Measuring Tail-Risk Cross-Country Exposures in the Banking Industry[1]

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Abstract

In this paper we analyze the state-dependent risk-spillover in different economic areas. To this end, we apply the quantile regression-based methodology developed in Adams, Füss and Gropp (2014) approach to examine the spillover in conditional tails of daily returns of indices of the banking industry in the US, BRICs, Peripheral EMU, Core EMU, Scandinavia, the UK and Emerging Markets. This methodology allow us to characterize size, direction and strength of financial contagion in a network of bilateral exposures to address cross-border vulnerabilities under different states of the economy. The general evidence shows as the spillover effects are higher and more significant in volatile periods than in tranquil ones. There is evidence of tail spillovers of which much is attributable to a spillover from the US on the rest of the analyzed regions, specially on European countries. In sharp contrast, the US banking system show more financial resilience against foreign shocks.

Key words: Spillover Effects, Bank Contagion, SDSVaR, Expected Shortfall, VaR, Expectiles

JEL clasification codes: C23, G15, Q43

1 Introduction

Financial contagion has received considerable attention in empirical finance, particularly, after the recurrent episodes of financial crisis that have followed the October 1987 stock market crash. The main interest in this literature is to analyze how shocks to prices of certain financial assets are transmitted into prices of other financial assets. Early papers analyzed the existence of Granger-type causal relationships in the conditional mean of returns during periods of distress; see, for instance, Eun and Shim (1989) and Becker, Finnerty and Gupta (1990); see also Longstaff (2010) and Cheung, Fung and Tsai (2010) for recent analyses. In a similar vein, a considerable body of research has analyzed causality in variance and time-varying conditional correlations aiming to characterize the existence of volatility spillovers; see, among others, Hamao, Masulis and Ng (1990), Engle, Ito and Lin (1990), King and Wadhwani (1990), Susmel and Engle (1994), Baele (2005), and Dungey, Gonzalez-Hermosillo and Martin (2005). More recently, the severity of the global recession has motivated a considerable interest in understanding the linkages that interconnect financial losses during periods of distress, particularly, in financial institutions. This systemic crisis, albeit initiated in the US subprime mortgage-backed securities market, resulted in the collapse of major financial institutions, bankruptcies, declines in credit availability, and sharp drops in global real Gross Domestic Product (GDP). This has motivated a new regulatory setting in the banking industry in the aftermath of the crisis, and a rapidly-growing literature devoted to systemic risk and tail-spillover modelling; see, among others, Segoviano and Goodhart (2009), Acharya, Pedersen, Philippon and Richardson (2010), Adrian and Brunnermeier (2011), Brownlees and Engle (2012), López-Espinosa, Moreno, Rubia and Valderrama (2012), Diebold and Yilmaz (2012), Kim and Hwang (2012), and Rodríguez-Moreno and Peña (2013).

In this paper, we characterize the existence of state-dependent risk-spillovers in the daily returns of representative indices of the banking industry in different economic areas. The main aim is to appraise the sensitivity that characterizes the local vulnerability of domestic banking sectors to shocks originated in or transmitted by banks in a foreign area under different (stressed and non-stressed) characteristic scenarios. This analysis allows us to formally identify the main transmission channels in the international banking system and provide a quantitative risk assessment of the size of contagion. Cross-country contagion in the banking industry typically occurs because large-scale banks usually hold an important proportion of claims on foreign borrowers over total assets in their balance sheets. A shock in a foreign counterparty that decreases the market value of these claims leads to a balance-sheet contraction which may be further transmitted (and even amplified) into the domestic system through the local interbank network. In this context, we can assess the vulnerability to cross-country shocks in foreign countries by measuring the sensitivity of expected losses in domestic banks to *contemporaneous* changes in the expected losses of foreign banks. In this study, we consider different economic scenarios, all of which are endogenously determined by the empirical distribution of expected losses in the local industry. Our main interest is to analyze contagion under adverse market conditions.

To this end, we focus on representative indices of the banking industry in the US, the UK, peripheral and non-peripheral countries in Europe, and emerging-country economies. All these data, focused on most of the major financial areas of the world, are directly available from Datastream. The sample spans December 1999 through November 2013 and includes periods 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. Using these data, we characterize the empirical links in the lower tails of the bank-industry portfolio returns building on a variant of the two-stage quantile-regression methodology (henceforth 2SQR) implemented in Adams, *et al.* (2014). The most distinctive feature of this methodology is that it generates state-dependent estimates that are robust to endogeneity bias. Hence, we can consistently estimate the coefficients that characterize the direction and the strength of financial contagion in a network of bilateral exposures using a contemporaneous equation system. Based on these estimates, we address the existence of significant cross-border vulnerabilities whose intensity can vary as a function of the underlying economic conditions. Furthermore, we characterize impulse-response functions that determine the rapidity and persistence of contagion of a shock under different economic scenarios.

Analyzing tail-interdependences requires suitable estimates of conditional expected losses, a latent process that cannot be observed directly. While the analysis in Adams *et al.* (2014) is conducted on GARCH-type based estimates of the VaR process of US institutions, we rely on estimates of the Expected Shortfall (ES henceforth) process in our international sample. In the financial industry, VaR is an important measure because it is normally computed to meet regulatory capital. However, it has been widely criticized because it is not a coherent measure of risk (Artzner, Delbaen, Eber and Heath, 1999) and, more importantly, it may be completely insensitive to extreme, but infrequent market movements. In contrast, ES is a coherent risk measure that overcomes all these critiques. We proceed to estimate ES at the usual 1% shortfall probability using the expectile-based approach suggested by Taylor (2008a). Although other alternative estimation procedures are available, expectile-based modelling does not require specification of the underlying distribution of the data. This property is particularly appealing in the current context because it preserves the semi-parametric nature of the 2SQR methodology. As a result, the main conclusions from our analysis are not driven by any particular assumption concerning 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 in a global context. While previous studies have shown the existence of tail-interconnections between individual banks and the global financial system (e.g., López-Espinosa *et al.* 2012), our analysis provides a complete picture of bilateral relationships that feature transmission channels. Consistent with the previous literature, the main results from our analysis suggest that the degree of interconnectedness and, hence, financial vulnerability, largely increases during periods of distress; see also King and Wadhwani (1990) and Ang, Chen and Xing (2006). For instance, under normal market conditions, a one percent increase in the expected losses in the US banking system increases the ES of core EMU banks by approximately 0.01 percentage points. Under adverse market circumstances, however, the same shock increases the expected losses by nearly 0.072 percentage points. Similar results hold consistently on the remaining areas, showing that cross-border contagion increases systematically and significantly during periods of distress.

This study also reveals 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 systemic relevance of the US banking industry. The global vulnerability to the US stems from the fact that large-scale local banks with a specific weight in the 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, Elahi and Penas (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 either directly or indirectly in the US.

On the other hand, and in sharp contrast, 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 would make the system more resilient to these shocks. This evidence seems particularly relevant for central banks and international supervisors concerned with macroprudential policies to mitigate systemic risk, since low borrower concentration could be a determinant factor to limit the systemic importance of financial institutions. This issue merits attention in further research.

The remainder of this is paper organized as follows. Section 2 introduces the methodology implemented to estimate ES and characterize risk spillovers through 2SQR. Section 3 presents the data and discusses the main stylized features. Section 4 discusses the estimation of the ES process on the data. Section 5 presents the main results from the 2SQR analysis. Finally, Section 6 summarizes and concludes.

2 Measuring tail interdependences

We start our analysis by introducing mathematical notation and technical definitions in order to characterize risk spillovers. Since our modelling approach relies mainly on the expectile-based methodology proposed by Taylor (2008a) to estimate ES, we first introduce this semi-parametric procedure. We then discuss the main features of the 2SQR methodology used to characterize tail spillovers in the global banking industry.

2.1 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. It is not sub-additive and, more importantly, 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.,

$$ES_t(\lambda) = E(r_t|\ r_t < VaR_t(\lambda)) \tag{1}$$

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

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, Frey and Embrechts (2005). Taylor (2008a) introduced a procedure based on the expectile theory developed by Aigner, Amemiya and Poirier (1976) and Newey and Powell (1987) that seems well suited for modelling both 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, Yeh and Hsu (2009), and De Rossi and Harvey (2009) for related approaches. In the remainder of this subsection, we review the concept of expectiles and its connection with ES, introducing the procedure suggested by Taylor (2008a).

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 $E(y_t | \mathscr{F}_{t-1}) = 0$. This assumption implies no loss of generality in practice, since we can consider the residuals from a demeaned process otherwise, as is customary in the literature devoted to downside risk modelling. For certain constant parameter $\theta \in (0,1)$, the population θ-expectile can be defined as the minimizer of an asymmetrically-weighted sum of squared errors, namely,

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

where $\mathbb{I}(\cdot)$ denotes the indicator function.[1] It is easy to see 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 $100\theta\%$ 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 $100\theta\%$ 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

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

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 $\widehat{\beta}_\theta$, defined as the solution of

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

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.

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). The advantage of conditional expectile regressions over quantile regressions is that the ALS loss-function (3) is absolutely differentiable, so computing conditional expectiles is considerably simpler. More importantly, as shown by Newey and Powell (1987), the asymptotic covariance matrix of the parameters can be determined without estimation of the density function of the errors.

Newey and Powell (1987) and Taylor (2008a) discuss the theoretical relationship between expectiles and ES. In particular, for a MDS process, it follows that

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

where the short-hand notation $m_t(\theta) := m(x_t;\beta_\theta)$ shall be conveniently used in the sequel to simplify notation. 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

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

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, $\sigma_t = \omega_0 + \omega_1 \sigma_{t-1} + \omega_2 |r_{t-1}|$; $\omega_0 > 0$, $\omega_1, \omega_2 \geq 0$), 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, 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 asymmetric expectile-based model.

2.2 Two-stage quantile regression

Given the shortfall probability λ, let $ES^*_{it}(\lambda)$ $t = 1, ..., T$, $i \in \mathscr{S}$, denote the estimates of the ES process related to the banking sector in the economic area i, with $\mathscr{S}$ representing a certain set of such areas. The superscript emphasizes that we build on feasible estimates of the unobservable 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 arise contemporaneously between the tails of the conditional distributions of the domestic indices included in $\mathscr{S}$.

To this end, we may run a system of linear regressions. Thus, for any $i \in \mathscr{S}$, we may regress $ES^*_{it}(\lambda)$ on the estimates of the remaining ES processes in $\mathscr{S}$, 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 first-order autoregressive dynamics, our interest is to estimate the system of equations:

$$ES^*_{it}(\lambda) = \alpha_i + \phi_i ES^*_{it-1}(\lambda) + \sum_{\substack{s \in \mathscr{S} \\ s \neq i}} \delta_{i|s} ES^*_{st}(\lambda) + \sum_{l=1}^{k} \xi_{il} z_{lt} + \varepsilon_{it} \tag{7}$$

for all $i \in \mathscr{S}$, 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 $i, j \in \mathscr{S}$, $i \neq j$.

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), 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.[2] Note that, while the shortfall probability λ that defines the ES process is fixed in our analysis (e.g.,

[2]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.

$\lambda = 0.01$), we can consider a sequence of quantiles $\{\tau_n\}$ that characterize the sample distribution of $ES^*_{it}(\lambda)$ 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 consider the system of quantile-regression equations

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

for all $i \in \mathscr{S}$, and estimate the parameters involved in these equations using the 2SQR procedure. Note that the size of all parameters may vary on the τ quantile. While we shall consider a broad range of quantiles $\tau \in [0.1, 0.9]$ in a general estimation of this equation system, 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 of $ES^*_{it}(\lambda)$ 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, the right-hand side variables $ES^*_{st}(\lambda)$ that characterize the i equation in (8), $s \in \mathscr{S}$, $s \neq i$, 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).[3]

In the second stage, the set of equations (8) are estimated individually using QR, treating the first-stage predicted values $ES^{**}_{st}(\lambda)$ as regressors. Under sufficient conditions, this procedure yields

[3]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.

consistent and asympotically-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.

3 Data

The dataset used in this paper is formed by daily continuously compounded returns from value-weighted portfolios representative of the local banking industry in different economic regions. 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. Data are directly available from Datastream, which provides closing prices of different banking-industry indices in the following economic regions: US, UK, Peripheral EMU area (PE), Core EMU area (CE), Scandinavia area (SC), the so-called BRICs area (BR), and Emerging Markets (EM). Together with this regions, we consider a Global Banking index (GB) to control for exposures to global shocks. All these indices are formed by the main banks which are publicly traded in the countries that make up 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 intense cross-border activities. All these characteristics are commonly associated to systemic importance. As in other studies concerned with systemic risk in the global banking industry, returns are computed from prices denominated in US dollars; see López-Espinosa *et al.* (2012).

The PE index, referred to as PIIGS index in Datastream, is formed by the main banks in Greece, Ireland, Italy, Portugal, and Spain. The CE index includes the main banks in countries that belong to the EMU, but not to the PE area, namely, Austria, Belgium, Cyprus, Finland, France, Germany, Luxembourg, Malta, Netherlands, and Slovenia. Scandinavia is formed by banks based in Denmark, Finland, Norway, and Sweden. We distinguish between PE and CE because both areas are characterized by different macroeconomic drivers and because these areas exhibited a considerable heterogeneity in response to the systemic shocks. The Scandinavian countries and the UK have local currencies, which provides them with an invaluable tool to handle an adverse economic scenario through currency devaluation.[4] The BR index is formed by banks in the so-called BRIC area, namely, Brazil, China, India, and Russia. It represents a subarea of emerging economies that has undergone remarkably strong development over the recent years. The EM is a global banking index formed by 300 banks operating in emerging-market economies, mainly, Central and Eastern Europe, Asia, and Latin America. Similarly, the GB is an index representative of the global banking industry. It pools data from 536 banks around the world. Appendix provides a list with the banks included in any of these areas.

Table 1 reports the usual descriptive statistics on the returns of all these indices. Returns at the daily frequency exhibit the usual stylized features, such as time-varying volatility, skewness, and excess kurtosis. Analysis of the (annualized) mean and volatility reveals the consequences of the financial crises in the banking sector, particularly, in advanced economies. Returns in the banking industry of the US and EMU areas over the period analyzed are characterized by large levels of volatility –mainly, in the second half of the sample– and low average returns. More specifically, the annualized mean return is approximately zero in the US (0.09%), and negative in the CE (-3.50%) and the UK (-4.02%). Countries in the peripheral EMU area have suffered the consequences of the crises more intensely, and exhibit the lowest mean annualized return (-5.04%) in the sample. 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.[5]

[Insert Table 1]

4 Estimating Expected Shortfall

To estimate the ES process of the returns, 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,

[4]Note that the SC index includes Finland, a country in the EMU area. Nevertheless, this country contributes with two banks to the total index. In our view, this is unlikely to introduce any form of bias.

[5]Some caution should be applied when comparing the mean-variance profile across these areas because of the influence of cross-country diverisfication. 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.

we compute ES on demeaned returns, $\widetilde{r}_t$, 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 $m_{it}(\theta) = \beta_{i0} + \beta_{i1} m_{it-1}(\theta_i) + \beta_{i2}|\widetilde{r}_{it-1}|$, $t = 1,...,T$. In the same spirit as Engle and Manganelli (2004), we initialize $m_{i0}(\theta_i)$ 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). Following Efron (1991) and Taylor (2008a), $\widehat{\theta}_i$ is optimally determined as the value for which the proportion of in-sample observations lying below the conditional expectile, say $\widehat{\lambda}_{i,T}$, matches the shortfall probability $\lambda = 0.01$ that characterizes exceptions in the ES. 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)[6], in a trial-and-error algorithm with stopping rule $|\lambda_i - \widehat{\lambda}_{i,T}| < 10^{-06}$. Note, therefore, that the estimates of $\zeta_i = (\beta_{i0}, \beta_{i1}, \beta_{i2}; \theta_i)'$ are determined simultaneously in this context, and the values ensure that the empirical coverage probability $\widehat{\lambda}_i$ is approximately 0.01.

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.[7] On average, the value of the optimal expectile θ 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 routinely 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 $\widehat{m}_t(\theta)$, $t = 1,...,T$. 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 $\widehat{\lambda}$ to be close enough to the nominal $\lambda = 0.01$. Since the optimal value of θ is chosen under the condition that $\widehat{\lambda}$ must match λ, correct

[6] We randomly generate 1000 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.

[7] 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 costumary to report both VaR in 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 2.

conditional coverage is trivially ensured. The conditional tests 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. The overall evidence suggests that expectiles do not generate unreliable estimates for downside risk modelling; see also Taylor (2008a). [8]

[Insert Table 2]

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 -3.84%, for the emerging market index EM, to -6.24%, in UK, the country with the lowest daily return in the sample. These series show a considerable degree of dispersion, with minimum values 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 different countries and economic areas, with correlations ranging from 51% (for the pair PE and BR) to 91% (for the pair PE and CE). This evidence suggests a considerable degree of commonality and the existence of global trends or common factors that propitiate systemic risk in the banking industry.[9]

[Insert Table 3]

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.

[Insert Figure 1]

[8] We obtain similar conclusions using alternative ES models such asymmetric expectile-based model and different parametric specifications based on GARCH model volatility estimates.

[9] 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.

5 Risk spillovers in the global banking industry: 2SQR estimation

Given the expectile-based estimates, 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 $\delta_{i|s}$ 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.[10] Furthermore, the inclusion of a global variables allows us to circumvent potential concerns related to neglected variables, for instance, associated to economic areas or individual countries which are not explicitly acknowledged in our analysis. The potential influence of all these areas is briefly resumed in the global index.

In addition, we consider two sets of economic regions. The first one focuses on tail interdependences in the US, peripheral and non-peripheral EMU countries, and emerging markets, namely, $\mathscr{S}_B = \{US, CE, PE, EM\}$. While this baseline set includes a reduced number of economic areas, these are of major global economic relevance and have been subject to considerable financial stress. This analysis allows us to present a detailed analysis, focused on the main interactions of this limited set. This discussion shall be completed later by considering an extended set which includes all the economic regions considered in this paper, $\mathscr{S}_E = \{\mathscr{S}_B, UK, SC, BR\}$. This analysis not only provides a more complete picture, but also allows us to address whether conclusions are generally sensitive to the omission of potentially economic regions.

5.1 Basic equation system

5.1.1 Main results

Table 4 reports the parameter estimates from equation system (8) given the set of countries $\mathscr{S}_B = \{US, CE, PE, EM\}$, the shortfall probability $\lambda = 0.01$, and the representative quantiles $\tau \in \{0.15, 0.50, 0.85\}$ that characterize the underlying economic conditions in the local industry that receives the spillover.

[10] 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.

In this system, we allow the global banking index GB to have feedback effects with the areas in $\mathscr{S}_B$ by modelling in the same way, i.e., the full system is estimated with 5 equations. Our main interest is in the coefficients $\delta_{i|s}(\tau)$ and $\xi_i(\tau)$ in these equations. The former capture 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. Similarly, the latter capture the exposure of the domestic banking system to systematic shocks in the global financial system. Statistical significance at the usual confidence levels is determined on the basis of maximum entropy bootstrap of Vinod and López-de-Lacalle (2009).

[Insert Table 4]

The estimates of $\xi_i(\tau)$ are positive and significant during normal periods ($\tau = 0.50$). 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). For instance, the parameter estimates $\widehat{\xi}_{PE}$ and $\widehat{\xi}_{CE}$ in EMU areas show that, during normal market periods, a one percent shock in the ES in the global system will increase the average ES of banks in PE and CE by 0.036% and 0.017%, respectively. Clearly, the exposure to global shocks under normal market conditions tends to be smaller for economies with better macroeconomic fundamental (US and CE), while economies which traditionally have had greater inflation ratios and higher unemployment rates (PE and EM) are more vulnerable to systemic shocks.

The picture that emerges under the two extreme scenarios in the tails is different. During tranquil periods ($\tau = 0.85$), the estimates of the slope ξ are not significant in any of the areas except in the US.[11] Hence, the small bank losses that typically occur during calm periods tend to obey idiosyncratic patterns which, in general, are not related to other areas. On the other hand, 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. Note, for intance, that the relative ratio $\widehat{\xi}(0.15)/\widehat{\xi}(0.5)$ is 4.15 on average, showing a sizeable increment in the overall sensitivity. This ratio is particularly large (7.46) in non-peripheral EMU countries. According to Table 4, banks in the Eurozone are more vulnerable to global shocks under a stressed scenario than banks in other areas. This general pattern is fully evident in Figure 2, which shows the shapes of the estimated coefficient functions $\widehat{\xi}_i(\tau)$, $i \in \mathscr{S}_B$, as a function of the quantiles $\tau \in [0.10, 0.90]$. Clearly, banks

[11] 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.

in both peripheral and core EMU exhibit the largest vulnerabilities to global shocks under adverse market circumstances. 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 estimates of the autoregressive coefficient ϕ_i lie in the neighborhood of unit. 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), these estimates 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 explossive patterns. Although explosive patterns are often related to model misspecification, in our view this evidence is not particularly surprising in the current context. 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.

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 commove, the estimates $\widehat{\delta}_{i|s}$ are mostly positive and highly significant, particularly, in the excited state. Furthermore, and 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, 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 $\widehat{\delta}_{i|s}(\tau)$ for $\tau \in [0.10, 0.90]$. This figure 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 analyses that merely focus on the conditional mean or the median analysis may lead to potentially misleading conclusions.

It is interesting to discuss the size of cross-border spillovers in the different banking systems as a response to a shock in a certain economic area, i.e., analyzing the coefficients reported by columns (second to sixth) in Table 4. For ease of exposition, we comment on the results in the most relevant context characterized by stressed conditions ($\tau = 0.15$). Under these 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), 0.043% (PE), and 0.041% (EM). 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 a 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. Idiosyncratic shocks originated in this country can affect all the other banking systems (particularly, those in European countries) which are under stressed conditions. The main reason for the global systemic importance of this country 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 fundings 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 core EMU area, characterized by a greater reliance on US lending.

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. The system with the largest vulnerability to shocks in the PE area is the one formed by the remaining banks in the EMU area. The main economies in CE keep large holdings of debt issued by European peripheral countries. Note, in Figure 3, that the exposure 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%. 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 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 core EMU area are much more important and largely significant in all cases. Among the different 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, the 2SQR estimates reveal that, under adverse market conditions, the banking sectors in the US and the Eurozone are sensitive to shocks in emerging-market economies. Over the last decades, emerging-market 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 is 0.065, which nearly doubles the size of the two EMU countries.

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.

[Insert Figures 2-3]

5.1.2 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), 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 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 $\mathscr{S}_B$ 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 the size of these coefficients and the autoregressive coefficients $\phi_i(\tau)$. As expected from the analysis reported in the previous section, the IRF characterize heterogenous responses across the economic regimes analyzed. 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.[12] 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 countries 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, particularly, in the US, for which the peak of the IRF of US 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

[12]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, Lin and Tamvakis (2012).

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

[Insert Figure 4]

Figures 5 to 7 show the IRFs that characterize the response of banks in each economic region in $\mathscr{S}_B$ 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 a 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 idosyncratic 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.

[Insert Figures 5-7]

5.2 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 $\mathscr{S}_B$, 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, furthemore, 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.

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.

[Insert Table 5]

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 a well-known fact that the US and UK stock markets show strong similarities (Shiller, 1989), the ultimate reason for this remarked sensitivity in the banking-industry may be 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.

6 Concluding Remarks

We investigate size, direction and persistence of tail risk spillover in the banking sector for international regions by applying the state dependent system developed in Adams *et al.* (2014). The main evidence states that 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. We obtain strong spillover effects from the US market to the rest of the regions considered, specially to Core Europe and UK. This result implies that downside movements in values of banks index returns caused increase in the contagion from US market to Europe due to the strong bilateral borrowing activities between these areas.

The impulse response analysis shows 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. The largest response against a country-specific idiosyncratic shock is triggered by the US. The most vulnerable area to systematic shocks is Europe in stressed scenario and US banking system has stronger resilience to global shocks. The empirical results show that not only does a volatility spillover exist but there is also an important spillover effects in bank returns distribution tails that still remain an unexplored area in spillover research.

The results of this paper are of particular interest for both policy makers and investors. The latter can improve their hedging and portfolio diversification strategies exploiting the knowledge regarding the way the financial markets influence one another. For policy makers an understanding of financial contagion would clearly be beneficial, providing them useful information about the formulation of possible decoupling strategies to insulate the economy from contagious effects and thus avoiding future spreading of crises and preserving the stability of the financial system.

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Tables

Table 1: Descriptive statistics for daily returns of representative indices of the local banking-industry in different economic regions

Region	Mean_a	Median_a	Std._a	Min.	Max.	Skew.	Kurt.
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

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 (Core 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.

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}
US	-0.0010	0.8645	-0.3804	-0.4867	0.0028	0.0100	0.9947	0.3934	0.6948
BR	-0.0033	0.7952	-0.4080	-0.4809	0.0018	0.0100	0.9947	0.4001	0.6930
PE	-0.0009	0.8975	-0.2561	-0.3153	0.0023	0.0100	0.9947	0.3934	0.6948
CE	-0.0017	0.8507	-0.3757	-0.4304	0.0014	0.0100	0.9947	0.3757	0.6754
UK	-0.0034	0.6900	-0.8902	-1.0932	0.0023	0.0100	0.9947	0.3646	0.6545
SC	-0.0010	0.8874	-0.2897	-0.3557	0.0023	0.0100	0.9947	0.3934	0.6948
EM	-0.0022	0.8043	-0.4165	-0.5337	0.0028	0.0100	0.9947	0.3934	0.6948
GB	-0.0008	0.8815	-0.2849	-0.3487	0.0022	0.0100	0.9947	0.4001	0.6930

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. The last three columns present the p-value for TUC, TI and TCC that denote the results for Unconditional Coverage, Independence and Conditional Coverage test. ES are estimated from daily demeaned returns of bank indices.

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

Panel A.- ES Descriptives Statistics							
Region	Mean	Median	Std.	Min.	Max.	Skew.	Kurt.
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 λ=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.

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

Spillover basic system coefficients estimation from (8) using the expectile-based SAV model in (6). The first column shows the constant estimation α for "i" region. The equations of each "i" region are in rows and the next four columns are the corresponding spillover coefficients $\delta_{i|s}$ (tail spillover in "i" region originated in "s" region). The last two columns present the results of the paramter 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, a for 1%, b for 5% and c for 10%.

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

Figures

Figure 1: Time series for daily demeaned returns (solid blue line) and Expected Shortfall processes from expectile based model (dotted green line) in (6)

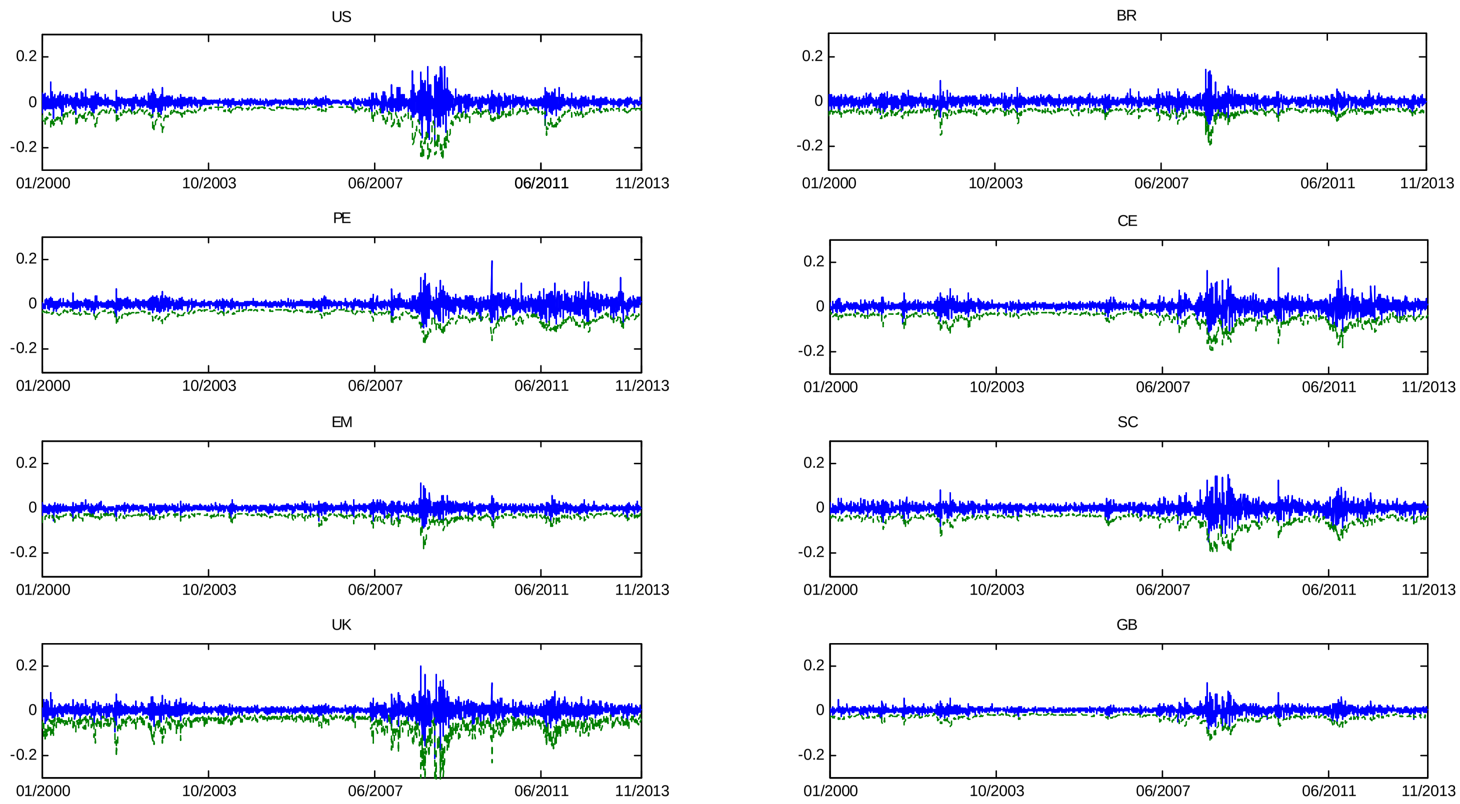


Figure 2: Estimated coefficients functions $\xi_i(\tau)$ from system (8) for a range value of quantiles $\tau \in [0.1,0.9]$. The graph shows the influence of the global index on the remaining areas

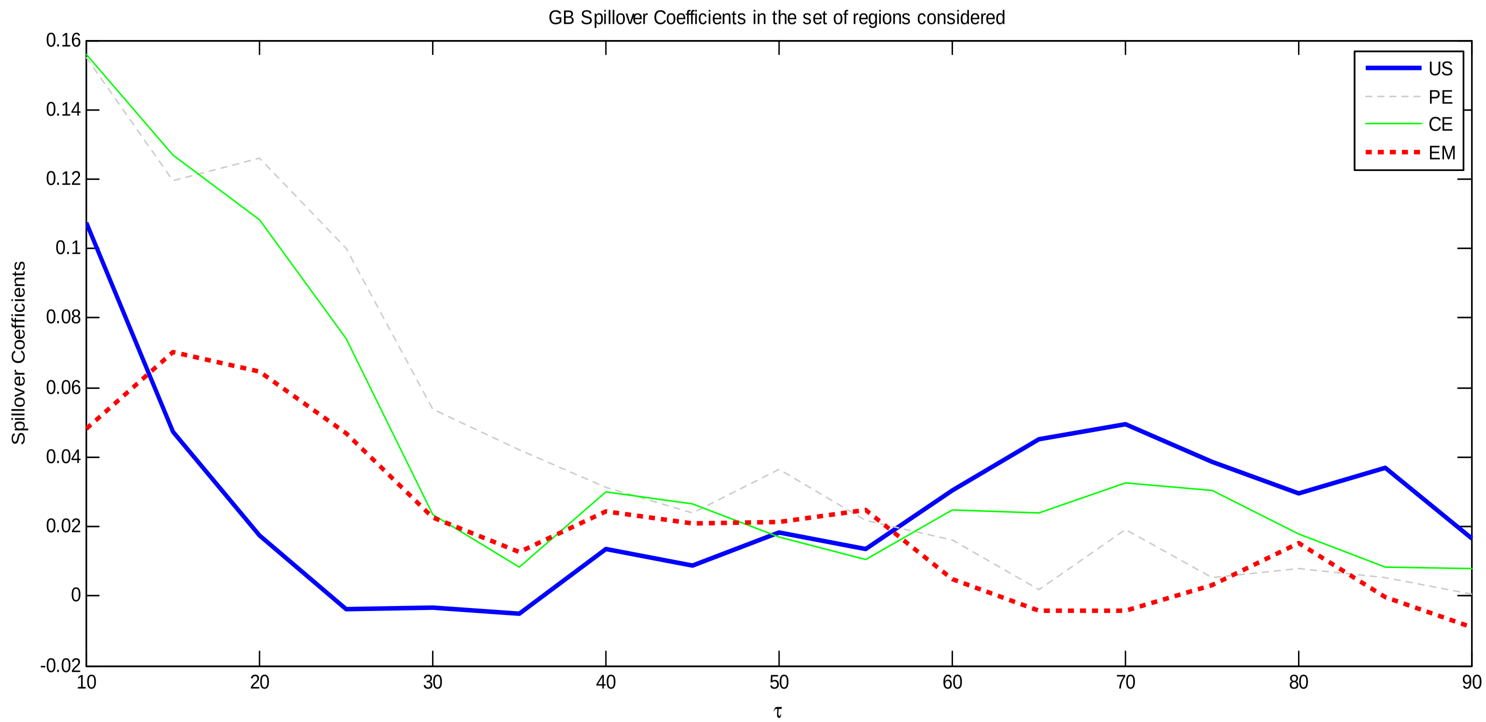


Figure 3: Estimated coefficients functions $\delta_{i|s}(\tau)$ from system (8) for a range value of quantiles $\tau \in [0.1,0.9]$. Left-upper graph shows the influence of the US on the remaining areas; right-upper graph presents the influence of PE to the other regions; left-lower graph depicts the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

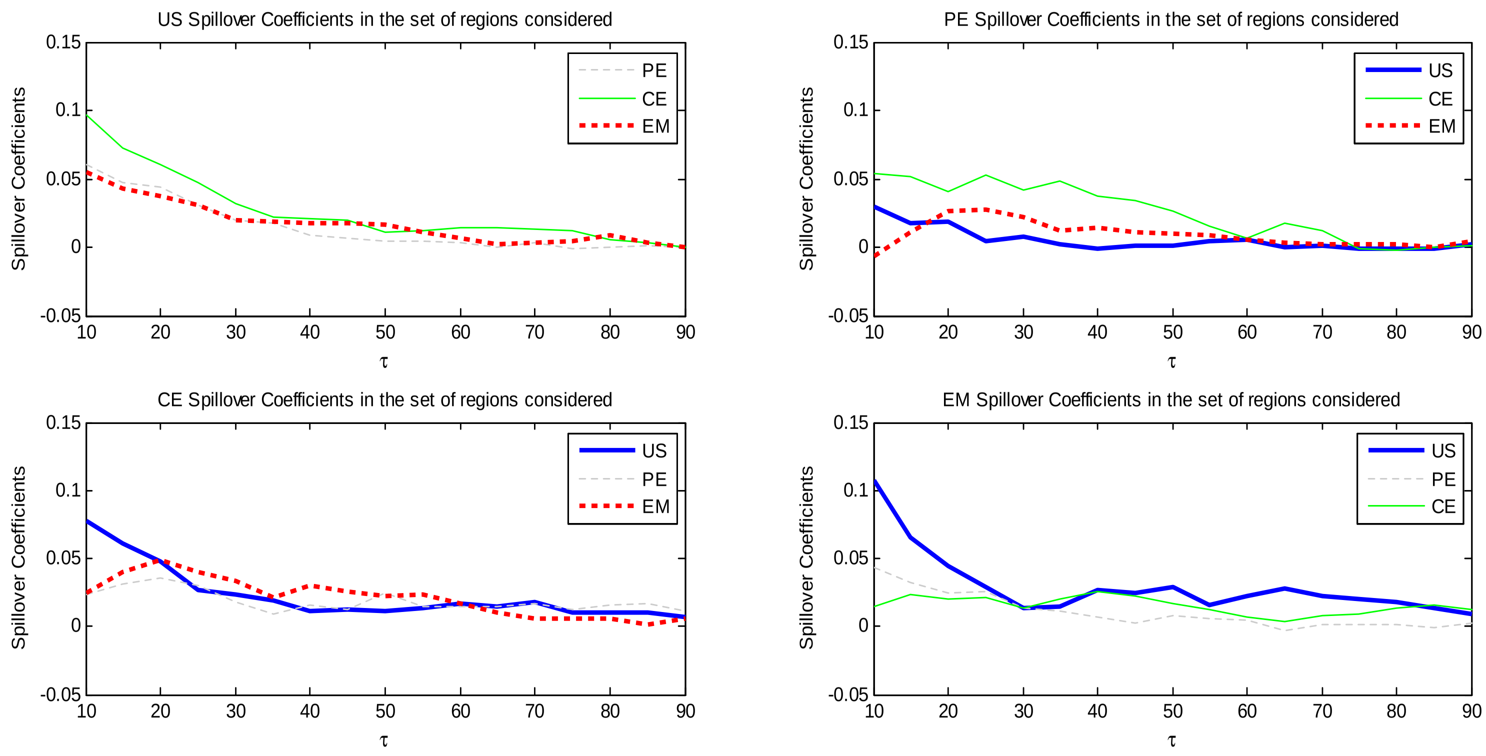


Figure 4: Impulse response functions of the domestic banking sector in each economic region against Global Banking shocks for tranquil, normal and volatile state of the economy from basic system (8) estimation

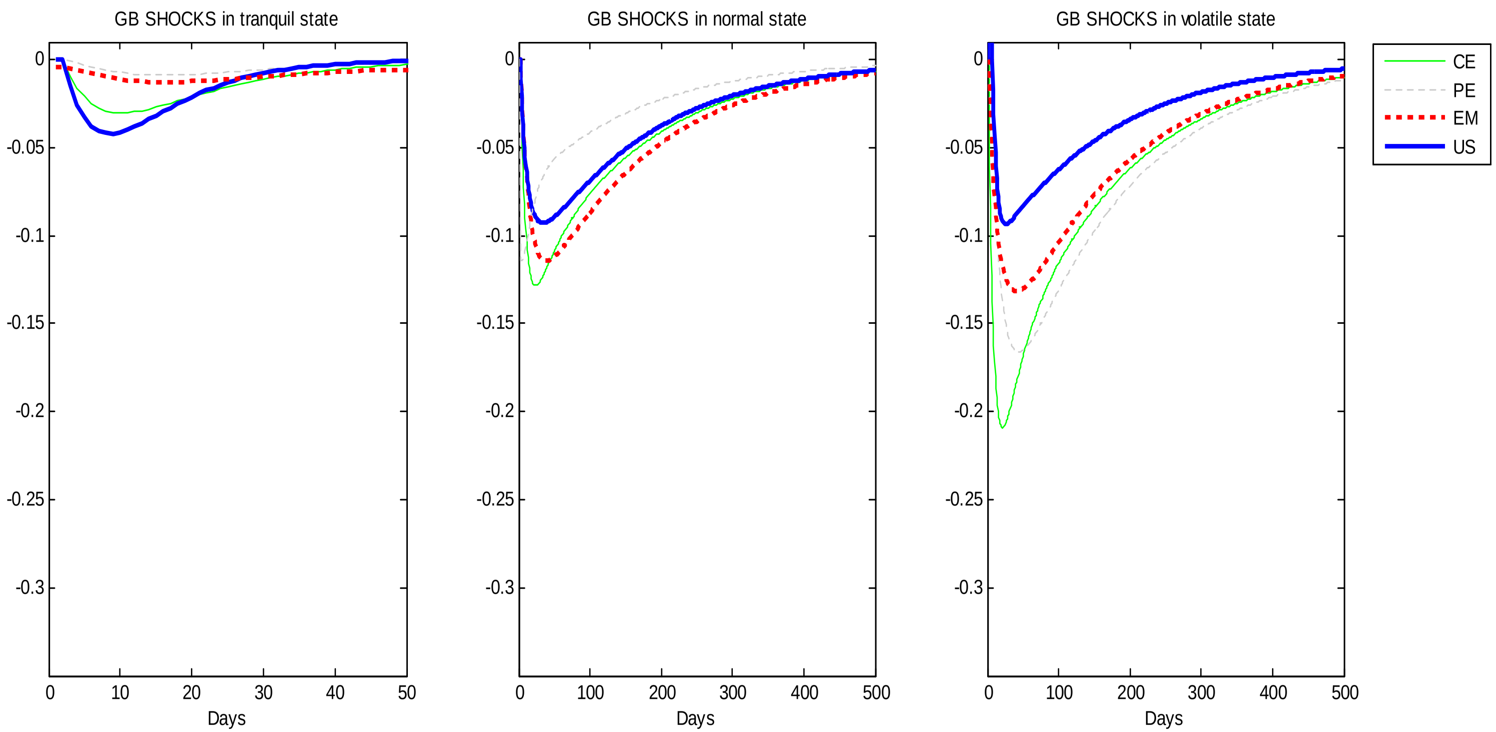


Figure 5: Impulse response functions of banks in each economic region against shocks in each area for basic system (8) from volatile state of economy

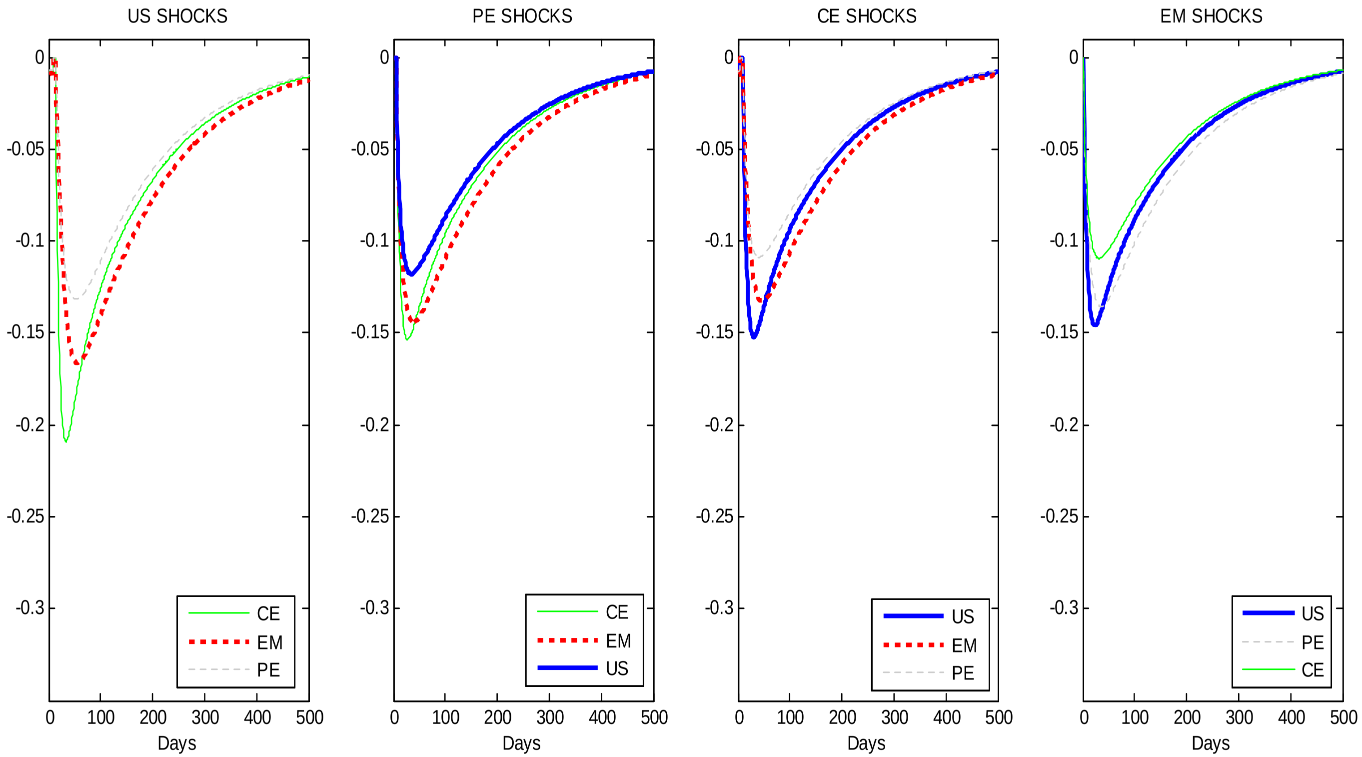


Figure 6: Impulse response functions of banks in each economic region against shocks in each area for basic system (8) from normal state of economy

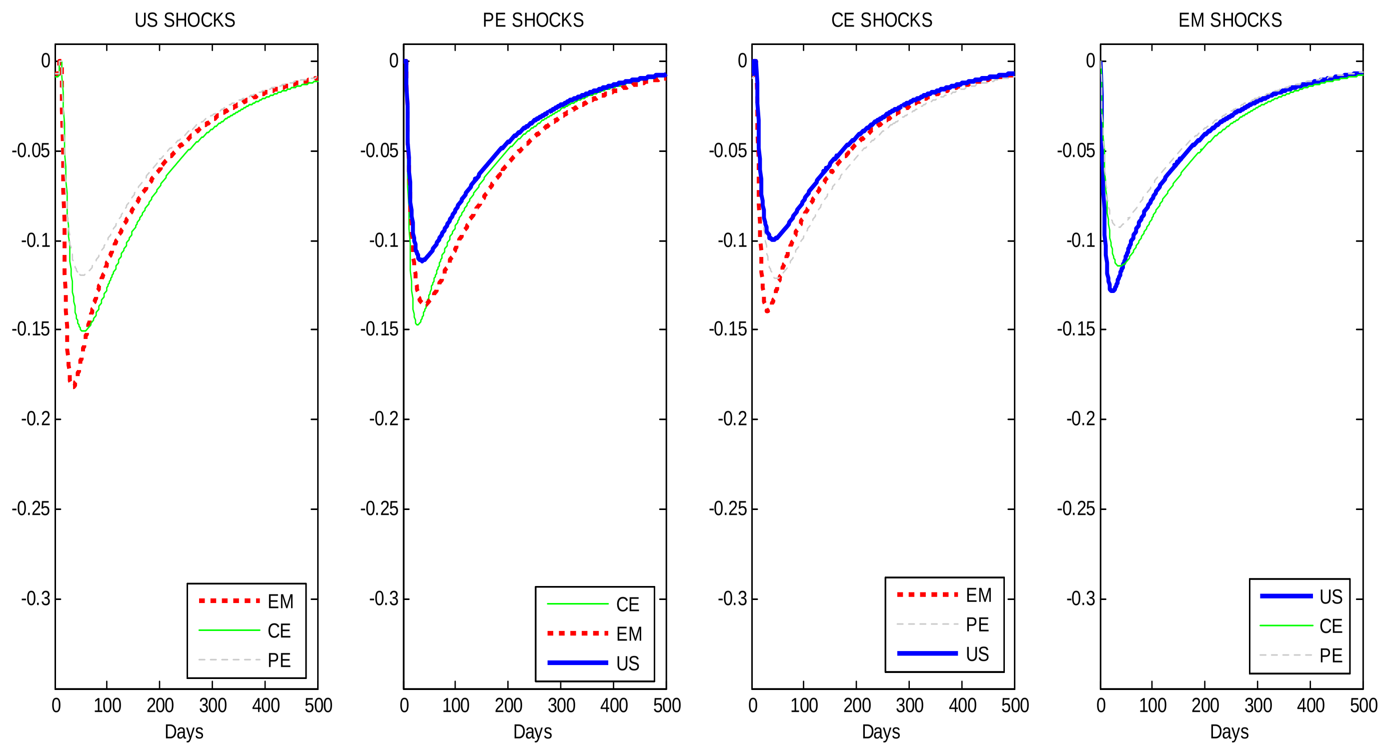
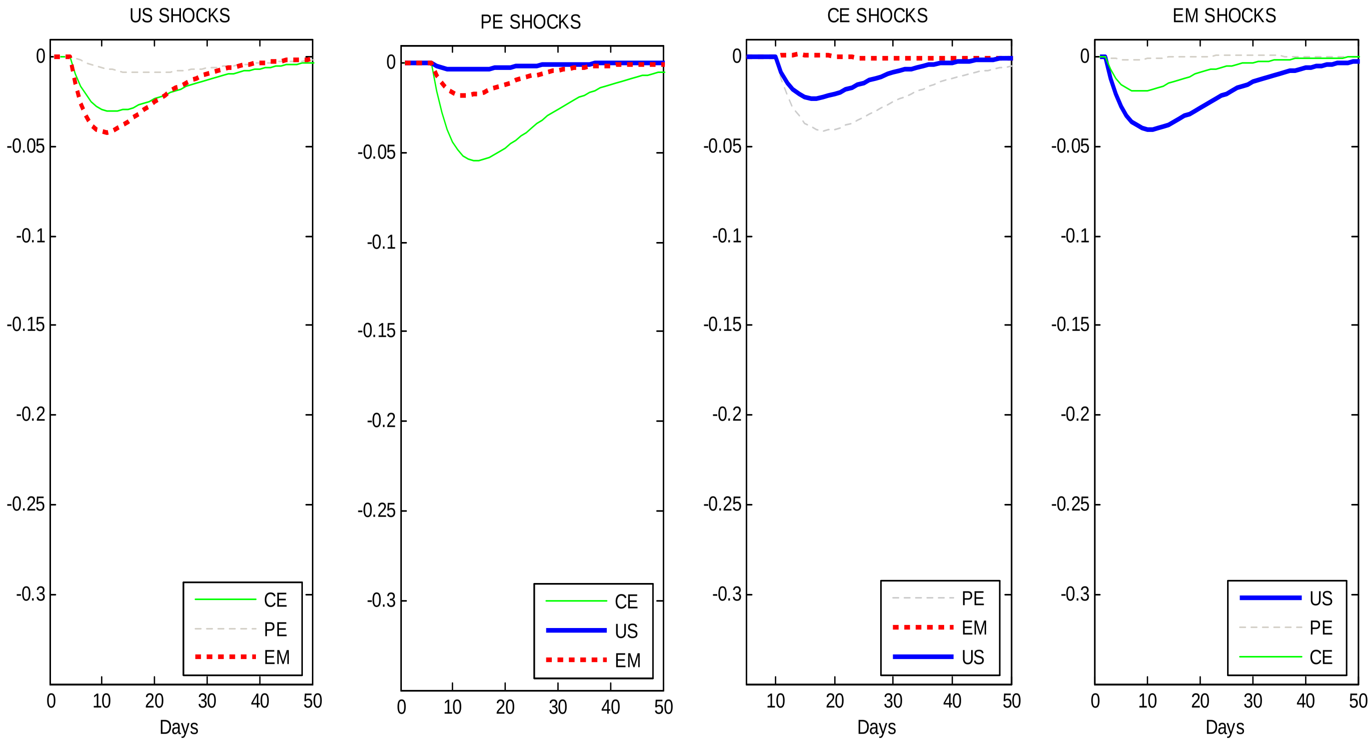


Figure 7: Impulse response functions of banks in each economic region against shocks in each area for basic system (8) from tranquil state of economy



Appendix: Bank Index details

In Section 3 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, Core 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 banks and countries or areas included in every index.

Table 6: United States Index.

Table 7: BRICS Index.

Table 8: Peripheral EMU Index.

Table 9: Core EMU Index.

Table 10: United Kingdom Index.

Table 11: Scandinavia Index.

Table 12: Emerging Markets Index.

Table 13: Global Banking Index

Table 6: 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

Table 7: 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

Table 8: 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

Table 9: Banks and countries included in the Core 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

Table 10: 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

Table 11: 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

Table 12: 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

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, Mejico, Peru and Venezuela.

Table 13: 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	Core EMU
51	Latin America
39	Peripheral EMU
57	Rest of Europe
14	Scandinavia
6	United kingdom
33	United States

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, Mejico, Peru and Venezuela. Finally, rest of Europe is made up of Bulgaria, Croatia, Czech Republic, Hungary, Poland, Romania, Slovenia Switzerland and Turkey.