BKS Bank AG				
	Bank für Tirol und Vorarlberg AG-BTV (3 Banken Gruppe)				
	Erste Group Bank AG		*	$	%
	Oberbank AG				
	Raiffeisen Bank International AG		*	$	%
	Volksbank Vorarlberg e.Gen.			$	
Belgium	KBC Groep NV/ KBC Groupe SA		*	$	%
Bulgaria	Bulgarian-American Credit Bank				
	First Investment Bank AD				%
Cyprus	Bank of Cyprus Public Company Limited-Bank of Cyprus Group		*	$	
	Hellenic Bank Public Company Limited		*	$	
	USB Bank Plc				%
Czech Republic	Komercni Banka				
Denmark	Danske Bank A/S		*		%
	Fynske Bank A/S				
	Bank of Greenland-Gronlandsbanken A/S				
	Jutlander Bank A/S				%
	Jyske Bank A/S (Group)		*		
	Kreditbanken A/S				
	Laan & Spar Bank A/S				
	Lollands Bank A/S				
	Moens Bank A/S				
	Nordjyske Bank A/S				
	Nordfyns Bank A/S				
	Oestjydsk Bank A/S				
	Ringkjoebing Landbobank				%
	Salling Bank A/S				
	Skjern Bank				
	Spar Nord Bank				%
	Sydbank A/S		*		
	Totalbanken A/S				
Finland	Alandsbanken Abp-Bank of Aland Plc				
France	Crédit Agricole S.A.	#	*	$	%
	BNP Paribas	#	*	$	%
	Caisse Régionale de Crédit Agricole mutuel de Paris et d'Ile-de-France SC				
	Caisse Régionale de Crédit Agricole Mutuel Toulouse 31 SC				
	Crédit Industriel et Commercial SA - CIC				%
	Caisse Régionale de Crédit Agricole mutuel de Normandie-Seine				
	Caisse Régionale de Crédit Agricole mutuel de l'Ille-et-Vilaine SC				
	Caisse Régionale de Crédit Agricole mutuel du Morbihan SC				
	Caisse Régionale de Crédit Agricole mutuel Nord de France SC				
	Caisse Régionale de Crédit Agricole mutuel d'Alpes-Provence SC				
	Caisse Régionale de Crédit Agricole Mutuel Brie Picardie SC				%
	Caisse Régionale de Crédit Agricole mutuel Loire Haute-Loire SC				
	Caisse Régionale de Crédit Agricole mutuel Sud Rhône -Alpes SC				
	Caisse Régionale de Crédit Agricole mutuel de la Touraine et du Poitou SC				
	Société Générale SA	#	*	$	%
	Natixis SA				
Germany	Commerzbank AG		*	$	
	Deutsche Bank AG	#	*	$	%
	Merkur-Bank KGaA				
	Oldenburgische Landesbank - OLB				
	quirin bank AG				
	UmweltBank AG				
Hungary	OTP Bank Plc		*		%
Ireland	Allied Irish Banks plc		*	$	
	Bank of Ireland-Governor and Company of the Bank of Ireland		*	$	%
Italy	Banca Popolare dell'Emilia Romagna		*	$	
	Banco di Sardegna SpA				
	Banca Carige SpA		*	$	
	Banca Piccolo Credito Valtellinese-Credito Valtellinese Soc Coop		*		%
	Intesa Sanpaolo		*	$	
	Mediobanca SpA		*	$	%
	Banca Popolare dell'Etruria e del Lazio Soc. coop.				
	Banca Popolare di Milano SCaRL		*	$	
	Banca Profilo SpA				%
	Banca Popolare di Spoleto SpA				%
	Unione di Banche Italiane Scpa-UBI Banca		*	$	
	UniCredit SpA	#	*	$	
Lithuania	Siauliu Bankas				
Malta	Bank of Valletta Plc		*	$	
	FIMBank Plc				
	HSBC Bank Malta Plc			$	
Netherlands	ING Groep NV	#	*	$	
	Van Lanschot NV				
Poland	Bank Handlowy w Warszawie S.A.		*		%
	Bank BGZ BNP Paribas SA				%
	Bank Ochrony Srodowiska SA - BOS		*		
	Bank BPH SA		*		%
	Bank Zachodni WBK SA				%
	Getin Holding SA				
	ING Bank Slaski SA - Capital Group				%
	mBank SA				%
	Bank Millennium				%
	Bank Polska Kasa Opieki SA-Bank Pekao SA				
	Powszechna Kasa Oszczednosci Bank Polski SA - PKO BP SA		*		%
Portugal	Banco Comercial Português SA-Millennium BCP		*	$	
	Banco Espirito Santo SA		*		
	Banco BPI SA		*	$	
Romania	Banca Comerciala Carpatica SA				%
	BRD-Groupe Societe Generale SA				
	Transilvania Bank-Banca Transilvania SA				
Slovakia	OTP Banka Slovensko a.s.				%
	Prima Banka Slovensko a.s.				%
	Tatra Banka a.s.			$	
	Vseobecna Uverova Banka a.s.			$	
Spain	Banco Bilbao Vizcaya Argentaria SA		*	$	%
	Bankinter SA		*	$	
	Caixabank SA				
	Banco Popular Espanol SA		*	$	
	Banco de Sabadell SA		*	$	
	Banco Santander SA	#	*	$	
Sweden	Nordea Bank AB	#	*		
	Skandinaviska Enskilda Banken AB		*		%
	Svenska Handelsbanken		*		%
	Swedbank AB		*		
United Kingdom	European Islamic Investment Bank Plc				
	Lloyds Banking Group Plc		*		%
	Royal Bank of Scotland Group Plc	#	*		%
	Standard Chartered Plc	#			
Total	110	10	44	32	37

Note: # denotes that the bank is included in the Financial Stability Board (FSB) list of G-SIBs (Global Systemically Important Banks). * denotes that the bank is included in the European Banking Association (EBA) stress testing exercise. $ denotes that the bank is included in the European Central Bank (ECB) Single Supervisory Mechanism (SSM). % represents SIBs, banks we identified as presenting a significant contribution to systemic risk (i.e., banks with a significant $\delta^{sys|i\,(-)}$ coefficient at 95% confidence level in Eq. (9)).

Appendix 2. Policy interventions implemented at bank level during 2008-2014 (events)

		State guarantees				Recapitalizations				Liquidity injections			
Country	**Bank**	**Size** (bil eur)	**Date**	**Type**	**Source**	**Size** (bil eur)	**Date**	**Type**	**Source**	**Size** (bil eur)	**Date**	**Type**	**Source**
Austria	Erste Group Bank AG	4.05	Jun//2009	Debt instruments	Erste Bank Group Annual Report 2009	1.22	Apr//2009	Participation capital	Erste Bank Group Annual Reports 2009, 2010				
Austria	Raiffeisen Bank International AG	2.75	28-Jan-09	Debt instruments	Raiffeisen Annual report 2009	1.75	6-Apr-09	Participation capital	Raiffeisen Annual report 2009				
		1.50	23-Apr-09	Debt instruments	Raiffeisen Annual report 2009								
Austria	Volksbank Vorarlberg e.Gen.	2.00	9-Feb-09	Debt instruments	EC Decision C(2015) 4635 on SA.31883 - 2015/N, 2011/C	1.00	Apr//2009	Participation certificates	EC Decision C(2015) 4635 on SA.31883 - 2015/N, 2011/C				
		1.00	14-Sep-09	Debt instruments	EC Decision C(2015) 4635 on SA.31883 - 2015/N, 2011/C	0.25	19-Sep-12	Ordinary shares	EC Decision C(2015) 4635 on SA.31883 - 2015/N, 2011/C				
		0.10	15-Mar-13	Asset guarantee	EC Decision C(2015) 4635 on SA.31883 - 2015/N, 2011/C								
Belgium	KBC Groupe SA					3.50	18-Dec-08	Core Tier-1 securities (Belgian State)	EC Decision C(2009) 5268 on C 18/2009 (ex N 360/2009)	20.00	30-Jun-09	Protection on CDO portfolio	EC Decision C(2009) 5268 on C 18/2009 (ex N 360/2009)
						3.50	30-Jun-09	Core Tier-1 securities (Flemish Region)	EC Decision C(2009) 5268 on C 18/2009 (ex N 360/2009)				
Bulgaria	First Investment Bank AD									0.60	29-Jun-14	State deposit received under the Liquidity Support Scheme (LSS)	EC Decision C(2014) 8959 on SA.39854 (2014/N)
Cyprus	Bank of Cyprus Public Company Limited	1.00	Nov//2013	Debt instruments	Bank of Cyprus Group Annual Report 2014					11.10	June//2013	Emergency Liquidity Assistance (following the absorption of Laiki Bank)	European Parliament. Beiefing - Cyprus' financial assistance programme (March 2016)
Denmark	Danske Bank A/S	4.69	16-Jun-09	Bonds 36.4 bil DKK	Danske Bank Annual Report 2009 & 2011	3.22	May//2009	Subordinated loan capital in the form of hybrid capital.	Danske Bank Annual Report 2009				
		4.87	Dec//2011	Bonds 37.8 bil DKK	Danske Bank Annual Report 2011								
Denmark	Ringkjoebing Landbobank					0.03	30-Jun-08	Tier 2 Subordinated loan capital	Ringkjoebing Landbobank Annual Report 2009				
Denmark	Spar Nord Bank					0.17	May//2009	Hybrid core capital	Spar Nord Bank Annual Report 2010				
France	BNP Paribas					2.55	8-Dec-08	Core Tier-1 securities	EC Decision C(2008) 8278 on SA.613/2008				
						2.55	31-Mar-09	Preferred shares	*Les concours publics aux établissements de crédits : Bilan et enseignements à tirer*, Rapport public thématique, Cour des comptes, May 2010.				
France	Crédit Agricole S.A.					3.00	8-Dec-08	Core Tier-1 securities	EC Decision C(2008) 8278 on SA.613/2008				
France	Natixis SA	0.84	Dec//2008	Debt instruments	Natixis Annual Report 2009	2.00	26-Jun-09	Deeply subordinated perpetual notes (Tier 1 capital)	Natixis Annual Report 2009				
						3.15	1-Jan-10	Deeply subordinated perpetual notes (Tier 1 capital)	Natixis Annual Report 2010				
France	Société Générale SA					1.70	8-Dec-08	Core Tier-1 securities	EC Decision C(2008) 8278 on SA.613/2008				
						1.70	19-May-09	Preferred shares	*Les concours publics aux établissements de crédits : Bilan et enseignements à tirer*, Rapport public thématique, Cour des comptes, May 2010.				
Germany	Commerzbank AG	15.00	19-Dec-08	Guarantee for debt securities	EC Decision C(2012) 2227 on SA.34539 (2012N)	18.20	31-Dec-08	EUR 8.2bn in Silent participation (1st), EUR 8.2bn in silent participation (2nd) - perpetual hybrid Tier 1 capital, and EUR 1.8bn in ordinary shares	EC Decision C(2012) 2227 on SA.34539 (2012N)	2.50	19/12/2008	Loans	Commerzbank Financial Report 2008
Hungary	OTP Bank Plc									1.40	26-Mar-09	Loan facility: the bank was	OTP Annual Report

												granted a total of EUR 500.8 million, GBP 135.9 million, JPY 20.1 billion and USD 818 million in two tranches	2009
										0.34	Q3//2009	EBRD provided a CHF 0.5 bil CHF/HUF swap facility	OTP Annual Report 2009
Ireland	Allied Irish Banks plc	6.00	Dec//2009	Bonds issue	AIB Annual Report 2009	3.50	13-May-09	Core Tier 1 new preference shares	EC Decision C(2011) 5177 on SA.33296 (2011/N)	8.50	Dec//2010	NAMA had acquired €21.3 billion of gross loans for consideration of €9.4 billion (ECB eligible, Government guaranteed senior notes)	National Asset Management Agency – Annual Report 2010
		6.00	Dec//2010	Bonds issue	AIB Annual Report 2010	3.70	23-Dec-10	Core Tier 1 ordinary shares	EC Decision C(2011) 5177 on SA.33296 (2011/N)	9.40	Dec//2011	NAMA had acquired €18.5 billion of gross loans for consideration of €8.5 billion (ECB eligible, Government guaranteed senior notes)	National Asset Management Agency – Section 227 Review (2011)
		3.70	Jan//2011	Bonds issue	AIB Annual Report 2011	13.30	5-Jul-11	recapitalization provided to facilitate the merger of Allied Irish Bank and EBS	EC Decision C(2011) 5177 on SA.33296 (2011/N)				
Ireland	Bank of Ireland-Governor and Company of the Bank of Ireland	1.25	Jun//2008	Debt instruments	Bank of Ireland Annual Report 2009	3.50	26-Mar-09	Core Tier 1 (preference stock)	State aid SA.33216 (2011/N); State aid SA.33443 (2011/N)	5.20	Dec//2010	NAMA had acquired €9.4 billion of gross loans for consideration of €5.2 billion (ECB eligible, Government guaranteed senior notes)	National Asset Management Agency – Section 227 Review (2010)
		2.00	Nov//2008	Debt instruments	Bank of Ireland Annual Report 2009	5.20	31-Jul-11	EUR 4.2 bil Core Tier 1 capital and EUR 1 bil contingent capital	State aid SA.33216 (2011/N); State aid SA.33443 (2011/N)	5.60	Dec//2011	NAMA had acquired €9.9 billion of gross loans for consideration of €5.6 billion (ECB eligible, Government guaranteed senior notes)	National Asset Management Agency – Section 227 Review (2011)
Italy	Banca Piccolo Credito Valtellinese-Credito Valtellinese Soc Coop					0.20	30-Dec-09	Tier 1 (Tremonti bonds)	Banca Piccolo Credito Valtellinese Annual Report 2009				
Italy	Banca Popolare di Milano SCaRL	1.50	23-Dec-11	Bonds	BPM Annual Report 2009	0.50	4-Dec-09	Tier 1 qualifying hybrid instruments	EC Decision C(2010) 7293 on SA.N 425/2010				
Italy	Intesa Sanpaolo	12.00	6-Dec-11	Bonds	Intesa Sanpaolo Annual Report 2011								
Italy	Mediobanca SpA	3.50	31-Dec-11	Bonds	Mediobanca Annual Report 2012								
Italy	Unione di Banche Italiane Scpa-UBI Banca	6.00	2-Jan-12 & 27-Feb-12	Bonds	UBI Annual Reports 2012, 2013								
Netherlands	ING Groep NV	11.28	Q1//2009	Bonds	ING Bank Annual Report 2009	10.00	12-Nov-08	Core Tier 1 securities	EC Decision C(2012) 8238 on SA.33305 (2012C) and SA.29832 (2012C)	19.70	26-Jan-09	'Illiquid Assets Back-up Facility (IABF). ING Bank has transferred 80% of the ownership of its Alt-A portfolio to the Dutch State	ING Bank Annual Report 2009
Portugal	Banco BPI SA					1.50	29-Jun-12	Contingent convertible subordinated bonds ("CoCos")	EC Discusion C(2013) 4802 on SA.35238 (2013N)				
Portugal	Banco Comercial Português, SA-Millennium bcp	1.50	9-Jan-09	Bond issue guarantee	Millenium BCP Annual Report 2009	3.00	29-Jun-12	Contingent convertible subordinated bonds ("CoCos")	EC Discusion C(2013) 5669 on SA.34724 (2013N)				
		1.75	Q3//2011	Bond issue guarantee	Millenium BCP Annual Report 2011								
		2.90	20-Feb-12	Bond issue guarantee	Millenium BCP Annual Report 2012								
		0.25	1-Jan-14	Bond issue guarantee	EC Discusion C(2013) 5669 on SA.34724 (2013N)								
Portugal	Banco Espirito Santo SA	1.50	9-Jan-09	Bond issue guarantee	BES Annual Report 2009								
		1.25	19-Jul-11	Senior notes guarantee	BES Annual Report 2011								
		1.00	23-Dec-11	Bond issue guarantee	BES Annual Report 2011								
		2.50	6-Jan-12	Debt guarantee	BES Annual Report 2012								
Spain	Banco de Sabadell SA	3.69	30-Dec-08	Bond issue guarantee (including those of Banco Guipuzcoano)	Banco de Sabadell Annual Report 2008	5.25	Dec//2011	Capital injection by CIDGF (Credit Institutions Deposit Guarantee Fund) to CAM prior to sale to Banco Sabadell	Banco de Espana. *Background note on the public financial assistance in the recapitalisation of the Spanish banking system (2009-2013)*, 02.09.2013				

		2.31	30-Sep-09	Bond issue guarantee (including those of Banco Guipuzcoano)	Banco de Sabadell Annual Report 2009	0.25	Apr//2013	Subscription of capital by FROB (Fondo de Reestructuracio Ordenada Bancaria) to Banco Gallego prior to sale to Banco Sabadell					
		1.50	22-Dec-11	Bond issue guarantee	Banco de Sabadell Annual Report 2011								
Spain	Caixabank, S.A.					1.00	May//2012	Subscription of capital by FROB in Banco de Valencia prior to integration in Caixagroup					
						4.50	Dec//2012	Subscription of capital by FROB in Banco de Valencia prior to integration in Caixagroup	Banco de Espana. *Background note on the public financial assistance in the recapitalisation of the Spanish banking system (2009-2013)*, 02.09.2013				
						0.98	Apr//2013	Subscription of preference shares by FROB in Banca Civica group prior to integration in Caixagroup					
Sweden	Swedbank AB	23.60	31-Dec-09	Debt issue SEK 242 bn	Swedbank Annual Report 2009								
United Kingdom	Lloyds Banking Group Plc	60.00	31-Dec-09	Debt issue £ 49 bn	Lloyds Annual Report 2009	19.00	19-Jan-09	Capital injection of GBP 13bn in ordinary shares and GBP 4bn in preference shares	EC Decision C(2009) 9087 on SA.N 428/2009	188.00	21-Apr-08	£157 billion from BoE swap temporarily illiquid assets for treasury bills through Special Liquidity Scheme (SLS)	Lloyd's Annual Report 2009
						6.25	3-Nov-09	Capital injection of GBP 5.9bn (rights issue)	EC Decision C(2009) 9087 on SA.N 428/2009	312.00	7-Mar-09	Asset Protection Scheme (APS), asset covered £ 260 bn	EC Decision C(2009) 9087 on SA.N 428/2009
United Kingdom	Royal Bank of Scotland Group Plc	40.00	31-Dec-08	Debt issue £ 32.2 bn	RBS Annual Report 2008	22.90	1-Dec-08	Capital injection of GBP 15bn in ordinary shares and GBP 5bn in preference shares	EC Decision C(2009) 10112 on SA.N 422/2009 and SA.N 621/2009	45.00	17-Oct-08	£ 36.6 bn from BoE to swap temporarily illiquid assets for treasury bills through Special Liquidity Scheme (SLS)	EC Decision C(2009) 10112 on SA.N 422/2009 and SA.N 621/2009
		25.00	31-Dec-09	Debt issue £ 19.3 bn	RBS Annual Report 2009	28.00	3-Nov-09	Capital injection of GBP 25.5bn in non-voting B shares	EC Decision C(2009) 10112 on SA.N 422/2009 and SA.N 621/2009	340.00	22-Dec-09	Asset Protection Scheme (APS), asset covered £ 282 bn	RBS Annual Report 2009

Note: Bank level policy interventions data extracted from banks' annual reports, financial statements, websites and State Aid Register of European Commission.

Appendix 3. Summary of policy interventions implemented at bank level during 2008-2014

Country	Bank	State guarantees			Recapitalizations			Liquidity injections		
		No. events	Total injection size (bil. Eur)	Average injection size (%Total Assets)	No. events	Total injection size (bil. Eur)	Average injection size (%Total Assets)	No. events	Total injection size (bil. Eur)	Average injection size (%Total Assets)
Austria	Erste Group Bank AG	1	4.05	1.98%	1	1.22	0.60%			
	Raiffeisen Bank International AG	2	4.25	2.68%	1	1.75	2.25%			
	Volksbank Vorarlberg e.Gen.	3	3.10	43.62%	2	1.25	26.06%			
Belgium	KBC Groep NV				2	7.00	1.00%	1	20.00	5.81%
Bulgaria	First Investment Bank AD							1	0.60	13.02%
Cyprus	Bank of Cyprus Public Company Li	1	1.00	3.29%				1	11.10	33.68%
Denmark	Danske Bank A/S	2	9.56	1.07%	1	3.22	0.74%			
	Ringkjoebing Landbobank				1	0.03	1.11%			
	Spar Nord Bank				1	0.17	1.98%			
France	BNP Paribas				2	5.10	0.12%			
	Crédit Agricole S.A.				1	3.00	0.18%			
	Natixis SA	1	0.84	0.15%	2	5.15	0.55%			
	Société Générale SA		0.00		2	3.40	0.16%			
Germany	Commerzbank AG	1	15.00	2.40%	1	18.20	2.91%	1	2.50	0.40%
Hungary	OTP Bank Plc							2	1.74	2.62%
Ireland	Allied Irish Banks plc	3	15.70	3.37%	3	20.50	4.99%	2	17.90	6.37%
	Bank of Ireland	2	3.25	0.82%	2	8.70	2.57%	2	10.80	3.36%
Italy	Banca Piccolo Credito Valtelline				1	0.20	0.80%			
	Banca Popolare di Milano SCaRL	1	1.50	2.89%	1	0.50	1.13%			
	Intesa Sanpaolo	1	12.00	1.88%						
	Mediobanca SpA	1	3.50	4.80%						
	Unione di Banche Italiane Scpa-U	1	6.00	4.56%						
Netherlands	ING Groep NV	1	11.28	0.89%	1	10.00	0.75%	1	19.70	1.55%
Portugal	Banco BPI SA				1	1.50	3.36%			
	Banco Comercial Português, SA-Mi	4	6.40	1.70%	1	3.00	3.23%			
	Banco Espirito Santo SA	4	6.25	1.95%						
Spain	Banco de Sabadell SA	3	7.50	2.97%	2	5.49	2.68%			
	Caixabank, S.A.				3	6.48	0.64%			
Sweden	Swedbank AB	1	23.60	13.48%						
United Kingdom	Lloyds Banking Group Plc	1	60.00	5.20%	2	25.25	2.35%	2	500.00	54.38%
	Royal Bank of Scotland Group Plc	2	65.00	1.45%	2	50.90	1.19%	2	385.00	9.81%
	Total	**36**	**259.78**	**6.06%**	**36**	**182.01**	**3.04%**	**15**	**969.34**	**13.84%**

Note: Bank level policy interventions data extracted from banks' annual reports, financial statements, websites and State Aid Register of European Commission.

Appendix 4. Assessing the robustness of VaR and CoVaR models through backtesting

This appendix presents the tests of Kupiec (1995) and Christoffersen (1998) used for testing the accuracy of systemic risk models. The backtesting procedure consists of comparing the losses estimated by the VaR and $CoVaR$ models with the real losses registered during the testing interval. Considering that the sample includes T observations, for each financial institution i we construct the VaR violation function (V_t^i). The variable takes the value 1 if bank's i real loss in week t is greater than the predicted loss for that that week and 0 otherwise:

$$V_t^i = \begin{cases} 1, if\ R^i_{Market\ Assets,t} \leq VaR^i_{q,t} \\ 0, if\ \ R^i_{Market\ Assets,t} > VaR^i_{q,t} \end{cases}, \forall\ t = \overline{1,T} \tag{A1.1}$$

Conditioning on the event that bank i is in financial distress $\left(R^i_{AssetsMV,t} \leq VaR^i_{q,t}\right)$, the $CoVaR$ violation variable $\left(V_t^{sys|i}\right)$ can be constructed in a similar way:

$$V_t^{sys|i} = \begin{cases} 1, if\ R^{sys}_{Market\ Assets,t} \leq ACoVaR^{sys|i}_{q,t}\ \ and\ R^i_{Market\ Assets,t} \leq VaR^i_{q,t} \\ 0, if\ \ R^{sys}_{Market\ Assets,t} > ACoVaR^{sys|i}_{q,t}\ \ and\ R^i_{Market\ Assets,t} \leq VaR^i_{q,t} \end{cases}, \forall\ t = \overline{1,T} \tag{A1.2}$$

The number of CoVaR violations for bank i is determined as below:

$$V = \sum_t V_t^{sys|i} \tag{A1.3}$$

Unconditional coverage backtesting. Kupiec (1995) proposed a likelihood ratio test which assesses if the model's failure rate is compatible with the confidence level. The following statistic is examined for each bank:

$$LR_{UC} = -2ln[(1-q)^{T-V}q^V] + 2ln\left[\left(1-\frac{V}{T}\right)^{T-V}\left(\frac{V}{T}\right)^V\right] \quad \sim \lambda^2(1) \tag{A1.4}$$

where q is the significance threshold used to estimate VaR (1% in our case corresponding to a confidence level of 99%), T represents the number of observations for which the test is performed and V is the number of $CoVaR$ violations. The statistic follows a $\chi^2(1)$ distribution. For a given significance threshold q, the model is correctly specified under the hypothesis H_0: $LR^i_{UC} = q$, with the alternative H_1: $LR^i_{UC} > q$ corresponding to a model that is not correctly specified.

Conditional coverage backtesting. Christoffersen (1998) proposed a likelihood ratio test that considers both the frequency of exceptions and their sequence and consists of two components. The first one indicates the conditional probability that after one exception follows another exception. The second one indicates the frequency of their occurrence. Let v_{ij} be the number of weeks during which state j is recorded conditioned by state i in the previous week. The variable can have the following states:

Table A1. Frequency of exceptions

State	$V_{t-1}=0$	$V_{t-1}=1$	
$V_t=0$	v_{00}	v_{10}	$v_{00}+v_{10}$
$V_t=1$	v_{01}	v_{11}	$v_{01}+v_{11}$
	$v_{00}+v_{01}$	$v_{10}+v_{11}$	V

The probability of having a loss exceeding in week t *($V_t=1$)* conditional on the state in the previous week (t-1) is determined as follows:

$$\pi_0 = \frac{v_{01}}{v_{00}+v_{01}}, \text{ if there is no exception in week t-1 } (V_{t-1}=0)$$
$$\pi_1 = \frac{v_{11}}{v_{10}+v_{11}}, \text{ if there is an exception in week t-1 } (V_{t-1}=1) \quad \text{(A1.5)}$$

Under the null hypothesis the exception occurred in week t is not conditional on the exception occurred in the previous week *(H_0: $\pi_0 = \pi_1$)* and the model is correctly specified. Based on the maximum likelihood method, *the independence test ratio* takes the next form:

$$LR_{IND} = -2ln\left[\frac{(1-\pi)^{n_{00}+n_{01}}\pi^{n_{01}+n_{11}}}{(1-\pi_0)^{n_{00}}\pi_0{}^{n_{01}}(1-\pi_1)^{n_{10}}\pi_1{}^{n_{11}}}\right] \sim \lambda^2(1) \quad \text{(A1.6)}$$

where

$$\pi = \frac{v_{01}+v_{11}}{v_{00}+v_{01}+v_{10}+v_{11}} \quad \text{(A1.7)}$$

The unconditional coverage probability is calculated using the maximum likelihood method and follows a $\chi^2(1)$ distribution:

$$LR_{UC} = -2ln\left[\left(\frac{1-q}{1-\frac{V}{T}}\right)^{T-V}\left(\frac{q}{\frac{V}{T}}\right)^{V}\right] \sim \lambda^2(1) \quad \text{(A1.8)}$$

Combining the unconditional coverage and the independence hypothesis, Christoffersen's test of *conditional coverage* statistic follows a χ^2 distribution with 2 degrees of freedom:

$$LR_{CC} = LR_{IND} + LR_{UC} \sim \lambda^2(2) \quad \text{(A1.9)}$$