Dynamic Conditional Beta and Systemic Risk in Europe

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Abstract

Systemic risk can be defined as the propensity of a financial institution to be under-capitalized when the financial system as a whole is under-capitalized. It combines the market capitalization of the firm, the sensitivity of its equity return to market shocks, and its financial leverage. In this paper, we describe an econometric approach designed to measure systemic risk for non-U.S. institutions. We extend the approach developed by Brownlees and Engle (2010) to the case with several factors explaining the dynamic of financial firms' return and with 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 error terms, and a dynamic t copula to estimate the dynamic of the dependence structure between the innovations. We apply this methodology to the 194 largest European financial firms and estimate their systemic risk over the 2000-2012 period. We find that banks and insurance companies bear about 80% and 20% of the systemic risk in Europe, whereas systemic risk is essentially unaffected by financial services and real estate firms. Over the recent period, the systemically riskiest countries are the UK and France, and the riskiest firms are Deutsche Bank and BNP Paribas.

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1 Introduction

The Global Financial Stability Report (2009) of the IMF 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, there has been an increasing interest in the concept of systemic risk. The rising globalization of financial services has strengthened the interconnection between financial institutions. While tighter interdependence may have fostered efficiency of the global financial system, it has also increased the risk of cross-market and cross-country disruptions.

A first component of systemic risk management is the assessment of systemic risk. It is typically based on the size of the financial institutions relative to the national or international financial system ("Too big to fail") or on the linkages between financial institutions ("Too interconnected to fail"). A second component is the detection of systemic events, which are composed by two elements: (1) the shock, which can be idiosyncratic, sector-wide, regional, or systemic; and (2) the propagation (or contagion) mechanism, which describes how the shock can propagate from one institution or market to the other. As the recent subprime crisis demonstrates, systemic events are intrinsically difficult to anticipate.

Measures of systemic risk are generally based on market data, which are by nature forward-looking. From such data two issues can be addressed, in as far as historical prices contain expectations about future events: how likely extreme events are in current financial markets? How closely connected the financial institutions are with each other and the rest of the economy? Obtaining those two pieces of information 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 essential to determine the speed of the propagation of shocks through the financial system and therefore to determine the level of vulnerability to shocks.

After the recent financial crisis, the literature mainly focused on externalities across financial firms that may give rise to liquidity spirals. In particular, it became clear that network effects need to be taken into account to fully capture the contribution of banks to systemic risk. These measures therefore considered the risk of extreme loss for a financial firm given a market dislocation. Acharya et alii (2010) and Brownlees and Engle (2010) have proposed an economic and statistical approach to measuring the systemic risk of financial firms. Following Acharya et alii (2010), the externality that generates systemic risk is the propensity of a financial institution to be under-capitalized when the financial system as a whole is under-capitalized. In this case, there are likely to be few firms willing to absorb liabilities and acquire the failing firm. Thus leverage and risk exposure are only serious when the economy is weak. This mechanism can be captured by the expected fall in equity values of each firm conditional on a weak economy. Then the capital shortage for each firm is considered to be the source of dead weight loss to the economy. The econometric methodology behind is described in Brownlees and Engle (2010). This methodology estimates a dynamic model of the volatility process of each firm, the correlation process with an overall equity index, and how sensitive these are to extremes and downturns. Innovations are described by a non-normal (non-parametric) joint distribution, which allows estimation of the marginal expected shortfall of the innovation processes. From this model, we infer the equity losses and capital shortage that can be expected if there is another financial crisis.[1]

This approach has been successfully applied to U.S. financial institutions by Brownlees and Engle (2010). In the case of non-U.S. institutions, which are the focus of the present paper, there are several additional interesting issues beyond the already-mentioned components to measure the risk exposure: for a given firm, a financial crisis may be triggered by a world crisis (like the subprime crisis), a regional crisis (like the European debt crisis), or even by a countrywide crisis (like the Greek debt crisis for Greek banks). As a consequence, a natural extension of the previous models is to consider a multi-factor model, where several elements can jeopardize a financial firms health. Furthermore, the parameters of the model may change over time. This in turn requires consideration of a model that allows for time-varying parameters. Another issue comes from the asynchronicity of the financial markets. A world crisis (say, initiated on the U.S. market)

[1]Other measures of contagion based on the property of the joint distribution of stock returns have been proposed. For instance, Adrian and Brunnermeier (2009) have introduced the CoVaR, i.e., the VaR of the financial system conditional on institutions being under stress.

may affect the other regions the same day or with one day lag. 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. Concerning asynchronicity of the financial markets, we design a specific econometric model dealing with this issue.

Our empirical investigation is based on a large set of 194 European financial firms, which includes all banks, financial services, insurance companies, and real estate firms with a minimum market capitalization of 1 billion euros and a price series starting before January 2005. This allows us to calibrate the model with data preceding the subprime crisis. We investigate several aspects of systemic risk among European financial firms. In particular, we evaluate the relative contribution of the industry groups, of the countries, and of the individual firms to the global systemic risk in Europe. Our approach also allows us to distinguish the effect of a world wide shock and the effect of a European wide shock.

The rest of the paper is organized as follows. Section 2 details the methodology adopted to estimate the model and to compute the marginal expected shortfall. Section 3 presents the data. Section 4 discusses to our estimates of systemic risk measures among European financial institutions. Section 5 concludes.

2 Methodology

In this section, we describe our model of the risk exposure of European financial firms to a financial crisis. Following the approach proposed by Acharya et alii (2010) and Brownlees and Engle (2010), we measure systemic risk as the propensity of a financial firm to be under-capitalized when the financial system as a whole is under-capitalized. As derived by Acharya et alii (2010), the systemic risk measure combines the size of the institution (market capitalization), the sensitivity of its equity return to shocks on the whole market (risk exposure) and its leverage. The expected capital shortfall for firm i, denoted by $CS_{i,t}$, is defined as:

$$CS_{i,t} = E_t[\theta A_{i,t+1} - W_{i,t+1} \mid \theta A_{F,t+1} < W_{F,t+1}], \quad (1)$$

where A_i and W_i denote the assets and equity of institution i, A_F and W_F the assets and equity of the aggregate financial system. A systemic crisis occurs when the aggregate equity, W_F, of the financial system is below a fraction θ of the assets, A_F. We can interpret θ as the regulatory fraction of the assets that has to be put aside by the institution.

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) minus the book value of equity (BW) plus the market value of equity (W, market capitalization), i.e., $A = BA - BW + W = D + W$, where the book value of the debt is $D = BA - BW$.

With this definition, equation (1) can be written as:

$$CS_{i,t} = E_t[\theta D_{i,t+1} - (1-\theta)W_{i,t+1} \mid \theta A_{F,t+1} < W_{F,t+1}], \tag{2}$$

Assuming that the value of the debt is not affected by the crisis in the short run, this expression can be rewritten as:

$$\begin{aligned}\frac{CS_{i,t}}{W_{i,t}} &= \frac{\theta D_{i,t}}{W_{i,t}} - (1-\theta)E_t\left[\frac{W_{i,t+1}}{W_{i,t}} \mid \theta A_{F,t+1} < W_{F,t+1}\right] \\ &= \theta(L_{i,t}-1) - (1-\theta)E_t\left[\frac{W_{i,t+1}}{W_{i,t}} \mid \theta A_{F,t+1} < W_{F,t+1}\right].\end{aligned} \tag{3}$$

where $L_{i,t} = A_{i,t}/W_{i,t}$ denotes the financial leverage, so that $D_{i,t} = (L_{i,t}-1)W_{i,t}$.

The first term on the RHS of equation (3) captures the effect of the initial leverage of the firm. The second term measures the expected return of the institution conditional on a financial crisis. We define a systemic event as one where the market return is below a given threshold. To set this threshold, we consider the worst return over a decade as a critical value. Given the limited size of the sample, this critical value is however subject to large measurement error. Therefore, we consider the expected loss in the 5% worst cases and then adjust the estimate as to match to a "once-per-decade" crisis. The second term on the RHS of (3) can be approximated as:

$$-E_t\left[\frac{W_{i,t+1}}{W_{i,t}} - 1 \mid \theta A_{F,t+1} < W_{F,t+1}\right] \approx k \times MES_{i,t},$$

where $MES_{i,t} = -E_t\left[r_{i,t+1}|r_{M,t+1} \leq q_{5\%}\right]$ denotes the marginal expected shortfall of institution i to a 5%-quantile shock ($q_{5\%}$) on the market return. The parameter k is the correcting factor. Its computation is described in Appendix 1. Combining those observations, the systemic risk measure can be rewritten as:

$$CS_{i,t} = (\theta(L_{i,t} - 1) + (\theta - 1)(1 - k\ MES_{i,t})) \times MC_{i,t}. \tag{4}$$

The systemic risk of firm i, denoted by $SR_{i,t}$, is defined as:

$$SR_{i,t} = \min(0, CS_{i,t}). \tag{5}$$

Finally, the marginal expected shortfall of the financial system, i.e., the expected loss of the financial system conditional on an extreme event, is defined as:

$$MES_{F,t} = -E_t[r_{F,t+1}|r_{M,t+1} \leq q_{5\%}],$$

where $r_{F,t+1}$ and $r_{M,t+1}$ denote the return of the financial industry and of the market as a whole at date t. Because the return of the industry is just the weighted sum of the financial institutions return ($r_{F,t} = \sum_{i=1}^{N} w_i r_{i,t}$), we obtain that the marginal contribution of a given institution to the overall MES is simply the MES of the institution (see also Brownlees and Engle, 2010):

$$\frac{\partial MES_{F,t}}{\partial w_i} = -E[r_{i,t+1}|r_{M,t+1} \leq q_{5\%}] = MES_{i,t},$$

with $MES_{F,t} = \sum_{i=1}^{N} w_i MES_{i,t}$.

2.1 Econometric Methodology

In the case of European markets, there exist substantial differences across the various countries in terms of regulation and in terms of macroeconomic dynamic. For this reason, unlike the U.S., a finer distinction of what drives the risk of a financial firm is required.

In our stratification, we distinguish as drivers the national index ($r_{C,t}$), the continental index ($r_{E,t}$), and the world index ($r_{W,t}$).

A further complication stems from the asynchronicity of the time zones. The stock market of a given country may be affected by a shock on the world index with a one-day lag. For these reasons, our system includes five series, $r_t = \{r_{i,t}, r_{C,t}, r_{E,t}, r_{W,t}, r_{W,t-1}\}$. The objective of the model is to capture the dependence of the return of institution i with respect to the return of the possible 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, joint distribution of the innovations.

We start with the multi-factor model and assume a recursive model with time-varying parameters of the form:

$$
\begin{aligned}
r_{i,t} &= \beta_{i,t}^{C} r_{C,t} + \beta_{i,t}^{E} r_{E,t} + \beta_{i,t}^{W} r_{W,t} + \beta_{i,t}^{L} r_{W,t-1} + \varepsilon_{i,t} \\
r_{C,t} &= \beta_{C,t}^{E} r_{E,t} + \beta_{C,t}^{W} r_{W,t} + \beta_{C,t}^{L} r_{W,t-1} + \varepsilon_{C,t} \\
r_{E,t} &= \beta_{E,t}^{W} r_{W,t} + \beta_{E,t}^{L} r_{W,t-1} + \varepsilon_{E,t} \\
r_{W,t} &= \beta_{W,t}^{L} r_{W,t-1} + \varepsilon_{W,t}.
\end{aligned}
$$

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 $t-2$, the return process is such that $E_{t-2}[r_t] = \mu$ and $V_{t-2}[r_t] = H_t$. The conditional covariance matrix H_t is estimated by a DCC model (Engle and Sheppard, 2001, Engle, 2002) as $H_t = D_t \Gamma_t D_t$. The conditional correlation matrix, Γ_t, is given by:

$$
\Gamma_t = \left(\operatorname{diag}(Q_t)\right)^{-1/2} \cdot Q_t \cdot \left(\operatorname{diag}(Q_t)\right)^{-1/2}, \tag{6}
$$

$$
Q_t = \Omega + \delta_1 Q_{t-1} + \delta_2 \left(\eta_{t-1}\eta_{t-1}'\right), \tag{7}
$$

where $\eta_t = \{\eta_{i,t}, \eta_{C,t}, \eta_{E,t}, \eta_{W,t}, \eta_{W,t-1}\} = D_t^{-1}\varepsilon_t$ is the vector of normalized unexpected returns, diag(Q_t) denotes a matrix with zeros, except for the diagonal that contains the diagonal of Q_t, and D_t is the diagonal matrix with the conditional volatilities of r_t on its diagonal and 0 elsewhere. Parameters δ_1 and δ_2 are restricted to ensure that the conditional correlation matrix is positive definite.

Armed with this model, we estimate the parameters of the individual financial institution equation as:

$$\beta_{i,t} = \begin{pmatrix} \beta_{i,t}^C \\ \beta_{i,t}^E \\ \beta_{i,t}^W \\ \beta_{i,t}^L \end{pmatrix} = \begin{pmatrix} H_{r_{C,t},r_{C,t}} & H_{r_{C,t},r_{E,t}} & H_{r_{C,t},r_{W,t}} & H_{r_{C,t},r_{W,t-1}} \\ H_{r_{C,t},r_{E,t}} & H_{r_{E,t},r_{E,t}} & H_{r_{E,t},r_{W,t}} & H_{r_{E,t},r_{W,t-1}} \\ H_{r_{C,t},r_{W,t}} & H_{r_{E,t},r_{W,t}} & H_{r_{W,t},r_{W,t}} & H_{r_{W,t},r_{W,t-1}} \\ H_{r_{C,t},r_{W,t-1}} & H_{r_{E,t},r_{W,t-1}} & H_{r_{W,t},r_{W,t-1}} & H_{r_{W,t-1},r_{W,t-1}} \end{pmatrix}^{-1} \begin{pmatrix} H_{r_{i,t},r_{C,t}} \\ H_{r_{i,t},r_{E,t}} \\ H_{r_{i,t},r_{W,t}} \\ H_{r_{i,t},r_{W,t-1}} \end{pmatrix}.$$

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

The error terms $\varepsilon_t = \{\varepsilon_{i,t}, \varepsilon_{C,t}, \varepsilon_{E,t}, \varepsilon_{W,t}\}$ are uncorrelated across time and across series, but they may display non-linear dependencies both in the time series (such as heteroskedasticity) and in the cross-section (such as dependence in the extremes). To capture the heteroskedasticity, we assume univariate asymmetric GARCH models (Glosten, Jagannathan, and Runkle, 1993):

$$\varepsilon_{k,t} = \sigma_{k,t}\ z_{k,t},$$

where:

$$\sigma_{k,t}^2 = \omega_k + \alpha_k \varepsilon_{k,t-1}^2 + \beta_k \sigma_{k,t-1}^2 + \gamma_k \varepsilon_{k,t-1}^2 1_{(\varepsilon_{k,t-1} \leq 0)}, \tag{8}$$

for $k = i$, C, E, and W. The innovations process $z_t = \{z_{i,t}, z_{C,t}, z_{E,t}, z_{W,t}, z_{W,t-1}\}$ is such that $E[z_t] = 0$ and $V[z_t] = I_5$. It is well known that the conditional distribution of stock market returns is fat tailed and asymmetric. To capture these features, the innovations are assumed to have a univariate skewed t distribution: $z_{k,t} \sim f(z_{k,t}; \nu_k, \lambda_k)$, where f denotes the pdf of the skewed t distribution, with ν_k the degree of freedom and λ_k the asymmetry parameter.

As we will show in the next subsection, to measure systemic risk, we need to compute expressions of marginal expected shortfall, like $E_{t-1}[z_{i,t}|z_{C,t} < c]$, which rely on the dependence structure of the innovation processes. Although the innovations have been preliminary orthogonalized, they cannot be a priori assumed to be independent. Therefore, we need to estimate a joint distribution that allows to capture the possible non-linear dependencies across the innovation processes. A convenient approach is to describe the joint distribution of z_t with a copula $C(u_t)$, where $u_t = \{u_{i,t}, u_{C,t}, u_{E,t}, u_{W,t}, u_{W,t-1}\}$ denotes the margin of z_t. In other words, we define $u_{k,t} = F(z_{k,t}; \nu_k, \lambda_k)$, where F denotes the cdf of the skewed t distribution with parameters (ν_k, λ_k). 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 also has some nice properties, as it allows fat tails in the joint distribution and its elliptical structure provides a convenient way to deal with large-dimensional systems. The cdf of the t copula is defined as:

$$C_{\Gamma,\bar{\nu}}(u_{i,t}, ..., u_{W,t-1}) = t_{\Gamma,\bar{\nu}}(t_{\bar{\nu}}^{-1}(u_{i,t}), ..., t_{\bar{\nu}}^{-1}(u_{W,t-1})), \tag{9}$$

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

Even if the innovations z_t have been already filtered and whitened, it is possible that the parameters of the copula vary over time. For instance, it may be the case that the degree of freedom $\bar{\nu}$ decreases during a crisis. Indeed, one would exect that during a crisis, not only the correlation increases but also the extreme tail behavior. For this reason, we allow the parameters of the copula (Γ and $\bar{\nu}$) to vary over time. To deal with the computation burden, we re-estimate the parameters of the copula every two months.[2]

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

2.2 Measuring Systemic Risk

We now turn to the estimation of the MES. Our approach is similar to the one proposed by Brownlees and Engle (2010), but it needs to be adapted to the multi-factor framework.

[2]The reason for re-estimating the copula instead of assuming a parametric dynamic for the parameters is that it is not clear how we should design the dynamic of the degree of freedom. See Jondeau and Rockinger (2003) for an illustration of the parametric approach.

First, we need to precisely define a financial crisis. We define a world crisis similarly as it is done by Brownlees and Engle (2010), namely as a realization of the world return below a given value c_W, i.e. $r_{W,t} < c_W$. A European crisis is defined as a realization of the European error term below a given value c_E, i.e. $\varepsilon_{E,t} < c_E$ (independently from the realization of world returns). Similarly, a country wide crisis is defined as a realization of the country error term below a given value c_C, i.e. $\varepsilon_{C,t} < c_C$ (independently from the realization of world and European returns).

How should we select the thresholds c_W, c_E, and c_C? This question arises because country specific returns are by far more volatile than the aggregate European market and the world market.[3] In addition, the volatility of the various markets has changed significantly over the period. Therefore, instead of using a unique threshold for all the markets, we define the thresholds c_W, c_E, and c_C as the 5% quantile of the distribution of $r_{W,t}$, $\varepsilon_{E,t}$, and $\varepsilon_{C,t}$. This quantile is re-estimated everyday, based on a rolling window of 4 years.

To compute the MES, we need to distinguish two different cases. On the one hand, the effect of a shock on the country or on the region can be computed in the usual way. On the other hand, the effect of a shock on the world market has to take asynchronicity into account.

Assuming no shock on the European and world markets ($r_{E,t} = r_{W,t} = r_{W,t-1} = 0$), the MES with respect to a country wide shock $\varepsilon_{C,t}$ is given by:

$$\begin{aligned} MES^C_{i,t} &= -E_{t-1}\left[r_{i,t}|\varepsilon_{C,t} \le c_C\right] = E_{t-1}\left[\beta^C_{i,t} r_{C,t} + \varepsilon_{i,t}|\varepsilon_{C,t} \le c_C\right] \\ &= -\beta^C_{i,t} E_{t-1}\left[r_{C,t}|\varepsilon_{C,t} \le c_C\right] - E_{t-1}\left[\varepsilon_{i,t}|\varepsilon_{C,t} \le c_C\right] \\ &= -\beta^C_{i,t}\sigma_{C,t} E_{t-1}\left[z_{C,t}|z_{C,t} \le c_C/\sigma_{C,t}\right] - \sigma_{i,t} E_{t-1}\left[z_{i,t}|z_{C,t} \le c_C/\sigma_{C,t}\right]. \end{aligned}$$

[3]The average of the annual standard deviation of stock returns across the countries under study between January 2000 and March 2012 is 25.8%, whereas the standard deviation of the European return and of the world return are 21.1% and 17.8%, respectively. In addition, the dispersion is wide across countries, from 15.1% for Slovenia to 47.5% for Turkey.

Assuming no shock for the world market ($r_{W,t} = r_{W,t-1} = 0$), the MES with respect to a European shock $\varepsilon_{E,t}$ is defined as:

$$\begin{aligned}
MES^E_{i,t} &= -E_{t-1}\left[r_{i,t}|\varepsilon_{E,t} \leq c_E\right] = -E_{t-1}\left[\beta^C_{i,t} r_{C,t} + \beta^E_{i,t} r_{E,t} + \varepsilon_{i,t}|\varepsilon_{E,t} \leq c_E\right] \\
&= -E_{t-1}\left[\beta^C_{i,t}(\beta^E_{C,t} r_{E,t} + \varepsilon_{C,t}) + \beta^E_{i,t} r_{E,t} + \varepsilon_{i,t}|\varepsilon_{E,t} \leq c_E\right] \\
&= -(\beta^C_{i,t}\beta^E_{C,t} + \beta^E_{i,t})\sigma_{E,t} E_{t-1}\left[z_{E,t}|z_{E,t} \leq c_E/\sigma_{E,t}\right] \\
&\quad -\beta^C_{i,t}\sigma_{C,t} E_{t-1}\left[z_{C,t}|z_{E,t} \leq c_E/\sigma_{E,t}\right] - \sigma_{i,t} E_{t-1}\left[z_{i,t}|z_{E,t} \leq c_E/\sigma_{E,t}\right].
\end{aligned}$$

In the case of the MES with respect to the world market, we need to adapt the usual definition of the marginal expected shortfall to take into account the asynchronicity of the various markets under consideration. As a world shock on day t may affect firm i on day t or $t+1$ in Europe, we need to consider the expected loss over the next two days. If we assume no shock for the lagged world market ($r_{W,t-2} = 0$) and no transmission through the country and European returns, the MES with respect to a world shock would be given by:

$$\begin{aligned}
MES^W_{i,t} &= -E_{t-2}\left[r_{i,t} + r_{i,t-1}|\varepsilon_{W,t-1} \leq c_W\right] \\
&= -E_{t-2}\left[(\beta^W_{i,t}\beta^L_{W,t} + \beta^L_{i,t} + \beta^W_{i,t-1}) r_{W,t-1}|\varepsilon_{W,t-1} \leq c_W\right] \\
&\quad -E_{t-2}\left[\beta^W_{i,t}\varepsilon_{W,t} + \varepsilon_{i,t} + \varepsilon_{i,t-1}|\varepsilon_{W,t-1} \leq c_W\right] \\
&= -(\beta^W_{i,t}\beta^L_{W,t} + \beta^L_{i,t} + \beta^W_{i,t-1})\sigma_{W,t-1} E_{t-2}\left[z_{W,t-1}|z_{W,t-1} \leq c_W/\sigma_{W,t-1}\right] \\
&\quad -\beta^W_{i,t}\sigma_{W,t} E_{t-2}\left[z_{W,t}|z_{W,t-1} \leq c_W/\sigma_{W,t-1}\right] - \sigma_{i,t} E_{t-2}\left[z_{i,t}|z_{W,t-1} \leq c_W/\sigma_{W,t-1}\right] \\
&\quad -\sigma_{i,t-1} E_{t-2}\left[z_{i,t-1}|z_{W,t-1} \leq c_W/\sigma_{W,t-1}\right].
\end{aligned}$$

When the transmission mechanisms of world shocks through the country and European markets are taken into account, the MES with respect to a world shock is:

$$\begin{aligned}
MES^W_{i,t} &= E_{t-2}\left[(((\beta^C_{i,t}\beta^E_{C,t}\beta^W_{E,t} + \beta^C_{i,t}\beta^W_{C,t} + \beta^E_{i,t}\beta^W_{E,t} + \beta^W_{i,t})\beta^L_{W,t} + (\beta^C_{i,t}\beta^E_{C,t} + \beta^E_{i,t})\beta^L_{E,t}\right. \\
&\quad +\beta^C_{i,t}\beta^L_{C,t} + \beta^L_{i,t} + ((\beta^C_{i,t-1}\beta^E_{C,t-1} + \beta^E_{i,t-1})\beta^W_{E,t-1} + \beta^C_{i,t-1}\beta^W_{C,t-1} + \beta^W_{i,t-1}) r_{W,t-1} \\
&\quad (\beta^C_{i,t}\beta^W_{C,t} + \beta^E_{i,t}\beta^W_{E,t} + \beta^W_{i,t})\varepsilon_{W,t} + (\beta^C_{i,t}\beta^E_{C,t} + \beta^E_{i,t})\varepsilon_{E,t} + \beta^C_{i,t}\varepsilon_{C,t} + \varepsilon_{i,t} \\
&\quad \left.+(\beta^C_{i,t-1}\beta^E_{C,t-1} + \beta^E_{i,t-1})\varepsilon_{E,t-1} + \beta^C_{i,t-1}\varepsilon_{C,t-1} + \varepsilon_{i,t-1}|\varepsilon_{W,t-1} \leq c_W\right].
\end{aligned}$$

Estimating the marginal expected shortfall in a copula framework is relatively straightforward, as we have, for instance:

$$
\begin{aligned}
E_{t-1}\left[z_{i,t}|z_{C,t} \leq \tilde{c}_C\right] &= \int_{-\infty}^{+\infty}\int_{-\infty}^{\tilde{c}_C} z_{i,t}h(z_t)dz_{C,t}dz_{i,t} \\
&= \int_{0}^{1}\int_{0}^{F_C(\tilde{c}_C)} F_i^{-1}(u_{i,t})c_{\Gamma,n}(u_t)du_{C,t}du_{i,t},
\end{aligned}
$$

where the second line is obtained by the change of variable $z_{k,t} = F_k^{-1}(u_{k,t})$. This expression can be computed by numerical integration or by Monte-Carlo simulation. In our empirical work, we follow Sancetta (2004) and adopt the simulation approach. We simulate large samples of $u^s = \{u_1^s, \cdots, u_T^s\}$ from the estimated copula (for $s = 1, ..., S$), compute the corresponding $z^s = \{z_1^s, \cdots, z_T^s\}$ and then compute the marginal expected shortfall as:

$$
E_{t-1}\left[z_{i,t}|z_{C,t} \leq \tilde{c}_C\right] = \frac{1}{\sum_{s=1}^{S}\mathcal{I}(z_{C,t}^s \leq \tilde{c}_C)}\sum_{s=1}^{S} z_{i,t}^s \times \mathcal{I}(z_{C,t}^s \leq \tilde{c}_C). \tag{10}
$$

This approach provides very accurate estimates of the true expectation provided the number of simulated data is large enough. In our empirical work, we use $S = 50'000$ simulations.

3 European Data

Our sample is the set of large financial institutions in Europe. We include all the firms with a minimum market capitalization of 1 billion euros (as of end of 2011) and a price series starting before January 2005. The whole sample starts in January 1990 (when available) and ends in March 2012. For comparability purpose, all data are converted into euros. The data includes daily information (stock return and market capitalization, from Datastream) and quarterly information (book value of the asset and of the equity, from Compustat).

Table 1 provides some information concerning the 194 financial firms in our sample. There are 72 banks, 51 in financial services firms, 36 insurance companies, and 35 real estate firms. There are 45 financial firms in Great Britain, 22 in France, 21 in Switzerland, 18 in Sweden, and 14 in Germany. The largest market capitalizations are HSBC Holdings (105.4 billion euros), Sberbank (40.8 billion), and Standard Chartered (40.2 billion). The largest insurance company is Allianz (33 billion), the largest financial services firm is ING (25.5 billion), and the largest real estate firm is Unibail-Rodamco (12.8 billion). The cumulative market capitalization for the 194 institutions is 1'262.2 billion euros, with a median of 2.6 billion euros.

Figure 1 provides a comparison of the cumulative performances of the European market as a whole and of the components of the financial institutions index. We notice that financial institutions offer very different patterns. Banks and insurance companies have been outperforming the other categories until 2001. Then, insurance companies started to under-perform the other categories. Financial services and real estate firms show similar dynamics, with a severe under-performance over the 90s and then following the market trend afterwards. With the subprime crisis, bank stocks suffered a dramatic fall. Over the whole period, the performances of the banks and real estate firms are similar (average return of 6.2% and 5.8%, respectively), insurance companies are below (5.4%). Financial services firms outperform the other categories (7.2%), although they are below the European market (7.3%).

As **Table 1** confirms, the banks and insurance companies have been the riskiest groups: high volatility, large kurtosis, large VaR and expected shortfall. The maximum draw down is particularly high for the banks (-80%), corresponding to the subprime crisis. Over the financial industry, financial services have been a relatively safe group, with rather high return, low volatility and kurtosis, and a low maximum draw down. As the characteristics of the extremes of the distribution show, the asymmetry of the distribution is not very pronounced.

4 Empirical Results

4.1 The dynamic of the beta parameters

As outlined in Section 2, the model consists of three components: the dynamic conditional beta model, the univariate GARCH models for the error terms, and the t copula for the dependence structure of the innovations. These components are estimated in successive steps for computational reasons. The main motivation is that we do not want to assume the parameters of the t copula to be constant over time. As a consequence, we have to re-estimate these parameters using a rolling window of 4 years. As we will show, it clearly appears that these parameters are indeed varying over time, which justifies our approach. As a consequence, it also slows down the estimation of the complete model.[4]

Given the large number of firms under consideration, we cannot report the individual parameter estimates and associated dynamics for all the firms. Instead, we focus on the aggregated results for the industry groups and the countries. We also focus in a case study on some particularly interesting firms: three of the largest banks (Deutsche Bank, BNP Paribas, and Barclays), the two largest insurance companies (Allianz and AXA), and the largest financial services firm (ING).[5] These firms allow us to describe the main features common to all financial institutions and the main differences that may appear between the banks and insurance companies.

We start with the estimation of the DCC model. The differences between the categories are small: as shown in **Table 2**, the individual variances display similar persistence across industry groups, and the correlations have the same persistence as well. For the univariate distribution of the innovation processes, we obtain again similar patterns. The univariate distributions have fat tails, as expected. The degree of freedom ν of the skewed-t distribution ranges between 3.4 and 4.8, reflecting levels of kurtosis close to those reported in Table 2. The asymmetry parameter λ is found to be positive on average for all categories, suggesting a positive skewness for the return distribution of individual firms.

The (time-varying) sensitivity of stock returns to their main drivers is estimated from the DCC model as described in Section 2.1 and summary statistics are reported in Panel D. We notice large differences between the categories. Financial firms are mostly driven by the European market (with a median beta between 0.37 and 0.7). The country wide market also plays an important role (with a sensitivity between 0.08 and 0.16), mostly

[4]The estimation of the complete model over the full sample for a given firm takes on average 10 minutes.

[5]Royal Bank of Scotland and Credit Agricole are not shown because of lack of data.

for large firms. Finally, the sensitivity of firms to world return (current and lagged) is positive, with a cumulative effect in the range (0.05;0.25).

The last component of the model is the copula model, designed to capture the dependence structure of the innovation processes. As Table 2 reveals, the degree of freedom of the t copula, $\bar{\nu}$, is rather large, between 35 and 41. This result suggests that most of the dependence has been already captured by the dynamic correlation beta model. A closer look at the evolution of the degree-of-freedom parameter shows that, in fact, this parameter is strongly altered by crisis periods: its average estimate ranges between 41 and 47 during the first subperiod, but decreases to 21-24 after the subprime crisis. During this period, we notice an increase in the tail dependence.

4.2 Leverage and Risk Measures

We now turn to our estimation of systemic risk measures. We start with a brief description of the main components, the leverage and the MES. Results are reported in **Table 3** and **Figure 2** for four industry groups and in **Table 4** and **Figure 3** for countries.

The comparison of the **leverage** between these various industry groups helps understanding the differences found in terms of systemic risk. First, as shown in Table 3, if we start with the full sample, we find that, on the one hand, banks and insurance companies have large and similar leverage, on average 17.7 and 15.7, respectively. On the other hand, financial services and real estate display relatively low leverage, between 4 and 2.2, respectively. This has obviously important consequences for the level of capital at risk borne by the financial firms. Inspection of subsamples also provides some interesting information about the last decade. Between 2000 and 2007, banks and insurance companies had the same, relatively low, leverage (around 13.5). As Figure 2 indicates, between 2002 and 2003, the leverage in insurance companies was even higher than the one in banks. Over the more recent period, however, the leverage in the banking industry has rocketed to 26.6, while it increased to 20 only for insurance companies. For financial services and real estate, there is an upward trend in leverage, however even during the subprime crisis it did not exceed 6 for both groups.

The **MES** estimates also display similar patterns. A 5%-quantile negative shock on the world market implies on average an expected loss of 3% for banks and insurance companies, but only 2.5% and 1.6% for financial services and real estate, respectively.[6] Again, these numbers have varied quite a lot over the recent period for banks and insurance companies. The expected loss after a world shock, with the same 5% probability of occurrence, was in the range [2.2%; 2.8%] between 2000 and 2007, and above 4% after 2008. This increase reflects that market shocks are now more severe and that the financial institutions have been more dependent from the market trend over the recent period.

If we turn to the effect of a shock on the European market, we observe that in general financial firms are less sensitive to European shocks than to world shocks. For instance, the MES of banks is 3% with respect to a world shock and 1.8% with respect to a European shock. In addition, this sensitivity has almost doubled over the recent period. It increased from 1.3% to 2.6% for banks. This evolution is confirmed by Figure 2. We also observe that the MES of insurance companies actually increased a first time in 2002-03, with on average a higher sensitivity to world shocks than in 2008-09.

The **systemic risk** measure combines the effects described above: the sensitivity to world/European shocks; and the fragility (measured by the leverage) of financial firms. Not surprisingly, we obtain again two groups of institutions: Banks and insurance companies have suffered from a high systemic risk over the whole period (on average, 763 and 208 billion euros, respectively), whereas financial services and real estate are barely concerned by systemic events.

If we consider more specifically the recent period (2008-12), we find that the exposure of banks has strongly increased: it has been multiplied by 3.5 compared to the 2000-07 period. At the same time, the systemic risk of insurance companies has been multiplied by 1.7 only. On average, banks account for 75% of the systemic risk across European financial firms, and insurance companies for 24%. The total exposure of the 194 largest financial institutions in Europe has been on average 616.9 billion euros between 2000 and

[6]Estimates for the real estate are not available because of a lack of accounting data for these firms before 2004.

2007 and 1’826 billion between 2008 and 2012. At the end of the period under study (March 16th, 2012), the total exposure is 2’039 billion euros.[7]

If we now consider a regional crisis (a 5% quantile shocks on the European market), we find that the implied systemic risk measure is about 90% of the systemic risk implied by a world crisis.

4.3 Systemic Risk across Countries

In Table 4, we report the average leverage, MES, and systemic risk measures for the countries, which show a minimum systemic risk of 75 billion euros over the recent period. The leverage displays large differences across countries, partly because countries do not have the same proportion of banks and insurance companies, but also because we have large differences in terms of leverage across countries within the same industry group. Over the full sample, Germany and France share high leverage, whereas Spain has relatively low leverage. Countries with high MES are the Netherlands, the UK, and France (see Figure 3).

All in all, over the last decade, the country with the highest systemic risk is France (245 billion euros on average), followed by the UK (211 billion) and Germany (185 billion). Although British firms have relatively low leverage, they have high MES and large market capitalization. During the recent crisis, the leverage and MES have increased in all countries, so that the systemic risk has also dramatically increased. Between 2008 and 2012, the UK is ranked first (459 billion) in terms of overall systemic risk, followed by France (432 billion) and Germany (271 billion). As of March 16th, 2012, the systemic risk estimates are still as high as 579.1 billion and 489.4 billion euros for the UK and France (contributing for about 50% of the total exposure of European financial firms).

4.4 Ranking of Financial Institutions

The last step of our work is the ranking of European financial firms in terms of systemic risk. **Table 6** shows the ranking for the last day of our sample, i.e. March 16th, 2012.

[7]This number can be compared to the 421 billion dollars for U.S. financial firms reported on the VLab website at Stern School of Business (http://vlab.stern.nyu.edu/welcome/risk).

On that day, the five riskiest institutions are banks: Deutsche Bank (156 billion euros), BNP Paribas (137 billion), Royal Bank of Scotland (133 billion), Barclays (130 billion), and Credit Agricole (130 billion).

The comparison between Deutsche Bank and BNP Paribas clearly shows that systemic risk may have different sources: Deutsche Bank has a high leverage with a relatively low market cap (65 and 32 billion euros, respectively). On the contrary, BNP Paribas has a relatively low leverage with a large market cap (43 and 44 billion, respectively). In addition, BNP Paribas' MES is much larger than Deutsche Bank's MES (7.1% vs. 5.3%). We also notice that banks with the largest market cap (HSBC) is only ranked 6. The reason is that it hasvery low leverage and low MES compared to other large cap banks.

Insurance companies are less systemically risky than banks. The first ones are AXA (15th, 44 billion euros) and Allianz (20th, 27.7 billion). Both companies have high MES and relatively large market cap, however their leverage is low compared to large banks. Among financial services firms, the only institutions in the top 25 is ING Groep, ranked 7th (90 billion euros). This firm has a high MES (5.9%) and a rather large leverage (49).

5 Conclusion

In this paper, we describe an econometric approach designed to measure systemic risk for non-U.S. institutions, therefore extending the approach developed by Brownlees and Engle (2010). Two issues have been addressed: first, there are several potential factors explaining the dynamic of European financial institutions' return; second, the world return is likely to affect European firms' return instantaneously or with a one-day lag, given 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 error terms, and a dynamic t copula to estimate the dynamic of the dependence structure between the innovations.

We apply this methodology to the 194 largest European financial institutions and estimate their systemic risk over the 2000-2012 period. At the end of the period under study (March 16th, 2012), the total exposure of these 194 firms is 2'039 billion euros.

Banks and insurance companies bear about 80% and 20% of the systemic risk in Europe, respectively. Systemic risk is essentially unaffected by financial services and real estate firms. Over the recent period, the systemically riskiest countries have been the UK and France, as these two countries have contributed for about 50% of the total exposure of European financial institutions. The two riskiest institutions over the recent period have been Deutsche Bank and BNP Paribas, bearing almost 300 billion euros together.

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Appendix: Computing the correcting factor k

We have daily returns on the world market and need to compute the expected shortfall of the firm i conditional on a financial crisis. We define a financial crisis as a drop of about 40-50% of the market over a 6-month period. We make two assumptions: first following Gabaix (2009), we assume a power law for the distribution of returns in the extremes; second we assume that returns are independent over time.

Historically, the kind of financial crisis defined above has a probability of occurrence of about 1% every semester (or one such financial crisis out of every 50 years). Assuming a power low, we obtain that:

$$E_t\left[r_{i,t+1}|Crisis\right] = k_0 E_t\left[r_{i,t+1}|r_{M,t+1} \leq q_{5\%}\right],$$

with $k_0 = (5\%/\Pr\left[Crisis\right])^{\xi}$, where ξ is the tail index of the return distribution. In the data at hand, our estimate of the tail index over the 1990-2011 period is $\xi = 0.277$, so that $k_0 = 1.6$, when the probability of a crisis is 1%.

Then, assuming time independence of returns, we obtain that:

$$E_t\left[\sum_{j=0}^{\tau} r_{i,t+j+1}|Crisis\right] = \sqrt{\tau} E_t\left[r_{i,t+1}|Crisis\right],$$

where $\tau = 126$ (for 6 months). Eventually, we find:

$$E_t\left[\sum_{j=0}^{\tau} r_{i,t+j+1}|Crisis\right] = k E_t\left[r_{i,t+1}|r_{M,t+1} \leq q_{5\%}\right],$$

where $k = k_0\sqrt{\tau} \approx 18$.

Captions

Table 1: This table provides summary statistics on the index return of European financial firms for the period from January 1990 until March 2012 (total return index, in euros). For each category, we report the average annual return, the volatility, the skewness, the kurtosis, the 5% VaR and expected shortfall for the left and right sides of the distribution.

Table 2: This table provides summary statistics on parameter estimates and dynamics for all of the industry groups. Panel A reports the median across the institutions of the parameter estimates of the GARCH model of the error terms. Panel B reports the median across firms of the parameter estimates of the correlation dynamic (DCC model). Panel C reports the median across firms of the parameters of the skewed t distribution for the innovations. Panel D reports the median across the firms of the mean over time of the beta parameters. Panel E reports the median across the firms of the mean over time of the degree-of-freedom parameter of the t-copula model. The mean is computed over the whole sample, and over the two subperiods 2000-07 and 2008-12.

Table 3: This table reports for all of the industry groups the median across firms of the mean over time of the leverage, the MES and the systemic risk measures (with respect to world and European shocks). MES is in % and systemic risk in million euros. The mean is computed over the whole sample, and over the two subperiods 2000-07 and 2008-12.

Table 4: This table reports for some countries the median across firms of the mean over time of the leverage, the MES and the systemic risk measures (with respect to world and European shocks). Reported countries are those with a systemic risk larger than 100 billion euros over the 2008-12 period. MES is in % and systemic risk in million euros. The mean is computed over the whole sample, and over the two subperiods 2000-07 and 2008-12.

Table 5: This table reports the ranking of European financial firms by systemic risk as of March 16th, 2012. For each firm, we report the name, country, systemic risk (in million euros), the MES (in %), the leverage, and the market capitalization (in million euros).

Figure 1: This figure displays the cumulative total return (including dividends) for the European market index and the indices reflecting the four industry groups (log-scale).

Figure 2: This figure displays the leverage, MES and systemic risk measures for all of the industry groups, between 2000 and 2012 (when available).

Figure 3: This figure displays the MES, market capitalization, leverage, and systemic risk measures for some countries, between 2000 and 2012 (when available). Reported countries are those with a systemic risk larger than 75 billion euros over the 2008-12 period.

Table 1: Summary statistics on returns by industry group

	World	Europe	Banks	Financial services	Insurance companies	Real estate
Ann. Return	5.83	7.30	6.16	7.15	5.35	5.79
Volatility	17.48	19.56	22.30	14.38	22.58	12.88
Skewness	0.22	0.27	0.28	-0.33	0.12	-0.42
Kurtosis	21.23	17.82	13.89	10.65	11.15	9.47
Max draw down	-59.68	-58.55	-80.02	-65.56	-72.56	-75.92
5%-VaR (left)	-1.48	-1.66	-2.14	-1.40	-2.13	-1.24
5%-ES (left)	-2.52	-2.87	-3.42	-2.24	-3.49	-2.03
5%-VaR (right)	1.48	1.71	2.07	1.33	2.11	1.14
5%-ES (right)	2.70	3.07	3.36	2.01	3.40	1.84

Table 2: Summary statistics on parameter estimates (medians)

		Banks	Financial services	Insurance companies	Real estate
Panel A: GARCH model (Volatility dynamic)					
ω		0.032	0.026	0.036	0.056
α		0.081	0.068	0.076	0.142
γ		0.031	0.018	0.027	0.026
β		0.898	0.916	0.903	0.840
Panel B: DCC model (Correlation dynamic)					
δ_1		0.012	0.012	0.011	0.010
δ_2		0.981	0.984	0.984	0.988
Panel C: Skewed t distribution					
ν		4.521	4.796	4.465	3.442
λ		0.039	0.034	0.034	0.020
Panel D: DCC, Conditional betas (median of means)					
$\beta_{i,t}^{C}$	(Country)	0.163	0.118	0.085	0.127
$\beta_{i,t}^{E}$	(Europe)	0.568	0.631	0.696	0.371
$\beta_{i,t}^{W}$	(World)	-0.006	0.096	0.013	0.035
$\beta_{i,t}^{L}$	(Lagged world)	0.059	0.152	0.099	0.086
Panel E: Copula model, Degree of freedom (median of means)					
$\bar{\nu}$	(2000-2012)	36.810	35.279	36.041	41.434
$\bar{\nu}$	(2000-2007)	47.709	41.444	44.621	45.963
$\bar{\nu}$	(2008-2012)	23.755	22.478	21.847	24.000

Table 3: Leverage and systemic risk by industry group

	Banks	Financial services	Insurance companies	Real estate
Panel A: Full sample				
Leverage	17.7	4.0	15.7	2.2
MES wrt World	3.0	2.5	3.2	1.6
MES wrt Europe	1.8	1.2	1.9	0.8
SR wrt World	763.3	13.8	242.8	0.1
SR wrt Europe	688.2	11.9	208.1	0.1
Panel B: 2000-2007 period				
Leverage	13.3	3.0	13.6	2.1
MES wrt World	2.3	2.1	2.8	0.9
MES wrt Europe	1.3	0.9	1.6	0.5
SR wrt World	413.7	7.1	196.1	0.0
SR wrt Europe	358.6	6.7	162.2	0.0
Panel C: 2008-2012 period				
Leverage	26.6	5.8	20.0	2.5
MES wrt World	4.3	3.3	4.0	3.0
MES wrt Europe	2.6	1.6	2.4	1.6
SR wrt World	1462.4	27.4	336.2	0.3
SR wrt Europe	1347.2	22.4	299.8	0.2

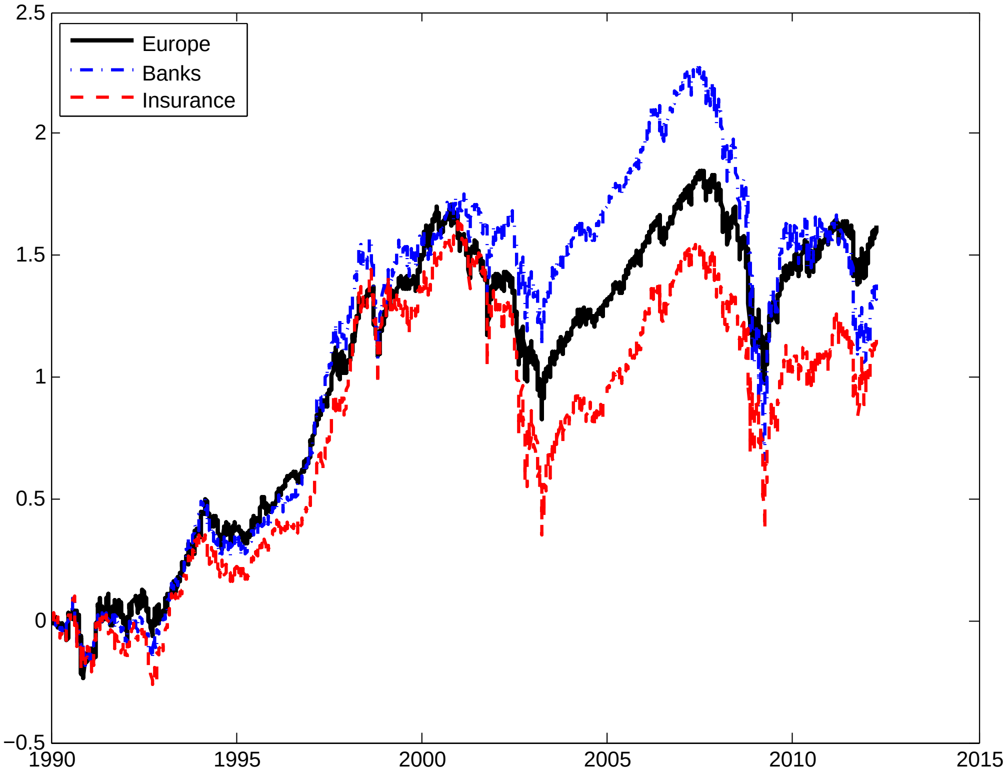
Table 4: Leverage and systemic risk by country

	France	Germany	Italy	Netherlands	Spain	Switzerland	UK
Panel A: Full sample							
Leverage	22.3	24.0	14.6	16.6	10.7	14.9	13.6
MES wrt World	3.1	2.8	2.4	3.5	2.7	2.8	3.2
MES wrt Europe	1.9	1.5	1.7	1.9	2.0	1.6	1.7
SR wrt World	244.7	185.4	63.0	67.2	37.8	98.1	210.6
SR wrt Europe	228.1	169.4	56.3	61.0	30.7	82.5	181.8
Panel B: 2000-2007 period							
Leverage	17.1	19.2	10.6	11.9	8.3	13.1	9.3
MES wrt World	2.3	2.5	1.8	2.9	2.2	2.4	2.5
MES wrt Europe	1.4	1.4	1.2	1.6	1.5	1.5	1.3
SR wrt World	150.9	142.5	24.7	47.3	10.1	79.2	86.3
SR wrt Europe	135.8	128.0	20.1	40.3	5.3	66.1	68.9
Panel C: 2008-2012 period							
Leverage	32.6	33.5	22.5	26.2	15.5	18.5	22.3
MES wrt World	4.5	3.5	3.7	4.6	3.9	3.7	4.5
MES wrt Europe	3.0	1.8	2.8	2.4	2.9	1.9	2.4
SR wrt World	432.1	271.0	139.5	107.1	93.0	135.9	459.1
SR wrt Europe	412.8	252.2	128.7	102.3	81.4	115.2	407.5

Table 5: Ranking of financial institutions by systemic risk (as of March 16th, 2012)

	Name	Country	Systemic risk (mln euros)	MES (in %)	Leverage	Market cap. (mln euros)
1	Deutsche Bank	Germany	156.4	5.3	65.1	32.8
2	BNP Paribas	France	137.3	7.1	43.0	44.2
3	Royal Bk of Scotland	UK	133.1	6.5	88.7	19.8
4	Barclays PLC	UK	130.2	5.8	50.6	35.7
5	Credit Agricole	France	130.0	7.0	139.6	12.0
6	HSBC Holdings	UK	96.7	4.5	16.3	119.4
7	ING Groep	Netherlands	89.9	5.9	49.0	25.5
8	Societe Generale	France	85.2	8.8	59.9	18.8
9	Lloyds Banking	UK	78.6	7.0	38.5	28.7
10	UBS	Switzerland	74.2	5.0	28.7	40.2
11	Banco Santander	Spain	67.4	4.2	21.3	56.5
12	Credit Suisse	Switzerland	55.1	4.0	34.9	24.3
13	Unicredit SPA	Italy	51.2	2.2	37.0	22.6
14	Commerzbank	Germany	47.3	8.4	64.6	9.7
15	AXA	France	44.4	5.7	24.6	28.5
16	Nordea Bank	Sweden	41.2	3.8	24.4	29.4
17	Intesa Sanpaolo	Italy	37.9	3.7	27.8	22.6
18	Natixis	France	35.9	5.9	58.7	8.4
19	Banco Bilbao	Spain	28.3	3.6	17.8	33.0
20	Allianz	Germany	27.7	4.2	14.7	41.4
21	Danske Bank	Denmark	27.1	2.1	35.8	12.6
22	Legal & General Group	UK	27.0	4.6	45.9	8.5
23	Aviva PLC	UK	23.3	5.4	28.1	12.8
24	Generali SPA	Italy	23.2	4.1	21.9	18.8
25	Aegon	Netherlands	22.2	5.5	42.3	7.5

Figure 1: Cumulative return by category (log-scale)



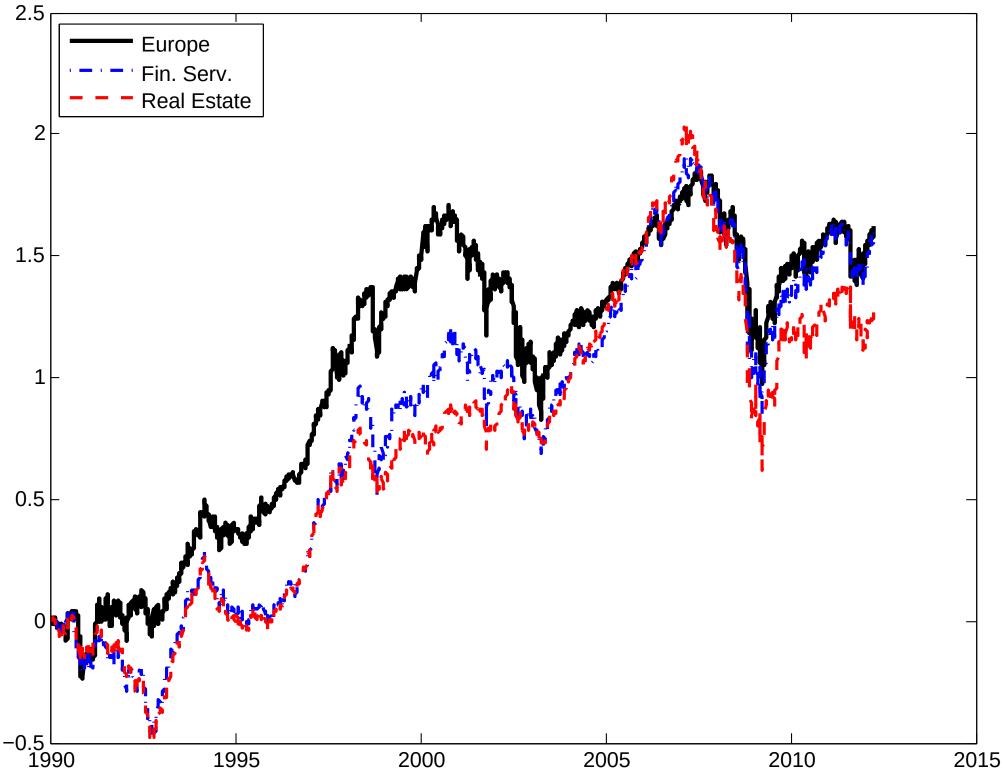
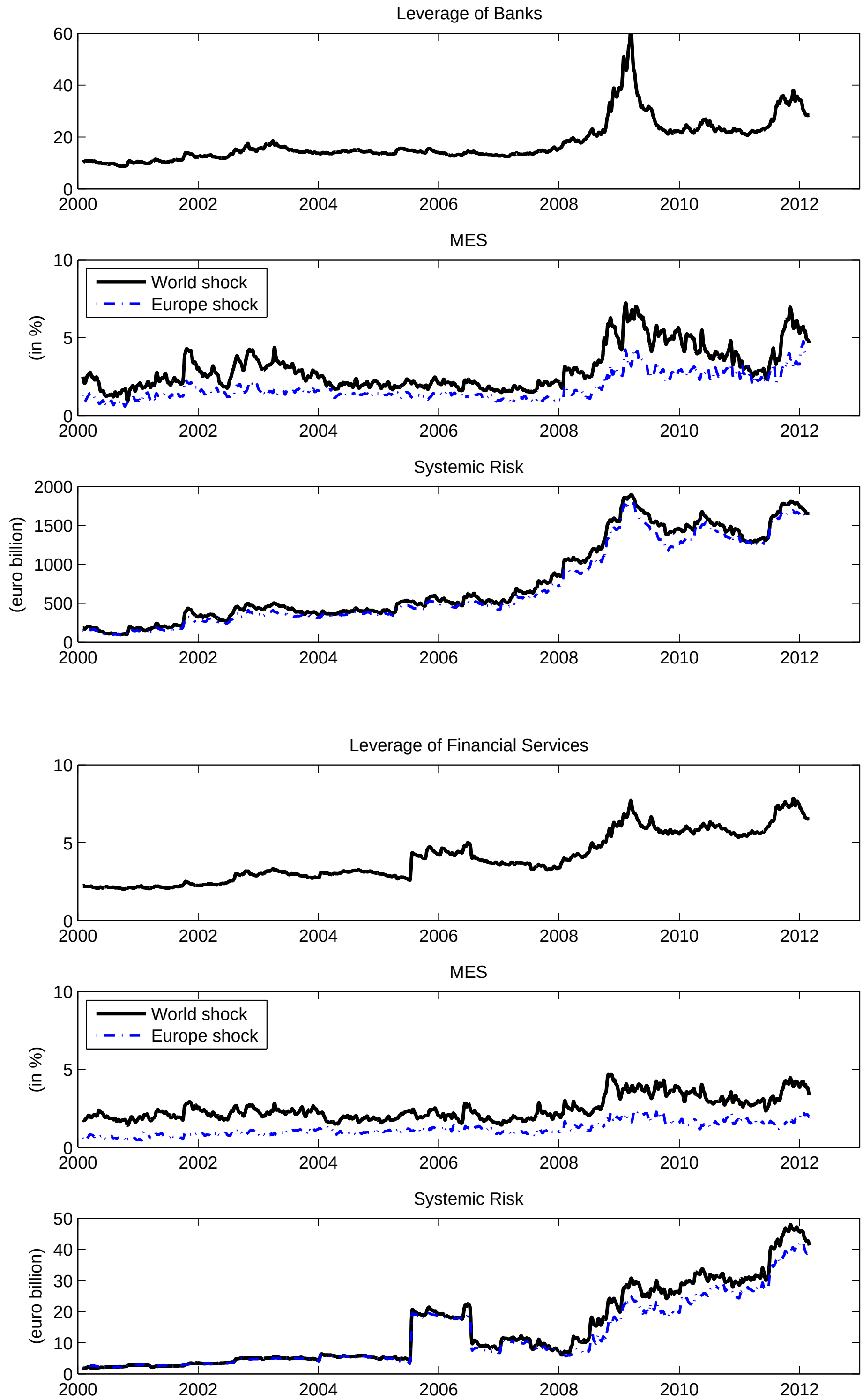
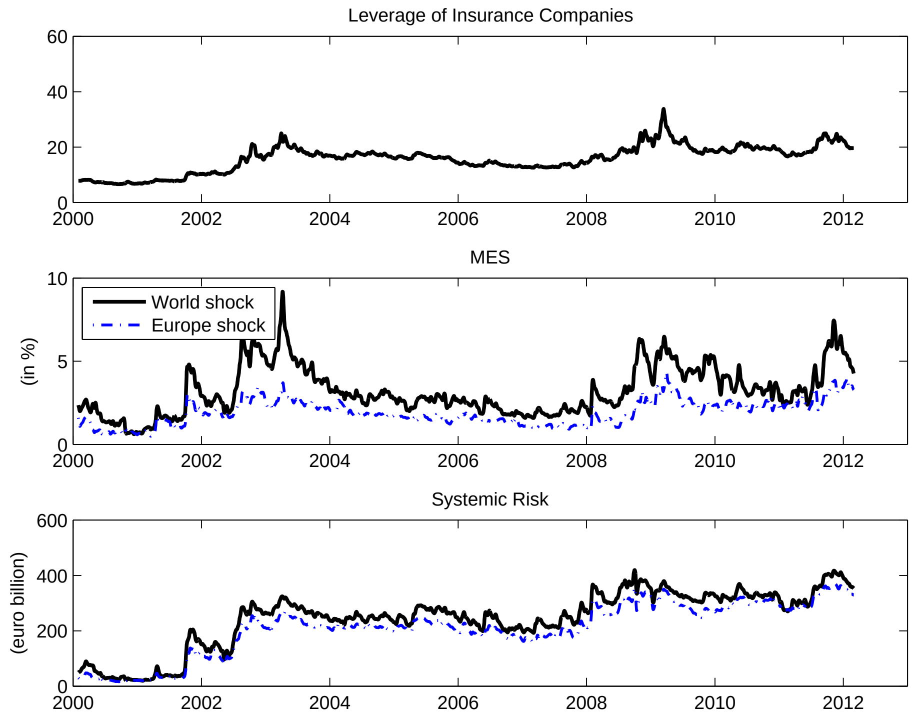


Figure 2: Leverage and risk measures by category




Leverage of Insurance Companies
MES
World shock
Europe shock
(in %)
Systemic Risk
(euro billion)

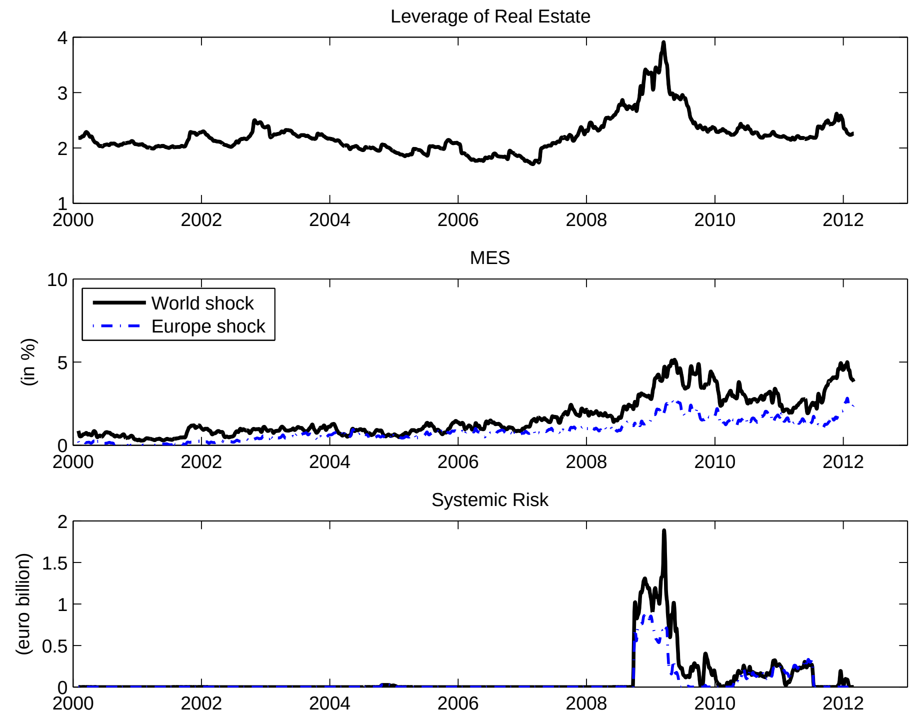
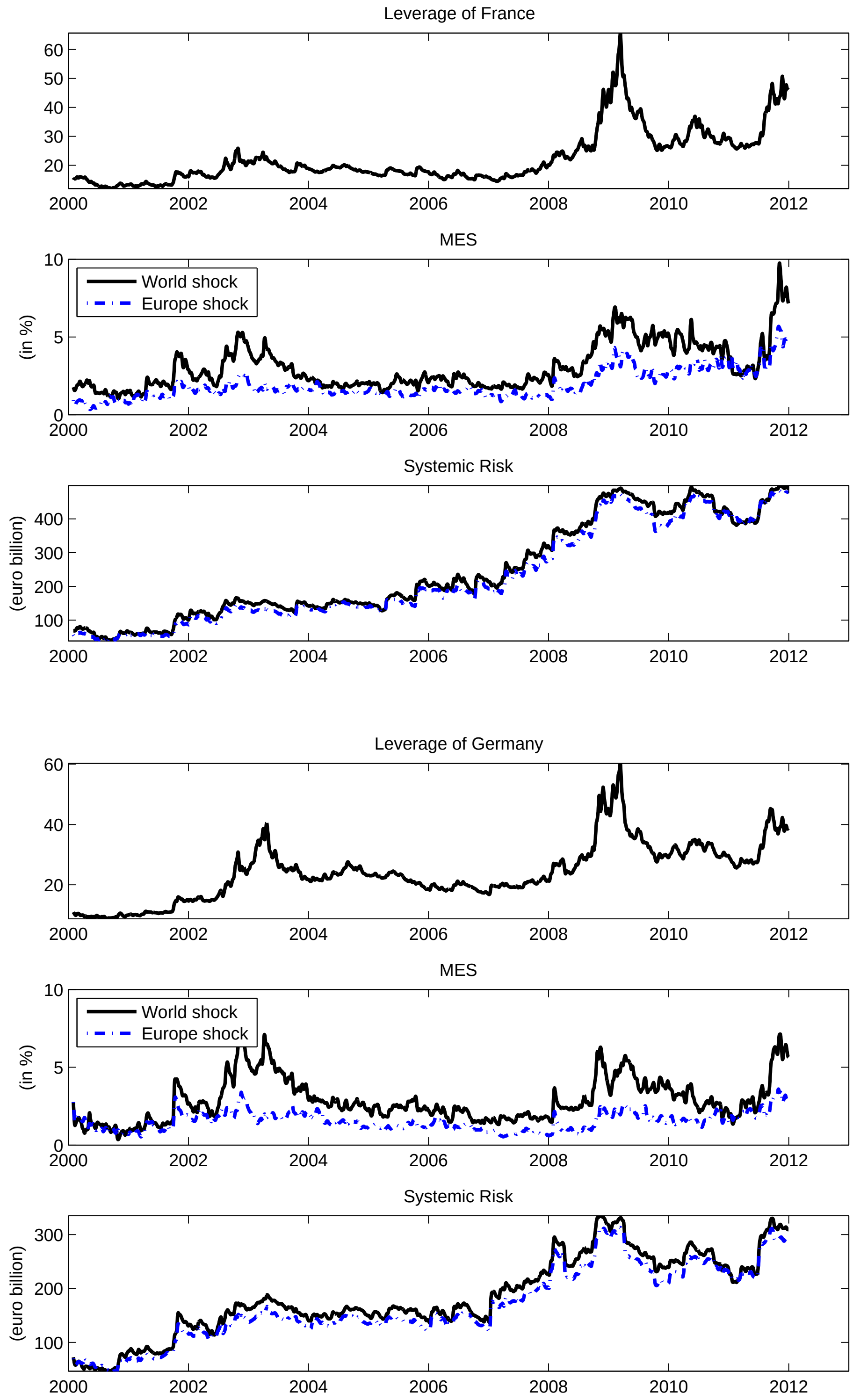
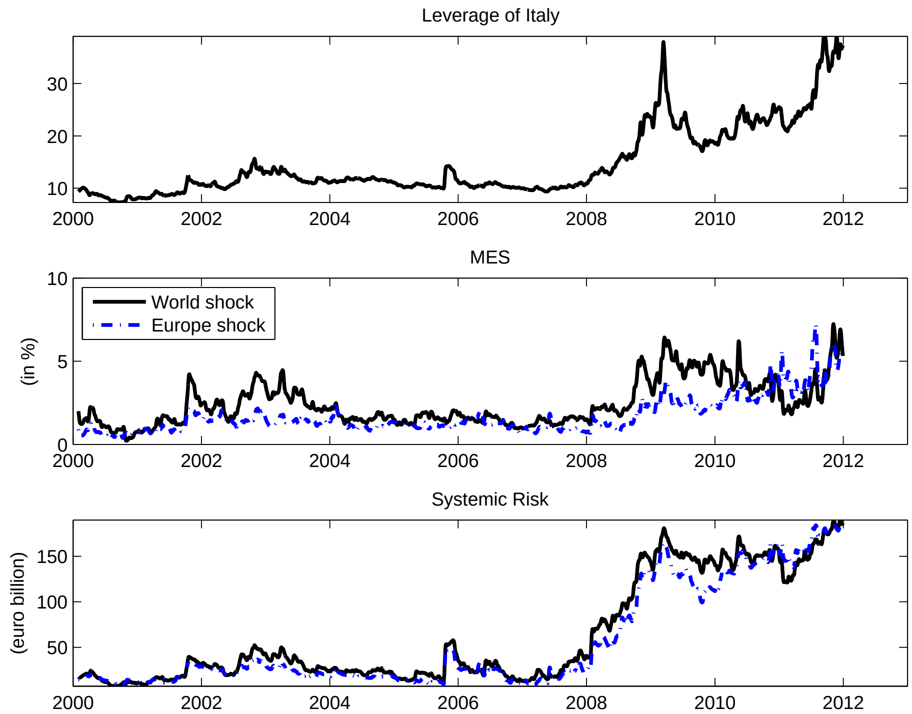
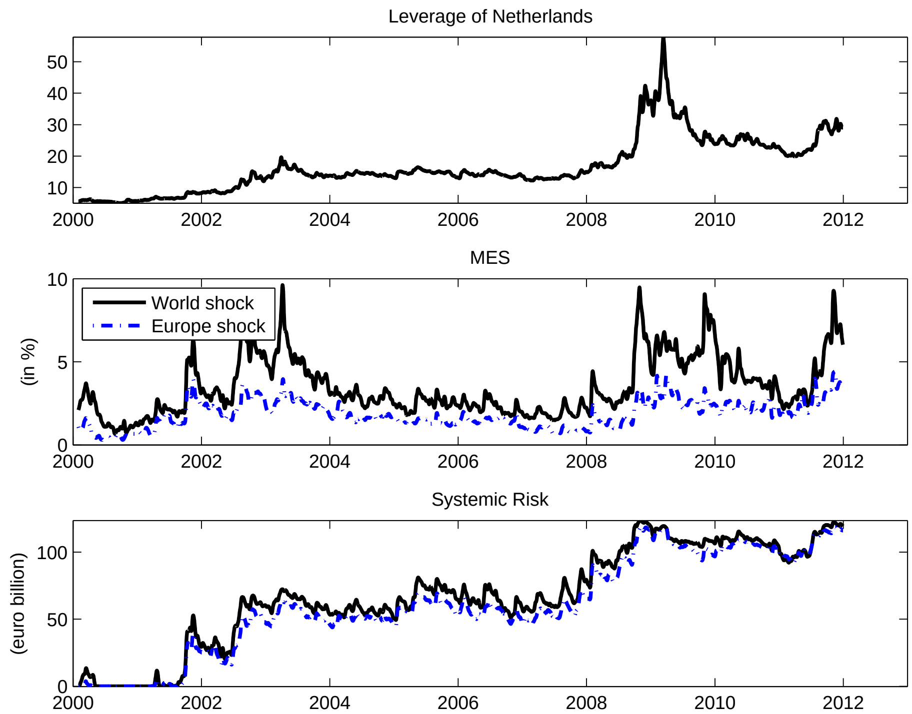
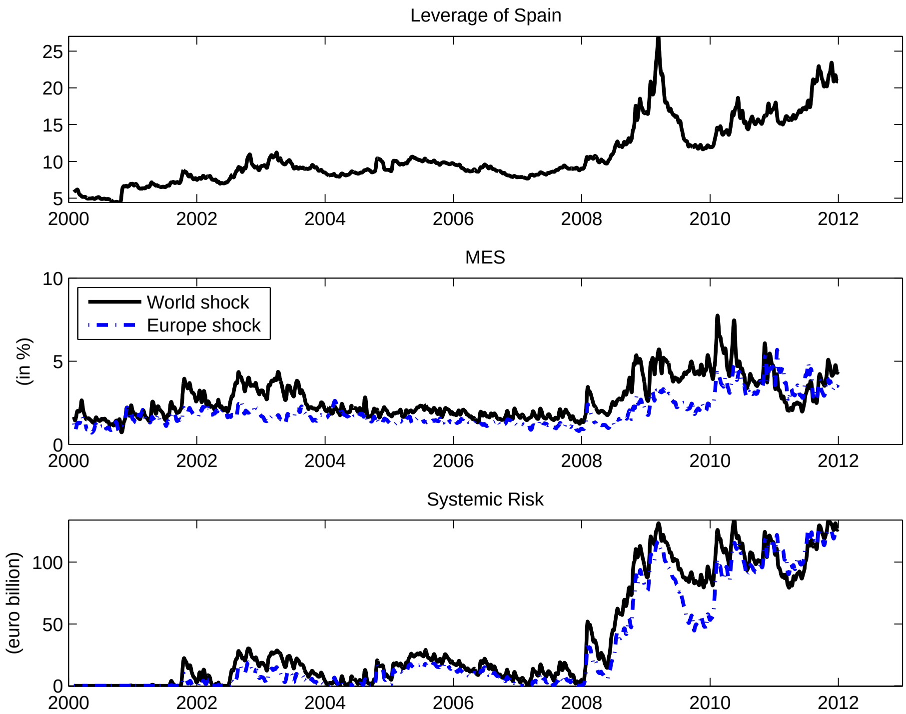

Leverage of Real Estate
MES
World shock
Europe shock
(in %)
Systemic Risk
(euro billion)

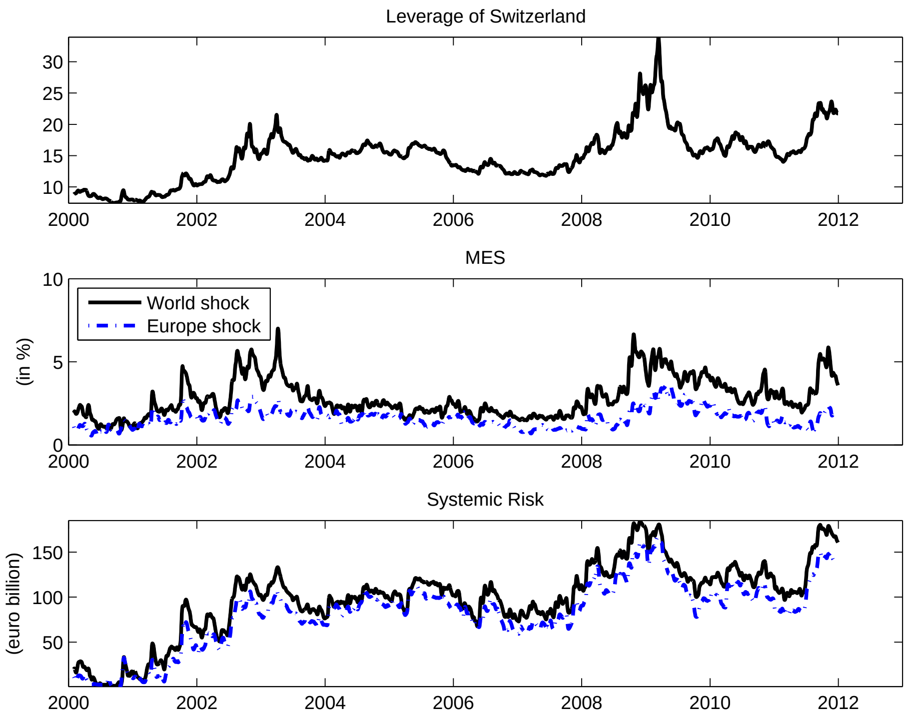
Figure 3: Leverage and risk measures by country

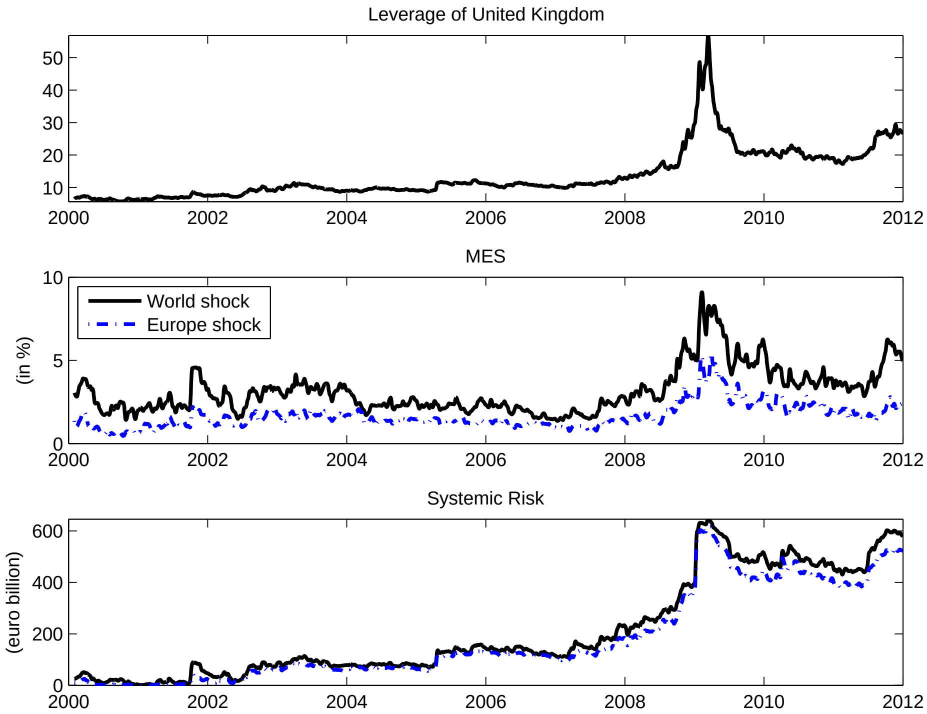



Leverage of Italy
30
20
10
2000
2002
2004
2006
2008
2010
2012
MES
10
5
0
(in %)
World shock
Europe shock
Systemic Risk
150
100
50
(euro billion)

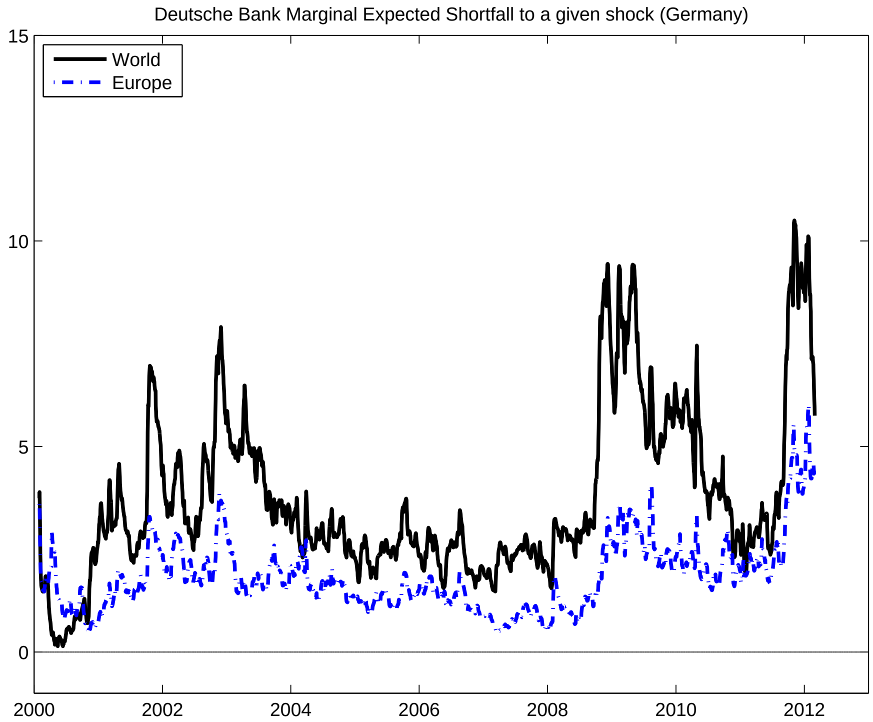

Leverage of Netherlands
50
40
30
20
10
2000
2002
2004
2006
2008
2010
2012
MES
10
5
0
(in %)
World shock
Europe shock
Systemic Risk
100
50
0
(euro billion)

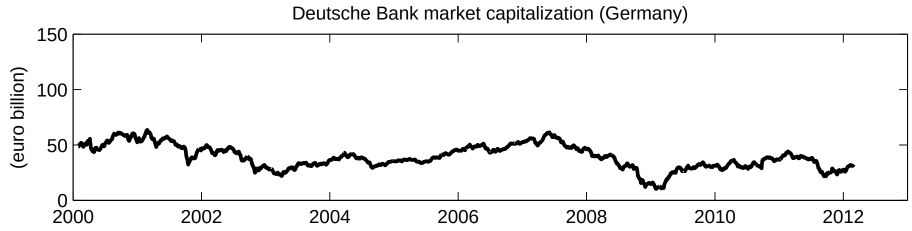

Leverage of Spain
MES
World shock
Europe shock
(in %)
Systemic Risk
(euro billion)
2000
2002
2004
2006
2008
2010
2012

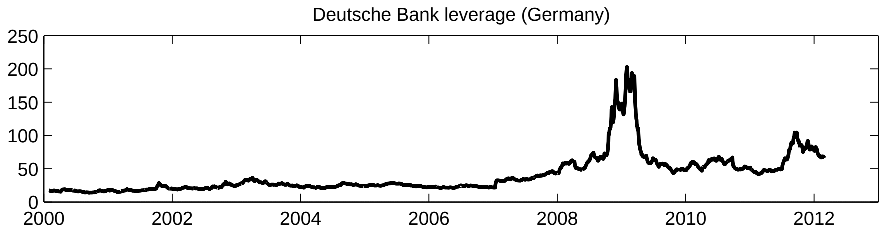

Leverage of Switzerland
MES
World shock
Europe shock
(in %)
Systemic Risk
(euro billion)
2000
2002
2004
2006
2008
2010
2012



Leverage of United Kingdom
50
40
30
20
10
2000
2002
2004
2006
2008
2010
2012
MES
10
5
0
(in %)
World shock
Europe shock
Systemic Risk
600
400
200
0
(euro billion)


Deutsche Bank Marginal Expected Shortfall to a given shock (Germany)
World
Europe
15
10
5
0
2000
2002
2004
2006
2008
2010
2012


Deutsche Bank market capitalization (Germany)
(euro billion)
150
100
50
0
2000
2002
2004
2006
2008
2010
2012


Deutsche Bank leverage (Germany)
250
200
150
100
50
0
2000
2002
2004
2006
2008
2010
2012

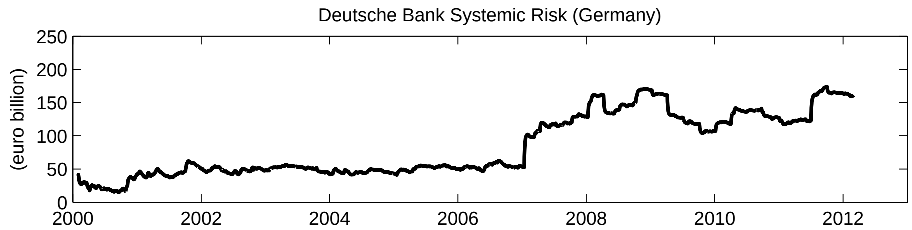
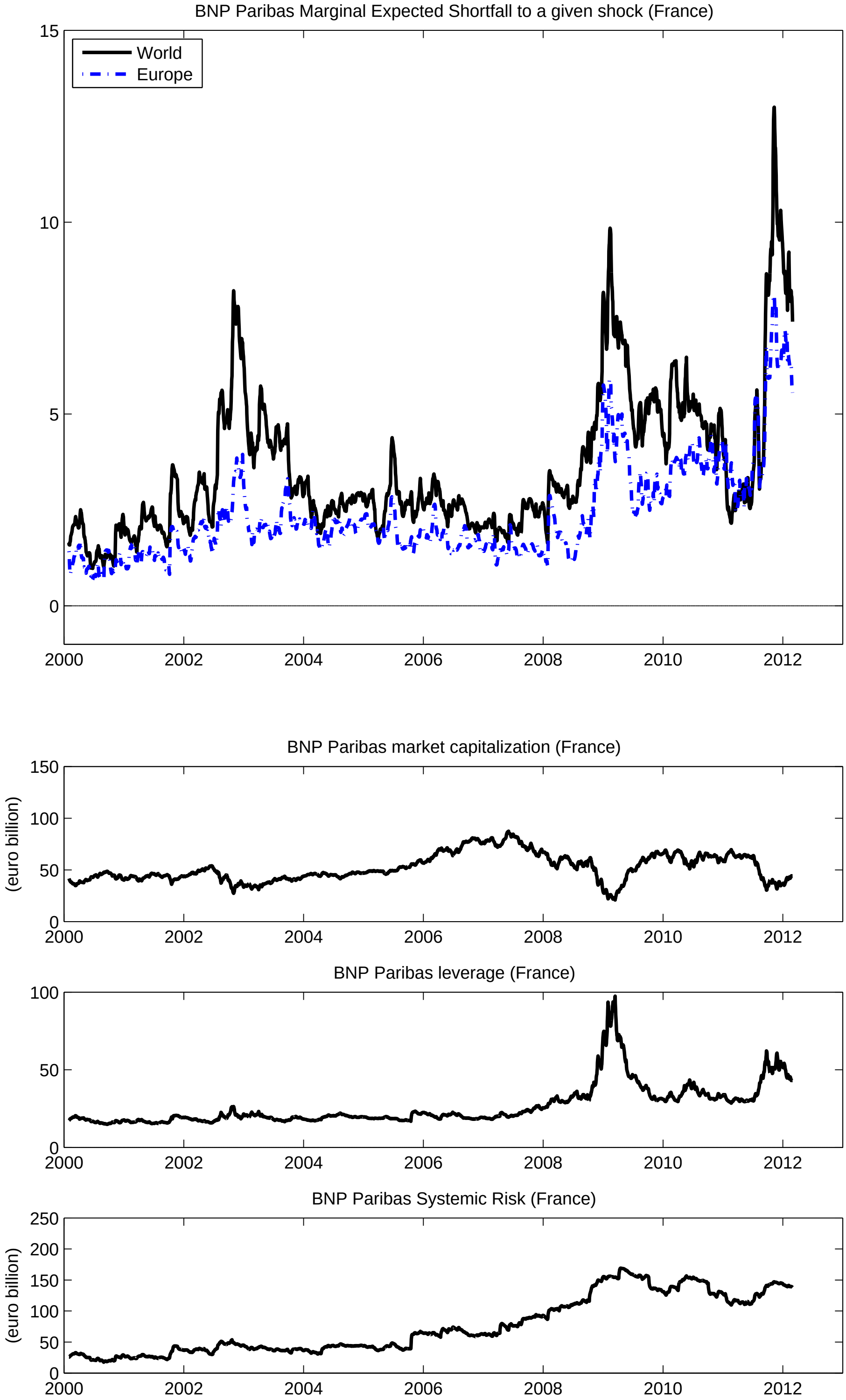
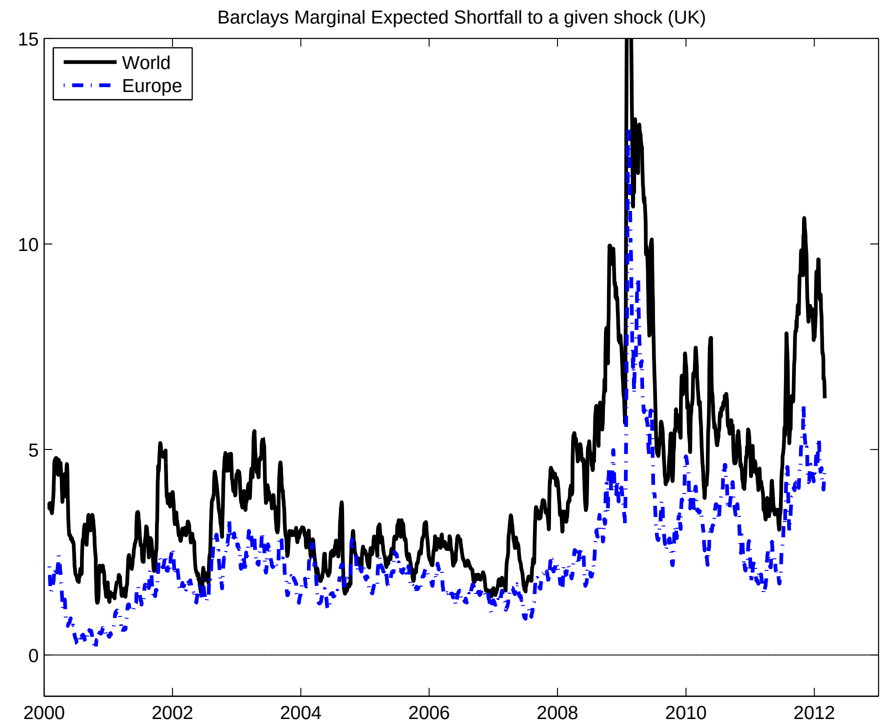
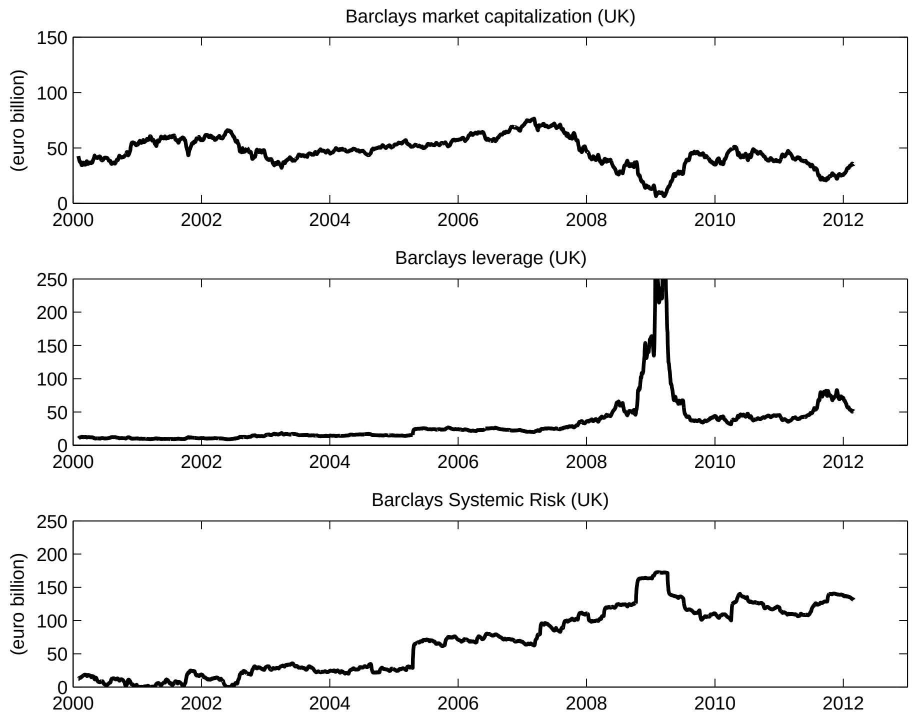
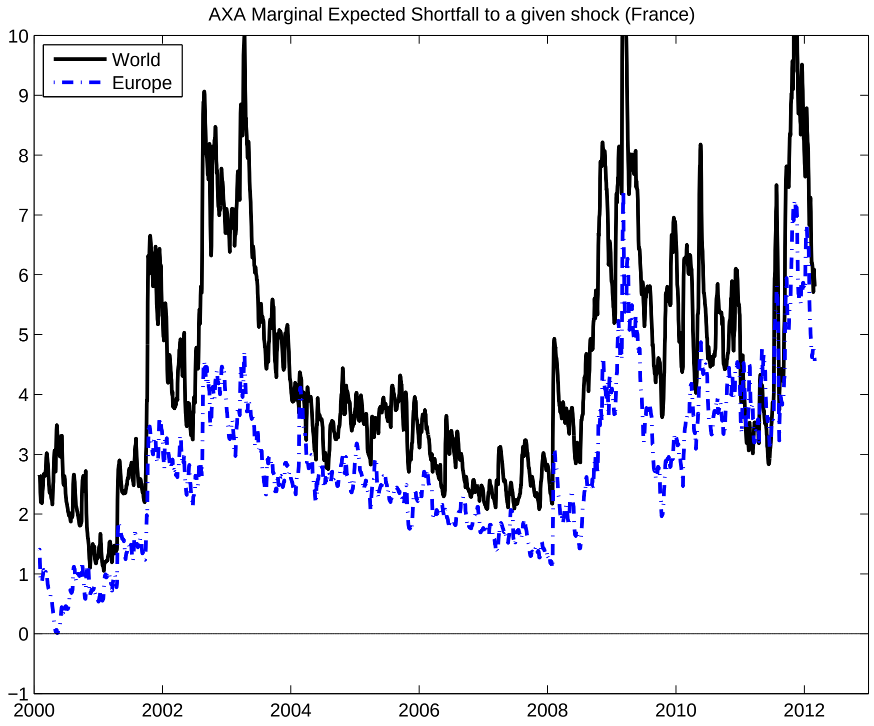

Deutsche Bank Systemic Risk (Germany)
(euro billion)
250
200
150
100
50
0
2000
2002
2004
2006
2008
2010
2012

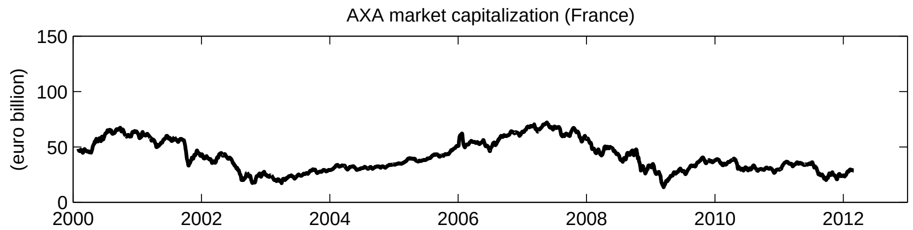
Figure 4: Leverage and risk measures by institution

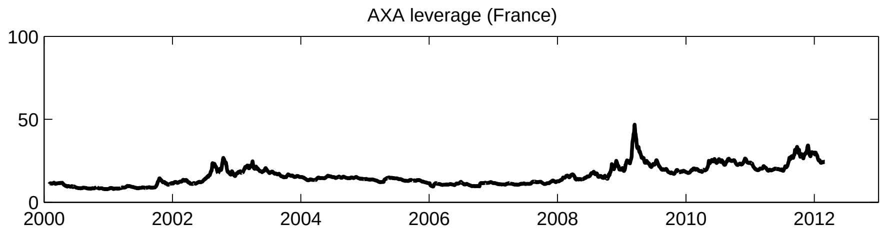


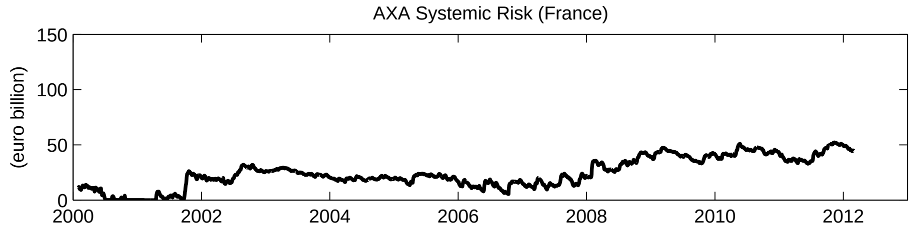

Barclays Marginal Expected Shortfall to a given shock (UK)
World
Europe
15
10
5
0
2000
2002
2004
2006
2008
2010
2012

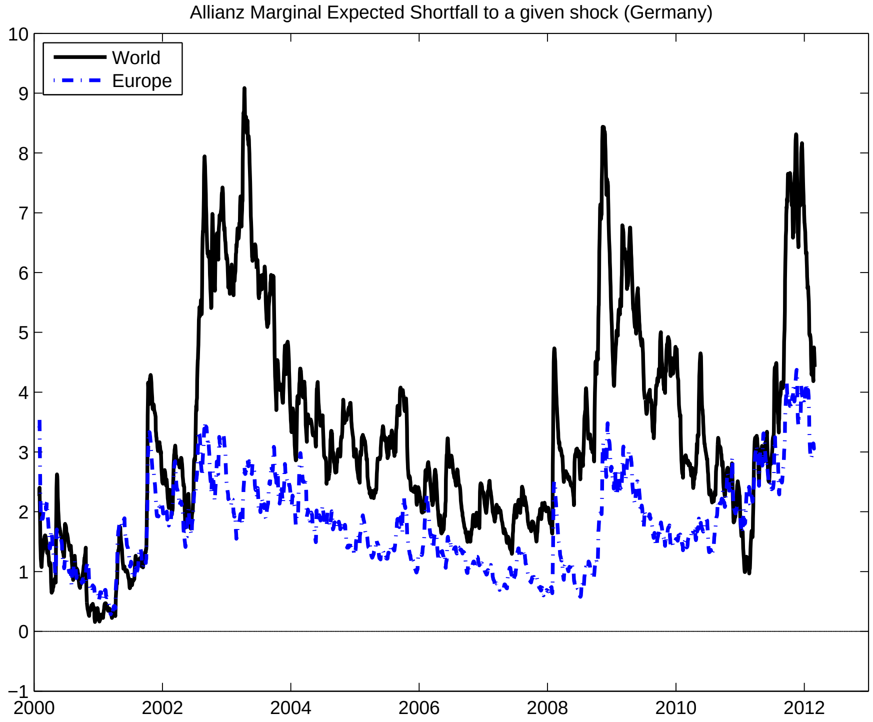

Barclays market capitalization (UK)
(euro billion)
150
100
50
0
2000
2002
2004
2006
2008
2010
2012
Barclays leverage (UK)
250
200
150
100
50
0
2000
2002
2004
2006
2008
2010
2012
Barclays Systemic Risk (UK)
(euro billion)
250
200
150
100
50
0
2000
2002
2004
2006
2008
2010
2012


AXA Marginal Expected Shortfall to a given shock (France)
World
Europe
10
9
8
7
6
5
4
3
2
1
0
−1
2000
2002
2004
2006
2008
2010
2012

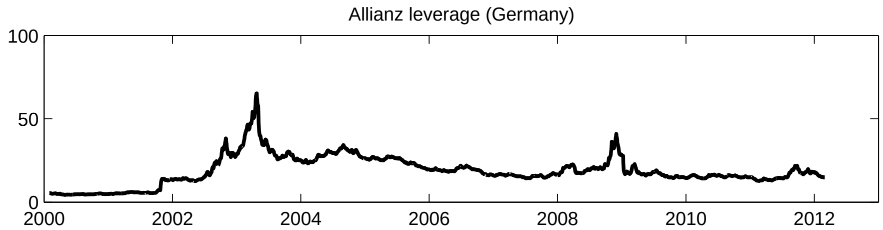

AXA market capitalization (France)
(euro billion)
150
100
50
0
2000
2002
2004
2006
2008
2010
2012

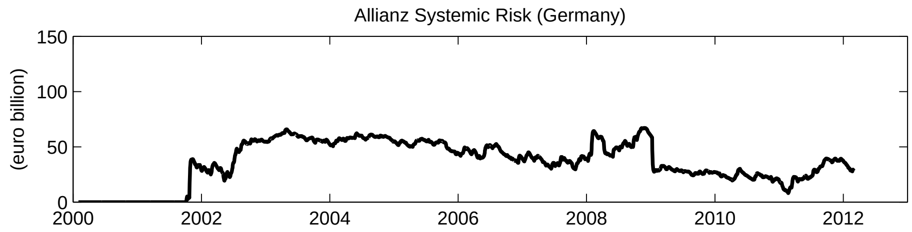

AXA leverage (France)
100
50
0
2000
2002
2004
2006
2008
2010
2012

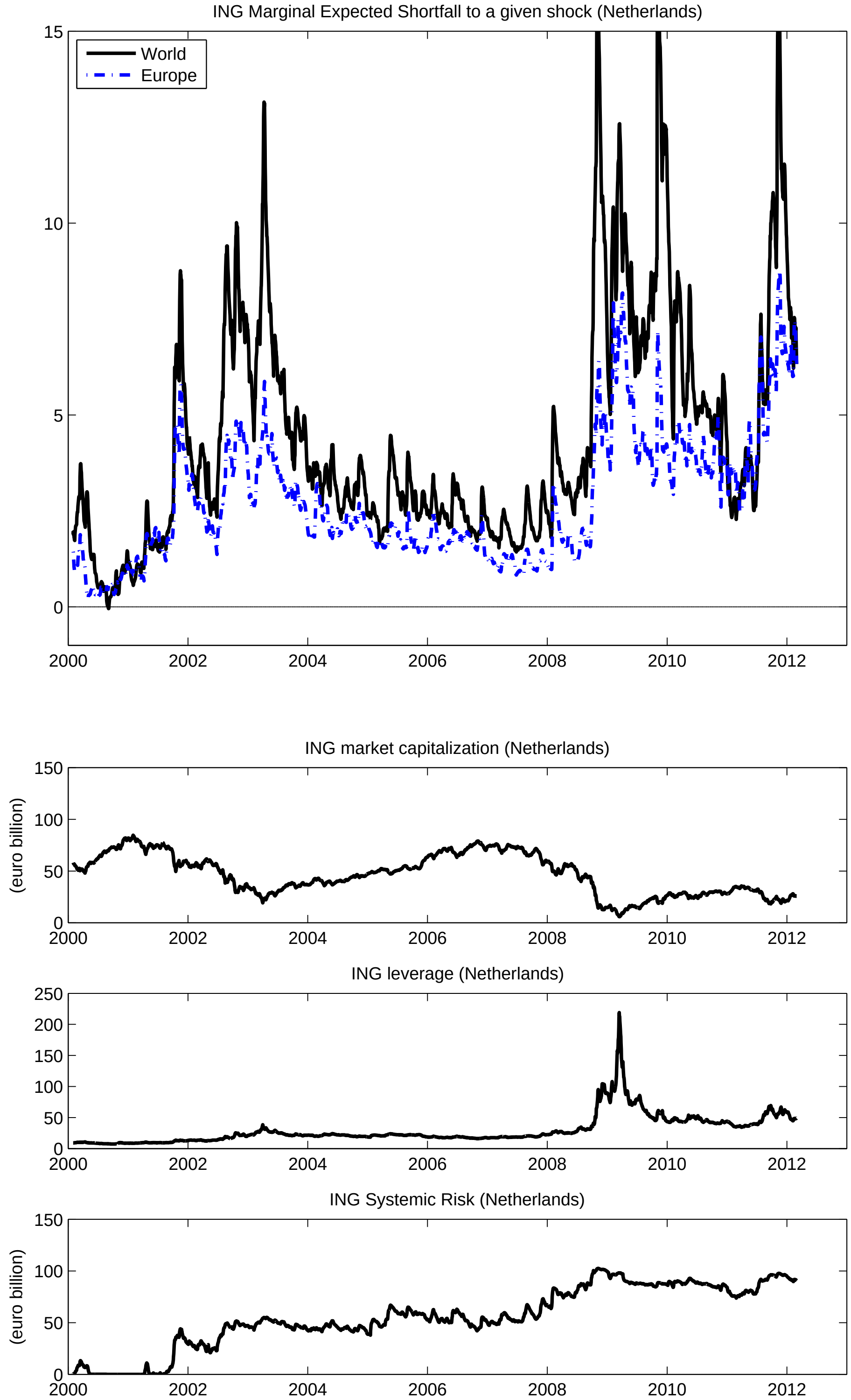

AXA Systemic Risk (France)
(euro billion)
150
100
50
0
2000
2002
2004
2006
2008
2010
2012


Allianz Marginal Expected Shortfall to a given shock (Germany)
World
Europe
10
9
8
7
6
5
4
3
2
1
0
−1
2000
2002
2004
2006
2008
2010
2012


Allianz market capitalization (Germany)
(euro billion)
150
100
50
0
2000
2002
2004
2006
2008
2010
2012


Allianz leverage (Germany)
100
50
0
2000
2002
2004
2006
2008
2010
2012


Allianz Systemic Risk (Germany)
(euro billion)
150
100
50
0
2000
2002
2004
2006
2008
2010
2012


ING Marginal Expected Shortfall to a given shock (Netherlands)
World
Europe
15
10
5
0
2000
2002
2004
2006
2008
2010
2012
ING market capitalization (Netherlands)
(euro billion)
150
100
50
0
ING leverage (Netherlands)
250
200
150
100
50
0
ING Systemic Risk (Netherlands)
(euro billion)
150
100
50
0