Systemic Risk in Europe

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Abstract

Systemic risk may be defined as the propensity of a financial institution to be undercapitalized when the financial system as a whole is undercapitalized. In this paper, we investigate the case of non-U.S. institutions, with several factors explaining the dynamics of financial firms returns and with asynchronicity of time zones. We apply this methodology to the 196 largest European financial firms and estimate their systemic risk over the 2000-2012 period. We find that, for certain countries, the cost for the taxpayer to rescue the riskiest domestic banks is so high that some banks might be considered too big to be saved.

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1 Introduction

The Global Financial Stability Report of the International Monetary Fund (2009) defines systemic risk as "a risk of disruption to financial services that is caused by an impairment of all or parts of the financial system and that has the potential to cause serious negative consequences for the real economy." With the recent financial crisis, interest in the concept of systemic risk has grown. The rising globalization of financial services has strengthened the interconnection between financial institutions. While this tighter interdependence may have fostered efficiency in the global financial system, it has also increased the risk of cross-market and cross-country disruptions.

Measures of systemic risk are generally based on market data, which are forward looking by their nature. Two questions may be answered with such data because historical prices contain expectations about future events. First, how likely is it that extreme events will occur in the current financial markets? Second, how closely connected are financial institutions with one another and the rest of the economy? Obtaining the answers to those questions is at the heart of most of the recent research on systemic risk. The shape of the distribution of financial returns and the strength of the dependence across financial institutions are both essential to determine the speed of the propagation of shocks through the financial system and the level of vulnerability to such shocks.

In the aftermath of the recent financial crisis, the literature has focused primarily upon externalities across financial firms that may give rise to liquidity spirals. In particular, it became clear that network effects must be addressed to fully capture the contribution of banks to systemic risk. Thus, these measures of systemic risk consider the risk of extreme losses for a financial firm in the event of a market dislocation. Acharya et al. (2012) and Brownlees and Engle (2012) have proposed an economic and statistical approach to measure the systemic risk of financial firms. Following Acharya et al. (2012), the externality that generates systemic risk is the propensity of a financial institution to be undercapitalized when the financial system as a whole is undercapitalized. In this context, there are likely to be few firms willing to absorb liabilities and acquire the failing firm. Thus leverage and risk exposure are more serious when the economy is weak. This mechanism can be captured by the expected fall in the equity value of each firm conditional on a weak economy. Then, the capital shortage for each firm is considered the source of deadweight loss to the economy. In the econometric methodology proposed by Brownlees and Engle (2012) for U.S. financial institutions, the model estimates the capital shortage that can be expected for a given firm if there is another financial crisis. The model is composed of a dynamic process for the volatility of each firm's return and its correlation dynamic with an overall equity index. Innovations are described by a non-normal (semi-parametric) joint distribution that allows the sensitivity of the firm's return to extreme downturns in the equity market to be estimated.[1]

In the case of non-U.S. institutions, which are the focus of the present paper, there are several additional issues beyond the aforementioned components to measure the risk exposure: For a given firm, a financial crisis may be triggered by a world crisis (such as the subprime crisis), a regional crisis (such as the European debt crisis), or even by a countrywide crisis (such as the Greek debt crisis for Greek banks). Thus, a natural extension of the previous models is a multi-factor model, where several elements may jeopardize a financial firm's health. Furthermore, the parameters of the model, in particular the sensitivity to market movements, may change over time. This in turn requires a model that allows for time-varying parameters. In this paper, we adopt the Dynamic Conditional Beta approach recently proposed by Engle (2012), in which a Dynamic Conditional Correlation (DCC) model is used to estimate the statistics that are required to compute the time-varying betas. Another issue with non-U.S. institutions arises from the asynchronicity of the financial markets. A world crisis (for instance, initiated in the

[1] Other measures of contagion based on the properties of the joint distribution of stock returns have been proposed. For instance, Adrian and Brunnermeier (2011) have introduced the CoVaR, i.e., the VaR of the financial system conditional on institutions being under stress. Another branch of the literature is investigating the degree of connectivity (or co-movement) among financial institutions, which is a key component of systemic risk, along the lines developed earlier by Kaminsky and Reinhart (2002). Recent papers in this field are Kritzman et al. (2011), Billio et al. (2012), and Hautsch et al. (2012).

U.S. market) may affect other regions either the same day or one day later. We design a specific econometric model to address asynchronous markets.

Our empirical analysis is based on a large set of 196 European financial firms, which includes all banks, insurance companies, financial-services firms, and real-estate firms with a minimum market capitalization of one billion euros and a price series starting before January 2000. We investigate several aspects of systemic and domestic risks among European financial firms. In particular, we evaluate the relative contribution of industry groups, countries, and individual firms to the global systemic risk in Europe. Our approach allows us to explicitly identify global systemically important financial institutions (G-SIFIs), using the terminology of the Basel Committee on Banking Supervision, by estimating a firm's capital shortfall in case of a worldwide shock or a Europe-wide shock. We also identify domestic systemically important financial institutions (D-SIFIs) by investigating the impact of the rescue of a firm on the domestic economy.

At the end of the study period (August 30, 2012), the total exposure of these 196 firms was 1,219 billion euros. Banks and insurance companies bear approximately 83% and 15% of the systemic risk in Europe, respectively. Systemic risk is essentially unaffected by financial services and real estate firms. Over the recent period, the countries with the highest levels of systemic risk have been France and the U.K., as these two countries have contributed to approximately 52% of the total exposure of European financial institutions. The five riskiest institutions over the recent period have been Deutsche Bank, Crédit Agricole, Barclays, Royal Bank of Scotland, and BNP Paribas, bearing almost 457 billion euros together, i.e., 37% of the total expected shortfall in the case of a new financial crisis. Even after correcting for differences in accounting standards, the total systemic risk borne by European institutions is much larger than the one borne by U.S. institutions.

Last, we investigate some properties of aggregate systemic risk measures at country level. We first show that our systemic risk measure Granger-causes industrial production and business confidence index in most European countries. It could therefore provide an early warning signal of distress in the real economy. Then we consider the potential financial determinants of systemic risk measures. We find that the main driver in most countries is the three-month interbank rate, which strongly affects both asset and liability sides of bank's balance sheet.

The remainder of the paper is organized as follows. Section 2 details the methodology adopted to estimate systemic risk measures. Section 3 presents the data and preliminary analysis. Section 4 discusses our estimates of systemic risk measures of European financial institutions. Section 5 provides some more detailed evaluation of domestic aggregate systemic risk measures, and the conclusions are presented in Section 6.

2 Methodology

2.1 Measuring Systemic Risk

In this section, we describe our model of the risk exposure of financial firms to a financial crisis. Following the approach proposed by Acharya et al. (2012) and Brownlees and Engle (2012), we measure systemic risk as the propensity of a financial firm to be undercapitalized when the financial system as a whole is undercapitalized. This measure of systemic risk combines the value of the equity of the firm (market capitalization), the ratio of the value of its assets to the value of its equity (financial leverage), and the sensitivity of its return on equity to whole-market shocks (risk exposure). We start with the following definition of capital shortfall of firm i in case of a crisis between t and $t+T$:

$$CS_{i,t:t+T} = E_t[\theta A_{i,t+T} - W_{i,t+T} \mid Crisis_{t:t+T}], \tag{1}$$

where $A_{i,t}$ and $W_{i,t}$ denote the value of the assets and equity of firm i at date t. Parameter θ is a prudential ratio of equity to assets. It represents the fraction of the assets that the firm should put aside in case of a crisis.[2] Our precise definition of a crisis is provided below.

Given the discrepancy between book and market values, we adopt the following approach. The "quasi-market value" of assets in Equation (1) is defined as the book value of assets (BA) plus the difference between the market value of equity (W, market capitalization) and the book value of equity (BW), i.e., $A = BA + (W - BW) = D + W$. The book value of debt is $D = BA - BW$.[3] With this definition, Equation (1) can be written as:

$$CS_{i,t:t+T} = \theta E_t[D_{i,t+T} \mid Crisis_{t:t+T}] - (1-\theta) E_t \left[W_{i,t+T} \mid Crisis_{t:t+T}\right]. \tag{2}$$

We assume that the expected value of the debt is not affected during the crisis and remains constant in the short run, so that $E_t[D_{i,t+T} \mid Crisis_{t:t+T}] = D_{i,t}$. Ex ante, there are arguments in favor of a decrease of short-term debt and an increase of long-term debt. On the one hand, in a crisis, the interbank market usually dries (as exemplified by the financial crisis in 2008) and short-term borrowing typically decreases. On the other hand, some components of long-term debt may increase during the crisis. In particular, positions in long-term interest rate swaps that appear as liabilities typically increase. All in all, we do not expect large changes in debt as the two effects compensate each other. By denoting financial leverage as $L_{i,t} = A_{i,t}/W_{i,t}$, we have that $D_{i,t} = (L_{i,t} - 1)W_{i,t}$.[4]

The second term of Equation (2) is:

$$E_t \left[W_{i,t+T} \mid Crisis_{t:t+T}\right] = \left(1 - LRMES_{i,t:t+T}\right) W_{i,t},$$

[2] In Basel II Accords, the minimum capital requirement is specified as a fraction (8%) of risk-weighted assets. However, the recent financial crisis has shown that risk-weighted assets may be poor measures of risk. Indeed, they may lead to an under-diversification of the asset mix because the risks of the assets are considered individually. The Basel Committee on Banking Supervision plans to introduce in the new Basel III Accords a leverage ratio based on a fraction (3%) of the total (unweighted) assets. As a benchmark, we adopt for European firms a capital ratio of $\theta = 5.5\%$, which approximately corresponds to a capital ratio of 8% in the U.S., once differences in accounting standards are taken into account (see below).

[3] This decomposition has been widely adopted because it provides a reasonable compromise between book values, which often underestimate the value of equity, and market values, which raise the issue of measuring the market value of debt.

[4] If the market capitalization of a firm is not affected by a financial crisis and if the capital ratio is $\theta = 5.5\%$, the leverage $L_{i,t}$ that will ensure that the firm has no capital shortfall is $1/\theta = 18.2$.

where $LRMES_{i,t:t+T} = -E_t\left[W_{i,t+T}/W_{i,t} - 1 \mid Crisis_{t:t+T}\right]$ is the long-run marginal expected shortfall of the firm's return in the event of a financial crisis. The forward-looking nature of the stressed capital shortfall ultimately relies on the expected change in the market capitalization of the firm in case of a financial crisis.

We now define a financial crisis as a major stock market decline. For a worldwide or a Europe-wide crisis, which we will call a systemic event, we consider the worst six-month market decline over the last decade, which corresponds to a fall of approximately 40%. Financial markets experienced two major drawdowns of this magnitude or more over the last two decades. Eventually, LRMES is defined as:

$$LRMES_{i,t:t+T} = -E_t\left[R_{i,t:t+T} \mid R_{M,t:t+T} \leq -40\%\right], \tag{3}$$

where cumulative returns are defined as:

$$R_{i,t:t+T} = \exp\left(\sum_{j=1}^{T} r_{i,t+j}\right) - 1 \qquad \text{and} \qquad R_{M,t:t+T} = \exp\left(\sum_{j=1}^{T} r_{M,t+j}\right) - 1,$$

with $r_{i,t}$ and $r_{M,t}$ denoting the log-return of firm i and the log-return of the market index, respectively.[5]

Finally, Equation (2) can be rewritten as:

$$CS_{i,t:t+T} = \{\theta(L_{i,t} - 1) - (1-\theta)E_t(1 - LRMES_{i,t:t+T})\}\, W_{i,t}, \tag{4}$$

and the systemic risk of firm i is defined as positive capital shortfall:

$$SRISK_{i,t:t+T} = \max(0, CS_{i,t:t+T}). \tag{5}$$

[5]Systemic risk measures are defined using simple returns, but our econometric model is written in log-returns. The main reason for this is that working with log-returns avoids unlimited losses. Indeed with an unbounded distribution (such as a normal or a t distribution), simple returns may fall below −100%, so that investors could loose more than their wealth. With log-returns, this will not happen. Once cumulative log-returns have been computed, we convert them back into simple returns to compute capital shortfall.

The marginal expected shortfall of the entire financial system, i.e., the expected loss of the financial system conditional on an extreme event, is given by:

$$LRMES_{F,t:t+T} = -E_t[R_{F,t:t+T} \mid R_{M,t:t+T} \leq -40\%],$$

where $R_{F,t:t+T}$ denotes the cumulative return of the financial industry between t and $t+T$. Because the return of the industry is the value-weighted sum of the financial institutions return ($R_{F,t:t+T} = \sum_{i=1}^{N} w_{i,t} R_{i,t:t+T}$, with $w_{i,t} = W_{i,t}/W_{F,t}$), the aggregate LRMES is the weighted average of individual LRMES:

$$LRMES_{F,t:t+T} = \sum_{i=1}^{N} w_{i,t} LRMES_{i,t:t+T}.$$

This aggregation property can be used to investigate systemic risk at the country-wide level and for some categories of financial institutions (see Brownlees and Engle, 2012).

The systemic risk measure defined above is the expected capital shortfall of a financial institution in case of a financial crisis. Thus, it measures the equity buffer that would be sufficient, *ex ante*, to face a financial crisis. In case of the default of the firm ($LRMES_{i,t:t+T} = 1$, i.e., the market capitalization goes to 0), the maximum *ex post* capital shortfall would be $\theta(L_{i,t} - 1)W_{i,t} = \theta A_{i,t}$, reflecting the firm's lack of equity. In fact, the final cost for the taxpayer in case of a bailout may be significantly larger if the government decides to endorse part of the debt of the defaulting firm. We also note that a lower bound for the capital shortfall can be obtained by assuming that the crisis does not affect the market capitalization of the firm ($LRMES_{i,t:t+T} = 0$), in which case we find a capital shortfall equal to $(\theta L_{i,t} - 1)W_{i,t}$. A crude measure of the range of the SRISK measure is therefore given by $[(\theta L_{i,t} - 1)W_{i,t} \; ; \; \theta(L_{i,t} - 1)W_{i,t}]$. The size of the range is $(1-\theta)W_{i,t}$. Thus, for highly leveraged firms (low market capitalization), the SRISK measure is relatively insensitive to the LRMES estimate and depends primarily on financial leverage. Conversely, the SRISK of a firm with low leverage can be significantly affected by a change in its LRMES.

2.2 Econometric Methodology

There are substantial differences across European countries in terms of macroeconomic dynamics, fiscal and monetary policy and regulation. For this reason, as opposed to the U.S., a finer distinction of what drives the risk of a financial firm is required. Our model can be interpreted as a generalized market model under market efficiency. On one hand, in our stratification, return of firm i ($r_{i,t+1}$) is allowed to depend on the country return ($r_{C,t+1}$), the European return ($r_{E,t+1}$), and world return ($r_{W,t+1}$). On the other hand, under market efficiency, return of firm i does not depend on lagged returns.

A further complication stems from the asynchronicity of time zones. If we take Greenwich Time as a reference, Asian markets close earlier the same day and American markets close later the same day. As a consequence, European markets at date $t+1$ will react to changes on Asian markets at date $t+1$ and to changes on American markets at date t.[6] For this reason, the lagged world index ($r_{W,t}$) is also a possible driver of firm i return at date $t+1$. Therefore, our system includes five series, $r_{t+1} = \{r_{i,t+1}, r_{C,t+1}, r_{E,t+1}, r_{W,t+1}, r_{W,t}\}$.

The objective of the model is to capture the dependence of the return of firm i with respect to the drivers. Our econometric approach aims at capturing this dependence by designing a factor model with time-varying parameters, time-varying volatility, and a general, non-normal dependence structure for the innovations. We begin with the following recursive multi-factor model with time-varying parameters, after having preliminarily

[6] Using daily returns between 2000 and 2012, the correlations between MSCI Europe and MSCI world indices are $\text{corr}(r_{E,t}, r_{W,t}) = 0.8$, $\text{corr}(r_{E,t+1}, r_{W,t}) = 0.18$, and $\text{corr}(r_{E,t}, r_{W,t+1}) = 0.03$, indicating that there is no information in the world index return at $t+1$ useful for the European index return at t, but that the world index return at $t-1$ contains relevant information for the European index return at t. Martens and Poon (2001) describe the issue of asynchronization and show that instantaneous correlation between international stock markets systematically underestimates the actual correlation because of the missing lagged effect.

demeaned all return series:

$$\begin{aligned}
r_{i,t+1} &= \beta^{C}_{i,t+1}\, r_{C,t+1} + \beta^{E}_{i,t+1}\, r_{E,t+1} + \beta^{W}_{i,t+1}\, r_{W,t+1} + \beta^{L}_{i,t+1}\, r_{W,t} + \varepsilon_{i,t+1}, && (6)\\
r_{C,t+1} &= \beta^{E}_{C,t+1}\, r_{E,t+1} + \beta^{W}_{C,t+1}\, r_{W,t+1} + \beta^{L}_{C,t+1}\, r_{W,t} + \varepsilon_{C,t+1}, && (7)\\
r_{E,t+1} &= \beta^{W}_{E,t+1}\, r_{W,t+1} + \beta^{L}_{E,t+1}\, r_{W,t} + \varepsilon_{E,t+1}, && (8)\\
r_{W,t+1} &= \beta^{L}_{W,t+1}\, r_{W,t} + \varepsilon_{W,t+1}, && (9)
\end{aligned}$$

where the L superscript corresponds to the lagged world-market index. The parameters of the model are estimated using the Dynamic Conditional Beta approach proposed by Engle (2012). The estimation is performed as follows. We assume that, conditional on the information set at date $t-1$, the return process at $t+1$ has mean $E_{t-1}[r_{t+1}] = 0$ and covariance matrix $V_{t-1}[r_{t+1}] = H_{t+1}$. The conditional covariance matrix H_{t+1} is estimated by a DCC model (Engle and Sheppard, 2001; Engle, 2002) as:

$$\begin{aligned}
H_{t+1} &= D^{-1/2}_{t+1}\Gamma_{t+1}D^{-1/2}_{t+1}, && (10)\\
\Gamma_{t+1} &= \left(\mathrm{diag}\left(Q_{t+1}\right)\right)^{-1/2} Q_{t+1} \left(\mathrm{diag}\left(Q_{t+1}\right)\right)^{-1/2}, && (11)\\
Q_{t+1} &= \Omega + \delta_1 Q_t + \delta_2\, D^{-1/2}_{t-1} r_{t-1} r'_{t-1} D^{-1/2}_{t-1}, && (12)
\end{aligned}$$

where $\mathrm{diag}(Q_{t+1})$ denotes a matrix with zeros, except for the diagonal that contains the diagonal of Q_{t+1}, and D_{t+1} is the diagonal matrix with the variances of r_{t+1} (conditional on $t-1$) on its diagonal and zero elsewhere. Parameters δ_1 and δ_2 are restricted to ensure that the conditional correlation matrix, Γ_{t+1}, is positive definite. Armed with this model, we estimate the parameters associated with firm i return as:

$$\beta_{i,t+1} = \begin{pmatrix} \beta^{C}_{i,t+1} \\ \beta^{E}_{i,t+1} \\ \beta^{W}_{i,t+1} \\ \beta^{L}_{i,t+1} \end{pmatrix} = \begin{pmatrix} H_{CC,t+1} & H_{CE,t+1} & H_{CW,t+1} & H_{CL,t+1} \\ H_{CE,t+1} & H_{EE,t+1} & H_{EW,t+1} & H_{EL,t+1} \\ H_{CW,t+1} & H_{EW,t+1} & H_{WW,t+1} & H_{WL,t+1} \\ H_{CL,t+1} & H_{EL,t+1} & H_{WL,t+1} & H_{LL,t+1} \end{pmatrix}^{-1} \begin{pmatrix} H_{iC,t+1} \\ H_{iE,t+1} \\ H_{iW,t+1} \\ H_{iL,t+1} \end{pmatrix}.$$

The sets of parameters for the other equations, $\beta_{C,t+1}$, $\beta_{E,t+1}$, and $\beta_{W,t+1}$, are estimated accordingly.

As conditional information is defined two periods earlier, the error term $\varepsilon_{t+1} = \{\varepsilon_{i,t+1}, \varepsilon_{C,t+1}, \varepsilon_{E,t+1}, \varepsilon_{W,t+1}\}$ has potentially a moving average MA(1) structure. It may also be non-linearly dependent both in the time series (due to heteroskedasticity) and in the cross-section (due to tail dependence). To deal with heteroskedasticity, we assume a univariate asymmetric GARCH model (Glosten et al., 1993), where, as before, the volatility is conditional on the information set at date $t-1$:

$$\varepsilon_{k,t+1} = \sigma_{k,t+1}\ (z_{k,t+1} + \theta_k\ z_{k,t}), \tag{13}$$

where θ_k denotes the MA(1) parameter and

$$\sigma^2_{k,t+1} = \omega_k + \alpha_k \varepsilon^2_{k,t-1} + \beta_k \sigma^2_{k,t} + \gamma_k \varepsilon^2_{k,t-1} 1_{(\varepsilon_{k,t-1} \leq 0)}, \tag{14}$$

for $k \in \{i, C, E, W\}$. The innovation process $z_{t+1} = \{z_{i,t+1}, z_{C,t+1}, z_{E,t+1}, z_{W,t+1}\}$ is such that $E[z_{k,t+1}] = 0$, $V[z_{k,t+1}] = 1/(1+\theta_k^2)$, and $Cov[z_{k,t+1}, z_{l,t+1}] = 0$, for $k \neq l$. As innovations z_{t+1} have been preliminarily orthogonalized, they are not correlated across series. However, they cannot a priori be assumed to be independent from each other.[7] As systemic risk measures are based on marginal expected shortfall (Equation (3)), they rely on the dependence structure of the innovations. Therefore, we adopt a joint distribution for z_{t+1} that is able to capture the possible non-linear dependencies across innovation processes. A convenient approach is to use a copula.[8] First, the marginal distributions are assumed to be univariate skewed t distributions, $z_{k,t+1} \sim f(z_{k,t+1}; \nu_k, \lambda_k)$, where f denotes the pdf of the skewed t distribution, with ν_k

[7] The Dynamic Conditional Beta model is likely to capture more than the mere linear dependence between the variables. It is not clear, however, how much of the non-linear dependence is left in the innovation process. This is the reason why we do not assume a priori that the innovations are independent from each other.

[8] Alternatively, the expected shortfall could be estimated using a nonparametric tail expectation estimator, as in Scaillet (2005) or Brownlees and Engle (2012).

the degree of freedom and λ_k the asymmetry parameter (see Jondeau and Rockinger, 2003). We define $u_{t+1} = \{u_{i,t+1}, u_{C,t+1}, u_{E,t+1}, u_{W,t+1}\}$ as the value of the marginal distribution evaluated at the observed z_{t+1}. Thus $u_{k,t+1} = F(z_{k,t+1}; \nu_k, \lambda_k)$, where F is the cdf of the skewed t distribution $f(z_{k,t+1}; \nu_k, \lambda_k)$. Then, the copula defines the dependence structure of u_{t+1}, denoted by $C(u_{t+1})$. After investigating several alternative copulas, we eventually selected the t copula, which has been found to capture the dependence structure of the data very well. It accommodates tail dependence and its elliptical structure provides a convenient way to deal with large-dimensional systems. The cumulative distribution function (cdf) of the t copula is defined as:

$$C_{\Gamma,\bar{\nu}}(u_{i,t+1}, ..., u_{W,t+1}) = t_{\Gamma,\bar{\nu}}(t_{\bar{\nu}}^{-1}(u_{i,t+1}), ..., t_{\bar{\nu}}^{-1}(u_{W,t+1})), \tag{15}$$

where $t_{\bar{\nu}}$ is the cdf of the univariate t distribution with degree of freedom $\bar{\nu}$ and $t_{\Gamma,\bar{\nu}}$ is the cdf of the multivariate t distribution with correlation matrix Γ and degree of freedom $\bar{\nu}$.

To summarize, our model combines a DCC model for the dynamic of the beta parameters, univariate GARCH models for the dynamic of the volatility of the error terms, and a t copula for the dependence structure between the innovations. To deal with the possible time variability of (some of) the model parameters, we estimate the model over a rolling window of ten years of data, moving forward as soon as a new observation is made available.

The estimation strategy is worth describing. Although we have a large number of models to estimate (one for each of the 196 financial institutions), the component that corresponds to the interaction between the European and world markets is common to all models. Therefore, we perform the estimation recursively as follows. We begin with the estimation of the dynamic of European and world markets, i.e., the model for $(r_{E,t+1}, r_{W,t+1})$. We estimate the DCC model for these series and the corresponding time-varying beta parameters. We also estimate the univariate GARCH processes for their error terms $(\varepsilon_{E,t+1}, \varepsilon_{W,t+1})$ and the parameters of the t copula. We call this model the *International model*. Next, we introduce the stock market return, $r_{C,t+1}$, for a given country (say, Austria) and estimate the parameters that correspond to this series, taking as given the parameters of the European and world market returns (*Country model*). Finally, for all of the Austrian financial institutions, we introduce the firm i return, $r_{i,t+1}$, and estimate the parameters corresponding to this series, taking as given the parameters of the Austrian, European, and world market returns (*Firm model*).

This approach has three advantages. First, it is coherent with the recursive structure of the model, assuming that the recursive model captures all the interconnections between the firms in a given country. Second, it ensures that the dynamics of the European and world market returns are the same for all sub-models. Third, it allows for a relatively fast estimation of the complete model and LRMES.

2.3 Measuring Long-run Marginal Expected Shortfall

We now turn to the estimation of the long-run MES ($LRMES_{i,t:t+T}$). Brownlees and Engle (2012) advocated for two complementary approaches to estimate the LRMES. The first approach consists of estimating the LRMES directly as the expected return of the firm in case of a 40% semiannual decline in the market return. In the second approach, the LRMES is based on the expected return of the firm in case of a (relatively modest) 2% decline in the daily market return, which is then extrapolated to match a "once-per-decade" crisis. For this study, we implemented both approaches and found that they provide similar systemic risk measures. To save space, we describe the methodology and report the results of the first approach only.

Directly estimating the LRMES relies on the simulation of the model over T periods using all information available at date t. As for the estimation strategy, our simulation strategy takes advantage of the recursive structure of the model. We start by simulating the International model over T periods (125 daily observations, for a six-month period). To this end, we draw a sample s of $(u_{E,\tau}^{(s)}, u_{W,\tau}^{(s)})_{\tau=t+1,\cdots,t+T}$ from the t copula and then deduce the innovation terms $(z^{(s)}_{E,\tau}, z^{(s)}_{W,\tau})$ from the skewed t distribution. Using the GARCH estimates of the volatility, we compute the errors terms $(\varepsilon^{(s)}_{E,\tau}, \varepsilon^{(s)}_{W,\tau})$. We then estimate the dynamic betas, which depend on the correlation matrix and therefore on $\varepsilon^{(s)}_{\tau}$. Eventually, we recover a six-month time series of European and world market returns, $(r^{(s)}_{E,\tau}, r^{(s)}_{W,\tau})$. The cumulative returns at $t+T$ tell us whether a crash occurred in the European market, in the world market, or in both over this simulated sample s (if the European or world cumulative return is below -40%). If we do not have a crash, we simulate a new series. If we do have a crash, then we move to the Country model. We simulate the $u^{(s)}_{C,\tau}$ from the t copula (using the same chi-square in the simulation of the t random variable to keep the same dependence structure between the three shocks $u^{(s)}_{C,\tau}$, $u^{(s)}_{E,\tau}$, and $u^{(s)}_{W,\tau}$) and proceed as before to obtain the country market return. Finally, we move to the Firm model and simulate firm returns using the same methodology.

It is worth emphasizing that the recursive structure is critical in the simulation step to obtain systemic risk measures in a decent amount of time. To obtain an accurate estimate of the marginal expected shortfall of the firm return conditionally on a market crash, many draws of the International model are required to simulate a sufficient number of crashes.[9]

Eventually, the LRMES of firm i conditional on a world shock is estimated by:

$$LRMES^{(W)}_{i,t:t+T} = \frac{-1}{\sum_{s=1}^{S} \mathcal{I}(R^{(s)}_{W,t:t+T} \leq -40\%)} \sum_{s=1}^{S} R^{(s)}_{i,t:t+T} \times \mathcal{I}(R^{(s)}_{W,t:t+T} \leq -40\%), \quad (16)$$

where $\mathcal{I}(x) = 1$ if x is true and 0 otherwise. This approach provides very accurate estimates of the true expectation when the number of simulated data is sufficiently large. In our empirical work, we use $S = 50,000$ draws. We eventually deduce the SRISK of firm i as the positive value of the capital shortfall conditional on a world or European

[9]If we had to simulate the complete model for all the firms simultaneously, the computation burden would be too heavy to estimate systemic risk measures. To give an order of magnitude of the computation burden, estimating the systemic risk for all firms for one date takes approximately one hour for the model estimation and the simulation steps, whereas it would take several days if we had to estimate and simulate the complete model for all of the firms simultaneously.

crisis as:

$$CS^{(W)}_{i,t:t+T} = \left\{\theta(L_{i,t} - 1) - (1 - \theta)(1 - LRMES^{(W)}_{i,t:t+T})\right\} W_{i,t}. \tag{17}$$

We proceed in a similar way for a European shock to obtain $LRMES^{(E)}_{i,t:t+T}$ and $CS^{(E)}_{i,t:t+T}$ and for a domestic shock to obtain $LRMES^{(C)}_{i,t:t+T}$ and $CS^{(C)}_{i,t:t+T}$.[10]

3 European Data

3.1 Data

Our sample is the set of large financial institutions in Europe. We include all firms with a minimum market capitalization of one billion euros (as of end of 2011) and a price series that started before January 2000. The entire sample starts in January 1990 (when available) and ends in August 2012. The data set includes daily data (stock returns and market capitalizations, from Datastream) and quarterly data (book value of the assets and equity, from Compustat). For stock market indices, we proceed as follows. For world and Europe, we take MSCI indices. For countries, we take the domestic benchmarks. All series are converted into euros.

In our sample, there are 72 banks, 36 insurance companies, 53 financial-services firms, and 35 real-estate firms. There are 45 financial firms in the U.K., 22 in France, 21 in Switzerland, 18 in Sweden, and 14 in Germany. The largest market capitalizations at the end of August 2012 are HSBC Holdings (126.2 billion euros), Banco Santander (56 billion), and Sberbank (49.4 billion). The largest insurance company is Allianz (39.6 billion), the largest financial-services firm is ING (23.3 billion), and the largest real-estate

[10] It should be mentioned that, for a domestic crisis, we may account for the differences in the volatility of the market returns across countries. In fact, a semiannual 40% crash would be perceived as much more severe in Switzerland than in Hungary because the annual market volatilities for these countries were 17% and 32%, respectively, over the last ten years. To avoid this problem, we may use a shock of 1.6 times the annualized volatility of the domestic market return over the last ten years, which corresponds to a semiannual 40% shock on average. A shock of 1.6 times the annual market volatility corresponds to a market decline of 27% for the Swiss market and 52% for Hungary.

firm is Unibail-Rodamco (14.9 billion). The cumulative market capitalization for the 196 institutions is 1'448 billion euros, with a median capitalization of 2.9 billion euros.

Similar data have been already investigated, in particular for the U.S. (Billio et al., 2012, or Brownlees and Engle, 2012, among others), but very few for European firms. A motivation for considering different categories of financial institutions is that there are some specificities in their business that are likely to affect their systemic risk. As we have seen in Equation (4), a prominent determinant of expected capital shortfall is financial leverage, but also the interconnection between categories on some business lines (such as credit default swaps issued by insurance companies and bought by banks and other financial institutions). See Diebold and Yilmaz (2011) and Billio et al. (2012).

Figure 1 shows a comparison of the cumulative performances of the global European market and of the components of the financial institutions index. The European market index has experienced two drawdowns worse than 50%. The first one occurred over the period 2000-2003 with the Internet bubble burst, and the second one occurred over the period 2007-2009 with the subprime crisis. Our threshold of a 40% crash per decade is consistent with these numbers.

Financial institutions offer widely varying patterns. Banks and insurance companies were in line with the European market and outperformed the other financial groups until 2001. At that time, insurance companies experienced their most severe drawdown (79% between November 2001 and March 2003) and then underperformed the other groups. During the subprime crisis, bank stocks suffered a dramatic fall, with a drawdown of 82%. Financial-services and real-estate firms show similar dynamics, with a significant underperformance during the 1990s and catching up with the market trend just before the subprime crisis.

As **Table 1** confirms, banks and insurance companies have similar performances over the entire period (with an average annualized return of 1.9% and 2.1%, respectively). Financial-services firms slightly outperform the other categories (3.5%), while real-estate firms underperform (1.5%). Banks and insurance companies are also characterized by high volatility and a positive skewness, whereas financial-services and real-estate firms have relatively low volatility and a negative skewness. For all groups, the distribution of returns has fat tails.

One key ingredient of systemic risk measures is the firm's financial leverage, defined as the quasi-market value of a firm's assets divided by the market value of its equity. It is notable that the leverage measures of European institutions are hardly comparable with those of U.S. institutions. The reason is that the firms in the two zones are currently under two different accounting standards: Generally Accepted Accounting Principles (GAAP) in the U.S. and International Financial Reporting Standards (IFRS) in Europe. Based on the zone to which a bank belongs, derivatives are reported differently on the balance sheet. Under the U.S. GAAP, derivatives are generally reported as net rather than gross. Banks are allowed to net their derivatives transactions if they are subject to a legally enforceable Master Netting Agreement (MNA). In addition, banks are allowed to present their balance sheet on a net basis (offsetting). In contrast, under the IFRS standard, netting and offsetting are typically not possible. The ability to offset is limited even for derivatives traded with the same counterparty with an MNA. Additionally, offsetting requires that the bank intended to settle on a net basis or simultaneously, which is typically not the case.

For these reasons, the balance sheet of U.S. banks presents derivatives on a net basis, meaning that derivatives represent a negligible part of the assets, whereas the balance sheet of European banks reports derivatives on a gross basis. Because banks do not publish their balance sheet simultaneously under the two standards, it is difficult to clearly measure the effect on the resulting leverage. Some crude estimates suggest that the total assets (and therefore the leverage) of large U.S. banks (which are highly active in derivatives markets) would be 40-60% larger under IFRS than under U.S. GAAP. Although crude, these numbers partly explain why the leverage measures we report in this paper are large according to U.S. numbers. To deal with this potentially important source of bias, we use a parameter θ equal to 5.5% to be comparable with U.S,. systemic risk measures computed with $\theta = 8\%$.

Figure 2 reports the evolution of financial leverage and market capitalization by industry groups. Between 2000 and 2007, banks and insurance companies had similar, relatively low, leverage (approximately 13.5). Between 2002 and 2003, the leverage of insurance companies was even higher than that of banks. Over the more recent period, however, leverage in the banking industry rocketed to an average of 31 in August 2012, after a peak of 44 in mid-2009. During the same period, leverage increased to 20 for insurance companies. For the other two groups, leverage is moderate. There is an upward trend for financial services and the current average level is at 6.9. For real-estate firms, leverage is limited, with a maximum of 4 during the subprime crisis. It is currently only slightly over 2.

We notice that the leverage ensuring no capital shortfall is 18.2 for a capital ratio of $\theta = 5.5\%$. Financial-services and real-estate firms have leverage far below this level and consequently we do not expect large measures of systemic risk for these institutions even if the sensitivity to global shocks may be large. In contrast, banks and insurance companies are often above this threshold and therefore would exhibit capital shortfall in the event of a financial crisis even if their market capitalization were not affected by the crisis.

3.2 Model Estimation

Given the large number of firms under consideration, we do not report individual parameter estimates and associated dynamics for all the firms. Instead, we focus on results aggregated by industry groups and countries and on certain individual results for the banks (Deutsche Bank and Barclays), insurance company (AXA), and financial-services firm (ING Group) with the highest levels of systemic risk. This approach permits us to illustrate the main features common to all financial institutions and the main differences that appear between banks and insurance companies.

We start with the estimation of the model parameters based on the last ten years of data. As **Table 2** reveals, the differences between industry groups are relatively small (Panel A). The estimates of the MA(1) parameter are close to 0 and similar across industries. This component does not contribute significantly to the model, as time-varying multi-factor terms capture most of the dynamics of stock returns. The parameters driving individual variances are similar across industry groups with a volatility persistence ranging between 0.98 and 0.99. The univariate distributions have fat tails, as expected. The degree of freedom ν of the skewed-t distribution ranges from 4.3 to 5.5, reflecting large levels of kurtosis, as reported in Table 1. Finally, the dependence structure is described by a t copula with a degree of freedom $\bar{\nu}$ ranging from 16 to 18.5. This result suggests that the Dynamic Conditional Beta multi-factor model is able to capture a significant part of the dependence across the series but that the t copula is needed to capture the tail dependence remaining in the innovation processes.[11]

Figure 3 presents the dynamic of the beta parameters in the International model, i.e., between the European and world markets, and for certain Country models. The lagged world return has a relatively stable and positive effect on the world return ranging between 0 and 0.15. This effect is the result of the asynchronicity of time zones. The aggregate effect of the (current and lagged) world return on the European market is close to one, with fluctuations between 0.7 and 1.3. However, during certain periods (such as 2008-2009), the relative weight of the lagged return increases. Contemplating the betas for certain country market returns, we note significant differences across countries. For the U.K., in particular, the weight of the European market decreased during the 2011-2012 period, whereas the weight of the world market increased. We note the opposite for the French and German markets, which reflects the importance of the debt crisis in Greece for countries belonging to the euro area.

[11] We do not report the correlation matrix of the copula to save space. As expected, given that we preliminarily filtered for the time-varying linear correlation between returns (through the Dynamic Conditional Beta), the correlation matrix Γ_t is close to the identity matrix. This result suggests that the recursive multi-factor model is able to capture the high correlation between the European and world returns, and that the causal ordering we have chosen is consistent with the data.

The (time-varying) sensitivity of stock returns to their main drivers (conditional betas) is estimated via the DCC model described in Section 2.1. In the summary statistics reported in Table 2 (Panel B), we note that the main driver of a firm's return is the domestic market but that there are differences between the categories. Banks and insurance companies are more sensitive to this market (median beta of 0.93 and 0.73, respectively), whereas real-estate firms are much less sensitive (median of 0.34). The European market also plays an important role (with a sensitivity between 0.05 and 0.3). Finally, the sensitivity of firms to the (current and lagged) world return is typically positive, with a cumulative effect between 0 and 0.15. We notice that, on average, a firm's current return is more affected by the lagged world return than by the current return.

Figure 4 displays the beta dynamics for the four firms under scrutiny. As mentioned previously, the domestic market is the main driver, although its role is more pronounced for the insurance company (AXA) and financial-services firm (ING). In addition, we observe that the sensitivity to the domestic market has increased for all firms in 2008-2009 and, to a lesser extent, in 2011-2012. Comparing Deutsche Bank and Barclays illustrates that banks' return may be driven by a different combination of factors. Both banks depend primarily on the domestic market. However, the second factor is the world market for Deutsche Bank and the European market for Barclays.

4 Analysis of Systemic Risk

4.1 Systemic Risk across Industry Groups

We now turn to the measures of systemic risk. Statistics on the main components (market capitalization, leverage, and LRMES) and the systemic risk are reported in **Table 3** for the four industry groups. The dynamics of LRMES and SRISK are displayed in **Figure 5** for a world crash (solid line) and European crash (dotted line).

The LRMES estimates display different patterns across groups and over time. A 40% semiannual decline of the world market implies an average expected loss of approximately

40% for banks and insurance companies but only 27% and 13% for financial-services and real-estate firms, respectively. These numbers have varied substantially over the recent period for banks and insurance companies. The expected loss after a world shock was in the range of 27% to 30% between 2000 and 2007 but above 37% after 2008. We also observe that the LRMES of insurance companies actually increased for the first time in 2002-2003, with a higher average sensitivity to world shocks than in 2008-2009. Changes in LRMES are also significant for financial-services and real-estate firms, increasing from 25% to 31% for the former and from 11% to 17% for the latter. This increase for all industry groups reflects the fact that financial institutions have become more dependent on market trends during difficult economic times.

If we turn to the effect of a shock on the European market, we note that financial firms are generally more sensitive to European shocks than to world shocks of the same magnitude. For instance, the LRMES of banks is 31% with respect to a world shock and 37% with respect to a European shock over the entire sample. This sensitivity has also increased over the recent period from 33% (2000-2007) to 43% (2008-2012) for banks. This evolution is confirmed by Figure 5.

The systemic risk measure combines the various effects described above, including the sensitivity to world/European shocks and the fragility (measured by leverage) of financial firms. Not surprisingly, we note again that banks and insurance companies have suffered from substantial systemic risk over the entire period (on average, 403 and 110 billion euros, respectively), representing on average 77% and 22% of the total systemic risk across European financial firms, respectively. The importance of insurance companies as a potential source of systemic risk has been highlighted by Billio et al. (2012) and Diebold and Yilmaz (2011). One possible explanation is that European insurance companies are more and more involved in financial asset management, including in some cases large leverage ratios.

On the other hand the expected capital shortfalls of financial-services and real-estate firms have been barely affected by the recent financial crisis. This result can be explained by the low financial leverage used by these firms. For financial services, it increased from 2.8 before the crisis to 5.9 after. For real-estate firms, leverage remained as low as 2.5 even after the crisis. For instance, the largest European commercial real estate company, Unibail-Rodamco, had a leverage of 2 by the end of August 2012. It is therefore unlikely that the default of such firms ignites a run on the financial system. It is noteworthy that this does not imply that an economic or financial crisis cannot originate in the real estate market, as illustrated by the recent financial crisis. This mechanism has been analyzed in detail by Allen and Carletti (2013) and Crowe et al. (2011). Systemic risk in this market is mostly driven by the high leverage of the borrowers (households) and lenders (banks), much less by the financing structure of the real estate developers. More generally, the interactions between real shocks and systemic risk have been put forward by De Nicolò and Lucchetta (2010, 2012) from a macroeconomic perspective. We will investigate the effect of real shocks more deeply in Section 5.

If we consider the recent period (2008-2012), we find that the exposure of financial institutions has strongly increased compared to the 2000-2007 period: in fact, it has been multiplied by 5.8 for banks and by 2.4 for insurance companies. The total exposure of the 196 largest financial institutions in Europe has increased from an average of 217 billion euros between 2000 and 2007 to 1,018 billion euros between 2008 and 2012. At the end of the study period (August 30, 2012), the total exposure was 1,219 billion euros.[12]

If we now consider a European crisis, we find that the implied capital shortfall is slightly above the capital shortfall that would occur after a world shock of the same magnitude. Over the 2000-2007 period, the average SRISK measure for banks was 160 billion euros after a European crisis, as opposed to 142 billion euros after a world crisis. The most recent estimates (August 2012) were 1,052 and 1,011 billion euros, respectively. These numbers reveal that a European crash would have at least as severe consequences for European banks as a world crash. We observe similar patterns for insurance com-

[12]This number is slightly larger than, but comparable to, the 705 billion dollars reported for U.S. financial firms with $\theta = 8\%$ for the same date on the VLab website at Stern School of Business (http://vlab.stern.nyu.edu/welcome/risk). The total systemic risk of European firms would be 2,000, 1,219, and 446 for θ decreasing from 8% to 5.5% and 3%.

panies. The relatively thin difference between the world and European SRISK can be explained by the large correlation between the two types of shocks under consideration.

4.2 Systemic Risk across Countries

In **Table 4**, we report the average leverage, LRMES, and systemic risk measures for the eight riskiest countries. The leverage presents significantly large differences across countries because countries do not have the same proportion of banks and insurance companies and because there are great differences in terms of leverage across countries within the same industry group. Over the entire sample, Germany and France share higher leverage, whereas Spain, Sweden, and the U.K. have relatively low leverage levels (see **Figures 6 to 8**). As of August 2012, the average leverage is as high as 39 for France, and 36 for Italy and Germany, whereas it is only 15 for Sweden and 21.5 for Switzerland and Spain.

The LRMES measures are noteworthy across countries over the recent period. The 2008-2012 period has been characterized by a sharp increase in LRMES with respect to the world crisis. The largest values are obtained for the Netherlands and U.K. (44% and 40%, respectively). These numbers have decreased over the recent period for the non-euro countries (the U.K. and Switzerland) but increased for the more fragile countries of the euro area (from 37% to 44% for Spain and from 31% to 36% for Italy).

Another important characteristic of the SRISK measure is its relation to market capitalization. SRISK measures the fraction of the capital requirement that is not covered by the current market capitalization. Thus, it may be below or above the current market capitalization depending on the severity of the firm's situation. As Table 4 reveals, over the 2000-2007 period, SRISK was well below the market capitalization for most countries, with a maximum of 43% of the market capitalization for Germany. By the end of August 2012, the situation had dramatically changed because SRISK has rocketed while the market capitalization has plummeted. At present, SRISK represents a minimum of 31% of the market capitalization for Sweden and a maximum of 175% for France. This result clearly illustrates that market capitalization is only a crude measure of systemic risk, which may be severely underestimated in bad times. Another financial crisis would imply a significant cost for the taxpayer in case of a rescue by the government that would greatly exceed the current market capitalization of the rescued firms.

All in all, over the last decade, the country with the highest systemic risk is France (135 billion euros on average), followed by the U.K. (111 billion) and Germany (102 billion). Although British firms have relatively low leverage, they have high LRMES and large market capitalization. During the recent crisis, the leverage and LRMES increased in all countries, so the systemic risk has also dramatically increased. Between 2008 and 2012, France ranked first (282 billion) in terms of overall systemic risk, followed by the U.K. (249 billion) and Germany (156 billion). As of the end of August 2012, the systemic risk estimates are as high as 333 and 304 billion euros for France and the U.K., together contributing approximately 52% of the total exposure of European financial firms.

4.3 Ranking of Financial Institutions

The next step of our study of systemic risk is ranking European financial firms. **Table 5** shows the ranking for the last day of our sample, August 30, 2012.[13] It shows the ranking for the banks and for the insurance companies separately. On that day, the five riskiest institutions were Deutsche Bank (106 billion euros), Crédit Agricole (94 billion euros), Barclays (93 billion euros), Royal Bank of Scotland (83 billion euros), and BNP Paribas (81 billion euros).

The comparison between BNP Paribas and Crédit Agricole clearly shows that systemic risk may have different sources. BNP has relatively large market capitalization and relatively low leverage (43 billion euros and 44, respectively). In contrast, Crédit Agricole has a relatively large leverage level and relatively small market capitalization (88 and 22

[13]For some cooperative banking groups (Crédit Agricole and BPCE), SRISK measures are computed at the group level, whereas only the main bank (Crédit Agricole S.A. and Natixis, respectively) are listed. To do this, we assume the same book-to-market ratio at the bank level and at the group level. Details on this approach are provided on the CRML website.

billion euros, respectively). We also notice that the two banks with the largest market capitalization (HSBC and Banco Santander) are only ranked 15th and 12th. The reason for this relatively low ranking is that they both have very low leverage and low LRMES compared to other major banks.

There are 8 insurance companies, which are in the second half of our ranking. The riskiest companies are AXA (16th, 26 billion euros) and Legal & General (19th, 17 billion euros). The former firm has high LRMES and relatively large market capitalization, whereas the latter has a high leverage, comparable to large banks.

4.4 Comparison with Other Measures

In order to investigate the sensitivity of our measure of systemic risk to the modeling assumptions, we consider alternative measures of capital shortfall, which are less affected by these assumptions. We first define two measures of "unstressed capital shortfall", based on book equity and market capitalization, respectively:

$$\begin{aligned} UCS_1 &= \max(0, (\theta BA - BW)), \\ UCS_2 &= \max(0, (\theta A - W)), \end{aligned}$$

which we compare to our measure of "stressed capital shortfall", $SRISK$, defined in Equation (5). UCS_1 and UCS_2 measure the lack of equity capital corresponding to the leverage being larger than $1/\theta$, when equity capital is defined as the book equity and market capitalization of the institution, respectively. These measures do not rely on our econometric model used to estimate $LRMES$. We note that, if the book and market values of equity coincide, then $UCS_1 = UCS_2$, and if $LRMES = 0$ (no stress), then $UCS_2 = SRISK$. For comparability purposes, we take the same value $\theta = 5.5\%$ for all three measures.

Table 6 reports, for the same financial institutions as Table 5, the three measures of capital shortfall. All institutions are sorted by decreasing SRISK. We first notice that the level of unstressed capital shortfall is significantly smaller than the level of stressed capital shortfall: the aggregated capital shortfalls for all these institutions are $UCS_1 = 361$ billion euros and $UCS_2 = 799$ billion euros for the unstressed measures, and $SRISK = 1,072$ billion euros for the stressed capital shortfall. The comparison of the last two numbers clearly shows the effect of a stressed period on the expected capital shortfall.

Although the levels of capital shortfall obtained with the three approaches are rather different, it is interesting to analyze how much correlated they are. If we start with the direct correlation of these measures, we find that the correlations of UCS_1 and UCS_2 with $SRISK$ are 85% and 98%, respectively. If we adjust for the level effect and consider rank correlations, we still find high values, 73% and 93%, respectively. These correlations clearly indicate that the estimate of $LRMES$ does not strongly alter the ranking of the institutions, although it allows to account for stressed situations. Similarly, the use of book equity instead of market capitalization would barely change the ranking of the institutions.

We also compare our ranking of systemically risky financial institutions with the list of G-SIFIs provided by regulators. In the aftermath of the financial crisis, the Basel Committee on Banking Supervision (2011) has proposed a methodology to identify G-SIFIs. This indicator-based measurement approach relies on five criteria reflecting different dimensions of systemic risk: size, interconnectedness, availability of substitutes, cross-jurisdictional activity and complexity. Each category receives an equal weight of 20%. The Financial Stability Board (FSB, 2011) has adopted this methodology to identify a first list of global systemically important banks (G-SIBs) in November 2011. The first list had 29 banks, including 18 European banks. From this pool, 16 are listed among the 17 riskiest banks in our ranking (identified with a star in Table 5). The only bank in FSB list not listed in our ranking is Dexia because it has been bailed out several times since 2008 and should be viewed as partly nationalized. Since 2011, the list published by the FSB is updated every November. In 2012 list, two banks have been added (Banco Bilbao and Standard Chartered, ranked 19 and 24 in our ranking, respectively), whereas three banks have been removed (Dexia, because of its resolution process, and Commerzbank and Lloyds Banking, because of their reduced systemic importance). In 2013, the FSB list of European banks has not been changed.

More recently, in 2013, the International Association of Insurance Supervisors (IAIS) has published a methodology to identify global systemically important insurers (G-SIIs) (IAIS, 2013). Based on this methodology, the FSB has published a first list of G-SII using data as of end 2011 (FSB, 2013). This list has 9 insurance companies, including 5 European companies. All of them are listed in the 8 companies of our ranking (identified with two stars in Table 5). We notice that Legal & General, Aegon, and CNP are not included in the FSB list, but are ranked 2, 3, and 5 according to our measures. The IAIS methodology relies on the value of total assets to measure size. For these three companies, the value of assets is indeed smaller than that of the other listed companies. However, their leverage is significantly larger than the leverage of the other companies (as high as 43, 43, and 52, respectively). This explains why these companies appear in our list.

4.5 Fragility of the European Financial System

Estimates of the SRISK measures discussed above have two important implications. First, the European financial system is significantly more fragile than the U.S. system because of the size of the total capital shortfall in case of a new (world or European) financial crisis. Second, and perhaps more importantly, the SRISK of large European financial institutions is large compared to the size of the countries. This issue is related to the notion of domestic systemically important financial institutions (D-SIFIs). Following the definition adopted by the Basel Committee on Banking Supervision (2012) for banks, we define D-SIFIs as financial institutions whose failure may have systemic implications on the domestic economy. D-SIFIs are typically firms whose SRISK will be very high in comparison to the GDP.

Table 7 reports the ranking of D-SIFIs, sorted by decreasing ratios of SRISK to nominal GDP (as of August 30, 2012). As before, the shock corresponds to a 40%

semiannual decline of the world market return. This ranking allows us to identify some firms that may not be too risky at the European level (because their size is limited) but that are very risky at the domestic level. Not surprisingly, the riskiest banks are based in relatively small countries. The SRISK of the five riskiest firms represents more than 5% of the GDP (ING Group in the Netherlands, UBS and Credit Suisse in Switzerland, Danske Bank in Denmark, and Nordea Bank in Sweden). These institutions are in the second tier of the G-SIFIs ranking (between 7th and 18th). Rescuing these banks would have a huge cost for taxpayers. In addition to being too big to fail, these banks are also "too big to be saved".

In the second group of banks with large SRISK, as calculated as a percentage of GDP, we find some of the largest European banks that are also in the top five for systemic risk in banks (Barclays, Crédit Agricole, Royal Bank of Scotland, Deutsche Bank, and BNP Paribas). Their expected capital shortfall in case of a domestic crash represents approximately 4-5% of the domestic GDP. Bank of Ireland, which has already been bailed out during the Irish banking crisis, still has a very low market capitalization and is highly undercapitalized. Finally, some relatively smaller institutions (such as KBC Group in Belgium, DNB in Norway, SEB in Sweden, or the National Bank of Greece) have a capital shortfall of 1.5-3% of the GDP.

As the table also clearly demonstrates, certain countries have several financial institutions that are considered D-SIFIs. This finding clearly raises the issue of the capability of the domestic authorities to rescue two or more firms at the same time. In **Table 8**, we report the market capitalization and SRISK of the firms with the highest levels of systemic risk in proportion to the GDP of the country where they are located. Beginning with the U.S., the capital shortfall of the four riskiest banks (Bank of America, JP Morgan Chase, Citigroup, and MetLife) is 2.7% of the U.S. GDP (with $\theta = 8\%$). In Europe, the capital shortfall of the four riskiest banks (Deutsche Bank, Crédit Agricole, Barclays, and Royal Bank of Scotland) is 3.7% of the European GDP. These numbers are similar. However, the SRISK of the four riskiest U.S. banks only slightly exceeds their market capitalization (116%), whereas it is much larger (445%) for the four riskiest European banks. This observation confirms that the under-capitalization of banks in Europe is more severe than in the U.S.

If we now consider the importance of large institutions relative to the size of their respective countries, we obtain an even more worrisome picture. The capital shortfall of the four riskiest French banks (Crédit Agricole, BNP Paribas, Société Générale, and BPCE) represents 14% of French GDP, while the capital shortfall of the four riskiest British banks (Barclays, Royal Bank of Scotland, Lloyds Banking, and HSBC) represents 13% of U.K. GDP. UBS and Credit Suisse alone have a total capital shortfall equal to 16% of the Swiss GDP. For other countries, such as the Netherlands and Sweden, the capital shortfall of the riskiest banks amounts to 8-12% of nominal GDP. We note that the two or four riskiest banks account for at least 80% of the total capital shortfall that European countries would suffer in case of a new 40% world market decline. In other words, the government might be unable to bail out such banks in the event of a new market crash.

5 Evaluating SRISK

As a final step of our analysis, we investigate some properties of the SRISK measures. First, we investigate the interaction between macroeconomic activity and systemic risk. Then we attempt to identify its determinants using financial explanatory variables.

5.1 SRISK and the Macroeconomy

Following the approach described by Brownlees and Engle (2012), we estimate the interactions between the aggregate SRISK and a set of macroeconomic variables, available at monthly frequency, including industrial production, unemployment rate, producer and consumer prices, consumer and business confidence indices, and trade balance. We estimate the following VAR model for the annual change in the various variables:

$y_t = \mu + \sum_{i=1}^{p} A_i \, y_{t-i} + \varepsilon_t$. More specifically, we estimate a VAR(1) model for SRISK and the four macro variables: the annual change in industrial production, in producer price, in unemployment rate, and in business confidence index.[14]

Table 9 reports for the eight countries with the highest domestic aggregate SRISK the t-stat of the VAR model, which correspond to the Granger causality test statistic. For six out of the eight countries, SRISK Granger-causes industrial production and business confidence index at all standard significance levels. For four countries, SRISK also Granger-causes producer inflation and unemployment rate. All the t-stat have the expected sign. The relation could reflect a real effect of frictions on the credit market when banks are in capital shortage, as proposed by Laeven and Valencia (2013). From this perspective, aggregate SRISK provides an early warning signal of distress in the real economy.

For most countries, we find some feedback effects from macro variables to SRISK. A similar finding was already underscored by De Nicolò and Lucchetta (2010 and 2012) in their international analysis. In particular, producer inflation has a positive feedback effect on SRISK in four countries. The other effects are less pronounced and sometimes inconsistent with the expectation.

5.2 Financial Determinants of SRISK

In order to identify financial determinants of SRISK, we consider the following potential candidates, most of them already explored in Brownlees and Engle (2012) for U.S. firms: the 3-month interbank rate, the stock market index, the stock-market volatility index, and the aggregate bank lending. All these variables (except the volatility index) are defined in annual changes.[15]

[14]The other variables did not add any information about SRISK. The consumer confidence index was found to have the same effect as the business confidence index and the consumer price the same effect as the producer price. Including more lags did not change the main results of the table. We also estimated the model with quarterly data, such as real GDP, GDP deflator, and current account. We found in this quarterly model that SRISK has high explanatory power for real GDP and unemployment rate.

[15]We also investigated the role of the 10-year government bond rate and corporate spread, but did not find any effect of these variables.

Table 10 reports the t-stat of the VAR(1) model. We find that changes in the 3-month rate play a determinant role for European SRISK measures. For all countries but Switzerland, the coefficient is significantly positive, consistent with the fact that an increase of the 3-month interbank rate implies a decrease in the value of the bonds held by the firms and therefore in the value of their assets. It also implies an increase in the financing cost of the financial institutions. Aggregate bank lending is found to play a significant role for SRISK measures in the U.K. and Netherlands. For both variables, we observe some feedback effect: the increase in SRISK is in general followed by a decrease in bank lending, which is consistent with the drying of credit markets after the financial crisis. A rise in SRISK is also followed by a decrease in the short-term rate, which we can interpret as a monetary policy easing after the crisis to stimulate credit markets.

In general, stock market return and volatility do not affect SRISK measures significantly. Although the coefficients are almost always negative for stock market return and positive for volatility, they are never significantly different from 0.[16]

6 Conclusion

In this paper, we investigate the systemic risk borne by European financial institutions over the recent period. For this purpose, we extend the approach developed by Brownlees and Engle (2012) for U.S. institutions. Our extension consists of an econometric approach designed to measure systemic risk of non-U.S. institutions, with the two following characteristics. First, there are several potential factors driving the dynamic of European financial institutions' returns. Second, the world return is likely to affect European firms' return instantaneously or with a one-day lag, due to the asynchronicity of the time zones. Our model combines a DCC model to estimate the dynamic of the beta parameters, univariate GARCH models to estimate the dynamic of the volatility of the

[16]This result contrasts with the evidence reported for U.S. firms by Brownlees and Engle (2012), who find a highly significant effect of the CBOE volatility index (VIX) on the aggregate SRISK. Our empirical evidence is robust to the definition of the volatility (in level or in difference) and to the use of the Euro STOXX 50 volatility index (VSTOXX) or VIX.

error terms, and a t copula to estimate the dynamic of the dependence structure between the innovations.

We apply this methodology to the 196 largest European financial institutions and estimate their systemic risk over the 2000-2012 period. Our main finding is that the global exposure of these firms was 1,219 billion euros at the end of the study period (August 30, 2012). Even after correcting for differences in accounting standards, the total systemic risk borne by European institutions is much larger than the one borne by U.S. institutions. For certain countries, the cost for the taxpayer to rescue the riskiest domestic banks is so high that some banks might be considered "too big to be saved", such as UBS and Credit Suisse in Switzerland, ING Group in the Netherlands, Danske Bank in Denmark, or Nordea Bank in Sweden.

The European Banking Union will start in 2014. At the end of that year, the European Central Bank (ECB) will be the single supervisor of the largest banks of the Eurozone. Given the uncertainty about the quality of bank's balance sheets, the ECB has undertaken an Asset Quality Review (AQR) and stress tests to evaluate the potential capital shortfall of large banks, including domestic systemically important banks. The AQR and stress tests are relatively expensive and time consuming processes, which require a lot of inputs from banks. Our methodology can be viewed as a preview of what the AQR will find. Furthermore, it will show how bank conditions have changed over time and can serve as a monitoring system as the Eurozone banking system evolves.

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Table 1: Summary statistics on returns by industry group

(in % per year)	World	Europe	Banks	Insurance companies	Financial services	Real estate
Ann. return	3.59	4.16	1.93	2.10	3.47	1.72
Ann. volatility	16.12	18.33	22.35	22.57	14.35	12.85
Skewness	-0.07	-0.04	0.27	0.11	-0.32	-0.41
Kurtosis	7.58	8.89	13.55	10.98	10.55	9.39
Max drawdown	-65.24	-61.72	-82.04	-79.05	-67.49	-77.65
5%-VaR (left)	-1.63	-1.82	-2.17	-2.17	-1.42	-1.25
5%-ES (left)	-2.40	-2.77	-3.44	-3.49	-2.24	-2.04
5%-VaR (right)	1.58	1.73	2.07	2.10	1.32	1.13
5%-ES (right)	2.32	2.63	3.35	3.39	1.99	1.82

This table provides summary statistics on the index return of European financial firms for the period from January 1990 until August 2012 (in euros). For each category, we report the average annualized return, annualized volatility, skewness, kurtosis, maximum draw down, 5% VaR and expected shortfall (ES) for the left and right sides of the distribution.

Table 2: Summary statistics on parameter estimates

	Banks	Insurance companies	Financial services	Real estate
Panel A: Parameter estimates (median)				
MA(1) term				
θ	-0.011	-0.049	-0.030	-0.024
Volatility dynamics				
ω	0.030	0.029	0.019	0.034
α	0.084	0.058	0.056	0.090
γ	0.023	0.005	0.017	0.026
β	0.895	0.929	0.920	0.911
Skewed t distribution				
ν	4.602	4.666	5.478	4.398
λ	0.049	0.041	0.019	0.014
Copula degree of freedom				
$\bar{\nu}$	16.061	16.485	16.862	18.435
Panel B: Conditional betas (median of means)				
$\beta_{i,t}^{C}$	0.930	0.734	0.625	0.337
$\beta_{i,t}^{E}$	0.051	0.299	0.258	0.189
$\beta_{i,t}^{W}$	-0.027	-0.006	0.027	0.032
$\beta_{i,t}^{L}$	0.027	0.111	0.123	0.113

This table provides summary statistics on parameter estimates and dynamics for all of the industry groups. Panel A reports the median of the parameter estimates across the institutions. Panel B reports the median of the average conditional beta parameters estimated in the cross-section of firms. The estimates correspond to the model estimated over the last ten years.

Table 3: Systemic risk and its components by industry group

	Banks	Insurance companies	Financial services	Real estate
Panel A: Entire sample				
Market capitalization	923.7	399.2	138.2	66.8
Leverage	18.8	16.2	4.0	2.2
LRMES wrt World	31.1	32.6	27.5	13.5
LRMES wrt Europe	36.7	38.5	32.0	15.9
SRISK wrt World	398.9	110.4	6.3	0.0
SRISK wrt Europe	425.2	122.1	6.5	0.0
Panel B: 2000-2007 period				
Market capitalization	913.6	446.4	133.2	58.0
Leverage	13.3	13.8	2.8	2.1
LRMES wrt World	27.5	29.9	25.2	11.1
LRMES wrt Europe	32.9	35.9	29.9	13.5
SRISK wrt World	142.5	71.8	3.1	0.0
SRISK wrt Europe	160.1	83.3	3.1	0.0
Panel C: 2008-2012 period				
Market capitalization	940.7	319.8	146.6	81.7
Leverage	28.0	20.3	5.9	2.5
LRMES wrt World	37.3	37.2	31.4	17.3
LRMES wrt Europe	42.9	42.7	35.6	19.9
SRISK wrt World	830.8	175.4	11.6	0.0
SRISK wrt Europe	871.9	187.6	12.2	0.0
Panel D: As of August 2012				
Market capitalization	873.1	320.2	156.2	93.6
Leverage	31.4	20.2	6.9	2.2
LRMES wrt World	37.6	39.0	32.4	21.6
LRMES wrt Europe	43.5	45.3	36.7	24.9
SRISK wrt World	1011.0	186.7	21.3	0.0
SRISK wrt Europe	1052.3	200.7	22.0	0.0

This table reports for all of the industry groups the median across firms of the mean over time of the market capitalization, leverage ($L_{i,t} = A_{i,t}/W_{i,t}$), the LRMES and the systemic risk measures (with respect to world and European shocks). LRMES is in % and systemic risk in billion euros. The mean is computed over the entire sample period, over the two subperiods 2000-07 and 2008-12, and for the last date of the sample.

Table 4: Systemic risk and its components by country

	France	U.K.	Germany	Italy	Switz.	Netherl.	Spain	Sweden
Panel A: Entire sample								
Market capitalization	197.1	379.1	152.4	124.5	174.3	93.9	133.5	77.3
Leverage	23.1	14.2	25.3	16.0	15.6	17.6	11.5	13.3
LRMES wrt World	32.1	33.5	31.2	25.1	30.2	37.2	30.4	30.2
LRMES wrt Europe	37.2	39.1	36.6	29.8	35.8	43.5	36.6	35.3
SRISK wrt World	135.0	110.9	101.9	28.8	42.0	37.8	14.2	15.2
SRISK wrt Europe	143.3	118.7	107.0	30.9	47.0	40.8	17.0	17.2
Panel B: 2000-2007 period								
Market capitalization	181.1	389.5	164.8	129.8	194.0	113.3	133.2	72.9
Leverage	16.1	9.3	20.3	10.5	13.3	11.9	8.3	11.3
LRMES wrt World	27.8	29.8	29.7	21.6	27.1	33.1	26.6	27.2
LRMES wrt Europe	33.7	35.5	35.8	26.0	32.9	39.4	32.6	31.9
SRISK wrt World	48.0	28.9	70.1	4.9	25.6	20.0	0.0	5.1
SRISK wrt Europe	55.0	33.0	75.6	5.5	30.7	23.2	0.3	6.4
Panel C: 2008-2012 period								
Market capitalization	224.0	361.7	131.4	115.6	141.2	61.3	134.0	84.1
Leverage	33.2	22.3	33.9	25.4	19.5	27.3	16.9	16.3
LRMES wrt World	37.2	39.8	33.6	31.1	35.5	44.2	36.8	35.1
LRMES wrt Europe	43.3	45.2	38.1	36.1	40.8	50.4	43.3	40.7
SRISK wrt World	281.6	249.1	155.6	69.0	69.6	67.8	38.0	31.2
SRISK wrt Europe	292.1	263.0	159.9	73.6	74.6	70.5	45.0	34.3
Panel D: As of August 2012								
Market capitalization	190.0	396.2	129.0	74.1	131.8	59.4	110.2	107.9
Leverage	39.3	23.3	36.0	36.4	21.5	26.6	21.6	14.7
LRMES wrt World	38.6	37.6	33.4	35.9	32.5	44.7	44.1	35.9
LRMES wrt Europe	45.7	42.6	38.9	41.9	37.1	51.6	52.3	41.3
SRISK wrt World	333.4	303.8	172.3	100.1	82.7	70.2	69.5	33.7
SRISK wrt Europe	343.8	319.4	177.7	104.2	85.8	73.3	77.6	37.7

This table reports for some countries the median across firms of the mean over time of the market capitalization, leverage ($L_{i,t} = A_{i,t}/W_{i,t}$), the LRMES and the systemic risk measures (with respect to world and European shocks). Reported countries are those with a systemic risk larger than 30 billion euros at the end of the period. LRMES is in % and systemic risk in billion euros. The mean is computed over the entire sample period, over the two subperiods 2000-07 and 2008-12, and for the last date of the sample.

Table 5: Ranking of G-SIFIs (as of August 30, 2012)

Rk	Institution	Country	World shock SRISK (bln eur)	World shock LRMES (%)	European shock SRISK (bln eur)	European shock LRMES (%)	Leverage	Market cap. (bln eur)
Banking groups								
1	Deutsche Bank (*)	Germany	106.4	43.4	108.2	50.6	84.8	26.1
2	Crédit Agricole (*)	France	93.7	47.0	95.0	53.1	87.9	21.9
3	Barclays (*)	U.K	92.5	48.2	94.2	54.4	69.4	28.3
4	RBS (*)	U.K	82.9	39.7	83.9	46.0	96.8	17.6
5	BNP Paribas (*)	France	81.1	46.1	84.9	55.5	44.3	43.3
6	Société Générale (*)	France	57.9	50.3	59.1	58.3	73.6	16.4
7	ING Group (*)	Netherl.	55.5	56.9	57.8	67.6	51.7	23.3
8	BPCE Group (*)	France	49.9	38.6	50.6	42.7	58.3	19.4
9	Lloyds Banking (*)	U.K	43.4	33.5	44.6	38.0	39.1	29.5
10	UBS (*)	Switz.	42.9	40.8	44.6	46.2	34.0	34.1
11	UniCredit (*)	Italy	38.5	39.9	39.4	45.0	49.8	18.2
12	Banco Santander (*)	Spain	36.9	46.4	42.1	56.3	22.2	56.0
13	Credit Suisse (*)	Switz.	33.6	36.7	34.5	41.8	42.0	20.3
14	Commerzbank (*)	Germany	31.1	37.2	31.5	42.8	88.9	7.3
15	HSBC (*)	U.K	26.6	31.8	32.4	36.7	16.5	126.2
16	Intesa Sanpaolo	Italy	22.2	39.3	23.6	46.9	32.3	19.4
17	Nordea Bank (*)	Sweden	20.7	40.6	22.6	47.3	23.9	29.7
18	Danske Bank	Denmark	15.9	28.6	16.2	31.1	35.7	12.9
19	Banco Bilbao	Spain	15.7	49.0	18.2	57.1	18.5	32.7
20	KBC Group	Belgium	11.4	43.4	11.8	51.2	44.1	6.2
Insurance groups								
1	AXA (**)	France	26.1	52.9	28.9	63.8	26.6	27.1
2	Legal & General	U.K	16.5	38.6	16.9	43.1	43.1	9.5
3	Aegon	Netherl.	14.8	54.5	15.4	63.6	42.7	7.9
4	Aviva (**)	U.K.	13.7	46.9	14.2	51.2	30.9	12.0
5	CNP	France	13.2	30.2	13.5	35.3	51.6	6.2
6	Generali (**)	Italy	11.7	35.0	12.8	41.8	24.2	17.7
7	Allianz (**)	Germany	10.8	39.5	10.8	39.4	16.4	39.6
8	Prudential (**)	U.K.	6.3	50.1	6.4	50.4	14.1	25.4

This table reports the ranking of European financial firms by systemic risk as of August 30, 2012. For each firm, we report the name, country, SRISK (in billion euros), LRMES (in %), leverage ($L_{i,t} = A_{i,t}/W_{i,t}$), and market capitalization (in billion euros). We report SRISK and LRMES for both world and European shocks. (*) indicates that the bank belongs to the list of G-SIBs of the FSB. (**) indicates that the insurer belongs to the list of G-SIIs of the FSB.

Table 6: Alternative measures of capital shortfall (as of August 30, 2012)

	Unstressed measures		Stressed measure
	UCS_1	UCS_2	SRISK
Banking groups			
Deutsche Bank	70.6	95.7	106.4
Crédit Agricole Group	41.9	76.6	93.7
Barclays	31.8	79.6	92.5
RBS	41.2	76.3	82.9
BNP Paribas	21.7	62.2	81.1
Société Générale	14.8	50.1	57.9
ING Group	17.6	43.0	55.5
BPCE Group	14.2	44.5	49.9
Lloyds Banking	3.4	34.0	43.4
UBS	21.3	29.7	42.9
UniCredit	0.0	31.7	38.5
Banco Santander	0.0	12.3	36.9
Credit Suisse	16.6	26.5	33.6
Commerzbank	13.1	28.5	31.1
HSBC	0.0	0.0	26.6
Intesa Sanpaolo	0.0	15.1	22.2
Nordea Bank	10.2	9.3	20.7
Danske Bank	4.4	12.4	15.9
Banco Bilbao	0.0	0.6	15.7
KBC Group	0.0	8.8	11.4
Insurance groups			
AXA	0.0	12.5	26.1
Legal & General	15.8	13.1	16.5
Aegon	0.0	10.7	14.8
Aviva	2.5	8.4	13.7
CNP	8.1	11.4	13.2
Generali	4.8	5.9	11.7
Allianz	0.0	0.0	10.8
Prudential	6.7	0.0	6.3
Total Capital shortfall	360.7	798.8	1071.8
Correlation with SRISK	0.854	0.976	–
Rank correlation with SRISK	0.732	0.932	–

This table compares different measures of capital shortfall for European financial firms as of August 30, 2012. For each firm, we report the name, "unstressed capital shortfall", based on book equity (UCS_1) and market capitalization (UCS_2), and our "stressed capital shortfall" based on market capitalization (SRISK). All measures are in billion euros. The table also reports the correlation of the first two capital shortfall measures with SRISK.

Table 7: Ranking of D-SIFIs (as of August 30, 2012)

Rk	Institution	Country	SRISK (bln eur)	World shock SRISK (% GDP)	LRMES (%)	Leverage	Market cap. (bln eur)
1	ING Group	Netherl.	55.5	9.3	56.9	57.8	23.3
2	UBS	Switz.	42.9	8.8	40.8	44.6	34.1
3	Credit Suisse	Switz.	33.6	6.9	36.7	34.5	20.3
4	Danske Bank	Denmark	15.9	6.6	28.6	16.2	12.9
5	Nordea Bank	Sweden	20.7	5.1	40.6	22.6	29.7
6	Barclays	U.K.	92.5	4.9	48.2	94.2	28.3
7	Crédit Agricole Group	France	93.7	4.7	47.0	87.9	21.9
8	Royal Bk of Scotland	U.K.	82.9	4.4	39.7	83.9	17.6
9	Deutsche Bank	Germany	106.4	4.1	43.4	108.2	26.1
10	BNP Paribas	France	81.1	4.0	46.1	84.9	43.3
11	Bank of Ireland	Ireland	6.5	4.0	35.5	6.6	2.7
12	Banco Santander	Spain	36.9	3.6	46.4	42.1	56.0
13	KBC Group	Belgium	11.4	3.1	43.4	11.7	6.2
14	Société Générale	France	57.9	2.9	50.3	59.1	16.4
15	National Bank of Greece	Greece	4.9	2.6	31.3	5.0	1.3
16	UniCredit	Italy	38.5	2.5	39.9	39.4	18.2
17	Aegon	Netherl.	14.8	2.5	54.5	15.4	7.9
18	BPCE Group	France	49.9	2.5	38.6	58.3	19.4
19	Lloyds Banking	U.K.	43.4	2.3	33.5	44.6	29.5
20	DNB	Norway	6.6	1.7	30.7	7.3	14.9
21	Banco Espirito Santo	Portugal	2.8	1.7	24.9	2.8	2.2
22	SEB	Sweden	6.3	1.6	37.7	6.9	13.2
23	Banco Bilbao	Spain	15.7	1.5	49.0	18.2	32.7
24	Intesa Sanpaolo	Italy	22.2	1.4	39.3	23.6	19.4
25	HSBC	U.K.	26.6	1.4	31.8	32.4	126.2

This table reports the ranking of European financial firms by SRISK as of August 30, 2012 in percentage of domestic nominal GDP. For each firm, we report the name, country, SRISK (in billion euros and % GDP), LRMES (in %), leverage, and market capitalization (in billion euros). We report SRISK and LRMES for a world shock. We take the 2012 GDP estimate.

Table 8: Importance of D-SIFIs in proportion to country-wide aggregate indicators

	x	Market cap. (% GDP)	SRISK (% total SRISK)	SRISK (% GDP)	SRISK (% Mkt cap.)
U.S.	4	2.3	57.6	2.7	116.0
Euro area	4	0.8	31.4	3.7	445.0
France	4	5.0	85.7	14.1	280.9
U.K.	4	10.8	80.8	13.1	121.7
Germany	4	3.0	90.8	5.7	193.1
Italy	4	3.4	83.2	4.9	143.9
Switzerland	2	11.1	92.3	15.6	140.6
Netherlands	2	4.9	100.0	10.9	224.9
Spain	4	8.5	91.1	5.5	65.0
Sweden	4	17.7	100.0	8.1	46.1

This table reports the market capitalization and systemic risk of the x largest firms as of August 30, 2012 as a fraction of country-wide aggregate indicators (nominal GDP, total SRISK, and market capitalization).

Table 9: Granger-causality tests – SRISK and macro variables

		SRISK	IPI	PPI	URATE	Bus.Conf.
France	SRISK	15.73	-1.05	2.34	-1.29	-0.29
	IPI	-3.08	10.45	1.10	-1.54	2.78
	PPI	0.63	3.09	30.00	-0.03	4.05
	URATE	1.46	-1.64	0.51	37.81	-2.35
	Bus. Conf.	-0.46	0.56	-3.43	1.35	29.91
U.K.	SRISK	24.48	2.27	-1.03	-0.25	-0.65
	IPI	-2.72	8.17	1.06	-2.66	2.44
	PPI	-2.80	1.08	18.78	0.77	-1.11
	URATE	2.06	-0.35	-1.26	31.31	-1.36
	Bus. Conf.	-6.77	0.34	-0.43	4.95	41.19
Germany	SRISK	15.69	2.52	0.64	-0.59	-2.37
	IPI	0.11	17.77	-1.18	0.65	5.17
	PPI	1.25	3.51	32.78	2.41	1.85
	URATE	1.10	-0.59	-0.99	25.23	-0.42
	Bus. Conf.	-2.06	-1.99	-2.48	0.80	33.03
Italy	SRISK	13.78	-1.38	3.63	0.66	-0.36
	IPI	-4.74	12.74	1.66	1.25	4.63
	PPI	-5.56	0.84	36.96	4.75	1.51
	URATE	-0.09	-2.54	1.83	16.26	1.13
	Bus. Conf.	-3.46	-0.81	-2.01	1.87	23.02
Switzerland	SRISK	22.17	0.76	0.83	-1.08	0.08
	IPI	-2.27	12.96	-2.74	-1.59	1.80
	PPI	-1.86	-0.81	18.73	-1.59	1.47
	URATE	4.57	-2.39	0.32	69.29	-7.20
	Bus. Conf.	-2.97	1.85	-0.57	1.94	26.68
Netherlands	SRISK	15.11	1.29	4.13	1.57	-3.49
	IPI	-1.19	6.76	0.50	0.27	2.34
	PPI	-3.81	2.27	28.84	2.31	1.16
	URATE	2.05	0.08	-0.29	58.15	-3.10
	Bus. Conf.	-3.91	0.44	-0.91	2.64	16.16
Spain	SRISK	13.81	-0.39	3.34	0.77	-0.22
	IPI	-2.21	5.66	-1.14	-4.83	6.35
	PPI	-3.17	-0.24	40.80	0.73	3.28
	URATE	2.09	0.05	4.20	48.16	-4.42
	Bus. Conf.	-1.06	1.34	-4.21	1.45	18.63
Sweden	SRISK	16.48	0.44	1.42	-0.68	-1.93
	IPI	-2.61	13.93	1.63	-1.28	1.28
	PPI	1.19	1.47	9.60	-1.21	5.67
	URATE	0.59	-2.80	-2.16	9.67	1.52
	Bus. Conf.	-2.96	-1.82	-1.06	1.11	22.65

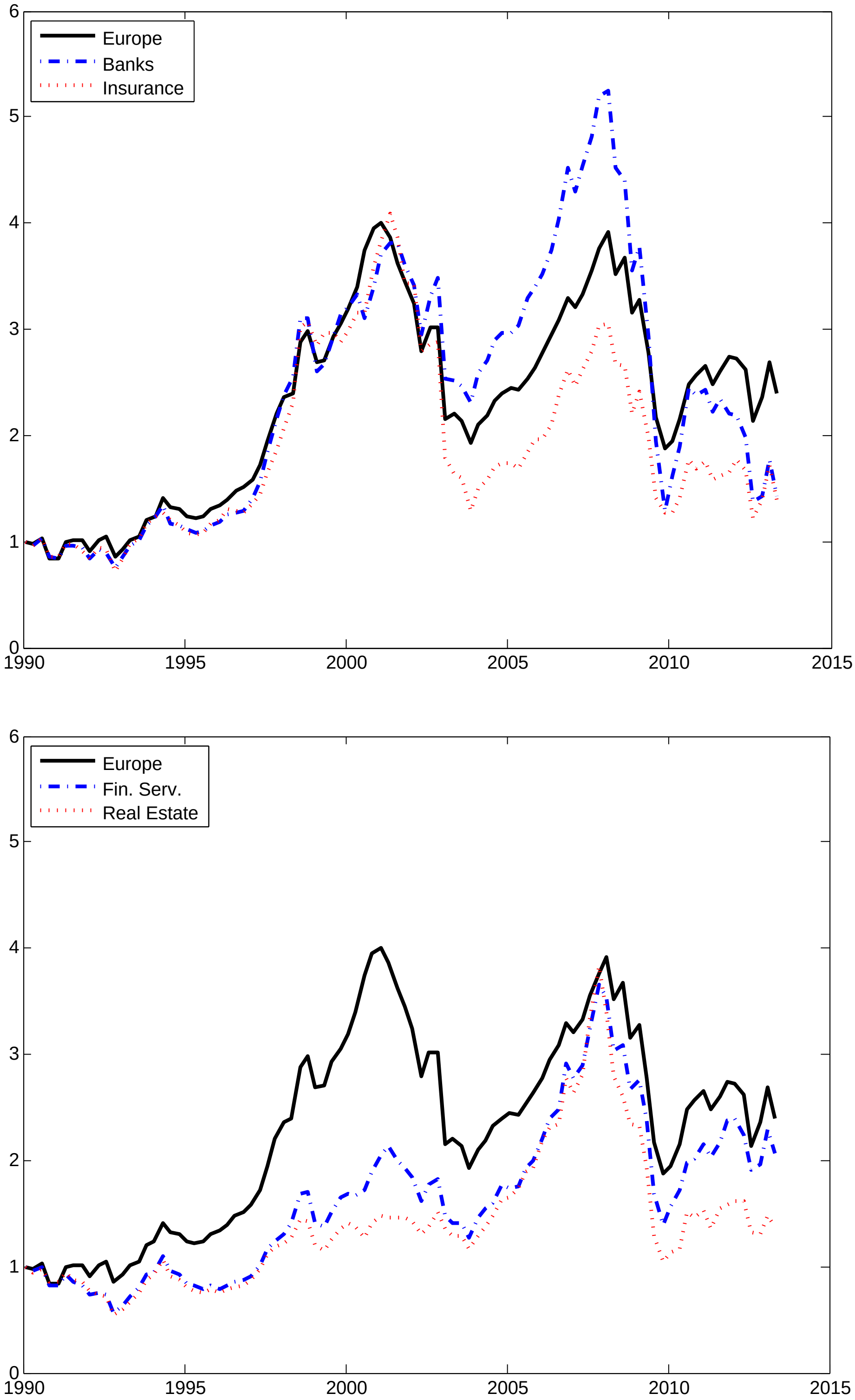
This table reports the test statistics for the Granger-causality tests. The i, j entry of the table reports the t-stat for the null hypothesis that series j Granger-causes series i, i.e., that columns predict rows.

Table 10: Granger-causality tests – SRISK and financial variables

		SRISK	Short rate	Stock market	Volatility	Bank lending
France	SRISK	18.70	2.97	-1.03	-0.50	0.00
	Short rate	-3.99	58.77	6.11	2.42	0.88
	Stock market	-0.78	-3.58	22.69	-0.05	0.15
	Volatility	0.78	0.65	-3.02	8.60	-1.18
	Bank lending	-3.00	2.35	2.95	-0.03	86.30
U.K.	SRISK	25.06	3.55	0.09	0.17	0.98
	Short rate	-3.91	48.58	3.39	1.59	-1.92
	Stock market	-1.57	-2.18	19.46	-0.34	-1.51
	Volatility	0.95	-0.47	-2.37	9.55	1.79
	Bank lending	0.65	-0.48	1.35	0.16	21.68
Germany	SRISK	17.18	2.33	-0.21	0.43	0.19
	Short rate	-3.79	47.51	7.21	1.58	-1.24
	Stock market	0.42	-2.26	26.35	-0.37	-0.88
	Volatility	-0.58	0.11	-3.37	10.66	0.46
	Bank lending	-2.29	2.46	2.15	-1.39	34.95
Italy	SRISK	13.33	3.10	-0.98	0.19	0.98
	Short rate	-3.00	68.17	4.17	1.19	-1.35
	Stock market	-0.80	-4.00	18.31	-0.33	-1.05
	Volatility	0.82	0.04	-2.70	10.25	-1.16
	Bank lending	1.05	2.21	-1.20	-0.63	23.67
Switzerland	SRISK	16.49	0.72	-0.26	0.80	2.14
	Short rate	-0.23	19.31	4.07	1.02	0.90
	Stock market	-0.66	-0.57	19.63	-0.74	-1.47
	Volatility	0.57	-0.89	-1.68	10.26	0.81
	Bank lending	-0.97	2.44	-0.52	-0.49	21.27
Netherlands	SRISK	15.03	2.10	-1.04	0.02	2.49
	Short rate	-2.68	62.94	7.61	2.80	1.22
	Stock market	-0.96	-3.85	22.56	-0.04	-0.44
	Volatility	0.92	0.00	-2.73	9.84	0.03
	Bank lending	0.57	1.30	1.62	1.09	20.77
Spain	SRISK	12.72	2.32	-0.88	0.23	-0.72
	Short rate	-1.77	62.44	6.20	1.70	-3.53
	Stock market	-1.15	-2.53	21.07	-0.07	-1.56
	Volatility	-0.11	-1.28	-3.27	10.51	2.50
	Bank lending	-2.07	1.30	0.13	-1.01	18.10
Sweden	SRISK	20.97	3.98	-0.67	0.04	-0.16
	Short rate	-5.39	60.06	2.20	-0.17	-0.31
	Stock market	-0.83	-5.10	26.84	0.46	0.57
	Volatility	0.45	0.67	-3.06	10.25	-0.23
	Bank lending	-1.70	0.59	1.09	-0.58	128.04

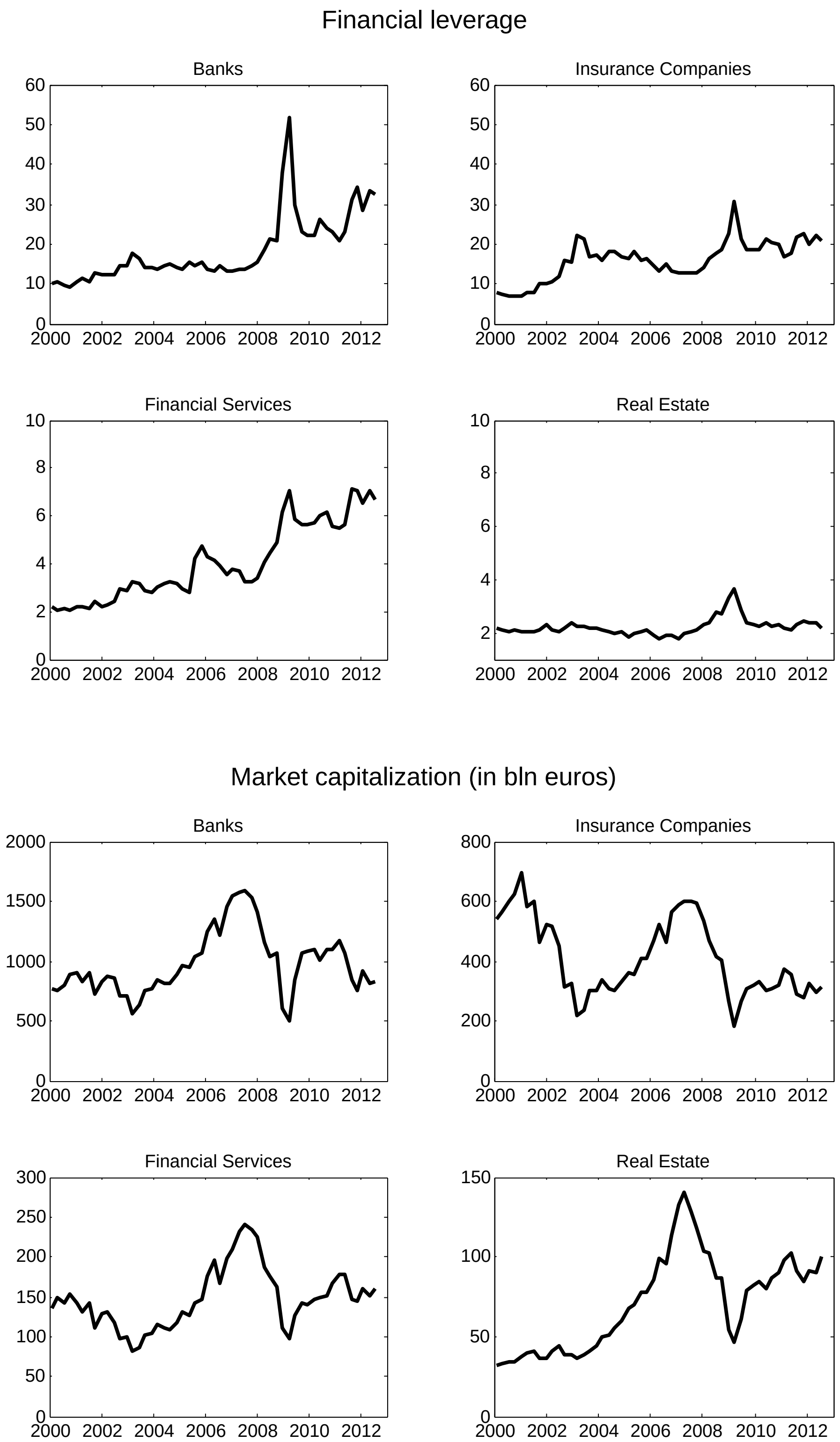
This table reports the test statistics for the Granger-causality tests. The i, j entry of the table reports the t-stat for the null hypothesis that series j Granger-causes series i, i.e., that columns predict rows.

Figure 1: Cumulative return by category



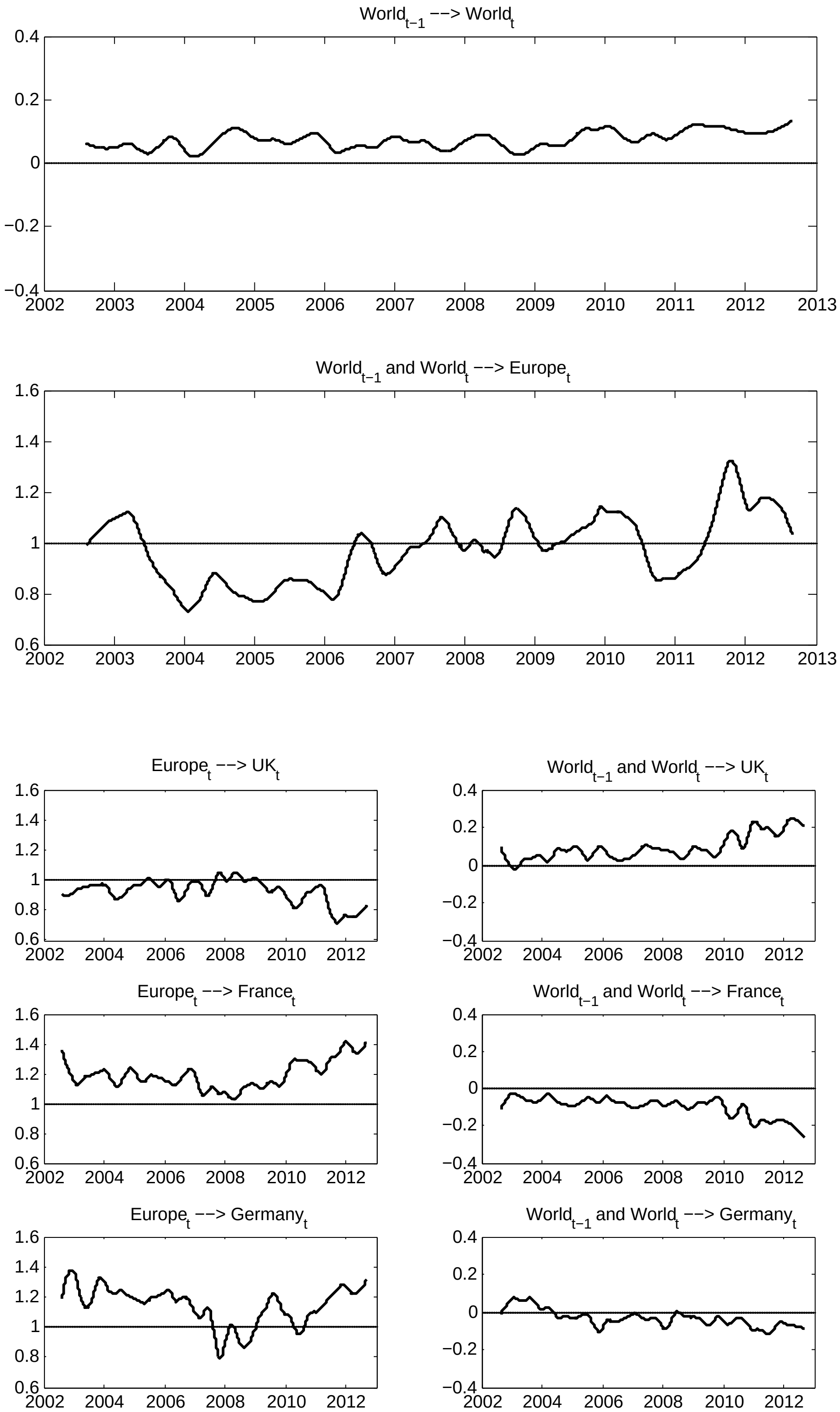
Note: This figure displays the European market index and the indices reflecting the four industry groups between 1990 and 2012. The top panel focuses on banks and insurance companies, the lower panel on financial-services and real-estate firms.

Figure 2: Leverage and market capitalization by industry group



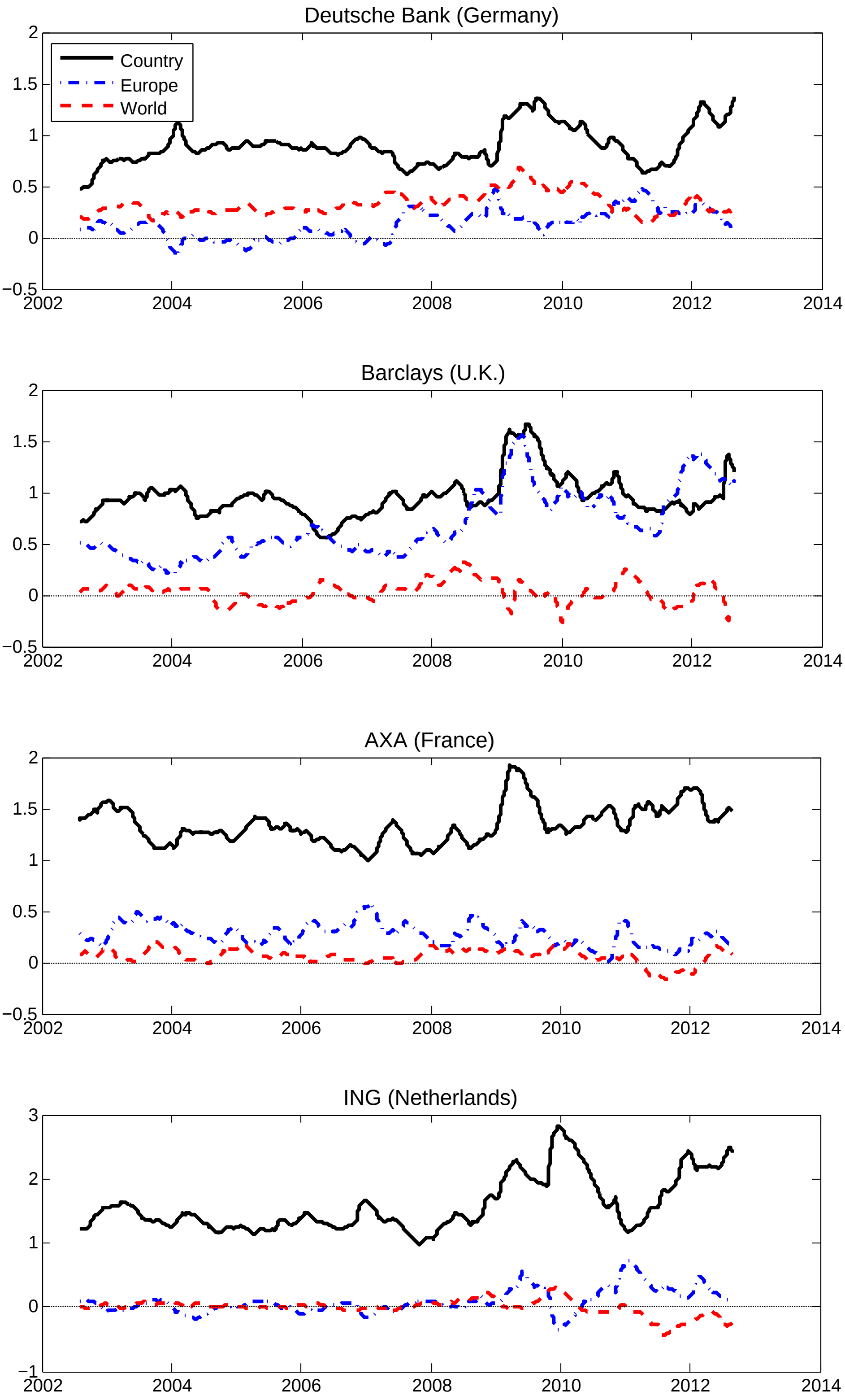
Note: This figure displays the leverage (top panel) and market capitalization (bottom panel) for the four industry groups between 2000 and 2012.

Figure 3: Dynamics of betas in the International model and Country models



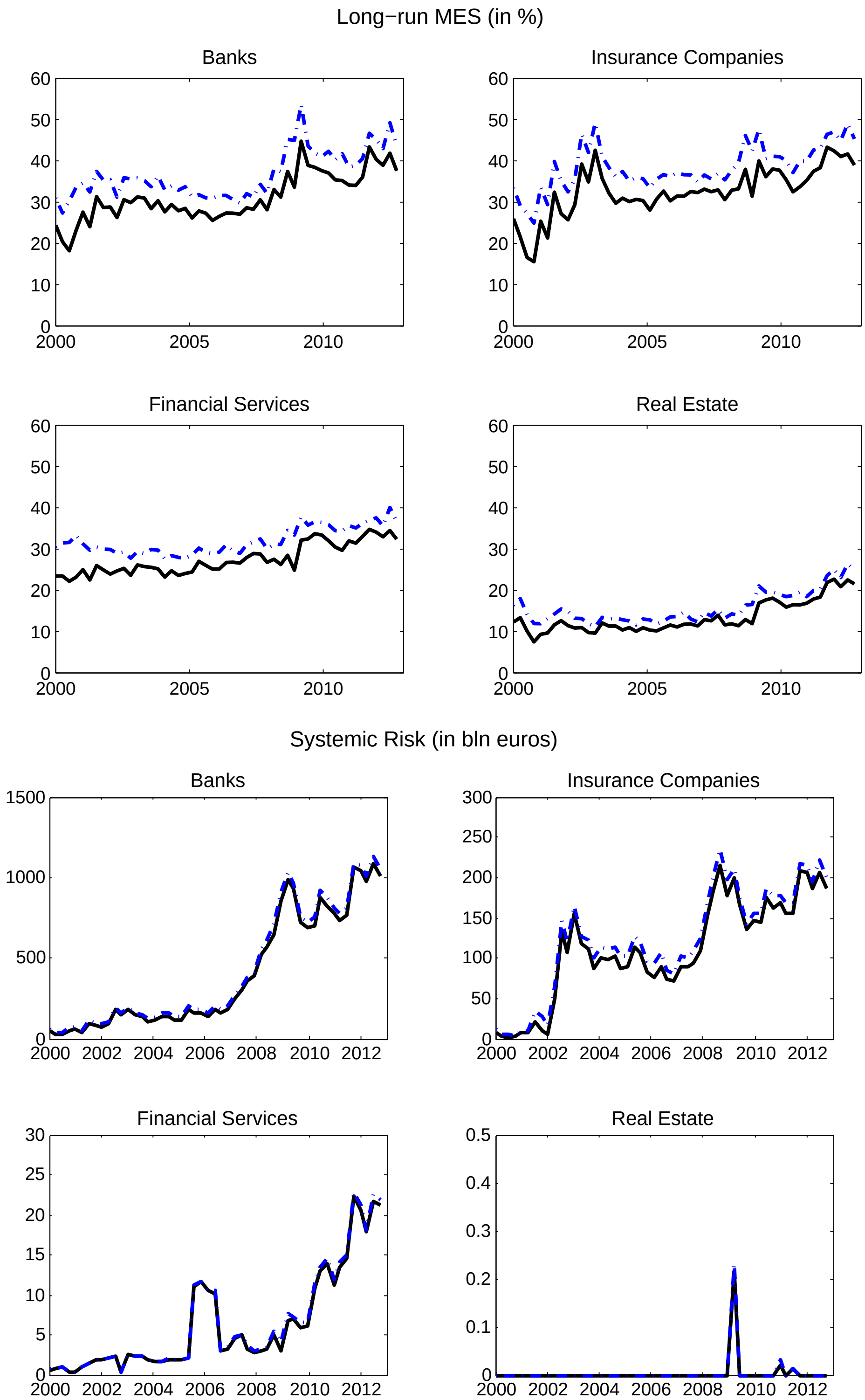
Note: This figure displays the dynamics of the betas in the International model and in some of the Country models (U.K., France, Germany).

Figure 4: Dynamics of betas in some Firm models



Note: This figure displays the dynamics of the betas in some Firm models.

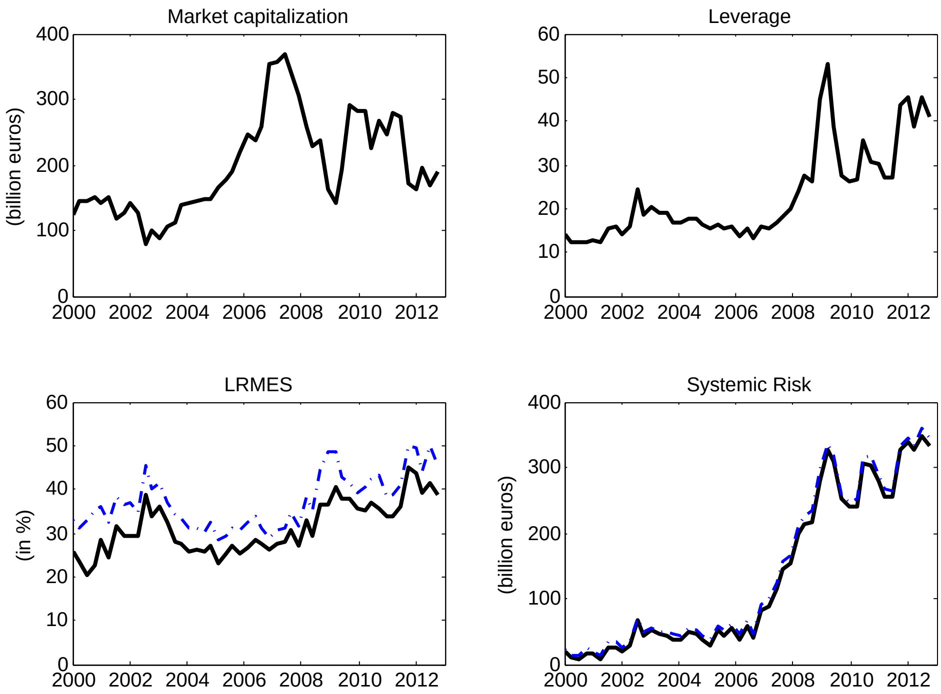
Figure 5: LRMES and SRISK by industry group



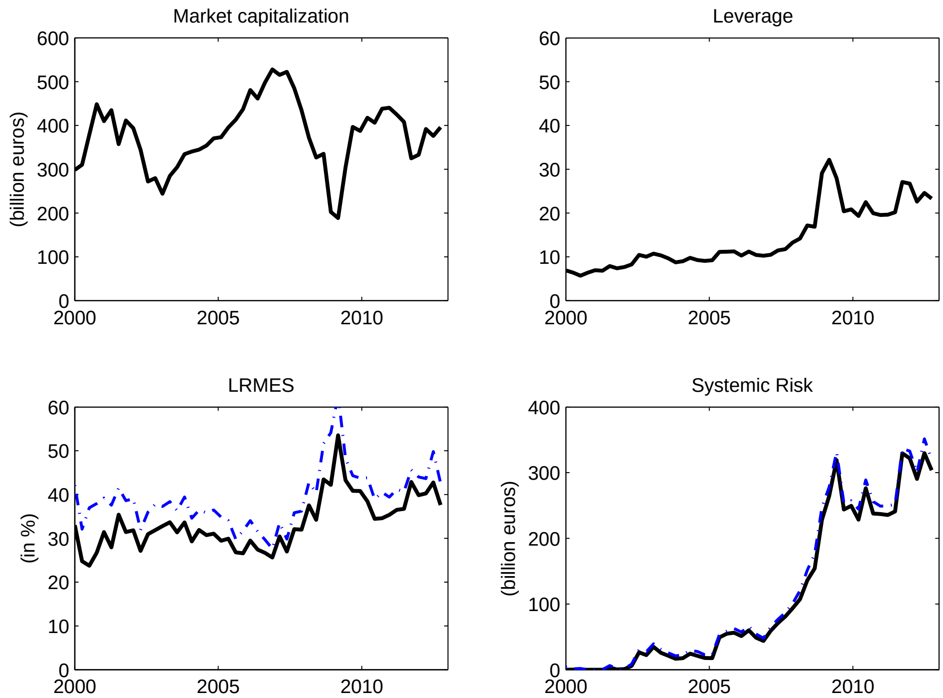
Note: This figure displays the LRMES and systemic risk for the four industry groups between 2000 and 2012. The black line corresponds to a world shock, the blue dashed line to a European shock.

Figure 6: Market capitalization, Leverage, LRMES, and SRISK by country

France

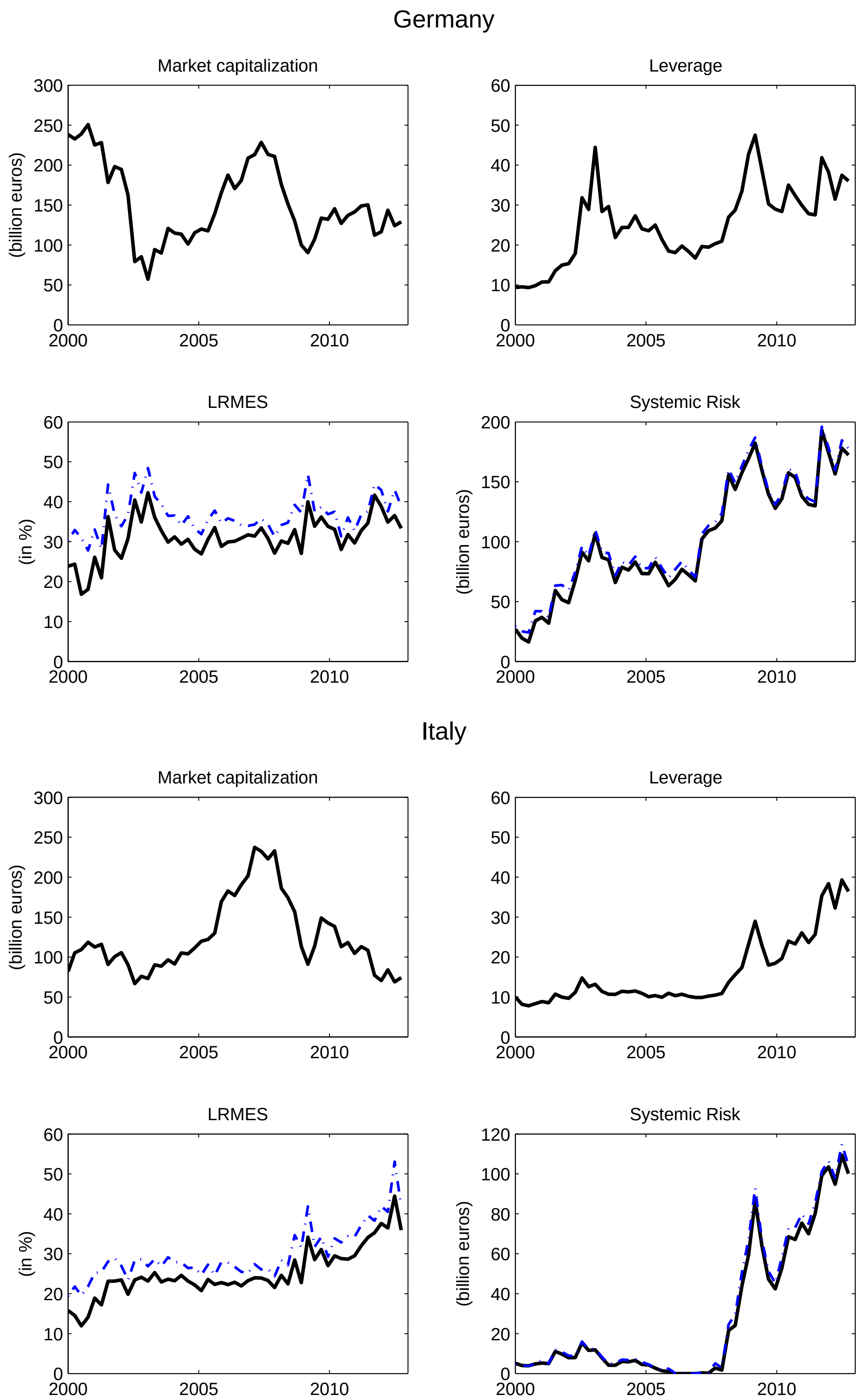


U.K.



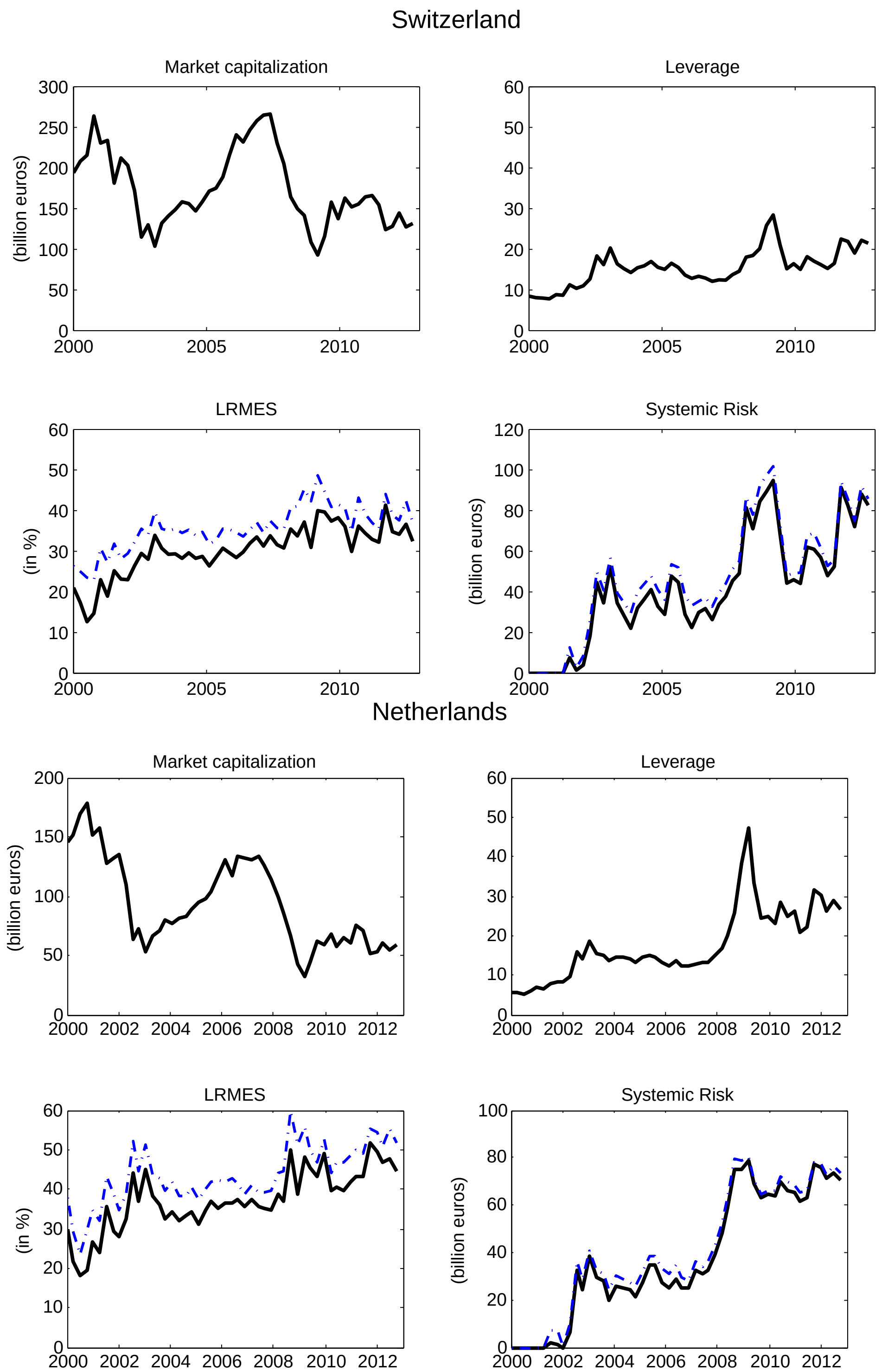
Note: These figures display the market capitalization, leverage, LRMES, and systemic risk measures for some countries, between 2000 and 2012. Reported countries are those with a systemic risk larger than 70 billion euros at the end of the period. The black line corresponds to a world shock, the blue dashed line to a European shock.

Figure 7: Market capitalization, Leverage, LRMES, and SRISK by country (cont'd)



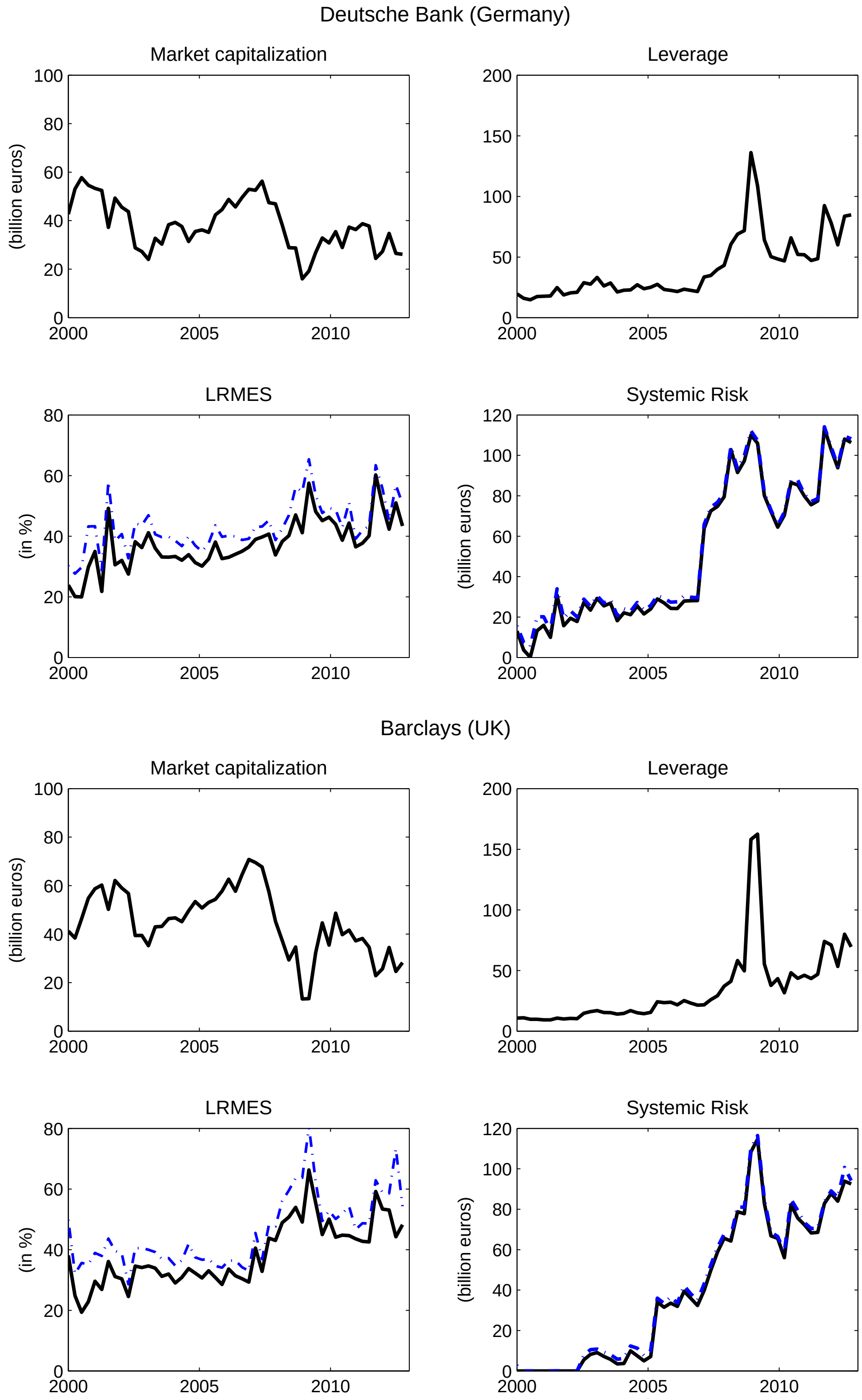
Note: These figures display the market capitalization, leverage, LRMES, and systemic risk measures for some countries, between 2000 and 2012. Reported countries are those with a systemic risk larger than 70 billion euros at the end of the period. The black line corresponds to a world shock, the blue dashed line to a European shock.

Figure 8: Market capitalization, Leverage, LRMES, and SRISK by country (cont'd)



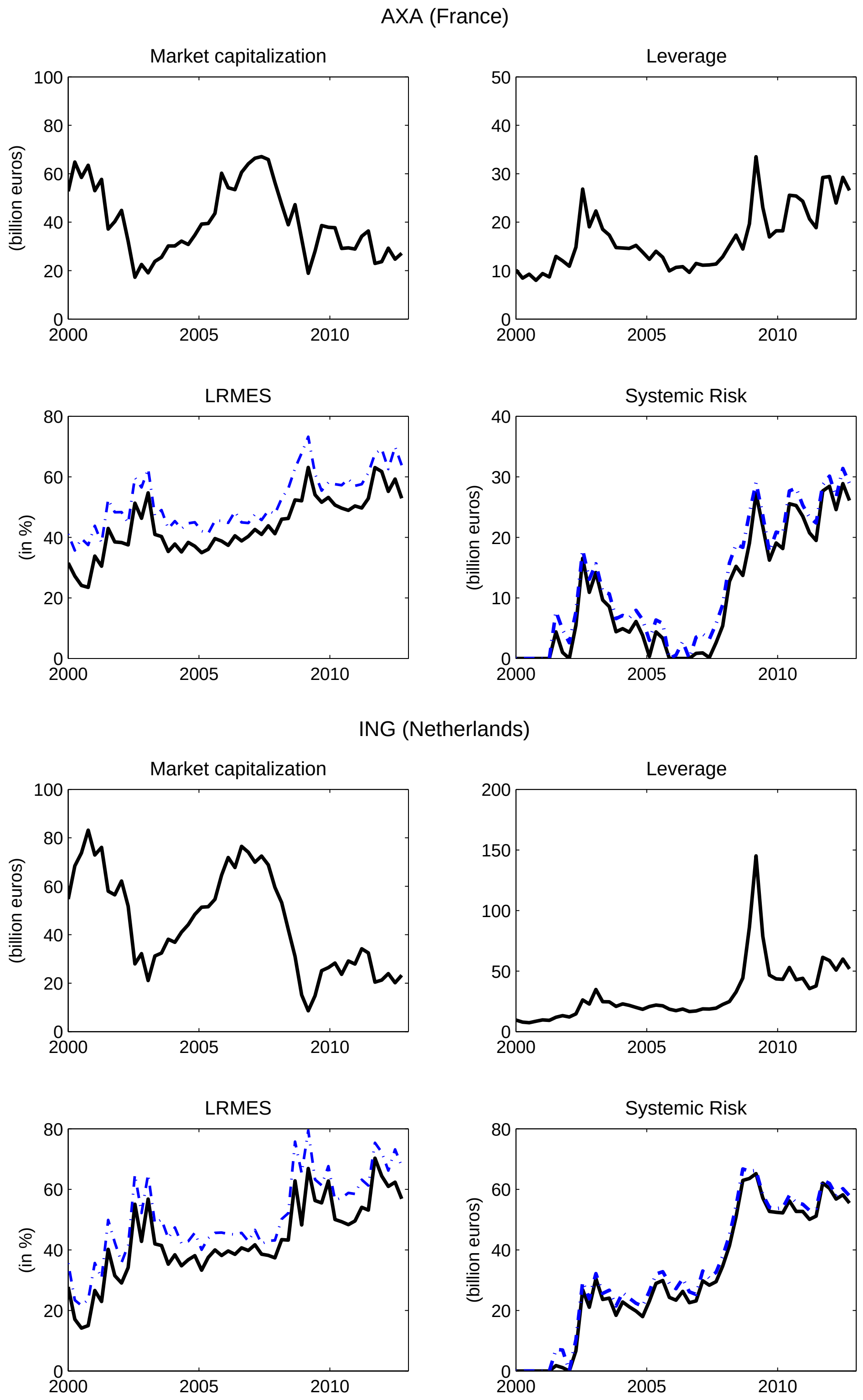
Note: These figures display the market capitalization, leverage, LRMES, and systemic risk measures for some countries, between 2000 and 2012. Reported countries are those with a systemic risk larger than 70 billion euros at the end of the period. The black line corresponds to a world shock, the blue dashed line to a European shock.

Figure 9: Market capitalization, Leverage, LRMES, and SRISK by institution



Note: These figures display the market capitalization, leverage, LRMES, and systemic risk measures for some institutions, between 2000 and 2012. The black line corresponds to a world shock, the blue dashed line to a European shock.

Figure 10: Market capitalization, Leverage, LRMES, and SRISK by institution (cont'd)



Note: These figures display the market capitalization, leverage, LRMES, and systemic risk measures for some institutions, between 2000 and 2012. The black line corresponds to a world shock, the blue dashed line to a European shock.