Which Are the SIFIs?

A *Component Expected Shortfall (CES) Approach* to Systemic Risk *

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Abstract

In this paper we propose a *component approach* to systemic risk which makes it possible to decompose the risk of the aggregate financial system (measured by *Expected Shortfall, ES*) while accounting for the level of firm characteristics. Developed by analogy with the *Component Value-at-Risk* concept (Jorion, 2007), our new simple and parsimonious method for identifying systemically important institutions, labelled *Component ES (CES)*, presents several advantages. First, it relies on higher frequency (daily) publicly available data, which incorporates useful information for forecasting systemic risks, and it encompasses the popular *Marginal ES* measure. It thus does not consider liabilities (not available in daily frequency) when assessing the systemic riskiness of a firm as the SRISK (Engle and Brownlees, 2011) does. Second, it allows us to select the riskiest financial firms on the market by directly ranking them according to their riskiness. The larger the contribution, the more systemically important the institution. Most importantly, our measure can be used not only to assess the contribution of a firm to systemic risk at a precise date (in-sample), but also to forecast its contribution over a certain period (out-of-sample). An empirical application on a set of financial institutions similar to that employed by Brownlees and Engle (2011) verifies the ability of *CES* to identify the most systemically risky firms during the 2007-2009 financial crisis.

- *Keywords* : Systemic Risk, Component Expected Shortfall, Marginal Expected Shortfall, Forecasting

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1 Introduction

The recent global financial crisis has led to the renewal of the financial regulation debate through the emergence of concepts like systemic risk and the notion of a macroprudential approach to regulation and supervision, *i.e.* limitation of financial system-wide distress. This debate on financial stability in fact constitutes a major concern not only for academics, who have argued long and hard that bank regulation should be designed for the system as a whole and not for each of its components, but also for regulatory authorities and international institutions.

Limiting systemic risk has hence emerged as a possible way to prevent systemic financial crises as it makes it possible to contain the domino effect taking down financial institutions one after the other. To this end, each financial institution should face a 'surcharge' determined according to the 'negative externalities' it generates, *i.e.* its contribution to the risk in the financial system.

How can the institutions to which this macroprudential policy should be applied, *i.e.* systemically risky firms, be identified? This is the key question in the design of a framework for implementation of macroprudential regulation. And although the systemic importance of individual financial institutions has been investigated in numerous recent papers, it still awaits final resolution. Two main perspectives can be identified in this literature. One stream of research proposes a balance sheet approach based on a network model and an interbank clearing algorithm (Elsinger et al. 2006; Aikman et al., 2009). Systemically important financial institutions (SIFIs) can be identified either by analogy with "Too Big To Fail", by imposing an arbitrary threshold on public balance sheet data (*e.g.* by the FED), or by analyzing correlated bank balance-sheet positions / strategies (*e.g.* in terms of credits). However, these data are not publicly available, rendering the regulators using them unable to reveal to the markets the reasons behind their decisions.

Another approach proposes econometrically measuring interdependencies based on public data (market returns or total asset returns), without requiring knowledge of the cross-positions of financial institutions.

A number of market data-based methods[1] to measure systemic risk have been proposed to date, the first and most intuitive one being *Marginal Expected Shortfall (MES),* proposed by Acharya (2010). Computed as the first derivative of the aggregate risk (measured by *Expected Shortfall, ES*) with respect to a firm's position (defined as the weight of its market capitalization in the market capitalization of the aggregate system), it reflects the sensitivity of the systemic risk to a unit change in a firm's position, *i.e.* relative size. It follows that it does not account for the level of the firm's characteristics (size, leverage, etc.), as it only represents the marginal contribution of the institution to the total loss. Major consequences in terms of riskiness follow from this stylized fact:

[1]For a survey on systemic risk measures, see VanHoose, (2011).

a small, unlevered firm can appear more 'dangerous' for the financial system than a big, levered one. Furthermore, the sum of *MES* associated with the firms in the system does not equal the system's aggregate loss as measured by *ES*, which makes accurate interpretation rather difficult. Browlees and Engle (2011) rely on the same statistical *marginal approach*, *i.e. MES*, but then add an economic layer to overcome *MES*'s shortcomings by taking into account some characteristics of the firms. They hence propose *SRISK*, which measures the capital shortfall of the financial system during a crisis due to a financial institution.

In this paper, we take a *component approach* to systemic risk by proposing a new, simple and parsimonious alternative method for identifying systemically important institutions to which more restrictive policies should be applied. In contrast to the aforementioned *marginal approach*, our method includes by definition the weight of the firm in the system, and makes it possible to easily decompose the risk of the aggregate financial system (measured by *ES*), which is extremely useful in managing risk. Indeed, the additive tool[2] it defines reflects the correlation between the elements of the system, while the components add up precisely to the total systemic risk.

Our statistical measure is inspired by the work of Jorion (2007), who introduced the 'Component Value-at-Risk' concept as a measure of the contribution of each asset in a portfolio to the Value-at-Risk (VaR) of the portfolio. By analogy, we hence propose a *Component Expected Shortfall* (CES) systemic risk measure to quantify each firm's contribution to the overall risk, given that the system's risk is measured by (ES). This original measure presents several advantages. First, it allows us to select the riskiest financial firms in the market by directly ranking institutions according to their riskiness. The larger the contribution, the more systemically important the institution. In addition, CES can be normalized by the total *ES*, so as to reflect the percentage contribution of a firm to total loss. This is an appealing characteristic of CES that greatly simplifies interpretability and makes it a good candidate for regulatory authorities selecting which institutions to penalize, with a view to discouraging practices that increase systemic risk. Second, it relies on higher frequency (daily) publicly available data which incorporate useful information for forecasting systemic risks, and it encompasses the popular MES systemic risk measure. These higher frequency data seem to do better in prediction than lower frequency balance-sheet variables and hence allow us to assess banks' correlation structure and the presence of potential spillovers in real-time. Our CES measure depends on the firm's size, as given by its market capitalization relative to that of the entire financial system, and on the expected loss of the firm when the system is in distress (crisis). It follows that it can be immediately computed once the MES is obtained. Most importantly, our systemic risk measure can be used not only to assess the contribution of a firm to systemic risk at a precise date (one-

[2] The additivity property of risk contributions characterizes all the risk measures that are homogenous, such as volatility, Value-at-Risk and ES.

step-ahead, in-sample), but also to forecast its contribution over a certain period (out-of-sample). Our innovative, forward-looking risk measure is hence well-suited to policy decisions oriented toward preventing the accumulation of systemic risk.

An empirical application on a set of financial institutions similar to that employed by Brownlees and Engle (2011) and Acharya (2010) evaluates the ability of CES to identify the most systemically risky financial institutions at a specific date. Indeed, we show that CES not only classifies as systemically risky the firms that historically experienced distress one day later (in-sample, one-step-ahead analysis), but it also correctly identifies the largest contributors to systemic risk in the following six months (out-of-sample, long-term analysis).

Moreover, our results emphasize the fundamental role of a firm's size in determining its contribution to the distress of the whole financial system. A similarity analysis with respect to the rankings obtained by Brownlees and Engle (2011) supports this finding.

The rest of the paper is structured as follows. Section 2 introduces the econometric methodology lying behind our CES systemic risk measure. Section 3 details the estimation and forecasting procedures. Section 4 presents the main empirical results for a set of top US financial institutions, while section 5 concludes.

2 Methodology

In this paper, we propose an original method to identify systemically risky financial institutions. Let us consider a financial system composed of the institutions whose riskiness is assessed.[3] Denote by r_{mt} and r_{it}, $t = \{1, 2, ..., T\}$, the log-return[4] series for the market, *i.e.* the financial system, and firm i on day t, respectively, where the market return is the value-weighted average of all firms

$$r_{mt} = \sum_{i=1}^{n} w_{it} r_{it}, \tag{1}$$

with w_{it} the weight of the i^{th} firm in the portfolio at time t.

The risk associated with this financial system is measured by the Expected Shortfall, ES. [5] By actuarial convention, the ES, *i.e.* the expected market loss conditional on the return being less than the distress event, *e.g.* the α quantile, *i.e.* the VAR, (or less than a threshold C, in a more general

[3]A more general market index could be considered, *e.g.* SP500, but in that case the sum of all firms' contribution to systemic risk would no longer add up to 100%.

[4]The use of log-returns instead of arithmetic returns entails an approximation error. See Caporin, M. and De Magistris, P. S. (2010) for the adjustment term that solves this issue.

[5]VaR and ES are the standard measures of individual risk. ES has received a lot of attention in the systemic risk context, as, contrary to VaR, it is a coherent and more robust risk measure (Artzner et al., 1999).

case) is given by

$$ES_{m,t-1}(C) = -\mathbb{E}_{t-1}(r_{mt}|r_{mt} < C). \tag{2}$$

The main question in the systemic risk literature is hence how to measure the contribution of each financial institution to the whole risk (measured by ES). To put it differently, how to identify the *Systemically Important Financial Institutions*, $SIFI$, *i.e.* the institutions that contribute the most to this risk. One systemic risk measure, proposed by Acharia (2010) and then transformed by Engle and Brownlees (2011), is MES. This measures the marginal contribution of a firm to the risk of the system by indicating the modification in ES engendered by a unit increase in the weight corresponding to the i^{th} institution

$$MES_{it}(C) = \frac{\partial ES_{m,t-1}(C)}{\partial w_{it}} = \mathbb{E}_{t-1}(r_{it}|r_{mt} < C). \tag{3}$$

In contrast, in this paper we propose an original risk measure, the *Component Expected Shortfall*, CES.

Definition 1. *CES measures the absolute contribution of a firm to the risk of the financial system (as opposed to the marginal contribution). It is obtained by calibrating the first derivative of the ES using weights defined for each financial institution as follows:*

$$CES_{it} = w_{it}\frac{\partial ES_{m,t-1}(C)}{\partial w_{it}}. \tag{4}$$

We hence assess the systemic riskiness of financial institutions at a given date t by measuring each firm's contribution to the financial system's expected loss measured by ES. The larger the contribution, the more systemically important the firm.

Our *Component Expected Shortfall* systemic risk measure is defined as a natural extension of *Component Value-at-Risk* introduced by Jorion (2007) to Expected Shortfall. Indeed, in the literature on portfolio risk management we can distinguish between *marginal* and *component* risk measures. While the *Marginal VaR* measures the effect of one unit change in the position of a given component on portfolio risk (measured by VaR), the *Component VaR* indicates approximately how the portfolio VaR would change if the component was deleted from the portfolio.

By analogy, both types of measure can be used to assess the origins of the systemic risk, *i.e.* to measure the impact of a firm on the risk characterizing the whole financial system. The marginal measure, *MES* does not fit best in this context, as it does not take into account the firm's size. It hence generally leads to an improper ranking of the firms in which small minor firms emerge as $SIFI$. To correct this issue, Brownlees and Engle (2011) incorporate nominal measures, such as the size or the leverage of the firm apart from MES, in the spirit of the *too big to fail* logic.

Our approach is much simpler and more direct. The size of the firms is taken into account in the systemic risk measure itself. The MES is thus expressed as a component measure, CES, without adding other economic layers, which, for example, are necessary to compute the systemic risk measure in the case of $SRISK$ proposed by Brownlees and Engle (2011). Besides, we do not need to include liabilities or leverage, which constitutes an advantage as these indicators are subject to availability problems, especially at a high (daily) frequency.

The main property of this systemic risk measure is that, by construction, the expected loss of the financial system at time t can be measured by linearly aggregating the component losses:

$$ES_{m,t-1}(C) = \sum_{i=1}^{n} CES_{it}(C), \tag{5}$$

where $CES_{it}(C) = w_{it}\mathbb{E}_{t-1}(r_{it}|r_{mt} < C)$ measures the total contribution of component i to the overall ES. Indeed, as shown by Tasche (2000), under mild conditions, *i.e.* at least one return process r_{it} must have a continuous distribution, the ES is differentiable. Since the conditional expectation is a random variable and the market return is a linearly homogenous function of degree one of the weights w_{it}, Euler's theorem can be applied (see Scaillet, 2005 *inter alii*) to get the equality in 5. Note also that this result is not restricted to a multivariate normal framework, although an analytical expression for CES exists only for some particular distributions such as the gaussian one. In what follows, we do not make any assumptions with respect to the underlying distribution of the innovations and hence rely on a non-parametric approach for inference.

We now introduce an original simple and efficient measure of a firm's contribution to overall risk, the percentage version of the *Component Expected Shortfall* ($CES\%$).

Definition 2. *$CES\%_{it}(C)$ measures the proportion of systemic risk at time t due to firm i. It is hence computed as the component loss normalized by the total loss:*

$$CES\%_{it}(C) = \frac{CES_{it}(C)}{\sum_{i=1}^{n} CES_{it}(C)} \times 100 = \frac{w_{it}\mathbb{E}_{t-1}(r_{it}|r_{mt} < C)}{\sum_{i=1}^{n} w_{it}\mathbb{E}_{t-1}(r_{it}|r_{mt} < C)} \times 100. \tag{6}$$

This systemic risk measure presents several advantages. First, it allows the identification of pockets of risk concentrations by directly ranking institutions according to their riskiness. For a given period t, $CES\%_{it}(C)$ add up to 100 by construction, which clearly simplifies interpretability. The larger the contribution, the more systemically important the institution. Second, $CES\%(C)$ is computed only with publicly available data and it encompasses the popular systemic risk measure MES. Most importantly, our systemic risk measure can be used not only to assess the contribution of a firm to systemic risk at a precise past date (in-sample), but also to forecast the evolution of its contribution in a certain period (out-of-sample).

Notice that the $CES\%_{it}(C)$ risk measure can be immediately computed once the weights w_{it} are defined and the conditional expectation $\mathbb{E}_{t-1}(r_{it}|r_{mt} < C)$ is calculated (see eq. 6). While the weights are easily obtained using market capitalization data for all the institutions in the sample, the expected value of firm i's returns conditional on the market being in stress requires a more in-depth analysis. For this, we use the fact that $\mathbb{E}_{t-1}(r_{it}|r_{mt} < C)$ corresponds to the MES (see eq. 3 and Appendix 1).

3 Estimation and forecasting

To compute the CES, we rely on the market model, as in the theoretical setup of Brownlees and Engle (2011)

$$\begin{aligned} r_{mt} &= \sigma_{mt}\varepsilon_{mt} \\ r_{it} &= \sigma_{it}\rho_{it}\varepsilon_{mt} + \sigma_{it}\sqrt{1-\rho_{it}^2}\xi_{it} \\ (\varepsilon_{mt}\ \xi_{it}) &\sim F, \end{aligned} \tag{7}$$

where σ_{mt} and σ_{it} are the conditional standard deviations for the system and the firm, respectively, and the shocks ε_{mt} and ξ_{it} are independently and identically distributed with zero mean and identity covariance matrix. It follows that CES is given by a combination of volatility, correlation, conditional expectations of the standardized innovations distribution and the size of the firm:[6]

$$\begin{aligned} CES_{it}(C) =& w_{it}[\sigma_{it}\rho_{it}\mathbb{E}_{t-1}(\varepsilon_{mt}|\varepsilon_{mt} < C/\sigma_{mt}) \\ & + \sigma_{it}\sqrt{1-\rho_{it}^2}\mathbb{E}_{t-1}(\xi_{it}|\varepsilon_{mt} < C/\sigma_{mt})]. \end{aligned} \tag{8}$$

Notice that the linear dependency between market and firm returns is completely captured by the time-varying conditional correlations, whereas the possible non-linear dependency passes through the second conditional expectation, $\mathbb{E}_{t-1}(\xi_{it}|\varepsilon_{mt} < C/\sigma_{mt})$. Equally important, to calculate CES at the last period T we construct hypothetical market returns based on (constant) weights defined at time T, w_{iT}.

3.1 In-sample systemic risk measure

To obtain one-period ahead estimates for our CES measure, we follow four steps.

[6]Similarly, $MES_{it}(C) = \sigma_{it}\rho_{it}\mathbb{E}_{t-1}(\varepsilon_{mt}|\varepsilon_{mt} < C/\sigma_{mt}) + \sigma_{it}\sqrt{1-\rho_{it}^2}\mathbb{E}_{t-1}(\xi_{it}|\varepsilon_{mt} < C/\sigma_{mt})$.

Step 1. First, we obtain conditional volatilities and standardized residuals for the market and each instititution by modelling volatilities in a GJR-GARCH(1,1) framework (Glosten et al., 1993).[7] We rely on the QML estimation method because it provides consistent and asymptotically normal estimators under mild regularity conditions, without any assumption about the process observed.

Step 2. The time-varying correlations of each couple 'market' - 'firm' are modelled in a dynamic conditional correlation (DCC) framework, as in Engle and Shepard, 2001.

Step 3. Relying on the *i.i.d.* property of the innovations, we proceed to a non-parametric kernel estimation of the tail expectations $\mathbb{E}_{t-1}(\varepsilon_{mt}|\varepsilon_{mt} < C/\sigma_{mt})$ and $\mathbb{E}_{t-1}(\xi_{it}|\varepsilon_{mt} < C/\sigma_{mt})$ along the lines of Scaillet (2005):

$$\widehat{\mathbb{E}}_{t-1}(\varepsilon_{mt}|\varepsilon_{mt} < c) = \frac{\sum_{t=1}^{T} \varepsilon_{mt} \Phi(\frac{c-\varepsilon_{mt}}{h})}{\sum_{t=1}^{T} \Phi(\frac{c-\varepsilon_{mt}}{h})} \tag{9}$$

$$\widehat{\mathbb{E}}_{t-1}(\xi_{it}|\varepsilon_{mt} < c) = \frac{\sum_{t=1}^{T} \xi_{it} \Phi(\frac{c-\varepsilon_{mt}}{h})}{\sum_{t=1}^{T} \Phi(\frac{c-\varepsilon_{mt}}{h})}, \tag{10}$$

where $c = C/\sigma_{mt}$ is the threshold, and h is the bandwidth. In the empirical application we set C to $VaR\text{-}HS(5\%)$ of the system and h to $T^{-1/5}$, as in Scaillet (2005). Besides, Φ represents the normal c.d.f., since the standard normal p.d.f. has been used as the kernel function. For a formal proof, see appendix 2. At the end of the third step we can rely on eq. 8 to compute CES for institution i at each date t. Recall that we are interested only in the last value of CES, for which the sequence of hypothetical market returns, r_{mt}, has been defined as a function of the weights w_{iT}.

Step 4. We hence obtain our *Component Expected Shortfall* systemic risk measure $CES\%$ at time T by using eqs. 6 and 8.

3.2 Out-of-sample systemic risk measure

Policy decisions require forecasts of firms' contributions to systemic risk. Being able to provide such results constitutes a distinctive feature of our method.

Let us denote by $T+1 : T+h$ the out-of-sample period, where h represents the forecast horizon, set to six months in the empirical application. To compute the contribution of an institution to the system's riskiness over a certain period in the future, we elaborate on Brownlees and Engle (2011), who show that long-term MES can be obtained through a simulation exercise which departs from the second step of the in-sample analysis. For this, the following four-step procedure is implemented

[7] This specification is appealing, as it takes into account one of the main characteristics of financial series, originally put forward by Black (1976), known as *the leverage effect*.

for each couple 'market-institution'.

Step 1. Draw with replacement S sequences of length h of pairs of innovations $(\varepsilon_{m,t},\, \xi_{i,t})$ from the empirical c.d.f. of the innovation series F

$$\{\varepsilon^s_{m,t}, \xi^s_{i,t}\}^{T+h}_{t=T+1},\ for\ s = \{1, 2, ..., S\}. \tag{11}$$

Step 2. Compute the sequences of market and firm returns by using as starting condition the returns and conditional volatilities corresponding to the last in-sample period and by iterating on the GJR-Garch and DCC equations.

Step 3. Calculate the cumulative returns associated with the paths considered both for the system and institution by relying on the properties of logarithmic returns:

$$R^s_{k,T+1:T+h} = \exp\left(\sum_{j=1}^{h} r^s_{k,T+j}\right) - 1,\ k = \{m, i\}, \tag{12}$$

where $r^s_{k,T+j}$ is the series of returns corresponding to the s^{th} path of the market if $k = m$ and of institution i if $k = i$. S sequences are considered for each asset, so as to obtain a $(S, 1)$ vector of cumulated returns.

Step 4. The long-run MES can be obtained by relying on Acharya (2010):[8]

$$MES_{i,T+1:T+h}(\tilde{C}) = \frac{\sum\limits_{s=1}^{S} R^s_{i,T+1:T+h}\mathbb{I}_{(R^s_{m,T+1:T+h}<\tilde{C})}}{\sum\limits_{s=1}^{S} \mathbb{I}_{(R^s_{m,T+1:T+h}<\tilde{C})}}, \tag{13}$$

where $\tilde{C}$ stands for the threshold defining the systemic event in out-of-sample. It differs according to the forecast horizon, *e.g.* if it is set to $VaR\ \alpha\%$ of the monthly cumulated returns for a forecasting horizon of one month, for h equal to six months it corresponds to $VaR\ \alpha\%$ of the biannual cumulated returns, where α is the coverage rate. To select this cut-off, we proceed by analogy with the in-sample analysis, and set it to the out-of-sample VaR-HS for cumulative market returns at a coverage rate of 5% (empirical quantile of the simulated paths).

Once the $MES(\tilde{C})$ is computed for all the firms, the out-of-sample systemic risk measure can be written as

$$CES\%_{i,T+1:T+h}(\tilde{C}) = \frac{CES_{i,T+1:T+h}(\tilde{C})}{\sum\limits_{i=1}^{n} CES_{i,T+1:T+h}(\tilde{C})}, \tag{14}$$

where $CES_{i,T+1:T+h}(\tilde{C}) = w_{iT}MES_{i,T+1:T+h}(\tilde{C})$ and w_{iT} are the weights corresponding to the last

[8]Note that Scaillet's method (2005) could be used to compute the CES% risk measure in out-of-sample too.

in-sample period (date up to which the market index has been constructed by using eq. 1).

4 Empirical Application

If the system is at a risky level, which firms contribute the most to this risk? We address and answer this question by relying on our component measure of systemic risk to analyze the systemic riskiness of financial institutions at a specific date. Indeed, we not only classify as systemically risky the firms that historically experienced distress one day later (in-sample exercise), but we also assess the largest contributors to systemic risk in the following six months (out-of-sample exercise).

4.1 Data

The dataset used in this paper is very similar to the one used by Brownlees and Engle (2011) and previously by Acharya et al. (2010), with the exception that the market index is computed as discussed in the previous section (see eq. 1). The series of share prices, the number of shares outstanding (used to compute the market capitalization), and the daily returns of the financial institutions were extracted from CRSP and cover the period between January 3, 2000 and December 31, 2010. The panel contains all the U.S. financial institutions whose market capitalization exceeds 5bln USD as of the end of June 2007. Moreover, the sample can be categorized into four groups: Depositories (*e.g.* Citigroup, JPMorgan, Bank of America, etc.), Insurance firms (*e.g.* A.I.G., Berkshire Hathaway Inc Del, etc.), Brokers and Dealers (*e.g.* Lehman Brothers, Morgan Stanley, etc.) and Others (*e.g.* American Express, etc).

The market index refers to the financial system including only the firms under analysis at a given period. It is thus reconstructed for each date of interest, and for this reason the market capitalization and consequently the weight of each firm in the panel are computed for those specific dates and then considered constant for all the past periods in the analysis. More generally, the weight of each firm in the system can be determined by the regulators by taking into account various indicators (of size, leverage, etc.). For the sake of simplicity, we therefore consider a left censored panel of data and exclude from our analysis the institutions listed later than January, 2000. For a complete list of companies studied, see Table 1. Note that the two star symbol indicates the financial institutions which effectively disappear during the crisis period.

4.2 In-sample analysis

We define a crisis as a situation in which market distress exceeds the VaR(5%), and derive a non-parametric measure of MES. The latter is subsequently calibrated using the individual weight of each firm in order to complete the calculation of CES. It is worth noting that all our results are very similar to those obtained by simply considering that distress corresponds to a 2% market drop over a day, as in Brownlees and Engle (2011)[9], since this cut-off reflects the average VaR(5%) over the specific dates under investigation.

The analysis is performed for seven dates ranging from June 30, 2007 to June 30, 2010, which are chosen to coincide with the periods of pre-crisis, crisis and post-crisis, respectively. Besides, the market index obtained as the value-weighted average of all firms corresponds to the financial sector composed of the firms in the panel at each date under analysis.

The main purpose of the paper is to select the riskiest financial firms in the market by directly ranking the institutions according to their riskiness. Table 2 (Panel A) displays the first fifteen firms contributing the most to the total systemic risk for the seven dates previously indicated. The ranking captures firms such as: Citigroup, Bank of America, Merrill Lynch, A.I.G., Lehman Brothers, JPMorgan, which effectively suffered major transformations during the crisis (*i.e.* failure, merger, bailout, etc.) and contribute to a significant share of the total risk of the financial system. For example, 39.20% (58.14%) of the total loss can be attributed to the first five (ten) firms in the ranking on December 31, 2007, while by January 30, 2009, the first five (ten) firms in the ranking cover 50.76% (69.08%) of the total loss. We notice that almost exactly the same firms show up consistently in the top fifteen, although with some modifications at the end of the period. It is only the order that changes from one period to another. From an economic point of view, what really matters is to indicate the classes or "buckets", as they are called by the Basel Committee, of financial institutions according to their level of riskiness (*i.e.* Basel III demands a repartition of the most systematically risky firms into five buckets), and not their precise order. From this viewpoint, we observe that the cluster of the top four most risky financial institutions (Citigroup, Bank of America, JPMorgan and A.I.G.) is always the same, albeit in different order (with the exception of A.I.G., which failed at the end of 2008 and was replaced in the cluster by Wells Fargo & Co New).

One interesting idea is also to verify whether different systemic risk measures identify the same SIFIs. Table 3 displays the tickers of the top 10 financial institutions according to their systemic risk contribution measured by MES and $CES\%$, respectively, for the last two dates of our analysis. On January 30, 2009 two financial institutions (Bank of America and Citigroup) are simultaneously identified by the two risk measures. In addition, on June 30, 2010, there is only one financial institution (Citigroup) in common with MES. This empirically supports the use of component-based measures, as $CES\%$ based ranking reports the largest financial institutions (Citigroup, Bank of America, JPMorgan, etc.), whereas the marginal approach, MES, is tilted towards the smallest financial institutions.

[9]This set of results is available upon request

We subsequently propose a brief comparison of our ranking based on $CES\%$ with the SRISK%-based ranking proposed by Brownlees and Engle (2011). Table 4 (Panel A) reports the value of the rank similarity measure between the two approaches for each date in the analysis, by considering the top five and ten most systematically risky institutions. We define the similarity ratio as the proportion of common institutions in the two rankings on a given date. For instance, considering the top ten firms contributing the most to the total systemic risk, a similarity ratio equal to 0.20 means that among the top ten firms, two can be found in both rankings simultaneously. Notice that the similarity ratio can go up to 0.80 for the top five and to 0.70 for the top ten (and this at the peak of the crisis). This exercise emphasizes the fact that our measure of systemic risk gives similar, but not identical results to those obtained by Brownlees and Engle (2011), by correctly identifying the most systemically risky financial institutions at a specific date. These results could be reinforced by the application of a statistical test of ranking similarity. It is also worth noting that three companies which appear in the SRISK% based ranking of Engle and Brownlees (2011) are not in our sample and therefore the similarity measure cannot reach 1 for the cases in which at least one of these three firms is in their ranking. The differences between the rankings obtained with the three measures are not necessarily due to the inadequacy of a particular measure, but to the computational methodology itself.

Several interesting empirical facts can also be observed when we focus on the individual firm results. Figure 1 displays the short run CES and MES evolution over the period of January, 2007 to December, 2010 for some representative leading systemic firms from each group: Bank of America, Citigroup, JPMorgan, Morgan Stanley, A.I.G. and American Express. Overall, all the firms exhibit a similar time trend, but the amplitude of the measure is different. The pre-crisis period features lower levels, with a progressive increase in these two measures. Notice that for some firms CES is even more volatile than MES during this period. Moreover, the series of short run predictions peak at the end of 2008 or the beginning of 2009 and then decay slowly to a level comparable to that registered before the crisis. The two risk indicators become highly volatile during September 2008 for all the groups of institutions. This finding is perfectly explained by the events which hit important financial markets (*i.e.* Insurance, Brokers and Dealers, etc.) at that time. On September 14, 2008 Lehman Brothers filed for bankruptcy after the financial support facility offered by the Federal Reserve Bank stopped. A few days after, on Sunday, September 21, the two remaining US investment banks, Goldman Sachs and Morgan Stanley, converted into bank holding companies. The situation became even more stressful when, on September 16, the important insurer American International Group (A.I.G.) suffered a liquidity crisis which naturally led to a downgrade of its credit rating. The situation continued to be agitated even at the beginning of 2009 for firms such as Bank of America, JPMorgan, Morgan Stanley and American Express. After this disturbing period, US financial markets entered a recovery period.

Moreover, Figure 2 displays the average of CES by industry group from the end of June 2007 to July 2010. Several observations are in order. First, this histogram highlights the degree of stability from year to year of this particular systemic risk measure. The evolution of average CES is quite obvious in total with some interesting remarks tied to the magnitude of the measure for each group of institutions. There is considerable variation in CES over time in terms of amplitude, with a general increase in its average level during the pre-crisis and crisis periods and a significant peak during the latter. The post-crisis period (2010) is characterized by a gentle decrease. This time variation is generally given by the state of the financial system during this same period. Second, there is a clear ordering of the average level of contribution to the systemic risk according to the type of institution. In particular, much of the systemic risk emerging in the crisis derives from Depositories and Broker-Dealers, while Insurance and Others exhibit the lowest contribution. All groups reach their maximum average at the beginning of 2009, precisely at the height of the crisis, emphasizing the CES's ability to detect the increase in vulnerability of financial institutions. In addition, during this period, the Depositories group seems to be by far the most systemically risky of all. For the other periods its average level is comparable with that of the Dealer-Brokers category. Furthermore, the two other categories, Insurance and Others, also present similar average levels.

Finally, Table 5 (Panel A) reports the composition by type of institutions of the top ten and fifteen most risky institutions according to our $CES\%$ measure. We notice that the Depositories group dominates the others in terms of number of risky institutions. It is followed by the Dealer-Brokers category of financial institutions. Besides, not only do Depositories and Dealer-Brokers exibit the largest average increase in risk (Figure 1), but they are generally the main contributors to systemic risk.

4.3 Out-of-sample analysis

In the previous subsection, we analyzed the results obtained by considering one-period ahead estimates of our CES measure. Our systemic risk measure can be used not only to assess the contribution of a firm to the systemic risk at a precise date, but also to forecast its contribution for a future period. The aim of this section is hence to check if the results previously presented remain valid when increasing the forecasting horizon, by using a historical MES method "à la" Acharya, based on the simulated paths of out-of-sample returns, along the lines of Engle and Brownlees (2011). In particular, we extend the perspective of our analysis by proposing out-of-sample results for an enlarged six-month forecasting horizon.

The multi-period ahead forecasts of CES are obtained by using the principle of daily rolling window forecasting of returns based on the resampled residuals. We then compute the cumulative returns and hence the MES and the CES over the six month horizon. Nevertheless, several problems occur in this context and deserve our attention. First, we encounter a stationarity problem, because there are some firms that do not respect the GARCH stationarity constraint at the time of the estimation. Second, the paths of the innovations drawn have an important impact on the amplitude of MES. For example, we find some firms for which MES forecasts present some extreme values. This is a direct consequence of the persistence of the volatility in time (*i.e.* the shocks are not rapidly absorbed and a second shock (a large innovation) is enough for the returns estimates path to explode. This leads to extreme and wrong values, not stable across experiments, in the MES and subsequently in the CES forecasts). In order to achieve a good level of accuracy for our forecasts, we eliminate the firms exhibiting this kind of problem.

The forecasts are computed for the same dates previously used for the validation of the in-sample results. As with in-sample, we define the systemic event as the situation in which the market return exceeds a threshold (it is set here to an out-of-sample VaR-HS for cumulative market returns at a coverage rate of 5%, *i.e.* empirical quantile of the simulated paths).

For the out-of-sample exercise we perform the same analysis as for the in-sample exercise. Table 2 (Panel B) shows the first fifteen most systematically important financial institutions at seven precise dates. Like in the in-sample analysis, the ranking is based on the $CES\%$ measure and includes almost the same risky financial institutions, but in a slightly different order. For instance, the similarity ratio between the top fifteen most risky firms in-sample and out-of-sample, respectively, ranges from 80% to 93.33%. In addition, over the seven periods, the proportion of the total loss covered by the first ten firms in the ranking varies from 58.17% to 71.77%.

The comparison of our out-of-sample ranking with the SRISK% based ranking proposed by Brownlees and Engle (2011) stresses the fact that the results are comparable to those obtained in-sample. There is even a small improvement. The similarity ratio ranges from 0.20 to 0.80 for the top five and from 0.50 to 0.80 for the top ten. Complete results are given in Table 4 (Panel B). This part of the analysis highlights the fact that even in out-of-sample our systemic risk measure succeeds in correctly identifying the financial institutions contributing the most to the global risk of the system with a six month horizon.

Figure 3 displays the average forecasts of CES by industry group from the end of June 2007 to July 2010. In outline, the evolution of CES is the same as that previously observed. To be more precise, a slow increase in the average measure over the period from July, 2007 to September, 2008 can be identified. The insurance group reaches its maximum average in September, 2008, while Depository and Broker-Dealer institutions attain it at the beginning of 2009. After this period of maximal tension, we observe a slowly decaying shape of the average CES forecasts for each of the four categories.

Concerning the composition of the ranking in terms of type of financial institution, we remark the same configuration as in the previous section: the Depository firms dominate the ranking (with a proportion which varies from 40% to 70%). They are followed by the Broker-Dealer category, less present in the ranking (*i.e.* 20% to 40%), as is indicated in Table 5 (Panel B).

Overall, the out-of-sample results strongly support the in-sample ones, giving an idea about the good predictive abilities of this new systemic risk measure. Indeed, both the in-sample and out-of-sample analyses support the efficiency of the parsimonious systemic risk measure introduced by this paper.

5 Conclusion

Up to the collapse of the worldwide economy and financial markets during the financial crisis of 2008-2009, the negative externalities induced by each financial institution on the system (*i.e.*, the systemic risk) were not seriously taken into account by the existing regulations. Nowadays, this aspect is intensively debated by academics and regulators who try to measure each financial institution's contribution to systemic risk. Using a *component approach to systemic risk*, this paper has proposed a simple intuitive and parsimonious alternative method to identify systemically important institutions. Based mainly on the firm's size and its expected loss, and conditional on the decline of the whole market by at least a level equal to VaR(5%), this measure can be computed both for absolute (CES) and relative ($CES\%$) levels, in-sample as well as out-of-sample. Moreover, it uses publicly available data to quantify systemic risk, by simply encompassing the standard MES.

Our findings can be summarized in five points. First, our measure allows us to accurately rank the institutions according to their riskiness. Our ranking captures firms that effectively suffered major transformations during the crisis (*i.e.* failure, merger, bailout, etc.) and constituted a significant part of the total risk of the financial system. Concerning the composition of the ranking in terms of type of financial institution, the Depositories firms seem to dominate the ranking, followed by Broker-Dealers, Insurance and Other (with a smaller rate of presence in the ranking).

Second, this ranking is supported by the results of other studies using measures of systemic risk which are more complex in terms of information set. Our ranking is hence comparable to the SRISK% based-one obtained by Brownlees and Engle (2011) for the same dates, according to a rank similarity measure, which is simply computed as the percentage of firms that are concurrently in the two rankings on a given date. The two rankings present similar patterns, but they are not identical and this is not because of the weakness of a particular measure, but instead because of differences resulting from the computational approaches considered.

Third, we have shown that the average level of CES for the four categories of financial institutions (*i.e.* Depositories, Broker-Dealers, Insurance, Others) matches the evolution of the state of the financial markets along the pre-crisis, crisis and post-crisis periods. We remark a general increase in the average level of CES during the pre-crisis and crisis periods, with a significant peak during the latter. The post-crisis period is characterized by a gently declining shape, which corresponds to the slow recovery of the economy.

Fourth, there is a clear ordering of the average level of contribution to the systemic risk according to the type of institution. In particular, much of the systemic risk emerging during the crisis derives from Depositories and Broker-Dealers, while Insurance and Others make a lower contribution. Finally, to check the robustness of our results, an out-of-sample analysis in which we enlarge the forecasting horizon to six months was carried out. The two analyses provide comparable results, supporting the good forecasting abilities of our measure.

Furthermore, the analysis could be extended for the period after 2010, in order to see the impact of the European crisis on the US market state. Moreover, a multivariate approach could also be envisaged, but we keep these issues for future research.

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Appendix 1: Marginal Expected Shortfall

Starting with the expression for the expected loss of the financial system at time t,

$$ES_{m,t-1}(C) = \mathbb{E}_{t-1}(r_{mt}|r_{mt} < C), \tag{15}$$

we follow Scaillet (2004) and show that the first order derivative with respect to the weight associated with the i^{th} asset, *i.e.* MES, is given by

$$\frac{\partial ES_{m,t-1}(C)}{\partial w_i} = \mathbb{E}_{t-1}(r_{it}|r_{mt} < C). \tag{16}$$

For this, we denote by $\breve{r}_{mt}$ the return for the financial system except for the contribution of the i^{th} asset, where $\breve{r}_{mt} = \sum_{j=1\ j\neq i}^{n} w_j r_{jt}$ and $r_{mt} = \breve{r}_{mt} + w_i r_{it}$. Besides, we do not restrict the threshold C to being a scalar. It is assumed to depend on the distribution of the market returns and hence on the weights and the specified probability to be in the tail of the distribution p, as in the case of the VaR, thus providing a general proof for eq. 16.

It follows that

$$\begin{aligned} ES_{m,t-1}(C) &= \mathbb{E}_{t-1}(\breve{r}_{mt} + w_i r_{it}|\breve{r}_{mt} + w_i r_{it} < C(w_i,p)) \\ &= \frac{1}{p}\int_{-\infty}^{\infty}\left(\int_{-\infty}^{C(w_i,p)} (\breve{r}_{mt} + w_i r_{it}) f(\breve{r}_{mt}, r_{it})\ d\breve{r}_{mt}\right) dr_{it}, \end{aligned} \tag{17}$$

where $f(\breve{r}_{mt}, r_{it})$ stands for the joint probability density function of the two series of returns. Consequently,

$$\begin{aligned} \frac{\partial ES_{m,t-1}(C)}{\partial w_i} &= \frac{1}{p}\int_{-\infty}^{\infty}\left(\int_{-\infty}^{C(w_i,p)} (\breve{r}_{it}) f(\breve{r}_{mt}, r_{it})\ d\breve{r}_{mt}\right) dr_{it} \\ &+ \frac{1}{p}\int_{-\infty}^{\infty}\left(\frac{\partial C(w_i,p)}{\partial w_i} - r_{it}\right) C(w_i,p) f\left(C(w_i,p) - w_i r_{it}, r_{it}\right) dr_{it} \end{aligned} \tag{18}$$

However, the probability of being in the left tail of the distribution of the market return is constant, *i.e.* $\Pr(\breve{r}_{mt} + w_i r_{it} < C) = p$. A direct implication of this fact is that the first order derivative of this probability is null. To put it differently, using simple calculus rules for cumulative distribution functions, it can be shown that

$$\left(\frac{\partial C(w_i,p)}{\partial w_i} - r_{it}\right) f\left(C(w_i,p) - w_i r_{it}, r_{it}\right) = 0. \tag{19}$$

Therefore, eq. 18 can be written compactly as

$$\begin{aligned}\frac{\partial ES_{m,t-1}(C)}{\partial w_i} &= \frac{1}{p}\int_{-\infty}^{\infty}\left(\int_{-\infty}^{C(w_i,p)} (\breve{r}_{it}) f(\breve{r}_{mt}, r_{it})\ d\breve{r}_{mt}\right) dr_{it} \\ &= \mathbb{E}_{t-1}(r_{it}|\breve{r}_{mt} + w_i r_{it} < C(w_i,p)) \\ &= \mathbb{E}_{t-1}(r_{it}|r_{mt} < C),\end{aligned} \tag{20}$$

which completes the proof.

Appendix 2: Tail Expectations

We show that the tail expectations $\mathbb{E}_{t-1}(\varepsilon_{mt}|\varepsilon_{mt} < C/\sigma_{mt})$ and $\mathbb{E}_{t-1}(\xi_{it}|\varepsilon_{mt} < C/\sigma_{mt})$ can be easily estimated in a non-parametric kernel framework by elaborating on Scaillet (2005).

For ease of notation, let us denote the systemic risk event C/σ_{mt} by c. We first consider the tail expectation on market returns $\mathbb{E}_{t-1}(\varepsilon_{mt}|\varepsilon_{mt} < C/\sigma_{mt})$, which becomes

$$\mathbb{E}_{t-1}(\varepsilon_{mt}|\varepsilon_{mt} < c). \tag{21}$$

Using the definition of the conditional mean, we rewrite 21 as a function of the probability density function f

$$\mathbb{E}_{t-1}(\varepsilon_{mt}|\varepsilon_{mt} < c) = \int_{-\infty}^{c} \varepsilon_{mt} f(u|u < c)\ du, \tag{22}$$

where the conditional density $f(u|u < c)$ can be stated as

$$\frac{f(u)}{Pr(u < c)}. \tag{23}$$

To complete the proof, we must compute the numerator and denominator in 23. For this, we first consider the standard kernel density estimator of the density f at point u given by

$$\hat{f}(u) = \frac{1}{Th}\sum_{1}^{T}\phi(\frac{u - \varepsilon_{mt}}{h}),$$

where h stands for the bandwidth parameter, and T is the sample size (Silverman, 1986, Wand and Jones, 1995, Simonoff, 1996). Second, the probability of being in the tail of the distribution can be defined as the integral of the probability density function over the domain of definition of the variable

u, *i.e.* $p = Pr(u < c) = \int\limits_{-\infty}^{c} f(u)\, du$. Consequently, by replacing $\hat{f}(u)$ with the kernel estimator, we obtain

$$\hat{p} = \frac{1}{Th} \sum_{t=1}^{T} \Phi(\frac{c - \varepsilon_{mt}}{h}).$$

The expectation in 21 hence takes the form

$$\hat{\mathbb{E}}_{t-1}(\varepsilon_{mt} | \varepsilon_{mt} < c) = \frac{\sum\limits_{t=1}^{T} \varepsilon_{mt} \Phi(\frac{c - \varepsilon_{mt}}{h})}{\sum\limits_{t=1}^{T} \Phi(\frac{c - \varepsilon_{mt}}{h})}. \tag{24}$$

Similarly, it can be shown that

$$\hat{\mathbb{E}}_{t-1}(\xi_{it} | \varepsilon_{mt} < c) = \frac{\sum\limits_{t=1}^{T} \xi_{it} \Phi(\frac{c - \varepsilon_{mt}}{h})}{\sum\limits_{t=1}^{T} \Phi(\frac{c - \varepsilon_{mt}}{h})}. \tag{25}$$

Tables and Figures

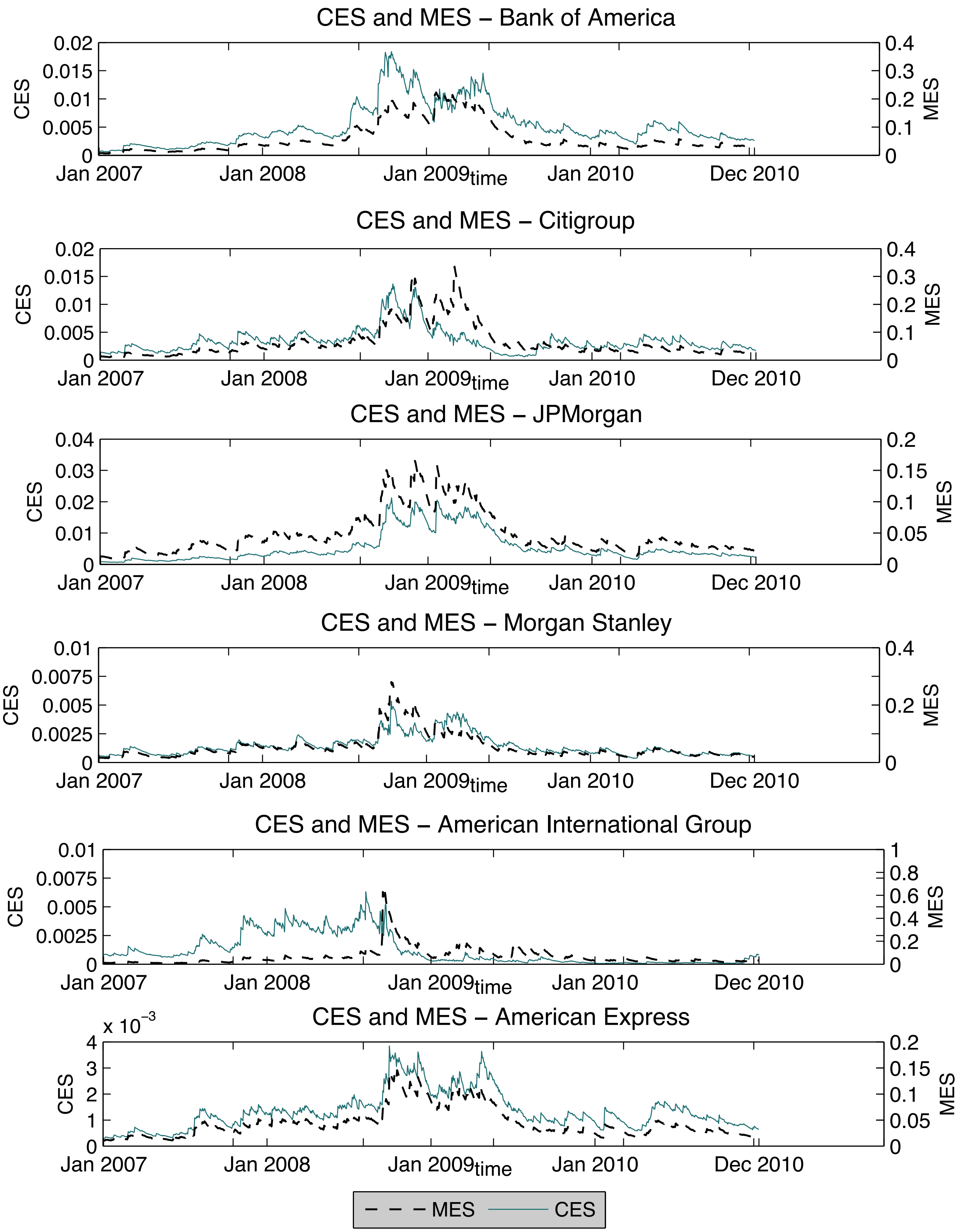

Figure 1: Short run Component Expected Shortfall and Marginal Expected Shortfall

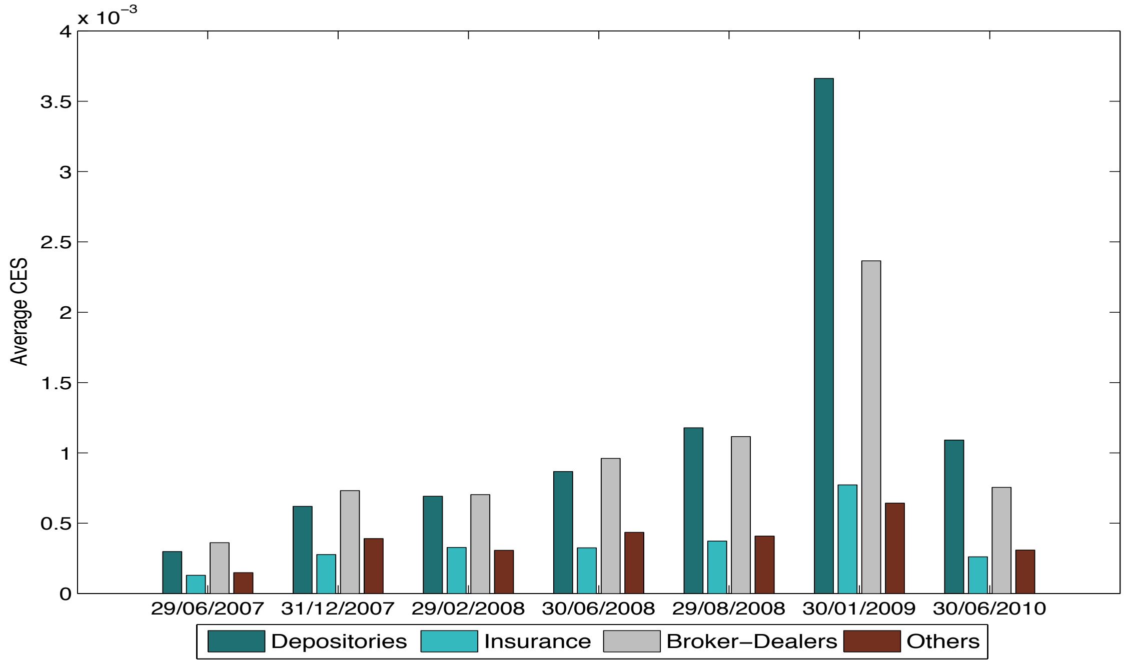

Figure 2: In-sample average CES by type of institution

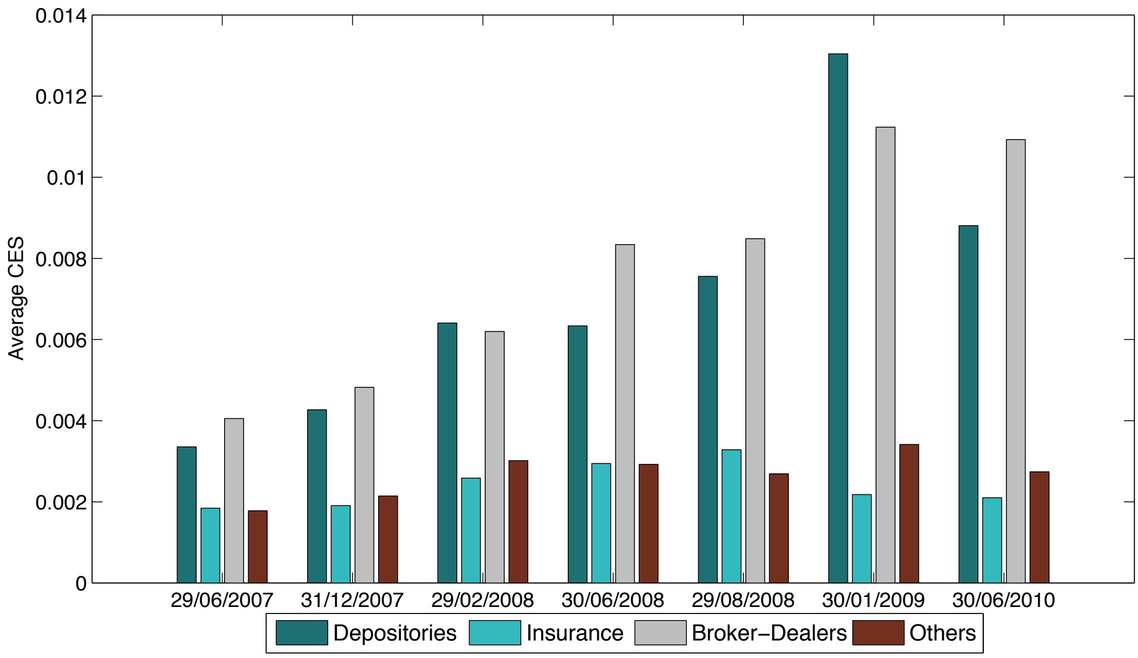

Figure 3: Out-of-sample average CES by type of institution

Table 1: Dataset

	Depositories (29)			Insurance (32)			Broker-Dealers (10)			Others (23)	
BAC	BANK OF AMERICA CORP		ABK	AMBAC FINANCIAL GROUP INC	**	AGE	EDWARDS A G INC	**	ACAS	AMERICAN CAPITAL LTD	
BBT	B B & T CORP		AFL	A F L A C INC		BSC	BEAR STEARNS COMPANIES INC	**	AMTD	T D AMERITRADE HOLDING CORP	
BK	BANK OF NEW YORK MELLON CORP		AIG	AMERICAN INTERNATIONAL GROUP INC		ETFC	E TRADE FINANCIAL CORP		AXP	AMERICAN EXPRESS CO	
C	CITIGROUP INC		ALL	ALLSTATE CORP		GS	GOLDMAN SACHS GROUP INC		BEN	FRANKLIN RESOURCES INC	
CBH	COMMERCE BANCORP INC NJ	**	AOC	AON CORP		LEH	LEHMAN BROTHERS HOLDINGS INC	**	BLK	BLACKROCK INC	
CMA	COMERICA INC		BRK	BERKSHIRE HATHAWAY INC DEL		MER	MERRILL LYNCH & CO INC	**	CBSS	COMPASS BANCSHARES INC	**
HBAN	HUNTINGTON BANCSHARES INC		CB	CHUBB CORP		MS	MORGAN STANLEY DEAN WITTER & CO		COF	CAPITAL ONE FINANCIAL CORP	
HCBK	HUDSON CITY BANCORP INC		CFC	COUNTRYWIDE FINANCIAL CORP	**	SCHW	SCHWAB CHARLES CORP NEW		EV	EATON VANCE CORP	
JPM	JPMORGAN CHASE & CO		CI	C I G N A CORP		TROW	T ROWE PRICE GROUP INC		FITB	FIFTH THIRD BANCORP	
KEY	KEYCORP NEW		CINF	CINCINNATI FINANCIAL CORP					FNM	FEDERAL NATIONAL MORTGAGE ASSN	**
MI	MARSHALL & ILSLEY CORP		CNA	C N A FINANCIAL CORP					FRE	FEDERAL HOME LOAN MORTGAGE CORP	**
MTB	M & T BANK CORP		CVH	COVENTRY HEALTH CARE INC					HRB	H&R Block	
NCC	NATIONAL CITY CORP	**	HIG	HARTFORD FINANCIAL SVCS GRP INC					LM	LEGG MASON INC	
NTRS	NORTHERN TRUST CORP		HNT	HEALTH NET INC					SEIC	S E I INVESTMENTS COMPANY	
NYB	NEW YORK COMMUNITY BANCORP INC		HUM	HUMANA INC					SLM	S L M CORP	
PBCT	PEOPLES UNITED FINANCIAL INC		LNC	LINCOLN NATIONAL CORP IN							
PNC	P N C FINANCIAL SERVICES GRP INC		MBI	M B I A INC							
RF	REGIONS FINANCIAL CORP NEW		MMC	MARSH & MCLENNAN COS INC							
SNV	SYNOVUS FINANCIAL CORP		PGR	PROGRESSIVE CORP OH							
SOV	SOVEREIGN BANCORP INC	**	SAF	SAFECO CORP	**						
STI	SUNTRUST BANKS INC		TMK	TORCHMARK CORP							
STT	STATE STREET CORP		UNH	UNITEDHEALTH GROUP INC							
UB	UNIONBANCAL CORP	**	UNM	UNUM GROUP							
USB	U S BANCORP DEL										
WFC	WELLS FARGO & CO NEW										
WM	WASHINGTON MUTUAL INC	**									
ZION	ZIONS BANCORP										

Note: This Table reports the panel of companies with the corresponding tickers. The financial institutions marked with the two star symbol are those which disappear during the period of analysis.

Table 2: In-sample and Out-of-sample $CES\%$ based rankings

Panel A: In-sample

$CES\%$ **29/06/2007**		$CES\%$ **31/12/2007**		$CES\%$ **29/02/2008**		$CES\%$ **30/06/2008**		$CES\%$ **29/08/2008**		$CES\%$ **30/01/2009**		$CES\%$ **30/06/2010**	
C	12.99%	BAC	9.47%	BAC	10.49%	JPM	9.73%	BAC	14.47%	WFC	16.18%	BAC	13.03%
JPM	8.76%	C	8.94%	JPM	9.68%	BAC	9.47%	JPM	10.59%	JPM	15.14%	JPM	11.77%
BAC	7.46%	JPM	7.58%	AIG	9.51%	C	9.09%	C	8.48%	BAC	9.98%	C	11.62%
AIG	5.02%	AIG	7.55%	C	7.82%	AIG	7.17%	AIG	6.77%	C	4.74%	WFC	10.87%
GS	4.89%	WFC	5.66%	WFC	6.61%	WFC	6.41%	WFC	6.69%	GS	4.73%	GS	4.54%
WFC	4.70%	GS	4.95%	GS	3.77%	GS	4.11%	MER	4.56%	PNC	4.08%	AXP	4.33%
MS	4.51%	MS	4.14%	MER	3.77%	MS	3.88%	USB	3.82%	USB	4.08%	BRK	3.22%
MER	4.44%	AXP	3.70%	AXP	3.10%	AXP	3.82%	GS	3.28%	BK	3.84%	MS	2.96%
AXP	2.94%	FNM	3.09%	MS	2.96%	USB	3.24%	MS	3.02%	STT	3.37%	USB	2.89%
FNM	2.41%	MER	2.81%	BK	2.41%	MER	3.24%	AXP	2.66%	AFL	2.95%	PNC	2.54%
LEH	2.14%	BK	2.41%	USB	2.24%	BK	2.85%	BK	2.33%	MS	2.92%	BK	2.13%
UNH	1.72%	LEH	2.25%	LEH	2.19%	FNM	1.85%	LEH	1.67%	AXP	1.86%	AFL	1.89%
USB	1.57%	USB	2.15%	FNM	1.63%	LEH	1.73%	STT	1.62%	ALL	1.70%	BEN	1.63%
BK	1.45%	FRE	2.14%	STT	1.50%	STT	1.58%	STI	1.43%	SCHW	1.56%	COF	1.63%
BEN	1.44%	STT	1.34%	STI	1.32%	SCHW	1.49%	SCHW	1.40%	BRK	1.51%	STI	1.40%

Panel B: Out-of-sample

$CES\%$ **29/06/2007**		$CES\%$ **31/12/2007**		$CES\%$ **29/02/2008**		$CES\%$ **30/06/2008**		$CES\%$ **29/08/2008**		$CES\%$ **30/01/2009**		$CES\%$ **30/06/2010**	
C	13.88%	C	13.96%	C	13.56%	BAC	10.44%	BAC	11.52%	BAC	15.78%	JPM	15.71%
AIG	9.27%	JPM	8.10%	BAC	8.30%	C	9.83%	JPM	9.99%	JPM	12.54%	BAC	12.03%
JPM	6.94%	BAC	7.22%	JPM	7.47%	JPM	8.66%	C	9.12%	C	9.76%	WFC	11.85%
BAC	5.99%	AIG	7.14%	AIG	7.25%	AIG	7.96%	AIG	8.36%	WFC	8.72%	GS	7.80%
MS	4.68%	GS	4.66%	WFC	5.50%	WFC	5.95%	WFC	6.70%	USB	4.87%	C	6.98%
GS	4.51%	WFC	4.44%	MS	4.02%	GS	5.18%	GS	4.16%	GS	4.55%	MS	4.20%
WFC	3.74%	MS	4.19%	GS	3.89%	MS	4.12%	MER	3.78%	MS	3.94%	AXP	4.17%
MER	3.73%	MER	4.08%	AXP	3.71%	AXP	3.80%	MS	3.42%	AXP	3.02%	USB	3.95%
AXP	3.09%	AXP	3.17%	MER	3.67%	MER	3.06%	AXP	3.31%	MER	2.75%	BK	2.91%
LEH	2.34%	FNM	2.34%	FNM	2.62%	BK	2.78%	BK	2.94%	BK	2.58%	STT	2.17%
FNM	2.20%	LEH	2.14%	USB	2.56%	USB	2.68%	USB	2.90%	STT	1.87%	BRK	1.95%
USB	2.04%	USB	1.90%	BK	2.20%	LEH	2.48%	LEH	2.35%	SCHW	1.68%	SCHW	1.82%
UNH	1.78%	UNH	1.58%	LEH	2.17%	FNM	1.99%	STT	1.61%	PNC	1.67%	BEN	1.78%
COF	1.59%	BEN	1.49%	BEN	1.61%	UNH	1.54%	UNH	1.29%	BEN	1.44%	AFL	1.75%
WM	1.48%	BK	1.40%	WM	1.45%	STT	1.50%	SCHW	1.28%	BBT	1.42%	BBT	1.48%

Table 3: CES and MES Systemic Risk Rankings

30/01/2009		30/06/2010	
$CES\%$	MES	$CES\%$	MES
WFC	STT	BAC	ABK
JPM	PNC	JPM	FNM
BAC	AFL	**C**	MI
C	FITB	WFC	STI
GS	**C**	GS	ACAS
PNC	**BAC**	AXP	FRE
USB	HBAN	BRK	LNC
BK	LNC	MS	ZION
STT	RF	USB	SNV
AFL	STI	PNC	**C**

Note: This Table displays the ranking of the top 10 financial institutions based on $CES\%$ and MES, respectively, for the last two days of our analysis.

Table 4: Rank similarity for the most risky institutions

Panel A: In-sample

	Similarity ratio ($CES\%$ vs SRISK%)						
	29/06/2007	**31/12/2007**	**29/02/2008**	**30/06/2008**	**29/08/2008**	**30/01/2009**	**30/06/2010**
Top 5	0.20	0.20	0.20	0.60	0.60	0.80	0.60
Top 10	0.50	0.60	0.60	0.70	0.70	0.50	0.60

Panel B: Out-of-sample

	Similarity ratio ($CES\%$ vs SRISK%)						
	29/06/2007	**31/12/2007**	**29/02/2008**	**30/06/2008**	**29/08/2008**	**30/01/2009**	**30/06/2010**
Top 5	0.40	0.20	0.20	0.60	0.60	0.80	0.60
Top 10	0.50	0.60	0.70	0.70	0.70	0.60	0.60

Note: This Table presents the rank similarity measure between $CES\%$ and SRISK% based rankings for each date in the analysis by considering the top five and ten most risky financial institutions. The similarity measure is simply defined as the proportion of firms that are concurrently in the two rankings on a given date. The results are reported for both in-sample (Panel A) and out-of-sample (Panel B) analyses.

Table 5: In-sample and Out-of-sample ranking composition

Panel A: In-sample

	29/06/2007		31/12/2007		29/02/2008		30/06/2008		29/08/2008		30/01/2009		30/06/2010	
	Top 10	Top 15	Top 10	Top 15	Top 10	Top 15	Top 10	Top 15	Top 10	Top 15	Top 10	Top 15	Top 10	Top 15
Depositories	40.00%	40.00%	40.00%	47.00%	50.00%	53.33%	50.00%	46.67%	50.00%	53.33%	80.00%	53.33%	60.00%	53.33%
Broker-Dealers	30.00%	26.67%	30.00%	26.67%	30.00%	26.67%	30.00%	33.33%	30.00%	33.33%	10.00%	20.00%	20.00%	13.33%
Insurance	10.00%	13.33%	10.00%	6.67%	10.00%	6.67%	10.00%	6.67%	10.00%	6.67%	10.00%	20.00%	10.00%	13.33%
Others	20.00%	20.00%	20.00%	20.00%	10.00%	13.33%	10.00%	13.33%	10.00%	6.67%	0.00%	6.67%	10.00%	20.00%

Panel A: Out-of-sample

	29/06/2007		31/12/2007		29/02/2008		30/06/2008		29/08/2008		30/01/2009		30/06/2010	
	Top 10	Top 15	Top 10	Top 15	Top 10	Top 15	Top 10	Top 15	Top 10	Top 15	Top 10	Top 15	Top 10	Top 15
Depositories	40.00%	40.00%	40.00%	40.00%	40.00%	46.67%	50.00%	46.67%	50.00%	46.67%	60.00%	60.00%	70.00%	53.33%
Broker-Dealers	40.00%	26.67%	30.00%	26.67%	30.00%	26.67%	30.00%	26.67%	30.00%	33.33%	30.00%	26.67%	20.00%	20.00%
Insurance	10.00%	13.33%	10.00%	13.33%	10.00%	6.67%	10.00%	13.33%	10.00%	13.33%	0.00%	0.00%	0.00%	13.33%
Others	10.00%	20.00%	20.00%	20.00%	20.00%	20.00%	10.00%	13.33%	10.00%	6.67%	10.00%	13.33%	10.00%	13.33%

Note: This Table displays the composition by type of institution of the top ten and fifteen most risky institutions according to the $CES\%$ measure. The results are reported for both in-sample (Panel A) and out-of-sample (Panel B) analyses.