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MEASURING TAIL-RISK CROSS-COUNTRY EXPOSURES IN THE BANKING INDUSTRY*

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This paper analyzes the vulnerability of the banking industry in advanced and emerging economic to shocks originated in or transmitted by banks in a foreign area under stressed and non-stressed conditions. The main aim is to measure cross-country sensitivities that feature systemic contagion in the international banking system and characterize how systemic shocks are propagated. To this end, we estimate the sensitivity of the expected-loss function in the local banking industry to contemporaneous shocks in foreign expected-loss functions in a dynamic equation system during the period December 1999 through November 2013, after controlling for global exposures to common factors, and considering stressed and non-stressed economic scenarios. We implement instrumental estimation to ensure robust estimates against endogeneity and characterize impulse-response functions to appraise the expected duration of tail-contagion. Our study reveals that cross-country vulnerabilities exhibit strong state-dependent patterns which largely increase during periods of distress. During tranquil or normal periods, shocks cause minor or no significant impacts are quickly absorbed by the domestic systems. Under stressed market conditions, however, even idiosyncratic shocks can trigger a pronounced response in other areas with effects that tend to last over long periods of time. Our analysis also reveals the existence of directionality in cross-border contagion, with the US banking sector being the greatest source of financial contagion worldwide and, simultaneously, being more resilient than other areas. Furthermore, systematic exposures to Central EMU area are largely significant than Peripheral Europe, being US the most vulnerable country to shocks originating in Central EMU. Finally, US and Eurozone are sensitive to shocks in Emerging banking system.

Key words: bank contagion, SDSVaR, expectiles.

JEL classification: C23, G15, Q43.

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Financial contagion has received considerable attention in empirical finance. The main interest in this literature is to analyze how shocks to prices are transmitted among different financial assets. Early papers analyzed Granger-type causal relationships in the conditional mean of returns; see, for instance, Eun and Shim (1989), Becker *et al*. (1990), Longstaff (2010) and Cheung *et al.* (2010). Subsequent studies analyzed causality in variance and time-varying conditional correlations, aiming to detect spillovers in volatility; see, among others, Hamao *et al*. (1990), Engle *et al*. (1990), King and Wadhwani (1990), Susmel and Engle (1994), Baele (2005), and Dungey *et al*. (2005). More recently, the global financial crisis has originated a considerable interest in understanding the empirical linkages that interconnect losses of financial institutions during periods of distress. The financial crisis, albeit initiated in the US subprime mortgage-backed securities market, resulted in the systemic collapse of major institutions worldwide, motivating a new international regulatory setting and a fast-growing literature devoted to systemic-risk modelling; see, among others, Segoviano and Goodhart (2009), Acharya *et al.* (2010), Adrian and Brunnermeier (2011), Brownlees and Engle (2012), López-Espinosa *et al*. (2012, 2015), Diebold and Yilmaz (2012), Kim and Hwang (2012), and Rodríguez-Moreno and Peña (2013).

In this paper, we address contagion in the tails of daily returns of representative indices of the banking industry in several economic areas around the world. Our main aim is to appraise the sensitivity that characterizes domestic vulnerabilities to shocks originated in or transmitted by foreign banks under different economic conditions. Cross-country contagion in the banking industry typically occurs because large-scale banks hold an important proportion of claims on foreign borrowers over total assets in their balance sheets. As a result, a shock in a foreign counterparty that decreases the market value of these claims can lead to a balance-sheet contraction which may be further transmitted into the domestic system through the local interbank network. In our analysis, we characterize cross-country vulnerabilities by estimating the network of bilateral sensitivities of the expected-loss function of local banks to *contemporaneous* shocks in the expected-loss functions of foreign banks at the 1% shortfall probability level. To this end, we estimate a system of dynamic equations, controlling for global exposures to common factors, and considering stressed and non-stressed economic scenarios which are endogenously determined by the conditional distribution of expected losses in the local industry. In contrast to most studies in the previous literature, we explicitly deal with the problem of endogeneity and reverse causality that characterizes contemporaneous contagion using instrumental-based estimation to ensure consistent estimation. Finally, we characterize the impulse- response functions (IRF henceforth) embedded in the dynamic system to determine the rapidity, intensity, and persistence of systemic tail-contagion. This analysis provides a quantitative assessment of the systemic relevance of the banking industry in each economic area, identifies the main transmission channels of contagion, and characterizes how shocks are propagated in the global banking system.

More specifically, we focus on representative indices of the banking industry in individual countries, such as US and UK, and different economic areas that include peripheral and non-peripheral countries in Western Europe and emerging-market economies around the world. The dataset is directly available from Datastream and spans the period December 1999 through November 2013, including several episodes of expansion and financial recession that caused considerable distress in the banking sector, more prominently, during the 2007-2009 global recession and the 2010 European sovereign debt crisis. We characterize cross-border contagion in the left tails of the conditional distribution of daily returns of these indices building on a variant of the two-stage quantile-regression methodology (henceforth 2SQR) proposed by Adams *et al.* (2014). Analyzing tail-interdependences requires suitable estimates of the latent conditional loss process. While the analysis in Adams *et al.* (2014) is conducted on GARCH-type estimates of the VaR process of US institutions, a specific contribution of this paper is to extend this analysis to cope with Expected Shortfall (ES henceforth) in an international sample. In particular, we characterize ES in the economic areas under study at the usual 1% regulatory shortfall probability using the expectile-based model suggested by Taylor (2008a). This approach is particularly convenient in our context because it does not require specification of the underlying distribution of returns. This property preserves the semiparametric nature of the 2SQR methodology and, as a result, the main conclusions are not driven by or sensitive to a specific assumption on the formally unknown distribution of returns.

Our analysis provides specific insight into the degree of vulnerability of the banking industry in the main economic areas under study, characterizing how financial contagion of extreme losses occurs. Whereas the existence of tail-interconnections in the financial industry has been discussed in the extant literature, the methodological analysis implemented in most of these papers distinctively focus on a single direction of contagion: Either from individual banks to the total system (e.g., Adrian and Brunnermeir 2011; López- Espinosa *et al.* 2012) in the study of individual contributions to systemic risk, or from the system to individual banks (e.g., Acharya *et al.* 2010) in the analysis of individual exposures to systemic risk. In relation to these studies, this paper provides a more detailed picture because it characterizes the network of bilateral relationships among banks in an international sample explicitly recognizing the possibility of feedback effects in a dynamic equation system. This is particularly important because shocks can be propagated indirectly. Similarly, while the topic of cross-country contagion has received considerable attention in the aftermath of the financial crisis (see, for instance, Buchholz and Tonzer 2013, and Ballester *et al*. 2014 for recent studies relying on different methodologies), most of these papers ignore the crucial dependence of this phenomenon on time-varying market conditions. The 2SQR methodology implemented in this paper allows us to recognize different responses characterizing the intensity and duration of tail-spillovers during downturning or expansive cycles of the economy.

Our paper reveals a number of outstanding empirical features. Consistent with previous studies, cross- country vulnerabilities exhibit a considerable degree of state-dependency featured by sensitivity coefficients which largely increase during periods of distress; see, for instance, King and Wadhwani (1990), Ang *et al*. (2006), and Ludwig and Sobański (2014). According to the estimates of the system, under normal market conditions –characterized by the median of the conditional distribution of local ES– a one percent increase in the ES of the US banking system increases *directly* the ES of the so-called CE area (formed by all EMU countries except Portugal, Greece, Italy, Ireland and Spain) in just 0.01 percentage points. In contrast, under adverse market circumstances –characterized endogenously by the 15th quantile of the conditional distribution of local ES– the same shock would increase the ES of CE-based banks in nearly 0.071 percentage points. This effect is further compounded *indirectly* by the dynamic feedback effects caused by the network of cross-country exposures. Similar results hold on the remaining areas, showing that cross-border contagion increases systematically and significantly during periods of market distress. For instance, a one percent increase in the ES of large-scale banks in the peripheral Euro area (formed by Portugal, Greece, Italy, Ireland and Spain) increases the ES of banks in the CE area in just 0.026% in normal circumstances. However, in a stressed scenario, the same shock increases ES in banks in the CE in 0.051%, nearly doubling the intensity of the contagion.

Our study also reveals strong directionality in cross-border contagion. According to our estimates, the US banking sector is the greatest source of financial contagion in the financial industry. In a stressed scenario, the largest estimates of cross-country spillover coefficients are systematically related to this country. While previous literature in contagion agrees that shocks that originate in the US are larger and more persistent (Hamao *et al.* 1990), and that the US is a major exporter of volatility in financial markets (Theodossiou and Lee 1993), there are specific reasons that explain the worldwide systemic relevance of the US banking industry in our context. The global vulnerability to the US stems from the fact that large-scale local banks with a specific weight in their local sector are typically internationally-diversified institutions for which, characteristically, a large portion of their foreign exposures and cross-border activities over total assets are held on US-issued financial instruments; see, among others, Weistroffer and Möbert (2010) and Degryse *et al*. (2010). Hence, write-downs can have a direct impact on the balance sheets of these banks, which are further transmitted to other domestic banks through the local network. As a result, most financial sectors are particularly vulnerable to idiosyncratic shocks originating directly or indirectly in the US. The evidence in our paper largely agrees with this hypothesis. On the other hand, and in relative terms, the US banking system tends to show more financial resilience against foreign shocks. When compared to European banks, the characteristic business model in US banks is featured by a combination of low foreign lending to total assets ratio and low borrower concentration (Weistroffer and Möbert 2010). As a result, US banks use local lending more intensively than European banks and, simultaneously, their foreign lending activities are more diversified across different countries. While our analysis makes clear that the US banking sector is vulnerable to shocks in European countries (particularly, the UK) as well as emerging-market economies, this characteristic business model makes the system more resilient in relative terms. This evidence seems particularly relevant for central banks and international supervisors concerned with macro-prudential policies to mitigate systemic risk, since low borrower concentration could be a determinant factor to limit the systemic importance of financial institutions.

Finally, our analysis provides specific insight on the intensity of systemic tail-contagion across the economic areas involved and its expected duration through the characterization of the IRF of the system. During tranquil periods, local shocks cause minor or no significant impacts on the remaining areas, being quickly absorbed by local systems. Under stressed market conditions, however, even small idiosyncratic shocks in a particular area can trigger pronounced responses which tend to last over long periods of time in the remaining areas. Remarkably, there are meaningful differences across the economic areas involved. For instance, particularizing in the two subgroups of countries in the EMU area, our estimates reveal that against a one-standard-deviation shock in the global system, the immediate response in expected losses of banks in the CE area tends to be slightly greater than that in the PE, but the adverse consequences of the systemic shock tend to be much more persistent in the latter. The half-life of the IRF, defined as the number of periods required for the IRF to dissipate the response to a unit shock by half, is 87 days in the CE, but largely increases up to 133 days in the PE area. Shocks under adverse market conditions are extremely persistent and it takes over 500 days to dissipate the effects of the shock completely.

The remainder of this paper is organized as follows. Section 1 introduces the expectile methodology implemented to estimate ES and the 2SQR used to characterize risk spillovers. Section 2 presents the data and discusses the main stylized features. Section 3 discusses the estimation of the ES process on the data. Section 4 presents the main results from the 2SQR analysis. Finally, Section 5 summarizes and concludes.

1. Measuring tail interdependences

We start our analysis by introducing mathematical notation and technical definitions. Since our modelling approach relies heavily on the expectile-based methodology proposed by Taylor (2008a), we first introduce this semiparametric procedure. We then discuss the main features of the 2SQR methodology used to characterize tail spillovers.

1.1. Estimating expected shortfall: an expectile-based approach

VaR, defined as the conditional quantile of the loss-function of a portfolio at a certain horizon, is a fundamental tool for downside-risk measurement and risk management in the financial industry. However, this statistic has been widely criticized because is not a coherent measure of risk as it is not sub-additive[1]. More importantly, it is insensitive to the magnitude of extreme losses as it only accounts for their probability; see, among others, Artzner *et al.* (1999) and Acerbi and Tasche (2002). The ES, proposed by Artzner *et al.* (1999), constitutes a valid alternative to VaR which has gained increasing prominence.

Formally, ES is defined as the conditional expectation of the return of certain portfolio, r_t, when it exceeds the VaR threshold $VaR_t(\lambda)$ associated to a certain shortfall probability $\lambda \in (0, 1)$, i.e.,

$$ES_t(\lambda) = E\left(r_t \mid r_t < VaR_t(\lambda)\right) \qquad [1]$$

noticing that $VaR_t(\lambda)$ denotes the λ-quantile of the conditional distribution of r_t, i.e., it verifies $\Pr(r_t \leq VaR_t(\lambda) \mid \mathrm{F}_{t-1}) = \lambda$, where F_t is the set of available information up to time t.

(1) Given the returns of two financial portfolios A and B, and given certain arbitrary risk measure $\rho(\cdot)$, the sub-additivity condition states axiomatically that $\rho(A+B) \leq \rho(A) + \rho(B)$ must hold true in order to claim that $\rho(\cdot)$ is a coherent risk measure. Intuitively, the total risk of a portfolio cannot be larger than the sum of the individual risk measures attached to its sub-portfolios. This property must hold true in practice by virtue of the portfolio-diversification principle. Furthermore, sub- additivity is not merely a technical requirement, but turns out to be an essential property for correct capital adequacy meeting and to ensure the existence and uniqueness of a global optimum in the portfolio-optimization problem; see Acerbi and Tasche (2002) for a discussion.

The estimation of the ES process can be more demanding than VaR and typically requires explicit assumptions on the conditional distribution of the data; see McNeil *et al*. (2005). Taylor (2008a) introduced a procedure based on the expectile theory developed by Aigner *et al*. (1976) and Newey and Powell (1987) that seems well suited for modelling ES and VaR. The distinctive characteristic of this methodology is that it builds on estimates of the conditional dynamics of expectiles, a quantile-related statistic that can be related to ES. The main advantage of this procedure is that it yields estimates of the ES process without relying on a particular distribution; see Kuan *et al*. (2009), and De Rossi and Harvey (2009) for related approaches.

Let $\{y_t\}$, $t = 1, ..., T$, be a stochastic process with finite moments $E(|y_t|^{\kappa})$ for some positive large enough κ. For ease of exposition, we assume that $\{y_t\}$ is a Martingale Difference Sequence (MDS) such that $E(y_t | \mathrm{F}_{t-1}) = 0$. This assumption implies no loss of generality in practice, since we can consider the residuals from a demeaned process otherwise, as it is customary in the literature devoted to downside-risk modelling. For certain arbitrary constant probability $\theta \in (0, 1)$, the population θ-expectile, m_θ, can be defined as the minimizer of an asymmetrically-weighted sum of squared errors, namely,

$$\min_{m_\theta \in R} \sum_{t=1}^{T} \left[\theta(y_t - m_\theta)^2 I(y_t \geq m_\theta) + (1-\theta)(y_t - m_\theta)^2 I(y_t < m_\theta)\right] \qquad [2]$$

where $I(\cdot)$ denotes the indicator function[2]. It is easy to verify that when $\theta = 1/2$, the so-called Asymmetric Least-Squares (ALS) estimate of m_θ reduces to the sample mean. Therefore, in the same way in which quantiles generalize the median for $\theta \neq 1/2$ (in the sense that the θ-quantile specifies the position below which $100 \times \theta\%$ of the probability mass of the random process Y lies), expectiles generalize the mean for $\theta \neq 1/2$. In particular, the expectile function [2] determines the value point such that $100 \times \theta\%$ of the mean distance between this value and Y comes from the mass below it; see Yao and Tong (1996). Kuan *et al.* (2009) provide an additional economic interpretation for expectiles in a financial risk setting. According to these authors, m_θ can be seen as the ratio of expected margin shortfall to the expected total cost of the capital requirement and, hence, represents the relative cost of the expected margin shortfall in the derivative contracts framework.

Expression [2] can be generalized straightforwardly to allow for time-varying conditional dynamics, considering a measurable function, say $m(x_t; \beta_\theta)$, with x_t denoting a k-dimensional vector of covariates and β_θ a conformable vector of unknown parameters. Setting $m(x_t; \beta_\theta) = x_t' \beta_\theta$, Newey and Powell (1987) show the consistency and asymptotic normality under the i.i.d condition of the ALS estimator $\hat{\beta}_\theta$, defined as the solution of

$$\min_{b \in R^k} \sum_{t=1}^{T} \left[\theta\ u_t^2(b)\ \ I(u_t(b) \geq 0) + (1-\theta) u_t^2(b)\ \ I(u_t(b) < 0)\right] \qquad [3]$$

with $u_t(b) := y_t - m(x_t; b)$. Kuan *et al.* (2009) generalize this setting, permitting stationary and weakly- dependent data under suitable regularity conditions.

(2) Note the similitude between expectiles m_θ and quantiles, say q_θ, since the latter arise as the solution of the objective function $\min_{q_\theta} \sum_{t=1}^{T} [\theta|y_t - q_\theta|\ I(y_t \geq q_\theta) + (1-\theta)|y_t - q_\theta|\ I(y_t < q_\theta)]$.

As pointed out by Koenker (2005), linear conditional quantile functions in a location-scale setting imply linear conditional expectile functions, and so there is a convenient rescaling of the expectiles to obtain the quantiles and vice versa. The existence of a one-to-one mapping implies that the conditional θ-expectile is equivalent to the, say, λ_θ-quantile, where the latter is characterized by the probability with which observations would lie below the conditional expectile, noting that typically $\theta < \lambda_\theta$ for values in the lower tail (Efron 1991). Because any expectile is also a quantile, conditional expectile functions can be used to estimate VaR functions given a suitable choice of θ that ensures the desired λ-coverage level; see, for example, Taylor (2008a) and Kuan *et al.* (2009). An outstanding advantage of conditional expectile regressions over quantile regressions is that the related loss-function, [3], is absolutely differentiable, so computing conditional expectiles is considerably simpler in practice. More importantly, as shown by Newey and Powell (1987), the asymptotic covariance matrix of the parameters can be determined without estimation of the conditional density function of errors.

Newey and Powell (1987) and Taylor (2008a) discuss the theoretical relationship between expectiles and ES. In particular, for a MDS process, and for λ_θ probabilities in the lower tail of the distribution, it follows that:

$$ES_t\left(\lambda_\theta\right) = \left(1 + \frac{\theta}{\left(1 - 2\theta\right)\lambda_\theta}\right) m_t\left(\theta\right) \tag{4}$$

where the short-hand notation $m_t(\theta) := m(x_t; \beta_\theta)$ shall be conveniently used in the sequel to simplify notation, since it is already understood that the conditional expectile depends on unknown parameters. Hence, the ES at certain shortfall level λ_θ is proportional to the λ_θ-th empirical quantile, which in turn could be estimated as the θ-*th* conditional expectile. The fact that ES can be seen as a simple rescaling of a suitable expectile is not surprising since, as pointed out by Newey and Powell (1987), $m_t(\theta)$ is determined by the properties of the expectation of the random variable Y conditional on Y being in a tail of the distribution. Consequently, expression [4] allows us to generate estimates of the ES process without making any explicit assumption on the particular distribution of the data, only specifying the functional form that characterizes $m_t(\theta)$ as a function of (unknown) parameters. More generally, Yao and Tong (1996) have discussed non-parametric techniques to infer this process.

In the same spirit as the class of non-linear quantile models introduced by Engle and Manganelli (2004), Taylor (2008a) considers a non-linear autoregressive-type specification for the conditional expectile function. In this class of models, $m_t(\theta)$ varies smoothly over time and depends on the lagged values of the volatility process as proxied by $|y_t|$. For instance, the so-called Symmetric Absolute Value (SAV) model assumes

$$m_t\left(\theta\right) = \beta_0 + \beta_1 m_{t-1}\left(\theta\right) + \beta_2 |y_{t-1}| \tag{5}$$

which implies that the ES process is driven by

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

with $\gamma_1 := \beta_1$, and $\gamma_i := \beta_i \left[1 + \frac{\theta}{(1-2\theta)\lambda_\theta}\right]$, $i \in \{0, 2\}$.

This parametric specification is strongly reminiscent of the characteristic GARCH-type equation used to model the conditional variance of returns, widely known because of its parsimony and superior forecasting power in practice. In fact, if $\{y_t\}$ is an MDS with conditional volatility σ_t driven by the linear GARCH model of Taylor (1986) (namely, $\sigma_t = \omega_0 + \omega_1\sigma_{t-1} + \omega_2 |r_{t-1}|$; $\omega_0 > 0$, ω_1, $\omega_2 \geq 0$), then both the conditional quantile and the expectile functions are driven by SAV-type dynamics, and so is the ES process, although the contrary is not necessarily true. Because of the simplicity and parsimony, we shall estimate ES using [6], noting that the main conclusions are not qualitatively different from other alternative specifications that involve further parameters such as an asymmetric expectile-based model.

1.2. Two-stage quantile regression

Given the shortfall probability λ, let $ES_{it}^{*}(\lambda)$ $t = 1, ..., T$, $i \in S$, denote the estimates of the ES process related to the banking sector in the economic area i, with S representing a set of such areas. The superscript in $ES_{it}^{*}(\lambda)$ emphasizes that we build on feasible estimates of this latent process obtained, for instance, by applying the procedures described in the previous section. Recall that our main interest is to characterize the bilateral relationships that may contemporaneously arise between the tails of the conditional distributions of the indices included in the set S.

To this end, we may run a system of linear regressions. Thus, for any $i \in S$, we may regress $ES_{it}^{*}(\lambda)$ on the estimates of the remaining ES processes in S, possibly accounting for persistence through lags of the dependent variable, and additionally including a number of controlling variables, say $(z_{1t}, ..., z_{kt})'$. For instance, if we assume a model characterized by first-order autoregressive dynamics, our interest would be to estimate the main parameter of the following system of equations:

$$ES_{it}^{*}(\lambda) = \alpha_i + \phi_i ES_{it-1}^{*}(\lambda) + \sum_{\substack{s\in\mathcal{S}\\ s\neq i}} \delta_{i|s} ES_{st}^{*}(\lambda) + \sum_{l=1}^{k} \xi_{il} z_{lt} + \varepsilon_{it} \qquad [7]$$

for all $i \in S$, where ε_{it} is a random error term, and the parameters $\delta_{i|s}$ would capture the intensity of the tail spillover in portfolio i given portfolio s. Note that the analysis recognizes bidirectionality in tail spillovers, since it may generally follow that $\delta_{i|j} \neq \delta_{j|i}$, for any $i, j \in S$, $i \neq j$.

In the estimation of this system, two important features should be noted. First, the size of the cross-border risk-spillover coefficients $\delta_{i|s}$ are likely to vary depending on the underlying economic conditions. During normal or tranquil periods, tail-interrelations may be of little or no economic importance, yet become largely significant in periods of financial distress, particularly when dealing with portfolios related to the banking industry; see, for instance, Adrian and Brunnermeier (2011) and López-Espinosa *et al.* (2012). More importantly, the ES processes involved in [7] are generated simultaneously, so least-squares (LS) and other standard estimation procedures may not render consistent estimates in this context owing to endogeneity.

While a number of alternative procedures are possible, the 2SQR methodology implemented in Adams *et al.* (2014) overcomes both challenges in a simple and particularly tractable way. First, the procedure builds on the quantile-regression (QR) methodology at different quantiles $\tau \in (0, 1)$ of the distribution of the left-hand side

ES process in [7] to endogenously capture state-related effects on the coefficients $\delta_{i|s}$; see Koenker (2005) for an outstanding overview of the QR methodology[3]. Note that, while the shortfall probability λ that defines the ES process is fixed in this analysis (e.g., $\lambda = 0.01$), we can consider a sequence of quantiles $\{\tau_n\}$ that characterize the empirical distribution of $ES^*(\lambda)$ to capture the effects of different economic scenarios on the coefficients $\delta_{i|s}$. Normal and tranquil periods would feature the upper tail of the conditional distribution of $ES^*_{it}(\lambda)$, whereas low percentiles in the left tail would be determined by the excess of volatility observed during periods of financial distress. Second, the 2SQR procedure uses the same estimating strategy as the well-known two-stage least squares (2SLS) in order to correct the endogeneity bias. In particular, the endogenous right-hand side variables, $ES^*_{st}(\lambda)$, are replaced with suitable predictions from ancillary equations based on (weakly) exogenous variables; see, Amemiya (1982), Powell (1983), and Kim and Muller (2004).

Consequently, in the spirit of Adams *et al.* (2014), we shall consider the following dynamic system of equations:

$$ES^*_{it}(\lambda) = \alpha_i(\tau) + \phi_i(\tau)\, ES^*_{it-1}(\lambda) + \sum_{\substack{s\in\mathcal{S}\\ s\neq i}} \delta_{i|s}(\tau)\, ES^*_{st}(\lambda) + \sum_{l=1}^{k} \xi_{il}(\tau)\, z_{lt} + \varepsilon_{it} \qquad [8]$$

estimating the parameters involved in these equations using the 2SQR procedure; see Section 4 for further details. Note that the size of all parameters involved in these equations may vary on the τ quantile that characterizes the conditional distribution of the left-hand variables in the system. While we shall consider a broad range of quantiles $\tau \in [0.1, 0.9]$, for the sake of conciseness we shall report and discuss the results focusing on the *representative* quantiles $\tau = 0.15$, $\tau = 0.5$, and $\tau = 0.85$. These quantiles in the left, center, and right tail of the empirical distribution attempts to characterize the local banking sector during volatile (or excited), normal (or average), and tranquil (or low-volatile) periods, respectively.

The 2SQR methodology proceeds as follows. In the first stage, and for a fixed value of λ, the right- hand side variables $ES^*_{st}(\lambda)$ that characterize the *i*-th equation in [8], for all $s \in S$, $s = i$, are regressed on a set of instruments to generate predicted values, say $ES^{**}_{st}(\lambda)$, which are computed as the fitted values from LS instrumental estimation. Following standard practices, we take a constant and a number of lags from the right-hand side variables $ES^*_{st}(\lambda)$ as instruments. Note that, in order to ensure that the system is identified, the set of instruments does not include lags from the left-hand side variable, $ES^*_{it-l}(\lambda)$, $l \geq 1$; see Adams *et al.* (2014)[4]. In the second

(3) The LS methodology is useful to characterize the conditional mean of the dependent variable in a (linear) regression given the set of regressors. When the series take values that depart from the center of the distribution, LS-based estimates may not capture accurately the underlying relationship between the dependent variable and the regressors, leading to misleading conclusions. When the main interest is to characterize the relationship during extreme or 'abnormal' periods, the quantile-regression methodology is better suited, as it is specifically intended to characterize parameters at any quantile of the conditional distribution of the data.

(4) This restriction implies that lags of the dependent variable only affect the ES of the *i* region. In other words, after controlling for contemporaneous spillovers from other areas, there is no additional spillover effect in a certain area related to the lagged values of the ES in other areas.

stage, and for a fixed value of the τ-th percentile that captures the state of the economy, the set of equations [8] are estimated individually using QR, treating the first-stage predicted values $ES_{st}^{**}(\lambda)$ as regressors. Under regularity conditions, this procedure yields consistent and asymptotically-normal distributed estimates of the main coefficients in [8]; see, for instance, Powell (1983) and Kim and Muller (2004). The estimation of the covariance matrix in this context, however, may not be trivial, because it depends on a number of nuisance terms that characterize both the variability of the main parameter estimates in the main equation as well as the parameter uncertainty stemming from the first-stage estimation. To deal with this issue, we implement a bootstrapping scheme based on the maximum entropy algorithm proposed in Vinod and López-de-Lacalle (2009); see also Chevapatrakul and Paez-Farrel (2014) for related work.

2. Data

The dataset is formed by daily continuously compounded returns from several value-weighted indices representative of the local banking industry in different economic regions around the world. These data are directly available from Datastream, which originally provides closing prices denominated in US dollars. The choice of portfolio data allows us to eliminate the idiosyncratic noise that may affect the main conclusions in a study on individual firms. The sample comprises the period from 31/12/1999 through 07/11/2013, with 3,596 daily observations.

The banking indices are formed by the main banks which are publicly traded in the countries integrated in the different economic areas. In turn, publicly-traded banks are usually bank holding companies characterized by a representative size in the local industry, sophisticated business models, and/or intense cross-border activities. All these characteristics are commonly associated to systemic importance. We select the following indices (initial nomenclature given by Datastream in parenthesis): *i*) US index (US-DS-Banks), formed by 33 banks in the US; *ii*) UK index (UK-DS-Banks), formed by 6 banks in the UK; *iii*) PE index (PIIGS-DS-Banks) index, standing for Peripheral EMU, formed by 39 banks in Greece, Ireland, Italy, Portugal, and Spain; *iv*) CE index (EMU-EX-PIIGS-DS-Banks), standing for Central EMU, formed by 39 banks in Austria, Belgium, Cyprus, Finland, France, Germany, Luxembourg, Malta, Netherlands, and Slovenia, i.e., all the countries in the EMU area except those included in the PE index; *v*) SC index (SCANDINAVIA-DS-Banks), standing for Scandinavia, formed by 14 banks in Denmark, Finland, Norway, and Sweden; *vi*) BR index (BRIC-DS- Banks), standing for the so-called BRIC area, formed by 45 banks in Brazil, Russia, India and China; *vii*) EM index (EMERGING MARKETS-DS-Banks), formed by 288 banks operating in emerging economies. Along with these indices, we consider a Global Banking index (WORLD-DS-Banks) that pools data from 543 banks around the world to control for exposures to global shocks in any of these regions. This index shall be referred to as GB in the sequel. Appendix A provides a list with the banks included in any of these areas.

Some comments on the specific choice of these economic areas follow. The financial sectors in the US and the UK are major international centers and dominant players worldwide and, therefore, deserve specific interest in the analysis of risk spillovers. Together with these countries, our main interest is on the banking industry in Western

Europe and, particularly, in the EMU area, owing to the systemic importance of large-capitalization European banks worldwide. In order to ensure tractability and, mainly, for ease of exposition of results, we consider economic areas rather than individual countries in this analysis. The most natural division would distinguish between EMU and non-EMU countries, since the former defines a common economic area formed by different countries with the same currency. Within the EMU, furthermore, it seems appropriate to distinguish between countries whose financial industries proved fairly sensitive structurally to shocks in the earlier stages of the financial crisis. Therefore, in the same spirit as related studies [e.g., Ludwig and Sobański (2014); Ballester *et al*. (2014)], such distinction is characterized in our study attending to the PE and CE classification, noting that the related indices are directly provided by Datastream[5]. This separation allows us to address heterogeneous responses in cross-country vulnerabilities within the EMU and characterize differences in the way in which systemic shocks are propagated[6]. Together with the two EMU subareas, we consider an index formed by Scandinavian banks, SC, and an index of banks in emerging economies that undergone remarkably strong development over the recent years, BR[7]. More generally, and focusing exclusively on emerging economies, we can consider a broader index that includes a fully diversified portfolio of emerging economies, namely, the EM index. Finally, it should be noted that the sample is not meant to exhaustively cover all possible economic areas (e.g., individual countries such as Japan, Canada, or Switzerland have not been included in the analysis) owing to considerations related to parsimonious modelling in the equation system and, mainly, for ease of exposition and discussion of results. An analysis dealing with individual countries only, seeking to obtain a more refined picture based on country-specific vulnerabilities, may constitute an interesting topic for future research.

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(5) The PE area has attracted considerable attention from both public authorities, economic media, and market investors (currency traders and global investors) that found it convenient to group these countries together, motivating, among others, a specific index in Datastream. Countries in the PE have been traditionally characterized by weaker macroeconomic indicators and greater political instability in relation to other countries in the EMU. More importantly for the purpose of this paper, their financial sectors have suffered in a greater extense the adverse consequences of the global recession and the European Sovereign debt crisis. On May 10, 2010, the EU approved a 750 billion euro stabilization package to support these countries.

(6) Whereas PE-CE division seems to be meaningful enough for the purpose of this paper, some readers may find that the financial sectors of small economies, such as Cyprus, Malta or Slovenia, may perhaps fit better in the PE group. We remark, nevertheless, that the banking indices analyzed in this paper are constructed by value-weighting the returns of the individual banks. Hence, it is the large-capitalization banks included in each of the representative areas which ultimately define the time- series dynamics of the resultant index. As result, including medium-sized banks that operate in Malta, Cyprus or Slovenia in the CE group or not is unlikely to lead to major differences. For instance, in the CE group, the bank with the largest average market capitalization over the period 2010-2014, is BNP, valued in USD 74,350 million. The largest bank in Cyprus, Malta and Slovenia is the Bank of Cyprus, with an average capitalization of USD 1,620 millions.

(7) The SC index includes Finland, a country belonging to the CE area. Nevertheless, this country contributes with just two banks to the total index. Because of the little representativity of this country, and because of the value-weighted design of the sample, it is unlikely that having this country in both SC and CE areas causes any significant form of distortion in the main conclusions. We checked this point by excluding SC in a first analysis (see Section 4.1), noting no qualitative difference in the main conclusions with respect to a more general analysis including this area (see Section 4.2).

Table 1 reports the usual descriptive statistics on the returns of all these indices over the total sample and given the pre-crisis and crisis period subsamples, namely, 1999-2006 and 2007-2013. Returns exhibit the usual stylized features at the daily frequency, such as skewness and excess kurtosis. Returns in the banking industry of the US and EMU areas are characterized by large levels of volatility –mainly, in the second half of the sample– and low average returns. The annualized mean return over the total period is approximately zero in the US (0.09%), and negative in the CE (-3.50%) and the UK (-4.02%). Consistent with the division of the EMU area into PE and CE regions, it is immediately clear that the banks in the countries belonging to the PE area suffered the consequences of the crises more intensely than any other area in our sample. The PE index exhibits the lowest mean annualized return (-5.04%) over the total period. On the other hand, banks in emerging countries have shown more resilience to the global financial recession and the subsequent European sovereign debt crisis. The returns in emerging countries over the period are characterized by lower volatility levels and higher mean returns[8].

3. Estimating expected shortfall

To characterize the dynamics of the ES process, we set $\lambda = 0.01$, the regulatory shortfall probability level required by Basel disposals and the most common choice in downside-risk analysis. The daily frequency is consistent with the holding period targeted for internal risk control by most financial firms; see, among others, Taylor (2008b). Consistent with standard procedures in downside-risk analysis, we compute ES on demeaned $\tilde{r}_{it}$, determined as the residuals from a first-order autoregression; see, for instance, Poon and Granger (2003). The ES processes are then estimated individually for any of the economic areas using the expectile- based model discussed in the previous section. In particular, given $\lambda = 0.01$, the latent conditional expectile in the i-th area is assumed to obey time-varying dynamics given by $m_{it}(\theta) = \beta_{i0} + \beta_{i1} m_{it-1}(\theta) + \beta_{i2}|\tilde{r}_{it-1}|$, $t = 1, ..., T$. In the same spirit as Engle and Manganelli (2004), we initialize $m_{i0}(\theta)$ in the i-th economic area to the empirical θ_i-expectile based on the first 300 observations in the sample for each series. Giving θ_i, the unknown parameters $(\beta_{i0}, \beta_{i1}, \beta_{i2})'$ that characterize the time-varying dynamics of ES are determined as the numerical solution of the ALS problem [3]. More specifically, following Efron (1991) and Taylor (2008a), $\hat{\theta}_i$ is optimally determined as the value for which the proportion of in-sample observations lying below the conditional expectile, say $\hat{\lambda}_{i,T}(\theta)$, matches the shortfall probability $\lambda = 0.01$. To this end, we estimated the model for different values of this parameter using the optimization procedure described in Engle and Manganelli (2004) and Taylor (2008a) in a trial-and-error algorithm with stopping rule $|\lambda - \hat{\lambda}_{i,T}(\theta)| < 10^{-06}$ [9]. Note, therefore, that the estimates

(8) Some caution should be applied when comparing the mean-variance profile across these areas because of the influence of cross-country diversification. Whereas the US- and UK-related ones are country specific indices, the other series represent the banking industries in different countries, which introduces a certain level of diversification.

(9) We randomly generate 1,000 parameter vectors in order to evaluate the ALS loss-function. The ten vectors that produced the lowest values were then used as initial values in a Quasi-Newton algorithm. The estimates from the vector producing the lowest value in the loss-function is to be chosen as the final parameter vector.

Table 1: DESCRIPTIVE STATISTICS FOR DAILY RETURNS OF REPRESENTATIVE INDICES OF THE LOCAL BANKING-INDUSTRY IN DIFFERENT ECONOMIC REGIONS

Region	Mean	Median	Std.	Min.	Max.	Skew.	Kurt.
Panel A. All sample							
US	0.0960	0.9463	32.4195	-0.1774	0.1602	0.0903	17.1664
BR	12.1923	25.9466	26.7714	-0.1062	0.1434	0.0154	9.7893
PE	-5.0453	4.4639	31.2875	-0.1061	0.1860	0.1738	10.0923
CE	-3.5099	12.0845	34.2854	-0.1338	0.1641	0.0716	9.9634
UK	-4.0268	12.0845	33.8417	-0.2161	0.1954	-0.1537	16.0296
SC	7.1017	4.6113	32.2620	-0.1462	0.1489	0.1792	10.6774
EM	8.2132	25.4218	20.4843	-0.0928	0.1130	-0.3839	10.9448
GB	0.9145	16.3191	20.5831	-0.0865	0.1244	-0.0792	16.0296
Panel B. Subsample 2000-2006							
US	7.1483	4.5424	21.3367	-0.0699	0.0839	0.1681	7.0796
BR	24.5373	35.7655	23.6549	-0.0640	0.1028	-0.1093	5.7595
PE	8.1175	13.2878	18.0595	-0.0591	0.0662	-0.0762	5.3710
CE	7.8650	16.0453	21.5742	-0.0773	0.0754	-0.1699	7.2734
UK	5.9250	2.9155	22.8570	-0.0941	0.0760	-0.0651	6.7155
SC	15.8207	10.8853	20.8107	-0.0781	0.0788	-0.0939	6.5990
EM	13.4543	29.3442	15.2587	-0.0552	0.0378	-0.6735	5.7827
GB	7.4541	19.0974	14.2393	-0.0416	0.0556	-0.0233	6.7155
Panel C. Subsample 2007-2013							
US	-6.4903	0.9389	40.5792	-0.1774	0.1602	0.0907	13.4518
BR	2.4667	24.7716	29.5535	-0.1062	0.1434	0.1014	10.8333
PE	-16.3859	2.7895	40.3798	-0.1061	0.1860	0.2168	7.0776
CE	-13.5756	5.1843	43.4144	-0.1338	0.1641	0.1279	7.3172
UK	-12.8978	-0.2345	42.0430	-0.2161	0.1954	-0.1188	12.8677
SC	-0.4828	0.3949	40.6002	-0.1462	0.1489	0.2187	8.0713
EM	3.8756	28.6903	24.6244	-0.0928	0.1130	-0.2610	9.6276
GB	-5.2174	16.4311	25.3843	-0.0865	0.1244	-0.0482	12.8677

This table shows the main descriptive statistics for bank portfolio daily returns in the set of regions considered: US (United States), BR (BRICs), PE (Peripheral EMU), CE (Central EMU), UK (United Kingdom), SC (Scandinavia), EM (Emerging Markets), GB (Global Banking). Mean, median and standard deviation are computed by annualizing return data. Minimum, maximum, skewness, kurtosis and sample size are computed from daily return data. Panel A presents the descriptives for all sample, Panel B depicts the results from 2000 to 2006 and Panel C shows the main statistics from 2007 to 2013.

Source: Own elaboration.

of the parameter vector $\zeta_i = (\beta_{i0}, \beta_{i1}, \beta_{i2}; \theta_i)'$ are determined simultaneously in this context through a recursive algorithm, and the values ensure that the empirical coverage probability is approximately 0.01 in each area.

Table 2 reports the ALS estimates for the different economic areas analyzed. Since the latent ES is a volatility-related process, the estimates of the ES are strongly persistent, with the autoregressive coefficient $\beta_1 := \gamma_1$ ranging from 0.69 (UK) to nearly 0.90 (PE). Similarly, absolute-valued returns, the most common proxy of volatility in practice, have a strong influence on ES[10]. On average, the value of the optimal expectile θ_i is 0.002, which as expected, is smaller than the target quantile, $\lambda = 0.01$. Table 2 also reports the *p*- values of several test statistics which are implemented to backtest VaR-type forecasts. Since expectiles can be used to estimate VaR, as discussed previously, we can analyze if the resultant estimates provide a reasonable fitting to the data using backtesting procedures on the in-sample estimates $\hat{m}_t(\theta_i)$, t = 1, ..., T. More specifically, we implement the unconditional coverage test by Kupiec (1995) and the conditional coverage test by Christoffersen (1998). The Kupiec test requires the empirical coverage $\hat{\lambda}$ to be close enough to the nominal level $\lambda = 0.01$. Since the value of θ for each series is chosen under the condition that $\hat{\lambda}_{i,T}(\theta)$ must match λ, correct unconditional coverage is trivially ensured in our analysis. The conditional test by Christoffersen (1998) address simultaneously the hypotheses of correct unconditional coverage and first-order independence in the sequence of VaR exceptions. Table 2 shows massive *p*-values associated to both test statistics, thereby supporting the empirical suitability of the model.

On the other hand, Christoffersen's (1998) backtests have been criticize because are known to exhibit low power, particularly, when analyzing serial independence. This observation is important in our context because whereas unconditional coverage is ensured by construction, there is no guarantee that expectile-based VaR exceptions behave as a MDS. In order to ensure that the results reported previously are not spurious, Table 2 also reports the *p*-values of the duration-based test proposed by Berkowitz *et al*. (2011). This procedure uses a likelihood-ratio test to address the null hypothesis that VaR exceptions behave as MDS by analyzing the duration between consecutive exceptions. Christoffersen and Pelletier (2004) argue that, in the context of VaR modelling, duration-based tests are generally better indicated that other alternatives, such as the density-forecast test proposed by Berkowitz (2001). Indeed, the experimental analysis in Berkowitz *et al.* (2011) show that the duration-based test exhibits considerably enhanced statistical properties. According to Table 2, the evidence based on the duration test fully agrees with the evidence in Christoffersen's (1998) backtests and supporting the hypothesis that expectile-based exceptions behave as MDS, thereby ensuring correct conditional coverage. The main conclusion from the backtesting analysis, therefore, suggest that expectiles do not generate unreliable estimates for downside risk modelling; see also Taylor (2008a)[11].

(10) Note that the estimates of β_2 in the expectile-related equation (and, hence, γ_2 in the ES-related equation) are negative, reflecting that higher levels of volatility give rise to a greater ES. While it is customary to report both VaR and ES in absolute levels (as it is understood that they refer to losses), we respect the negative sign that characterizes both downside-risk measures according to the definitions in Section 1.

(11) We obtain similar conclusions using alternative ES models such asymmetric expectile-based model and different parametric specifications based on GARCH model volatility estimates.

Table 2: Expected Shortfall processes parameters estimation from the expectile-based SAV model in equations [5] and [6] for the set of analyzed regions

Region	β_{i0}	β_{i1}	β_{i2}	γ_{i2}	θ_i	$\hat{\lambda}_i$	pv_{TUC}	pv_{TI}	pv_{TCC}	pv_{LRDur}
US	-0.0010	0.8645	-0.3804	-0.4867	0.0028	0.0100	0.9947	0.3934	0.6948	0.6004
BR	-0.0033	0.7952	-0.4080	-0.4809	0.0018	0.0100	0.9947	0.4001	0.6930	0.8647
PE	-0.0009	0.8975	-0.2561	-0.3153	0.0023	0.0100	0.9947	0.3934	0.6948	0.2489
CE	-0.0017	0.8507	-0.3757	-0.4304	0.0014	0.0100	0.9947	0.3757	0.6754	0.3951
UK	-0.0034	0.6900	-0.8902	-1.0932	0.0023	0.0100	0.9947	0.3646	0.6545	0.2821
SC	-0.0010	0.8874	-0.2897	-0.3557	0.0023	0.0100	0.9947	0.3934	0.6948	0.5735
EM	-0.0022	0.8043	-0.4165	-0.5337	0.0028	0.0100	0.9947	0.3934	0.6948	0.1894
GB	-0.0008	0.8815	-0.2849	-0.3487	0.0022	0.0100	0.9947	0.4001	0.6930	0.1589

This table presents the ALS ES parameter estimation from the expectile-based SAV-model in the entire set of regions considered for equations [5] and [6] and the main backtesting tests under the null hypothesis that the model is correct. The last four columns present the *p*-value for TUC, TI, TCC and LRDur that denote the results for Unconditional Coverage, Independence, Conditional Coverage test and LR-Duration test. ES are estimated from daily demeaned returns of bank indices.

Source: Own elaboration.

Table 3 reports the usual descriptive statistics for the estimates of the expectile-based ES processes as well as the sample correlation between these series. The daily average ranges from -3.37%, for the Global Banking index GB, to -6.24%, in UK, the country with the lowest daily return in the sample. These series show a considerable degree of dispersion, with a minimum value that, for instance, reached -38.57% in the UK in March 2009. The analysis on sample correlations shows that extreme expected losses in the banking industry are largely correlated across differ ent countries and economic areas, with correlations ranging from 52% (for the pair PE and BR) to 93% (for the pair SC and GB). This evidence suggests a considerable degree of commo-

Table 3: DESCRIPTIVE STATISTICS AND CORRELATIONS FOR THE ESTIMATES OF THE EXPECTILE-BASED EXPECTED SHORTFALL PROCESSES FROM EQUATION [6] FOR THE SET OF ANALYZED REGIONS

Region	Mean	Median	Std.	Min.	Max.	Skew.	Kurt.
Panel A. ES Descriptive Statistics							
US	-0.0537	-0.0423	0.0377	-0.2563	-0.0155	-2.5469	10.5655
BR	-0.0462	-0.0429	0.0159	-0.1931	-0.0250	-3.6073	23.3516
PE	-0.0517	-0.0439	0.0245	-0.1804	-0.0198	-1.4161	5.2391
CE	-0.0544	-0.0455	0.0279	-0.1997	-0.0211	-1.8280	6.8485
UK	-0.0624	-0.0520	0.0382	-0.3857	-0.0178	-2.8131	14.9801
SC	-0.0533	-0.0440	0.0282	-0.1972	-0.0219	-2.2824	8.9210
EM	-0.0384	-0.0344	0.0151	-0.1802	-0.0197	-3.5055	22.7557
GB	-0.0337	-0.0296	0.0163	-0.1353	-0.0161	-2.4042	14.9801
Panel B. ES Correlations							
Region	US	BR	PE	CE	UK	SC	EM	GB
US	1.00							
BR	0.65	1.00						
PE	0.66	0.52	1.00					
CE	0.77	0.64	0.91	1.00				
UK	0.82	0.65	0.71	0.82	1.00			
SC	0.85	0.67	0.84	0.91	0.83	1.00		
EM	0.70	0.87	0.62	0.72	0.71	0.76	1.00	
GB	0.91	0.77	0.80	0.90	0.86	0.93	0.83	1.00

Panel A presents the main descriptive statistics (mean, median, standard deviation, maximum, minimum, skewness and kurtosis) of the Expected Shortfall processes at the shortfall probability $\lambda = 0.01$ for the daily demeaned returns banks portfolios corresponding to the whole set of regions considered. Panel B shows the cross correlations between the Expected Shortfall estimations.

Source: Own elaboration.

nality and the existence of global trends or common factors that propitiate systemic risk in the banking industry[12].

Finally, Figure 1 shows the time-series of (demeaned) returns and the expectile-based estimates of the ES for each economic area in the sample. As expected, ES exhibit persistent time-varying dynamics characterized by massive bursts of volatility which are directly related to the events that characterized a backdrop of extreme volatility associated to the episodes of crises in the sample.

4. Risk spillovers in the global banking industry: 2SQR estimation

We now discuss the main results from 2SQR estimation. In the implementation of this methodology, we follow Adams *et al.* (2014) and estimate equation system (8) controlling for variables that may systematically affect the left-hand side variables. Because the banking industry is vulnerable to global trends, as discussed previously, we use the ES of the global banking index GB to capture the exposure of banks in domestic areas to this class of shocks. This ensures that the spillover coefficients $\delta_{il,s}$ that relates bank losses in two economic areas can be interpreted in a causal way, as they characterize vis-à-vis the cross-border transmission of downside risk once global-related effects are controlled for[13]. Furthermore, the inclusion of a global variable allows us to circumvent potential concerns related to neglected variables associated to economic areas or individual countries which are not explicitly acknowledged in this analysis.

We carry out two different analysis that only differ in the sets of economic regions analyzed. We firstly address tail interdependences among the banks belonging to US, PE, CE, and EM areas, i.e., considering the set $S_B = \{US, CE, PE, EM\}$. This analysis focuses on a set formed by a reduced number of economic areas, which nevertheless comprises some of the major areas of global economic relevance, and, as such, has received considerable attention in the literature. The reduced number of areas involved in the equation system allows to present and discuss results in a concise way. In addition, we focus on an extended set which includes all the economic regions considered in this paper, namely, $S_E = \{S_B, UK, SC, BR\}$. The analysis on the extended set S_E not only provides a broader picture of systemic interrelations and tail-contagion, but also allows us to address empirically whether the initial conclusions are generally sensitive to the omission of potentially economic regions or not.

4.1. *Basic equation system*

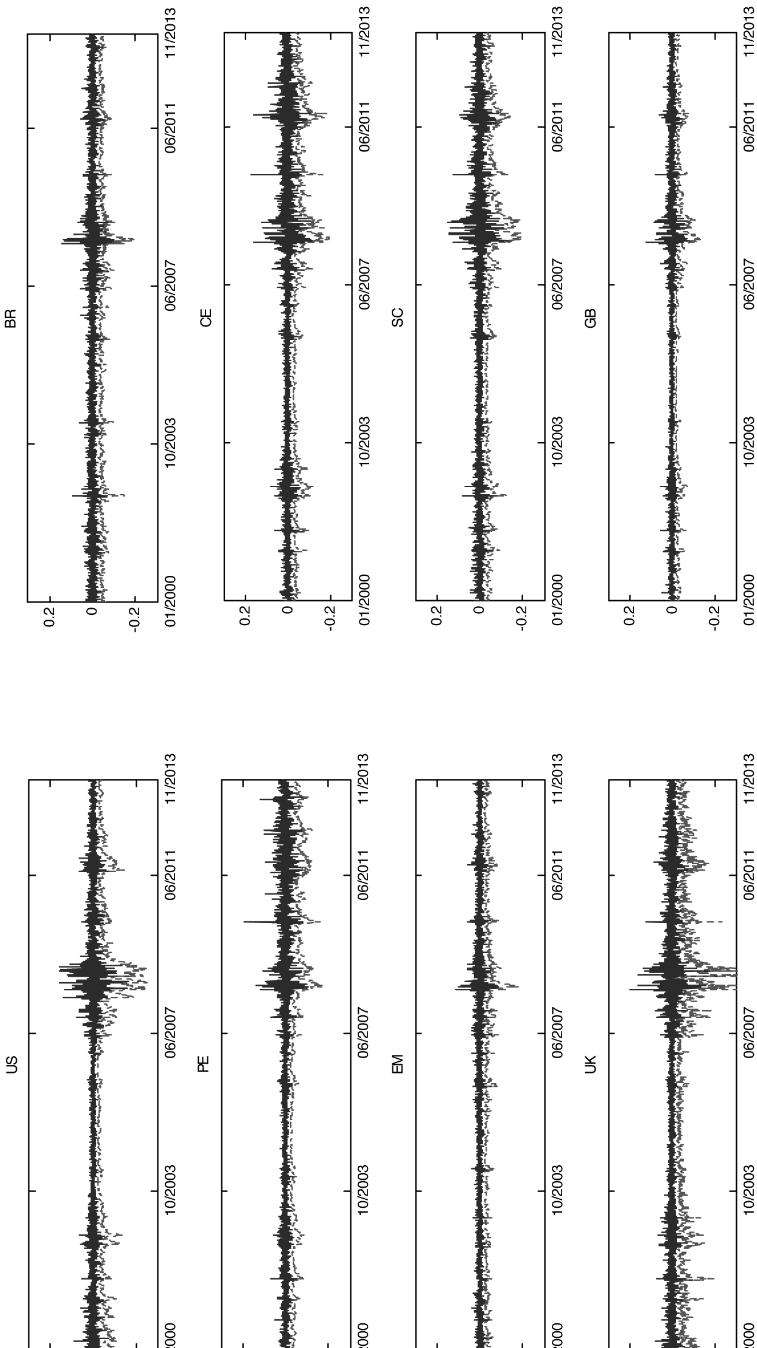
4.1.1. Main results

Table 4 reports the parameter estimates from equation system [8] given the set of countries $S_B = \{US, CE, PE, EM\}$, the shortfall probability $\lambda = 0.01$, and the repre-

(12) Several papers have exploited commonality to characterize systemic risk. For instance, Rodríguez-Moreno and Peña (2013), who use the first principal component in CDS spreads to measure systemic risk. Ballester *et al*. (2014) also gather the commonality using PC analysis.

(13) In the literature of financial contagion, it is usual to distinguish between shock transmission through common channels, which affect multiple countries at the same time (e.g., through blanket withdrawals by common lenders), or through country-specific channels, which depend on variables that characterize country-specific financial and trade linkages. Our modelling approach implicitly captures both channels.

Figure 1: Time series for daily demeaned returns (in the solid black line the yields) and Expected Shortfall processes from expectile based model (in the dotted black line the VaR) in [6]



Source: Own elaboration.

Table 4: ESTIMATION OF BASIC SPILLOVER SYSTEM FROM EXPRESSION [8] USING THE EXPECTED SHORTFALL FROM EXPECTILE-BASED SAV MODEL IN [6] AS A DOWNSIDE RISK MEASURE

	α_i	δ_{ils}				ξ_i	ϕ_i
		US	PE	CE	EM	GB	
				$\tau = 0.15$ (Volatile)			
US	0.0013**		0.0177***	0.0613***	0.0651***	0.0475***	1.0546***
PE	0.0003	0.0469***		0.0307***	0.0323***	0.1196***	1.0469***
CE	-0.0000	0.0722***	0.0515***	0.0233**		0.1269***	1.0354***
EM	-0.0017***	0.0430***	0.0109**	0.0397***		0.0703***	1.0161***
GB	-0.0001	0.0415***	-0.0006	0.0379***	0.0286***		0.9113***
				$\tau = 0.50$ (Normal)			
US	0.0001		-0.0007	0.0113***	0.0293***	0.0185**	0.9570***
PE	-0.0010***	0.0045**		0.0247***	0.0084**	0.0363***	0.9485***
CE	-0.0007***	0.0107***	0.0264***		0.0168***	0.0170**	0.9282***
EM	-0.0024***	0.0165***	0.0094***	0.0225***		0.0214***	0.8897***
GB	-0.0005***	0.0127***	0.0065***	0.0204***	0.0236***		0.8982***
				$\tau = 0.85$ (Tranquil)			
US	-0.0008***		0.0007	0.0098**	0.0133**	0.0369**	0.8986***
PE	-0.0011***	0.0010		0.0168***	-0.0005	-0.0052	0.9011***
CE	-0.0015***	0.0028	-0.0005		0.0155**	-0.0083	0.8761***
EM	-0.0024***	0.0036**	0.0003	0.0012		0.0001	0.8368***
GB	-0.0009***	0.0029***	0.0042*	0.0066**	0.0046*		0.8904***

Spillover basic system coe cients estimation from [8] using the expectile-based SAV model in [6]. The first column shows the constant estimation α for "i-th" region. The equations of each "i-th" region are in rows and the next four columns are the corresponding spillover coe cients δ_{ils} (tail spillover in "i-th" region originated in "s" region). The last two columns present the results of the parameter estimates for control variable z_t and ES lag parameter ϕ for "i-th" region of the system respectively. The significances are detailed in each coe cient with the superscript text, *** for 1%, ** for 5% and * for 10%.

Source: Own elaboration.

sentative quantiles $\tau \in \{0.15, 0.50, 0.85\}$. In the estimation of the dynamic equation system, we allow the global banking index GB to have feedback effects with the areas in S_B, i.e., the full system is estimated with 5 equations. Our main interest is on discussing the estimated values of the coefficients $\xi_i(\tau)$ and, mainly, $\delta_{i|s}(\tau)$ from these equations. Recall that $\xi_i(\tau)$ captures the exposure of the domestic banking system to systematic shocks in the global financial system while, more importantly for the purpose of this paper, $\delta_{i|s}(\tau)$ captures the contemporaneous response in the ES of the banking system in area *i* against a one percent change in the ES of the banking system in area *s,* for all $i, s \in S_B$[14]. Statistical significance at the usual confidence levels is determined on the basis of maximum entropy bootstrap of Vinod and López-de-Lacalle (2009).

A) Sensitivity to global shocks

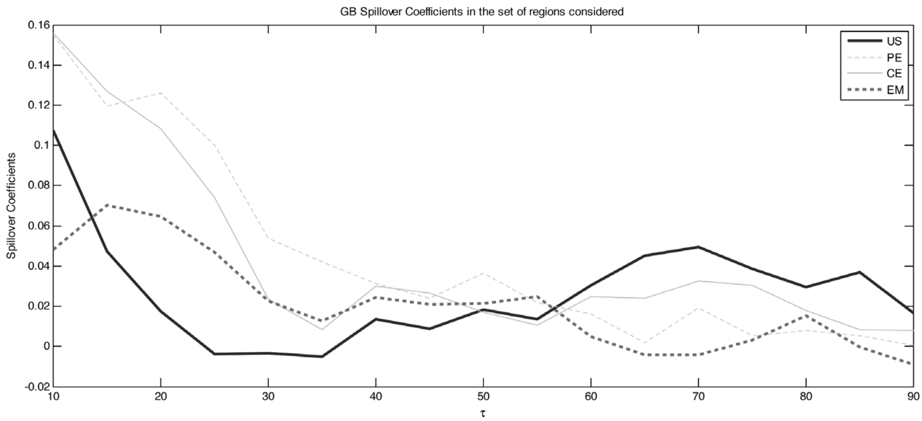
We start our discussion by focusing on the results from the estimation of $\xi_i(\tau)$. We first focus our attention on the estimates based on the normal scenario, characterized by the quantile $\tau = 0.5$. During normal periods, the estimates of $\xi_i(\tau)$ are positive and significant for all the areas included in S_B. This result shows that the conditional median of expected losses in the banking industry is driven by a global component, which essentially agrees with the correlation analysis discussed previously (see Table 3), and the empirical evidence put forward in previous studies; see, for instance, Rodríguez-Moreno and Peña (2013). According to these estimates, a one percent shock in the ES in the global system during normal conditions will increase the average ES of banks in PE and CE by 0.036% and 0.017%, respectively. Remarkably, the exposure to global shocks under normal market conditions tends to be smaller for economic areas with better overall macroeconomic fundamental (US and CE), while economies which traditionally have had greater inflation ratios and higher unemployment rates (PE and EM) prove more vulnerable to systemic shocks.

Remarkably, the picture that emerges under the two extreme scenarios in the tails is completely different. During tranquil periods ($\tau = 0.85$), the estimates of the slope coefficient $\xi_i(\tau)$ are not significant in any of the areas, except in the US[15]. Consequently, the small bank losses that typically occur during calm periods tend to mostly obey idiosyncratic patterns which, in general, are not related to other areas. In sharp contrast, during periods of financial distress ($\tau = 0.15$) the local vulnerability to global systematic shocks largely increases and becomes highly significant in all the areas analyzed. Note, for instance, that the sample average of the ratio $\hat{\xi}(0.15)/\hat{\xi}(0.5)$ is 4.15, and that this ratio is particularly sizeable in the CE area, with a value of 7.46. According to Table 4, banks in the Eurozone (both in PE and CE areas) are more vulnerable to global shocks under a stressed scenario than banks in any other area. This general pattern is fully evident in Figure 2, which shows the shapes of the estimated coefficient functions $\hat{\xi}_i(\tau)$, $i \in S_B$, as a function of the quantiles $\tau \in [0.10, 0.90]$.

(14) As a robustness check, we alternatively estimated the system considering VaR measures, generated from GARCH-type models, as in Adams *et al.* (2014). The qualitative evidence of contagion was similar to the one based on ES; See Appendix B for details.

(15) The coefficient remains positive and significant at the 95% confidence level. In contrast to other countries, the US shows significant links to the global system even during calm periods. This evidence is probably related to the importance and relative weight of the US banking system in the global financial system.

Figure 2: ESTIMATED COEFFICIENTS FUNCTIONS $\xi_i(\tau)$ FROM SYSTEM [8] FOR A RANGE VALUE OF QUANTILES $\tau \in [0.1,0.9]$. THE GRAPH SHOWS THE INFLUENCE OF THE GLOBAL INDEX ON THE REMAINING AREAS



Source: Own elaboration.

The lack of a common regulatory setting and a banking supervisory system, as well as the absence of effective instruments to handle the consequences of a systemic crisis (e.g., the collapse of large-scale banks), have been pointed out as major weaknesses of the European financial industry. It was not until June 2012 when EU authorities committed to making decisive steps towards creating an effective Banking Union, adopting measures that, among others, will lead to the implementation of a single supervisory mechanism and a common bank resolution program. The empirical evidence shown by our analysis, clearly agrees with these concerns and justifies the need of a new regulatory setting to strengthen the resilience of the area.

For completeness in our analysis, we also discuss the estimates of the autoregressive coefficient, $\phi_i(\tau)$, in this subsection. Such estimates lie in the neighborhood of unit for all the quantiles analyzed. This is expected because, as shown in the previous section (see Table 2), ES is a persistent process. Consistent with the evidence reported by Adams *et al.* (2014), the estimates of this coefficient are strictly smaller than unit during tranquil and normal periods, characterizing mean-reverting paths, and tend to be slightly greater than one during periods of distress, suggesting non-linear or mildly explosive patterns. Although explosive patterns are often related to model misspecification, in our view this evidence is not particularly surprising in the context of the current paper. The dynamics of the 1% ES process during the more volatile days that characterize lower quantiles are distinctively driven by the largest outliers in the sample. An autoregressive coefficient equal to or greater than one is the only way in which an autoregressive process can accommodate the non-linear patterns which are usually associated with large volatility bursts that cause extreme market movements.

B) Cross-border tail-contagion

We now turn our attention to the coefficients $\delta_{i|s}$ that characterize cross-border tail contagion between different economic areas. Consistent with the hypothesis that the conditional tails of financial returns are prone to comove, the estimates $\hat{\delta}_{i|s}$ are mostly positive and highly significant in all the cases, particularly, in the excited state. With regard to global shocks, the size of cross-country spillovers are characterized by state-dependencies that lead to a great deal of variability as a function of τ. In particular, that cross- country spillovers are greater during periods of distress, but tend to weaken and eventually vanish during calm periods. This general pattern is fully evident in Figure 3, which shows the shapes of the estimated coefficient functions $\hat{\delta}_{i|s}(\tau)$ for $\tau \in [0.10, 0.90]$. This graph and the estimates of Table 4 make clear that the severity of financial contagions under adverse conditions can be largely underestimated under normal market circumstances. Consequently, and as noted in Adams *et al.* (2014), standard analysis that merely focus on the conditional mean or the median analysis may lead to potentially misleading conclusions.

We now discuss in detail the estimates of the cross-border spillovers in the different banking systems as a response to a shock in a certain economic area, reported by columns (second to sixth) in Table 4, throughout the following subsections. For ease of exposition, we comment on the results in the most relevant context characterized by stressed conditions ($\tau = 0.15$).

B.1) Sensitivity of domestic banks to shocks in the US

Under stressed conditions, all the regions –including the global financial sector– become particularly sensitive to shocks in the US banking system. In particular, during periods of local stress, a one percent increase in the ES of US banks *directly* increases the local ES by 0.072% (CE), 0.047% (PE), and 0.043% (EM); see Table 4, second column. US banks are the main contributors to the ES of the global financial system under stressed conditions, noting that a one percent increment in the expected losses of US bank increases the ES of the global financial system by 0.041%. The idiosyncratic shocks originated in this country are further amplified *indirectly* through the feedback effects caused by the network of cross-border exposures. For instance, every percentage point increase in the ES of the global system caused by the shock in the US is further transmitted into the local banking areas (including the US) with an intensity which ranges from 0.070% in emerging markets, to 0.127% in the CE. Consequently, and according to the 2SQR estimates, the US banking system is the most important source of financial contagion in the sample considered. Idiosyncratic shocks originated in this country can affect all the other banking systems (particularly, those in European countries) under stressed conditions.

The main reason for the global systemic importance of the US is that, when considering the international network of global cross-border exposures, the US banking system has a central and predominant position, since the remaining countries typically hold large portions of US-issued financial assets, particularly, European countries. For instance, according to the statistics elaborated by Degryse *et al.* (2010) on annual data from Bank for International Settlements (BIS) Consolidated Banking statistics on reporting countries in the period 1996-2006, the bank credits to the US represent, on average, 25%, 28%, and 30% of the total foreign credits held by Germany, France, and Netherlands on reporting countries, respectively. The same ratio ranges from 10% (Ireland) to 16% (Italy) in the PE area, showing a smaller exposition to the US. European banks kept large holdings of illiquid US dollar assets which were financed with short-term wholesale funding and heavy reliance on cross-currency swaps; see McGuire and Von Peter (2009). When the market value of these claims collapsed as a consequence of the subprime crisis, European banks suffered massive losses, which were further amplified when the interbank and swap markets became impaired in 2008; see Acharya and Schnabl (2010). The estimates in our analysis successfully capture the sensitivity of EMU banks to the US and, furthermore, identify a greater sensitivity in the Central EMU area, characterized by a greater reliance on US lending.

B.2) Sensitivity of domestic banks to shocks in the EMU: PE and CE subareas

The analysis of the spillover coefficients related to the PE banking system shows that the shocks originated in this area –mainly associated to the European sovereign debt crisis– essentially had a more local nature than those originated in the early stages of US subprime crisis; see Table 4, third column. The system with the largest vulnerability to shocks in the PE area is the one formed by the remaining banks in the EMU area. This is not surprising, because the main economies in CE, such as Germany, France or Holland, keep large holdings of debt issued by European peripheral countries. Note, in Figure 3, that the vulnerability of CE to PE is highly significant for a large range of percentiles τ but, once more, the interdependence seems stronger in the low quantiles that characterized stressed conditions. In particular, for $\tau = 0.15$, the average response of expected losses of CE banks against a one percent shock in the ES of PE is 0.051%. This result agrees with the empirical evidence discussed by Ludwig and Sobański (2014), who on the basis of a different methodology, find that the PE area (called GIIPS in that paper) was the epicenter of risk spillovers during the crisis years 2007-2010. In contrast, banks in the US and emerging-market economies exhibit weaker exposures to this area. For instance, the spillover coefficient of US on PE is only 0.017. Although this coefficient is statistically significant, it seems of little economic relevance. In a similar vein, the exposure of the global banking system to the PE area is not significant. This evidence suggests that idiosyncratic shocks originating as a consequence of the European sovereign debt crisis in peripheral Europe did not affect the remaining banking systems systematically.

On the other hand, the systemic exposures of international banks to banks in the CE area are much more important and largely significant in all cases; see Table 4, fourth column. Among the different economic areas considered, the US banking sector, with a tail spillover coefficient of 0.061, is the most vulnerable country to shocks originating in the CE. This sensitivity is nearly twice as big as that in the remaining areas. The reason underlying the vulnerability of US banks to CE banks relative to PE banks can be related to the existence of strong bilateral borrowing activities between these areas. According to Degryse *et al.* (2010), the aggregate claims on the reporting countries in the CE area (Austria, Belgium, Finland, France, Germany and Netherlands) represent around 34% of the total foreign claims held by US. Among these countries, Germany is the largest borrower, representing 17% of the foreign bank credits issued by the US. In contrast, Italy, Portugal and Spain together represent 6% of foreign claims in the US system. Note that although the *direct* exposure of US to PE is relatively moderate (the estimated spillover coefficient is 0.017), as discussed previously, the network of cross-border interconnections within the EMU defines a powerful *indirect* channel of contagion through the CE such that idiosyncratic shocks originated in peripheral EMU countries could spread to CE and, from here, to other economic areas, particularly, the US. Finally, it is interesting to note that, after the US, the CE is the second largest contributor to the ES of global risk under volatile conditions, since the sensibility of GB to CE is 0.0379%.

B.3) Sensitivity of domestic banks to shocks in EM

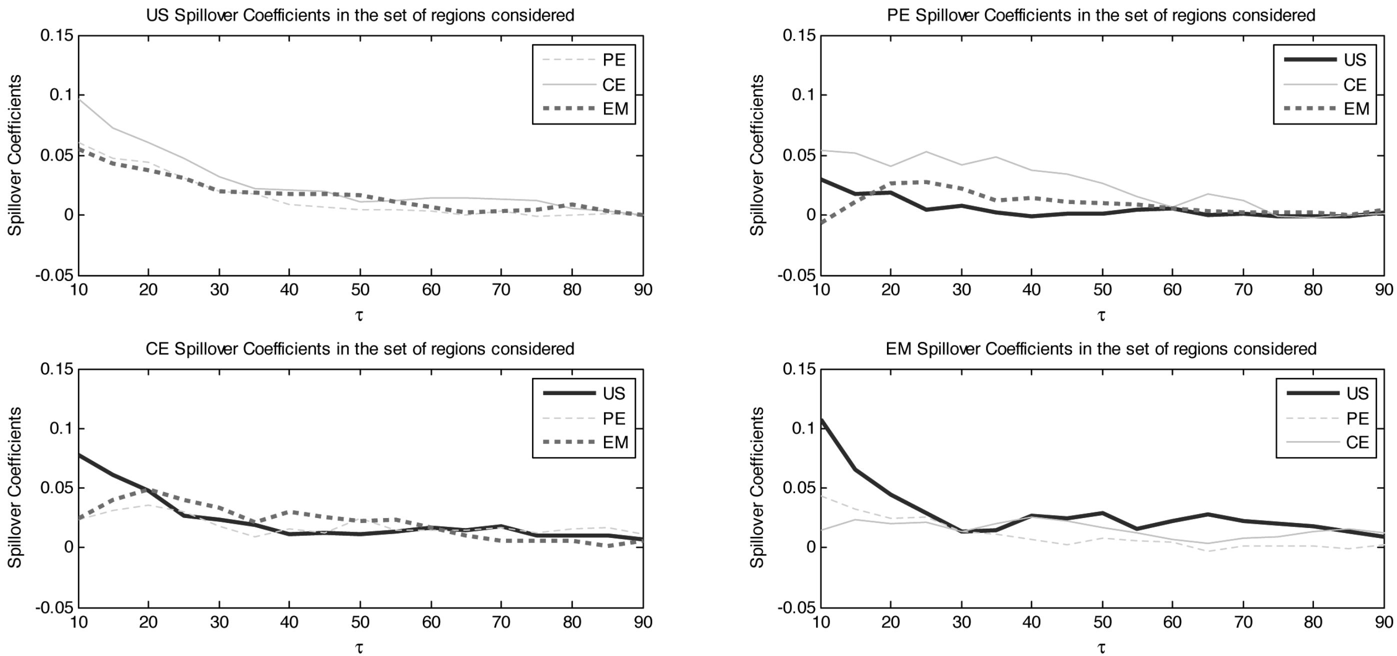
Finally, the 2SQR estimates reveal that, under adverse market conditions, the banking sectors in the both the US and the Eurozone are sensitive to shocks in emerging-market economies. Over the last decades, emerging economies have evolved from being peripheral players to become systemically important trade and financial centers (IMF, 2011a). Financial linkages between advanced and emerging economies are now stronger and as a result advanced economies are more exposed to the latter group. In the years preceding the global recession, the bigger banks of these areas increased their participation in emerging markets through local affiliates, which resulted in increased networks of bilateral exposures; see Tressel (2010). Financial exposures to emerging markets are mainly concentrated in foreign bank claims (IMF, 2014). According to our analysis, the exposure to emerging-market risk spillovers varies in importance across the three different regions analyzed, with the US being the banking sector with the largest vulnerability. The size of the US spillover coefficient at $\tau = 0.15$ is 0.065, which nearly doubles the size of the two EMU countries. The importance of the EM spillover coefficient is fully evident in Figure 3, showing that $\hat{\delta}_{US|EM}$ largely increases for lower values τ. For instance, whereas $\hat{\delta}_{US|EM}$ is close to zero for values of τ greater than 0.30, it takes sizeable values that reach $\hat{\delta}_{US|EM} = 0.11$ at the quantile $\tau = 0.1$.

The relative sensitivity of the US economy to emerging-country economies poses a serious threat that has been recently outlined by an International Monetary Fund report. This report estimates that a current drop of one percentage point in emerging-market GDP could hit US GDP by around a fifth of a percentage point; see IMF (2014). This estimate is, nevertheless, conservative, as it does not account for direct financial spillovers through the financial sector. As their own report remarks, if risk premiums react further to the growth shock –due to balance-sheet exposures of financial intermediaries– financial channels would come into play and the size of the spillover in the real economy could be larger. Indeed, the analysis in this paper reveals the existence of financial channels that can introduce contagion in advanced economies from shocks in emerging economies under adverse market conditions.

4.1.2. Expected duration of risk spillovers

Given the estimates of the equation system [8], we can characterize the expected duration of a shock through the Impulse Response Function (IRF) analysis. We adopt the same identification strategy as Adams *et al.* (2014), i.e., orthogonalizing IRF using the standard Cholesky decomposition, and ordering the shock transmitting variable last, since there is no theoretical guidance for a priori ordering. Note that this implies that a shock on the ES of certain region at time *t* will only affect this region at that time, spreading to the remaining areas in the following periods. Although this

Figure 3: Estimated coefficients functions $\delta_{i|s}(\tau)$ from system [8] for a range value of quantiles $\tau \in [0.1,0.9]$. Left-upper graph shows the influence of the US on the remaining areas; right-upper graph presents the influence of PE to the other regions; left-lower graph depicts the sensibility of the remaining areas to CE. Finally, right-lower graph shows the influence of EM to the other regions



Source: Own elaboration.

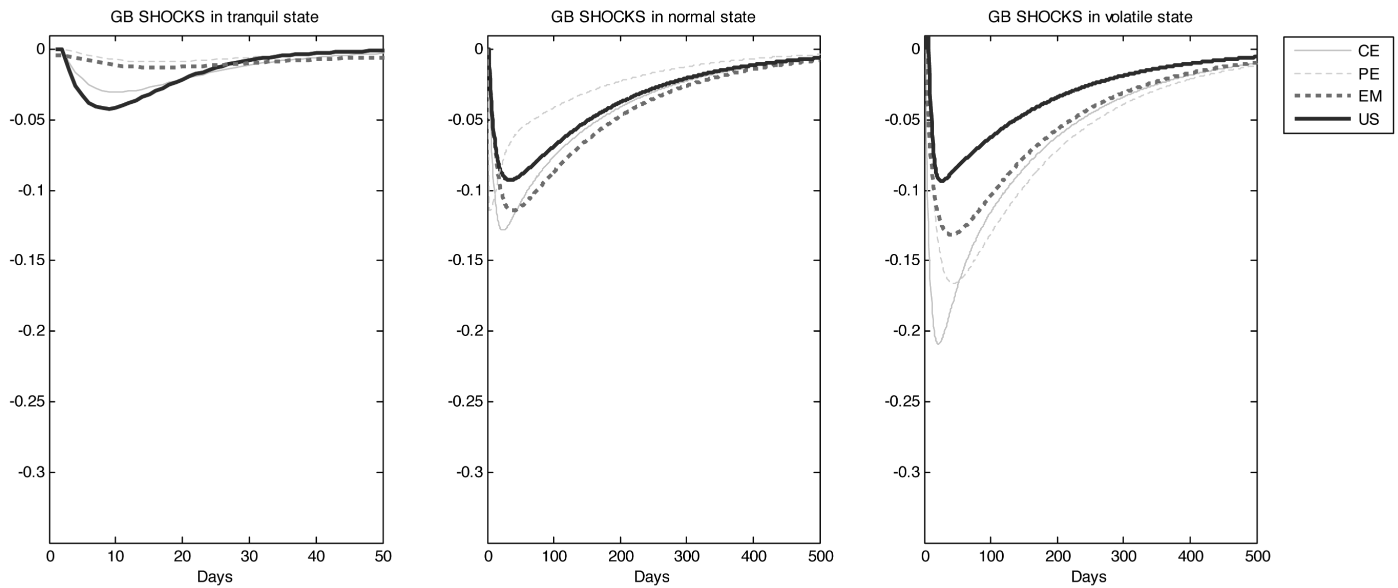
approach may lead to conservative IRF (which, consequently, can be regarded as the smallest estimated response given a shock), the main benefit is that it is not necessary to impose a potentially ad-hoc ordering because all economies are treated equally; see Adams *et al.* (2014) for details. As usual in this literature, we assume a unit shock of one standard deviation.

Figure 4 depicts the time-profile of the IRFs, characterizing the reaction of the domestic banking sector in each economic region in S_B against a unit shock in the ES of the global financial system. We consider tranquil, normal, and volatile market conditions. In this context, the size the immediate response depends on the spillover coefficients $\xi_i(\tau)$, whereas the persistence that characterizes the IRF depends on both $\xi_i(\tau)$ and $\phi_i(\tau)$. As expected from the previous analysis, the IRF characterize heterogeneous responses across the economic regimes. In particular, during tranquil periods, a systematic shock in the global financial industry tends to cause minor or no significant impact in the domestic areas, being quickly absorbed by the local systems. Under normal market conditions, however, systematic shocks trigger a more pronounced response in the local areas which, furthermore, tend to last over a considerably larger period of time. On average, a one-standard-deviation shock in the global system increases the domestic ES in absolute terms in an amount which ranges from 9.27% (US) to 12.81% (CE) of the size of the shock. The half-life of the IRF, defined as the number of periods required for the IRF to dissipate the response to a unit shock by half, ranges from 45 days (PE) to 130 days (EM). Nevertheless, the IRFs are strongly persistent, and it takes around 400 days to dissipate completely the effect of the shock[16]. While the shock seems to cause a greater impact on CE, the overall response under normal circumstances is very similar in all the areas analyzed.

In a stressed scenario, the overall reaction against systematic shocks in the global banking industry is more pronounced. Furthermore, the differences across economic areas are now much more evident. In particular, the most vulnerable area to systematic shocks is the Eurozone. The peaks of the IRFs in CE and PE lead to spillovers of about 20.91% and 16.64% of the size of the global shock. These represent substantial increments in the size of the spillover with respect to the normal scenario, particularly, in the CE area, although we stress that estimates should be regarded as potentially conservative in our approach. Interestingly, while the immediate response to a global shock is greater in CE, the IRF of PE decays at a slower rate, suggesting that the effects of a systematic shock in that area tend to remain significant over an extended period. Indeed, the half-life in the CE and PE areas is 87 and 133 days, respectively. On the other hand, systematic shocks cause a more moderate response in emerging-market economies, and particularly in US, for which the peak of the IRF is located at 9.32% the size of the unit shock. Clearly, the IRF of the US is dominated by the remaining IRFs, suggesting that, broadly speaking, the US banking system has a stronger resilience to global shocks. This empirical evi-

(16) We are not aware of any other paper characterizing the IRF of the expected shortfall process. However, previous literature has characterized IRF to address volatility spillovers in different markets. The papers dealing with contagion in financial and commodity market show strongly persistent IRFs in which it takes considerable time (between two and four years of trading days) for volatility to revert completely after a large shock; see, for instance, Panopoulou and Pantelidis (2009) and Jin *et al*. (2012).

Figure 4: IMPULSE RESPONSE FUNCTIONS OF THE DOMESTIC BANKING SECTOR IN EACH ECONOMIC REGION AGAINST GLOBAL BANKING SHOCKS FOR TRANQUIL, NORMAL AND VOLATILE STATE OF THE ECONOMY FROM BASIC SYSTEM [8] ESTIMATION



Source: Own elaboration.

dence essentially agrees with the simulation-based results shown in Degryse *et al.* (2010). This paper provides further evidence using a formal econometric approach.

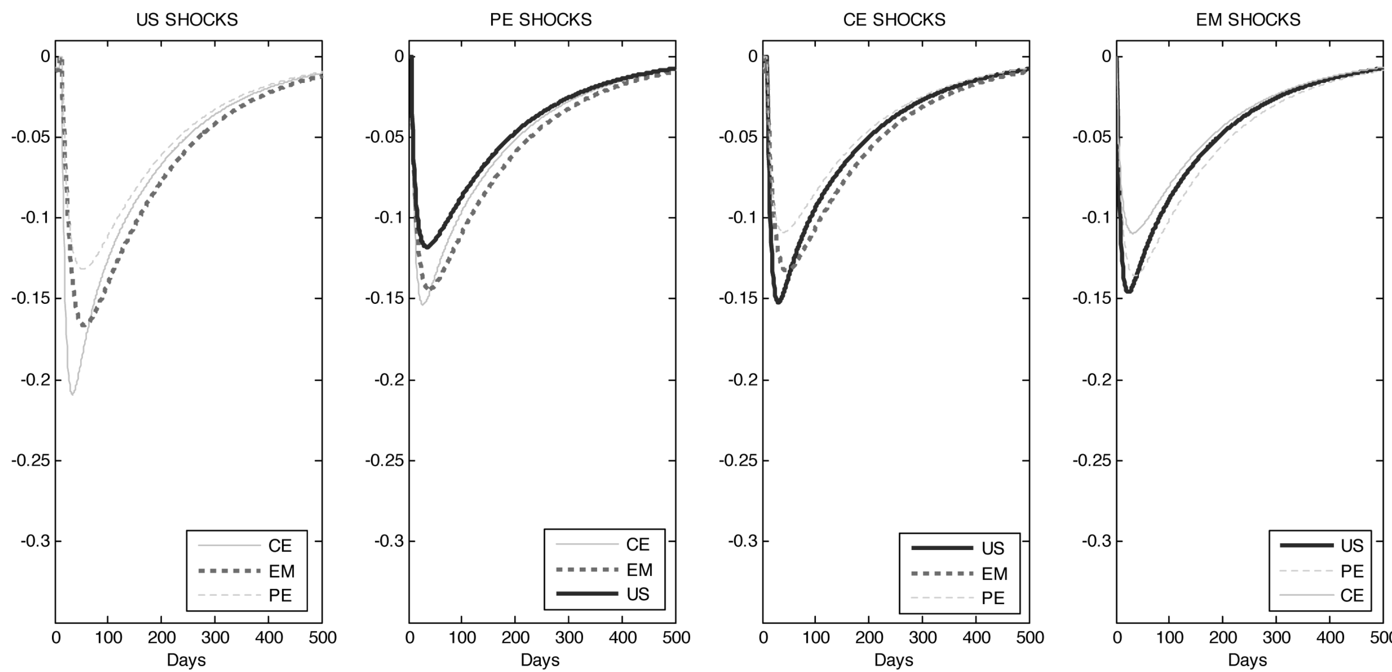
Figures 5 to 7 show the IRFs that characterize the response of banks in each economic region in S_B against an (idiosyncratic) unit shock in each of the remaining areas under the three economic scenarios analyzed. In the stressed scenario, the long-term persistence of a shock would be characterized by explosive patterns (see Table 4), implying that ES becomes more and more negative in the long-term. In practice, however, the extreme outliers that give rise to non-linearities and bursts of volatility in low quantiles only occur during very short periods of time. Consequently, we adopt the same approach as Adams *et al.* (2014), and assume that, although a shock occurs under stressed conditions (which characterize the size of the spillovers at the time of the shock), long-term persistence is better characterized by the estimates under the normal state. We, therefore, assume in the characterization of the IRF that the market returns to normal state coefficients after the day of the shock.

The main picture that emerges under country-specific idiosyncratic shocks is completely similar to that discussed under systematic shocks, showing large differences in both the intensity and the duration of contagion across the different economic scenarios. In particular, foreign shocks trigger a larger cross-country response in the expected losses of local banks in a stressed scenario in the domestic economy. For ease of exposition, we briefly discuss the main results for this scenario, as it poses the most relevant case. The largest response against a country-specific idiosyncratic shock is triggered by the US, which causes the ES of CE banks to increase in absolute terms about 20.9% the size of the standard shock. The half-life of the spillover in this area is 93 days. Nevertheless, the IRF exhibits a considerable persistence characterized by a low-decay to zero, and it takes over 500 days to completely remove the effects of the shock. In addition, the CE banking area is very sensitive to idiosyncratic shocks originating in the PE area. A unit shock in peripheral EMU countries leads the ES of banks in the remaining EMU countries to increase the size of this shock by about 14.75% as a consequence of cross-border contagion. Persistence, as measured by the half-life, is 107 days. Shocks initiated in the PE area trigger a smaller response in the US (11.78%) with a shorter half-life (97 days). According to these estimates, the US is more sensitive to the other regions, since shocks in the CE and EM area increase the ES in the US banking system in about 15.2% and 14.5% the size of this shock, respectively, with half-lives of 95 and 109 days, respectively.

4.2. Extended equation system

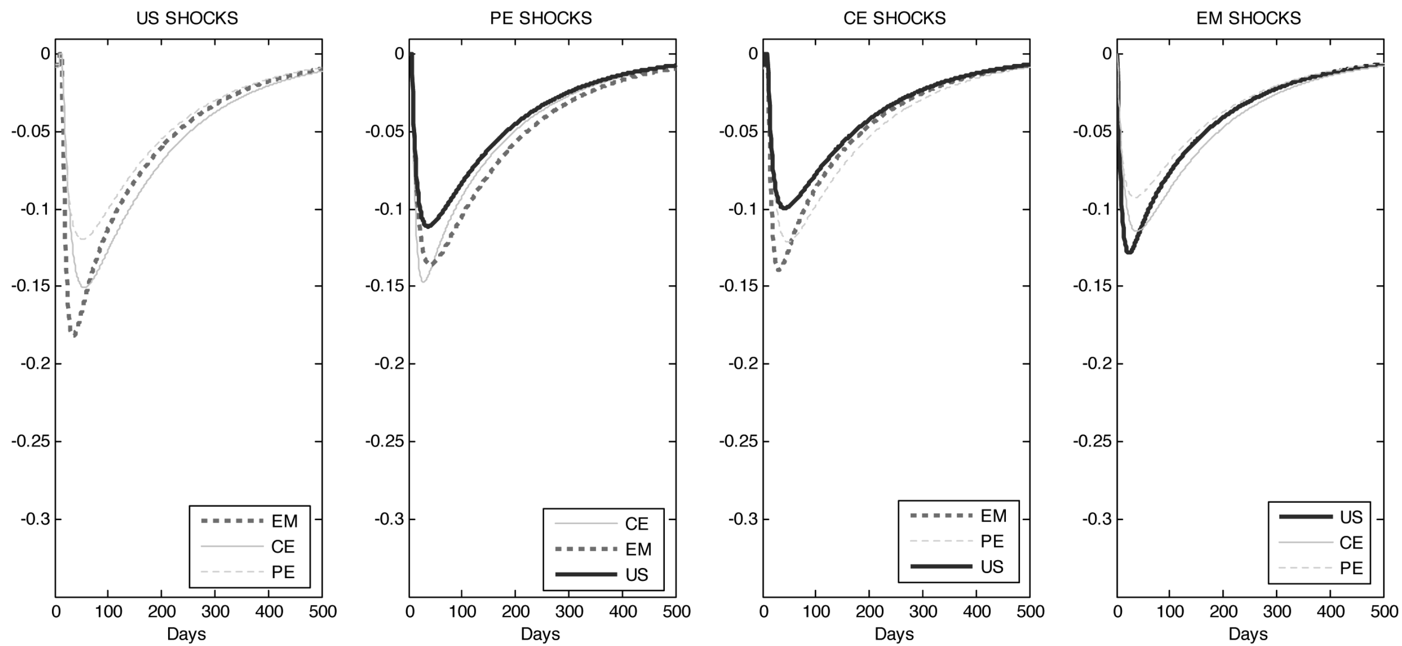
In this section, we discuss the main results from the analysis based on an extended set of economic areas. Together with the areas in $S_{B,}$ we consider the banking sectors in the UK, Scandinavian countries, and the BRICs subset of emerging-market economies. This analysis offers a more complete picture and, furthermore, offers us insight into the robustness of the overall conclusions to omitted variables. As we discuss below, adding new representative countries (UK) or new economic regions in both advanced and emerging areas (BR and SC) does not lead to any significant change in the main conclusions. From a robustness perspective, this result is important because it shows that the global index is able to control for the effects of omitted areas in the analysis.

Figure 5: IMPULSE RESPONSE FUNCTIONS OF BANKS IN EACH ECONOMIC REGION AGAINST SHOCKS IN EACH AREA FOR BASIC SYSTEM [8] FROM VOLATILE STATE OF ECONOMY



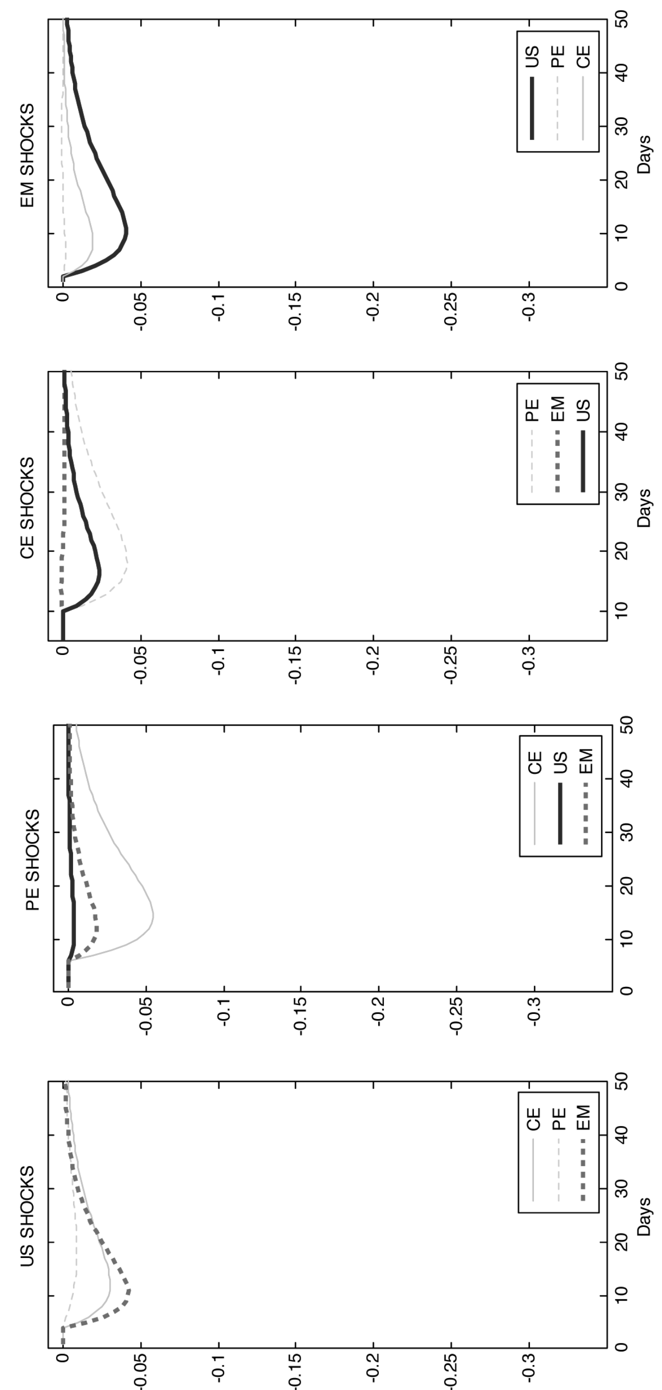
Source: Own elaboration.

Figure 6: IMPULSE RESPONSE FUNCTIONS OF BANKS IN EACH ECONOMIC REGION AGAINST SHOCKS IN EACH AREA FOR BASIC SYSTEM [8] FROM NORMAL STATE OF ECONOMY



Source: Own elaboration.

Figure 7: Impulse response functions of banks in each economic region against shocks in each area for basic system [8] from tranquil state of economy



Source: Own elaboration.

Table 5: ESTIMATION OF EXTENDED SPILLOVER SYSTEM FROM EXPRESSION [8] USING EXPECTED SHORTFALL FROM EXPECTILE-BASED SAV MODEL IN [6] AS A DOWNSIDE RISK MEASURE. SEE DETAILS IN TABLE 4

	α_i	δ_{ils}							ξ_i	ϕ_i
		US	BR	PE	CE	UK	SC	EM	GB	
$\tau = 0.15$ (Volatile)										
US	0.0013*		0.0175*	0.0273***	0.0357***	0.0544***	0.0380***	0.0671***	0.0998***	1.0369***
BR	-0.0041***	0.0288***		0.0369***	0.0274**	0.0185***	0.0092**	0.0056***	0.0113	0.9431***
PE	0.0005	0.0440***	0.0132*		0.0367***	-0.0012	0.0048	0.0242**	0.1257***	1.0417***
CE	0.0000	0.0746***	-0.0013	0.0524***		0.0067*	0.0017	0.0262**	0.1221***	1.0344***
UK	-0.0004	0.3240***	0.0636***	0.0433***	0.1199***		0.0748**	0.0331**	0.2245***	0.7600***
SC	0.0001	0.0532***	0.0132***	0.0015	0.0596***	-0.0060		0.0594***	0.0821***	0.9881***
EM	-0.0025***	0.0425***	0.0311***	0.0243***	0.0290***	-0.0057	0.0426***		0.0745***	1.0186***
GB	0.0003	0.0443***	0.0175**	0.0027	0.0337***	0.0125***	0.0168***	0.0217***		0.9003***
$\tau = 0.50$ (Normal)										
US	0.0001		0.0187***	-0.0005	0.0119**	0.0110**	-0.0033	0.0110**	0.0370***	0.9560***
BR	-0.0034***	0.0031		0.0168***	0.0186***	0.0004	0.0078***	0.0170***	0.0095	0.8618***
PE	-0.0009***	0.0052**	0.0052***		0.0135***	0.0042*	0.0175***	0.0027	0.0396***	0.9501***
CE	-0.0004***	0.0112***	0.0229***	0.0297***		0.0039	0.0080***	0.0005	0.0344**	0.9218***
UK	-0.0013***	0.0948***	0.0272***	0.0235***	0.0502***		0.0310***	0.0498***	0.0519***	0.7371***
SC	-0.0009***	0.0139***	0.0197***	0.0056	0.0028	0.0117***		0.0171***	-0.0033	0.9371***
EM	-0.0025***	0.0148***	0.0058**	0.0128***	0.0216***	-0.0028	0.0149***		0.0280***	0.8913***
GB	-0.0003***	0.0100***	0.0098***	0.0057***	0.0164***	0.0053***	0.0064***	0.0164***		0.8870***
$\tau = 0.85$ (Tranquil)										
US	-0.0007***		0.0071	-0.0004	0.0033	0.0091**	0.0122**	0.0041	0.0458***	0.8936***
BR	-0.0040***	0.0067**		0.0046*	0.0094**	0.0001	-0.0038	-0.0001	-0.0117	0.8163***
PE	-0.0010***	0.0015	0.0014		0.0166***	-0.0002	-0.0007	-0.0017	-0.0053	0.9017***
CE	-0.0015***	0.0053*	0.0067	0.0023		-0.0011	-0.0113	0.0131*	-0.0057	0.8788***
UK	-0.0027***	0.0271***	0.0240**	0.0109*	0.0050		-0.0078	0.0326**	0.0348**	0.7153***
SC	-0.0015***	0.0075**	0.0095***	-0.0044	0.0085**	0.0052**		0.0007**	0.0192***	0.9026***
EM	-0.0024***	0.0052**	0.0011	-0.0010	0.0035	-0.0020*	0.0020*		-0.0058	0.8368***
GB	-0.0009***	0.0029***	0.0033	-0.0026	0.0049**	0.0033**	-0.0016	0.0020		0.8863***

Source: Own elaboration.

Parameter estimates from the 2SQR estimation of the extended equation system and bootstrapped significance through the maximum-entropy algorithm are presented in Table 5. The overall analysis of the parameter estimates leads to the same conclusions discussed previously. Cross-country exposures largely increase and become highly significant in both economic and statistical terms during periods of distress. Financial vulnerabilities show a considerable degree of heterogeneity across the different areas involved, which can be related to the network of bilateral exposures that characterize international diversification in these areas. Since none of the main conclusions discussed previously change, we discuss directly the evidence related to the new areas included in the analysis, focusing particularly on the UK.

While all the economic areas exhibit significant exposures to US shocks in stressed conditions, the most vulnerable financial system to idiosyncratic shocks originating in this area is the UK. According to the 2SQR estimates, a one percent change in the expected losses of US increases expected losses in UK banks by 0.324 percentage points. While it is well-known that the US and UK stock markets show strong similarities (Shiller 1989), the ultimate reason for this remarked sensitivity is most likely related to the fact that US-issued claims account for the largest portion of total foreign holdings within the UK banking system. According to Degryse *et al.* (2010), US claims represent, on average, about 52% of the total foreign claims held by the UK over BIS reporting countries. More generally, since large-scale banks in the UK have engaged actively in international diversification since late 1990, the British system shows large relative vulnerabilities to any of the remaining areas, particularly, the CE. The vulnerability to this area is characterized by a contemporaneous spillover coefficient of 0.119. Not surprisingly, therefore, the UK financial system turns out to be the most vulnerable area to global shocks in the sample, exhibiting a global spillover coefficient ξ of 0.224. Note that the size of this coefficient nearly doubles the size of the estimated coefficients in the European regions.

Finally, regarding the vulnerability of other economic areas to shocks originating in the UK financial system, the US exhibits the largest tail spillover coefficient (0.054). This is not surprising, in the light that the UK represents about 30% of US-held foreign liabilities in other advanced economies (Degryse *et al.* 2010). Once more, this result underlines the importance of cross-border diversification in defining the strength of financial contagion across international areas.

5. Concluding remarks

In this paper, we have characterized the size, direction, and persistence of tail-spillovers in the local banking industries of several major economic regions around the world. A special focus has been given to address the heterogeneous patterns that feature contagion as a consequence of state-dependent market environmental conditions. To this end, we have considered a dynamic system of contemporaneous equations and implemented the 2SQR estimation methodology in Adams *et al.* (2014). The most distinctive features of the procedure is that it builds on instrumental estimation within the quantile regression setting to estimate state-dependent coefficients and ensure robustness against endogeneity.

We have implemented a refinement of the original methodology and focused on a system of equations in which the main variables involved are estimates of the expected shortfall process, rather than the VaR process, of each economic area. In our view, dealing with expected-shortfall loss functions can provide more accurate estimation in downside-risk modelling, since expected shortfall is a coherent measure of risk and, more importantly, VaR-type measures can be insensitive to large losses. We have used the expectile-based methodology in Taylor (2008a) to estimate expected shortfall, thereby ensuring that the overall estimation process builds entirely on semiparametric procedures which make results robust to the (unknown) distribution of the data. Finally, given the resultant estimates, we have estimated impulse-response functions to determine the expected duration and time-profile of contagion.

The main evidence that emerges from this analysis essentially shows that the sensitivity of expected losses in local banks to shocks initiated in or transmitted by foreign banks tends to be small and of little economic relevance during normal or tranquil period. However, cross-border vulnerabilities largely increase during periods of financial distress, allowing idiosyncratic losses to quickly morph into systemic shocks and spill over the remaining financial areas at a global scale. Our spillover system is able to capture and quantify this expected result. The impulse-response analysis agrees with this evidence, and further shows important differences on the expected duration of shocks, showing that the size of contagion is more important and the effects more persistent under stressed conditions. This pattern, which emerges when analyzing comovements in the left tails of the conditional distributions of returns through a suitable methodology, cannot be uncovered by traditional methods focused on the standard modelling of the conditional mean of returns, which perhaps explains why systemic vulnerabilities did not received sufficient attention in the literature before the financial crisis. Another major conclusion of our analysis is that local vulnerabilities to foreign shocks exhibit a considerable degree of cross-country heterogeneity. Certain economic areas exhibit greater resilience to foreign shocks than other areas and, similarly, the overall financial system is more vulnerable to shocks originated in certain areas. This evidence can be founded in the network of bilateral exposures featured by international diversification strategies in the local industries as well as bilateral borrowing activities across banks. Not surprisingly, therefore, the major source of systemic contagion is the global banking system turns out to be the US system, since large-scale banks around the world keep large holdings of securities issued by US financial institutions in their balance sheets. In contrast, US banks, which are known not to excessively over-rely on securities issued by a particular country, are relatively more resilient against foreign shocks.

According to the estimates of the equation system, we note that Central EMU area is fairly vulnerable to shocks originated in the Peripheral EMU, whereas the US and Emerging economies exhibit weaker direct vulnerabilities to this area. This evidence is fully consistent with the existence of cross-border exposures that feature contagion in the banking industry. The same phenomenon explains the sheer vulnerability of the US to shocks in the UK. Finally, the estimates of the model reveal the existence of financial channels that introduce contagion in advanced economies caused by shocks in emerging countries under market adverse conditions, which are particularly relevant for the US. This result agrees the importance of the bilateral relationships with certain countries, among which China takes a predominant position.

The results in this paper are of particular interest for banking regulators and supervisors as they provide insight on the empirical role played by international diversification in systemic risk. From a micro-prudential perspective, international diversification has been advocated as an effective tool to diversify away idiosyncratic risks in traditional risk management practices. From a macro-prudential perspective, however, international diversification increases the systemic importance of a financial institution as the bank becomes increasingly intertwined with foreign competitors. The Basel Committee on Banking Supervision (BCBS) introduced in December 2011 an assessment methodology to identify Global Systemically Important Banks (G-SIBs) based on five categories that include cross-border activity; see BCBS (2011) for details. The evidence in this paper supports the central hypothesis underlying these regulation proposals, namely, that international diversification defines a powerful channel of systemic contagion, particularly, under stressed conditions.

Appendix A: Bank Index details

In Section 2 we describe the dataset formed by international banking portfolios. This appendix contains several tables that report the banks and countries that form the representative indices of the local banking- industry in different economic regions such as the US, BRICs, Peripheral EMU, Central EMU, Scandinavia, the UK, Emerging Markets and the Global Banking index. This information is available in Datastream for the DS Banks Index construction of each region. We report the banks and countries for specific regional and country indices. In order to save space, we report the main areas and number of banks in emerging and global indices. Complete lists are available upon request.

Therefore, the following tables provide a list with the name and number of banks and countries or areas included in every index.

Table A1: United States Index

Table A2: BRICS Index

Table A3: Peripheral EMU Index

Table A4: Central EMU Index

Table A5: United Kingdom Index

Table A6: Scandinavia Index

Table A7: Emerging Markets Index

Table A8: Global Banking Index

Table A1: BANKS INCLUDED IN THE UNITED STATES INDEX

Bank	Country
Bank of America	US
Bankunited	US
BB&T	US
Bok Financial	US
Citigroup	US
City National	US
Comerica	US
Commerce Bancshares	US
Credicorp	US
Cullen Frost Bankers	US
East West Bancorp	US
Fifth Third Bancorp	US
First Niagara Financial Group	US
First Republic Bank	US
Firstmerit	US
Hudson City Bancorp	US
Huntington Bancshares	US
JP Morgan Chase and Company	US
Keycorp	US
M&T Bank	US
New York Community Bancorp	US
Peoples United Financial	US
PNC Financial Services Group	US
Prosperity Bancshares	US
Regions Financial New	US
Signature Bank	US
Suntrust Banks	US
SVB Financial Group	US
Synovus Financial	US
TFS Financial	US
United States Bancorp	US
Wells Fargo and Company	US
Zions Bancorporation	US
Total Number of Banks	33

Source: Own elaboration.

Table A2: BANKS AND COUNTRIES INCLUDED IN THE BRICS INDEX

Bank	Country
Banco Brasil On	Brazil
Bradesco On	Brazil
Bradesco PN	Brazil
Itauunibanco On	Brazil
Itauunibanco PN	Brazil
Santander Bearer On	Brazil
Santander Bearer PN	Brazil
Agricultural Bank of China ‘H’	China
Bank of China ‘H’	China
Bank of Communications ‘H’	China
China Citic Bank ‘H’	China
China Construction Bank ‘H’	China
China Everbright Bank ‘H’	China
China Merchants Bank ‘H’	China
China Minsheng Banking ‘H’	China
Industrial and Commercial Bank of China ‘H’	China
Allahabad Bank	India
Axis Bank	India
Bank of Baroda	India
Bank of India	India
Canara Bank	India
Central Bank of India	India
Corporation Bank	India
Federal Bank	India
HDFC Bank	India
I N G Vysya Bank	India
Icici Bank	India
Idbi Bank	India
Indian Bank	India
Indian Overseas Bank	India
Indusind Bank	India
Jammu and Kashmir Bank	India
Oriental Bank of Commerce	India
Punjab National Bank	India
State Bank of India	India
Syndicate Bank	India
UCO Bank	India
Union Bank of India	India
Yes Bank	India
Moscow Municipal Bank Moscow	Russian Federation
Mosobl Bank	Russian Federation
Rosbank	Russian Federation
Sberbank of Russia	Russian Federation
Sberbank Russia Preference	Russian Federation
VTB Bank	Russian Federation
Total Number of Banks	45

Source: Own elaboration.

Table A3: BANKS AND COUNTRIES INCLUDED IN THE PERIPHERAL EMU INDEX

Bank	Country
Alpha Bank	Greece
Attica Bank	Greece
Bank of Greece	Greece
Bank of Piraeus	Greece
Eurobank Ergasias	Greece
General Bank of Greece	Greece
National Bank of Greece	Greece
Bank of Ireland	Ireland
Banca Carige	Italy
Banca Finnat Euramerica	Italy
Banca Monte dei Paschi	Italy
Banca Piccolo Credito Valtell	Italy
Banca Popolare di Milano	Italy
Banca Popolare di Sondrio	Italy
Banca Popolare Emilia Romagna	Italy
Banca Popolare Etruria Lazio	Italy
Banca Profilo	Italy
Banco di Desio E Della Brianza	Italy
Banco Popolare	Italy
Credito Bergamasco	Italy
Credito Emiliano	Italy
Intesa Sanpaolo	Italy
Intesa Sanpaolo RSP	Italy
Mediobanca Banca di Credito Financial	Italy
Unicredit	Italy
Unione di Banche Italian	Italy
Banco BPI	Portugal
Banco Comercial Portugues ‘R’	Portugal
Banco Espirito Santo	Portugal
Banif	Portugal
Montepio	Portugal
Banco Bilbao Vizcaya Argentaria	Spain
Banco de Sabadell	Spain
Banco Intercontinental Espanol ‘R’	Spain
Banco Popular Espanol	Spain
Banco Santander	Spain
Bankia	Spain
Caixabank	Spain
Liberbank	Spain
Total Number of Banks	39

Source: Own elaboration.

Table A4: Banks and countries included in the Central EMU Index

Bank	Country
Bank FUR Tirol und Vorarlberg	Austria
Banks Bank	Austria
Erste Group Bank	Austria
Oberbank	Austria
Oberbank Preference	Austria
Raiffeisen Bank International	Austria
Banque Nationale de Belgique	Belgium
KBC Ancora	Belgium
KBC Group	Belgium
Hellenic Bank	Cyprus
USB Bank	Cyprus
Aktia ‘A’	Finland
Pohjola Pankki A	Finland
Banque Nationale de Paris Paribas	France
CIC ‘A’	France
Crcam Nord de France CCI	France
Credit Agricole	France
Credit Agricole Brie Picardie	France
Credit Agricole Ile de France	France
Credit Foncier de Monaco	France
Natixis	France
Societe Generale	France
Commerzbank	Germany
Deutsche Bank	Germany
Deutsche Postbank	Germany
IKB Deutsche Industriebank	Germany
Oldenburgische Landesbank	Germany
Umweltbank	Germany
Espirito Santo Financial Group	Luxembourg
Espirito Santo Financial Group Registered	Luxembourg
Bank of Valletta	Malta
Fimbank	Malta
HSBC Bank Malta	Malta
Lombard Bank	Malta
American Hypobank	Netherlands
Van Lanschot	Netherlands
Abanka Vipa	Slovenia
Nova Kreditna Banka Maribor	Slovenia
Probanka Prednostne Preference	Slovenia
Total Number of Banks	39

Source: Own elaboration.

Table A5: Banks included in the United Kingdom Index

Bank	Country
Bank of Georgia Holdings	UK
Barclays	UK
HSBC Holdings (Ordinary $0.50)	UK
Lloyds Banking Group	UK
Standard Chartered	UK
Royal Bank of Scotland Group	UK
Total Number of Banks	6

Source: Own elaboration.

Table A6: Banks and countries included in the Scandinavian Index

Bank	Country
Danske Bank	Denmark
Jyske Bank	Denmark
Ringkjobing Landbobank	Denmark
Spar Nord Bank	Denmark
Sydbank	Denmark
Aktia ‘A’	Finland
Pohjola Pankki A	Finland
DNB	Norway
Sparebank 1 Series Bank	Norway
Sparebank 1 SMN	Norway
Nordea Bank	Sweden
SEB ‘A’	Sweden
Svenska Handelsbanken ‘A’	Sweden
Swedbank ‘A’	Sweden
Total Number of Banks	14

Source: Own elaboration.

Table A7: NUMBER OF BANKS AND AREAS INCLUDED IN THE EMERGING MARKETS INDEX

Number of Banks	Area
33	Africa
118	Asia
45	BRICs
41	Europe
51	Latin America
Total Number of Banks	288

This table reports the main areas in the emerging markets index and the corresponding number of banks. Africa is formed by Egypt, Morocco, Nigeria and South Africa; Asia contains Bahrain, Dubai, Indonesia, Jordan, Kuwait, Malasya, Oman, Pakistan, Philippines, Qatar, Sri Lanka, Taiwan and Thailand; Europe is formed by Bulgaria, Croatia, Czech Republic, Hungary, Poland, Romania, Slovenia and Turkey. Finally, Latin America is composed of Argentina, Chile, Colombia, Mexico, Peru and Venezuela.

Source: Own elaboration.

Table A8: NUMBER OF BANKS AND AREAS INCLUDED IN THE GLOBAL BANKING INDEX

Number of Banks	Area
33	Africa
213	Asia
6	Australia
45	BRICs
8	Canada
38	Central EMU
51	Latin America
39	Peripheral EMU
57	Rest of Europe
14	Scandinavia
6	United kingdom
33	United States
Total Number of Banks	543

This table reports the main areas in the global banking index and the corresponding number of banks. Africa is formed by Egypt, Morocco, Nigeria and South Africa; Asia covers Abu Dabi, Bahrain, Dubai, Dubai, Hong Kong, Indonesia, Israel, Japan, Jordan, Kuwait, Malasya, Oman, Pakistan, Philippines, Qatar, Singapur, South Korea, Sri Lanka, Taiwan and Thailand; Latin America is comprised of Argentina, Chile, Colombia, Mexico, Peru and Venezuela. Finally, rest of Europe is made up of Bulgaria, Croatia, Czech Republic, Hungary, Poland, Romania, Slovenia Switzerland and Turkey.

Source: Own elaboration.

Appendix B: Spillover Results using Value at Risk from GARCH approach as a risk measure

In Section 4 we present the results for Expected Shortfall as a more coherent measure than Value at Risk. In this appendix, we repeat the estimations for basic and extended spillover equation system using VaR for $\lambda = 0.01$ instead of ES using the GARCH-approach as in Adams *et al*. (2014). The main results for basic and extended equation are presented in Table B1 and B2 respectively.

Table B1: ESTIMATION OF BASIC SPILLOVER SYSTEM USING THE VALUE AT RISK FROM GARCH MODEL AS A DOWNSIDE RISK MEASURE

	α_i	δ_{ils}				ξ_i	ϕ_i
		US	PE	CE	EM	GB	
$\tau = 0.15$ (Volatile)							
US	0.0350**		0.0115***	0.0854***	0.0262***	0.0205***	1.0546***
PE	0.0135	0.0720***		0.0350***	0.0199***	0.0795***	1.0469***
CE	-0.0004	0.1075***	0.0452***		0.0126**	0.0741***	1.0354***
EM	-0.1147***	0.0870***	0.0177**	0.0732***		0.0357***	1.0161***
GB	-0.0043	0.0959***	0.0009	0.0650***	0.0266***		0.9113***
$\tau = 0.50$ (Normal)							
US	0.0016		-0.0005	0.0084***	0.0118***	0.0080**	0.9570***
PE	-0.0406***	0.0070**		0.0281***	0.0052**	0.0241***	0.9485***
CE	-0.0263***	0.0144***	0.0232***		0.0091***	0.0099**	0.9282***
EM	-0.1555***	0.0410***	0.0152***	0.0415***		0.0230***	0.8897***
GL	-0.0297***	0.0293***	0.0098***	0.0350***	0.0219***		0.8982***
$\tau = 0.85$ (Tranquil)							
US	-0.0224***		0.0005	0.0073**	0.0053**	0.0159**	0.8986***
PE	-0.0430***	0.0015		0.0191***	-0.0003	-0.0035	0.9011***
CE	-0.0552***	0.0038	-0.0004		0.0084**	-0.0048	0.8761***
EM	-0.1564***	0.0089**	0.0004	0.0022		0.0002	0.8368***
GB	-0.0564***	0.0067***	0.0063*	0.0113**	0.0042*		0.8904***

Spillover basic system coefficients estimation using the VaR GARCH-based model. The first column shows the constant estimation α for i-th region. The equations of each i-th region are in rows and the next four columns are the corresponding spillover coefficients $\delta_{i|s}$ (tail spillover in i-th region originated in s-region). The last two columns present the results of the parameter estimates for control variable z_t and ES lag parameter ϕ for "i" region of the system respectively. The significances are detailed in each coefficient with the superscript text, *** for 1%, ** for 5% and * for 10%.

Source: Own elaboration.

Table B2: ESTIMATION OF EXTENDED SPILLOVER SYSTEM USING THE VALUE AT RISK FROM GARCH-BASED MODEL AS A DOWNSIDE RISK MEASURE

	α_i	δ_{ils}							ξ_i	ϕ_i
		US	BR	PE	CE	UK	SC	EM	GB	
$\tau = 0.15$ (Volatile)										
US	0.0337*		0.0074*	0.0178***	0.0265***	0.0551***	0.0284***	0.0369***	0.0432***	1.0369***
BR	-0.2556***	0.0683***		0.0370***	0.0482**	0.0444***	0.0163**	0.0053***	0.0841***	1.0416***
PE	0.0214	0.0678***	0.0087*		0.0422***	-0.0021	0.0055	0.0150**	0.0116	0.9431***
CE	0.0004	0.1006***	0.0007	0.0461***		0.0091*	0.0017	0.0142**	0.0713***	1.0344***
UK	-0.0092	0.3199***	0.0265***	0.0278***	0.0877***		0.0552**	0.0131**	0.0959***	0.7600***
SC	0.0048	0.0712***	0.0074***	0.0013	0.0591***	-0.0081		0.0319***	0.0475***	0.9881***
EM	-0.1680***	0.1058***	0.0326***	0.0393***	0.0535***	-0.0145	0.0793***		0.0802***	1.0186***
GB	0.0192	0.1026***	0.0169**	0.0040	0.0578***	0.0293***	0.0292***	0.0202***		0.9003***
$\tau = 0.50$ (Normal)										
US	0.0034		0.0079***	-0.0003	0.0088**	0.0112**	-0.0025	0.0044**	0.0160***	0.9560***
BR	-0.2167***	0.0074		0.0260***	0.0325***	0.0012	0.0136***	0.0163***	0.0098	0.8618***
PE	-0.0384***	0.0077**	0.0032***		0.0155***	0.0062*	0.0199***	0.0017	0.0264***	0.9499***
CE	-0.0139***	0.0151***	0.0130***	0.0261***		0.0053	0.0081***	0.0003	0.0201**	0.9218***
UK	-0.0332***	0.0936***	0.0113***	0.0151***	0.0368***		0.0229***	0.0197***	0.0221*	0.7371***
SC	-0.0308***	0.0186***	0.0111***	0.0048	0.0029	0.0159***		0.0092***	-0.0019	0.9371***
EM	-0.1644***	0.0368***	0.0061**	0.0207***	0.0399***	-0.0070	0.0277***		0.0302***	0.8913***
GB	-0.0200***	0.0230***	0.0096***	0.0086***	0.0281***	0.0125***	0.0111***	0.0153***		0.8870***
$\tau = 0.85$ (Tranquil)										
US	-0.0173***		0.0030	-0.0003	0.0024	0.0092**	0.0091**	0.0016	0.0198***	0.8936***
BR	-0.2517***	0.0160**		0.0072*	0.0165**	0.0002	-0.0068	-0.0001	-0.0121	0.8163***
PE	-0.0424***	0.0022	0.0009		0.0190***	-0.0002	-0.0008	-0.0012	-0.0036	0.9017***
CE	-0.0527***	0.0072*	0.0038	0.0021		-0.0015	-0.0114	0.0071*	-0.0033	0.8788***
UK	-0.0719***	0.0267***	0.0100**	0.0070*	0.0037		-0.0057	0.0129**	0.0149**	0.7153***
SC	-0.0539***	0.0099**	0.0053***	-0.0039	0.0086**	0.0070**		0.0003***	0.0110***	0.9026***
EM	-0.1585***	0.0130**	0.0011	-0.0017	0.0064	0.0052*	0.0037***		-0.0062	0.8368***
GB	-0.0548***	0.0068***	0.0032	-0.0039	0.0085**	0.0077**	-0.0028	0.0018		0.8863***

Source: Own elaboration.

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RESUMEN

Este artículo analiza la vulnerabilidad de la industria bancaria en economías avanzadas y emergentes frente a shocks en distintas áreas en periodos de inestabilidad financiera. El principal objetivo es, por un lado, medir las sensibilidades cruzadas entre las diferentes zonas que caracterizan el contagio sistémico en el sistema bancario internacional. Por otro lado, se pretende caracterizar la forma en la que se propagan los shocks sistémicos a lo largo del tiempo. Para ello estimamos las sensibilidades de la función de pérdida esperada en la industria bancaria del cada área local frente a shocks contemporáneos en las funciones de pérdida esperada de las áreas extranjeras utilizando un sistema de ecuaciones dinámico. Controlamos por exposiciones globales a factores comunes y consideramos diferentes escenarios o estados de inestabilidad económica. Para asegurar la robustez de las estimaciones frente a la endogeneidad implementamos una estimación instrumental y calculamos las funciones de impulso respuesta para analizar la duración esperada del contagio en las colas. El estudio revela que las vulnerabilidades cruzadas entre países dependen del estado de la economía de tal forma que se incrementan durante periodos de gran inestabilidad económica y tienen un mayor efecto a largo plazo en el resto de sistemas. Por el contrario, para periodos más tranquilos los shocks tienen muy poco impacto y son rápidamente absorvidos por los sistemas domésticos. El análisis también muestra evidencia acerca de la existencia de direccionalidad en el contagio siendo US el sector bancario que produce mayores contagios y el más resistente frente a shocks en otras áreas. Obtenemos también que las exposiciones sistemáticas al área de Europa Central son más significativas que a la Europa Periférica, siendo US el país más vulnerable frente a shocks originados en Europa Central. Finalmente, US y la Eurozona son sensibles frente a shocks en el sistema bancario de la zona de países emergentes.

Palabras clave: contagio bancario, SDSVaR, expectiles.

Clasificación JEL: C23, G15, Q43.