



European
University
Institute

MAX WEBER
PROGRAMME
FOR
POSTDOCTORAL
STUDIES

WORKING PAPERS

MWP 2013/23
Max Weber Programme

Which are the SIFIs?
A Component Expected Shortfall (CES) Approach to
Systemic Risk

Georgiana-Denisa Banulescu and Elena-Ivona Dumitrescu

European University Institute
Max Weber Programme

Which are the SIFIs?
A Component Expected Shortfall (CES) Approach to Systemic Risk

Georgiana-Denisa Banulescu and Elena-Ivona Dumitrescu

EUI Working Paper **MWP** 2013/23

This text may be downloaded for personal research purposes only. Any additional reproduction for other purposes, whether in hard copy or electronically, requires the consent of the author(s), editor(s). If cited or quoted, reference should be made to the full name of the author(s), editor(s), the title, the working paper or other series, the year, and the publisher.

ISSN 1830-7728

© Georgiana-Denisa Banulescu and Elena-Ivona Dumitrescu, 2013

Printed in Italy
European University Institute
Badia Fiesolana
I – 50014 San Domenico di Fiesole (FI)
Italy
www.eui.eu
cadmus.eui.eu

Abstract

This paper proposes a *component approach* to systemic risk which allows to decompose the risk of the aggregate financial system (measured by *Expected Shortfall, ES*) while accounting for the firm characteristics.

Developed by analogy with the *Component Value-at-Risk* concept, our new systemic risk measure, called *Component ES (CES)*, presents several advantages. It is a hybrid measure, which combines the *Too Interconnected To Fail* and the *Too Big To Fail* logics. CES relies only on publicly available daily data and encompasses the popular *Marginal ES* measure. CES can be used to assess the contribution of a firm to systemic risk at a precise date but also to forecast its contribution over a certain period. The empirical application verifies the ability of CES to identify the most systemically risky firms during the 2007-2009 financial crisis. We show that our measure identifies the institutions labeled as SIFIs by the Financial Stability Board.

Keywords

Systemic Risk, Component Expected Shortfall, Marginal Expected Shortfall.

JEL Classification: C22, C53, G01, G32

August 2013

Georgiana-Denisa Banulescu

LEO, University of Orléans and Maastricht University, email: georgiana.banulescu@univ-orleans.fr

Elena-Ivona Dumitrescu

Max Weber Fellow, 2012-2013

European University Institute, email: elena-ivona.dumitrescu@eui.eu

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. In this context, a key issue for regulators is the identification of the so-called *Systemically Important Financial Institutions, SIFIs*. The Financial Stability Board (2010) defines the SIFIs as financial institutions “*whose disorderly failure, because of their size, complexity and systemic interconnectedness, would cause significant disruption to the wider financial system and economic activity*”. According to the Basel III agreements, these institutions should face a capital ‘surcharge’ determined according to the ‘negative externalities’ they generate, *i.e.* their contribution to the aggregate risk of the financial system.¹

How can these SIFIs be identified? This is the key question in the design of a framework for implementing macroprudential regulation such as the one proposed by the Basel Committee for Banking Supervision. Two main perspectives can be identified in this literature. One stream of research focuses on the structural modeling of a bank’s balance-sheet positions / strategies in terms of assets and debt (Greenwood, Landier, Thesmar, 2012; Gouriéroux, Héam, Montfort, 2012). However, the corresponding data are not publicly available, rendering the regulators using them unable to reveal to the markets the reasons behind their decisions.

The second approach relies on public market data (market returns, total asset returns, option prices or CDS spreads).² The baseline idea is to reveal the financial interdependencies from these market-data without any knowledge of the (publicly unavailable) cross-positions of financial institutions. One common feature of these market-based approaches is that they consider an aggregate risk measure for the financial system, typically the *Value-at-Risk, VaR* or the *Expected Shortfall, ES* and they aim at quantifying the contribution of each firm to the overall risk of the system. Then, the systemic risk analysis is closely related to the portfolio risk analysis. The logic is the same: it consists in determining the contribution of a given asset (respectively a financial institution) to the risk of the portfolio (respectively the financial system).

In this context, the simplest procedure to implement is a *marginal* one, that reflects the sensitivity of the risk of the system to a unit change in a firm’s weight in the financial system, *i.e.* relative size. A representative example is the *Marginal Expected Shortfall, MES* proposed by Acharya et al. (2010). But the marginal approach has the major inconvenience that it does not account for the level

¹In particular, the Basel Committee on Banking Supervision distinguishes between the factors useful for assessing whether a financial institution in general is systemically important (size, complexity, interconnectedness) and the exact factors used to identify Global Systemically Important Banks (G-SIB) which, apart from the three aforementioned ones also include the lack of readily available substitutes for the financial infrastructure it provides, and its global (cross-jurisdictional) activity.

²For a survey on systemic risk measures, see VanHoose, (2011).

of the firm's characteristics, *e.g.* size, leverage, in line with the Too Big To Fail paradigm. Major consequences in terms of SIFIs' identification follow from this stylized fact: a small, unlevered firm can appear more systemically risky than a big, levered one. For example, the financial institutions that make the top five ranking of Acharya et al. (2010), for the period between June 2006 and June 2007, according to *MES*, are *IntercontinentalExchange Inc*, *E Trade Financial Corp*, *Bear Stearns Companies Inc*, *N Y S E Euronext*, and *C B Richard Ellis Group Inc*. Apart from *Bear Stearns*, which was bought by JPMorgan in March 2008, little was said about these firms during the global financial crisis. The reason behind this is simple: *MES* clearly privileges the *Too Interconnected To Fail* logic to that of *TBTF*. Furthermore, the sum of *MES* associated with the firms in the system does not equal the financial system's aggregate loss as measured by *ES*.

Brownlees and Engle (2012) extended the *MES* to *SRISK* by taking into account the size and the leverage of the financial institution. *SRISK* measures the capital shortfall of a financial institution during a crisis in the whole financial system. Formally, it depends on the long-run *MES*, market value and liabilities and in this sense it can be considered as a good compromise between the *TITF* and the *TBTF* paradigms. Brownlees and Engle show that this measure allows to identify the SIFIs as done by the Bank for International Settlements / Financial Stability Board (FSB) / G-20 (Financial Stability Board, 2011). The main advantage of the *SRISK*, compared to the list of SIFIs released by FSB, is that it can be computed at a higher frequency (daily) with no cost (see the NYU's website, Vlab). However, it should be noted that in fact, the *SRISK* measure combines high frequency market data (daily stock prices and market capitalization) and low frequency balance sheet data (leverage). To provide a daily forecast of their measure, Brownless and Engle are then constrained to assume that the liabilities of the firm are constant over the period of crisis.

In this paper we propose a new systemic risk measure called *Component Expected Shortfall* (*CES* thereafter), which addresses the main drawbacks of *MES* and *SRISK*. The *CES* of a financial institution measures the firm's 'absolute' contribution to the *ES* of the financial system. Formally, *CES* corresponds to the product of *MES* and the weight of the institution in the financial system, *i.e.* relative market capitalization. Our measure can be easily used to identify the SIFIs: the larger *CES*, the greater the contribution and the more systemically risky the institution. In addition, *CES* makes it possible to easily decompose the risk of the aggregate financial system (measured by *ES*) according to the institutions therein.

This original measure presents several advantages. First, in contrast to the aforementioned *marginal approach*, our method includes by definition the weight of the firm in the financial system and hence the size of the institution. Similarly to *SRISK*, *CES* can be labeled as a hybrid systemic risk measure, which combines the *TBTF* and the *TITF* paradigms. Second, our systemic risk measure relies only on daily market data and hence could be used as a real-time systemic risk

measure. Contrary to *SRISK*, no assumption is made on the constancy of the liabilities or the leverage during the crisis period. In addition, the *ES* of the financial system at a precise date equals the sum of *CES* for all the institutions in the system at that moment. This is an appealing characteristic of *CES* that greatly simplifies interpretation since it is possible to compute at each date the contribution in percentage of each financial institution to the global risk of the financial system (measured by *ES*). Therefore it becomes a good candidate for regulatory authorities selecting which institutions to monitor, with a view to discouraging practices that increase systemic risk. Most importantly, *CES* can be used not only to assess the contribution of a firm to the risk of the system at a precise date in-sample, but also to forecast (out-of-sample) its contribution over a period. 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 Acharya et al. (2012), Brownlees and Engle (2012) and Acharya et al. (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).

Two major implications in terms of policy can be emphasized. First, we show that most of the systemic risk is concentrated in a small number of institutions. For example, the first five SIFIs on 29/08/2008, Bank of America, JPMorgan, Citigroup, AIG, and Wells Fargo and Co regroup 46.99% of the aggregate risk. Therefore, imposing a tighter supervision on a handful of institutions can improve the stability of the financial system. Second, SIFIs' ranking provided by *CES* is relatively stable in time. The riskiest financial institutions are the same from one period to another, supporting the revision of regulatory rules every few years.³ Moreover, this simple systemic risk measure allows us to find the same ranking as Brownlees and Engle (2012) who, in turn, compared theirs with that published by the FSB (2011).

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.

³BCBS suggests revising the cluster of SIFIs every three years.

2 Methodology

In this paper, we propose an original method to identify systemically risky financial institutions. Let us consider a financial system composed of n institutions. r_{mt} denotes the aggregate return of the financial system, and r_{it} is the return of firm i on day t . The financial system's global return (market return thereafter) is defined as the value-weighted average of all firm returns

$$r_{mt} = \sum_{i=1}^n w_{it} r_{it}, \quad (1)$$

with w_{it} the weight of the i^{th} firm in the financial system at time t .⁴ These weights are given by the relative market capitalization of the financial institutions.

Let us assume that the aggregate risk of the financial system is measured by the conditional ES .⁵ By actuarial convention, the ES is the expected market loss conditional on the return being less than the α quantile, *i.e.* the VaR . It can also be extended to a more general case, where the distress event is defined by a threshold C . The conditional ES (with respect to past information) is formally given by

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

SIFIs' identification requires us to measure the contribution of each financial institution to the whole risk of the system. Acharya et al. (2010) proposed the concept of MES . This systemic risk measure corresponds to the *marginal* contribution of a firm to the risk of the financial system measured by ES . It corresponds to the change in the market's ES engendered by a unit increase in the weight of the i^{th} institution in the financial system (see Appendix A for the derivation of this expression)

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

In contrast, in this paper we propose a *component* systemic risk measure, the CES , that is precisely not a marginal but an absolute measure of systemic risk.

Definition 1. *The Component Expected Shortfall (CES) is defined as the part of the ES of the financial system due to the i^{th} institution*

$$CES_{it} = w_{it} \frac{\partial ES_{m,t-1}(C)}{\partial w_{it}} = -w_{it} \mathbb{E}_{t-1}(r_{it} | r_{mt} < C). \quad (4)$$

⁴Since we use log-returns instead of arithmetic returns, as in Engle and Brownlees, 2012, an approximation error appears. 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).

CES corresponds to the product of MES and the weight of the firm in the system and it is set out in the same measurement unit as ES . This measure quantifies the *absolute* contribution of firm i to the risk of the financial system. The larger the contribution, the more systemically important the institution.

One appealing property of CES is that, by construction, the sum of all the financial institution's CES is equal to the expected loss of the financial system at each date⁶

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

Consequently, CES can be easily expressed as a percentage of ES .

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

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

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. While the weights are easily obtained using market capitalization data, the expected value of firm i 's returns conditional on the market being in stress has to be estimated, as we will see in the next section.

This Component Expected Shortfall measure of systemic risk can be considered as the equivalent of the Component Value-at-Risk measure (Jorion, 2007) for portfolio analysis. Indeed, such measures allow us to decompose the overall risk of the financial system / portfolio according to the institutions / assets therein. In this perspective, the systemic risk analysis can be viewed as a macroeconomic portfolio risk analysis, where the portfolio assets are the financial institutions.

This new systemic risk measure presents several advantages. First, CES takes into account the weight of the financial institutions in the system and hence their relative size. As $SRISK$, CES can be considered as a hybrid measure, which combines the $TITF$ and the $TBTF$ paradigms. By contrast, MES does not take into account at all the size of the firm, although it is an essential characteristic of SIFIs. It follows that this marginal systemic risk measure generally leads to an improper ranking of the institutions in which the small minor ones emerge as systemically important. Second, as MES , our measure depends only on daily data. We hence do not make any assumptions on the stability of the leverage ratio within a quarter, as in Brownlees and Engle (2012). Indeed, $SRISK$ includes

⁶Since the conditional expectation is a random variable and the market index is a linearly homogeneous 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 eq. (5).

economic indicators sampled at different frequencies: daily stock prices, market capitalization and quarterly leverage. Third, for a given period t , $CES\%_{it}(C)$ add up to 100 by construction, which clearly simplifies interpretation. In addition, the weights can be defined in a very flexible way, by including not only market value data but also other relevant indicators for the institutions in the sample. Given our definition of the weights, CES relies only on market data and can be qualified as a homogeneous systemic risk measure. This is not the case of $SRISK$, which mixes market and balance-sheet data.

3 Estimation and forecasting

Let us consider a bivariate GARCH model for the demeaned return processes, which corresponds to a simple market model (CAPM) with time-varying conditional *betas* (Engle, 2012)

$$r_t = H_t^{1/2} \epsilon_t, \quad (7)$$

where $r_t = (r_{mt} \ r_{it})'$ is the vector of market and firm returns and $\epsilon_t = (\epsilon_{mt} \ \xi_{it})'$ is the vector of independently and identically distributed shocks with zero mean and identity covariance matrix. H_t denotes the time-varying conditional covariance matrix

$$H_t = \begin{pmatrix} \sigma_{mt}^2 & \sigma_{mt}\sigma_{it}\rho_{it} \\ \sigma_{mt}\sigma_{it}\rho_{it} & \sigma_{it}^2 \end{pmatrix} \quad (8)$$

where σ_{mt} and σ_{it} are the conditional standard deviations for the system and the firm, respectively, and ρ_{it} is the time-varying conditional correlation. Given this framework, CES can be expressed as follows

$$\begin{aligned} CES_{it}(C) = & -w_{it}[\sigma_{it}\rho_{it}\mathbb{E}_{t-1}(\epsilon_{mt}|\epsilon_{mt} < C/\sigma_{mt}) \\ & + \sigma_{it}\sqrt{1 - \rho_{it}^2}\mathbb{E}_{t-1}(\xi_{it}|\epsilon_{mt} < C/\sigma_{mt})]. \end{aligned} \quad (9)$$

CES is a non-linear combination of four elements: volatility, correlation, tails expectations and the weight of the firm.⁷ Notice also that the linear dependency between market and firm returns is completely captured by the time-varying conditional correlations, whereas the remaining non-linear dependencies are captured by the second conditional expectation, $\mathbb{E}_{t-1}(\xi_{it}|\epsilon_{mt} < C/\sigma_{mt})$.

⁷Similarly, $MES_{it}(C) = \sigma_{it}\rho_{it}\mathbb{E}_{t-1}(\epsilon_{mt}|\epsilon_{mt} < C/\sigma_{mt}) + \sigma_{it}\sqrt{1 - \rho_{it}^2}\mathbb{E}_{t-1}(\xi_{it}|\epsilon_{mt} < C/\sigma_{mt})$.

3.1 In-sample systemic risk measure

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

Step 1. The time-varying correlations of each couple ‘market’ - ‘firm’ are modelled using a dynamic conditional correlation (DCC) model (Engle, 2000; Engle and Shepard, 2001). From this, we obtain conditional volatilities and standardized residuals for the market and each institution by modelling volatilities in a GJR-GARCH(1,1) framework (Glosten et al., 1993).⁸ The parameters are estimated by QML, since it provides consistent and asymptotically normal estimators under mild regularity conditions, without making any distributional assumptions about the innovations process.

Step 2. 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):

$$\widehat{\mathbb{E}}_{t-1}(\varepsilon_{mt}|\varepsilon_{mt} < c) = \frac{\sum_{t=1}^T \varepsilon_{mt} \Phi\left(\frac{c-\varepsilon_{mt}}{h}\right)}{\sum_{t=1}^T \Phi\left(\frac{c-\varepsilon_{mt}}{h}\right)} \quad (10)$$

$$\widehat{\mathbb{E}}_{t-1}(\xi_{it}|\varepsilon_{mt} < c) = \frac{\sum_{t=1}^T \xi_{it} \Phi\left(\frac{c-\varepsilon_{mt}}{h}\right)}{\sum_{t=1}^T \Phi\left(\frac{c-\varepsilon_{mt}}{h}\right)}, \quad (11)$$

where $c = C/\sigma_{mt}$ is the threshold, $\Phi(\cdot)$ represents the normal c.d.f. (Gaussian Kernel function), and h is the bandwidth. In the empirical application we set C to *VaR-HS*(5%) of the system and h to $T^{-1/5}$, as in Scaillet (2005). For a formal proof, see Appendix B. At the end of the third step we can rely on (9) to compute *CES* for institution i at each date t .

Step 3.

We hence obtain a daily *Component Expected Shortfall* systemic risk measure *CES%* by using eq. (15) and (9).

3.2 Out-of-sample systemic risk measure

Policy decisions require forecasts of firms’ contributions to systemic risk. A particularity of systemic risk analysis is hence that regulators are generally interested in the contribution of a financial institution to the aggregate risk of the system over a *period* and not a precise date. Let us consider that we aim at forecasting the systemic risk of the financial institution i over a future period that ranges between the dates $T + 1$ and $T + h$, where h is the forecast horizon (see the upper part of

⁸This 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*.

Figure 1). Typically, we will consider a period of 6 months. This constitutes a major difference with respect to the way forecasts are traditionally constructed, by focusing only on a specific future date, $T + h$ (see the bottom part of Figure 1). Being able to provide such results constitutes a distinctive feature of our method. Let us formally denote by $T + 1 : T + h$ the out-of-sample period, where

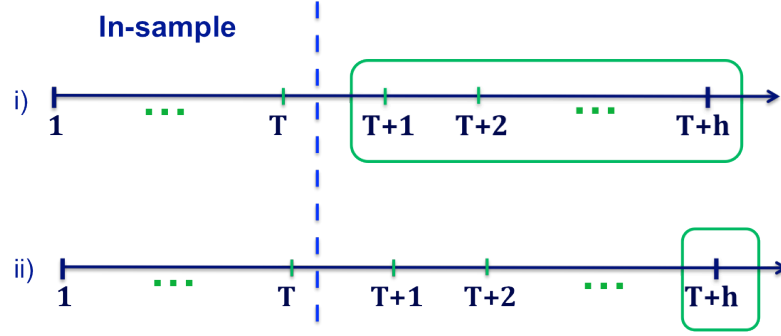


Figure 1: Out-of-sample Forecasting Scheme

h represents the forecast horizon, set to six months in the empirical application. To forecast the *CES* of an institution over the out-of-sample period $T + 1 : T + h$, we use the same methodology as Brownlees and Engle (2012) for their long-run *MES*. They show that the 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 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

$$\{\varepsilon_{m,t}^s, \xi_{i,t}^s\}_{t=T+1}^{T+h}, \text{ for } s = \{1, 2, \dots, S\}. \quad (12)$$

Step 2. Compute the sequences of market and firm returns by using as a 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:

$$R_{k,T+1:T+h}^s = \exp \left(\sum_{j=1}^h r_{k,T+j}^s \right) - 1, \quad k = \{m, i\}, \quad (13)$$

where $r_{k,T+j}^s$ 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 estimated by⁹

$$MES_{i,T+1:T+h}(\tilde{C}) = \frac{\sum_{s=1}^S R_{i,T+1:T+h}^s \mathbb{I}_{(R_{m,T+1:T+h}^s < \tilde{C})}}{\sum_{s=1}^S \mathbb{I}_{(R_{m,T+1:T+h}^s < \tilde{C})}}, \quad (14)$$

where \tilde{C} stands for the threshold defining the systemic event in out-of-sample (Acharya et al., 2010). 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

$$CES\%_{i,T+1:T+h}(\tilde{C}) = \frac{CES_{i,T+1:T+h}(\tilde{C})}{\sum_{i=1}^n CES_{i,T+1:T+h}(\tilde{C})}, \quad (15)$$

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

3.3 Choice of weighting scheme

An essential element in the computation of one and multi-periods ahead *CES* is the choice of the weights w_{it} . Note that the contribution of these weights to *CES* is twofold: i) they enter directly into eq. (9) where they represent the relative size of the institution along the lines of the *TBTF* logic and ii) they are required in the construction of the returns of the financial system (eq. 1) that are used to estimate the conditional volatilities, innovations and tail expectations. To be more precise, the *CES* estimates (and forecasts) are based on a sequence of past market returns defined as a weighted average of firm returns. In this context, a fundamental question is: at which date should these weights be considered? By analogy with the literature devoted to backtesting and to risk model validation (where one distinguishes between hypothetical profit and loss (P&L) and actual P&L), there are mainly two ways to proceed in the selection of firms weights.

First, we can define the in-sample weights as the historical relative market capitalization (see eq. (1) and the top part of Figure 2). In portfolio analysis, these returns correspond to the “actual returns” or actual P&L. This type of weighting scheme is used in particular by Brownlees and Engle

⁹Note that Scaillet’s method (2005) could be used to compute the $CES\%$ risk measure in out-of-sample too.

(2012) and Acharya et al. (2010), *inter alii*.

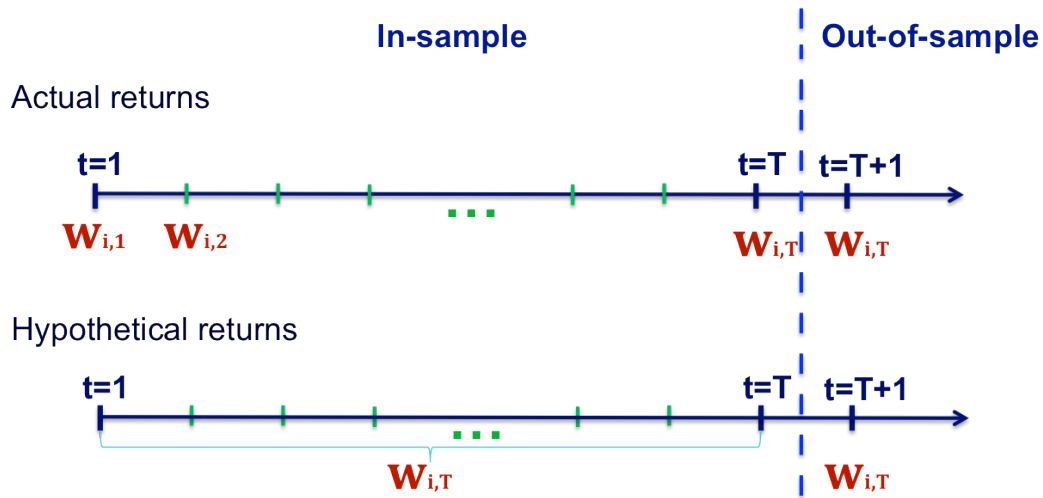


Figure 2: Weighting Scheme

The second approach relies on the concept of “hypothetical” returns generally used in the risk management analysis. In our context it means that at each date the past hypothetical market returns are defined by using the current (and not the past) weights of the financial institutions in the financial system. Out-of-sample forecasts are hence conditional to the weights of the firms in the portfolio at the last in-sample period (see the bottom part of Figure 2). To put it differently, in this case, the *CES* forecast measures the contribution of a financial institution to the aggregate risk over a future period, whereas the composition of the financial system (weights of the institutions) remain unchanged during this period. This approach allows to clearly identify the systemic risk of a given firm without any compositional effect.

Following this standard methodology in portfolio analysis, we choose the second approach for our empirical illustration.

4 Empirical Application

In this section we use the technique previously presented and propose an empirical application of our *CES* measure in order to identify the most systemically important financial institutions. Our purpose is not only to classify as systemically risky the financial institutions that historically experienced distress one day later (in-sample exercise), but also to 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 similar to the one used by Brownlees and Engle (2012) 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 74 U.S. financial institutions whose market capitalization exceeds 5bln USD as of the end of June 2007. Moreover, the firms 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 is based on the financial system including only the surviving financial institutions among the 74 considered in our sample. It is thus reconstructed for each date of interest, and for this reason the weight (based here on the market capitalization concept) of each firm in the panel is computed for those specific dates and then considered constant for all the past periods in the analysis (see Section 3.1). Of course, financial regulators are free to implement their own weight definition, that could take into account various other indicators (size, leverage, etc.).

For the sake of simplicity, we 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 that effectively disappear during the crisis period.

4.2 In-sample analysis

We define a crisis as a situation in which market distress exceeds the $\text{VaR}(5\%)$, 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 the distress corresponds to a 2% market drop over a day, as in Brownlees and Engle (2012)¹⁰, since this cut-off reflects the average $\text{VaR}(5\%)$ 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.

¹⁰This set of results is available upon request.

The main purpose of the paper is to identify the riskiest financial institutions in the market by directly ranking the institutions according to their *CES*. Table 2 (Panel A) displays the first fifteen firms contributing the most to the total loss of the financial system for the seven dates previously indicated. First, 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.). Second, the risk is very concentrated. For instance, 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. This observation is very important for regulators because imposing specific regulation to a small number of financial institutions seems to increase the stability of the whole financial system. Third, the clusters of SIFIs are stable in time, practically the same, and it is only the order of financial institutions that changes from one period to another. 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. Indeed, what really matters from the regulators perspective is to identify 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 systemically risky firms into five buckets), and not their precise order. So that, the financial regulation decisions do not have to be changed very often. From this viewpoint, we observe that the cluster of the top four most risky financial institutions according to *CES* (Citigroup, Bank of America, JPMorgan and A.I.G.) is always the same, albeit in a 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 seven dates of our analysis. On average, there are two financial institutions that are simultaneously identified as SIFIs by the two systemic risk measures. For instance, on September 29, 2008 only three financial institutions (Bank of America and Citigroup) are simultaneously identified by the two risk measures. In addition, on June 30, 2010, Citigroup is the only common financial institution with *MES*. This result highlights the difference between the marginal and the component systemic risk measures in terms of the characteristics of the SIFIs taken into account by each of them. Supporting the *TITF* logic, the *MES*-based ranking contains only small firms that are indeed very interconnected, but which cannot be considered the main triggers of the failure of the financial system. The ranking according to *CES* is more coherent, as it contains financial institutions (Citigroup, Bank of America, JPMorgan, etc.) that contributed substantially to the system’s crash. This difference between the two rankings is due to the fact that *CES* includes both the *TITF* and *TBTF* paradigms.

Several interesting empirical facts can also be observed when we focus on the individual firm results. Figure 3 displays the evolution of the short run *CES* and *MES* over the period of January, 2007 to December, 2010 for some representative leading systemic firms from each group of institutions: Bank of America, Citigroup, JPMorgan, Morgan Stanley, A.I.G. and American Express. Overall, all the firms exhibit a similar time trend, but there are also some specific features that mirror the differences between the two measures. Taking the example of AIG, we observe that *CES* increases before *MES*. This is because its capitalization increases, whereas the same level of interconnectedness characterizes AIG since 2007. *CES* is hence able to identify the systemic character of AIG before *MES*.

For the other firms, the evolution of both *CES* and *MES* is alike. The pre-crisis period features lower levels of risk contribution, with a progressive increase in these two measures as the crisis unfolds. Notice that for some firms *CES* is even more volatile than *MES* during this period. Moreover, the series of short run predictions peaks at the end of 2008 or the beginning of 2009 and then decays 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. It is well known that on September 14, 2008 Lehman Brothers filed for bankruptcy after the financial support facility offered by the Federal Reserve Bank stopped. A few days later, 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 4 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. Overall, the evolution of average *CES* is quite obvious, with some interesting remarks tied to the magnitude of the measure for each group of institutions. There is a considerable variation of *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 an obvious order of the average contribution to the systemic risk by 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 level

at the beginning of 2009, precisely at the height of the crisis, emphasizing *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 Broker-Dealers category. Furthermore, the two other categories, Insurance and Others, present similar average levels of contribution to the aggregate financial risk.

Finally, Table 5 (Panel A) reports the composition by type of institutions of the top ten and fifteen most risky financial institutions according to our *CES*% measure. Considering the risk allocation for the top ten most risky financial institutions, we notice that the Depositories group dominates the other groups in terms of number of risky institutions: between 40% (in 2007) and 80% (at the height of the crisis). It is followed by the Broker-Dealers category of financial institutions that represents about 30% of the SIFIs in the top ten. Besides, not only Depositories and Dealer-Brokers exhibit the largest average increase in risk (Figure 4), but they are generally the main contributors to systemic risk. The results for the top fifteen go along the same lines as the ones for the top ten.

4.3 Out-of-sample analysis

In the previous subsection, we analyzed the results obtained when considering one-period ahead estimates of our *CES* measure. However, *CES* can be used not only to assess the contribution of a firm to the aggregate risk of the system 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. For this we use a historical *MES* method “à la” Acharya, based on the simulated paths of out-of-sample returns, along the lines of Engle and Brownlees (2012). More precisely, 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.

The forecasts are computed for the six month period preceding the same dates previously used for the in-sample analysis. The systemic event is defined as the situation in which the market return exceeds a threshold (set here to the out-of-sample VaR-HS for cumulative market returns considering a risk level of 5%, *i.e.* empirical quantile of the simulated paths).

Table 2 (Panel B) shows the first fifteen most systemically important financial institutions at the seven dates under analysis. Just like in the in-sample analysis, the ranking is based on the *CES*% and includes almost the same risky financial institutions, but in a slightly different order. It always captures systemically important financial institutions such as: Citigroup, Bank of America,

JPMorgan, etc. To compare the two $CES\%$ -based rankings we have computed a similarity ration defined 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 between the top fifteen most risky firms in-sample and out-of-sample, respectively, ranges from 80% to 93.33%. In addition, the risk continues to be very concentrated as the proportion of the total loss covered by the first ten firms in the ranking varies from 58.17% to 71.77%.

Figure 5 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, we observe a slow increase in the average measure over the period of July, 2007 to September, 2008, and a slowly decaying shape of the average CES forecasts for each of the four categories after this period of extreme financial stress. The insurance group reaches its maximum average in September, 2008, while Depository and Broker-Dealer institutions attain it at the beginning of 2009. 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-Dealers category, less present in the ranking (*i.e.* 20% to 40%), as indicated in Table 5 (Panel B).

We subsequently propose a brief comparison of our $CES\%$ -based ranking with the one based on a systemic risk measure recently introduced by Brownlees and Engle (2012), namely $SRISK\%$ ¹¹. Given the way the sequence of returns of the financial system is computed for $CES\%$, we first reconstruct the market return (based on the market capitalization) and then compute $SRISK\%$ on our sample of financial institutions by using the same methodology as in Acharya, Engle, Richardson (2012). Table 4 reports the top 10 financial institutions according to their contribution to systemic risk measured by $CES\%$ and $SRISK\%$, respectively, for the seven dates of our analysis. Bold entries mirror the financial institutions that are simultaneously identified as SIFIs by the two systemic risk measures¹². We remark that the two rankings capture almost the same risky financial institutions that effectively contributed to the struggle of the financial system during the last financial crisis.

The last two lines of Table 4 display the value of the rank similarity ratio between the two approaches for each date under analysis, by considering the top five and ten most systematically risky institutions. The two top ten rankings are strongly correlated, as the measure can go up to 0.80. Using

¹¹This tool was proposed to overcome some drawbacks of the marginal approach, by further considering for its computation the size and liabilities of financial institutions. In their article, Brownlees and Engle compute $SRISK$ by considering a sample of the 94 biggest US financial institutions and the CRSP market index. From this point of view, one could argue that a direct comparison between our ranking and theirs is not a fair one. The possible differences could hence have two sources: the sample of firms and the market index used.

¹²For an easy identification they are also marked by a star symbol.

only daily market data we can hence identify almost the same SIFIs as when we use a method whose computation requires data sampled at different frequencies (to compute *SRISK* we need daily stock prices, market capitalization and quarterly leverage). We also perform a Kendall rank correlation analysis between the two rankings, but considering the whole sample of financial institutions under analysis. Overall, the correlation between the rankings provided by the two systemic risk measures is not statistically significant. But what really matters is the correct identification of the bucket of the first ten / fifteen riskiest firms. In Figure 6 we compare the values of *CES* and *SRISK* at four precise dates. Notice the presence of a cluster of financial institutions that have simultaneously higher values of *CES* and *SRISK*, which confirms our previous findings. Another interesting point to discuss is the way the market index used to compute the two measures (*CES* and *SRISK*) impacts the correlation between the rankings associated with them. In our approach we consider that the sequence of returns for the financial system is computed by using only the financial institutions of our sample (as in Engle et al., 2012), while Brownlees and Engle (2012) use the CRSP index. In order to verify whether our results are statistically sensitive to the change of the market index used to compute the *SRISK* measure, we perform the same exercise by considering the CRSP public index for the computation of *SRISK*. The results are almost identical since the similarity ratio between the two *SRISK*%-based rankings obtained by considering both the CRSP index and our market return definition varies from 90% (80%, respectively) to 100% for the top ten (five, respectively) riskiest financial institutions and the Kendall correlation coefficient is highly significant at each date under analysis. This exercise emphasizes the fact that our parsimonious systemic risk measure identifies the key SIFIs reported in the *SRISK* ranking, which are also present in FSB's ranking of G-SIFIs published in November 2011. The main advantage of *CES* is that it uses only daily market data to correctly identify the most systemically risky financial institutions over a certain period, whereas *SRISK* mixes daily market data and balance-sheet data, namely the debt, that is available at most at a quarterly frequency.

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 parsimony of the 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 $\text{VaR}(5\%)$, 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 simply by 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 (2012) for the same periods, according to a rank similarity measure, which is simply computed as the percentage of firms that are concurrently in the two rankings at a given date. The two rankings have quite similar patterns, which is a really nice result knowing that for our measure one only needs daily (publicly available) market data.

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 classification 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.

Acknowledgments

We thank Christophe Hurlin for the most enlightening discussions and useful comments on a previous version of this paper. We also thank Christian Brownlees, Olivier Scaillet, Bertrand Maillet, the participants at the 11th CREDIT conference in Venice, 2012, at the Banque de France seminar, at the 3rd Humboldt-Copenhagen conference in Berlin, 2013, at the 18th Meeting of Young Economists in Aarhus, 2013 and especially those at the 3rd International Conference of the Financial Engineering and Banking Society, Paris, 2013. The usual disclaimers apply.

References

- [1] Acharya, V., Pedersen, L., Philippe, T., and Richardson, M., 2010, Measuring Systemic Risk. Technical Report, Department of Finance, NYU.
- [2] Acharya, V., Engle, R., Richardson, M., 2012, Capital Shortfall: A New Approach to Ranking and Regulating Systemic Risks, *American Economic Review* 102(3), 59?64.
- [3] Adrian, T., and Brunnermeier, M. K., 2011, CoVaR, Technical report, Federal Reserve Bank of New York. Staff report No. 34.
- [4] Aikman, D., Alessandri, P., Eklund, B., Gai, P., Kapadia, S., Martin, E., Mora, N., Sterne, G., and Willison, M., 2009, Funding Liquidity Risk in a Quantitative Model of Systemic Stability, Bank of England Working Paper.
- [5] Artzner, P., Delbaen, F., Eber, J.-M., Heath, D., 1999, Coherent Measures of Risk, *Mathematical Finance* 9, 203-228.
- [6] Black R., 1976, Studies in Stock Price Volatility Changes. Proceedings of the Business Meeting of the Business and Economics Statistics Section, American Statistical Association, 177-181.
- [7] Brownlees, T.C., and Engle, R.F., 2012, Volatility, Correlation and Tails for Systemic Risk measurement, Working Paper, NYU-Stern.
- [8] Buiter, W., 2009, Regulating the New Financial Sector, comments made at the 6th Annual Conference: Emerging from the Financial Crisis, Columbia University, February 20 (<http://blogs.ft.com/maverecon/2009/02/regulating-the-new-financial-sector/>).
- [9] Caporin, M., and De Magistris, P.S., 2010, On the Evaluation of Marginal Expected Shortfall, Technical report.

- [10] Engle, R., 2012, Dynamic Conditional Beta, SSRN 2084872.
- [11] Engle, R., 2002, Dynamic Conditional Correlation: A Simple Class of Multivariate Generalized Autoregressive Conditional Heteroskedasticity Models, *Journal of Business & Economic Statistics* 20(3), 339-50.
- [12] Engle, R. F., Jondeau, E., Rockinger, M., 2012, Systemic Risk in Europe, Swiss Finance Institute, Research Paper Series Working Paper No. 12-45.
- [13] Engle, R. F. and K. Sheppard, 2001, Theoretical and Empirical Properties of Dynamic Conditional Correlation Multivariate GARCH, Technical Report, NBER, Working Paper No. W8554.
- [14] Financial Stability Board, 2011, Policy Measures to Address Systemically Important Financial Institutions, November.
- [15] Financial Stability Board, 2010, Reducing the moral hazard posed by systemically important financial institutions.
- [16] Glosten, L. R., Jagannathan, R., and Runkle, D. E., 1993, On the Relation between the Expected Value and the Volatility of the Nominal Excess Return on Stocks, *The Journal of Finance* 48, 1779-1801.
- [17] Gouriéroux, C., Héam, J.-C., Monfort, A., 2012, Bilateral exposures and systemic solvency risk, *Canadian Journal of Economics* 45(4), 1273-1309.
- [18] Greenwood, R., Landier, A., Thesmar, D., (2012), Vulnerable Banks, working paper.
- [19] Jorion, P., 2007, *Value at Risk: The New Benchmark for Managing Financial Risk*, McGraw-Hill, 3rd Edition.
- [20] Scaillet, O., 2004, Nonparametric Estimation and Sensitivity Analysis of Expected Shortfall, *Mathematical Finance* 14, 115-129.
- [21] Scaillet, O., 2005, Nonparametric Estimation of Conditional Expected Shortfall, *Revue Assurances et Gestion des Risques/Insurance and Risk Management Journal* 74, 639-660.
- [22] Silverman, B.W., 1986, *Density Estimation for Statistics and Data Analysis*. London: Chapman and Hall.
- [23] Simonoff, J.S., 1996, *Smoothing Methods in Statistics*. New York: Springer.

- [24] VanHoose, D., 2011, Systemic Risks and Macroprudential Bank Regulation: A Critical Appraisal, *Journal of Financial Transformation* 33, 45-60.
- [25] Wand, M.P. and Jones, M.C., 1995, *Kernel Smoothing*. London: Chapman and Hall.

Appendix A: Marginal Expected Shortfall

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

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

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

$$\frac{\partial ES_{m,t-1}(C)}{\partial w_i} = \mathbb{E}_{t-1}(r_{it} | r_{mt} < C). \quad (\text{A.2})$$

For this, we denote by \check{r}_{mt} the return for the financial system except for the contribution of the i^{th} asset, where $\check{r}_{mt} = \sum_{j=1}^n w_j r_{jt}$ and $r_{mt} = \check{r}_{mt} + w_i r_{it}$. 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. A.2.

It follows that

$$\begin{aligned} ES_{m,t-1}(C) &= \mathbb{E}_{t-1}(\check{r}_{mt} + w_i r_{it} | \check{r}_{mt} + w_i r_{it} < C(w_i, p)) \\ &= \frac{1}{p} \int_{-\infty}^{\infty} \left(\int_{-\infty}^{C(w_i, p) - w_i r_{it}} (\check{r}_{mt} + w_i r_{it}) f(\check{r}_{mt}, r_{it}) d\check{r}_{mt} \right) dr_{it}, \end{aligned} \quad (\text{A.3})$$

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

$$\begin{aligned} \frac{\partial ES_{m,t-1}(C)}{\partial w_i} &= \frac{1}{p} \int_{-\infty}^{\infty} \left(\int_{-\infty}^{C(w_i, p) - w_i r_{it}} (\check{r}_{it}) f(\check{r}_{mt}, r_{it}) d\check{r}_{mt} \right) dr_{it} \\ &\quad + \frac{1}{p} \int_{-\infty}^{\infty} \left(\frac{\partial C(w_i, p)}{\partial w_i} - r_{it} \right) C(w_i, p) f(C(w_i, p) - w_i r_{it}, r_{it}) dr_{it} \end{aligned} \quad (\text{A.4})$$

However, the probability of being in the left tail of the distribution of the market return is constant,

i.e. $\Pr(\check{r}_{mt} + w_i r_{it} < C) = p$. 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

$$\left(\frac{\partial C(w_i, p)}{\partial w_i} - r_{it} \right) f(C(w_i, p) - w_i r_{it}, r_{it}) = 0. \quad (\text{A.5})$$

Therefore, eq. A.4 can be written compactly as

$$\begin{aligned} \frac{\partial ES_{m,t-1}(C)}{\partial w_i} &= \frac{1}{p} \int_{-\infty}^{\infty} \left(\int_{-\infty}^{C(w_i, p) - w_i r_{it}} (\check{r}_{it}) f(\check{r}_{mt}, r_{it}) d\check{r}_{mt} \right) dr_{it} \\ &= \mathbb{E}_{t-1}(r_{it} | \check{r}_{mt} + w_i r_{it} < C(w_i, p)) \\ &= \mathbb{E}_{t-1}(r_{it} | r_{mt} < C), \end{aligned} \quad (\text{A.6})$$

which completes the proof.

Appendix B: 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

$$\mathbb{E}_{t-1}(\varepsilon_{mt} | \varepsilon_{mt} < c). \quad (\text{B.1})$$

Using the definition of the conditional mean, we rewrite B.1 as a function of the probability density function f

$$\mathbb{E}_{t-1}(\varepsilon_{mt} | \varepsilon_{mt} < c) = \int_{-\infty}^c \varepsilon_{mt} f(u | u < c) du, \quad (\text{B.2})$$

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

$$\frac{f(u)}{\Pr(u < c)}. \quad (\text{B.3})$$

To complete the proof, we must compute the numerator and denominator in B.3. For this, we first

consider the standard kernel density estimator of the density f at point u given by

$$\hat{f}(u) = \frac{1}{Th} \sum_1^T \phi\left(\frac{u - \varepsilon_{mt}}{h}\right),$$

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

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

The expectation in B.1 hence takes the form

$$\hat{\mathbb{E}}_{t-1}(\varepsilon_{mt} | \varepsilon_{mt} < c) = \frac{\sum_{t=1}^T \varepsilon_{mt} \Phi\left(\frac{c - \varepsilon_{mt}}{h}\right)}{\sum_{t=1}^T \Phi\left(\frac{c - \varepsilon_{mt}}{h}\right)}. \quad (\text{B.4})$$

Similarly, it can be shown that

$$\hat{\mathbb{E}}_{t-1}(\xi_{it} | \varepsilon_{mt} < c) = \frac{\sum_{t=1}^T \xi_{it} \Phi\left(\frac{c - \varepsilon_{mt}}{h}\right)}{\sum_{t=1}^T \Phi\left(\frac{c - \varepsilon_{mt}}{h}\right)}. \quad (\text{B.5})$$

Figures and Tables

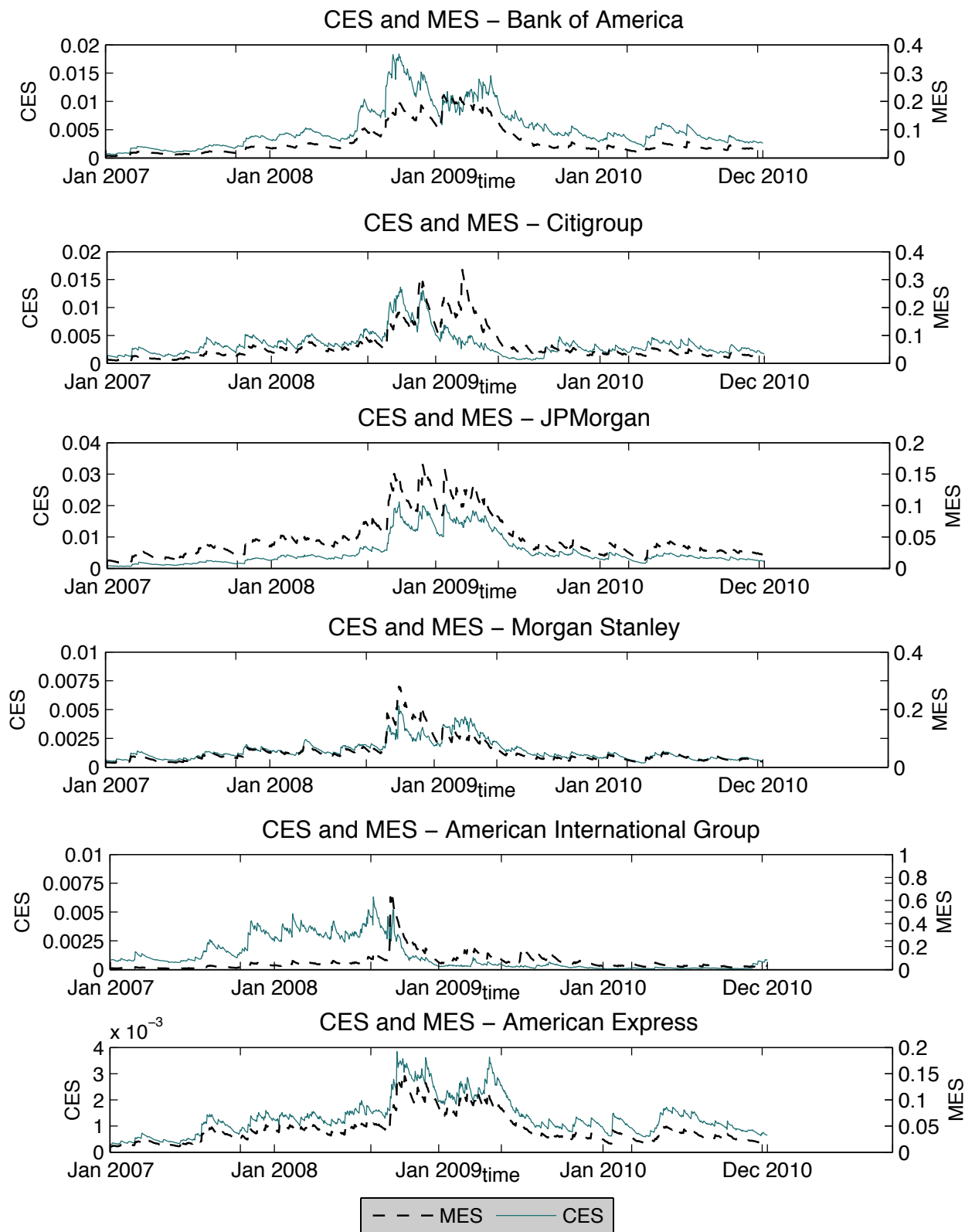


Figure 3: Short run Component Expected Shortfall and Marginal Expected Shortfall

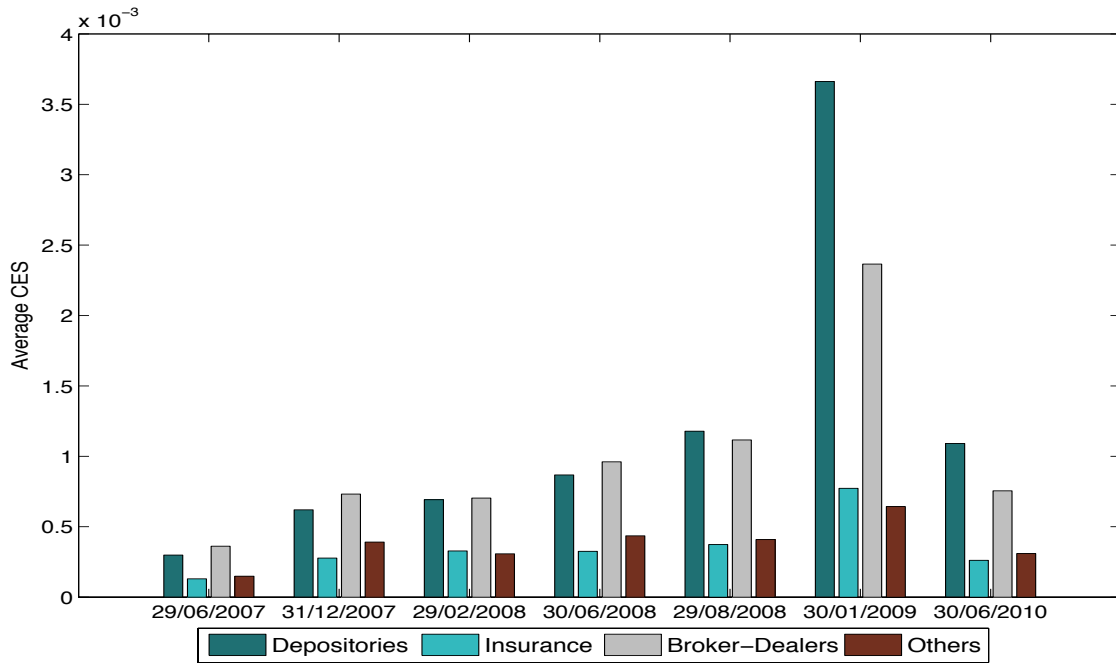


Figure 4: In-sample average *CES* by type of institution

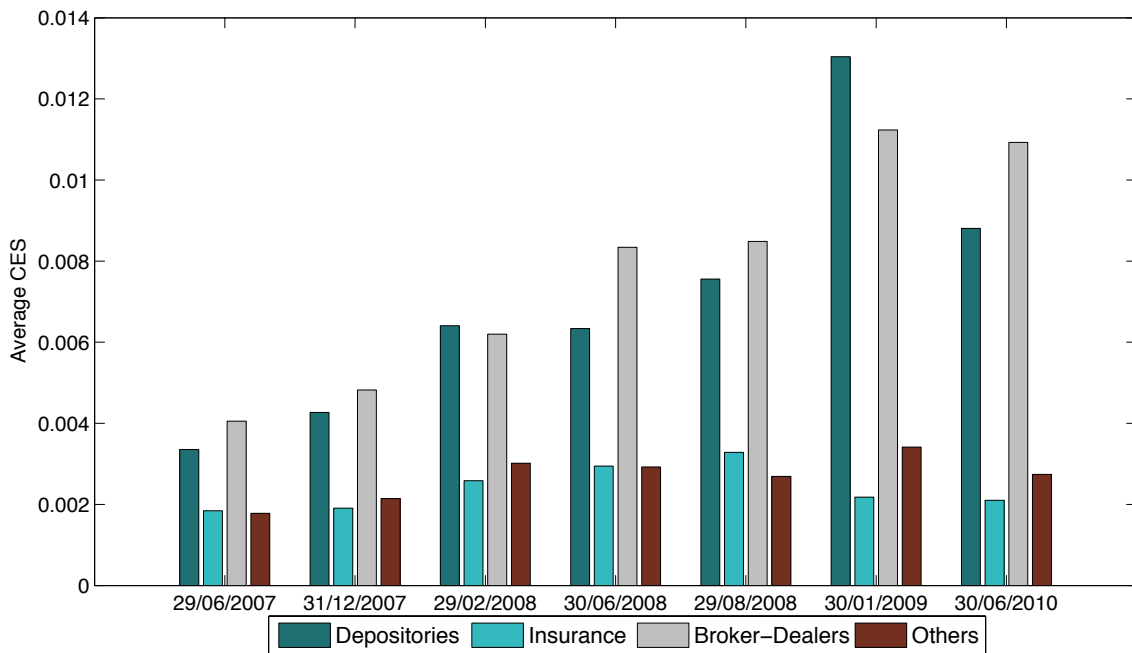


Figure 5: Out-of-sample average *CES* by type of institution

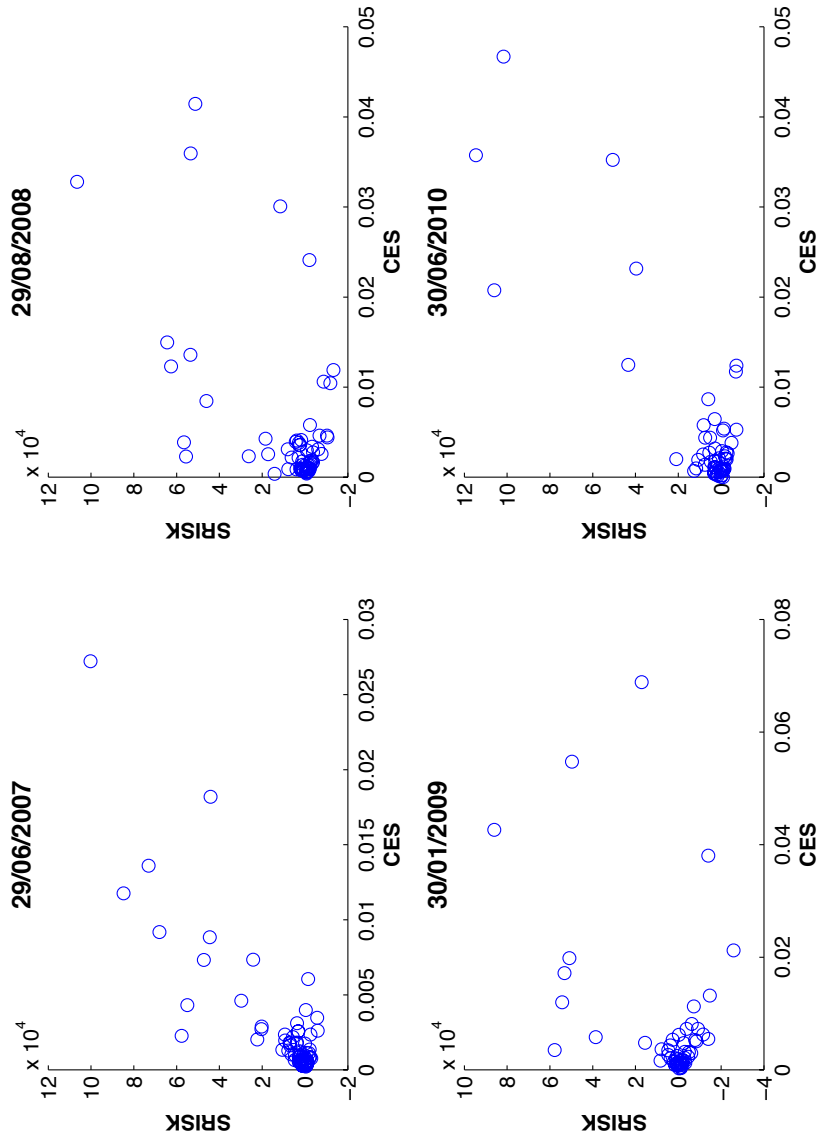


Figure 6: Scatter plot CES vs SRISK

Table 1: Dataset

Depositories (27)		Insurance (23)		Broker-Dealers (9)		Others (15)	
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	CS	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 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	LINGCOLN 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						
WMI	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													
<i>CES%</i> 29/06/2007	<i>CES%</i> 31/12/2007	<i>CES%</i> 29/02/2008	<i>CES%</i> 30/06/2008	<i>CES%</i> 29/08/2008	<i>CES%</i> 30/01/2009	<i>CES%</i> 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													
<i>CES%</i> 29/06/2007	<i>CES%</i> 31/12/2007	<i>CES%</i> 29/02/2008	<i>CES%</i> 30/06/2008	<i>CES%</i> 29/08/2008	<i>CES%</i> 30/01/2009	<i>CES%</i> 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

29/06/2007		31/12/2007		29/02/2008		30/06/2008		29/08/2008		30/01/2009		30/06/2010	
CES	MES	CES	MES	CES	MES	CES	MES	CES	MES	CES	MES	CES	MES
C	BSC	C	MBI	C	ABK	BAC	MBI	BAC*	FNM	BAC*	STT	JPM	ABK
AIG	MER*	JPM	ETFC	BAC	MBI	C*	LEH	JPM	FRE	JPM	PNC	BAC	FNM
JPM*	MBI	BAC	ABK	JPM	CNA	JPM	WM	C	LEH	C*	AFL	WFC	MI
BAC	AMTD	AIG	FRE	AIG*	WM	AIG	ABK	AIG*	ABK	WFC	FITB	GS	STI
MS	GS	GS	SLM	WFC	LEH	WFC	KEY	WFC	AIG*	USB	C*	C*	ACAS
GS	SCHW	WFC	WM	MS	AIG*	GS	FITB	GS	MBI	GS	BAC*	MS	FRE
WFC	LEH*	MS*	CFC	GS	MER*	MS	RF	MER*	RF	MS	HBAN	AXP	LNC
MER*	JPM*	MER	NCC	AXP	RF	AXP	C*	MS	WM	AXP	LNC	USB	ZION
AXP	CFC	AXP	FNM*	MER*	MI	MER*	HBAN	AXP	MER*	MER	RF	BK	SNV
LEH*	STT	FNM*	MS*	FNM	HBAN	BK	MER*	BK	BAC*	BK	STI	STT	C*

Note: This Table displays the ranking of the top 10 financial institutions based on *CES* and *MES*, respectively. Bold entries highlight the financial institutions that are simultaneously in the two rankings. They are also marked by a star symbol.

Table 4: Rank similarity for the most risky institutions

29/06/2007		31/12/2007		29/02/2008		30/06/2008		29/08/2008		30/01/2009		30/06/2010	
CES	SRISK	CES	SRISK	CES	SRISK	CES	SRISK	CES	SRISK	CES	SRISK	CES	SRISK
C*	C*	C*	C*	C*	C*	BAC*	C*	BAC*	C*	BAC*	C*	JPM*	BAC*
AIG*	BAC*	JPM*	BAC*	BAC*	MS*	C*	JPM*	JPM*	GS*	JPM*	FRE	BAC*	C*
JPM*	JPM*	BAC*	MS*	JPM*	MER*	JPM*	MER*	C*	MS*	C*	FNM	WFC	JPM*
BAC*	MS*	AIG*	JPM*	AIG	FRE	AIG	BAC*	AIG	FNM	WFC	MER*	GS*	AIG
MS*	FRE	GS*	MER*	WFC	JPM*	WFC	MS*	WFC	FRE	USB	MS*	C*	WFC
GS*	FNM	WFC	FRE	MS*	BAC*	GS*	FRE	GS*	MER*	GS*	GS*	MS*	MS*
WFC	MER*	MS*	FNM*	GS*	FNM*	MS*	GS*	MER*	JPM*	MS*	JPM*	AXP	GS*
MER*	GS*	MER*	AIG*	AXP	GS*	AXP	FNM	MS*	BAC*	AXP	LEH	USB	HIG
AXP	AIG*	AXP	GS*	MER*	LEH	MER*	LEH	AXP	LEH	MER*	AIG	BK	SLM
LEH*	LEH*	FNM*	LEH	FNM*	BSC	BK	BSC	BK	BSC	BK	BAC*	STT	PNC
Top 5	0,80	0,60		0,40		0,60		0,20		0,20		0,60	
Top 10	0,80	0,80		0,70		0,60		0,60		0,60		0,50	

Note: This Table displays the ranking of the top 10 financial institutions based on *CES* and *SRISK*, respectively. Bold entries highlight the financial institutions that are simultaneously in the two rankings. They are also marked by a star symbol. The last two lines report 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.

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%	50.00%	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%	30.00%	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%	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%	10.00%	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%	50.00%	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%	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%	10.00%	0.00%	0.00%	0.00%	13.33%
Others	10.00%	20.00%	20.00%	20.00%	20.00%	20.00%	20.00%	13.33%	10.00%	6.67%	10.00%	10.00%	13.33%	10.00%	13.33%

Note: This Table reports the composition of the aggregate financial risk by type of institution according to the *CES%* measure. This is computed for the top ten and fifteen most risky firms. The results are reported for both in-sample (Panel A) and out-of-sample (Panel B) analyses.