Uncertainty, Systemic Shocks and the Global Banking Sector:

Has the Crisis Modified their Relationship?

Abstract

We estimate the impact of equity market uncertainty and an unobservable systemic risk factor on the returns of the major banks in the global banking sector. Our estimation combines quantile regressions, structural changes, and factor models and allows us to explore the stability of systemic risk propagation among financial institutions. We find that risk propagation has remained stable over the last decade, and we report evidence indicating that equity market uncertainty is a major factor for the global banking system. Additionally, we provide a new simple tool for measuring the resilience of financial institutions to systemic shocks.

Keywords: systemic risk, uncertainty, global banking, quantile breaks.

JEL: C32, E44, G21, G32.

1. Introduction

Systemic risk can be defined as the risk that a financial institution faces during periods of widespread financial distress, following exposure to an extreme negative shock in the market. This shock may arise either as a consequence of the failure of an individual firm of sufficient size and connectedness that it imposes significant marginal distress costs on the rest of the system, or as a common shock to the financial structure that is absorbed and amplified by various firms depending on their own particular resilience (Jobst, 2014a). The materialization of systemic risk may lead to disruptions in the provision of key financial services due to impairments of all or parts of the financial system, which may in turn have adverse consequences for the functioning of the real economy (see Acharya et al., 2010, and Adrian and Brunnermeier, 2014).

For these reasons, in recent years systemic risk has become a growing concern for regulators, who have made great efforts not only to measure the impact of systemic risk on individual firms, but also to identify systemically important financial institutions (SIFIs) that should adhere to stronger capital requirements to avoid giving rise to shocks which might destabilize the whole system. As a result, significant advances have been made in systemic risk regulation, as documented by both the Financial Stability Board (FSB) and the International Association of Insurance Supervisors (IAIS).[1]

Several methodologies have been proposed for measuring systemic risk, above all in the banking sector.[2] The most common seek to estimate marginal increments in the value-at-risk statistics (VaR) of financial institutions, or increments in the marginal expected shortfall (ESF) of each firm, under a scenario of financial turmoil.[3] The reason for focusing on a financial institution's VaR or ESF is because extreme negative scenarios are naturally related to the lowest quantiles of the distribution of a set of financial variables (including, stock returns) and, hence, to systemic risk scenarios. However, traditional methods based on quantiles do not allow the researcher to identify the source of the shocks to the system; rather, they calculate the marginal contribution of each company to the risk of the system as a whole.

Our contribution to the literature is the examination of the characteristics and stability of systemic risk and uncertainty, in relation to the dynamics of the banking sector stock returns. Particularly, we are interested in exploring relevant hypotheses for the economics discipline regarding the stability of the systemic risk propagation mechanism across the global banking sector, and about the importance of equity market uncertainty as a source of systemic risk for global financial institutions. Both issues are instrumental for the design of macro policies, seeking to reduce systemic risk materialization episodes, or to construct a more resilient global banking sector in the forthcoming decades. Hence, we aim to measure the systemic risk in the global banking sector that arises from two primary sources: an unobservable systemic risk factor by White et al. (2015) and an economic equity market uncertainty factor (EMU) provided by Baker et al (2016). Our proposal is novel in three respects. First, we consider the evolving nature of systemic risk, a characteristic mainly overlooked in the literature despite having evident policy and practical implications for the banking industry.[4] We provide evidence regarding the stability of the relationship between systemic shocks and the banks' responses over the last decade. This sort of evidence is new to the literature and is supportive of past claims, made in the field of macroeconomics (Stock and Watson, 2012),

[1] See for example FSB (2011, 2012, 2013) and IAIS (2009, 2012, 2013).

[2] See Bisias et al. (2012) for a review.

[3] These methods were originally proposed by Acharya et al. (2010) and Adrian and Brunnermeier (2014). Numerous empirical implementations followed, for example, in the work of Anginer et al. (2014a, 2014b), Bernal et al. (2014), or Drakos and Kouretas (2015).

[4] Two exceptions to this point are the studies by Straetmans and Chaudry (2015) and Kolari and Sanz (2015), which we discuss in the next section.

which hold that during the global financial crisis the financial system may have faced stronger versions of traditional shocks rather than a new type of shock.

Second, we undertake an empirical study of the role of equity market uncertainty, as measured by Baker et al. (2016), as a systemic risk factor for the banking industry. Uncertainty is known to play a critical role in determining economic dynamics during episodes of crisis and, in recent years, its study has attracted much attention in the literature to account for the nonlinear negative dynamics that arise during episodes of economic distress (Bloom, 2009; Jurado et al., 2015). Empirical tools are now available that can provide accurate measurements of uncertainty (Baker et al. 2016), and its inclusion as an unobservable factor enhances our understanding of banking sector behavior during episodes of systemic stress in the financial markets. We report that for most of the banks analyzed, especially over the last decade, uncertainty is indeed a relevant consideration. As expected, more uncertainty leads to a reduction in equity prices in the banking industry, and this behavior has become more pronounced in the last few years, especially when compared to the situation 15 years ago.

Finally, we emphasize the vulnerability of each institution to systemic shocks (either EMU or systemic risk factors), rather than the vulnerability of the system as a whole to the failure of one specific, perhaps important, financial institution. The perspective we adopt has received considerably less attention in the literature[5]. By implementing our model, we are able to rank banks in accordance with their vulnerability to two common shocks: an unobservable systemic risk factor and the equity market uncertainty shock. Thus, we seek to identify systemically vulnerable financial institutions under scenarios of financial distress. Notice that the two factors in our model were selected as to measure two main different sources of vulnerability in the global banking sector. While the systemic risk indicator may be interpreted as a “financial” risk shock, the EMU index quantifies "economic" uncertainty related to equity markets. This distinction and its inclusion in the empirical exercise that we conduct in what follows are crucial to achieve a deeper understanding of the way in which the propagation of shocks occurs within and between financial and real markets.[6]

Our model involves combining dynamic factor models with quantile regressions, in line with Ando and Tsay (2011) and White et al. (2015).[7] Yet, unlike Ando and Tsay (2011), who are not concerned with systemic risk but rather with forecasting asset returns, we construct the factors for inclusion in the factor-augmented quantile regression by differentiating between a traditional systemic risk factor and an equity market uncertainty factor. Similar to White et al. (2015), we consider the systemic factor as being contemporaneously exogenous from the point of view of each bank. In contrast with them, we do not construct (pseudo) quantile impulse response functions, and this allows us to expand the analysis by including more relevant factors (e.g., the uncertainty factor). That is, our model lacks dynamics, and therefore it may exist additional feedback beyond the first period going from the idiosyncratic bank dynamics to the system dynamics. This can conduce to a total impact of the systemic shock higher than the one observed in the first period, which we report here. Nevertheless, we restrict our attention to the effect observed when the systemic shock first arises, which is the most relevant point in the total dynamic impact[8]. This

[5] Some noticeable recent examples are given by Hartmann et al. (2006), Jonghe (2010) and Straetmans and Chaudhry (2015).

[6] See for example the theoretical framework by Brunnermeier and Sannikov (2014) to motivate the importance of considering the interplay between macro and financial markets.

[7] Factor models are popular in the asset pricing literature (Fama and French, 1993; Cochrane, 2005), while quantile regressions have gained considerable impetus in the financial branch in recent years (Engle and Manganelli, 2004; Li and Miu, 2010; Ciner et al. 2013; Mensi et al., 2014; among others).

[8] See for example Figures 2 to 4 in White et al. (2015) in which the first effect is always the maximum of the pseudo impulse responses.

contemporaneous reaction is crucial in terms of systemic risk and we aim at examining its stability through time. To this end we test for the stability of the quantile coefficients in an endogenous fashion, following the proposals made by Oka and Qu (2011). This last step allows us to determine whether there were changes in the propagation of systemic risk in the global banking industry during and after the crisis. The outcome we report is, in general, negative in this regard.

In sum, we measure, by the first time, the role of equity market uncertainty as a systemic risk factor for the global banking sector. We also endogenously test whether the relationship between banks' returns and economic uncertainty and a systemic risk factor, respectively, is stable during the sample period. We employ a methodology that allows us to focus on a specific quantile of interest**,** conditional on the systemic risk factors that we identify. This is also new, given that in the systemic risk exercises that have used quantiles so far, systemic risk factors are omitted and the estimates refer to unconditional quantiles of the dynamic distribution of returns (or to estimates conditional on certain observation as opposed to quantiles). Finally, we also provide a ranking of systemically vulnerable financial institutions that focuses on the vulnerability of each institution to the systemic risk factors, as opposed to the extant literature that has mainly focused on the effect of each institution on the rest of the system.

The rest of this paper is organized as follows. In the next section we undertake a general review of the literature examining systemic risk, so as to place our study in a broader context and to illustrate just where our contribution fits in the field. The third section provides a detailed explanation of our methodology. In the fourth section we present our main results and, finally, in the fifth section we conclude and discuss the limitations of this study and identify future lines of research.

2. Related literature

Systemic risk is traditionally considered as comprising various phenomena that represent substantial costs to the real economy and which, as such, have attracted significant research efforts. Allen and Carletti (2013) summarize these phenomena as panics (associated with banking crises due to multiple equilibria); banking crises due to asset price falls; contagion; and, foreign exchange mismatches in the banking system. The authors stress the historical importance of panics in accounting for systemic risk. Panics, they argue, are self-fulfilling events that arise because agents have uncertain consumption patterns and, consequently, uncertain investment plans, which are costly to implement. In a scenario in which depositors believe that other depositors will withdraw their funds prematurely, then all agents find it optimal to redeem their claims, sending the market into panic (see the seminal works by Bryant, 1980, and Diamond and Dybvig, 1983).

In the case of banking crises, Allen and Carletti (2013) identify several possible reasons as to why the prices of assets held by banks might drop, generating the appearance of systemic risk in the real economy. They include, but are not limited to, the business cycle dynamics, the bursting of real estate bubbles, mispricing due to inefficient liquidity provision and limits to arbitrage, sovereign defaults and interest rate increases. In each of these cases, whether they are related to natural economic dynamics (for instance the real cycles of the economy, as reviewed by Allen et al., 2009) or to behavioral biases in agent decision-making (Allen and Gale, 2007), when asset prices fall, this might result in significant solvency problems for banks and, hence, in systemic risk.

Contagion is another important source of systemic risk that seems to have been particularly relevant in the most recent global financial crisis. This phenomenon refers to the possibility that the distress of one financial institution propagates to others in the system and, thus, leads to a systemic crisis (Allen et al., 2009, provide a survey of this literature). Finally, Allen and Moessner (2010) describe currency mismatches in the banking system, created by banks lending in a low interest rate foreign currency, and then funding these loans in domestic currency. When exchange rate reversals are made, as occurred during the Asian crisis in 1997, the solvency and liquidity of the whole banking system may be compromised.

More recently, systemic risk has received considerable attention from both academics and regulators, since it is thought to lie at the core of the 2007-2009 crisis and to be a key factor in understanding crisis propagation to the real economy. In the main, research has explored data series from the US and the Eurozone and has analyzed systemic risk from a range of perspectives.

One strand of this literature has analyzed the systemic risk arising from individual financial institution spillovers, i.e., it has focused on measuring the impact that individual shocks attributable to specific institutions may have on the system as a whole. For example, Avramidis and Pasiouras (2015), using factor models and multivariate extreme dependency statistics, study spillovers between individual financial institutions. They highlight the significant underestimation of the capital requirements of financial institutions if extreme event dependence is ignored when estimating solvency ratios. Kanno (2015) and Cont and Minca (2015) undertake network analyses to explore interbank bilateral exposures and over-the-counter credit default swaps, respectively, and report large spillovers during the global financial crisis. In the same line of research, Bongini et al. (2015) and Castro and Ferrari (2014) analyze systemically important financial institutions (SIFIs) and their market effects. While the former apply event study methodology to determine the impact of inclusion as a SIFI on market prices, the latter explore the use of CoVaR (Conditional Value at Risk) as a measure of an institution's systemic importance.[9]

Alternative measures, including V-Lab stress tests, designed to account for 'the risk that risk itself may change', have been compared with the stress test indicators used by the Supervisory Capital Assessment Program in the US and by the European Banking Authority (which replaced the Committee of European Banking Supervisors) in the EU (see Acharya et al., 2012; Acharya et al., 2014). In the same vein, nonlinear models using flexible parameterizations, such as those allowed by vine copulas, have been analyzed for example in Brechmann et al. (2013), with empirical applications to both the insurance and banking sectors. Finally, Singh et al. (2015) analyze the risk behavior of the banking sector at the individual level and then scale these outcomes at the EMU-country level, using distance-to-default models and vector autoregression estimates.

Another strand of the literature has analyzed the systemic risk arising from extreme market scenarios in an aggregate fashion. In other words, it has explored the sensitivity of financial institutions to 'systemic factors', which can be treated as observable or unobservable. The former are related, for example, to liquidity considerations, as studied by Pierret (2015) and Jobst (2014b). While the first of these authors constructs a model that blends questions of liquidity and solvency, the second proposes adjusting traditional systemic risk indicators using liquidity constraints. Other observable factors include disruptions in economic conditions, as studied for example by Calmès and Théoret (2014), and such factors as interbank exposures, asset prices, and sovereign credit risks (Paltalidis et al., 2015).

In contrast, a number of studies have preferred to focus on unobservable factors. For example, Kim and Kim (2014) estimate a 'systemic bubble index' to determine the investment dynamics of stock investors for financial institutions, and which should serve as an early warning signal of systemic fragility. Alter and Beyer (2014) quantify spillovers between sovereign credit markets and banks in the euro area, but they treat the factors as exogenous-unobservable forces affecting the dynamics of

[9] CoVaR was originally proposed by Adrian and Brunnermeier (2014) for the estimation of increments in a firm's marginal expected shortfall, under a scenario of financial turmoil. It has been extended to the bivariate setting, for example, by Lopéz-Espinosa et al., 2015.

CDSs.

Finally, a new branch of the systemic risk literature has started to explore the evolving nature of systemic risk. This branch (implicitly or explicitly) considers systemic risk as a policy regime-dependent problem. As such, it seeks to take into account changes in terms of the regulatory framework (i.e., Basel III, the Dodd-Frank reform), macro-prudential regulation, and individual risk preferences. Claessens et al. (2013) investigate the efficacy of macro-prudential policy for preventing systemic risk and report that such measures have helped mitigate bank leverage and exposure to the volatility of financial assets. However, others, such as Calluzzo and Dong (2015), question whether the reduction in risk faced by individual institutions correlates with a decrease in systemic risk. They conclude that it does not, and indeed, using a quasi-experimental design, they document an increment in the amount of contagion in the post-crisis financial system, and hence in the vulnerability of the financial market to systemic risk.

Similarly, Straetmans and Chaudhry (2015) evaluate multiple market-based measures for US and Eurozone individual bank tail risk and bank systemic risk, and report results that suggest that both are higher in the US than in the Eurozone regardless of the sample period (pre- and post-crisis). They also find that the magnitude of the two risk types increased in both samples, taking the crisis as a threshold. This contribution can be seen as the closest to ours. The authors analyze systemic spillovers using extreme value theory and they aim to test for the stability of the results. They carry out both an analysis of the whole system sensitiveness to each financial institution, and of each bank to aggregate systemic factors (such as stock market indices, sectorial world-wide and regional indices and housing prices). Nevertheless, their systemic factors are different to ours and their estimates correspond to co-crash probabilities of banks, conditioning on sharp drops on the non-diversifiable factors. To do the latter they need to focus on particular dates at which the systemic risk indicators drop in a significant magnitude. By the contrary, we use our full sample to estimate the conditional quantiles of the banks' return distributions. These quantiles are by construction conditional on our systemic factors and in this way we manage to use the information more efficiently. More importantly, we test for the stability of the estimates describing the propagation mechanism, but different from Straetmans and Chaudhry (2015) who impose *ad hoc* the possible structural change of the series, we do so in an endogenous fashion, following the proposal by Oka and Qu (2011). The latter approach has several advantages, which have been extensively documented in the literature of structural changes in time series analysis (see Perron (2006) for a survey). Basically, imposing the break dates might derive in spurious detection of changes in the data generating process. Therefore the search should be ideally carried up in an endogenous fashion.

The selection of our systemic factors and our quantile regression methodology, allows us to obtain stable model coefficients, before and after the global financial crisis. This means that our factors suffice to explain the quantile variations before and after the crisis, while Straetmans and Chaudry (2015) estimates experience a great amount of variation (with marked jumps of the "tail-betas" that they calculate). This is an advantage, because our model does not become invalid once the systemic risk factors achieve a certain threshold.

The present study is related to all three branches of the literature outlined above, but primarily with the last two. It is closely associated with the second group of studies because we are concerned with the sensitivity of individual institutions to factors of systemic risk. In line with Kim and Kim (2014) and White et al. (2015), we treat these factors as unobservable in nature and, in line with Calmès and Théoret (2014), Alter and Beyer (2014), and Paltalidis et al. (2015), we treat them as exogenous from the point of view of each financial institution. It is also closely associated with the third group because it focuses on the dynamics of systemic risk. We explicitly test for the stability of the parameters in our factor quantile model, seeking to identify any possible structural changes in the shape of risk transmission during the sample period, in an endogenous fashion. Finally, in relation to the first set of papers, our study can be considered as providing a tool to account for the ‘risk that risk itself may change’, in line with the V-Lab stress test (although using different methodologies).

Kolari and Sanz (2015) utilize neural network mapping technology to assess the dynamic nature of systemic risk over time in the banking industry. They report informal graphical evidence suggesting that systemic risk peaked in 2009 and remained thereafter. Their strategy consists of a visual inspection of the changes in the network’s maps of the 16 main commercial banks in the US during the crisis period. The changes reported by the authors are gradual, so they are not related to dramatic changes or structural breaks from one year to another. Different to these authors we focus here in permanent changes of the systemic risk propagation mechanisms following the global financial crisis and we provide statistical tests of such changes. We also analyze a longer period of time and a considerable greater number of banks.

Notice that different to ours, other measures of systemic risk, based on quantiles, such as the marginal expected shortfall (MES) of Acharya et al. (2016) estimate the stock return reaction of bank i to bad market outcomes. They are intended to provide a measure of the resilience of each individual institution to systemic distress scenarios. In this way, they aim to estimate the marginal contribution of each bank to systemic financial distress: The more negative the outcome of a particular bank is, the more this institution will contribute to destabilize the system during periods of generalized distress. You can notice that the emphasis of the exercise using MES is precisely on *how much the system will be affected by the idiosyncratic bank performance* during bad market times. On the contrary, our definition of SVFIs emphasizes on *how the system impacts on the bank i, at any time*, which is a complementary approach. For this reason, we do not restrict our attention to bad market outcomes, but to bad individual stock realizations of the financial institutions (i.e. to the lowest quantiles of the banks’ return distribution).

3. Methodology

As discussed, our methodological proposal involves combining dynamic factor models with quantile regression. Thus, we construct the factors to be included in the factor-augmented quantile regression, differentiating between a traditional, systemic risk factor affecting the global financial sector and an equity market uncertainty factor. We conduct the estimation in a three-step approach: first, we construct the systemic factor; second, we use this and the EMU factor provided by Baker et al. (2016) as explanatory variables in a traditional quantile regression; and, third, we test the stability of the parameters, seeking to identify changes in factor load coefficients that might be attributable to the crisis.

Following Bai and Ng (2008), let N be the number of cross-sectional units, that is, the number of banks in our sample, and let T be the number of time series observations. For $i = 1 \ldots N$ and $t = 1 \ldots T$, our factor model can be defined as:

$$x_{it} = \lambda_{1,i} f_{1,t} + \lambda_{2,i} f_{2,t} + e_{it} , \tag{1}$$

or more compactly as $\boldsymbol{x}_t = \boldsymbol{\alpha} \boldsymbol{f}_t + \boldsymbol{e}_t$ with $\boldsymbol{x}_t = (x_{1t}, \ldots, x_{Nt})'$, $\boldsymbol{f}_t = (f_{1t}, f_{2t})'$, $\boldsymbol{e}_t = (e_{1t}, \ldots, e_{Nt})'$. $\boldsymbol{x}_t$ is a *N*-dimensional observable random vector of stock returns of the banks in our sample, $\boldsymbol{f}_t$ is a *2*-dimensional vector of latent factors.

$f_{1,t}$ is an unobservable systemic risk factor that impacts the N financial institutions in our sample via coefficients $\lambda_{1,i}$. Thus, it can be estimated using the first principal component of the $(N \times T)$ matrix of financial institutions’ stock returns in the cross-sectional dimension. This procedure enables us to treat the consistently estimated factors as non-generated regressors in subsequent stages of our procedure (Bai and Ng, 2002; Stock and Watson, 2002), which is important for inference.[10]

$f_{2,t}$ is a general equity market uncertainty factor that may potentially impact the banks via $\lambda_{2,i}$. This uncertainty factor is, in principle, unobservable, as well. However, recent advances in the discipline mean we can construct indices of economic uncertainty that impact the equity market. Specifically, here, we use the equity market uncertainty factor proposed by Baker et al. (2016). These authors construct their measure of uncertainty by searching each paper in the NewsBank database looking for terms related to economic and policy uncertainty.[11] This direct measure of equity market uncertainty allows us to trace the dynamic of this unobservable and systemic factor.

The first unobservable factor was previously identified in the literature by White et al. (2015), as we already emphasized. Moreover, it is naturally related to a market factor, because it summarizes the common variation in all the series of stock returns in the financial sector in a CAPM' style, and therefore, it should be the starting point of any factor analysis about systemic risk (or asset pricing).

The inclusion of EMU requires a more detailed explanation. We need a factor that helps to identify recessionary states in the market, and that provides new information additional to the market factor. We ideally require a variable with predictive power on the state of the economy and at the same time with a theoretical justification to support its inclusion. Indeed, this is the case of very few factors in the literature and uncertainty is one of them. Balcilar et al. (2016) and Segnon et al. (2016) provide evidence of the predictive power of uncertainty in the GDP forecast and Balcilar and Gupta (2016) provide evidence of the prediction power of uncertainty in inflation. On the other side, Bansal and Yaron (2004), Bloom et al. (2007), Bloom (2009), Jurado et al. (2015) and Chuliá et al. (2017), to name just a few, have extensively documented, and modeled, how uncertainty may affect price formation in the market, or how it may shape the dynamics of the economic activity as a whole.

Finally, one could argue that while the market factor is more related to expected variations within the financial system, equity market uncertainty is more linked to unexpected movements in the time series returns, related to the economic system. Therefore they are complementary and hence natural candidates to construct our factor model (see for example Chuliá et al., 2017 for an extensive discussion of the differences between expected and unexpected shocks).

Here we keep the focus on the systemic risk interpretations accompanying our factors, but we acknowledge that this exercise is much related to those performed within the asset pricing literature aiming to explain the equity premium, and therefore, other factors such as size, book to market ratios, momentum, etc. might be explored in future exercises. Nevertheless, the theoretical

[10] We construct the systemic risk measure in line with White et al. (2015). Unlike us, they estimated the principal components of each financial sector (banks, insurers and others) and then aggregated the factors using the market capitalization of each sector as weights. We also tried estimating the factors that affect each sector separately, and included all three in the estimations, but the amount of multicollinearity among the three factors, indicated that they were likely to be measuring the same unobservable shocks. For this reason, we preferred to include only one general factor as we explain in the main text.

[11] Specifically, they search for articles containing the words 'uncertainty' or 'uncertain'; 'economic' or 'economy'; and, one or more of the following terms: 'equity market', 'equity price', 'stock market', or 'stock price'. Thus, to satisfy their criteria for inclusion, the article must include a term from each of the three categories (that is, uncertainty, the economy, and the stock market). Further details about the construction of the index can be found at www.policyuncertainty.com and in Baker et al. (2016).

constructs that underlie uncertainty are very appealing and for this reason we consider that it remains an attractive starting point for systemic risk analysis.

The model in Eq. 1 relates the 'average' scenarios for the bank stock returns distribution to the systemic factors. However, our definition of systemic risk means we need to focus on the shocks that occur during extreme negative scenarios. To this end we expand regression (1) as:

$$q_i^{\tau}(x_{it}|\boldsymbol{f_t};\boldsymbol{\alpha}) = \boldsymbol{\alpha}(\tau)' \ \boldsymbol{f_t}, \tag{2}$$

where $\alpha(\tau)$ is a vector of coefficients that depends on the quantile τ, q_i^{τ}. Unlike classical factor theory, which focuses on the factor's mean impact on the endogenous variables, quantile estimates allow us to explore different portions of the conditional distribution of the stock returns. Quantile regressions are known to be robust to outliers and this is particularly important when analyzing financial time series. They are also semi-parametric in nature and, therefore, we require minimal distributional assumptions on the underlying data generating process. Moreover, quantile regressions offer greater flexibility in the analysis of different market scenarios. For instance, lower quantiles can be interpreted as extreme negative situations, corresponding for example to setting $\tau = 0.1$, and therefore the estimations are directly related to systemic risk scenarios. Quantile regressions have been incorporated in the factor pricing literature, for instance in Gowlland et al. (2009), Ando and Tsay (2011), Allen et al. (2013) and Autchariyapanitkul et al. (2015), but they remain underexplored in the systemic risk framework.

Moreover, using the matrix $\widehat{\boldsymbol{\alpha}}(\tau)$, the banks can be sorted according to their sensitivity to each of the underlying factors. The ordering is bi-dimensional in nature, and so the companies with greatest exposure to the two factors can be identified as systemically vulnerable financial institutions (SVFIs), which we propose as a complementary concept to Global-SIFIs. This ranking provides valuable information from the point of view of the banks that participate in the market, since it provides the basis for capital adjustments that take into account the idiosyncratic vulnerabilities of each institution.

Finally, we use recent advances in the econometrics literature to test the stability of the load coefficients in the matrix $\widehat{\boldsymbol{\alpha}}(\tau)$**.** These include a test for multiple endogenous structural breaks in single quantile regression coefficients, as explored in Oka and Qu (2011). By so doing, we are able to determine whether the financial crisis has significantly shaped the systemic risk dynamics in the banking industry. The procedure devised by Oka and Qu (2011) involves constructing a break estimator that is the global minimizer of the check function over all permissible break dates. The underlying assumptions are mild, and they restrict only a neighborhood surrounding the quantiles of interest, which makes it a suitable tool for our purposes.

In what follows, we briefly review their proposal, but we invite the interested reader to consult the full article by Oka and Qu (2011) for further methodological details about derivations and their main underlying assumptions.

For the purposes of estimation, we assume the conditional quantile function in Eq. 2 to be linear in parameters and to be affected by m structural changes, as follows:

$$q_i^{\tau}(x_{it}|\boldsymbol{f_t};\boldsymbol{\alpha}) = \begin{cases} \boldsymbol{\alpha}_1(\tau)' \ \boldsymbol{f}_t, & t = 1, \dots, T_1^0 \\ \boldsymbol{\alpha}_2(\tau)' \ \boldsymbol{f}_t, & t = T_1^0 + 1, \dots, T_2^0 \\ & \vdots \\ \boldsymbol{\alpha}_{m+1}(\tau)' \ \boldsymbol{f}_t, & t = T_m^0 + 1, \dots, T \end{cases}, \tag{3}$$

where τ denotes the quantile of interest, and where, as stated before, $\boldsymbol{\alpha}_j(\tau)$ $(j = 1, \ldots, m+1)$ are the unknown parameters that are quantile dependent, and T_j^0 $(j = 1, \ldots, m)$ $(j = 1, \ldots, m)$ are the unknown break dates. In the absence of structural change, the model in Eq. 3 can be estimated by solving:

$$\min_{\boldsymbol{\alpha} \in \mathbb{R}^N} \sum_{t=1}^{T} \rho_\tau(x_{it} - \boldsymbol{\alpha}'\boldsymbol{f_t}), \tag{4}$$

where $\mathbb{R}^N$ are N-dimensional Real, for each cross-sectional unit in the factor model, but we eliminate the sub-index in $i = 1, \ldots, N$ to avoid unnecessary notation. $\rho_\tau(u)$ is the check function given $\rho_\tau(u) = u\big(\tau - 1(u < 0)\big)$ (see Oka and Qu, 2011, and Koenker, 2005, for further details). Now suppose that the τth quantile (in our case a low quantile, such as the 10th percentile) is affected by m structural changes, occurring at unknown dates $(T_1^0, \ldots, T_m^0)$. Then, we can define the following function for a set of feasible break dates $T^b = (T_1, \ldots, T_m)$:

$$S_T(\tau, \boldsymbol{\alpha}(\tau), T^b) = \sum_{j=0}^{m} \sum_{t=T_j+1}^{T_{j+1}} \rho_\tau\big(x_{it} - \boldsymbol{\alpha}_{j+1}'(\tau)\boldsymbol{f_t}\big), \tag{5}$$

where $\boldsymbol{\alpha}(\tau) = \big(\boldsymbol{\alpha}_1(\tau), \ldots., \boldsymbol{\alpha}_{m+1}(\tau)\big), T_0 = 0$ and $T_{m+1} = T$. Following Bai (1995, 1998), Oka and Qu (2011) propose estimating the break dates and coefficients $\boldsymbol{\alpha}(\tau)$ jointly by solving the following minimization problem:

$$\big(\widehat{\boldsymbol{\alpha}}(\tau), \hat{T}^b\big) = \operatorname{argmin}_{\boldsymbol{\alpha}(\tau), T^b \in \mathbb{T}} S_T(\tau, \boldsymbol{\alpha}(\tau), T^b), \tag{6}$$

where $\widehat{\boldsymbol{\alpha}}(\tau) = \big(\widehat{\boldsymbol{\alpha}}_1(\tau), \ldots, \widehat{\boldsymbol{\alpha}}_{m+1}(\tau)\big)$ and $\hat{T}^b = \big(\hat{T}_1, \ldots, \hat{T}_m\big)$. Specifically, for a given partition of the sample, the coefficients are estimated by minimizing $S_T(\tau, \boldsymbol{\alpha}(\tau), T^b)$. Then a search has to be conducted over all permissible partitions to find the break dates that achieve the global minimum. In Eq. 6, $\mathbb{T}$ denotes this set of possible partitions and ensures that each estimated regime is a positive fraction of the sample. This is what we referred to above when discussing the feasible break date.

In our empirical application, we permit a maximum number of regimes $m = 3$, corresponding to two structural changes, so as to limit computational costs. This means our break dates should be interpreted as the “biggest” structural changes in the sample. Nevertheless, we used the SQ_τ statistic proposed by Qu (2008) to determine the optimal number of breaks in case it was less than three. The SQ_τ test is designed to detect structural changes in a given quantile τ, and is defined as:

$$SQ_\tau = \sup_{\lambda \in [0,1]} \left\| \big(\tau(1-\tau)\big)^{-1/2} \left[H_{\lambda,T}\big(\widehat{\boldsymbol{\alpha}}(\tau)\big) - \lambda H_{1,T}\big(\widehat{\boldsymbol{\alpha}}(\tau)\big)\right] \right\|_\infty, \tag{7}$$

where,

$$H_{\lambda,T}\big(\widehat{\boldsymbol{\alpha}}(\tau)\big) = \left(\sum_{t=1}^{T} \boldsymbol{f_t}\boldsymbol{f_t}'\right)^{-1/2} \sum_{t=1}^{\lfloor \lambda T \rfloor} \boldsymbol{f_t}\, \psi_\tau(x_{it} - \widehat{\boldsymbol{\alpha}}'(\tau)\boldsymbol{f_t}), \tag{8}$$

$\widehat{\boldsymbol{\alpha}}'(\tau)$ is the estimate using the whole sample and assuming no structural change. $\|\cdot\|_\infty$ is the sup norm. We also require the test labeled $SQ_\tau(l+1|l)$ in case we detect more than one break. This test is employed as follows: suppose a model with l breaks has been estimated with the estimates denoted by $\hat{T}_1, \ldots, \hat{T}_l$. We proceed by testing each of the $l+1$ segments for the presence of an additional break. We let $SQ_{\tau,j}$ denote the SQ_τ test applied to the jth segment as follows:

$$SQ_{\tau,j} = \sup_{\lambda \in [0,1]} \left\| \left(\tau(1-\tau)\right)^{-1/2} \left[H_{\lambda,\hat{T}_{j-1},\hat{T}_j}\left(\hat{\boldsymbol{\alpha}}_j(\tau)\right) - \lambda H_{1,,\hat{T}_{j-1},\hat{T}_j}\left(\hat{\boldsymbol{\alpha}}_j(\tau)\right) \right] \right\|_{\infty}, \quad (9)$$

and analogous definitions for $H_{\lambda,\hat{T}_{j-1},\hat{T}_j}$ and $H_{1,,\hat{T}_{j-1},\hat{T}_j}$ to those presented in Eq. 8. In this case $SQ_\tau(l+1|l)$ is equal to the maximum of the $SQ_{\tau,j}$ over $l+1$ segments:

$$SQ_\tau(l+1|l) = \max_{1 \le j \le l+1} SQ_{\tau,j}. \quad (10)$$

We reject this in favor of a model with $l+1$ breaks if the resulting value is sufficiently large and provided $l < 2$, so as to keep the computational costs to a minimum. The critical values for performing these comparisons are provided by Oka and Qu (2011), while their construction is in line with the logic underpinning the work by Bai and Perron (1998).

4. Data

To construct the systemic risk factor affecting the financial institutions in our sample we used 113 banks, 59 insurance companies (life, non-life and reinsurance), and 50 firms providing other financial services (i.e., asset management, specialty finance, financial administration, and investment services). All 222 financial institutions are listed in Table 1 (banks) and Table A1 in the appendix. Our sample resembles that employed by White et al. (2015). Those authors used in their estimations firms belonging to three main global sub-indices: banks, financial services and insurance, according to the firms' market capitalization. We do so seeking for some comparability between our results, in terms of the stability of the quantile coefficients, and the main findings of White et al. (2015). Their data set include the biggest institutions in terms of market capitalization in each region and therefore we expect them to be the most relevant ones in terms of global financial stability. We eliminated from our original sample companies with a large number of missing observations at the beginning or the end of the sample period. All data were taken from Datastream. The sample includes weekly closing prices, for each Friday, from 21 July 2000 to 20 November 2015. Prices were transformed into continuously compounded log- returns, giving an estimation sample size of 800 weeks in total.

The equity market uncertainty index was retrieved from the webpage www.policyuncertainty.com. We aggregated this daily index over the week to obtain a weekly index. In this way, we avoided excluding any uncertainty episodes that occur on days of the week other than Friday. We transformed the original index to natural logarithms and performed two unit root tests (the augmented Dickey-Fuller test and the Dickey-Fuller generalized least squares test) on the series. In both cases, we rejected the null of a unit root with statistics equal to -4.52 and -6.48, respectively, and associated critical values at the 1% significance level: 2.58 and -2.57. This means that the equity market uncertainty index can be included without differentiating it in the quantile regressions that we present in what follows. This eases the explanation of the results, as the estimated effects will be directly attributable to the impact of log-uncertainty variations on the banks' returns.

[Insert Table 1 about here]

5. Results and discussion

In this section we present our main results, including, the number of break dates in the empirical model for Eq. 2 for each of the 113 banks in our sample, and a summary of the coefficients associated with each regime, which relate equity market uncertainty and systemic risk factor to the banks' returns. We imposed a maximum number of breaks equal to 2, in the interests of reducing computational costs. As we already mentioned in the methodology, we permit a maximum number of structural breaks equal to 2. This means our break dates should be interpreted as the biggest structural changes in the sample. In principle, it would be possible to find more breaks (although not many of them, because only 40.71% of the sample presents at least two breaks), but in any case, such breaks would be smaller than the ones reported here. We emphasize that the reported break dates would not change if we allow for a greater number of breaks, because the estimation procedure is recursive: only after one statistically significant break has been detected, the algorithm searches for a new break point. Therefore our results are robust, by construction, to setting a higher upper bound for the number of breaks. This strategy would not change our conclusions and instead would complicate, not only the estimation, but also the presentation of our results.

5.1. The stable nature of systemic risk

Figure 1 shows our main results. For the 10th percentile we plotted each bank and its corresponding estimated break dates (the latter only when the null of no breaks is rejected and, therefore, at least one break is identified during the sample). A summary of the SQ statistics associated with these dates and the critical values are provided in Table 2. From these estimates, we find that 30 of the 113 banks (26.54% of the sample) did not present any structural breaks during the sample period; 37 (32.74%) presented only one statistically significant break; and 46 banks (40.71% of the sample) achieved the maximum number of breaks allowed (i.e., 2).

When structural breaks were present, they tended to concentrate on two dates: the first corresponded to weeks 27-28 (26 January 2001) and the second to week 55 (10 August 2001). The institution that houses a break date furthest from the sample origin was Deutsche Bank, with a break located at week 213 (20 August 2004). The estimations of the first break dates, however, might be biased, since our sample partition started in the 27th week, which means this first break date might be earlier. However, this does not change our main finding, namely, in none of the 10th percentile cases (corresponding to the worst scenarios in terms of market returns for the banking industry) were we able to detect a structural change in the model's parameters at a date close to that of the global financial crisis (2007-2009). Most of the banking returns that presented structural changes did so during a short interval, usually less than a year, corresponding roughly to 2001-2002 (though perhaps commencing a little earlier).

The period spanning 2000-2001 was associated with the dotcom crisis. This crisis had more pronounced effects in North America and its main financial partners than in other markets (and the break points tend to concentrate in a greater proportion in these markets). The period 2001-2004 was also related to a change in the monetary policy posture of the US' Fed and some regulatory changes in the main financial markets. The burst of the dotcom bubble had small effects on the real economy, which could have contributed to a change in the parameters relating the individual returns of some banks and the systemic factors, rather than to a change in the systemic factors themselves. Indeed, if the shocks witnessed by the markets during those years (2001-2004) had been more associated with the state of the economy, the model would have likely captured them, via the systemic factor that is calculated as the first principal component of the system. Indeed, the latter was probably the case during the global financial crisis in which there was not change in the parameters relating the factors and the banks. Nevertheless, as we emphasize in what follows, after analyzing the results in Table 3 we observe that, considering these breaks, the empirical distribution of the model's parameters seems remarkably stable, when we compare the beginning with the end of the sample. This stability prevents us from pursuing a more detailed explanation of these particular break dates at the beginning of the sample, or to overemphasize in the statistical regimes that we found, even though they are practically equivalent in economic terms. In any case, our intuition points out more to idiosyncratic factors explaining the breaks in 2000-2001 and 2004, than to a dramatic change in the market conditions or in systemic risk propagation during the sample.

[Insert Table 2 about here]

[Insert Figure 1 about here]

The results may appear somewhat surprising at first glance, given that they point to the relative stability of systemic risk transmission over the last decade – i.e., the coefficients describing the relationship between the common shocks affecting the financial institutions around the globe and the financial returns of those firms did not experience significant changes after (or during) the global financial crisis. Yet, our results are in line with previous findings in the macroeconomics literature. Stock and Watson (2012), seeking to elucidate the macroeconomic dynamics of the 2007-2009 Great Recession in the United States and the subsequent slow recovery, use a dynamic factor model with 200 variables. They draw two general conclusions: first, that the macroeconomic effects of many of the events that occurred during the 2007-2009 collapse were just larger versions of shocks previously experienced, and, as such, the economy responded in an historically predictable fashion; and second, that uncertainty and financial disruptions were two major forces behind the macro shocks that hit the economy during the crisis.

These two main conclusions concern us here. First, we also found that the shocks to the financial industry during the crisis did not give rise to effects beyond those expected prior to the crisis. On the contrary, the banks' financial returns responded in a predictable way to the same shocks (uncertainty and the common shock). Stock and Watson's (2012) second conclusion also seems particularly relevant in this context. To understand why this is so, we first present (see Table 3) the summary statistics describing the set of coefficients for the "first" and "last" regimes in our sample. In other words, to make the estimations for the 113 banks comparable, we grouped the institutions' first and last regime coefficients, respectively. Note that the first regime for the 30 banks with no breaks is equal to the second and third regimes, given that there are no structural breaks in their models. For a further 37 banks (those with one break), these estimates correspond to the first and second regimes, and, finally, for the remaining 46 banks (those with two breaks), they correspond to the first and third regimes.

[Insert Table 3 about here]

Note that in most instances the coefficients accompanying the uncertainty factor display a negative sign. Indeed in 84.07% of cases during the first regime, these coefficients are negative, and only in 15.93% are they positive and in no instances are they statistically significant. The same is true for the last regime, where only 8.77% of the coefficients are positive, but none are statistically significant.

In Table 4, we also report the percentage of coefficients that are statistically different from zero $\alpha_1(\tau = 0.1)$, at the 95% confidence level, which relate the returns of each bank and the common components of the system at the 10th percentile, and $\alpha_2(\tau = 0.1)$, which relates the returns and the market uncertainty factor, also at the 10th percentile. Table 4 also discriminates between the banks with no breaks, and banks with at least one break.

[Insert Table 4 about here]

Several conclusions can be drawn from Tables 3 and 4. First, as expected, most of the time, α_1 is statistically significant at the 95% confidence level – that is, for 76.99% of the banks, the systemic shock (estimated as the first principal component of the system) matters during the first regime in the sample. The sign of the coefficient does not provide any information, because the factors are identified up to a column sign change when estimated using principal components (Bai and Ng, 2008). The number of significant relationships increases during the last regime when 99.12% of the institutions respond to this systemic factor in a statistically significant way.

Second, the uncertainty factor also seems relatively important as a systemic factor. During the first regime, 35.40% of the banks respond to this factor, and the proportion increases notably during the last regime, when 56.64% of the banks are affected by this equity market uncertainty factor in a statistically significant fashion. When we split the sample between those banks that faced no structural changes during the period analyzed, and those that faced at least one, we found that the equity market uncertainty factor was more important for banks with no breaks (56.67% of the times α_2 was significant at the 95% level) than it was for banks with breaks (27.71% in the first regime vs 56.63% in the last regime). Notice that the number of banks with a significant uncertainty-driven relationship may be even higher, because uncertainty and the unobservable component are likely to be correlated, and, moreover, for the first regime, the number of observation is considerably lower than for the second regime, which has well-documented effects on the estimated statistics for measuring significance.

All in all, equity market uncertainty is an important determinant of global banking system performance, and this importance seems to have increased after 2002. However, it remained equally important during and after the 2007-2009 global financial crisis, and it experienced no change after, for instance, the European debt crisis. The considerable shocks to the system during these episodes of crisis had predictable consequences on the banks' performance, but they did not change the nature or the shape of systemic risk. Notice that the two factors in our model measure two different sources of vulnerability in the global banking sector and for this reason, as expected, they both are significant. While the systemic risk indicator is to be interpreted as a "financial" risk shock, the EMU index quantifies "economic" uncertainty related with equity markets. This theoretical separation allows us to interpret our main findings as arising from the financial and macroeconomic (real) sides of the economic system.

We can also conclude that the impact of equity market uncertainty on the financial returns of the global banking sector is negative. This result is novel to the literature, but it is well grounded on theoretical preconceptions concerning uncertainty. Specifically, aggregate uncertainty shocks are thought to be preceded by a reduction in investment and, possibly, in labor, and, consequently, by a deterioration in real activity (Bernanke, 1983; Bertola and Caballero, 1994; Abel and Eberly, 1996; Leahy and Whited, 1996; Caballero and Pindyck, 1996; Bloom et al., 2007; Bachmann and Bayer, 2013), which in turn has obvious consequences for banking. Moreover, this impact on macroeconomic variables may be amplified as a result of financial market frictions (Arellano et al., 2012; Christiano et al., 2014; Gilchrist et al., 2014). In the case of financial markets, Bansal and Yaron (2004) explain why markets dislike uncertainty and how more uncertainty leads to worse long-run growth prospects, thus reducing equity prices. Basically, the intuition is linked to the fact that markets do not like uncertainty and after an increment in uncertainty, the discount of the expected cash flows is higher, which leads the market to reduce the price of the stock. Here we find that higher levels of uncertainty impact negatively and significantly on the financial performance of the global banking system. We believe therefore, that market uncertainty should be included as a major force behind the systemic shocks faced by financial institutions in the global financial markets, and that it should be consistently monitored by regulators and supervisors.

5.2. Systemically vulnerable financial institutions

The previous literature has routinely explored the case of systemically important financial institutions or SIFIs (FSB, 2011; 2012; 2013; IAIS, 2009; 2012; 2013). Here, in contrast, we have focused on systemically vulnerable financial institutions (SVFIs), which while not unrelated, respond to a different logic. The ranking we present is constructed by taking into account the magnitude of the responses of each bank to the two systemic shocks analyzed here, which is not the same as considering which institutions are more likely to disrupt the financial system after experiencing a sizeable loss. As such, SVFIs should be seen as complementing SIFIs.

Our ranking is bi-dimensional: on the one hand, it measures the sensitivity of each bank to the unobservable systemic risk factor and, on the other, it measures their response to the equity market uncertainty factor. The responses to the former were transformed using absolute values, because the principal component estimates do not allow us to interpret the sign of the factor. In Figure 2, we present a scattergram of the coefficients $|\alpha_1|(\tau = 0.1)$ plotted against the coefficients $\alpha_2(\tau = 0.1)$, where $|\cdot|$ denotes the absolute value function.

The banks were then sorted on the basis of these values and classified into quartiles – that is, the banks in quadrant IV (bottom-right) are our first SVFIs candidates. These banks are the ones that respond most to both the systemic traditional shock and to the uncertainty shock. In other words, the respective coefficient for each institution in quadrant IV is lower than the vertical median of α_2 and higher than the horizontal median of α_1. In contrast, the more resilient institutions lie in quadrant I (top-left), where the responses to both economic uncertainty and the systemic risk factor are the smallest in the sample.

The further a bank is from the origin in both directions considered here, the more vulnerable it is to the shocks. For instance, if we take the banks that lie above the 90th percentile in terms of α_1 and below the 10th percentile in terms of α_2, we find the most vulnerable financial institutions, namely, Allied Irish Bank, Bank of Ireland, Barclays, Mediobanca (France) and Royal Bank of Scotland. In contrast, the most resilient institutions are: Bank of Montreal, Bank of Nova Scotia, Canadian Imperial Bank of Commerce and Valiant 'R'.

[Insert Figure 2 about here]

In Table 5, we provide a full ranking for the two dimensions. Notice that the differences between the institutions are marked. For example, if we consider a shock to (log) uncertainty of one standard deviation in the market, the most vulnerable institution in our sample, Dexia, would experience a reduction in the 10th percentile of its weekly returns distribution of around 1.77 percentage points (Dexia's average weekly return during the sample was -0.33%), while the impact is practically negligible for institutions in the fourth quartile. The median impact is around -0.30 percentage points.

The same holds for the systemic factor retrieved as an unobservable and common component of the system. In this case, the most vulnerable institution is the Bank of Ireland, and a one standard deviation shock to the systemic factor would increase its weekly VaR in the 90th percentile by 2.80 percentage points. In this case, the median impact is around 1.09 and the impact for the least vulnerable institution is around 0.18 percentage points. We believe this ranking of SVFIs should be useful for regulators as well as for bank administrators since it provides new information when measuring the resilience of institutions to systemic shocks.

[Insert Table 5 about here]

5.3. Comparisons with marginal expected shortfall (MES)

In this section we compare our two dimensions of systemic risk with the MES proposed by Achayra et al. (2016). Recall that MES is defined as the bank's losses in the tail of the system's loss distribution and as such it is intended to measure the expected contribution to systemic risk of a particular bank, during episodes of financial distress. Therefore, our estimates, which are based on the quantiles of the banks' return distributions, instead of those of the system, can be thought of as natural complements in the analysis of systemic risk. Notice that in our case we have a direct estimation of the system's outcome, namely, the common unobservable market factor, calculated as the first principal component of our data set. Therefore, the construction of the MSE is straightforward: We average the banks' returns observed at the 5% lower tail of the market factor distribution.

In Figure 3 we plot the MES against the market factor (left) and the economic uncertainty factor (right). As it can be seen, the market factor and MES display a negative and clear relationship. Indeed, the coefficient of determination when we regress the market factor slopes on MES, is equal to 79.6%, and the slope of the regression (-3.8) is statistically significant at 99% level of confidence. This strong relationship is expectable although is not obvious. On the one hand MES is conditioned on the quantiles of the system, while in the other hand the market factor slopes are conditioned on the banks' quantiles. Also, there is around 20% of the variation in our measure that is not captured by the MSE.

The case for the uncertainty factor is even clearer. There is a positive relationship between the slopes associated to uncertainty and MES. In this case we document, once again, a statistically significant slope (12.9) at 99% of confidence, but now $R^2 = 25.1\%$. Thus, more or less 75% of the information provided by the uncertainty factor is not captured by MES.

[Insert Figure 3 about here]

Regulators are generally interested not only on the level of exposure to the systemic risk factors, but also in generating rankings among the institutions on these grounds. Once again, there is more information, otherwise absent, that we can assess using our proposed systemic factors. In Table 6 we present the first 11 institutions in each ranking, according to the three factors. That is, the 10% most vulnerable institutions. As can be noted, only 3 institutions belong to the three sets. Also the order is different in each ranking, indeed, not single bank in Table 5 remains in the same position of the three rankings. When we expand the analysis to the first quartile of the banks (28 institutions), 85.7% of those banks that belong to the first quartile of the MES' ranking also belong to the first quartile according to the market factor sensitivity; on the other side, 57.1% of those in the uncertainty ranking belong as well to the most vulnerable institutions according to MES.

[Insert Table 6 about here]

6. Conclusions

We measure systemic risk in the global banking sector attributable to two main sources: an unobservable common shock to the market, previously identified in the literature as a financial systemic shock, and an economic uncertainty factor in the equity market. The two measures are, in most instances, statistically significant in terms of explaining systemic risk, above all during the final regime of our sample. The two factors in our model measure two different sources of vulnerability in the global banking sector and for this reason, as expected, they both remain significant within the model. While the systemic risk indicator is to be interpreted as a "financial" risk shock, the economic equity market uncertainty index reflects "economic" uncertainty related with the equity market. This theoretical separation allows us to interpret our main findings as arising from the financial and macroeconomic (real) sides of the economic system.

We are able to identify regimes after conducting a recursive search for structural changes in the model's parameters. This allows us to test explicitly for the stability of systemic risk propagation in the global banking sector. We found that the parameters containing the expected impact of a given shock on the financial institutions have not experienced any significant change over the last decade, above all after and during the 2007-2009 global financial crisis. We interpret this as evidence that during the financial crisis the economy was not affected by a new type of shock, but rather the shocks were of the same nature, albeit of an unusually high magnitude.

We also provide a ranking of systemically vulnerable financial institutions, which serves to complement existing alternatives in the literature and allows regulators and administrators alike to identify the banks that are most vulnerable to the types of shock analyzed here.

Yet, inevitably, further research is required. Here, for example, we only consider the impact of contemporaneous systemic shocks on the system – that is, we do not estimate a dynamic model for each financial institution, which would clearly help enrich any description of the system's dynamics. The construction of dynamic lagged functions in this regard is critical, but the approach has yet to be resolved when employing quantile regressions. We leave this for future research.

We recognize that it is always possible to include other candidates as systemic shocks, in addition to that of equity market uncertainty. For example, traditional proxies based on CDS, sovereign credit risk, interbank exposures, liquidity ratios, or even other indices of policy uncertainty could be explored. We consider our proposal as representing one step in the direction of explaining systemic risk, and believe uncertainty to be one of the first natural candidates for consideration as a systemic shock. Eventually, any unobservable factor should optimally be replaced by more clearly identifiable factors identified in the literature.

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Tables

Table 1. Banks in our Sample

BANKS							
NAME	MNEM	NAME	MNEM	NAME	MNEM	NAME	MNEM
77 BANK	SSBK	COMMERZBANK (XET)	CBKX	HUNTINGTON BCSH.	HBAN	PEOPLES UNITED FINANCIAL	PBCT
ALLIED IRISH BANKS	ALBK	CREDIT SUISSE GROUP N	CSGN	HYAKUGO BANK	OBAN	ROYAL BANK OF SCTL.GP.	RBS
ALPHA BANK	PIST	BCA.PICCOLO CDT.VALTELL	CVAL	HYAKUJUSHI BANK	OFBK	REGIONS FINL.NEW	RF
AUS.AND NZ.BANKING GP.	ANZX	CANADIAN IMP.BK.COM.	CM	IYO BANK	ISP	RESONA HOLDINGS	DBHI
AWA BANK	AWAT	CHIBA BANK	CHBK	INTESA SANPAOLO	IYOT	ROYAL BANK OF CANADA	RY
BANK OF IRELAND	BKIR	CHUGOKU BANK	CHUT	JP MORGAN CHASE & CO.	ISP	SEB 'A'	SEA
BANKINTER 'R'	BKT	SUMITOMO MITSUI TST.HDG.	SMTH	JYSKE BANK	JYS	STANDARD CHARTERED	STAN
BARCLAYS	BARC	CITIGROUP	C	JOYO BANK	JOYO	SVENSKA HANDBKN.'A'	SVK
BB&T	BBT	COMERICA	CMA	JUROKU BANK	JURT	SWEDBANK 'A'	SWED
BANCA CARIGE	CRG	COMMONWEALTH BK.OF AUS.	CBAX	KBC GROUP	KB	SYDBANK	SYD
BANCA MONTE DEI PASCHI	BMPS	DANSKE BANK	DAB	KAGOSHIMA BANK	KABK	SAN-IN GODO BANK	SIGB
BANCA POPOLARE DI MILANO	PMI	DBS GROUP HOLDINGS	DBSS	KEIYO BANK	CSOG	SHIGA BANK	SHIG
BANCA PPO.DI SONDRIO	BPSO	DEUTSCHE BANK (XET)	DBKX	KEYCORP	KEY	SHINKIN CENTRAL BANK PF.	SKCB
BANCA PPO.EMILIA ROMAGNA	BPE	DEXIA	DEX	LLOYDS BANKING GROUP	LLOY	SUMITOMO MITSUI FINL.GP.	SMFI
BBV.ARGENTARIA	BBVA	DNB NOR (FRA)	DNB	M&T BANK	MTB	SUNTRUST BANKS	STI
BANCO COMR.PORTUGUES 'R'	BCP	DAISHI BANK	DANK	MEDIOBANCA (FRA)	MB	SURUGA BANK	SURB
BANCO ESPIRITO SANTO SUSP	BES	EUROBANK ERGASIAS	EFG	NATIONAL BK.OF GREECE	ETE	TORONTO-DOMINION BANK	TD
BANCO POPOLARE	BP	ERSTE GROUP BANK	ERS	NATIXIS	KN@F	US BANCORP	USB
BANCO POPULAR ESPANOL	POP	FIFTH THIRD BANCORP	FITB	NORDEA BANK	NDA	UBS 'R'	UBSN
BANCO SANTANDER	SCH	FUKUOKA FINANCIAL GP.	FUKU	NANTO BANK	NANT	UNICREDIT	UCG
BNP PARIBAS	BNP	SOCIETE GENERALE	SGE	NATIONAL AUS.BANK	NABX	UNITED OVERSEAS BANK	UOBS
BANK OF AMERICA	BAC	GUNMA BANK	GMAB	NAT.BK.OF CANADA	NA	VALIANT 'R'	VATN
BANK OF EAST ASIA	BEAA	HSBC HOLDINGS	HSBC	NEW YORK COMMUNITY BANC.	NYCB	WELLS FARGO & CO	WFC
BANK OF KYOTO	KYTB	HACHIJUNI BANK	HABT	NISHI-NIPPON CITY BANK	NSHI	WESTPAC BANKING	WBCX
BANK OF MONTREAL	BMO	HANG SENG BANK	HSBA	OGAKI KYORITSU BANK	OKBT	WING HANG BANK DEAD	WHBK
BK.OF NOVA SCOTIA	BNS	HIGO BANK DEAD	HIGO	OVERSEA-CHINESE BKG.	OCBC	YAMAGUCHI FINL.GP.	YMCB
BANK OF QLND.	BOQX	HIROSHIMA BANK	HRBK	BANK OF PIRAEUS	PEIR		
BANK OF YOKOHAMA	YOKO	HOKUHOKU FINL. GP.	HFIN	PNC FINL.SVS.GP.	PNC		
BENDIGO & ADELAIDE BANK	BENX	HUDSON CITY BANC.	HCBK	POHJOLA PANKKI A	POH		

Note: The other financial institutions included in our sample are listed in Table A1 in the appendix and adhere to the following sector classification: Asset Management, Specialty Finance, Investment Service, Consumer Finance, Financial Administration, Life Insurance, Property and Casualty Insurance, Full Line Insurance, Insurance Broker, and Reinsurance. Although we used all the institutions to estimate the systemic factor, we only employed the banks to estimate the systemic risk models. Data and classification were taken from Datastream.

Table 2. Summary Statistics of the Estimated ($SQ(\tau = 0.1)$ Statistics

	Number of Breaks	SQ1	SQ 2
25th percentile	0.00	1.496	1.45
50th percentile	1.00	1.871	1.70
75th percentile	2.00	2.345	2.27
Average	1.14	2.093	1.833
Critical value	-	1.624	1.521

Note: In the first column, we present summary statistics of the number of breaks detected (the maximum allowed being 2). In columns 2 and 3, we present the same information, plus the critical values for each SQ statistic at a 5% significance level. If the null is rejected, the associated break is statistically significant.

Table 3. First and Last Regime Summary Statistics of the Coefficients

	First regime			Last regime		
	α_0	α_1	α_2	α_0	α_1	α_2
Average	-0.271	0.129	-0.319	-0.366	0.145	-0.409
Std. Dev.	1.760	0.060	0.426	1.134	0.062	0.370
Median	-0.306	0.115	-0.253	-0.312	0.125	-0.365
75^{th} perc.	0.392	0.170	-0.108	0.245	0.191	-0.195
25^{th} perc.	0.392	0.170	-0.108	0.245	0.191	-0.195
Max	7.221	0.396	0.723	4.018	0.324	0.414
Min	-5.717	0.000	-2.441	-4.039	0.016	-2.184

Note: We present the summary statistics for the estimated coefficients for the first and last regimes in our sample: intercept, α_1 (τ =0.1) and α_2 (τ =0.1).

Table 4. Percentage of Statistically Significant Coefficients

	First regime		Last regime	
	α_1	α_2	α_1	α_2
Total	76.99%	35.40%	99.12%	56.64%
No breaks	100.00%	56.67%	100.00%	56.67%
At least one break	68.67%	27.71%	98.80%	56.63%

Note: We present the percentage of statistically significant coefficients at the 95% confidence level. We discriminated between banks with at least one break and banks with no breaks during the full period.

Table 5. SVFIs' ranking

Common unobservable factor								Market uncertainty factor							
Quartile 1		Quartile 2		Quartile 3		Quartile 4		Quartile 1		Quartile 2		Quartile 3		Quartile 4	
BKIR	0.32	CSGN	0.19	CVAL	0.13	CHUT	0.10	DEX	-2.18	BP	-0.55	HRBK	-0.37	BENX	-0.19
KB	0.30	DAB	0.19	BPE	0.12	NA	0.10	ALBK	-1.76	HIGO	-0.54	PBCT	-0.36	CVAL	-0.19
UCG	0.29	SCH	0.18	POH	0.12	USB	0.10	BKIR	-1.63	HBAN	-0.53	UOBS	-0.36	JOYO	-0.19
ERS	0.27	SWED	0.18	HFIN	0.12	BEAA	0.10	RBS	-1.22	YMCB	-0.53	ETE	-0.35	CBAX	-0.19
FITB	0.27	POP	0.18	YOKO	0.12	NSHI	0.10	PIST	-0.98	DNB	-0.53	BEAA	-0.35	PNC	-0.19
ALBK	0.26	EFG	0.17	HIGO	0.12	BOQX	0.10	DAB	-0.97	C	-0.52	FUKU	-0.35	SMFI	-0.17
BARC	0.25	SMTH	0.17	HABT	0.12	SIGB	0.10	LLOY	-0.95	CSGN	-0.5	PMI	-0.35	JURT	-0.16
BAC	0.24	WFC	0.17	OKBT	0.12	KABK	0.10	MB	-0.93	HFIN	-0.5	SVK	-0.35	YOKO	-0.16
BBVA	0.24	CMA	0.17	SVK	0.11	GMAB	0.09	JYS	-0.84	MTB	-0.49	ERS	-0.33	GMAB	-0.15
RBS	0.24	PMI	0.17	YMCB	0.11	SHIG	0.09	BARC	-0.78	KB	-0.49	BCP	-0.33	USB	-0.14
MB	0.24	SMFI	0.17	MTB	0.11	HCBK	0.09	KEY	-0.75	BOQX	-0.47	TD	-0.32	KABK	-0.12
BP	0.23	PIST	0.17	OFBK	0.11	SSBK	0.09	SGE	-0.75	SWED	-0.47	CHBK	-0.32	NA	-0.1
IYOT	0.23	DNB	0.17	HSBC	0.11	DBHI	0.09	STI	-0.74	BNP	-0.46	NABX	-0.31	BPSO	-0.1
LLOY	0.23	DEX	0.16	SURB	0.11	BPSO	0.09	BKT	-0.71	BAC	-0.45	SCH	-0.31	WBCX	-0.1
C	0.22	BES	0.16	ANZX	0.11	TD	0.09	RF	-0.7	ISP	-0.45	NSHI	-0.3	KYTB	-0.07
BMPS	0.22	BCP	0.16	HRBK	0.11	RY	0.09	FITB	-0.69	WFC	-0.44	CHUT	-0.29	CSOG	-0.07
KEY	0.22	DBKX	0.16	OBAN	0.11	AWAT	0.08	IYOT	-0.69	NDA	-0.44	AWAT	-0.29	HSBA	-0.06
CBKX	0.22	PNC	0.15	CSOG	0.11	DBSS	0.08	CBKX	-0.69	BBT	-0.43	DANK	-0.28	NANT	-0.05
STI	0.22	SYD	0.14	JURT	0.11	BENX	0.08	HCBK	-0.68	OKBT	-0.43	SSBK	-0.26	OBAN	-0.03
SGE	0.21	BKT	0.14	KYTB	0.11	ISP	0.08	CMA	-0.66	SIGB	-0.43	SURB	-0.26	VATN	0.01
ETE	0.21	NDA	0.14	WBCX	0.11	UOBS	0.08	EFG	-0.66	OFBK	-0.42	POH	-0.26	BMPS	0.08
KN@F	0.20	BBT	0.14	JOYO	0.11	BNS	0.07	SYD	-0.66	NYCB	-0.41	SKCB	-0.25	SHIG	0.09
HBAN	0.20	FUKU	0.14	NABX	0.10	BMO	0.07	SEA	-0.66	SMTH	-0.4	HABT	-0.25	CM	0.1
BNP	0.20	CRG	0.13	NANT	0.10	OCBC	0.07	KN@F	-0.62	UBSN	-0.38	PEIR	-0.24	BNS	0.11
RF	0.19	JYS	0.13	DANK	0.10	PBCT	0.07	DBSS	-0.62	UCG	-0.38	HSBC	-0.24	CRG	0.14
PEIR	0.19	ISP	0.13	NYCB	0.10	CM	0.06	BES	-0.6	BPE	-0.37	ANZX	-0.23	BMO	0.14
SEA	0.19	STAN	0.13	WHBK	0.10	HSBA	0.05	WHBK	-0.6	OCBC	-0.37	RY	-0.22	ISP	0.16
UBSN	0.19	CHBK	0.13	CBAX	0.10	VATN	0.04	POP	-0.57	DBHI	-0.37	BBVA	-0.2	STAN	0.28
						SKCB	0.02							DBKX	0.41

Note: In the first eight columns we provided the ranking of the institutions according to factor f_1, the common unobservable shock (in absolute values). We discriminated in each couple of columns between the quartiles of the ranking. In last eight columns we ordered from most sensitive to least sensitive the banks in our sample, according to f_2, the uncertainty factor. Again we separated in quartiles of 28-29 banks.

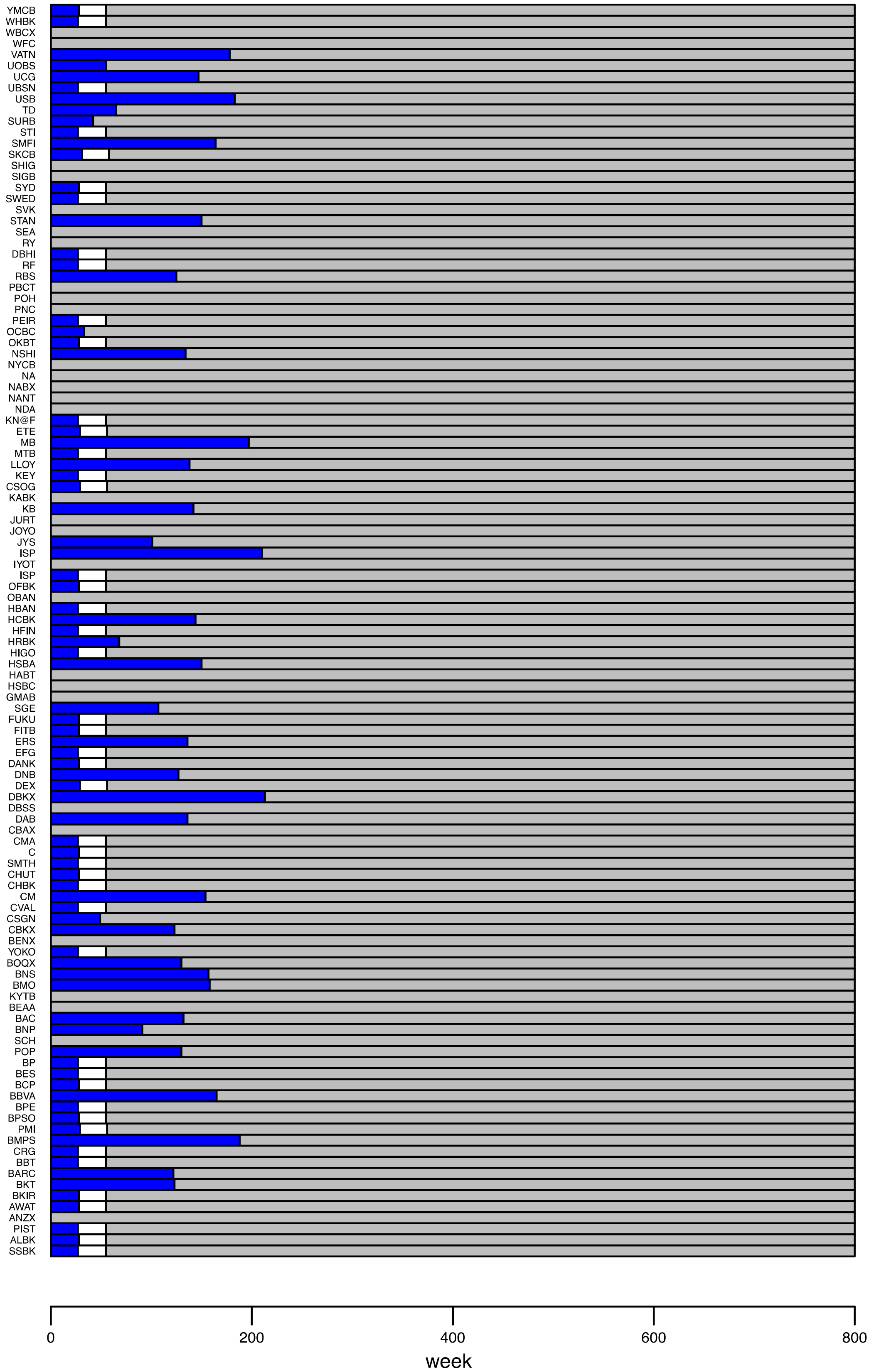
Table 6: Institutions' ranking according to different criteria

Market	Uncertainty	MSE
BKIR	DEX	KB
KB	**ALBK**	**ALBK**
UCG	**BKIR**	RBS
ERS	RBS	C
FITB	PIST	FITB
ALBK	DAB	**BARC**
BARC	LLOY	**BKIR**
BAC	MB	BAC
BBVA	JYS	LLOY
RBS	**BARC**	PEIR
MB	KEY	BP

Note: In the columns we provided the ranking of the institutions according to the market factor, the uncertainty factor and the MES. The bolded institutions belong to the 10% most vulnerable set according to the three measures.

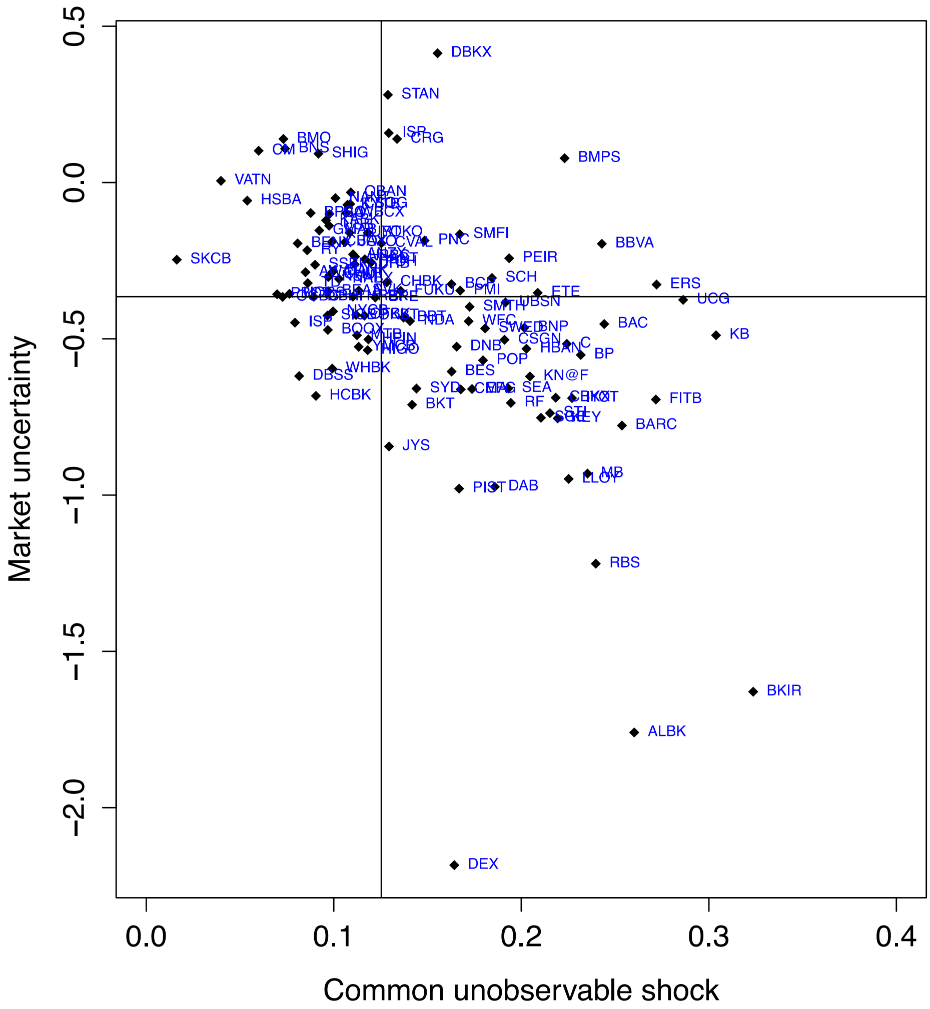
Figures

Figure 1. Structural Changes in Quantile Coefficients



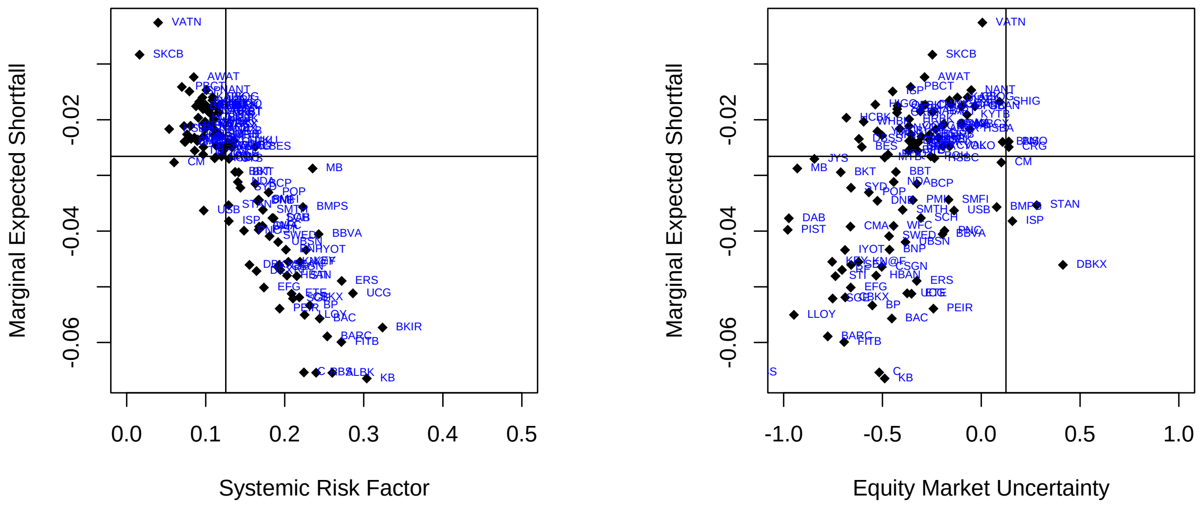
Note: Each horizontal bar represents a bank. The first regime in the sample is blue, the second regime is white and the third regime is grey. Only 30 banks display one regime, 37 two regimes and 46 three regimes (the maximum allowed). The regimes were identified endogenously, using a quantile regression with breaks. The model included two systemic factors: one common unobservable shock and equity market uncertainty.

Figure 2. Sensitivity to the two risk factors: uncertainty and common component



Note: For each of the 113 banks making up our sample, we plotted α_2 (τ =0.1) against α_1 (τ =0.1). The banks located in quadrant I (top-left) are the least vulnerable to the risk factors: f_1 (common unobservable shock – horizontal axis) and f_2 (market uncertainty – vertical axis). In contrast, the banks in quadrant IV (bottom-right) are the most vulnerable following exposure to the two risk factors.

Figure 3: Relationship between the market factor and MES (left) and the uncertainty factor and MES (right).



Note: For each of the 113 banks making up our sample, we plotted $\alpha_2(\tau=0.1)$ against MES and $\alpha_1(\tau=0.1)$ against MES. The banks located in quadrant I (top-left) are the least vulnerable to the risk factors. In contrast, the banks in quadrant IV (bottom-right) are the most vulnerable following exposure to the two risk factors.

Appendix

Table A1. Non-banking firms in the sample

INSURANCE		OTHER	
NAME	**NAME**	**NAME**	**NAME**
ACE	MANULIFE FINANCIAL	3I GROUP	MAN GROUP
AEGON	MAPFRE	ABERDEEN ASSET MAN.	MARFIN INV.GP.HDG.
AFLAC	MARKEL	ACKERMANS & VAN HAAREN	MITSUB.UFJ LSE.& FINANCE
AGEAS (EX-FORTIS)	MARSH & MCLENNAN	ACOM	MOODY'S
ALLIANZ (XET)	MS&AD INSURANCE GP.HDG.	AMERICAN EXPRESS	MORGAN STANLEY
ALLSTATE	MUENCHENER RUCK. (XET)	ASX	NOMURA HDG.
AMERICAN INTL.GP.	OLD MUTUAL	BANK OF NEW YORK MELLON	NORTHERN TRUST
AMLIN	PARTNERRE	BLACKROCK	ORIX
AMP	POWER CORP.CANADA	CHARLES SCHWAB	PARGESA 'B'
AON CLASS A	POWER FINL.	CHINA EVERBRIGHT	PERPETUAL
ARCH CAP.GP.	PROGRESSIVE OHIO	CI FINANCIAL	PROVIDENT FINANCIAL
ASSICURAZIONI GENERALI	PRUDENTIAL	CLOSE BROTHERS GROUP	RATOS 'B'
AVIVA	QBE INSURANCE GROUP	COMPUTERSHARE	SCHRODERS
AXA	RENAISSANCERE HDG.	CREDIT SAISON	SLM
AXA ASIA PACIFIC HDG.	RSA INSURANCE GROUP	DAIWA SECURITIES GROUP	SOFINA
CHALLENGER	SAMPO 'A'	EATON VANCE NV.	STATE STREET
CHUBB	SCOR SE	EQUIFAX	SUNCORP GROUP
CINCINNATI FINL.	STOREBRAND	EURAZEO	T ROWE PRICE GROUP
CNP ASSURANCES	SWISS LIFE HOLDING	FRANKLIN RESOURCES	TD AMERITRADE HOLDING
EVEREST RE GP.	SWISS RE 'R'	GAM HOLDING	WENDEL
FAIRFAX FINL.HDG.	TOPDANMARK	GBL NEW	
GREAT WEST LIFECO	TORCHMARK	GOLDMAN SACHS GP.	
HANNOVER RUCK. (XET)	TRAVELERS COS.	ICAP	
HARTFORD FINL.SVS.GP.	UNUM GROUP	IGM FINL.	
HELVETIA HOLDING N	VIENNA INSURANCE GROUP A	INDUSTRIVARDEN 'A'	
ING GROEP GDR	W R BERKLEY	INTERMEDIATE CAPITAL GP.	
JARDINE LLOYD THOMPSON	XL GROUP	INVESTOR 'B'	
LEGAL & GENERAL	ZURICH FINL.SVS. (IRS)	KINNEVIK 'B'	
LINCOLN NATIONAL	ZURICH INSURANCE GROUP	LEGG MASON	
LOEWS		MACQUARIE GROUP	

Note: The sector classification used in the sample includes Banks, Asset Management, Specialty Finance, Investment Service, Consumer Finance, Financial Administration, Life Insurance, Property and Casualty Insurance, Full Line Insurance, Insurance Broker, and Reinsurance. Although all the institutions were used to estimate the systemic factor, only the banks were used to estimate the systemic risk models. Data and classification were taken from Datastream.