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Systemic-systematic risk in financial system: A dynamic ranking based on expectiles

Laura Garcia-Jorcano [*,1], Lidia Sanchis-Marco

Department of Economic Analysis and Finance (Area of Financial Economics), Facultad de Ciencias Jurídicas y Sociales, Universidad de Castilla-La Mancha, 45071, Toledo, Spain

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ABSTRACT

We provide an international comparison of rankings for systematic and systemic risk in the financial system and examine whether both types of risk co-exist. The rankings are based on the information provided by a coherent downside risk measure, the expected shortfall (ES), which we compute from expectiles. Using rolling windows, we obtain dynamic rankings for different banks as well as for financial services and insurance firms from different international regions using principal components analysis (PCA). The main evidence for $ES_{5\%}$ indicates that banks from Asia are the most systematic and insurance groups from Europe are the most systemic during a crisis period. Our results have implications for supervisors regarding the regulation of financial firms, as well as for investors regarding the incorporation of diversifiable and non-diversifiable risks in their portfolios.

1. Introduction

The recent global financial crisis and the subsequent European sovereign debt crisis highlighted the importance of analyzing primary market risk. Financial institutions tend to leverage up to the maximum, which is revealed by the structure of their balance sheets. The complex network of exposures among financial institutions creates a significant threat that the surviving institutions will lose part or all of their investment in the financial system. If such a failure is sudden or unexpected, there could be sufficiently large losses to threaten or bring down the corresponding institutions. For these reasons, financial institutions can be especially vulnerable and even more causal to systematic and systemic risk than other sectors and components of the economy. Therefore, it is important to analyze and understand the nature of systematic and systemic risk.

Systematic risk is a well-established concept and it can be defined as the risk inherent to the financial market. It is unpredictable and cannot be mitigated through diversification, only through hedging or by using the correct asset allocation strategy. This risk is usually proxied by market risk using the conditional firm beta as in Benoit et al. (2013) or tail beta as in Straetmans and Chaudhry (2015). On the contrary, there is still no consensus on the proper way to define and measure systemic risk. In the literature, there are several definitions; one is the existence of any set of circumstances that threatens the stability of our public confidence in the financial system (Billio et al., 2012). The European Central Bank (2010) defines it as a risk of financial instability that becomes so widespread that it impairs the functioning of a financial system to the point where economic growth and welfare suffer materially. Zigrand (2014)

* Corresponding author.
E-mail addresses: Laura.Garcia@uclm.es, desico96@hotmail.com (L. Garcia-Jorcano), Lidia.Sanchis@uclm.es (L. Sanchis-Marco).

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indicates that, like systematic risk, systemic risk cannot be diversified either. However, the nonlinearities involved in the feedback loops suggest clearly that systemic risk is separate from what is usually called systematic risk, or non-diversifiable risk, in the finance literature, that represents the risk of an aggregate event. These systematic events may correspond to very large shocks, but the system is expected to continue functioning normally and properly. This distinction has also been emphasized by Hansen (2012).[2] It is evident, therefore, that systemic risk is not yet fully understood and the disparate definitions hinder its measurement.[3] Because both of these types of risk are different, it is important to measure them separately, which has relevance and implications for financial regulators as well as portfolio holders (see more details in De Bandt & Hartmann, 2000).

Given the increasingly interconnected nature of the global financial system, this study attempts to analyze international exposures of the main financial institutions to systematic and systemic risk over time. For this purpose, we provide a comprehensive study using a sample of 204 financial institutions that include banks, financial services and insurance firms from around the world. Academics and practitioners are interested in mitigating the factors behind systemic risk and studying the patterns of systematic risk. In this line, this paper proposes a new approach that is based on principal component analysis (PCA) and that use expectiles to estimate the expected shortfall (ES) to disentangle both types of risk, allowing dynamic rankings to be developed for systematic and systemic financial institutions. To the best of our knowledge, this is the first work that use expectiles as a tool to quantify both types of risk and that provides an in-depth analysis about this relationship in a dynamic framework. Dynamic rankings from measures of both types of risk that capture well-identified economic mechanisms could be used as inputs for regulatory tools. Our methodology allows us to establish rankings from both types of risks and it also captures the persistence of risk during different time periods. We also analyzed the link between the contributions of institutions' systematic and systemic risk and their characteristics, such as market value, leverage, tail beta, sector and geographical location in a cross-sectional framework. This research will be helpful to the Financial Stability Board (FSB), central banks and supervisors in order to promote the sharing of firm-level data on systematically and systemically important financial institutions.

Many new approaches have been developed to quantify and rank systematic and systemic risk contributions of firms in the financial sector. Common recent approaches for ranking financial institutions are based on other measures of systemic risk such as stock betas, return volatilities, tail dependence, or conditional value at risk, among others (see a summary in Nucera et al., 2016, and in Silva et al., 2017).[4] However, the quest for a global risk measure that encompasses different sources of systemic risk and yet produces a single/-simple metric that can directly be used for regulation (tax or capital surcharge) is still ongoing. Moreover, there is no consensus regarding the dynamic relationship between systematic and systemic risks. Part of the literature postulates that systemic risk is strictly related (if not equal) to systematic risk and therefore there is no need to distinguish between these types of risk. In fact, systemic risk measures, such as *MES* and ΔCoVaR, are largely driven by systematic risk (Benoit et al., 2013; Kubitza & Gründl, 2016, p. 20). Consequently, these measures exhibit a very strong correlation with systematic risk (market betas) and these often exhibit a very large estimation error (see Castro & Ferrari, 2012; Danielsson et al., 2016; Guntay & Kupiec, 2014), which makes it difficult to assess the significance of systemic risk. Indeed, market betas tend to increase during economic downturns, which makes these systemic risk measures procyclical (see Benoit et al., 2017). In response to these shortcomings, several studies have questioned the ability of common systemic risk measures to distinguish systemic from systematic risk, and to reliably identify systemically important institutions (see Billio et al., 2015; Kubitza & Gründl, 2016, p. 20).

Benoit et al. (2013, 2017) show that common systemic risk measures are theoretically and empirically related to simple systematic (i.e., market) risk measures, suggesting that indicators of the former type maybe not sufficient to quantify systemic risk since they seem to be driven by market risk measures and firms' characteristics. Differently from Benoit et al. (2013, 2017), our findings seem to suggest that systemic risk measures still have additional information content over systematic risk measures and leverage in line with the results from Cipollini et al. (2020). Therefore, it is important to analyze and measure both risks separately especially in crisis periods.

Our evidence should have to be taken into account in the design of future methodologies for identifying and regulating global systematically important financial institutions. On the one hand, the most systemic identified financial institutions could be subjected to a range of additional policy measures, including enhanced group-wide supervision recovery and resolution planning requirements, and higher loss absorbency (HLA) requirements. On the other hand, the most systematic financial institutions should be also controlled to prevent higher effects from global financial distress.

Furthermore, the usefulness of systemic risk measures for regulators and policymakers is determined by three factors: reliability, provision of new information, and focus on a clear direction of spillovers from institutions to a market. This implies, in particular, that

[2] Zigrand (2014) indicates that a systemic shock implies (i) either that the structure of the economy changes (say, with some of the institutions vanishing) and therefore that the system of equations that governs the evolution itself has radically changed, or (ii) that the institutions and the equations governing their behavior are still present, but that these equations are sufficiently non-linear or reflect sufficient hysteresis and path-dependencies that the local characteristics of the economy exhibit quite distinct properties. In both cases, the equations reflect an ex-post more dysfunctional system.

[3] Different papers have focused on several measures, including imbalances (Caballero, 2010), correlated exposures (Acharya, 2009; Acharya et al., 2016), spillovers to the real economy (Group of Ten, 2001), information disruptions (Mishkin, 2007), feedback behavior (Kapadia et al., 2009), asset bubbles (Rosengren, 2010), contagion (Moussa, 2011), and negative externalities (Financial Stability Board, 2009).

[4] Some prominent examples of such measures are the marginal expected shortfall (MES) of Acharya et al. (2016), the systemic risk measure (SRISK) of Acharya et al. (2012), and Brownlees and Engle (2017), the Delta conditional value at risk (ΔCoVaR) of Adrian and Brunnermeier (2016), and Mainik and Schaanning (2014), systemic expected shortfall (SES) from Pierret (2015), the distress insurance premium (DIP) of Huang et al. (2011), the microlevel systemic risk measures (conditional tail risk by Kelly, 2011; corisk by Chan-Lau et al., 2009; the contingent claims approach by Gray & Jobst, 2009; shapely values by Tarashev et al., 2009), the recent conditional shortfall probability (CoSP) proposed by Kubitza and Gründl (2016, p. 20) and Adapted Exposure CoVaR by Sedunov (2016).

regulators should be able to distinguish between systemic risk and systematic risk very clearly. However, the large unreliability of standard systemic risk measure such as ΔCoVaR (see Danielsson et al., 2016), indicates that this measure (and measures that are based on it) might violate the first condition of being useful for regulators. Moreover, by assuming that systemic risk materializes instantaneously, MES and ΔCoVaR exhibit a strong interconnection with systematic risk (see Benoit et al., 2017). Indeed, Kubitza and Gründl (2016, p. 20) find 96% correlation between MES and systematic risk, as given by the beta factor, and 51% correlation between the dependence consistent ΔCoVaR and systematic risk. Thus, it seems disputable that these measures fulfill the second condition of being fully useful for regulators. Eventually, the underlying assumption that systemic risk materializes instantaneously makes it difficult to establish a clear direction of spillovers, as required by the third condition. Our systemic risk measure displays a much smaller correlation with systematic risk than MES and the dependence-consistent ΔCoVaR and is thus better able to distinguish between systemic and systematic risk. By focusing on the persistence of rankings during different periods, we strengthen the attention to a clear direction of spillovers. This provides an advantage regarding the second and third conditions of being useful for regulators.

Finally, there are a large number of papers analyzing only the bank sector, especially in the US (see among others, Brownlees & Engle, 2017; Huang et al., 2009; Acharya et al., 2016) to develop systemic risk measures. Given the consequences of the financial distress of AIG for the overall financial sector, another strand of literature has analyzed systemic risk in different sectors of the financial system, and obtained opposite results. On the one hand, there are several studies that find insurance firms do not create systemic risk, in particular because they are not usually large enough and not as interconnected with each other as with banks (see among others, Baluch et al., 2011; Cummins & Weiss, 2014; Geneva Association, 2010; Harrington, 2009; Bijlsma & Muns, 2011, p. 175; Buhler & Prokopczuk, 2010). On the other hand, other studies have found that the financial sector is highly interconnected, and that banks can affect insurance firms more strongly than vice-versa (see among others, Gong et al., 2019; Billio et al., 2012; Chen et al., 2013; Grace et al., 2014). Therefore, the specific systematic-systemic role of insurance firms is still unclear and this is leading to controversial discussions among academics, regulators and insurance institutions. Our study attempts to alleviate this concern by analyzing the role of insurance firms and also financial services institutions.

In summary, our main contributions are: i) whereas most literature focuses on bank returns, we provide evidence in relation to the tail-risk exposures of individual institutions to global system risk across different sectors of the financial system. Our main novelty in this concern is the use of expectiles in expected shortfall (ES) modeling[5] using CARES models as an input with which to measure systematic and systemic risk; ii) we provide evidence for a link between systematic and systemic risk rankings in a static and a dynamic approach based on principal components analysis (PCA); iii) we consider the system as a global set of financial institutions belonging to different sectors and regions[6]; iv) we disaggregate our main results by sectors, regions and different time periods as a robustness analysis.

The results from our analysis for $ES_{5\%}$ can be summarized as follows. Our static analysis reveals that: i) big institutions are not the largest contributors to the systemic risk, ii) the geographical location of firms is more relevant than the sector they are associated with to the systemic risk, iii) institutions with high tail beta are the largest contributors to systematic risk and in less measure to systemic risk, iv) the sector of financial institution is relevant, especially banks and financial services, which presents a high and significant effect on systematic risk, and v) financial institutions from Europe are the largest contributors to systemic risk. Therefore, we have obtained evidence that a given institution may present a high exposure to systematic risk without presenting high systemic risk, and vice-versa. This result confirms that our approach is able to capture, separately, both types of risk, whereas other measures of systemic risk, such as MES and ΔCoVaR are incapable of distinguishing systemic from systematic risk (see Benoit et al., 2013; Kubitza & Gründl, 2016, p. 20). Moreover, our dynamic analysis shows that: i) banks are more systematic during the stress period and less systemic during all periods considered ii) insurance firms are more systematic during quiet periods but more systemic during all the periods considered, iii) financial institutions from North America are less systematic during the stressed period while those from Asia are more systematic for that same period, and iv) insurance institutions from Europe are more systemic than other regions for all periods considered, while Asia is the region that is less systemic.[7] Examples of the most systematic and systemic institutions are the Bank of New York Mellon, Royal Bank Canada, Franklin Resources, JP Morgan, Citigroup and Bank of America among others. Many of these banks appear as the most global systematically important institutions (G-SIBs) on the 2018 list, which was published by the Financial Stability Board (FSB).

These results suggest that systemic risk is not negligible for the insurance sector and in fact has grown in recent years, partly as a consequence of the insurers' increasing links with banks and their recent focus on non-traditional insurance activities, including structured finance. The insurance industry is vulnerable to the effects of the type of major disasters that they sell protection against. Furthermore, over the last decade, the magnitude and frequency of such fundamental risks faced by insurers have undoubtedly increased. This evidence should be relevant for regulators and investors in order to contain potentially devastating spillover to the rest of the economy. In fact, our proposed systemic risk measure captures the actual contribution of the insurance sector to systemic risk,

[5] We agree with Emmer et al. (2015) in the sense that ES can be considered as the best risk measure, and that there is not sufficient evidence to justify an all-inclusive replacement of ES by other risk measures in applications.

[6] Most of the literature about systemic risk uses, as a proxy for financial system, a sectorial or geographical index (see Straetmans & Chaudhry, 2015 and White et al., 2015, among others). On the contrary, we consider a global systemic index that involves all regions and sectors of our sample. In this way we better capture the collection of interconnected and more integrated institutions that have mutually beneficial business relationships through which illiquidity, insolvency, and losses can quickly propagate during periods of financial distress.

[7] The results for $ES_{1\%}$ are quite different for systematic risk by sectors as financial services are the most systematic during crisis periods and banks are the most systematic during post-crisis periods. For systemic risk, the main results that are different for $ES_{1\%}$ are that banks are the most systemic during crisis periods. This evidence suggests that the magnitude of the extreme losses is important, i.e. more extreme losses during crisis periods in financial services emerge as the most sensitive to the global distress and banks distress effect to the global system is higher.

beyond being a mere indicator of vulnerability to impairments of the financial sector (Darpeix, 2015; Eling & Pankoke, 2012). Our results confirm the evidence in Billio et al. (2012) and Chen et al. (2013), which indicated that the stock market returns of life as well as non-life insurers and banks have become more correlated in recent years. Cummins and Weiss (2014), and Weiss and Mühlnickel (2014) showed that, according to systemic risk measures, insurances companies do contribute to systemic risk and are vulnerable to distress in the financial system.

This paper is organized as follows. Section 2 explains the methods regarding ES estimation and the principal component technique for the computation of the risk rankings. Section 3 presents the data analysis and the estimation of the CARES model. Section 4 analyzes systematic risk. Section 5 studies systemic risk. Section 6 provides a comparison of both types of risk and their determinants analysis. Finally, Section 7 provides some concluding remarks.

2. Methodology

2.1. Using expectiles to estimate ES

After the recent financial crises and the increase in the complexity of the markets' financial institutions, measuring systemic risk has become one of the most important issues in the financial sector. Most of these measures are based on market risk measures such as VaR or ES. ES is preferred to other measures because it is the only one that is coherent, comonotonic additive, robust and conditionally elicitable (Artzner et al., 1999, Basel Committee on Banking; Emmer et al., 2015; Basel Committee on Banking Supervision, 2016). ES is defined as the conditional expectation of the return, given that it exceeds the VaR. We apply a recent ES modelling approach, which avoids distributional assumptions using expectiles as the estimation of quantiles, the conditional autoregressive expectile (CARE) model proposed by Taylor (2008). CARE models are based on asymmetric least squares (ALS) proposed by Aigner et al. (1976) and the conditional autoregresive value at risk (CAViaR) model by Engle and Manganelli (2004). The solution of an ALS regression, which is the least squares analogue of quantile regression, is known as an expectile. The use of expectiles as an alternative tool for quantifying tail risk has attracted a lot of interest recently, see for instance Martin (2014). Motivating advantages are that expectiles are more alert (than quantiles) to the magnitude of infrequent catastrophic losses, and they depend on both the tail realizations of a random variable and their probability, while quantiles only depend on the frequency of tail realizations (see Kuan et al., 2009). Besides, following Newey and Powell (1987), Abdous and Remillard (1995) and Sobotka and Kneib (2012), among others, the inference on expectiles is much easier than the inference on quantiles, and their estimation makes more efficient use of the available data since weighted least squares rely on the distance to data points, being that the check-loss function is continuously differentiable while empirical quantiles only use the information on whether an observation is below or above the predictor. Furthermore, unlike sample quantiles, sample expectiles provide a class of smooth curves as functions of order significance level, θ (see, Schulze Waltrup et al., 2015).

The τ-th expectile is the solution to the minimization of asymmetrically mean squared errors, with the weights τ and $(1-\tau)$ assigned to positive and negative deviations, respectively. The population τ-th expectile of returns y is the parameter x that minimizes the function,

$$e(\tau) \equiv arg \min_{x \in \mathbb{R}} \mathbb{E}[|\tau - 1_{\{y<x\}}|(y-x)^2] \tag{1}$$

Taylor (2008) provides insight into the result of the ALS minimization in expression (2) by considering the expectile as being conditional on information set up to period $t-1$, instead of considering the expectile as a scalar parameter as in expression (1),

$$\min_{\beta} \sum_t |\tau - 1_{\{y_t<e_t(\tau)\}}|(y_t - e_t(\tau))^2 \tag{2}$$

It is straightforward to show that the solution $e_t(\tau)$ of this minimization satisfies expression (3),

$$\left(\frac{1-2\tau}{\tau}\right)\mathbb{E}[(y_t - e_t(\tau))1_{\{y_t<e_t(\tau)\}}] = e_t(\tau) - \mathbb{E}[y_t] \tag{3}$$

Newey and Powell (1987) explain that the expression indicates that the solution $e_t(\tau)$ is determined by the properties of the expectation of the random variable y_t that is conditional on y_t and exceeds $e_t(\tau)$. This suggests a link between expectiles and ES (see Taylor, 2008, for technical details). Taylor (2008) provides a formula for the ES of the quantile that coincides with the τ expectile. Referring to the τ-expectile as the θ-quantile, we can set $F(e_t(\tau)) = \theta$ (where F is the cdf of y) and rewrite expression (3). We can estimate the expression conditioned on information set up for period $t-1$. This conditional expectile, $e_t(\tau)$, satisfies the following expression for the conditional ES,

$$ES_t(\theta) = \left(1 + \frac{\tau}{(1-2\tau)\theta}\right)e_t(\tau) - \frac{\tau}{(1-2\tau)\theta}\mathbb{E}(y_t) \tag{4}$$

This expression relates the ES associated with the θ-quantile of a distribution and the τ-expectile that coincides with that quantile in the lower tail of the distribution. We follow Efron's proposal (see Efron, 1991, for further details) of using a conditional model for the

τ-expectile to estimate the θ-quantile. Expression (4) serves as a simple way to calculate the ES associated with this estimate. Considering expression (4), note that it is intuitively reasonable that, over time, for a given value of θ, the conditional ES will be proportional to the conditional expectile model $e_t(\tau)$.

More concretely, we estimate the Symmetric Absolute Value (SAV) CARE model (Taylor, 2008),

$$e_t(\tau) = \beta_0 + \beta_1 e_{t-1}(\tau) + \beta_2 |y_{t-1}| \tag{5}$$

Using expression (4), it is straightforward to convert the CARE models into Conditional Autoregressive ES (CARES) models. The CARES model that we use is the SAV model defined as

$$ES_t^\theta = \gamma_0 + \gamma_1 ES_{t-1}^\theta + \gamma_2 |y_{t-1}| \tag{6}$$

where $\gamma_1 = \beta_1$, and, for $i = 0$ and 2, $\gamma_i = \left(1 + \frac{\tau}{(1-2\tau)\theta}\right)\beta_i$.

We implemented the SAV model for each financial institution. The model parameters can be estimated using ALS with a similar non-linear optimization routine to that used by Engle and Manganelli (2004) for CAViaR models. For each model, we first generated 10^5 vectors of parameters from a uniform random number generator between 0 and 1. For each of the vectors, we then evaluated the ALS Sum, which we define as the summation in the ALS regression objective function presented in expression (2). The 10 vectors that produced the lowest values of the ALS Sum were used as initial values in a quasi-Newton algorithm. The ALS Sum was then calculated for each of the 10 resulting vectors, and the vector producing the lowest value of the ALS Sum was chosen as the final parameter vector.

We set, as estimator of the θ-quantile, the τ-expectile for which the proportion of in-sample observations lying below the expectile is θ. To find the optimal value of τ, we estimated models for different values of τ over a grid with a step size of 0.0001. The final optimal value of τ was derived by linear interpolating between grid values.[8]

To estimate the parameters of CARE models, we use as initial conditions those estimated parameters generated by a simulated annealing algorithm proposed by Goffe et al. (1994), instead of a simplex algorithm or other conventional optimization algorithms because it encloses regions in the parameter space for which the function does not exist, being a very robust algorithm. It is a local random search algorithm that accepts values that increase the objective function (rather than lower it) with a probability that decreases as the number of iterations increases. Here, the primary aim is to prevent the search process from becoming trapped in a local optima, which in addition, provides a low sensitivity to the choice of the initial values. To minimize the possibility of convergence to a local optima, the optimization process was repeated 1000 times over the whole sample.[9]

2.2. Measuring systematic and systemic risk using principal components

Increased commonality among the ES series of banks, financial services and insurance companies can be empirically detected using PCA. PCA factor model reduces the number of risk factors to a manageable dimension and it helps us to identify the key sources of risk. PCA represents one the main methods at our disposal to estimate large a covariance matrix. In contrast to the CAPM model, which is a one-factor model, the PCA is used to generate multi-factor models and it can be used to estimate the decomposition of the covariance matrix of large samples of returns into factor loadings and residual components. The relative ease of computing the principal components makes them quite attractive. For the measuring of systematic risk, we use a PCA to construct estimators of the covariance matrix of the ES series in an increasing dimension setting, without requiring that a set of observable common factor be pre-specified.

We consider our set of standardized ES series, which is summarized in a TxN matrix $\boldsymbol{X}$, where T is the time series observations, N is the number of financial institutions, and $\boldsymbol{\Gamma}$ is the correlation matrix of $\boldsymbol{X}$.[10] The principal components of $\boldsymbol{\Gamma}$ are the columns of the TxN matrix $\boldsymbol{P}$, defined by $\boldsymbol{P} = \boldsymbol{XW}$, where $\boldsymbol{W}$ is the NxN orthogonal matrix of eigenvectors of $\boldsymbol{\Gamma}$. Thus, the original system of correlated ES series $\boldsymbol{X}$ has been transformed into a system of orthogonal ES $\boldsymbol{P}$, i.e. the system of principal components. We can turn this around into a representation of the original variables in terms of the principal components. Since $\boldsymbol{W}$ is orthogonal, $\boldsymbol{W}^{-1} = \boldsymbol{W}'$ and so $\boldsymbol{X} = \boldsymbol{PW}'$. A major aim of PCA is to use only a reduced set of principal components to represent the original variables, $\boldsymbol{X}$. For this purpose, $\boldsymbol{W}$ is ordered so that the first column of $\boldsymbol{W}$ is the eigenvector corresponding to the largest value eigenvalue of $\boldsymbol{\Lambda}$, being that $\boldsymbol{\Lambda}$ is the diagonal eigenvalues matrix, the second column of $\boldsymbol{W}$ is the eigenvector corresponding to the second eigenvalue of $\boldsymbol{\Lambda}$, and so on.

The next step in our analysis is the estimation of a factor model based on the previous PCA in order to study the optimal number of principal components that explain the de-meaned and variance standardized ES times series. Therefore, we estimate a linear regression for each standardized ES_{jt}^θ series on the first M principal component factors. Using more components in the model could increase the explanatory power of these regressions. So, the regression model is

$$ES_{jt}^\theta = \alpha_j + \sum_{i=1}^{M} \beta_{ij} P_{it} + e_{jt} \tag{7}$$

[8] The τ optimal values estimated are available upon request.

[9] We also applied the simplex algorithm described by Engle and Manganelli (2004), taking the solution from the simulating annealing algorithm as the initial value, and obtained no significant difference.

[10] In this case, it is indifferent considering correlation or covariance matrix because we work with standardized ES series.

where P_{it} are the first M principal components.

In order to obtain a systematic risk (***SR***) ranking in our sample, we compute principal components from the correlation matrix so they have zero mean, i.e. $\mathbb{E}(P_{it}) = 0$. Thus, the expected ES given by the factor model is $\mathbb{E}(\hat{ES}_{jt}^{\theta}) = \hat{\alpha}_j$. Taking variances and covariances of the ES_{jt}^{θ} factor model gives the systematic covariance matrix of ES_{jt}^{θ}, i.e. the covariance that is captured by the model.

Using matrix notation, we have

$$\mathbf{V} = \mathbf{B}'\mathbf{\Lambda}\mathbf{B} + \hat{\mathbf{\Sigma}}_{\epsilon} \tag{8}$$

where $\boldsymbol{V}$ is the variance-covariance matrix of $\boldsymbol{X}$, $\mathbf{\Lambda}$ denoting the MxM variance-covariance matrix of principal components from equation (7), which will be a diagonal matrix with eigenvalues along the diagonal, and $\boldsymbol{B}$ is the MxN matrix that has the M-vectors of betas in each column for each ES time series, i.e. the matrix of weights. The variance-covariance matrix of $\boldsymbol{X}$ is divided into $\boldsymbol{B}'\mathbf{\Lambda}\boldsymbol{B}$, which is the systematic covariance matrix, and $\hat{\mathbf{\Sigma}}_{\epsilon}$ (NxN), which is the covariance matrix of approximation errors, which is not necessarily diagonal. The elements of the systematic covariance matrix $\boldsymbol{B}'\mathbf{\Lambda}\boldsymbol{B}$ are

$$Var(ES_{jt}^{\theta}) = \sum_{i=1}^{M} \hat{\beta}_{ij}^{2} Var(P_{it}) \tag{9}$$

$$Cov(ES_{jt}^{\theta}, ES_{kt}^{\theta}) = \sum_{i=1}^{M} \hat{\beta}_{ij}\hat{\beta}_{ik} Var(P_{it}) \tag{10}$$

$\forall j, k = 1, 2, \ldots, N$, where (9) are in the diagonal of this matrix and (10) are out of the diagonal.

In the previous decomposition, $\boldsymbol{B}'\mathbf{\Lambda}\boldsymbol{B}$ represented the systematic risk in the set of assets due to the uncertainty in the future evolution of the principal components, while $\hat{\mathbf{\Sigma}}_{\epsilon}$ represented the size of idiosyncratic risk.

Therefore, from factor models we can quantify systematic and idiosyncratic risk. We focus on the systematic risk, which is an undiversifiable risk or the risk that cannot be reduced to zero by diversification. The idiosyncratic risk, also called specific risk or residual risk, is the risk that is not associated with the risk factor, i.e. principal components. In a sufficiently large and diversified portfolio, the specified risk may be reduced to almost zero since the specific risk on a large number of assets in different sectors of the economy, or in different countries, tend to cancel each other out.

We obtained $\hat{\beta}_{ij}$ from the factor model (7) where the principal components were obtained from the correlation matrix $\mathbf{\Gamma}$ of the original system of ES time series $\boldsymbol{X}$. To calculate the systematic and idiosyncratic risks, previously, we needed transform these $\hat{\beta}_{ij}$ into $\tilde{\beta}_{ij}$. Thus, $\tilde{\beta}_{ij}$ is calculated as,

$$\tilde{\beta}_{ij} = \hat{\beta}_{ij}\sigma_j \tag{11}$$

where $\sigma_j = Var(ES_{jt}^{\theta})$.

Once $\tilde{\beta}_{ij}$ are calculated, we obtain the systematic variance (***SV***) and the systematic risk (***SR***) as,

$$\boldsymbol{SV} = \tilde{\boldsymbol{\beta}}'\mathbf{\Lambda}\tilde{\boldsymbol{\beta}} \tag{12}$$

$$\boldsymbol{SR} = \sqrt{\boldsymbol{SV} \cdot 250} \tag{13}$$

where $\tilde{\boldsymbol{\beta}}$ is the matrix with $\tilde{\beta}_{ij}$.

And the idiosyncratic variance (***IV***) is calculated as,

$$\boldsymbol{IV} = \boldsymbol{V} - \boldsymbol{SV} \tag{14}$$

where $\boldsymbol{V}$ is the total variance, i.e. the variance-covariance matrix of $\boldsymbol{X}$.

Regarding the systemic risk, we estimate the following regression in (15) in order to obtain a systemic risk ranking based on the $\hat{c}$ coefficient. This regression is able to identify systematically important institutions without imposing any assumptions about the drivers of systemic risk or the actual number of systematically important institutions. Contrary to systematic risk, systemic risk is not concerned with the general co-movement of single institutions' assets with the overall market. Systemic risks arise from spillovers of particular severely distressing events; in our case, ES, since these will typically result in systemic consequences. In systemic risk, such spillover has a clear direction: from institutions to market. The main idea is that we can proxy the systemic risk as the first principal component of the ES time series. It will be our dependent variable. We use the first principal component of ES time series as a proxy for the financial system because this proxy measures the common factor that drives the ES of financial institutions. PCA simply identifies the eigenvector that maximally explains the variance of the system. It turns out that this is the "market factor", i.e. the tendency of ES to rise and fall together. It is the market factor because if you examine the weights (factor loadings) of the first eigenvector in a histogram you will find they are generally all of the same sign, whereas this is not the case for any of the subsequent eigenvectors (which represent other sources of risk).

The regressors we set are the first lag of the principal component and the ES time series from the financial institution.[11] Our key coefficient is that which corresponds with the institution ES as it gives us information about the contribution of the institution risk to the overall systemic risk measured by the first principal component. We estimate by ordinary least squares the following regression[12]

$$P_{1t} = a_j + b_j P_{1t-1} + c_j ES_{jt}^{\theta} \tag{15}$$

where P_{1t} is the first principal component of ES time series that we use as a proxy for systemic risk, P_{1t-1} is the lagged first principal component and ES_{jt}^{θ} is the expected shortfall at θ significance level time series for institution j, $j = 1, 2, \ldots, N$. If the c_j coefficient is significantly different from zero, we reject the null hypothesis of individual significance. For this reason, the $\hat{c}$ coefficient gives us information about which institutions are more systemic.[13] The higher this $\hat{c}$ is, the greater the contribution of the financial institution is to destabilizing the system during periods of generalized distress.

3. Data and CARES estimation models

3.1. Data analysis

The data considered are the dataset used in White et al. (2015), although we updated the sample period. The sample includes daily closing prices of 204 financial institutions from January 1st of 2000 until November 20th of 2017 (4667 observations). Prices were transformed into continuously compounded log returns (source: Datastream). We considered three main global sub-indices: banks, financial services, and insurance companies.

In the Appendix, Tables Ia - Ib report the names of the financial institutions in our sample, together with the country of origin and the sector with which they are associated, (according to the Datastream classification), and Table II shows the classification of the stocks by sector and by geographic area. There are almost twice as many financial institutions classified as banks in our sample relative to those classified as financial services or insurance. The distribution across geographic areas is more balanced, with a greater number of European financial institutions and a slightly lower North American representation. Note that we have a great number of US and Japanese banks. The time series of data belonging to different markets are not synchronized. To avoid the asynchronicity, we consider the data from Europe and North America to be lagged by one day with respect to data from Asia (Becker et al., 1990).

Table 1 reports the average of mean (in basic points), median (in basic points), standard deviation, minimum, maximum, skewness, kurtosis and first order autocorrelation for the returns of banks, financial services and insurance companies from January of 2000 until November of 2017 for different sample periods. In general, the returns exhibit the characteristic stylized features in the daily samples: excess kurtosis, a mild degree of skewness and negligible autocorrelation, which we can see in the full sample. More concretely, financial services have the highest daily mean of 1.67 bps, and the highest standard deviation of 2.29. Insurance companies have very large minimum, maximum, skewness and kurtosis. We calculated the same statistics for different time periods: 2000–2006 (pre-crisis), 2007–2008 (crisis period) and 2009–2017 (post-crisis). During the crisis period (2007–2008) we find the highest standard deviation for the financial sector as a whole. This period is also characterized by very large minimums and maximums. For the three sectors of financial institutions, the skewness is larger during the post-crisis period (2009–2017). Regarding the first order autocorrelation, we can also state that the returns series present low persistence for the different periods considered.

3.2. CARES estimation models

We use the relationship between τ-expectiles and θ-ES for transforming CARE parameters and convert the CARE model into the CARES model. From these estimated parameters, we generate ES series changing over time at $\theta = 5\%$ and $\theta = 1\%$ of significance levels. Table III from the Appendix shows the estimated coefficients of CARES models for $ES_{5\%}$ and $ES_{1\%}$ for twelve well-known financial institutions of different types (banks, financial services and insurance companies): Banco Santander, Bank of America, Citigroup, JP Morgan, American Express, Bank of NY Mellon, Goldman Sachs, Morgan Stanley, Allianz, Generali, Berkshire Hathaway 'B' and ING

[11] Following the generic CAViaR specification by Engle and Manganelli (2004) and CARE specification by Taylor (2008), by analogy, we use only the first lag in this regression, ensuring that the time series changes "smoothly" over time. We use the Wald test for determining the number of lags in our analysis. Moreover, we perform F-tests of the null hypothesis that our coefficient b_j are equal to zero. Only one lag is necessary to remove serial correlation from the model residuals. According to Getmansky et al. (2004), short-term asset-price changes should not be related to other lagged variables in an informationally efficient financial market.

[12] To test the endogenous regressor ES_{jt}^{θ} (predictor variable) in the regression model (15), we use the Hausman test for endogeneity. Having endogenous regressors in a model will cause ordinary least squares (OLS) estimators to fail, as one of the assumptions of OLS is that there is no correlation between a predictor variable and the error term. Instrumental variable estimators can be used as an alternative in this case. However, before deciding on the best regression method, we first need to figure out if our predictor variable ES_{jt}^{θ} is endogenous. The null hypothesis of the Hausman test is that the errors are correlated with the regressor, implying that the regressor is endogenous, with the alternative hypothesis being that it is not, thus, the regressor is exogenous. For the 204 regressions, we have a huge number of these that we reject the null hypothesis and the variable ES_{jt}^{θ} is exogenous.

[13] Several papers use principal components to measure systemic risk in different ways, such as Rodríguez-Moreno and Peña (2013), Billio et al. (2012), Kritzman et al. (2011), and Kaminsky and Reinhart (1999).

Table 1
Summary statistics for daily returns of banks, financial services and insurances for the full sample: January 2000 to November 2017, and three time periods: 2000–2006 (pre-crisis), 2007–2008 (crisis) and 2009–2017 (post-crisis). The average of mean (M, in basic points), median (Me, in basic points), standard deviation (SD), minimum (Min), maximum (Max), skewness (Skew), kurtosis (Kurt) and first order autocorrelation are reported.

	Full Sample							
	M (bps.)	**Me (bps.)**	**SD**	**Min**	**Max**	**Skewness**	**Kurtosis**	***ρ(1)***
Banks	−0.2452	0.0611	2.1917	−22.9384	20.1220	−0.1904	19.1848	−0.0114
Financial Services	1.6720	0.0000	2.2881	−24.8473	19.9854	−0.6019	35.3565	−0.0217
Insurances	1.4513	0.0676	2.1655	−29.0008	21.7714	−0.7971	41.8911	−0.0161
	Pre-crisis (2000–2006)							
	M (bps.)	**Me (bps.)**	**SD**	**Min**	**Max**	**Skewness**	**Kurtosis**	***ρ(1)***
Banks	2.9495	0.0853	1.7101	−11.1470	10.4478	0.0088	9.1207	−0.0212
Financial Services	3.8673	0.0000	2.1052	−14.0130	12.6209	−0.0090	8.5116	−0.0097
Insurances	2.4929	0.0862	2.0495	−17.1492	14.7863	−0.3287	21.5861	0.0093
	Crisis (2007–2008)							
	M (bps.)	**Me (bps.)**	**SD**	**Min**	**Max**	**Skewness**	**Kurtosis**	***ρ(1)***
Banks	−15.2967	−5.8296	2.9962	−16.6128	16.6706	0.0538	10.4581	−0.0173
Financial Services	−13.1161	−2.6053	3.3326	−18.4447	17.9378	−0.0318	10.1043	−0.0315
Insurances	−12.0899	−1.8814	3.1912	−22.4898	18.3817	−0.3992	18.1651	−0.034
	Post-crisis (2009–2017)							
	M (bps.)	**Me (bps.)**	**SD**	**Min**	**Max**	**Skewness**	**Kurtosis**	***ρ(1)***
Banks	0.6356	0.3648	2.2375	−20.2264	17.0367	−0.2091	17.7901	−0.0028
Financial Services	3.2802	1.1228	2.0719	−19.2837	14.9279	−0.7655	37.1446	−0.0244
Insurances	3.6864	1.0269	1.8685	−16.3464	15.2343	−0.1192	17.3644	−0.0441

Groep. The γ_1 coefficients are around 0.9, which indicates the ES processes are significantly autocorrelated and the γ_2 coefficients are negative, with a larger return implying lower ES. The resulting estimated 5% and 1% ES for the selected financial institutions are reported in Fig. 1. This Fig. 1 reveals the generalized sharp increase in risk during the Global Financial Crisis (GFC) period (2007–2008) after the Lehman bankruptcy. Careful inspection of the plots also reveals a noticeable cross-sectional difference, with the risk for Goldman Sachs being contained to around one half and around one third of the risk of Bank of NY Mellon and Morgan Stanley, respectively, at the height of the crisis. Table 2 shows the main descriptive statistics for the $ES_{5\%}$ series estimation for the different periods (pre-crisis, crisis and post-crisis). As we expected, the summary statistics are higher during the crisis period, especially for the financial services.

A preliminary study of the possible relationship between the tails of the financial institutions returns can be made by exploring the ES

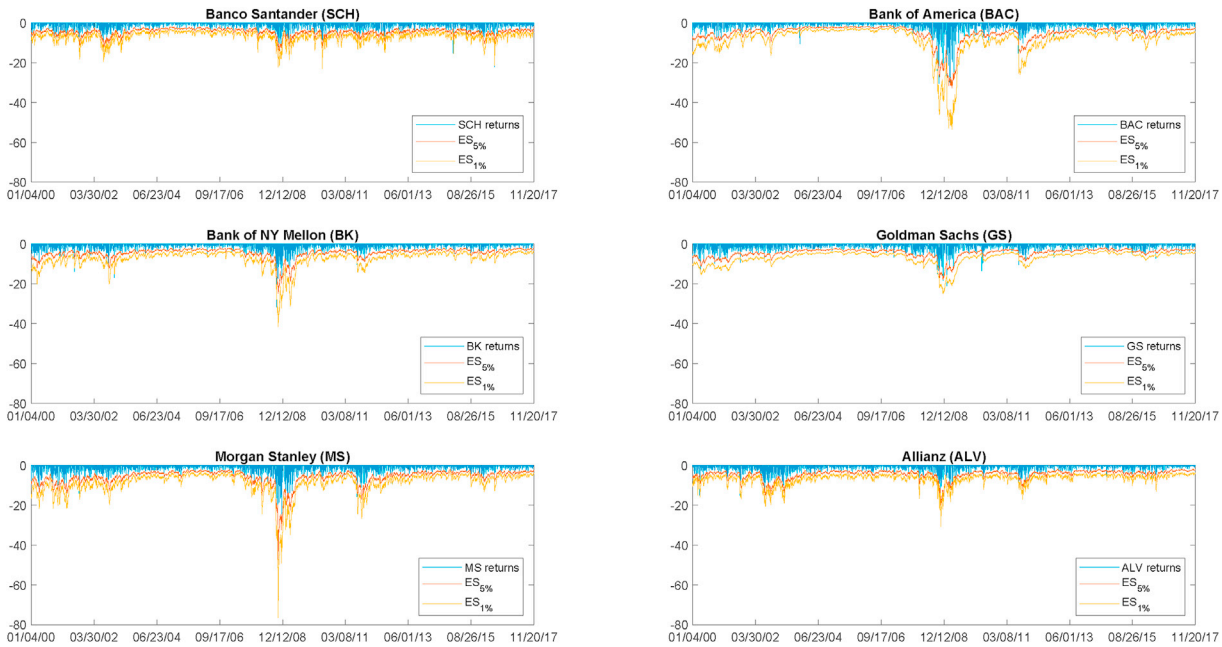

Fig. 1. $ES_{5\%}$ and $ES_{1\%}$ estimated via CARES model for selected financial institutions.

Table 2
Summary statistics for daily $ES_{5\%}$ of banks, financial services and insurances for the full sample: January 2000 to November 2017, and three time periods: 2000–2006 (pre-crisis), 2007–2008 (crisis) and 2009–2017 (post-crisis). The average of mean, median, standard deviation (SD), minimum (Min), maximum (Max), skewness (Skew), kurtosis (Kurt), 5%-quartile (Q5) and 95%-quartile (Q95) are reported.

	Full Sample						
	Mean	**Median**	**SD**	**Min**	**Max**	**Q5**	**Q95**
Banks	−4.3825	−3.7770	2.2408	−22.5629	−1.6730	−8.5093	−2.2922
Financial Services	−4.6363	−4.0653	2.0840	−20.7327	−1.9942	−8.5008	−2.6400
Insurances	−4.2654	−3.5512	2.5074	−26.5237	−1.1837	−8.7252	−2.1740
	Pre-crisis (2000–2006)						
	Mean	**Median**	**SD**	**Min**	**Max**	**Q5**	**Q95**
Banks	−3.8019	−3.4860	1.3322	−10.1504	−1.7599	−6.4362	−2.2631
Financial Services	−4.5328	−4.1893	1.5286	−11.3348	−2.1284	−7.4999	−2.6989
Insurances	−4.2435	−3.6663	1.9545	−15.8233	−1.3602	−8.1939	−2.2896
	Crisis (2007–2008)						
	Mean	**Median**	**SD**	**Min**	**Max**	**Q5**	**Q95**
Banks	−5.5948	−4.7842	3.1457	−18.5238	−2.0053	−12.5172	−2.5238
Financial Services	−6.1834	−5.3421	3.1982	−18.2400	−2.4797	−13.6341	−2.9946
Insurances	−5.6468	−4.4698	3.9555	−23.8429	−1.8177	−14.7899	−2.3736
	Post-crisis (2009–2017)						
	Mean	**Median**	**SD**	**Min**	**Max**	**Q5**	**Q95**
Banks	−4.5661	−3.9751	2.1737	−19.4946	−1.9511	−8.6674	−2.5748
Financial Services	−4.3686	−3.9017	1.7888	−15.8371	−2.0949	−8.0710	−2.6524
Insurances	−3.9708	−3.3915	2.0955	−18.4697	−1.4679	−7.9485	−2.1687

correlations. This study of correlations between ES is shown in Tables 3 and 4. In general, we find a high degree of co-movement between the ES of the countries. Pairwise correlations are positive, and higher than 0.7 in many cases. The average correlation is 0.63. The maximum correlation coefficients are around 0.93 (Canada-United States, Switzerland-Germany, Belgium-France, Belgium-Netherlands) and drop to 0.005 (Portugal-Finland) in the minimum cases. We observe high correlations between countries with similar levels of economic development. Most correlations are positive except for Portugal-Singapore, Canada-Portugal and Singapore-Greece, which are negatives. Table 4 seems to sketch a geographical cluster of correlations. For example, European countries have a correlation of 0.6, North American countries were found to have a higher correlation of around 0.9, and finally, Asian countries have a correlation of 0.7. Within Europe the correlation can be divided into three main areas such as Core, Peripheral and Nordic Europe with values of around 0.8, 0.5 and 0.7, respectively.[14] These results suggest a risk exposure integration of the different areas considered.

4. Systematic risk analysis

PCA yields a decomposition of the correlation matrix of the standardized ES series of the 204 financial institutions into the orthonormal matrix of loadings $\boldsymbol{W}$ (eigenvectors of the correlation matrix) and the diagonal matrix of eigenvalues λ. We chose the three first principal components in order to calculate systematic risk as they explain a large percentage of the total variation, some 68.52% for $ES_{5\%}$ and 64.34% for $ES_{1\%}$.[15]

Fig. 2 shows the first three principal components from the original standardized $ES_{5\%}$. To interpret each principal component we calculate the mean correlations between original variables and each PC (see Table 5). Interpretation of the principal components is based on finding which variables are most strongly correlated with each component, i.e., which of these numbers are large in magnitude, the farthest from zero in either direction. The first principal component is strongly correlated with the three sectors and the three regions of the original variables. The first principal component increases with increasing all scores. This suggests that these sectors and regions vary together. If one increases, then the remaining ones tend to increase as well. As we can observe in Fig. 2 this component can be viewed as a measure that captures the common trend in ES time series. In a perfectly correlated system of ES series on financial assets, the elements of the first eigenvector are equal. In this case, the values of the elements of the first eigenvector are similar but we could state that based on the correlation of 0.841 that this principal component is primarily a measure of the North American financial institutions with a correlation of 0.871 for banks, of 0.859 for financial services, and of 0.802 for insurance institutions, from North America. It follows that financial institutions with high values of ES tend to be in North America. In Table 5, we can observe that the

[14] Core countries include Austria, Belgium, Germany, Switzerland, France, and the Netherlands. Peripheral countries include Spain, Greece, Ireland, Italy, and Portugal. The Nordic countries are Denmark, Finland, Norway, and Sweden.

[15] We try to select the number of principal components taken as common determinants of the ES time series in a correct way and for this, several criteria are taken into account: the blocks of behaviors observed throughout the analysis carried out, the percentage of variability of the set of ES time series by the different principal components or the composition of its eigenvectors. There are some papers that choose three and four principal components in order to measure systemic risk. These include Giglio et al. (2016) and Zheng et al. (2012).

Table 3
Correlation of $ES_{5\%}$ series by sector.

	Banks	Financial Services	Insurances
Banks	1	0.938	0.925
Financial Services	0.938	1	0.966
Insurances	0.925	0.966	1

second principal component increases with only one of the values, increasing banks from Europe, and decreasing financial institutions from Asia. This component can be viewed as a measure of how the ES increase in terms of the region and the sector to which the financial institution belongs. This component can be viewed as a sectorial index specifically of the banks from Europe. We can observe in Fig. 2 that the deviation of the second component from the common trend is the difference in the magnitude of ES between banks and the other financial institutions. Table 5 shows that the third principal component increases with increasing banks from Asia and decreasing insurance firms from North America. This suggests that financial institutions from Asia also tend to have higher ES and from North America lower ES. This component can be viewed as a regional index, specifically of the banks from Asia. We can say that the magnitude of ES is driven by the sector and the direction of ES is driven by the region.

The next step in our analysis is the estimation of the linear regression defined in (7) of each $ES_{5\%}$ and $ES_{1\%}$ series on the first three principal component factors ($M = 3$)[16] using ordinary least squares to obtain each stock's alpha and factor betas.

Thus, we obtain $\boldsymbol{B}$, the $3x204$ matrix of stock betas. The estimated coefficients, p-values and multiple R^2 of the regressions are reported in Tables IVa-IVd of the Appendix. The first component is always the most significant variable in these regressions because it captures a common trend in the ES series. This pattern is not always followed by the second and third component. The regression R^2 ranges from 91% for JP Morgan (JPM) to 0.89% for Fukuoka Financial (FUKU). The R^2 of the regression is the squared correlation between the stock ES and the explained part of the model. Results obtained from the linear regression estimation of each $ES_{1\%}$ series are available from the authors upon request.

We compute the annual percentage of systematic and idiosyncratic risks over the total amount of risk for each financial institution. In Table 6, we find that the most systematic financial institutions for $ES_{5\%}$ are JP Morgan, Bank of NY Mellon, Franklin Resources, Seb 'A'. T Rowe Price GP, American Express, Citigroup, Bank of America, Travelers Cos and Northern Trust. For all of these, an important portion of their total risk is undiversifiable, and related to the market risk. The top ranking for $ES_{1\%}$ is very similar in the institutions for the tenth first positions (not in order) with the exception of Canadian Imp.Bk.Com and Royal Bank Canada which appear in the top ten most systematic.

We also introduce a dynamic analysis of systematic risk. The aim is to study the time-series dimension to determine the evolution of systematic risk over time due to, for example, changes in the default cycle, changes in financial market conditions, and the potential buildup of financial imbalances such as asset and credit market bubbles. We use the first three principal components of the ES time series obtained with each 1000-day window. We follow other authors like Haugom et al. (2016) for CAViaR models, and Taylor (2008) for CARE models, who use a moving window of 1000 days. The last one also considered windows of lengths 500 and 250 days. In terms of VaR estimation, the accuracy of the various methods did not weaken when using the smaller window sizes. This was also the case for ES estimation, with the one exception being a reduction in accuracy when using a smaller window size for the approach based on the CARE models. It seems that the smaller window size causes difficulty for the derivation of the optimal value of τ for a given θ quantile. Other authors as Alexander and Sheedy (2008) conclude that the estimation window is an important source of model risk. Considering a range of possible estimation windows (250, 500, 1000, and 2000 days) their results show that large windows should be preferred to smaller estimation windows for VaR risk estimation, especially in conditional models. Righi and Ceretta (2015) also use estimation windows of different sizes to forecast VaR and ES with a variety of unconditional and conditional models. They conclude that the larger the window, the more conservative risk predictions tend to be. Conditional models exhibit more homogeneity than unconditional models concerning these estimation windows because conditional models rely on parametric filtering and not only on the empirical data, which is sensitive to the bandwidth used in the estimation. With a rolling window of 1000 observations that is moving each day, we seem to be on the safe side, according to the papers mentioned. Fig. 3 shows the Cumulative Risk Fraction (i.e., eigenvalue for the first principal component) for standardized $ES_{5\%}$ and $ES_{1\%}$. The time-series graph of eigenvalues shows that the first principal component (PC1) is very dynamic, increasing significantly during the crisis period. The PC1 eigenvalue were found to increase from the beginning of May 2007 and peaked at almost 80% during February of 2009, which was during the Global Financial Crisis. We find also that the financial institutions are more correlated in tails during crisis periods than during calm periods, not only during the global financial crisis but also during the sovereign debt crisis after 2012 and the Asia deceleration during 2015. International Monetary Fund, Bank for International Settlements, and Financial Stability Board (2009) determine that systematically important institutions are not limited to those that are largest, but also include others that are highly interconnected and that can impair the normal functioning of financial markets when they fail. This interconnection is greater during financial crises (see Billio et al., 2013; Billio et al., 2018; Brownlees & Engle, 2012), and it is reflected in PC1 which explains a greater percentage of the variability of the original ES series (PC1 eigenvalue increases at almost 80% in the global financial crisis period). During the financial crisis, not only PC1 explains better the system but also the financial institutions are more systemic, for this reason, increase the coefficient c_j in the regression (15) implying that the tail risk of the financial institutions has a higher impact on the financial system in distress as we can observe in Fig. 5 with the Royal Bank Canada as an example.

[16] We repeat the analysis with more principal components but the conclusions are similar.

Table 4
Correlation of $ES_{5\%}$ series by country.

	AT	BE	DE	DK	CH	ES	FI	FR	GB	GR	IE	IT	NL	NO	PT	SE	CA	US	AU	HK	JP	SG
AT	1.000	0.789	0.619	0.776	0.554	0.700	0.502	0.780	0.777	0.341	0.752	0.609	0.721	0.824	0.354	0.719	0.662	0.802	0.764	0.679	0.538	0.403
BE	0.789	1.000	0.878	0.847	0.847	0.880	0.738	0.928	0.911	0.241	0.689	0.540	0.925	0.896	0.262	0.891	0.782	0.862	0.760	0.738	0.609	0.634
DE	0.619	0.878	1.000	0.771	0.933	0.862	0.756	0.900	0.866	0.183	0.501	0.481	0.918	0.835	0.243	0.878	0.757	0.780	0.686	0.718	0.636	0.678
DK	0.776	0.847	0.771	1.000	0.730	0.834	0.716	0.856	0.859	0.297	0.632	0.560	0.787	0.855	0.267	0.870	0.787	0.846	0.788	0.807	0.659	0.668
CH	0.554	0.847	0.933	0.730	1.000	0.836	0.701	0.861	0.821	0.145	0.461	0.445	0.905	0.790	0.232	0.844	0.693	0.709	0.611	0.648	0.594	0.618
ES	0.700	0.880	0.862	0.834	0.836	1.000	0.791	0.908	0.892	0.223	0.635	0.552	0.873	0.832	0.252	0.898	0.831	0.869	0.741	0.763	0.615	0.683
FI	0.502	0.738	0.756	0.716	0.701	0.791	1.000	0.757	0.763	0.074	0.411	0.271	0.733	0.677	0.004	0.818	0.800	0.783	0.660	0.726	0.572	0.770
FR	0.780	0.928	0.900	0.856	0.861	0.908	0.757	1.000	0.910	0.293	0.633	0.601	0.906	0.889	0.323	0.910	0.779	0.840	0.773	0.768	0.599	0.628
GB	0.777	0.911	0.866	0.859	0.821	0.892	0.763	0.910	1.000	0.198	0.695	0.507	0.890	0.887	0.219	0.915	0.846	0.900	0.822	0.798	0.672	0.681
GR	0.341	0.241	0.183	0.297	0.145	0.223	0.074	0.293	0.198	1.000	0.320	0.581	0.222	0.264	0.506	0.141	0.076	0.139	0.147	0.166	0.055	−0.016
IE	0.752	0.689	0.501	0.632	0.461	0.635	0.411	0.633	0.695	0.320	1.000	0.562	0.625	0.669	0.310	0.584	0.556	0.687	0.575	0.515	0.354	0.303
IT	0.609	0.540	0.481	0.560	0.445	0.552	0.271	0.601	0.507	0.581	0.562	1.000	0.539	0.537	0.704	0.432	0.301	0.393	0.366	0.357	0.296	0.136
NL	0.721	0.925	0.918	0.787	0.905	0.873	0.733	0.906	0.890	0.222	0.625	0.539	1.000	0.866	0.286	0.862	0.745	0.808	0.700	0.692	0.591	0.600
NO	0.824	0.896	0.835	0.855	0.790	0.832	0.677	0.889	0.887	0.264	0.669	0.537	0.866	1.000	0.257	0.876	0.776	0.855	0.789	0.767	0.645	0.600
PT	0.354	0.262	0.243	0.267	0.232	0.252	0.004	0.323	0.219	0.506	0.310	0.704	0.286	0.257	1.000	0.157	−0.003	0.097	0.154	0.123	0.090	−0.098
SE	0.719	0.891	0.878	0.870	0.844	0.898	0.818	0.910	0.915	0.141	0.584	0.432	0.862	0.876	0.157	1.000	0.886	0.898	0.809	0.832	0.689	0.750
CA	0.662	0.782	0.757	0.787	0.693	0.831	0.800	0.779	0.846	0.076	0.556	0.301	0.745	0.776	−0.003	0.886	1.000	0.929	0.820	0.820	0.663	0.776
US	0.802	0.862	0.780	0.846	0.709	0.869	0.783	0.840	0.900	0.139	0.687	0.393	0.808	0.855	0.097	0.898	0.929	1.000	0.854	0.827	0.660	0.718
AU	0.764	0.760	0.686	0.788	0.611	0.741	0.660	0.773	0.822	0.147	0.575	0.366	0.700	0.789	0.154	0.809	0.820	0.854	1.000	0.798	0.703	0.632
HK	0.679	0.738	0.718	0.807	0.648	0.763	0.726	0.768	0.798	0.166	0.515	0.357	0.692	0.767	0.123	0.832	0.820	0.827	0.798	1.000	0.692	0.783
JP	0.538	0.609	0.636	0.659	0.594	0.615	0.572	0.599	0.672	0.055	0.354	0.296	0.591	0.645	0.090	0.689	0.663	0.660	0.703	0.692	1.000	0.610
SG	0.403	0.634	0.678	0.668	0.618	0.683	0.770	0.628	0.681	−0.016	0.303	0.136	0.600	0.600	−0.098	0.750	0.776	0.718	0.632	0.783	0.610	1.000

Note: The abbreviations for countries are as follows: AT = Austria, BE=Belgium, DE = Germany, DK = Denmark, CH=Switzerland, ES = Spain, FI=Finland, FR=France, GB = Great Britain, GR = Greece, IE=Ireland, IT=Italy, NL=Netherlands, NO=Norway, PT=Portugal, SE=Sweden, CA=Canada, US=United States, AU = Australia, HK=Hong Kong, JP = Japan and SG=Singapore.

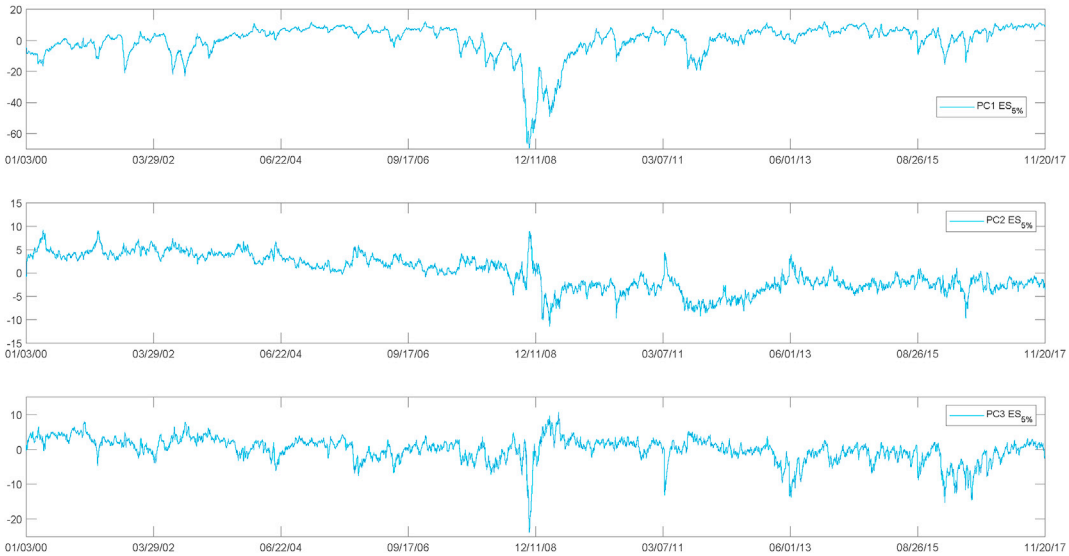

Fig. 2. The first three Principal Components for $ES_{5\%}$.

Table 5
Mean correlations between original variables and each of the first three PC. Boldface indicates the largest mean correlations in absolute value terms.

	PC1	PC2	PC3
Banks	**0.679**	0.077	0.137
Financial Services	**0.768**	−0.060	−0.024
Insurances	**0.751**	−0.053	−0.093
Europe	**0.685**	0.137	0.011
North America	**0.841**	−0.016	−0.142
Asia	**0.626**	−0.155	0.287
BK-EU	**0.637**	**0.329**	0.075
BK-NA	**0.871**	0.099	−0.149
BK-AS	**0.605**	**−0.176**	**0.364**
FS-EU	**0.719**	0.008	−0.016
FS-NA	**0.859**	−0.089	−0.116
FS-AS	**0.711**	−0.122	0.103
IN-EU	**0.728**	−0.042	−0.061
IN-NA	**0.802**	−0.067	**−0.153**
IN-AS	**0.570**	−0.042	0.090

Following the same scheme as the static analysis, we estimate the regression model defined in (7) of each standardized $ES_{5\%}$ and $ES_{1\%}$ series on the first three principal component factors using ordinary least squares to obtain each factor betas for each window. We compute the annual percentage of systematic and idiosyncratic risks over the total amount of risk for each financial institution in each window from previously calculated factor betas.[17] First, we analyze the dynamic ranking of systematic risk based on $ES_{5\%}$ in pre-crisis, crisis, and post-crisis periods. Table 7 depicts the systematic risk contingency table with the probabilities of a financial institution being in the top (Q1) or in the bottom quantile (Q12), out of the 12 considered quantiles, given that it belongs to a specific sector or country.[18]

During the pre-crisis and the post-crisis period, in Table 7, we find that insurance companies are the most systematic because they have the highest probability of being in Q1 for $ES_{5\%}$ (0.73% and 0.61%, respectively). This evidence could be explained by the increase of the interconnectedness of these financial institutions with the real sector. The interconnectedness can be defined as the exposure of an insurer or the insurance sector as a whole to macroeconomic risk factors, resulting in their financial position being highly correlated

[17] The residuals resulting from each of these regressions can be interpreted as idiosyncratic factors representative of the ES of each sector and country because these residuals are uncorrelated with each other as we consider a number of common factors suitable.

[18] We choose 12 quantiles because 204 (number of financial institutions) is divisible by 12 (204 = 12x17). In each quantile, we have the same number of financial institutions (17). The Q1 is the top quantile which includes the first 17 financial institutions on the ranking and Q12 is the bottom quantile which includes the last 17 ones on the ranking.

Table 6
Financial institutions ordered in decreasing order of percentage of systematic risk over total risk for $ES_{5\%}$ and $ES_{1\%}$.

$ES_{5\%}$					$ES_{1\%}$				
	RISKS (%)					RISKS (%)			
NAME	SEC	CTRY	SYSTEMATIC	IDIOSYNCRATIC	NAME	SEC	CTRY	SYSTEMATIC	IDIOSYNCRATIC
JP MORGAN CHASE & CO.	BK	US	0.910	0.090	**T ROWE PRICE GP.**	AM	US	0.907	0.093
BANK OF NEW YORK MELLON	AM	US	0.906	0.094	**BANK OF NEW YORK MELLON**	AM	US	0.900	0.100
FRANKLIN RESOURCES	AM	US	0.903	0.097	**FRANKLIN RESOURCES**	AM	US	0.898	0.102
SEB 'A'	BK	SE	0.900	0.100	**JP MORGAN CHASE & CO.**	BK	US	0.898	0.102
T ROWE PRICE GP.	AM	US	0.899	0.101	**CITIGROUP**	BK	US	0.897	0.103
AMERICAN EXPRESS	CF	US	0.894	0.106	**AMERICAN EXPRESS**	CF	US	0.897	0.103
CITIGROUP	BK	US	0.893	0.107	**SEB 'A'**	BK	SE	0.892	0.108
BANK OF AMERICA	BK	US	0.888	0.112	**BANK OF AMERICA**	BK	US	0.892	0.108
TRAVELERS COS.	PCI	US	0.883	0.117	**CANADIAN IMP.BK.COM.**	BK	CA	0.889	0.111
NORTHERN TRUST	AM	US	0.880	0.120	**ROYAL BANK CANADA**	BK	CA	0.883	0.117
…	…	…	…	…	**…**	…	…	…	…
MEDIOBANCA	BK	IT	0.333	0.667	**AMLIN**	PCI	GB	0.101	0.899
FAIRFAX FINL.HDG.	PCI	CA	0.281	0.719	**INTESA SANPAOLO**	BK	IT	0.047	0.953
COMPUTERSHARE	FA	AU	0.271	0.729	**INDUSTRIVARDEN 'A'**	SF	SE	0.043	0.957
ACOM	CF	JP	0.258	0.742	**JARDINE LLOYD THOMPSON**	IB	GB	0.030	0.970
MARFIN INV.GP.HDG.	SF	GR	0.222	0.778	**PROVIDENT FINANCIAL**	CF	GB	0.021	0.979
JARDINE LLOYD THOMPSON	IB	GB	0.186	0.814	**CHIBA BANK**	BK	JP	0.017	0.983
AMLIN	PCI	GB	0.149	0.851	**NANTO BANK**	BK	JP	0.009	0.991
PROVIDENT FINANCIAL	CF	GB	0.021	0.979	**EQUIFAX**	SF	US	0.009	0.991
QBE INSURANCE GROUP	RE	AU	0.013	0.987	**3I GROUP**	SF	GB	0.007	0.993
FUKUOKA FINANCIAL GP.	BK	JP	0.009	0.991	**CNP ASSURANCES**	LI	FR	0.003	0.997

Note: The abbreviations for countries (CTRY) are as follows: AT = Austria, BE=Belgium, DE = Germany, DK = Denmark, CH=Switzerland, ES = Spain, FI=Finland, FR=France, GB = Great Britain, GR = Greece, IE=Ireland, IT=Italy, NL=Netherlands, NO=Norway, PT=Portugal, SE=Sweden, CA=Canada, US=United States, AU = Australia, HK=Hong Kong, JP = Japan and SG=Singapore. The abbreviations for the sector (SEC) classification are as follows: BK=Bank, AM = Asset Management, SF=Specialty Finance, IS=Investment Service, CF=Consumer Finance, FA=Financial Administration, LI = Life Insurance, PCI=Property and Casualty Insurance, FLI=Full Line Insurance, IB=Insurance Broker, RE = Reinsurance.

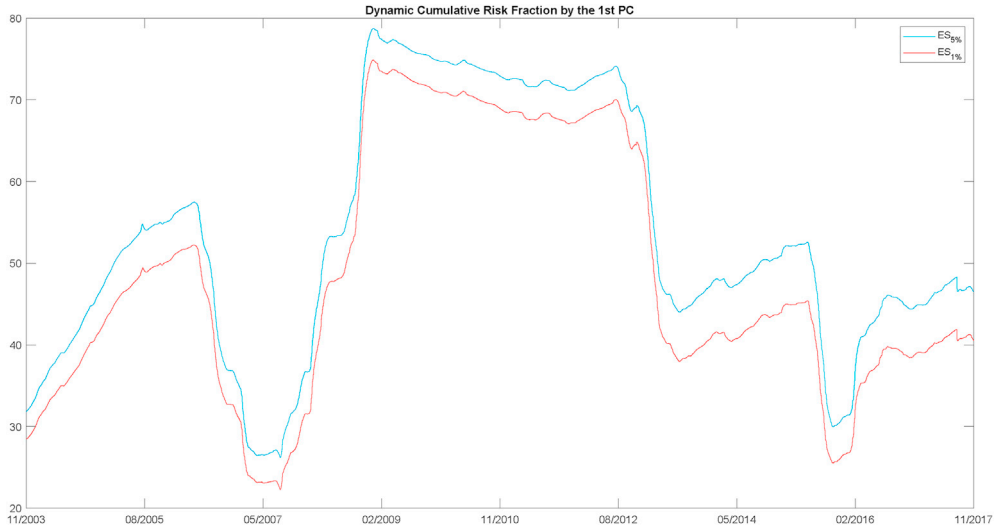

Fig. 3. Cumulative Risk Fraction (i.e. eigenvalues) that correspond to the fraction of total variance of $ES_{5\%}$ and $ES_{1\%}$ explained by the first principal component for each 1000-day window.

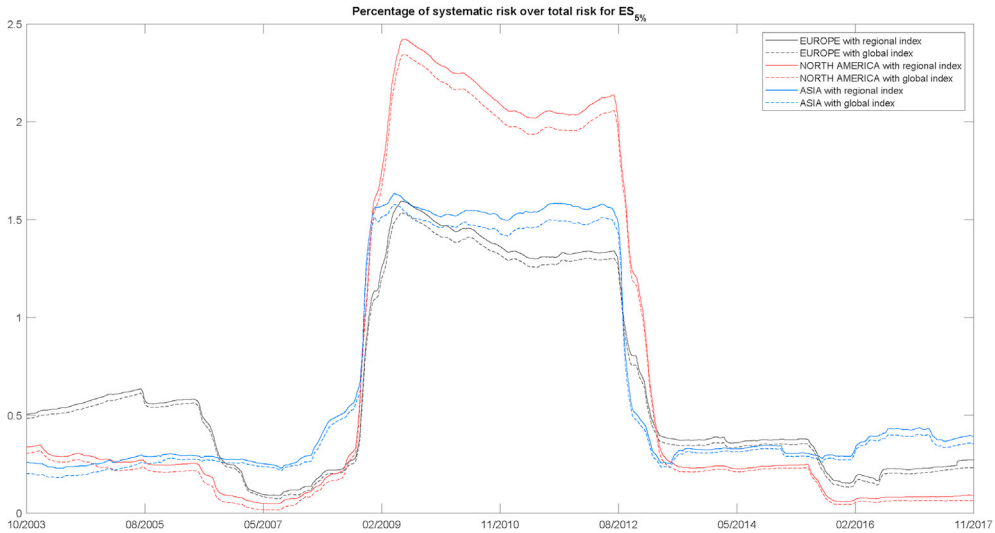

Fig. 4. The dynamic mean percentage of systematic risk over total risk for $ES_5\%$ across financial institutions belonging to different regions depending on whether the system is a regional index (Europe, North America, and Asia) or a global index.

with the broader financial markets and the real economy and with each other, thereby limiting the potential to diversify through the pooling of idiosyncratic risks. This macroeconomic exposure can accumulate through some types of insurance liabilities or may be created through non-insurance activities. Interconnectedness can also be defined as the exposure of an individual insurer to counterparties in the broader financial system and real economy resulting from asset-side interconnectedness and liability-side exposures, which leads to both parties being vulnerable to distress or failure of the other. Finally, insurance companies are large investors in the shares and bonds of other financial institutions. Through this transmission channel, insurers can be severely affected as a result of stress in financial institutions, such as banks, as any other institution, household, or individual would be affected.

Regarding regions, the financial institutions from Europe are more systematic than those from North America in the pre-crisis period, according to their higher probability of being in the first quantile, compared to the remaining regions. Finally, North American institutions present the highest probability of being in the first quantile for post-crisis periods. These results reflect the deeper effects of the

Fig. 5. The impact of ES time series of the Royal Bank Canada on financial system when it is in distress, measured by $\sigma_{ESj}\hat{c}$, over time.

Table 7
Contingency table with probabilities of a financial institution being in the top percentile (Q1) or in the bottom percentile (Q12) given that it belongs to a specific sector or country for systematic risk of $ES_{5\%}$ and $ES_{1\%}$. The rankings belonging to an specific period (pre-crisis, crisis, post-crisis and full period) have been divided into twelve percentiles. This table shows the first and the last percentile.

	pre-crisis		crisis		post-crisis		full	
$ES_{5\%}$	Q1	Q12	Q1	Q12	Q1	Q12	Q1	Q12
Banks	0.24	0.76	0.55	0.45	0.59	0.41	0.58	0.42
Financial Services	0.54	0.46	0.52	0.48	0.52	0.48	0.56	0.44
Insurances	0.73	0.27	0.44	0.56	0.61	0.39	0.54	0.46
Europe	0.58	0.43	0.43	0.58	0.58	0.42	0.62	0.38
North America	0.13	0.88	0.36	0.64	0.75	0.25	0.49	0.51
Asia	0.41	0.59	0.86	0.14	0.42	0.58	0.58	0.42
$ES_{1\%}$	Q1	Q12	Q1	Q12	Q1	Q12	Q1	Q12
Banks	0.30	0.70	0.61	0.39	0.72	0.28	0.65	0.35
Financial Services	0.46	0.54	0.63	0.37	0.53	0.47	0.34	0.66
Insurances	0.63	0.38	0.43	0.57	0.64	0.36	0.53	0.47
Europe	0.54	0.46	0.46	0.54	0.58	0.42	0.65	0.35
North America	0.08	0.92	0.39	0.61	0.83	0.17	0.49	0.51
Asia	0.47	0.53	0.86	0.14	0.53	0.47	0.65	0.35

global financial crisis on the US after 2008.[19]

During the crisis period, we find that banks are the most systematic during the crisis period as they present the highest probability (0.55%) of being in Q1 for $ES_{5\%}$. The financial institutions from Asia become more systematic, surpassing those from Europe and from North America. The first result is in line with previous literature as banks are normally the sector more affected by global financial crises. The second one, states evidence about the unexpected speed and force of the global financial crisis affected Asian economies through both the trade and financial channels, reflecting the region's deep economic integration with the rest of the world. While financial markets in emerging Asia had relatively limited exposure to subprime-related instruments, increased global market integration meant that the deleveraging process in advanced economies led to a substantial liquidation of assets in emerging Asian markets and large capital outflows. These developments, in turn, contributed to a sharp decline in the Asian equity markets, the widening of sovereign bond spreads, the depreciation of regional exchange rates, and the decline in offshore bank lending in the region. Furthermore, our evidence can be explained by the increase of interconnectedness in Asia. One example of this growth is the significant increase in cross-border capital flows into and out of Asia. Since 1990, capital inflows into Asia have increased by 870% and capital outflows from Asia have increased by 504%. Even as a percent of GDP these flows have more than doubled (Villafuerte & Yap, 2015). This means Asian

[19] Our evidence for post-crisis period could also be affect by our short period of crises considered (2007–2008). Therefore, from 2009 could there still were effects of the global financial crisis in the US. In this line, at the end of this section we provide a more exhaustive analysis for the post-crisis period in which different distress events have occurred in the different analyzed regions.

economies are more exposed to international financial volatility and international financial shocks which can have significant implications for macro-financial stability, liquidity, investment, savings, and exchange rates. Therefore, Asia seems less focused on mechanisms that are designated to respond when a financial or economic crisis occurs.[20]

We analyze the number and frequency of changes in positions in the systematic risk ranking that an institution suffers throughout the analyzed full period. We determined that insurance sector from Europe has a greater concentration in extreme, rather than in central positions and that banks have the highest concentration in a single position. Moreover, we can observe that the concentration in a low position in the ranking (low systematic risk) is always greater than that in a high position in the ranking (high systematic risk).

If we focus on time periods, according to dynamic rankings of systematic risk based on $ES_{5\%}$, in crisis and post-crisis, the banking sector presents the highest concentration for a given position. Financial institutions from Asia present the greatest concentration in extreme positions, in crisis and post-crisis periods. European insurance institutions present the highest concentration in positions in the pre-crisis period. Finally, in all time periods, North American financial institutions show the lowest concentration across positions.[21] This results regarding the persistence in positions should be interesting for regulators that are interested in monitoring the most systematic and riskier institutions by staying longer in extreme high positions.

For a more exhaustive analysis, especially for the post-crisis period that covers a very long time interval in which different distress events have occurred in the different analyzed regions, we show in Fig. 4 the dynamic mean percentage of systematic risk over total risk for $ES_{5\%}$ across financial institutions belonging to different regions depending on whether the system is a regional index (Europe, North America, and Asia) or a global index. We can observe that i) the financial institutions are more systematic if the system considered is the region to which they belong, instead of the financial global system (solid line superior to the dashed one), ii) in the pre-crisis period (2003–2006), the most systematic financial institutions are from Europe, iii) in crisis period (2007–2008) are the Asian institutions the most systematic and iv) in the post-crisis period (2009–2017), the first part of this period (2009–2012) the most extremely systematic financial institutions are from North America with still effects of the global financial crisis initiated in the US, in the second part of this period (2013–2015) are from Europe as a consequence of the sovereign debt crisis, and in the last one (2016–2017) are from Asia due to the growth deceleration from 2015. These conclusions derive from average results across financial institutions belonging to the same region and are robust with the results that we obtain when we evaluate the dynamic ranking in different quantiles in Table 7 to analyze the probability of financial institutions being in a top or in a bottom quantile, given it belongs to a specific sector or region, considering a global financial system.

5. Systemic risk analysis

With regard to the systemic risk, we carry out the regression (15) in order to obtain a systemic risk ranking based on the $\hat{c}$ coefficient. The main idea is that we can proxy the systemic risk as the first principal component of the ES time series. This will be our dependent variable. The regressors we set are the lagged first principal component and the ES time series from the financial institution. Our key coefficient is that which corresponds to the institution ES because it provides information about the contribution of the institution risk to the overall systemic risk measured by the first principal component. We estimate, using ordinary least squares, the model defined in expression (15).

The higher the c_j coefficient the greater the contribution of the financial institution is to destabilizing the system during periods of generalized distress.[22] The R^2 of these 204 regressions are around 0.99.

Table 8 presents a static ranking of institutions ordered in decreasing order of the value of the coefficient c_j (from more systemic to less).[23] We observe that the most systemic institutions are the Royal Bank of Canada, Franklin Resources, Bank of New York Mellon, GBL New, Danske Bank, Investor 'B', Equifax, Cincinnati Finl., Old Mutual and Canadian Imp.Bk.Com for $ES_{5\%}$. The G-SIBs common institution is Royal Bank Canada. Most of these institutions are different than those obtained in the systematic risk ranking. Therefore, the most systemic institutions are not the most systematic ones and vice-versa (with the exception of Franklin Resources and Bank of New York Mellon). The top ranking for $ES_{1\%}$ is quite different (in the institutions) as the only common institutions are Franklin

[20] The results obtained with $ES_{1\%}$ are different in crisis and post-crisis periods for sectors compared to the results obtained from $ES_{5\%}$. In the crisis period, it is financial services, rather than banks, that are the most systematic and in the post-crisis, it is banks (rather than insurance companies) which are the most systematic.

[21] The results that concern the frequency of changes in positions and concentration in a position in rankings of systematic risk are available upon request, not only for $ES_{5\%}$ but also $ES_{1\%}$.

[22] It is important to note that the b_j coefficients are significantly different from zero for the 204 regressions estimated. In the case of the a_j coefficient, it is not significantly different from zero and in the same regressions, neither is c_j. The coefficients estimated, t-statistics, p-values, R^2 of all regressions are available upon request.

[23] If we order the financial institutions based on the t-statistic of the coefficient c_j, the ranking is similar to that obtained with the value of this coefficient. The coefficient c_j measures the instantaneous effect (or the short-term effect) of ES^{θ}_{jt} onto P_{1t}. Note that P_{1t-1} is included in the model. Since ES^{θ}_{jt} has an effect on P_{1t}, ES^{θ}_{jt} will also have an effect on P_{1t+1} through the lagged dependent variable, and the size of this effect will be $b_j^2 c_j ES^{\theta}_{jt}$. The effect of ES^{θ}_{jt} on P_{1t+3} will be $b_j^3 c_j ES^{\theta}_{jt}$, and so on. If we sum up the instantaneous effect and all the delayed effects to infinity, we will obtain the cumulative effect of ES^{θ}_{jt} on P_{1t}, which will be the long-term effect $\frac{c_j}{1-b_j}$. If we use this long-term effect to elaborate the systemic ranking, the classification varies substantially with respect to those made from the short-term effect. Because we are more interested in the instantaneous effect (and to save space) only these rankings are shown. Results obtained using the long-term effect for elaborating systemic rankings are available from the authors upon request.

Table 8
Financial institutions ordered in decreasing order of $\hat{c}$ (i.e. systemic risk) for $ES_{5\%}$ and $ES_{1\%}$.

$ES_{5\%}$					$ES_{1\%}$				
NAME	**SEC**	**CTRY**	$\hat{c}$	**t-statistic**	**NAME**	**SEC**	**CTRY**	$\hat{c}$	**t-statistic**
ROYAL BANK CANADA	BK	CA	0.264	10.500	**3I GROUP**	SF	GB	0.493	10.704
FRANKLIN RESOURCES	AM	US	0.263	12.254	**RATOS 'B'**	SF	SE	0.396	13.558
BANK OF NEW YORK MELLON	AM	US	0.229	14.657	**INTESA SANPAOLO**	BK	IT	0.307	32.149
GBL NEW	SF	BE	0.223	11.094	**CNP ASSURANCES**	LI	FR	0.259	7.342
DANSKE BANK	BK	DK	0.204	14.955	**FRANKLIN RESOURCES**	AM	US	0.233	13.587
INVESTOR 'B'	SF	SE	0.203	11.768	**ROYAL BANK CANADA**	BK	CA	0.200	9.394
EQUIFAX	SF	US	0.200	16.502	**NORTHERN TRUST**	AM	US	0.196	18.102
CINCINNATI FINL.	PCI	US	0.199	15.707	**EQUIFAX**	SF	US	0.180	9.413
OLD MUTUAL	LI	GB	0.199	16.299	**GBL NEW**	SF	BE	0.177	8.614
CANADIAN IMP.BK.COM.	BK	CA	0.198	8.995	**EURAZEO**	SF	FR	0.177	15.482
...	...	...	...	...	**...**	...	...	...	...
CREDIT SAISON	CF	JP	0.000	0.035	**CHALLENGER FINL.SVS.GP.**	LI	AU	0.004	1.100
BANK OF IRELAND	BK	IE	0.000	0.001	**MS&AD INSURANCE GP.HDG.**	PCI	JP	0.003	0.280
VALIANT 'R'	BK	CH	−0.001	0.090	**MAPFRE**	FLI	ES	0.003	0.198
PROGRESSIVE OHIO	PCI	US	−0.001	0.084	**MITSUB.UFJ LSE.& FINANCE**	SF	JP	−0.002	0.123
MS & AD INSURANCE GP.HDG.	PCI	JP	−0.005	0.396	**NOMURA HDG.**	IS	JP	−0.002	0.189
NOMURA HDG.	IS	JP	−0.005	0.445	**HIROSHIMA BANK**	BK	JP	−0.004	0.337
NANTO BANK	BK	JP	−0.016	0.684	**ACOM**	CF	JP	−0.010	1.385
ACOM	CF	JP	−0.020	2.117	**DAIWA SECURITIES GROUP**	IS	JP	−0.017	1.888
DAIWA SECURITIES GROUP	IS	JP	−0.035	3.062	**CHIBA BANK**	BK	JP	−0.465	9.982
FUKUOKA FINANCIAL GP.	BK	JP	−0.249	7.352	**INDUSTRIVARDEN 'A'**	SF	SE	−2.092	26.819

Note: The abbreviations for countries (CTRY) are as follows: AT = Austria, BE=Belgium, DE = Germany, DK = Denmark, CH=Switzerland, ES = Spain, FI=Finland, FR=France, GB = Great Britain, GR = Greece, IE=Ireland, IT=Italy, NL=Netherlands, NO=Norway, PT=Portugal, SE=Sweden, CA=Canada, US=United States, AU = Australia, HK=Hong Kong, JP = Japan and SG=Singapore. The abbreviations for the sector (SEC) classification are as follows: BK=Bank, AM = Asset Management, SF=Specialty Finance, IS=Investment Service, CF=Consumer Finance, FA=Financial Administration, LI = Life Insurance, PCI=Property and Casualty Insurance, FLI=Full Line Insurance, IB=Insurance Broker, RE = Reinsurance.

Resources, Royal Bank of Canada, Equifax and GBL New. The most systemic institutions for $ES_{1\%}$ are 31 group, Ratos 'B', Intensa, SantaPaolo, CNP assurances, Northern Trust and Eurazeo.

These results clearly contribute to results from previous studies which were focused on different sectors. Our results present new and different evidence for the sample under consideration. For example, Bijlsma and Muns (2011, p. 175) found that systemic risk is significantly larger in the banking sector relative to the insurance, construction and food sectors in the US. According to Bijlsma and Muns (2011, p. 175), the dependencies in the banking sector are mostly driven by common factors, whereas in other sectors, they are generally driven by idiosyncratic factors. In this line of reasoning, Buhler and Prokopczuk (2010) also used extreme value theory to analyze systemic risk across several sectors in the U.S. financial system. They found that industry risk is significantly larger in the banking sector than in other sectors, particularly under adverse market conditions. However, our results suggest that the international insurance sector is also driven by common factors and is susceptible to systemic risk during distressed periods. Generally, institutions from Europe and North America are more systemic than those from Asia.

We also introduce a dynamic analysis of systemic risk. As a proxy for stress systemic risk, we use the first principal component of the ES time series which we obtain with each 1000-day window. First, we can also analyze the impact of each ES_{jt} in P_{1t} from equation (15) in each window. For example, Fig. 5 shows the impact of the ES time series of the Royal Bank Canada on the financial system when it is in distress, measured by $\sigma_{ESj}\hat{c}$, over time, where $\hat{c}$ is the impact on the P_1 of a unitary shock in ES over time and σ_{ESj} is the average size of the period-to-period variations in ES. The Royal Bank Canada was the most systemic financial institution according to the ranking obtained in the static analysis, whether we work with $ES_{5\%}$, and one of the top systemic risk institutions whether we work with $ES_{1\%}$. Fig. 5 shows the dynamics of this impact. During the crisis period (2007–2008) we can observe that the tail risk of this financial institution has an increasing impact on the financial system in distress. The impact in quantile 5% is greater than that obtained in the 1% quantile.

We summarize the information in Table 9 in order to study the differences between sectors, regions, and time periods. We analyze the dynamic ranking of systemic risk based on $ES_{5\%}$ and $ES_{1\%}$ during pre-crisis, crisis, and post-crisis periods. This table depicts the same information that is presented in Table 7, but for systemic risk. Therefore, by observing the probabilities in this contingency table for $ES_{5\%}$ for sectors, we can observe that insurance institutions present the highest probability of being in the first quantile (Q1) in the systemic institutions ranking, so they are the most systemic for all the periods considered. By contrast, banks present the highest probability of being in the lowest quantile positions in the ranking (Q12), so they are the least systemic for all the periods. This result can be unexpected as normally banks are the most systemic sector, especially in crisis periods although the question of whether insurers spread a substantial systemic risk for the global financial system has given rise to much controversy. In fact, the main factors why banks pose systemic risks, i.e. liquidity and maturity transformation, contagion effects, and negative externalities, do not directly apply to insurance firms. However, a potential negative externality caused by a crisis in the insurance sector cannot be easily dismissed. Most importantly, such externalities arise among those insurers that play an important role in financing the real economy, such as life insurers, bond and mortgage insurers, and reinsurers. Recently, this interconnectedness with the real sector has become even more important, as the distinction between the banking sector and the insurance sector has blurred. While regulation today is focused on a

Table 9
Contingency table with probabilities of a financial institution being in the top percentile (Q1) or in the bottom percentile (Q12) given that it belongs to a specific sector or country for systemic risk of $ES_{5\%}$ and $ES_{1\%}$. The rankings belonging to an specific period (pre-crisis, crisis, post-crisis and full period) have been divided into twelve percentiles. This table shows the first and the last percentile.

	pre-crisis		crisis		post-crisis		full	
ES5%	**Q1**	**Q12**	**Q1**	**Q12**	**Q1**	**Q12**	**Q1**	**Q12**
Bancos	0.40	0.60	0.40	0.60	0.53	0.47	0.51	0.49
Financial Services	0.53	0.47	0.53	0.47	0.56	0.44	0.56	0.44
Insurances	0.73	0.27	0.64	0.36	0.61	0.39	0.65	0.35
Europe	0.75	0.25	0.75	0.25	0.62	0.38	0.67	0.33
North America	0.62	0.38	0.62	0.38	0.63	0.37	0.67	0.33
Asia	0.03	0.97	0.03	0.97	0.46	0.54	0.31	0.69
ES1%	**Q1**	**Q12**	**Q1**	**Q12**	**Q1**	**Q12**	**Q1**	**Q12**
Bancos	0.33	0.67	0.55	0.45	0.38	0.62	0.49	0.51
Financial Services	0.33	0.67	0.40	0.60	0.58	0.42	0.44	0.56
Insurances	0.60	0.40	0.46	0.54	0.74	0.26	0.58	0.42
Europe	0.68	0.32	0.67	0.33	0.74	0.26	0.59	0.41
North America	0.58	0.42	0.50	0.50	0.75	0.25	0.62	0.38
Asia	0.00	1.00	0.28	0.73	0.06	0.94	0.30	0.70

small number of systemically important insurance firms, a differentiating approach should focus more on specific business activities within the insurance sector.

A possible explanation about the insurance systemic importance could be that the life insurance sector has become more systemically important across advanced economies. This increase is largely due to growing common exposures and to insurers' rising interest rate sensitivity. Overall, life insurers do not seem to have markedly changed their asset portfolios toward riskier assets, although smaller and weaker insurers in some countries have taken on more risk. Traditionally, however, they were not considered to pose systemic risks. Insurers have longer-term liabilities than banks, greater diversification of assets, and less extensive interconnections with the rest of the financial system. However, the near-collapse of AIG during the Global Crisis prompted a rethinking of the sector's systemic riskiness. A number of insurance firms were subsequently among the financial institutions designated as globally systemically important.

Systemic risk analysis has typically focused on the risks of failure of individual institutions and their potential knock-on effects (the 'domino' view of systemic risk; see Acharya, 2015). However, the contribution to systemic risk by insurers and other financial firms extends beyond this dimension. In the 'tsunami' or macroprudential view, even solvent firms may propagate or amplify shocks to the rest of the financial system and the real economy. Systemic risk may stem from common exposures of a few large firms or many small ones (Acharya, 2015, IMF, 2013). For example, insurance companies play a critical role in corporate bond markets, and if they are hit by a large common shock, a consequent cessation of funding could hurt other companies badly (Bank of England, 2015). In principle, the insurance sector could therefore be a significant contributor to systemic risk even if no single insurance company were systemically important. Our findings suggest that supervisors and regulators should take a more macroprudential approach to the sector. Doing so is necessary if supervision is to go beyond the solvency and contagion risks of individual firms and take on the systemic risk arising from common exposures. A step that would complement a push for stronger macroprudential policies would be the international adoption of capital and transparency standards for the sector. In addition, attention to smaller and weaker firms is also warranted since they are most likely to take on excessive risks (See Tables 6 and 8 in the static analysis, there are some insurance companies in the 10 first places on the systemic ranking: Cincinnati fnl and Old Mutual for 5% and CNP assurance for 1%).

By regions, Europe is the most systemic, except for during the post-crisis period where North America presents the highest probability to be in the first quantile (Q1) of the ranking. The higher systemic importance of Europe over the US in the crisis period can be explained by several economic reasons. First, the Global Crisis had non-negligible repercussions in Europe as well due to substantial purchases of subprime securities by European banks and financial institutions. However, those problems were subsequently amplified by European sovereign debt crises experienced by countries with weak fiscal institutions. Credit growth in both the Eurozone and the US went down following Lehman's collapse and Papandreou's announcement, the impact of the first event was stronger in the US and that of the second was stronger in the Eurozone. Since the first event precedes the second by over a year, the brunt of the Global Crisis hit the Eurozone later than the US, and, correspondingly, credit recovery in the Eurozone lags that of the US. Second, both, the Federal Reserve System (Fed) and the European Central Bank (ECB) reacted to their respective crises by injecting liquidity and generally loosening monetary policy. But due to structural and institutional differences as well as timing differences between the peaks of the US subprime crisis and the Eurozone sovereign debt crisis, there are noticeable differences between the policy responses of the Fed and the ECB. More in detail, the qualitative behavior of banks' credit following widely observed crisis triggers is similar in the Eurozone and in the US, but the behavior of their reserves is quite different. This is due to differences in the liquidity injections procedures between the Eurozone and the Fed. Those different procedures are traced, in turn, to differences in the relative importance of banking credit within the total amount of credit intermediated through banks and bond issues in the Eurozone and the US, as well as to the higher institutional aversion

of the ECB to inflation relative to that of the Fed. Third, since Lehman's collapse, rates of reserve growth are substantially lower and much more variable in the Eurozone than in the US. In particular, since September 2008 bank reserves are on a sustained upward trend in the US while in the Eurozone they fluctuate substantially, both upwards and downwards.[24]

By contrast, Asia is the region with the highest probabilities to be in the low positions quantile (Q12). Therefore, the least systemic financial institutions are those from Asia. This evidence suggests that financial institutions in Asian markets were less involved in spreading shocks to the global financial system during all the periods considered, especially during the global financial crisis period and upwards. This could be the result of the implementation of stimulus packages and assertive policies in the Asia Pacific countries, implying that the policies adopted by the regional governments had at least some immediate effectiveness in helping banks decentralize the international financial shocks. Financial integration in Asia is not only the cause of increased systemic risk it is also the solution to it. Our results find that Asian integration has been asymmetric. While efforts have focused on integration in financial systems, supply-chains, the movement of people, and other areas, there has been less focus on the integration of the institutions and mechanisms that are designated to respond when a financial or economic crisis occurs. Therefore, the risks which materialize in one Asian country can be transmitted more easily into others is lower than the risks that materialize globally can be transmitted more easily into Asia.[25]

We analyze the persistence in positions in the systemic risk ranking based on $ES_{5\%}$ and $ES_{1\%}$ for the full period and we obtain similar results as the systematic risk rankings. We determine that the concentration in low positions (low systemic risk) is always greater than in high positions (high systemic risk) for all the periods considered. On the other hand, by computing the maximum of the $\hat{c}$ mean values in the ranking, we reveal that insurance institutions from Europe are the most systemic and financial services from Asia are the least systemic.[26]

For a more exhaustive analysis, especially for the post-crisis period that covers a very long time interval in which different distress events have occurred in the different analyzed regions, we show in Fig. 6 the dynamic mean of estimated c_j coefficient (i.e. systemic risk) for $ES_{5\%}$ across financial institutions belonging to different regions depending on whether the system is a regional index (top subplot) or a global index (bottom subplot). We can observe that i) the financial institutions are more systemic if the system considered is the region to which they belong, instead of the financial global system (solid line superior to the dashed one), ii) in the pre-crisis period (2003–2006), the most systemic financial institutions are from Europe closely followed by those of North America, iii) in crisis period (2007–2008) are the Asian institutions the most systemic if we consider an Asian regional index as a financial system, but are the European institutions the most systemic if we consider a global financial system, and iv) in the post-crisis period (2009–2017), the first part of this period (2009–2012) the most systemic financial institutions are from Europe with the greatest difference with global financial index, in the second part of this period (2013–2015) are from Asia if we consider an Asian regional index as a financial system and are from Europe and North America if we consider a global financial system, and in the last one (2016–2017) are the most systemic the Asian financial institutions. These conclusions derive from average results and are robust with the results that we obtain when we evaluate the dynamic ranking in different quantiles to analyze the probability of financial institutions being in a top or in a bottom quantile, given it belongs to a specific sector or region, considering a global financial system.[27]

6. An empirical comparison of systematic and systemic risk

6.1. Static comparison of systematic and systemic risk

In the previous sections we obtain different rankings for systematic and systemic risk. An institution can have a high exposure to systematic risk, but this does not necessarily imply that it presents high systemic risk, and vice-versa. In order to analyze both categories of risk together in a static framework, we observe in Figs. 7–10 the financial institutions, which are more systematic and more systemic, less systematic and more systemic, more systematic and less systemic and less systematic and systemic, respectively.[28] The x-axis in these figures corresponds to the distance between the percentage of systematic risk out of the total risk of the different financial institutions and the median value of these percentages in the cross-section of financial institutions currently being analyzed.

In Figs. 7 and 9, we have positive values in the x-axis because these financial institutions are more systematic, i.e. the percentages of systematic risk of their total risk is greater than the median magnitude of the percentages of systematic risk of all the financial

[24] It is important to note that some of the US most important financial institutions in financial crises such as Lehman Brothers, Merrill Linch, Fannie Mae, and Bear Stearns were removed of our dataset because of the data limitation from 2009. This could be generated some distortion in the US role during the crisis period.

[25] These results are quite different for $ES_{1\%}$ as banks are the most systemic during crisis periods and financial services are the least systemic, except for post-crisis periods. By regions, we obtain the same results as those obtained with $ES_{5\%}$. These results for the more extreme tail losses are in line with previous literature (see among others, Bijlsma & Muns, 2011, p. 175, and Buhler & Prokopczuk, 2010).

[26] The results concerning the frequency of changes in positions and concentration in a position in rankings of systemic risk are available upon request, for both $ES_{5\%}$ and $ES_{1\%}$.

[27] We conclude that the systematic risk methodology proposed is not sensitive to the selection of the reference system, global or regional financial system, but not the systemic risk methodology proposed, producing different rankings of the most systemic financial institutions depending on the financial system, whether global or regional system, being the difference due to the fact that we capture the degree of interconnections of the financial institution with the regional system and the global system. This implies that the size of the system and the interconnectedness are relevant when measuring the systemic important institutions. Since this analysis is outside the scope of this paper, more in-depth analysis may be carried out in future research.

[28] We focus on $ES_{5\%}$. The results are similar for $ES_{1\%}$. The figures and results are available upon request.

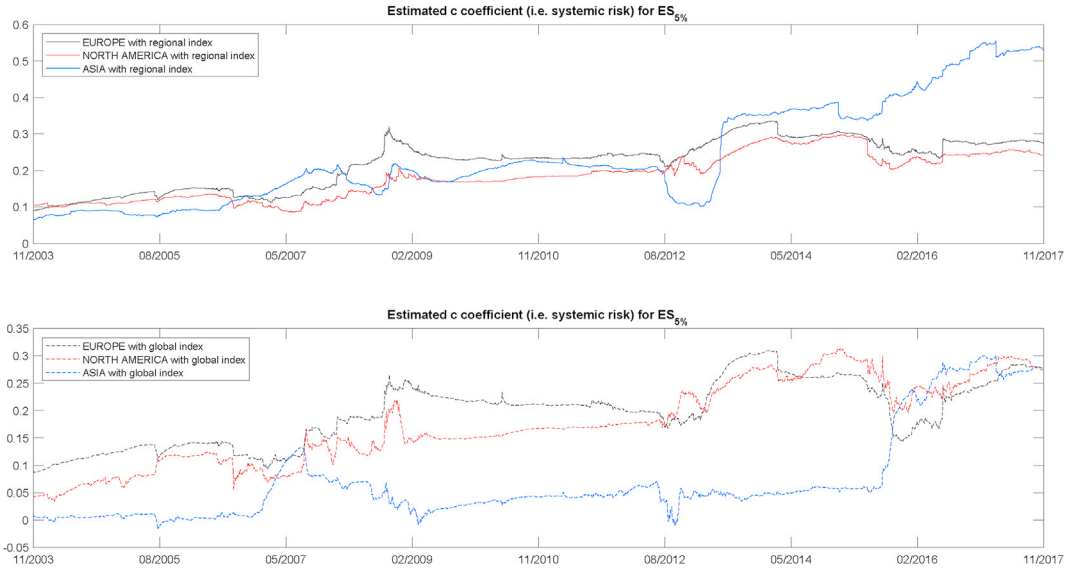

Fig. 6. The dynamic mean estimated c_j coefficient (i.e. systemic risk) for $ES_5\%$ across financial institutions belonging to different regions depending on whether the system is a regional index (top subplot) or a global index (bottom subplot).

institutions analyzed. In Figs. 8 and 10, we have negative values in the x-axis because these financial institutions are less systematic, i.e. percentages of systematic risk out of their total risk are lower than the median magnitude of the percentages of systematic risk for all financial institutions analyzed. The y-axis of these figures corresponds to the distance between the $\hat{c}$ coefficient of the different financial institutions and the median value of these coefficients in the cross-section of the financial institutions analyzed here.

In Figs. 7 and 8, we have positive values in the y-axis because these financial institutions are more systemic, i.e. the $\hat{c}$ coefficients are greater than the median magnitude of the $\hat{c}$ coefficients of all financial institutions analyzed. In Figs. 9 and 10, we have negative values in the y-axis because these financial institutions are less systemic, i.e. the $\hat{c}$ coefficients are lower than the median magnitude of the $\hat{c}$ coefficients of all financial institutions analyzed. The size of the different circles relates to market capital of the financial institutions and the colors of the circles represent the sector, i.e. banks (red), financial services (green) and insurance companies (blue). If these circles are closer to the bisector of the respective quadrant, the relationship between systematic and systemic risk is also closer, either in one direction or the other.

Moreover, in Fig. 7 we show that Royal Bank of Canada, Prudential, Morgan Stanley, Old Mutual and Legal & General and Cincinnati Finl. are the most systematic and the most systemic at the same time. We also find that major financial institutions (Market Value greater than $50000 million), are normally only slightly systematic, but very systemic, such as Lloyds Banking Group, AXA, ING and Danske Bank (Fig. 7), BBVA, Banco Santander, Credit Suisse, Allianz (Fig. 8). Although there are exceptions, especially in banks, which are very

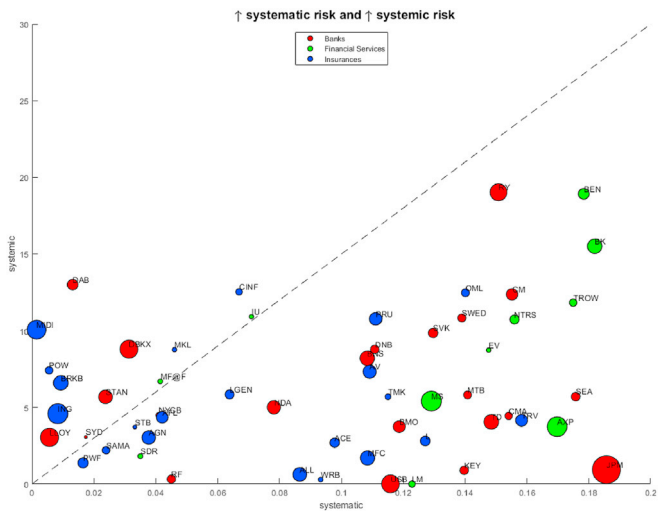

Fig. 7. Financial institutions more systematic and systemic for $ES_{5\%}$.

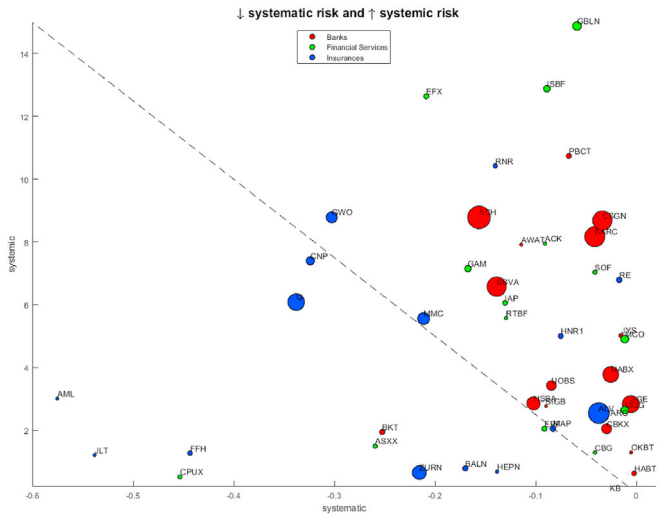

Fig. 8. Financial institutions less systematic and more systemic for $ES_{5\%}$.

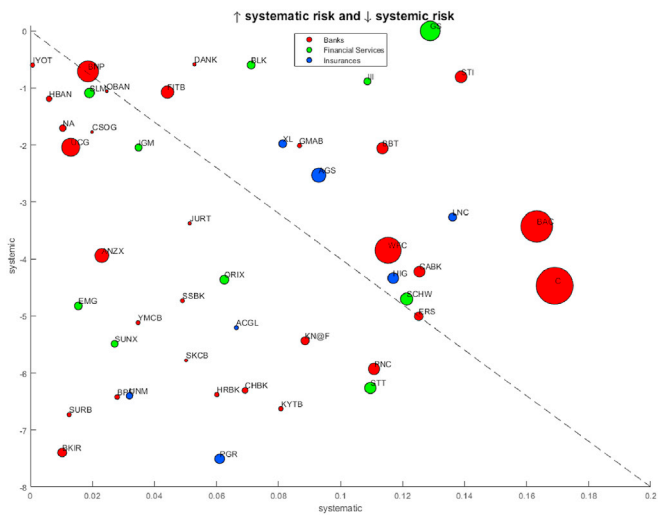

Fig. 9. Financial institutions more systematic and less systemic risk for $ES_{5\%}$.

systematic and only slightly systemic, such as Bank of America [BAC], Citigroup [C] or JP Morgan [JPM] (Figs. 7 and 9). Note that the major bank HSBC is only slightly systematic and systemic (Fig. 10). The institutions Lloyds Banking Group, ING and AXA are dangerous because they are very systemic, i.e. there exists a high degree of vulnerability of the system as a whole for failure of these specific financial institutions, but they are not vulnerable to the common systematic risk factors. Given that these results do not allow for a clear relationship to be established between the characteristics of institutions and their systematic and systemic risk, we will analyze this relationship in more detail in the following section.

6.2. Relation between systematic and systemic risk and individual characteristics

According to the relation between systematic and systemic risk and individual institutions' characteristics, which include size, leverage, tail beta, sector and region, Figs. 11–12 illustrate the cross-section plots of systematic and systemic risk contributions, respectively, and institutional characteristics. In these figures, we show a relationship between the systematic and systemic risk and the individual characteristics of the institutions, focusing on the full sample for $ES_{5\%}$.

Given the recent discussion regarding "too big to fail" and various proposals for close regulatory scrutiny that these institutions should receive, it is interesting to look at the relationship between the size of a financial institution and its contribution to systematic and systemic risk. The upper-left plots in Figs. 11 and 12 show the link between an institutions' size (measured in millions of total assets) and an institutions' systematic risk, measured by the systematic volatility, and systemic risk, measured by the $\hat{c}$ coefficient, respectively. The

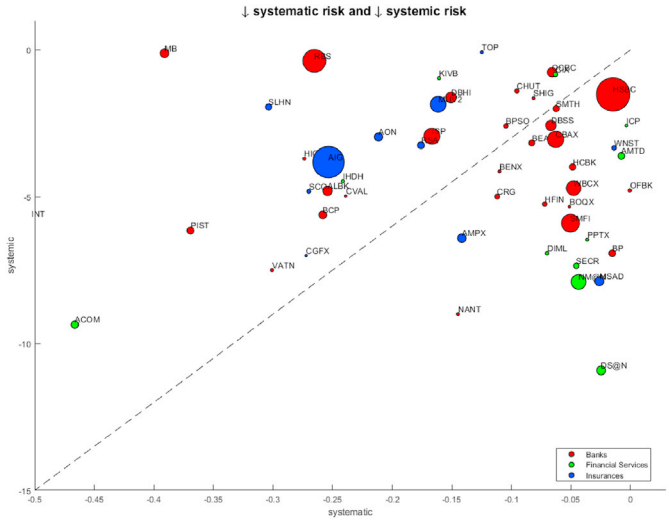

Fig. 10. Financial institutions less systematic and systemic for $ES_{5\%}$.

scatter plots reveal a weak relationship between the two measures, especially for those institutions whose size is smaller than around 50000 million dollars. However, it appears in the upper-right plots in Figs. 11 and 12 that the relationship between size and systematic and systemic risk contribution, respectively, is logarithmic because the relationship between the log of an institutions' size and systematic risk and systemic risk contribution seems to be somewhat positively correlated. For this reason, we will use the log(size) as a regressor in the cross-section analysis.

The relationship between leverage (measured by the average ratio of short and long debt over common equity) and systematic and systemic risk contribution seems to be similar to the relationship between the latter and size; the middle-left plots between leverage and systematic and systemic risk in 11 and 12 reveal a weak relationship, whereas the logarithm of the leverage in the middle-right plots seem to be somewhat positively correlated with systematic and systemic risk contribution, but is smaller than that obtained with the log of an institutions' size. For this reason, we will add the log(leverage) as a regressor in the analysis of the determinants of systemic and systematic risk.

The lower-left plots in Figs. 11 and 12 show the cross-section relationship between systematic and systemic risk and the beta of the financial institutions; obviously the beta is more correlated with systematic risk than with systemic risk, but it seems to be less correlated with systematic risk than log-size.

Finally, the lower-right plots in Figs. 11 and 12 show the cross-section relation between systematic and systemic risk and the tail beta of the financial institutions calculated as in Van Oordt and Zhou (2016). We find that the tail beta is more correlated with systemic and systematic risk than the market beta, especially with systematic risk. For this reason, we will use the tail beta as a regressor in the determinants analysis of the systemic and systematic risk.

To study in more detail the relationship between systematic and systemic risk and an institutions' characteristics, we now turn to a regression analysis. In order to investigate the relationship between systematic and systemic risk contribution and an institutions' characteristics, we regress the systematic risk measured using systematic volatility, and systemic risk measured through the $\hat{c}$ coefficient, respectively, for a set of institutions' characteristics. These characteristics are used as explanatory variables. We use log-size, log-leverage, and tail beta computed as in Van Oordt and Zhou (2016), and sector and region group dummies. Table 10 reports the estimation results. All two sector group dummies are significant at 1% in the systematic regression and the European dummies are significant in the systemic regression. The effect of the log-leverage is negative and not significant at 1%. The effect of the log-size on systematic and systemic risk is positive and not statistically significant, which suggests that bigger institutions do not impose more of systematic and systemic risk. Finally, the estimated coefficient on the tail beta is positive and is statistically significant at a 1% significance level on the systematic risk regression, suggesting that the higher is the tail beta of an institution, and the higher is its systematic and systemic risk contribution.

It is important to note that the tail beta coefficient is significantly lower in the systemic regression, suggesting that between the tail beta and systemic risk, there is only a weak relation in the cross-section. This is an important finding because, in contrast to other systemic risk measures, such as MES and ΔCoVaR, which exhibit a strong interconnection with systematic risk (given by the beta factor), our measure identifies (directly) which is the institution's contribution to systemic risk and distinguishes it of systematic risk.

6.3. Dynamic comparison of systematic and systemic risk

To compare better dynamic systematic and systemic rankings over time, we calculate the Spearman's rank correlation coefficient. Intuitively, the Spearman correlation between two variables will be high when observations have a similar ranking between the two variables, and low when observations have a dissimilar rank between the two variables. The Spearman correlation coefficient is defined

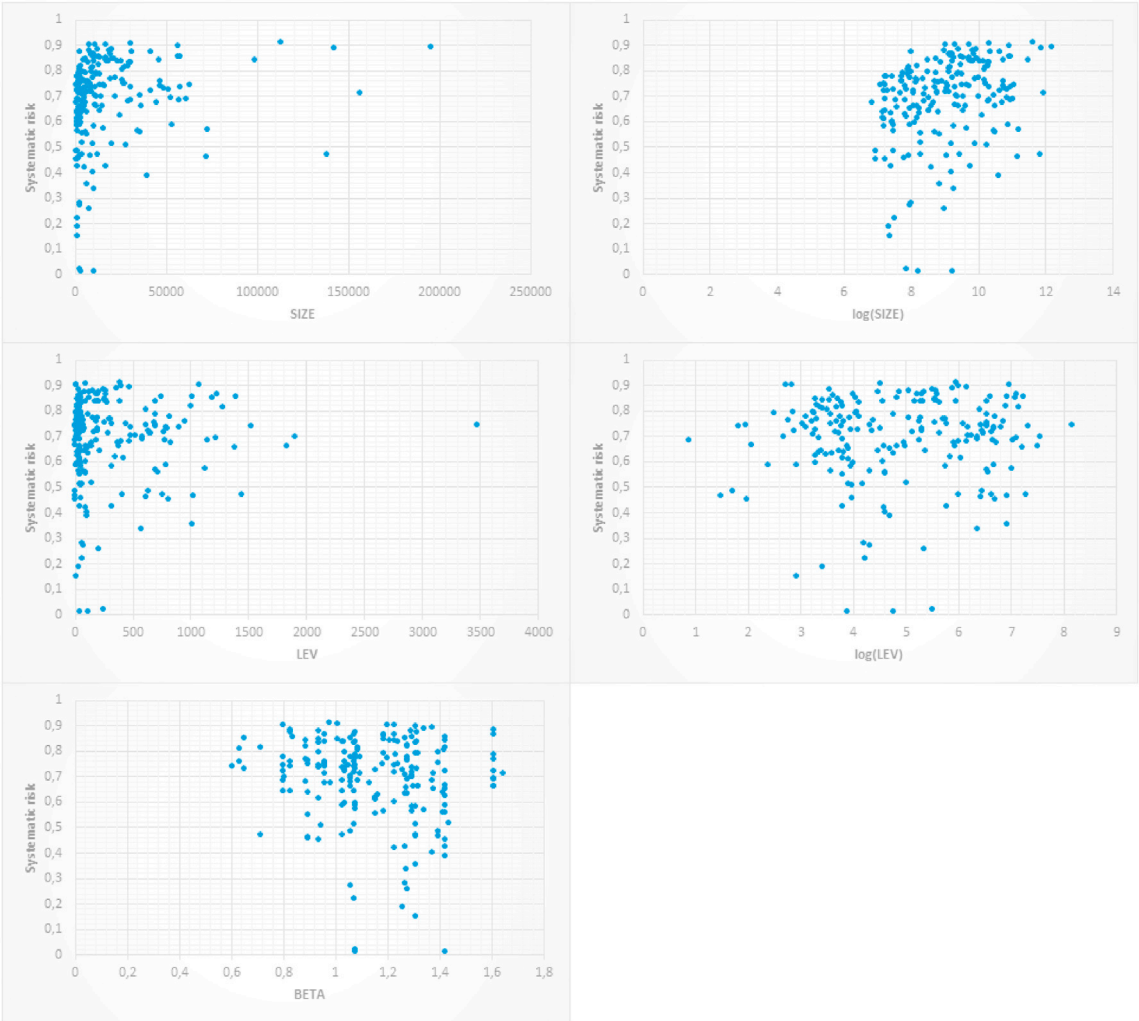

Fig. 11. Cross-section relation between financial institutions' characteristics and contribution to systematic risk. The figure reports the cross-section plots of contributions to systematic risk (measured by the systematic volatility of factor model based on $ES_{5\%}$) and institutions' size (in million of total assets), institutions' leverage (measured by the average ratio of short and long debt over common equity), institutions' beta, and institutions' tail beta.

as the Pearson correlation coefficient between the ranked variables. For a sample of size n, the n raw scores X_i and Y_i are converted to ranks $rg(X_i)$ and $rg(X_i)$ and r_s is computed from,

$$r_s = 1 - \frac{6\sum_{i=1}^{n} d_i^2}{n(n^2-1)}$$

because all n ranks are distinct integers, where $d_i = rg(X_i) - rg(Y_i)$ and n is the number of observations (in our case, $n = 204$). As there are no repeated data values, a perfect Spearman correlation of $+1$ or -1 occurs when each of the variables is a perfect monotone function of the other. We test for significance using

$$t = r_s\sqrt{\frac{(n-2)}{(1-r_s^2)}}$$

which is distributed approximately as a Student-t distribution with $n-2$ degrees of freedom under the null hypothesis of statistical independence ($r_s = 0$). This approximation is valid when $n \geq 10$.

In Table 11, we illustrate that during pre-crisis and crisis periods, there is a higher correlation than during the post-crisis period between systematic and systemic rankings because the number of null hypothesis rejections is higher. Table 11 shows that when we work with $ES_{5\%}$ there is more rank correlation in the top ranking positions (top positions are defined by 1–68) than in the bottom

Fig. 12. Cross-section relation between financial institutions' characteristics and contribution to systemic risk. The figure reports the cross-section plots of contributions to systemic risk (measured by the $\hat{c}$ coefficient of systemic risk regression based on $ES_{5\%}$) and institutions' size (in million of total assets), institutions' leverage (measured by the average ratio of short and long debt over common equity), institutions' beta, and institutions' tail beta.

positions (bottom positions are defined by 137–204) for all periods.[29]

In conclusion, the structural changes in the financial systems of these economic regions make the dynamic analysis particularly important for tracking risks over time. These results are relevant to determine when financial institutions simultaneously enter into a systematic and systemic situation in a global system, where gradually integrating financial systems increase the relationships between financial institutions across borders. This development raises the question of how financial institutions systems should be monitored in a context in which supervision, in contrast to monetary policy, remains a national responsibility. Our results provide some interesting perspectives for the ongoing debate on financial stability policies throughout the world. These results also encourage further regard to the best institutional structures for the supervision for European, North American and Asian financial systems that slowly overcomes the barriers imposed by national and economic borders. In addition, these results highlight the importance of macroprudential surveillance that takes a cross-border perspective, in particular the systematic and systemic risk issues.

[29] Regarding $ES_{1\%}$, the results are similar for the full, the pre-crisis and the crisis periods but generally the rejections are higher for $ES_{5\%}$. The highest percentage of rejection is 29.89% and 18.77% for top positions during pre-crises periods for $ES_{5\%}$ and $ES_{1\%}$, respectively. The remaining percentages are low, from 0% to 12.26%. In other words, the systemic and systematic rankings seem different, being that the rejection percentages very low.

Table 10
Estimated coefficients of systematic and systemic risk regressions based on $ES_{5\%}$. t-statistics reported in parentheses. * significance at the 1% level.

Dependent variable	Systematic risk	Systemic Risk
Constant	0.410*	0.010
	(5.808)	(0.350)
log(SIZE)	0.001	0.002
	(0.067)	(0.465)
log(LEV)	−0.004	−0.008
	(-0.474)	(-0.841)
TAIL BETA	0.292*	0.071*
	(9.328)	(5.410)
dummyBK	0.122*	0.013
	(4.834)	(1.270)
dummyFS	0.080*	0.021
	(3.100)	(1.920)
dummyEU	0.000	0.059*
	(0.002)	(5.839)
dummyNA	0.025	0.028
	(0.852)	(2.339)
Adj. R^2	45.00%	30.49%

Table 11
Percentage of H_0 rejections of statistical independence between both systematic and systemic rankings for different periods (pre-crisis, crisis, and post-crisis) and different parts of the ranking (top, medium, and bottom positions).

$ES_{5\%}$	**Spearman's rank correlation**			
% rejection H_0	*all*	*top*	*medium*	*bottom*
pre-crisis	82.76%	29.89%	2.49%	5.75%
crisis	34.99%	9.18%	0.38%	1.53%
post-crisis	6.83%	0.00%	4.47%	3.29%
full	32.00%	19.94%	2.26%	3.90%
$ES_{1\%}$	**Spearman's rank correlation**			
% rejection H_0	*all*	*top*	*medium*	*bottom*
pre-crisis	82.18%	18.77%	12.26%	1.72%
crisis	36.52%	0.96%	0.96%	4.40%
post-crisis	45.59%	0.79%	1.25%	12.35%
full	53.52%	10.65%	3.49%	14.62%

7. Conclusions

Systemic risk is a controversial concept in finance as there is no consensus regarding its definition, its potential role for ranking the level of risk in financial institutions and its relation to systematic risk. Benoit et al. (2013, 2017), Cipollini et al. (2020), and Danielsson et al. (2016) determine that the systemic risk measures have additional information content over systematic risk measures. In this study, we develop a new methodology to measure systematic and systemic risk separately and construct dynamic rankings and relationships for international financial institutions for the 2000–2017 period. The literature has usually focused on analyzing stock market returns from financial institutions, mainly from the point of view of systemic risk. Our main aim is to show evidence regarding the interrelation between rankings based on both types of risk for regulatory purposes. We use expected shortfall (ES) as our fundamental risk indicator, which we compute using expectiles, an interesting alternative to the standard use of quantiles. This is the first time that expectiles have been used to measure both systematic and systemic risk. Specifically, we use the CARE model proposed by Taylor (2008) to estimate the ES of the stock market returns of a given financial institution and use these ES estimates to rank systematic risk in a wide cross section of financial institutions using principal component (PCA) and regression analyses.

Our main contributions are: i) we study both types of risk from expected shortfall estimates that are obtained from expectiles in order to avoid the dependence on distributional assumptions or potential model specification errors, ii) we analyze the interrelations between both types of risk using a methodology based on PCA, iii) we use as a proxy for a financial system, a global index comprised of different sectors and regions, and iv) our analysis is based on a comprehensive sample of financial institutions that belong to different sectors and regions and over different time periods.

The main evidence we obtain for $ES_{5\%}$ suggests that banks are more systematic in the stressed period and insurance firms are the most systematic during quiet periods. However, insurance firms are the most systemic and banks are the least systemic across all the periods considered. This evidence reflects negative externalities and the increase of interconnectedness in insurance firms with the real sector. By regions, Asia is the most systematic during crisis periods, North America is the least systematic during pre-crisis and crisis periods. These results could be explained by the economic integration process in Asia through both the trade and financial channels. In

contrast, Europe is more systemic during pre-crisis and crisis periods, Asia is the least systemic over all periods considered and North America is the most systemic in the post-crisis period. This evidence reflects the important repercussions in Europe as well due to substantial purchases of subprime securities by European banks and financial institutions. Furthermore, these effects were amplified by European sovereign debt crises and the higher institutional aversion of the ECB to inflation relative to that of the Fed and also for the rates of reserve growth lower and much more variable in the Eurozone than in the US.[30]

Moreover, we find empirical evidence that systematic and systemic risk contributions are closely related to certain factors regarding institutional characteristics such as tail beta, sector and region. Therefore, European institutions are the main contributors to systemic risk, independent of the sector, and insurance and bank institutions with their high tail beta are more relevant for systematic risk. Institution size and leverage seem not be relevant for any risk and the tail beta effect is positive and significant for both risks, especially for systematic risk. These finding are relevant for regulators when establishing measures to reduce the risk of contagion from those companies that contribute most to the overall level of risk to the economy, and also to protect those that are more vulnerable.

Together, these results raise doubts regarding the independent study of both types of risk in the literature. In particular, a direct application to regulatory capital surcharges for systemic risk could create the wrong incentives for banks unless they also take into account systematic risk. Hence, regulatory capital surcharges for systematic and systemic risk should not rely exclusively on market-based measures of systemic risk, and more work needs to be done in order to assess the reliability of the information that can be drawn from a return-based analysis of systemic risk to more sophisticated measures that are based on higher order moments taken from the distribution of market returns. We hope that the ES computed from expectiles may be more reliable and informative as an input because it measures the inherent level of risk when the institution is in a distressed situation. Systematic and systematic rankings can be useful for regulatory purposes and also for investment diversification. Furthermore, these rankings could be used to monitor the many different channels of both risks and used to realign financial institutions' behavior with financial stability. In this sense, an important finding we have provided is that during crisis periods, financial services from Asian institutions seem to be the most affected by global system distress and by more extreme losses, while banks in Europe are the institutions that affect global system distress most significantly. Finally, we show evidence that there is a need for macro and micro-prudential regulation in the insurance sector given the vulnerability of this sectors to systemic and systematic risk. These results can contribute to the main systemic and systematic regulatory policy task, which is to capture system-wide risk and to adjust prudential tools based on individual institutions' contribution to that risk and vice-versa.

Some policies to mitigate the common exposures/interlinkages aspect of systemic risk are: i) firms that contribute to systemic risk (European banks) must internalise the externalities that they create, higher prudential standards are one way to do this. ii) Ensure that the counterparties of an important institution are not sheltered from loss in the event of failure so that market discipline is strengthened ex ante. This can further help to limit the probability of default. iii) Avoid perverse incentives that spur leverage and the pursuit of short-term profit. iv) Put in place more resilient market structures. v) More proactive supervision of systemic institutions is necessary to ensure that the perimeter of financial regulation is wide enough for supervisors to be able to see through a financial institution, no matter what the legal configuration may be. In this line of reasoning, an interesting question posed by the recent crisis is why the same regulation produced different results in different countries and sectors. As we found, banking systems in Asia, for instance, remained relatively resilient during the recent crisis while banks from Europe presented the high systemic risk during distressed periods. There were obviously many reasons for the differences seen across various jurisdictions, including differences in structure, the business models and type sector of the financial system. Still, another relevant factor was that regulation is not implemented across countries and different financial sectors with the same rigour. So, a key lesson in line with our evidence is that good regulation will not work without adequate supervision that looks through both the business cycle and the structures of the different financial institutions.

Credit author statement

Laura Garcia-Jorcano and Lidia Sanchis-Marco: Conceptualization, Methodology, Software, Data curation, Writing-Original draft preparation, Visualization, Investigation, Supervision, Software, Validation, Writing-Reviewing, and Editing.

I APPENDIX

Table Ia
Financial institutions in our sample.

	NAME	MNEM	CTRY	SEC		NAME	MNEM	CTRY	SEC
1	77 BANK	SSBK	JP	BK	**52**	HUNTINGTON BCSH.	HBAN	US	BK
2	ALLIED IRISH BANKS	ALBK	IE	BK	**53**	HYAKUGO BANK	OBAN	JP	BK
3	ALPHA BANK	PIST	GR	BK	**54**	HYAKUJUSHI BANK	OFBK	JP	BK
4	AUS.AND NZ.BANKING GP.	ANZX	AU	BK	**55**	INTESA SANPAOLO	ISP	IT	BK
5	AWA BANK	AWAT	JP	BK	**56**	IYO BANK	IYOT	JP	BK

(*continued on next page*)

[30] The results for $ES_{1\%}$ are different for systematic risk by sectors as financial services are the most systematic during crisis periods and banks are the most systematic during post-crisis periods. For systemic risk, the main difference in the $ES_{1\%}$ result suggests that banks are the most systemic sector and financial services are least systemic during crisis periods.

Table Ia (*continued*)

	NAME	MNEM	CTRY	SEC		NAME	MNEM	CTRY	SEC
6	BANK OF IRELAND	BKIR	IE	BK	**57**	JP MORGAN CHASE & CO.	JPM	US	BK
7	BANKINTER 'R'	BKT	ES	BK	**58**	JYSKE BANK	JYS	DK	BK
8	BARCLAYS	BARC	GB	BK	**59**	JUROKU BANK	JURT	JP	BK
9	BB&T	BBT	US	BK	**60**	KBC GROUP	KB	BE	BK
10	BANCA CARIGE	CRG	IT	BK	**61**	KEIYO BANK	CSOG	JP	BK
11	BANCA PPO.DI SONDRIO	BPSO	IT	BK	**62**	KEYCORP	KEY	US	BK
12	BANCA PPO.EMILIA ROMAGNA	BPE	IT	BK	**63**	LLOYDS BANKING GROUP	LLOY	GB	BK
13	BBV.ARGENTARIA	BBVA	ES	BK	**64**	M&T BK.	MTB	US	BK
14	BANCO COMR.PORTUGUES 'R'	BCP	PT	BK	**65**	MEDIOBANCA	MB	IT	BK
15	BANCO POPOLARE	BP	IT	BK	**66**	NATIXIS	KN@F	FR	BK
16	BANCO SANTANDER	SCH	ES	BK	**67**	NORDEA BANK	NDA	SE	BK
17	BNP PARIBAS	BNP	FR	BK	**68**	NANTO BANK	NANT	JP	BK
18	BANK OF AMERICA	BAC	US	BK	**69**	NATIONAL AUS.BANK	NABX	AU	BK
19	BANK OF EAST ASIA	BEAA	HK	BK	**70**	NAT.BK.OF CANADA	NA	CA	BK
20	BANK OF KYOTO	KYTB	JP	BK	**71**	NY.CMTY.BANC.	NYCB	US	BK
21	BANK OF MONTREAL	BMO	CA	BK	**72**	NORTHERN TRUST	NTRS	US	AM
22	BK.OF NOVA SCOTIA	BNS	CA	BK	**73**	OGAKI KYORITSU BANK	OKBT	JP	BK
23	BANK OF QLND.	BOQX	AU	BK	**74**	OVERSEA-CHINESE BKG.	OCBC	SG	BK
24	BENDIGO & ADELAIDE BANK	BENX	AU	BK	**75**	PNC FINL.SVS.GP.	PNC	US	BK
25	COMMERZBANK (XET)	CBKX	DE	BK	**76**	PEOPLES UNITED FINANCIAL	PBCT	US	BK
26	CREDIT SUISSE GROUP N	CSGN	CH	BK	**77**	ROYAL BANK OF SCTL.GP.	RBS	GB	BK
27	CREDITO VALTELLINES	CVAL	IT	BK	**78**	REGIONS FINL.NEW	RF	US	BK
28	CANADIAN IMP.BK.COM.	CM	CA	BK	**79**	RESONA HOLDINGS	DBHI	JP	BK
29	CHIBA BANK	CHBK	JP	BK	**80**	ROYAL BANK CANADA	RY	CA	BK
30	CHUGOKU BANK	CHUT	JP	BK	**81**	SEB 'A'	SEA	SE	BK
31	CHUO MITSUI TST.HDG.	SMTH	JP	BK	**82**	STANDARD CHARTERED	STAN	GB	BK
32	CITIGROUP	C	US	BK	**83**	SVENSKA HANDBKN.'A'	SVK	SE	BK
33	COMERICA	CMA	US	BK	**84**	SWEDBANK 'A'	SWED	SE	BK
34	COMMONWEALTH BK.OF AUS.	CBAX	AU	BK	**85**	SYDBANK	SYD	DK	BK
35	DANSKE BANK	DAB	DK	BK	**86**	SAN-IN GODO BANK	SIGB	JP	BK
36	DBS GROUP HOLDINGS	DBSS	SG	BK	**87**	SHIGA BANK	SHIG	JP	BK
37	DEUTSCHE BANK (XET)	DBKX	DE	BK	**88**	SHINKIN CENTRAL BANK PF.	SKCB	JP	BK
38	DNB NOR	DNB	NO	BK	**89**	SUMITOMO MITSUI FINL.GP.	SMFI	JP	BK
39	DAISHI BANK	DANK	JP	BK	**90**	SUNTRUST BANKS	STI	US	BK
40	ERSTE GROUP BANK	ERS	AT	BK	**91**	SUNCORP-METWAY	SUNX	AU	SF
41	FIFTH THIRD BANCORP	FITB	US	BK	**92**	SURUGA BANK	SURB	JP	BK
42	FUKUOKA FINANCIAL GP.	FUKU	JP	BK	**93**	TORONTO-DOMINION BANK	TD	CA	BK
43	SOCIETE GENERALE	SGE	FR	BK	**94**	US BANCORP	USB	US	BK
44	GUNMA BANK	GMAB	JP	BK	**95**	UNICREDIT	UCG	IT	BK
45	HSBC HOLDINGS	HSBC	HK	BK	**96**	UNITED OVERSEAS BANK	UOBS	SG	BK
46	HACHIJUNI BANK	HABT	JP	BK	**97**	VALIANT 'R'	VATN	CH	BK
47	HANG SENG BANK	HSBA	HK	BK	**98**	WELLS FARGO & CO	WFC	US	BK
48	HIGO BANK	HIGO	JP	BK	**99**	WESTPAC BANKING	WBCX	AU	BK
49	HIROSHIMA BANK	HRBK	JP	BK	**100**	YAMAGUCHI FINL.GP.	YMCB	JP	BK
50	HOKUHOKU FINL. GP.	HFIN	JP	BK	**101**	3I GROUP	III	GB	SF
51	HUDSON CITY BANC.	HCBK	US	BK	**102**	ACKERMANS & VAN HAAREN	ACK	BE	SF

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Table Ib
Financial institutions in our sample.

	NAME	MNEM	CTRY	SEC		NAME	MNEM	CTRY	SEC
103	AMP	AMPX	AU	LI	**154**	AGEAS (EX-FORTIS)	AGS	BE	LI
104	ASX	ASXX	AU	IS	**155**	ALLIANZ (XET)	ALV	DE	FLI
105	ACOM	ACOM	JP	CF	**156**	AMLIN	AML	GB	PCI
106	AMERICAN EXPRESS	AXP	US	CF	**157**	AON	AON	US	IB
107	BANK OF NEW YORK MELLON	BK	US	AM	**158**	GENERALI	G	IT	FLI
108	BLACKROCK	BLK	US	AM	**159**	AVIVA	AV	GB	LI
109	CI FINANCIAL	CIX	CA	AM	**160**	AXA	MIDI	FR	FLI
110	CLOSE BROTHERS GROUP	CBG	GB	IS	**161**	ALLSTATE	ALL	US	PCI
111	CRITERIA CAIXACORP	CABK	ES	BK	**162**	AMERICAN INTL.GP.	AIG	US	FLI
112	CHALLENGER FINL.SVS.GP.	CGFX	AU	LI	**163**	ARCH CAP.GP.	ACGL	US	PCI
113	CHARLES SCHWAB	SCHW	US	IS	**164**	BALOISE-HOLDING AG	BALN	CH	FLI
114	CHINA EVERBRIGHT	IHDH	HK	SF	**165**	BERKSHIRE HATHAWAY 'B'	BRKB	US	RE
115	COMPUTERSHARE	CPUX	AU	FA	**166**	CNP ASSURANCES	CNP	FR	LI

(*continued on next page*)

Table Ib (*continued*)

	NAME	MNEM	CTRY	SEC		NAME	MNEM	CTRY	SEC
116	CREDIT SAISON	SECR	JP	CF	**167**	CINCINNATI FINL.	CINF	US	PCI
117	DAIWA SECURITIES GROUP	DS@N	JP	IS	**168**	EVEREST RE GP.	RE	US	RE
118	EURAZEO	ERF	FR	SF	**169**	FAIRFAX FINL.HDG.	FFH	CA	PCI
119	EATON VANCE NV.	EV	US	AM	**170**	GREAT WEST LIFECO	GWO	CA	LI
120	EQUIFAX	EFX	US	SF	**171**	HANNOVER RUCK. (XET)	HNR1	DE	RE
121	FRANKLIN RESOURCES	BEN	US	AM	**172**	HELVETIA HOLDING N	HEPN	CH	FLI
122	GAM HOLDING	GAM	CH	AM	**173**	HARTFORD FINL.SVS.GP.	HIG	US	FLI
123	GBL NEW	GBLN	BE	SF	**174**	ING GROEP	ING	NL	LI
124	GOLDMAN SACHS GP.	GS	US	IS	**175**	JARDINE LLOYD THOMPSON	JLT	GB	IB
125	ICAP	IAP	GB	IS	**176**	LEGAL & GENERAL	LGEN	GB	LI
126	IGM FINL.	IGM	CA	AM	**177**	LINCOLN NAT.	LNC	US	LI
127	INDUSTRIVARDEN 'A'	IU	SE	SF	**178**	LOEWS	L	US	PCI
128	INTERMEDIATE CAPITAL GP.	ICP	GB	SF	**179**	MAPFRE	MAP	ES	FLI
129	KINNEVIK 'B'	KIVB	SE	SF	**180**	MS&AD INSURANCE GP.HDG.	MSAD	JP	PCI
130	INVESTOR 'B'	ISBF	SE	SF	**181**	MUENCHENER RUCK. (XET)	MUV2	DE	RE
131	LEGG MASON	LM	US	AM	**182**	MANULIFE FINANCIAL	MFC	CA	LI
132	MAN GROUP	EMG	GB	AM	**183**	MARKEL	MKL	US	PCI
133	MARFIN INV.GP.HDG.	INT	GR	SF	**184**	MARSH & MCLENNAN	MMC	US	IB
134	MACQUARIE GROUP	MQG	AU	IS	**185**	OLD MUTUAL	OML	GB	LI
135	MITSUB.UFJ LSE.& FINANCE	DIML	JP	SF	**186**	PRUDENTIAL	PRU	GB	LI
136	MOODY'S	MCO	US	SF	**187**	POWER CORP.CANADA	POW	CA	LI
137	MORGAN STANLEY	MS	US	IS	**188**	POWER FINL.	PWF	CA	LI
138	NOMURA HDG.	NM@N	JP	IS	**189**	PROGRESSIVE OHIO	PGR	US	PCI
139	ORIX	ORIX	JP	SF	**190**	QBE INSURANCE GROUP	QBEX	AU	RE
140	PARGESA 'B'	PARG	CH	SF	**191**	RSA INSURANCE GROUP	RSA	GB	FLI
141	PROVIDENT FINANCIAL	PFG	GB	CF	**192**	RENAISSANCERE HDG.	RNR	US	RE
142	PERPETUAL	PPTX	AU	AM	**193**	SAMPO 'A'	SAMA	FI	PCI
143	RATOS 'B'	RTBF	SE	SF	**194**	SCOR SE	SCO	FR	RE
144	SCHRODERS	SDR	GB	AM	**195**	STOREBRAND	STB	NO	FLI
145	SLM	SLM	US	CF	**196**	SWISS LIFE HOLDING	SLHN	CH	LI
146	SOFINA	SOF	BE	SF	**197**	TOPDANMARK	TOP	DK	PCI
147	STATE STREET	STT	US	AM	**198**	TORCHMARK	TMK	US	LI
148	T ROWE PRICE GP.	TROW	US	AM	**199**	TRAVELERS COS.	TRV	US	PCI
149	TD AMERITRADE HOLDING	AMTD	US	IS	**200**	UNUM GROUP	UNM	US	LI
150	WENDEL	MF@F	FR	SF	**201**	VIENNA INSURANCE GROUP A	WNST	AT	FLI
151	ACE	ACE	US	PCI	**202**	W R BERKLEY	WRB	US	PCI
152	AEGON	AGN	NL	LI	**203**	XL GROUP	XL	US	PCI
153	AFLAC	AFL	US	LI	**204**	ZURICH FINANCIAL SVS.	ZURN	CH	FLI

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Table II
Classification of financial institutions by sector and by geographic area.

		Banks	Financial Services					Total	Insurances					*Total*	*TOTAL*
		BK	AM	SF	IS	CF	FA		LI	PCI	FLI	IB	RE		
Europe	AT	1	0	0	0	0	0	**0**	0	0	1	0	0	**1**	***2***
	BE	1	0	3	0	0	0	**3**	1	0	0	0	0	**1**	***5***
	DE	2	0	0	0	0	0	**0**	0	0	1	0	2	**3**	***5***
	DK	3	0	0	0	0	0	**0**	0	1	0	0	0	**1**	***4***
	CH	2	1	1	0	0	0	**2**	1	0	3	0	0	**4**	***8***
	ES	4	0	0	0	0	0	**0**	0	0	1	0	0	**1**	***5***
	FI	0	0	0	0	0	0	**0**	0	1	0	0	0	**1**	***1***
	FR	3	0	2	0	0	0	**2**	1	0	1	0	1	**3**	***8***
	GB	4	2	2	2	1	0	**7**	4	1	1	1	0	**7**	***18***
	GR	1	0	1	0	0	0	**1**	0	0	0	0	0	**0**	***2***
	IE	2	0	0	0	0	0	**0**	0	0	0	0	0	**0**	***2***
	IT	8	0	0	0	0	0	**0**	0	0	1	0	0	**1**	***9***
	NL	0	0	0	0	0	0	**0**	2	0	0	0	0	**2**	***2***
	NO	1	0	0	0	0	0	**0**	0	0	1	0	0	**1**	***2***
	PT	1	0	0	0	0	0	**0**	0	0	0	0	0	**0**	***1***
	SE	4	0	4	0	0	0	**4**	0	0	0	0	0	**0**	***8***
Total		***37***	***3***	***13***	***2***	***1***	***0***	***19***	***9***	***3***	***10***	***1***	***3***	***26***	***82***
North America	CA	6	2	0	0	0	0	**2**	4	1	0	0	0	**5**	***13***
	US	17	8	2	4	2	0	**16**	4	10	2	2	3	**21**	***54***

(*continued on next page*)

Table II (*continued*)

Total		***23***	***10***	***2***	***4***	***2***	***0***	***18***	***8***	***11***	***2***	***2***	***3***	***26***	***67***
Asia	AU	6	1	1	2	0	1	**5**	2	0	0	0	1	**3**	***14***
	HK	3	0	1	0	0	0	**1**	0	0	0	0	0	**0**	***4***
	JP	27	0	2	2	2	0	**6**	0	1	0	0	0	**1**	***34***
	SG	3	0	0	0	0	0	**0**	0	0	0	0	0	**0**	***3***
Total		***39***	***1***	***4***	***4***	***2***	***1***	***12***	***2***	***1***	***0***	***0***	***1***	***4***	***55***
TOTAL		***99***	***14***	***19***	***10***	***5***	***1***	***49***	***19***	***15***	***12***	***3***	***7***	***56***	***204***

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Table III
Estimated coefficients of CARES models for $ES_{1\%}$ and $ES_{5\%}$ for selected financial institutions. The abbreviations are: SCH=Banco Santander, BAC= Bank of America, C=Citigroup, JPM = JP Morgan, AXP = American Express, BK= Bank of NY Mellon, GS = Goldman Sachs, MS = Morgan Stanley, ALV = Allianz, G = Generali, BRKB= Berkshire Hathaway 'B' and ING= ING Groep.

Banks		**SCH**	**BAC**	**C**	**JPM**
γ_0	$ES_{1\%}$	−0.579	−0.032	0.018	−0.030
	$ES_{5\%}$	−0.212	−0.016	0.010	−0.030
γ_1	$ES_{1\%}$	0.781	0.934	0.954	0.965
	$ES_{5\%}$	0.857	0.946	0.954	0.950
γ_2	$ES_{1\%}$	−0.600	−0.325	−0.267	−0.146
	$ES_{5\%}$	−0.288	−0.166	−0.163	−0.129
Financial Services		**AXP**	**BK**	**GS**	**MS**
γ_0	$ES_{1\%}$	−0.127	−0.150	−0.034	−0.122
	$ES_{5\%}$	−0.059	−0.082	−0.034	−0.052
γ_1	$ES_{1\%}$	0.938	0.912	0.966	0.893
	$ES_{5\%}$	0.924	0.921	0.949	0.913
γ_2	$ES_{1\%}$	−0.204	−0.342	−0.133	−0.443
	$ES_{5\%}$	−0.194	−0.191	−0.130	−0.246
Insurances		**ALV**	**G**	**BRKB**	**ING**
γ_0	$ES_{1\%}$	−0.622	−0.414	−0.088	−0.403
	$ES_{5\%}$	−0.133	−0.162	−0.046	−0.184
γ_1	$ES_{1\%}$	0.791	0.836	0.916	0.823
	$ES_{5\%}$	0.890	0.861	0.914	0.838
γ_2	$ES_{1\%}$	−0.538	−0.389	−0.276	−0.552
	$ES_{5\%}$	−0.248	−0.290	−0.203	−0.399

Table IVa
PCA factor models for $ES_{5\%}$ series of financial institutions' stocks. *p*-values are reported in parentheses.

R^2	77.34%	47.02%	35.51%	74.74%	61.01%	73.47%	47.19%	68.32%	83.79%	61.25%	61.97%	75.24%	58.57%	46.61%	70.90%	56.82%	74.30%
Stocks	**SSBK**	**ALBK**	**PIST**	**ANZX**	**AWAT**	**BKIR**	**BKT**	**BARC**	**BBT**	**CRG**	**BPSO**	**BPE**	**BBVA**	**BCP**	**BP**	**SCH**	**BNP**
Intercept	−6.03E-15	6.60E-16	−2.00E-16	−6.47E-15	5.28E-15	1.25E-15	4.58E-15	1.38E-15	−3.29E-15	−3.67E-15	−3.65E-16	−1.47E-15	−2.79E-15	−1.31E-15	−3.54E-15	−2.99E-15	5.86E-15
	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)
PC1	0.061	0.043	0.014	0.079	0.033	0.068	0.059	0.073	0.083	0.024	0.015	0.013	0.069	0.015	0.045	0.069	0.075
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
PC2	−0.084	0.138	0.147	0.032	−0.065	0.121	0.075	0.069	0.051	0.159	0.187	0.206	0.051	0.155	0.171	0.037	0.087
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
PC3	0.145	0.001	0.057	0.035	0.189	−0.017	0.005	−0.022	−0.038	0.131	0.100	0.113	0.005	0.097	0.083	0.008	−0.017
	(0.000)	(0.362)	(0.000)	(0.000)	(0.000)	(0.000)	(0.050)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.022)	(0.000)	(0.000)	(0.003)	(0.000)
R^2	88.76%	64.15%	80.51%	84.31%	83.27%	67.30%	61.44%	69.49%	69.07%	48.54%	87.95%	79.36%	62.90%	66.19%	89.34%	87.84%	66.15%
Stocks	**BAC**	**BEAA**	**KYTB**	**BMO**	**BNS**	**BOQX**	**BENX**	**CBKX**	**CSGN**	**CVAL**	**CM**	**CHBK**	**CHUT**	**SMTH**	**C**	**CMA**	**CBAX**
Intercept	4.00E-15	3.02E-15	2.77E-15	9.16E-15	−5.17E-15	−2.88E-15	4.44E-15	−1.08E-15	−3.89E-15	−3.51E-15	5.14E-15	7.67E-15	−3.20E-15	5.00E-15	9.13E-16	2.70E-15	2.45E-15
	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)
PC1	0.082	0.075	0.054	0.084	0.084	0.071	0.071	0.075	0.078	0.011	0.085	0.063	0.042	0.063	0.085	0.085	0.076
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
PC2	0.082	0.000	−0.047	−0.040	−0.025	0.069	0.047	0.060	0.013	0.158	−0.046	−0.082	−0.087	−0.089	0.061	0.056	0.015
	(0.000)	(0.466)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
PC3	−0.044	0.017	0.193	−0.043	−0.044	0.054	0.034	0.020	0.000	0.104	−0.042	0.144	0.165	0.094	−0.046	−0.027	0.025
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.456)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
R^2	73.75%	65.75%	75.57%	83.52%	77.73%	84.96%	76.86%	0.89%	71.90%	81.12%	70.97%	72.22%	62.23%	45.06%	78.45%	65.23%	67.57%
Stocks	**DAB**	**DBSS**	**DBKX**	**DNB**	**DANK**	**ERS**	**FITB**	**FUKU**	**SGE**	**GMAB**	**HSBC**	**HABT**	**HSBA**	**HIGO**	**HRBK**	**HFIN**	**HCBK**
Intercept	5.20E-15	5.17E-16	−2.80E-15	−4.29E-16	−6.80E-15	5.96E-15	−1.10E-15	−5.48E-14	3.99E-15	2.62E-16	1.71E-15	−9.12E-15	−8.80E-16	−8.10E-15	3.45E-15	−8.89E-15	−9.52E-15
	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)
PC1	0.079	0.066	0.080	0.083	0.050	0.077	0.078	−0.006	0.073	0.055	0.077	0.051	0.073	0.044	0.043	0.049	0.072
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
PC2	0.049	−0.098	0.041	0.055	−0.069	0.113	0.063	0.006	0.087	−0.087	0.047	−0.091	−0.018	−0.112	0.009	−0.106	0.058
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.052)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
PC3	−0.005	−0.049	0.011	0.002	0.189	0.013	−0.043	−0.020	0.000	0.174	−0.003	0.161	0.019	0.068	0.219	0.135	−0.050
	(0.007)	(0.000)	(0.000)	(0.084)	(0.000)	(0.000)	(0.000)	(0.000)	(0.441)	(0.000)	(0.106)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Table IVb
PCA factor models for $ES_{5\%}$ series of financial institutions' stocks. *p*-values are reported in parentheses.

R^2	73.04%	74.91%	72.37%	55.77%	72.51%	91.01%	70.91%	77.57%	69.84%	74.43%	86.40%	73.00%	86.52%	33.33%	81.30%	80.26%	57.95%
Stocks	**HBAN**	**OBAN**	**OFBK**	**ISP**	**IYOT**	**JPM**	**JYS**	**JURT**	**KB**	**CSOG**	**KEY**	**LLOY**	**MTB**	**MB**	**KN@F**	**NDA**	**NANT**
Intercept	7.02E-16	1.42E-14	2.72E-15	−5.93E-15	−1.53E-15	6.78E-15	3.15E-15	2.12E-15	6.35E-16	2.21E-15	−3.85E-15	2.61E-16	−2.42E-15	1.11E-15	4.06E-15	4.26E-15	−4.86E-15
	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)
PC1	0.076	0.047	0.047	0.065	0.042	0.087	0.073	0.055	0.068	0.051	0.084	0.074	0.085	0.034	0.066	0.082	0.048
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
PC2	0.067	−0.064	−0.013	0.072	−0.091	0.000	0.084	−0.070	0.112	−0.021	0.061	0.077	0.049	0.118	0.147	0.002	0.010
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.344)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.103)	(0.000)
PC3	−0.039	0.191	0.197	0.011	0.186	−0.061	0.026	0.174	−0.009	0.193	−0.023	−0.049	−0.027	0.032	0.043	−0.050	0.163
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
R^2	69.91%	73.48%	76.52%	88.03%	71.92%	65.84%	83.52%	65.74%	45.91%	76.94%	57.37%	87.52%	90.02%	74.81%	85.41%	86.34%	74.18%
Stocks	**NABX**	**NA**	**NYCB**	**NTRS**	**OKBT**	**OCBC**	**PNC**	**PBCT**	**RBS**	**RF**	**DBHI**	**RY**	**SEA**	**STAN**	**SVK**	**SWED**	**SYD**
Intercept	−4.62E-15	1.48E-16	−4.29E-16	−2.71E-15	5.85E-15	−5.01E-15	−5.48E-16	9.63E-16	1.58E-15	−1.84E-15	−4.97E-15	−1.39E-15	1.15E-15	−1.52E-15	−8.63E-15	3.33E-15	−2.51E-16
	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)
PC1	0.077	0.079	0.081	0.087	0.055	0.068	0.081	0.075	0.059	0.076	0.049	0.087	0.088	0.080	0.086	0.085	0.072
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
PC2	0.024	−0.024	−0.011	−0.024	−0.073	−0.092	0.047	−0.031	0.068	0.085	−0.124	−0.010	0.012	0.001	0.017	0.049	0.089
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.387)	(0.000)	(0.000)	(0.000)
PC3	0.035	−0.028	−0.037	−0.038	0.160	−0.039	−0.073	−0.018	−0.013	−0.025	0.085	−0.032	−0.028	0.043	−0.012	−0.016	0.061
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
R^2	63.47%	64.30%	77.46%	67.40%	86.32%	75.15%	73.69%	87.28%	84.02%	73.74%	64.01%	42.35%	83.97%	67.65%	75.91%	83.31%	63.37%
Stocks	**SIGB**	**SHIG**	**SKCB**	**SMFI**	**STI**	**SUNX**	**SURB**	**TD**	**USB**	**UCG**	**UOBS**	**VATN**	**WFC**	**WBCX**	**YMCB**	**III**	**ACK**
Intercept	1.42E-14	−1.66E-15	1.13E-15	1.07E-14	2.45E-16	3.04E-15	8.48E-15	5.16E-15	−2.89E-15	−1.82E-15	−1.42E-16	9.72E-16	−2.10E-15	−1.50E-15	4.66E-15	8.08E-16	5.96E-16
	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)
PC1	0.047	0.041	0.061	0.065	0.081	0.078	0.057	0.083	0.081	0.063	0.069	−0.011	0.082	0.074	0.065	0.084	0.074
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
PC2	−0.066	−0.037	−0.078	−0.106	0.081	0.060	−0.148	−0.045	0.020	0.134	−0.073	0.153	0.061	0.036	−0.067	−0.028	−0.017
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
PC3	0.165	0.190	0.151	0.056	−0.047	0.002	0.073	−0.070	−0.083	0.060	−0.041	0.088	−0.050	0.048	0.133	−0.041	−0.024
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.176)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Table IVc
PCA factor models for $ES_{5\%}$ series of financial institutions' stocks. *p*-values are reported in parentheses.

R2	***58.27%***	***46.50%***	***25.80%***	***89.41%***	***90.63%***	***79.56%***	***66.13%***	***68.34%***	***84.98%***	***45.21%***	***84.57%***	***48.29%***	***27.11%***	***67.88%***	***69.96%***	***63.32%***	***87.20%***
Stocks	**AMPX**	**ASXX**	**ACOM**	**AXP**	**BK**	**BLK**	**CIX**	**CBG**	**CABK**	**CGFX**	**SCHW**	**IHDH**	**CPUX**	**SECR**	**DS@N**	**ERF**	**EV**
Intercept	1.49E-14	−1.69E-15	−1.06E-15	−3.54E-15	−2.93E-15	−1.18E-14	−2.86E-15	−1.30E-15	1.57E-15	3.66E-15	−4.35E-16	2.64E-15	−5.50E-15	−9.83E-16	7.45E-15	−1.59E-15	5.22E-15
	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)
PC1	0.071	0.061	0.042	0.086	0.089	0.083	0.065	0.073	0.082	0.063	0.076	0.061	0.038	0.074	0.069	0.071	0.087
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
PC2	−0.020	−0.053	−0.012	−0.016	−0.004	−0.006	−0.103	−0.069	−0.016	−0.017	−0.100	−0.065	−0.088	−0.040	−0.103	0.062	0.011
	(0.000)	(0.000)	(0.000)	(0.000)	(0.002)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
PC3	−0.017	0.014	0.066	−0.056	−0.025	−0.018	−0.052	−0.021	−0.076	0.006	−0.068	−0.004	−0.017	0.047	0.018	−0.017	−0.015
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.036)	(0.000)	(0.122)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
R2	***51.58%***	***90.27%***	***55.71%***	***66.55%***	***85.33%***	***59.40%***	***75.93%***	***79.53%***	***72.08%***	***56.37%***	***63.55%***	***84.72%***	***73.98%***	***22.16%***	***71.30%***	***65.42%***	***71.30%***
Stocks	**EFX**	**BEN**	**GAM**	**GBLN**	**GS**	**IAP**	**IGM**	**IU**	**ICP**	**KIVB**	**ISBF**	**LM**	**EMG**	**INT**	**MQG**	**DIML**	**MCO**
Intercept	4.80E-15	2.69E-15	4.79E-15	−1.24E-15	−5.55E-15	1.07E-14	−2.83E-15	4.66E-15	1.88E-15	1.97E-15	7.72E-15	8.70E-15	−5.85E-15	−8.10E-15	5.49E-15	4.77E-15	2.54E-16
	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)
PC1	0.064	0.089	0.070	0.074	0.085	0.067	0.076	0.082	0.068	0.062	0.071	0.086	0.072	0.015	0.077	0.067	0.078
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
PC2	−0.046	−0.007	0.001	−0.047	−0.023	0.059	−0.077	−0.025	0.119	−0.095	−0.064	0.010	0.092	0.112	0.035	−0.066	0.029
	(0.000)	(0.000)	(0.307)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
PC3	−0.034	−0.009	0.006	−0.015	−0.044	0.047	−0.041	−0.030	0.024	−0.020	−0.007	−0.013	0.050	0.045	0.043	0.083	0.009
	(0.000)	(0.000)	(0.015)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.005)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
R2	***85.35%***	***68.08%***	***78.69%***	***69.33%***	***2.14%***	***68.79%***	***59.49%***	***75.94%***	***74.34%***	***68.34%***	***83.40%***	***89.93%***	***71.66%***	***76.58%***	***82.22%***	***76.21%***	***76.64%***
Stocks	**MS**	**NM@N**	**ORIX**	**PARG**	**PFG**	**PPTX**	**RTBF**	**SDR**	**SLM**	**SOF**	**STT**	**TROW**	**AMTD**	**MF@F**	**ACE**	**AGN**	**AFL**
Intercept	2.45E-15	2.94E-15	4.64E-15	5.25E-15	−8.12E-15	−7.56E-15	5.79E-15	−5.38E-15	−1.83E-15	−1.43E-15	−4.28E-15	3.53E-15	2.65E-15	4.52E-15	−4.49E-16	−4.14E-15	4.37E-16
	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)
PC1	0.086	0.074	0.080	0.077	0.013	0.076	0.070	0.077	0.079	0.076	0.083	0.087	0.061	0.081	0.076	0.081	0.078
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
PC2	0.003	−0.059	−0.043	−0.018	−0.008	0.037	0.048	−0.076	0.052	−0.035	0.024	−0.029	−0.128	0.029	−0.089	0.014	0.039
	(0.044)	(0.000)	(0.000)	(0.000)	(0.018)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
PC3	−0.016	0.035	0.047	−0.036	−0.005	0.024	0.018	−0.014	−0.004	−0.023	−0.059	−0.050	−0.071	−0.021	−0.064	−0.031	−0.065
	(0.000)	(0.000)	(0.000)	(0.000)	(0.099)	(0.000)	(0.000)	(0.000)	(0.021)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Table IVd
PCA factor models for $ES_{5\%}$ series of financial institutions' stocks. *p*-values are reported in parentheses.

R2	***81.73%***	***68.72%***	***14.92%***	***51.29%***	***38.66%***	***83.35%***	***72.58%***	***81.09%***	***47.09%***	***79.08%***	***55.46%***	***73.37%***	***40.05%***	***79.13%***	***70.74%***	***28.11%***	***42.19%***
Stocks	**AGS**	**ALV**	**AML**	**AON**	**G**	**AV**	**MIDI**	**ALL**	**AIG**	**ACGL**	**BALN**	**BRKB**	**CNP**	**CINF**	**RE**	**FFH**	**GWO**
Intercept	−4.11E-15	4.94E-15	−5.44E-14	−3.81E-16	−8.96E-16	−2.35E-15	−6.98E-16	7.34E-16	2.73E-15	−1.54E-15	−9.16E-16	2.93E-15	−4.58E-15	2.55E-15	1.50E-15	3.50E-15	−1.84E-15
	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)
PC1	0.084	0.075	0.035	0.054	0.053	0.085	0.079	0.083	0.062	0.077	0.068	0.078	0.058	0.082	0.074	0.037	0.058
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
PC2	0.033	−0.053	−0.024	−0.085	0.070	0.016	0.006	0.000	0.040	−0.073	−0.044	−0.004	0.037	−0.014	−0.065	−0.084	0.008
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.003)	(0.450)	(0.000)	(0.000)	(0.000)	(0.026)	(0.000)	(0.000)	(0.000)	(0.000)	(0.006)
PC3	−0.017	−0.027	−0.020	−0.081	0.002	−0.034	−0.024	−0.049	−0.019	−0.059	−0.022	−0.053	−0.017	−0.034	−0.043	−0.048	−0.060
	(0.000)	(0.000)	(0.000)	(0.000)	(0.235)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
R2	***64.94%***	***58.61%***	***84.14%***	***73.27%***	***18.63%***	***78.82%***	***86.05%***	***85.15%***	***64.16%***	***69.81%***	***56.29%***	***83.28%***	***77.04%***	***51.31%***	***86.45%***	***83.55%***	***72.99%***
Stocks	**HNR1**	**HEPN**	**HIG**	**ING**	**JLT**	**LGEN**	**LNC**	**L**	**MAP**	**MSAD**	**MUV2**	**MFC**	**MKL**	**MMC**	**OML**	**PRU**	**POW**
Intercept	4.39E-15	−1.65E-15	1.99E-15	6.26E-15	5.99E-15	−3.78E-16	2.55E-15	−2.96E-15	−1.35E-14	2.21E-15	8.40E-16	4.45E-15	2.21E-15	−3.27E-15	7.60E-15	1.29E-15	3.98E-15
	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)
PC1	0.074	0.071	0.085	0.078	0.038	0.082	0.084	0.086	0.073	0.069	0.060	0.083	0.082	0.060	0.087	0.085	0.079
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
PC2	−0.039	−0.030	0.034	0.049	0.011	0.011	0.056	−0.027	0.047	−0.005	−0.087	0.057	0.005	−0.069	−0.008	−0.016	0.005
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.006)	(0.000)	(0.000)	(0.006)	(0.000)	(0.000)	(0.000)	(0.009)
PC3	−0.024	−0.023	−0.021	−0.005	0.040	−0.043	−0.023	−0.019	0.015	0.113	−0.059	−0.024	−0.015	−0.059	0.015	−0.004	−0.044
	(0.000)	(0.000)	(0.000)	(0.008)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.008)	(0.000)
R2	***74.09%***	***78.54%***	***1.30%***	***54.86%***	***58.43%***	***74.83%***	***45.44%***	***75.76%***	***42.07%***	***59.96%***	***83.94%***	***88.26%***	***75.63%***	***71.05%***	***81.77%***	***80.58%***	***50.90%***
Stocks	**PWF**	**PGR**	**QBEX**	**RSA**	**RNR**	**SAMA**	**SCO**	**STB**	**SLHN**	**TOP**	**TMK**	**TRV**	**UNM**	**WNST**	**WRB**	**XL**	**ZURN**
Intercept	3.14E-15	1.29E-16	−1.63E-15	−1.05E-15	−6.07E-15	5.51E-15	2.74E-15	−2.07E-15	3.25E-15	1.07E-15	−1.39E-15	−4.91E-15	−2.81E-15	5.30E-15	−7.28E-17	−2.31E-15	−1.26E-15
	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)
PC1	0.078	0.078	0.011	0.053	0.066	0.077	0.048	0.080	0.060	0.066	0.083	0.084	0.079	0.063	0.081	0.084	0.060
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
PC2	0.002	−0.047	−0.002	−0.117	−0.070	−0.048	−0.109	0.044	−0.028	−0.082	0.030	−0.064	−0.010	0.125	−0.061	0.015	−0.072
	(0.134)	(0.000)	(0.303)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
PC3	−0.057	−0.075	0.001	−0.057	−0.033	−0.062	−0.049	0.017	−0.022	−0.023	−0.054	−0.048	−0.055	0.059	−0.044	−0.006	−0.041
	(0.000)	(0.000)	(0.386)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)

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