Tail risk and systemic risk of US and Eurozone financial institutions in the wake of the global financial crisis

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Abstract

We evaluate multiple market-based measures for US and eurozone individual bank tail risk and bank systemic risk. We apply statistical extreme value analysis to the tails of bank equity capital losses to estimate the likelihood of individual institutions' financial distress as well as individual banks' exposure to each other ("spillover risk") and to global shocks ("extreme" systematic risk). The estimation procedure presupposes that bank equity returns are "heavy tailed" and "tail dependent" as identifying assumption. Using both US and eurozone banks allows one to make a cross-atlantic comparison of tail risks and systemic stability. We also assess to what extent magnitudes of tail risk and systemic risk have been altered by the global financial crisis. The results suggest that both tail risk and systemic risk in the US are higher than in the eurozone regardless of the considered sample period.

Keywords: Banking, Systemic Risk, Asymptotic Dependence, Multivariate Extreme Value Theory

JEL Classification: G21, G28, G29, G12, C49

1 Introduction

The banking and economic crisis that started in 2007 has reminded everybody that financial systems - and the banking sector in particular - are inherently fragile and that financial stability should not be taken for granted. The negative impact on the real economy is undeniable although spectacular contractions in real economic activity have been smoothened by the sustained efforts of central banks and national governments to stabilize the financial system.[1] Banks not only play a key role in the money creation process and in the international payments system but bank credit is also a determining factor in the financing of investment and growth. Moreover, monetary history learns that badly managed institutions have sometimes turned the real economy into depression and hyperinflation. Thus, monitoring (preventive action) or restoring (curative action) financial stability has regained central bankers' and supervisory authorities' attention as one of the top priorities.

The ongoing global financial crisis has clearly revealed the limitations of the existing regulatory framework. While the Basel I and Basel II accords mainly focussed on monitoring the financial soundness of individual banks, there is by now growing consensus that regulators also have to consider a bank's contribution to overall systemic instability. The crisis has indeed shown that financial regulation and supervision should focus more on systemic risk. The minimum requirements envisaged in the Basel III accord aim at establishing rules that take account of this systemic risk. Systemic risk indicators could, for example, be used as a basis to impose taxes or capital surcharges on systemically important financial institutions (Acharya et al., 2010; Allen et al., 2012).

Measuring individual risks and systemic risks is a complex affair in highly developed financial systems. Moreover, pre-crisis structural shifts in developed financial systems suggest that systemic risk measurement and monitoring cannot be approached in a purely static fashion. The fact that supposed triggers of systemic instability like, e.g., the degree of interbank interconnectedness, the location of banks within the interbank "network" or the correlations between loan portfolios are often difficult to observe constitutes an additional complication when assessing financial stability. Therefore, a majority of the empirical banking stability literature has proposed more indirect "market-based" indica-

[1] see Aizenman et al. (2011) for a multi-country panel data study on financial expansions and contractions and their real economic impact.

tors of systemic risk. The oldest strand of literature on bank equity "spillovers" applies event study methodology to measure the impacts of specific bank distress or bank failures on other banks' stock prices (Swary, 1986; Wall and Peterson, 1990; Slovin et al., 1999. Other authors applied various regression approaches to link abnormal bank stock returns to asset-side risks, including those related to aggregate shocks (Smirlock and Kaufold, 1987; Kho et al., 2000). De Nicolo and Kwast (2002) use a proxy of banking consolidation as explanatory variable for the changes in bank equity return correlations over time. Gropp and Moerman (2004) measure conditional co-movements of large abnormal bank stock returns and of equity-derived distances-to-default. Gropp et al. (2009) use an ordered logit specification to identify spillovers between banks based on the changes in their distances-to-default. More recent market-based measures of systemic risk include the Shapley Value (Tarashev et al., 2010), Conditional Value-at-Risk (Adrian and Brunnermeier, 2011) and Marginal Expected Shortfall (Acharya et al., 2010; Brownlees and Engle, 2012), conditional tail risk (Kelly and Jiang, 2013; Chan-Lau, 2009).[2]

Whereas the literature described above mainly focused on identifying contagion-type bank equity spillovers, other papers argued that banking instability may be due to aggregate shocks. Using historical data on banking panics and business cycle proxies going back to the 19th Century, Gorton (1988) shows that business cycles have often been leading indicators of bank panics. Gonzalez-Hermosillo et al. (1997) do the same for the 1994-1995 Mexican crisis and Demirgüc-Kunt and Detragiache (1998) provide further multi-country evidence. Hellwig (1994) suggests that the fact that deposit contracts are non-contingent on the state of the macro economy may also partly explain their vulnerability towards aggregate shocks. Recent work by Allen et al. (2012) also fits within this latter tradition.[3] They construct a tail measure of aggregate systemic risk (called CATFIN) using the cross-sectional distribution of financial institutions' equity returns.[4]

[2]Alternative approaches to systemic risk modelling have been developed that do not depend on market variables like, e.g., stock prices, CDS spreads or distance-to-default. Deposit withdrawals or survival times of healthy banks during banking crises have been studied (Saunders and Wilson, 1996; Calomiris and Mason, 1997, 2000). A more recent literature tries to relate bank contagion risk to central bank data on interbank exposures (Upper and Worms, 2004; Degryse and Nguyen, 2007; van Lelyveld and Liedorp, 2006; Mistrulli, 2005). Purely theoretical models of bank contagion have also been proposed (Allen and Gale, 2000; Freixas et al., 2000). Bisias et al. (2012) provide a a comprehensive survey of 21 systemic risk indicators that have been proposed through time.

[3]As to date, the empirical literature on the consequences of systemic instability for real economic activity is surprisingly underdeveloped. Giglio et al. (2013) constitutes one of the few other examples.

[4]The CATFIN index is defined as the equally weighted average of three Value-at-Risk (VaR) estimates (for p-values equal to 1%) based on the Generalized Pareto distribution (GPD), the Skewed Generalized Error Distribution (SGED) and the empirical distribution (purely nonparametric).

The authors also show that the CATFIN index acts as an early warning indicator towards future real economic activity. More specifically, it exhibits predictive ability up to the 6-month time horizon and for different proxies of real economic activity. The predictability remains when performing a whole set of robustness checks. For example, a CATFIN indicator constructed on the basis of smaller banks preserves its early warning character which illustrates that contagion-type phenomena due to interbank interconnectedness only constitute one dimension of systemic risk. Allen et al. (2012) argue that their forward-looking indicator could be used by regulators to e.g. calibrate a micro-level systemic risk tax that could be implemented in a countercyclical fashion.[5]

The systemic risk indicators we are going to work with complement both the spillover (contagion) literature as well as the literature on aggregate shocks that potentially destabilize the whole banking system. We partly follow the statistical extreme value (EVT) approach of Hartmann et al. (2006) towards identifying systemic risk.[6] In line with the existing empirical systemic risk literature reviewed above, which distinguishes between "bank contagion" and "aggregate macro shocks" as different forms of bank instability, we distinguish conditional "co-crash" probabilities between bank equity returns (to identify "spillover" or "contagion" risk) from crash probabilities of bank stock returns conditional on aggregate shocks (to identify "extreme systematic risk" or "tail-β").[7]. Notice the proposed risk indicators are also market-based indicators because they make use of banks' equity returns.[8] More specifically, the EVT approach presupposes that bank stocks are efficient in the sense that large daily losses in bank stocks are not sunspots

[5]They also argue that the bulk of the micro-level systemic risk measures only exhibits weak macroeconomic foreasting power.

[6]Other applications of multivariate EVT to assessing asset market linkages during stress periods include Straetmans (2000), Longin and Solnik (2001) and Poon et al. (2004) on stock markets, Hartmann et al. (2003) on currency linkages and Hartmann et al. (2004) on stock-bond linkages.

[7]The terms bank "spillovers" or bank "contagion" will be used interchangeably throughout the paper. For definition, See Hartmann et al. (2006)

[8]In terms of definition, the Marginal Expected Shortfall (MES) and the Conditional Value-at-Risk (CoVaR) come close to our indicators as they are also probabilistic-based: MES is the expected loss on individual bank equity capital conditional on large market portfolio losses. CoVaR is the Value-at-Risk (VaR) of the financial system conditional on institutions being under distress. In contrast to previous approaches towards modelling market linkages and spillovers that were often correlation-based, both MES, CoVaR and our indicators allow for non-linear dependence in the data. There are, however, also two major differences between MES, CoVaR and our approach. First, we also consider purely multivariate measures of spillover risk whereas both MES and CoVaR are bivariate in nature. Second, and most importantly, the current empirical literature on CoVaR and MES does not evaluate these indicators very deep into the joint tail of bank stock returns; one may actually wonder whether one truly captures systemic events with the latter indicators. This constitutes the main difference with our approach.

but fundamentals-based and reflect that banks are financially distressed. Moreover, joint sharp falls in bank stocks reflect the risk of a problem in one bank spreading to other banks ("spillover" risk). Finally, joint sharp falls in individual bank stocks and a non-diversifiable risk factor like the market index reflect the extreme systematic risk exposure (or "tail-β") of an individual bank to aggregate shocks.[9]

The current study contributes to existing studies on banking system stability in different dimensions. First, statistical extreme value theory has hardly been used in the context of systemic risk assessment and enables one to focus on very low frequency events.[10] Second, we perform a cross-Atlantic comparison of tail risk and systemic risk over time. We earlier argued that varying degrees of financial integration and banking market consolidation at both sides of the Atlantic justifies such a comparison. Moreover, there are hardly any papers that compare the two continents in terms of systemic risk apart from the Hartmann et al. (2006) paper. Third, the current study imposes the identifying restriction of "tail dependence" on the systemic risk indicators' estimation procedure. Loosely speaking, a pair of bank stock return losses $(X_1, X_2) > (0, 0)$ is tail dependent when the conditional co-crash likelihood does not vanish to zero in the tail area, i.e., $lim_{s\to\infty} P\{X_1 > s | X_2 > s\} > 0$. Previous studies that applied extreme value techniques towards measuring bank spillovers like e.g. Hartmann et al. (2006) or De Jonghe (2010) allowed for tail independence; but this implies that the systemic risk estimates may have underscored the true value if the actual data were tail dependent. Moreover, imposing tail dependence is a reasonable assumption given the interconnectedness of banks via either interbank markets or common asset exposures (De Vries, 2005). The tail dependence assumption is not only statistically convenient but also economically relevant

[9]Market-based indicators of tail risk or systemic risk also have their limitations: they are unsuited to evaluate the systemic risk contribution of non-listed banks; and they are supposed to act as "canaries in the coal mine" or "early warning indicators" of accumulating systemic risks. This can only be the case if bank stocks are informationally efficient and thus fully reflect balance sheet risks and relationships between different banks' risks due to interbank lending, overlapping loan portfolios or other sources of common exposures, which is probably too strong an assumption. We nevertheless believe that market-based indicators may be a useful tool in that they may at least partly reflect the risks that threaten banks.

[10]The vast majority of estimation methodologies employed in the systemic risk context do not go beyond p-values of 1%. One may wonder whether this truly captures the rare nature of systemic events. For example, Adrian and Brunnermeier (2011) use quantile regressions and Brownlees and Engle (2012) exploit Dynamic Conditional Correlation (DCC) models as devices for systemic risk quantification; but these methodologies are unable to evaluate systemic risk measures for p-values beyond 1%. Hartmann et al. (2006) and Zhou (2010) are part of the few EVT studies that actually evaluate indicators of systemic risk for p-values below 1%.

because it renders conservative estimates (i.e. upperbounds) for the proposed systemic risk indicators; we believe this is a desirable property of systemic risk indicators primarily developed for regulatory and supervisory bodies with "prudential" considerations. Fourth, our indicator of extreme systematic risk (tail-β) is conditioned on a much wider set of non-diversifiable risk factors than previously including sharp market fluctuations in real estate and sovereign debt indices. Fifth, we apply Huang (1992)'s expectational linkage measure in a banking context as an indicator of multivariate contagion risk.[11] The indicator reflects the expected number of banks jointly triggered into distress when at least one bank in the system is distressed. To our knowledge, we are the first to apply this multivariate measure of extreme co-movement to banking. Sixth, we investigate whether EVT-based systemic risk measures exhibit additional informational content as compared to simple linear dependence measures by comparing the ranks of financial institutions based on CAPM-$\beta's$ and tail-$\beta's$. Finally, we generate pre-crisis and crisis estimates of downside risk and systemic risk indicators.

By using daily bank stock returns of 15 US and 15 eurozone banks between April 1992 and June 2011, we find that extreme downside risk of US bank equity capital (tail quantiles and expected shortfalls) seems to dominate its eurozone equivalent, but only over the crisis sample. Second, multivariate spillover (contagion) risk for US banks also exceeds its equivalent for European banks. Third, and in line with the multivariate spillover risk estimates, the effects of macro shocks emphasized by the estimated tail-βs are somewhat higher for the US than for the eurozone, although not for all considered conditioning factors. The tail-β estimates are found to be surprisingly high, even for the pre-crisis periods. Individual banks seem most exposed to sharp drops in a banking index but exposures towards real estate and sovereign debt shocks are far from negligible either and have grown in importance during the recent crisis. Nonsurprisingly, both extreme downside risk and systemic risk have increased through time in a statistically and economically significant way; but the indicators already exhibit time variation for rolling sample estimates in the pre-crisis period showing that time variation is a structural phenomenon that is not limited to the systemic banking crisis only.

The paper is structured as follows. The next section discusses indicators of downside

[11] Previous research has used this indicator of extreme co-movement to assess international stock market linkages (Straetmans, 1998), stock-bond linkages (Hartmann et al., 2004) or currency linkages (Hartmann et al., 2010).

bank risk (2.1) and systemic risk (2.2). Section 3 presents estimation procedures for both measures as well as test statistics to compare differences in tail risk and systemic risk across continents and across time. Empirical results are summarized in Section 4. After a short description of data selection and descriptive statistics (4.1) we discuss full sample, pre-crisis and crisis estimates of downside risk (4.2), bank spillover risk (4.3) and extreme systematic risk (4.4) for both the eurozone and the US. The final section concludes. All individual bank outcomes are provided in the appendix.

2 Indicators of Downside Risk and Systemic Risk

2.1 Extreme Downside Risk of Bank Equity

We define (in)solvency risk as the probability of adverse shocks in the market value of the bank's equity capital relative to other liabilities. Given that financial markets reveal information about the state of affairs of a bank in an efficient way, problems with the credit portfolio, interbank liquidity constraints or failing asset-liability management should be reflected in the bank's stock price. Thus, the market-based measure of "bank tail risk" that we will use can be seen as an umbrella for many different types of financial risk including, e.g., liquidity risk, credit risk, operational risk or interest rate risk.

We exploit the statistical theory for univariate extreme values (univariate EVT) to determine tail risk. The cornerstone of univariate EVT constitutes the Generalized Extreme Value (GEV) distribution which is the limit law for (appropriately scaled) maxima of a stationary process. We adopt Peaks-over-threshold (POT) model of EVT that exploits the property that the distribution of excess losses over a given high threshold converges to a Generalized Pareto distribution (GPD) and fit the distributional tail beyond some high threshold in a semi-parametric way.[12]

We define downside risk measures for financial institutions by exploiting the empirical stylized fact that equity returns of financial institutions - just like all other financial returns - exhibit "heavy" tails, see, e.g., Mandelbrot (1963) for an early reference to non-normality and heavy tails in financial markets. Let S_t stand for the dividend-corrected

[12]Examples of parametric GEV and GPD estimation include Longin (1996), Neftci (2000), Bali (2003) or Bali and Neftci (2003). Semi-parametric tail estimation approaches include Dekkers and de Haan (1989), Jansen and De Vries (1991) and Danielsson and de Vries (1997). Finally, notice that one can also opt for modelling the complete (conditional or unconditional) return distribution in a parametric way instead of only looking at the tails, see e.g. Bali and Theodossiou (2007) or Bali et al. (2008).

stock price of a financial institution. Define $X = -ln(S_t/S_{t-1})$ as the loss distribution we are interested in.[13] Loosely speaking, the heavy tail feature implies that the marginal tail probability for X as a function of the corresponding quantile can be approximately described by a power law (or "regularly varying" tail):

$$P\{X > x\} \approx \mathcal{L}(x)x^{-\alpha}, x \text{ large}, \tag{1}$$

and where $\mathcal{L}(x)$ stands for a "slowly varying" function.[14]

The so-called tail index α determines the tail probability decay if one looks at more extreme parts of the distributional support. Clearly, lower values of α imply a slower decay to zero and a higher tail probability for given x. The regular variation property implies that all distributional moments higher than α, i.e., $E\left[X^r\right],\ r > \alpha,$ are unbounded. In contrast, all statistical moments exist (and are thus bounded), e.g., the thin-tailed normal distribution, i.e., $E\left[X^r\right] < \infty,\ \forall r.$ Popular distributional models like the Student-t, the class of symmetric stable distributions or the Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model all exhibit heavy tails. The exceedance probability in (1) is defined for given values of the barrier or Value-at-Risk (VaR) level x. Alternatively, the tail-VaR x can be calculated for a given value of the tail probability p.

Although VaR is a crucial part of a financial risk manager's toolkit, it is not a "coherent" risk measure and alternative risk measures have therefore been proposed like, e.g., the conditional expected loss on a bank's equity capital given a sharp fall in that equity capital ($X > x_p$). It can be easily shown that the expected shortfall is closely related to VaR:

$$E\left(X - x_p\,|X > x_p\right) \approx \frac{x_p}{\alpha - 1}, \tag{2}$$

which shows that the expected shortfall is a linear transformation of x_p within an EVT framework. The expected shortfall indicator signals the risk manager how severe the violation of the VaR boundary may be whereas a calculated VaR quantile in itself does not provide that information.

[13]For sake of convenience, negative equity returns (losses on equity capital) are mapped into positive numbers which implies that all formulae of downside risk measures will be defined for the distribution's upper tail.

[14]This implies that $lim_{x\to\infty}\mathcal{L}(tx)/\mathcal{L}(x) = 1$ and t > 0.

2.2 Systemic Risk Indicators

Similar to the downside risk measures, the systemic risk indictors are also market-based. We measure co-crash probabilities for bank pairs (bivariate spillover risk) and for more than two banks (multivariate spillover risk). Extreme co-movements between individual banks' stock returns and the returns of a general stock market index or another measure of non-diversifiable risk (the so-called "tail-β") are used to assess the exposure to aggregate shocks.

Starting with the contagion measures, we want to know to what extent financial distress at one bank tends to affect other banks and tends to ripple through the system. One identification approach is to calculate the probability of joint distress on a set of $N - L$ bank stocks, conditional on the near-insolvency (or distress) of another set of $L < N$ banks.

Since we limit ourselves to calculating the multivariate conditional probability for $L = 1$ which implies evaluating the systemic co-crash probability for a whole banking system of $N - 1$ banks conditioned on a single distressed bank:

$$\begin{aligned} P_{N|1} &= P\left\{\bigcap_{i=2}^{N} X_i > Q_i(p) | X_1 > Q_1(p)\right\} \\ &= \frac{1}{p} P\left\{X_1 > Q_1(p), ..., X_i > Q_i(p), ..., X_N > Q_N(p)\right\} \end{aligned} \tag{3}$$

where N represents number of banks in a banking system, the upper tail observations for X_i $(i = 1, ..., N)$ reflect bank $i's$ stock return losses and the "crisis" levels or quantiles Q_i $(i = 1, ..., N)$ are chosen such that the corresponding tail probabilities are equal across banks.[15]

Risk managers can calculate such an indicator to stress test what may happen to certain institutions when other institutions in the system collapse. Similarly, knowing the "hot spots" is useful for the supervisory surveillance of international financial markets. Obviously, the previous indicator allows for a nearly unlimited amount of possible conditioning bank sets. This flexibility in conditioning is at the same time a disadvantage because it may not always be obvious what the relevant conditioning set of banks should

[15] Hartmann et al. (2003a, 2003b, 2006) provide earlier applications of this multivariate contagion measure to evaluate the breadth of currency crisis and the systemic risk in the banking sector, respectively.

be. Moreover, one would like to limit the dimensionality of the estimation problem by not having to calculate so many contagion probabilities.

The multivariate generalization of the two-dimensional conditional expectation indicator presented in Hartmann et al. (2004) constitutes an attractive alternative indicator. It boils down to the conditional expectation $E[\kappa|\kappa \geq 1]$ where κ stands for the number of banks that are jointly triggered into distress. It reflects the expected number of distressed banks given at least one distressed bank in the financial system.

The conditional expectation indicator further specializes to:

$$E[\kappa|\kappa \geq 1] = \frac{Np}{P\left\{\bigcup_{i=1}^{N} X_i > Q_i(p)\right\}}, \tag{4}$$

which solely reflects dependence in the multivariate tail. In other words, this variant of the E-measure is not "contaminated" by any information on the marginal distributions' bank returns. Under the special case of statistical independence, the expectational linkage measure reduces to $E[\kappa|\kappa \geq 1] = Np/(1-(1-p)^N)$ which acts as a lower bound to judge the degree of true bank contagion.[16]

As a complement to the multivariate indicators, we also consider a bivariate version with $(L, N) = (1, 2)$ and where the conditioning set refers to extreme downturns of a "market portfolio" or some other indicator of non-diversifiable aggregate risk. This "tail-β" measure reflects "extreme systematic risk" and can be seen as a tail equivalent of the classic regression-based CAPM-β, see Hartmann et al. (2006) and Straetmans et al. (2008). Upon denoting minus the (log) return on the market portfolio by X_M the multivariate probability measure in (3) reduces to:

$$P\{X_1 > Q_1(p)|X_M > Q_M(p)\} = \frac{P\{X_1 > Q_1(p), X_M > Q_M(p)\}}{p}. \tag{5}$$

The indicator reflects how likely it is that an individual bank's equity capital sharply drops overnight if there is an extreme negative systematic shock. Whereas the Marginal Expected Shortfall (MES) indicator reflects the severity of the impact of an aggregate shock in X_M on the bank capital of an individual financial institution, the tail-β provides the corresponding likelihood.[17] Under the special case of statistical independence, the

[16] It can be easily shown that $\lim_{p\to 0} E\{\kappa|\kappa \geq 1\} = 1$. This simply reflects that full statistical independence is a sufficient condition for tail independence.

[17] However, both the MES and the tail-β are micro-level systemic risk measures, i.e., they cannot be

tail-β reduces to $p^2/p = p$ which acts as a lower bound to the true value of extreme systematic risk. Our tail-β analysis of extreme systemic risk in this paper encompasses a variety of choices for X_M ranging from bank stock indices, general stock indices, real estate indices and sovereign bond indices.

3 Estimation of Tail Risk and Systemic Risk Indicators

Upon assuming parametric probability distributions as the true underlying distributional model, the calculation of the proposed univariate and multivariate measures of tail risk and systemic risk is straightforward because it only requires the estimation of the distributional parameters by, e.g., maximum likelihood techniques. However, if one makes the wrong distributional assumptions, the tail risk and systemic risk estimates may be severely biased due to misspecification. As there is no evidence that stock returns are identically distributed - even less so for the crisis situations we are interested in - we want to avoid very specific distributional assumptions for bank stock returns. Therefore, univariate tail risk measures and multivariate systemic risk indicators will be quantified with semi-parametric estimation procedures.

3.1 Estimating Downside Bank Risk

We earlier noticed that bank stock returns exhibit heavy tails:

$$P\{X > x\} = \mathcal{L}(x)x^{-\alpha},$$

with x large and where $\mathcal{L}(tx)/\mathcal{L}(x)$ converges to 1 for large x and $t > 0$. In this function, α is the so called tail index, which determines the tail-probability's rate of decline if the quantile x is increased. The lower the α, the slower the probability decline and the higher the probability mass in the tail of X. With this background in mind, we can introduce the following quantile estimator:

$$\hat{x}_p \cong X_{n-m,n}\left(\frac{m}{np}\right)^{1/\alpha}. \tag{6}$$

classified as aggregate measures of risk like CATFIN.

De Haan et al. (1994) establish consistency and asymptotic normality of the estimator. The tail-VaR estimator $\hat{x}_p$ extends the empirical distribution function outside the domain of the sample by means of its asymptotic Pareto tail from (1). The quantile estimator still requires plugging in a value for the tail index α. In line with the majority of empirical studies on heavy tails and extreme events, we use the Hill (1975) estimator:

$$\hat{\alpha} = \left(\frac{1}{m} \sum_{j=0}^{m-1} ln \left(\frac{X_{n-j,n}}{X_{n-m,n}} \right) \right)^{-1}, \tag{7}$$

Further details on the Hill estimator and related procedures to estimate the tail index are provided in Jansen and De Vries (1991) or the monograph by Embrechts et al. (1997). Finally, notice that an estimator for the expected shortfall (2) easily follows by imputing the Hill statistic (7) and the quantile estimator (6) in the definition of the expected shortfall (2):

$$\hat{E}(X - \hat{x}_p | X > \hat{x}_p) = \frac{\hat{x}_p}{\hat{\alpha} - 1}. \tag{8}$$

Notice the Hill statistic (7) and the quantile estimator (6) still require selecting a value for m. Goldie and Smith (1987) suggest to select m such as to minimize the Asymptotic Mean-Squared Error (AMSE) of the Hill statistic. Such a minimum should exist because of the bias-variance trade-off that is characteristic for the Hill estimator. Balancing the bias and variance constitutes the starting point for most empirical techniques to determine m. We determined m by looking at both the curvature of so-called Hill plots $\hat{\alpha} = \hat{\alpha}(m)$ as well as implementing the Beirlant et al. (1999) algorithm to minimize a sample equivalent of the AMSE that corresponds with the Hill statistic. Figure 1 shows a few Hill plots for representative eurozone and US banks. The vertical lines indicate where the threshold is selected.

[Insert Figure 1]

3.2 Estimating the Systemic Risk Indicators

In order to estimate multivariate probabilities, we follow the Ledford and Tawn (1996) approach (see also Poon et al. (2004), Hartmann et al. (2006) and Straetmans et al. (2008)). To identify the dependence structure between sharp falls in the market value of banks' equity capital, it is convenient to transform the original return series such that they exhibit an identical marginal distribution. After such a transformation, differences in joint tail probabilities across banking systems (eurozone versus the US) can be solely attributed to differences in the tail dependence structure of the extremes and are thus not contaminated by any marginal influences or asymmetries. This is different from correlation-based measures that are still influenced by the differences in marginal distribution shapes.

We map the bank stock returns $(X_1, ..., X_i, ..., X_N)$ to unit Pareto marginals (Draisma et al., 2004) and estimate the following marginal tail probability. This can now be easily estimated assuming that the auxiliary variable's tail inherits the original bank returns' heavy tail property.

$$P\left\{\bigcap_{i=1}^{N} \tilde{X}_i > q\right\} = P\left\{min_{i=1}^{N}(\tilde{X}_i) > q\right\} = P\left\{\tilde{X}_{min} > q\right\}. \tag{9}$$

In other words, we assume that

$$P\left\{\tilde{X}_{min} > q\right\} \approx \mathcal{L}(q)q^{-\alpha}, \tag{10}$$

with q large (p small) and where $\mathcal{L}(q)$ is a slowly varying function. Obviously, higher (lower) values of α imply lower (higher) values of the original joint probability $P\left\{\bigcap_{i=1}^{N} X_i > Q_i\right\}$. The auxiliary variable's tail index α is therefore also dubbed the "tail dependence" parameter that governs the tail dependence structure of the original returns. The case of $\alpha = 1$ is of particular interest. Starting with the simplest case of a *single* conditioning asset as in (3) and (5), substituting (10) into these co-crash probability measures renders $\mathcal{L}(q)q^{1-\alpha}$. This *conditional* probability stays bounded away from zero when q grows large provided $\alpha = 1$. When co-crash probabilities do not vanish asymptotically, the corresponding return vectors on which the co-crash probabilities are defined are classified as being "tail dependent". Summarizing, the tail index α of the auxiliary variable $\tilde{X}_{min}$ reflects whether the original return vector components $(X_1, ..., X_i, ..., X_N)$ exhibit tail dependence ($\alpha = 1$) or tail independence ($\alpha > 1$). For *multiple* conditioning assets, the multivariate co-crash probabilities in denominator and numerator can be identified by means of (10) which renders the expression

$$\left(\frac{\mathcal{L}_1(q)}{\mathcal{L}_2(q)}\right) q^{\alpha_2 - \alpha_1}. \tag{11}$$

The above discussion on tail dependence vs. tail independence makes clear that tail dependence in (11) requires $\alpha_1 = \alpha_2 = 1$.

Whether return pairs exhibit tail dependence or not ultimately remains an empirical issue. For example, Hartmann et al. (2004) test the null hypothesis of tail dependence for pairs of stock and bond return indices. They found that the null hypothesis of tail dependence could not be rejected in a majority of cases and therefore imposed tail dependence on the estimates. There are strong theoretical arguments to impose tail dependence for vectors of bank stock returns as well. Fore example, De Vries (2005) argues that bank linkages (via e.g. the interbank market, common asset exposures) can be either "strong" or "weak", depending on whether bank stock returns exhibit tail dependence or tail independence. Assuming that different banks' asset portfolios contain common investments, de Vries shows that bank stock returns are tail dependent (tail independent) across banks whenever the common risk exposures of the banks' portfolios are heavy tailed (thin tailed). Assuming that common underlying risk drivers exhibit heavy tails seems reasonable given the predominance of fat tails in financial markets. Imposing tail dependence has several advantages. First, the estimation risk of the systemic risk indicators is reduced because there is no need to estimate the tail dependence parameter. Also, expression (11) makes clear that the corresponding systemic risk indicator becomes independent from the crisis level q upon assuming tail dependence. This invariance is convenient because it makes a discussion on the required extremity of the threshold q redundant. Most importantly, however, imposing tail dependence produces upper bounds for the systemic risk measures under consideration. We believe that interested parties like financial regulators, central banks etc. prefer conservative measures instead of measures that bear the risk of underestimating the true potential of financial fragility.

Univariate tail probabilities for heavy-tailed random variables - like the one in (9) - can be estimated by using a semi-parametric probability estimator (De Haan et al., 1994):

$$\hat{p}_q = \hat{P}\{\tilde{X}_{min} > q\} = \frac{m}{n}(C_{n-m,n})^{\alpha} q^{-\alpha}, \tag{12}$$

where the "tail cut-off point" $C_{n-m,n}$ is the $(n-m)th$ ascending order statistic from the cross-sectional minimum series $\tilde{X}_{min}$. This is the inverse of the quantile estimator (6) for calculating the tail-VaR in the univariate section.

An estimator of the multivariate spillover risk indicator in (3) easily follows by using

(12) and dividing with p:

$$P_{N|1} = \frac{\hat{p}_q}{p} = \frac{m}{n}(C_{n-m,n})^{\alpha} q^{1-\alpha}, \tag{13}$$

for large but finite $q = 1/p$. For $N = 2$, this reduces to the tail-β estimator. When the original return vector exhibits tail independence ($\alpha > 1$), the systemic risk estimator is a declining function of the threshold q and eventually reaches zero if $q \to \infty$. However, when $\alpha = 1$, as we impose throughout the paper, systemic risk is no longer influenced by changes in q. We determine the nuisance parameter m by plotting the estimated probability against m and by selecting m in a stable region. Figure 2 shows a few tail-β plots for representative eurozone and US banks. The conditioning risk factor is the Eurozone and US bank index, respectively. The vertical lines indicate where the threshold is selected.

[Insert Figure 2]

The alternative systemic risk measure in (4) is defined on another type of failure region which implies it cannot be estimated by using the Ledford and Tawn (1996) approach.

We estimate the following expression to determine the number of banks in distress given that at least one bank is in distress:

$$\hat{E}\left[\kappa | \kappa \geq 1\right] \approx \frac{N}{\frac{n}{k}\frac{1}{n}\sum_{i=1}^{n} I\left\{\bigcup_{i=1}^{N} X_i > X_{i,n-k}\right\}}, \tag{14}$$

and where the denominator is an estimator of the stable tail dependence function $\hat{l}(1, ..., 1, ..., 1)$. The upper order statistic $X_{i,n-k}$ estimates the quantile $Q_i(\frac{k}{n})$ and $I\{.\}$ stands for the indicator function. The threshold parameter k plays a similar role as the parameter m for the Hill estimator: it determines how many extreme returns are used in estimating $E\left[\kappa | \kappa \geq 1\right]$. Just like the multivariate spillover risk indicator in (13), the estimator (14) is invariant to changes in p (or, alternatively, to choices in the crisis quantiles Q_i). The homogeneity property of the l-function implies that p can be skipped form numerator and denominator. Thus, a discussion on the proper choice of p - and thus the area on which one wants to evaluate systemic risk - becomes redundant as systemic risk estimators like (13) or (14) render a single “asymptotic” value.

Estimation of $E[\kappa|\kappa \geq 1]$ still requires choosing a value for k. Huang (1992) suggests selecting k such as to minimize the Asymptotic Mean-Squared Error (AMSE) of estimator $\hat{l}(1, ..., 1, ..., 1)$. Such a minimum should exist because of the bias-variance trade-off that is characteristic for this estimator. Alternatively, We determine k by calculating (14) over a whole range of k and by choosing k in a horizontal range of $\hat{E} = \hat{E}(k)$ just as we did in Figures 1 and 2 for Hill estimates and tail-β estimates, respectively.

3.3 Hypothesis Testing

We want to make cross-Atlantic comparisons between these different risk measures (cross sectional equality tests). Given the estimators' asymptotic normality, a test for the equality of tail indices, tail quantiles, tail probabilities or tail copulae (either across continents or across time), readily follows by implementing a conventional T-statistic:

$$T_{est} = \frac{\hat{est}_1 - \hat{est}_2}{s.e.(\hat{est}_1 - \hat{est}_2)}, \tag{15}$$

with $s.e.[.]$ denoting the standard deviation of the estimation difference. The estimator used as an input either stands for the Hill statistic (7), the tail quantile estimator (6), the tail probability estimator (12) or the tail dependence function estimator (14). The test statistic is approximately standard normally distributed in sufficiently large samples.

The question arises how the standard deviation in the denominator of (15) should be calculated. Given the temporal dependence (mainly volatility clustering in bank stock returns) and cross sectional dependence in the data, the denominator's standard deviation is block bootstrapped using 1,000 replications and block lengths equal to $n^{1/3}$ with n the sample size, see Hall et al. (1995) for a theoretical justification and Straetmans et al. (2008) for an earlier application within the extreme value context.

Given the enormous amount of possible comparisons that can be made (pre-crisis vs. crisis and cross-continent) for both individual bank tail risk and systemic risk, we do not include the disaggregated testing results but they are available upon request from the authors. In contrast, we do report equality tests on a more aggregate level, i.e., we test whether the US and the eurozone sample means of the considered risk measures differ across time and across the continents in a statistically and economically significant way.

Finally, notice that candidate-break dates are chosen exogenously when testing for structural change, i.e., we split the sample according to generally accepted dates for the start of the crisis. Previous work that looked into financial system stability, see Hartmann et al. (2006), implemented endogenous stability tests like the Quintos et al. (2001) procedure. However, the former test is designed to look into the temporal stability of the tail index or the tail dependence parameter. Given that we restrict the tail dependence parameter to be equal to 1, this type of endogenous structural change test would not make sense in the current paper.

4 Empirical Results

4.1 Data

We collect daily stock price data from Datastream (dividend-corrected total return indices) for 15 eurozone banks and 15 US banks. For sake of comparison, we consider those banks from the Hartmann et al. (2006) study that are still listed today. Hartmann et al. study selected banks on the basis of size and interbank activity and we believe that the remaining banks are still systemically important according to these two criteria. Stock price series start on 2 April 1992 and end on 24 June 2011, which implies 5,016 return observations per bank. For sake of the tail-β calculations, we downloaded Datastream-calculated bank indices, stock indices, real estate indices and sovereign debt indices. Bank indices and general stock indices are sampled over the same time period as the individual bank stocks. A US real estate index is sampled over the same time period as the banks while eurozone country real estate indices are downloaded from 23 September 1993 onwards (we take the starting point in Datastream of the German real estate index as the cutoff point). An unweighted average of PIIGS 10-year benchmark government debt indices (total return index) is constructed from 31 March 1999 onwards (starting point of the Greek sovereign debt total return index in Datastream). Consistent with the bank stocks, real estate and bond series end on 24 June 2011.

4.2 Downside Risk Estimates of Individual Bank Equity Capital

We exploit the untabulated property of non-normality or "heavy tail" to calculate alternative downside risk measures like tail-VaR or conditional expected shortfall for banks' equity capital. To address this issue more systematically, we report in appendix Tables A.1 (US and eurozone; full sample), A.2 (Eurozone; pre-crisis and crisis samples) and A.3 (US; pre-crisis and crisis subsamples) estimates of the tail index α and corresponding values of tail-VaR and expected shortfall.

Extreme quantiles are calculated for p-values equal to 0.2% and 0.1%. The corresponding tail-VaRs are expected to be violated every 500 days and every 1,000 days, respectively. We also report expected shortfall estimates conditioned on either the p% tail-VaRs or on crisis barriers s=25% or 50%. Given the extreme quantile estimates $\hat{x}_p$ nearly always fall below s, expected shortfalls conditioned on the threshold s are the more extreme expected shortfall measure.

It turns out that the tail indexes vary around 3, which is in line with the evidence presented in Jansen and De Vries (1991) for general stocks and Hartmann et al. (2006) for bank stocks. The appendix Tables A.1, A.2 and A.3 reveal a lot of heterogeneity in tail risk across individual banks and across time. Comparing pre-crisis results with crisis results, one observes that the majority of bank stock returns seems to exhibit more tail risk during the crisis which is hardly surprising (crisis spikes in the return data induce lower values of the tail index which in turn produce higher values of tail-VaR and expected shortfall). Whereas US Hill estimates all dropped over time, the temporal behavior of eurozone Hill estimates is less straightforward: some eurozone tails have become thinner which is somewhat counterintuitive. Some drops in α-estimates are such that the crisis values fall below 2, especially for the US bank panel. As noticed in the methodology section, $\alpha < 2$ implies an unbounded variance for the corresponding bank stock return series.[18] For Allied Irish Bank, the drop in tail index is even more spectacular with the crisis value $\hat{\alpha} = 0.4$ falling below 1 signifying that even the population mean no longer exists. Unsurprisingly, the full sample values for the tail index and the different tail risk measures often lie in between the pre-crisis and crisis values. Banks that experienced financial distress in the crisis period or that were involved in some form of government bailout over the sample period typically show spectacular increases in tail risk during the crisis period, see, e.g., Commerzbank, Deutsche Bank, Natixis, ING or Allied Irish Bank in the eurozone and Citigroup in the US.[19] Bank of America's tail risk is also noteworthy:

[18]This invalidates the use of traditional risk measures such as standard deviation or CAPM-βs, which require the existence of the second moment or $\alpha > 2$.

[19]Deutsche Bank is generally seen as one of the key players in boosting the CDO market, which caused the subprime mortgage crisis but the bank never became so financially distressed that it needed state

it played an active role in rescuing other financial institutions. Bank of America bought ailing financial institutions like Countrywide Financial (mortgages) and Merrill Lynch (the acquisition of Merrill Lynch being financially supported by the US government). However, huge trading losses at Merrill Lynch nearly brought down Bank of America themselves in 2009.[20]

Upon comparing the tail quantiles and expected shortfalls across the continents, US tail risk estimates exceed eurozone tail risk estimates for the crisis sample; whereas continental tail risk seems of comparable magnitude before the crisis erupted. The economic interpretation of the outcomes on an individual bank basis is rather straightforward. For example, consider the subsample results for Citigroup. The tail index of Citigroup dropped from 3 to 1.8 indicating that the probability mass in the tails spectacularly increased during the crisis period. Unsurprisingly, the crisis values of extreme quantiles and expected shortfall measures have skyrocketed as compared to their pre-crisis levels. Citigroup's 0.1% tail-VaR has quintupled since the outbreak of the crisis (from 11% to a record 65.1%). The pre-crisis p=0.1% VaR of 11% implies that a daily erosion of Citigroup's market value of equity capital with 11% or more is expected to happen once every 1,000 days = 1,000/260$\approx$ 3.8 years. The corresponding (p=0.1%) expected shortfall of 5.4% implies that once the tail-VaR of 11% is exceeded, the expected loss given this exceedance equals an "additional" 5.4%. All these numbers are much higher during the crisis period.

[Insert Table 1]

Upon comparing pre-crisis and crisis values for tail risk, the point estimates for $\hat{\alpha}, \hat{x}_p$ and $\hat{E}(X - \hat{x}_p | X > \hat{x}_p)$ change quite dramatically indeed. To assess whether the crisis altered the tail risk properties in a statistically and economically significant way, and to assess the statistical and economic significance in cross-Atlantic differences between these measures, we applied the equality test statistic T_{est} (15). We find that tail-VaR differences across time and across individual banks differ in a statistically and economically

aid or other rescue packages. The crisis tail risk of 18.6% is nevertheless substantial and most probably due to the importance of its investment leg and resulting trading losses. The French bank Natixis was also strongly involved in investment banking and subprime products in particular. Its shareholder value dropped dramatically over the crisis sample but the bank did not need to be bailed out by the French government.

[20]Unsurprisingly, the banks exhibiting the highest tail risks during the crisis sample are most of the time also those that experienced the lowest capital buffers in the considered cross section of US and eurozone banks at the start of the crisis in August 2007.

significant way for the vast majority of banks. Statistically significant differences in the Hill estimates for the tail index changes are found to be less predominant which suggests that temporal tail-VaR changes are mainly driven by changes in the scaling constant rather than shifts in the tail index.[21]

To simplify cross-continent and cross-time comparisons of tail risk, we also present tail risk results and accompanying test statistics on a more aggregate level in Tables 1 and 2, respectively. Based on the point estimates in appendix Tables A.1, A.2 and A.3, Table 1 reports estimated means, medians and standard deviations for the US and the eurozone and for the pre-crisis and crisis episodes separately. Table 1 reveals that US tail risk measures exceed their eurozone counterparts for the full sample as well as for the crisis sample but extreme downside risk is of comparable magnitude in the pre-crisis periods. Upon comparing tail risk for pre-crisis and crisis samples, we see that tail indices decline and accompanying tail risk increases for both continents. Finally, notice that mean and median estimates are always close to each other. Table 2 contains the corresponding mean equality tests for the tail index and the (p=0.1%) tail quantile. Equality of the continental means is tested across time (panel I) as well as across continents (panel II). In order to perform the tests, we first calculate the cross sectional mean for bank tail indices and tail quantiles per continent and for the pre-crisis and crisis sample separately. Next, we apply a simple t-test for (time series/cross sectional) equality of sample averages. The approximate normality of the tail index and tail quantile estimators (6)-(7) ensures that the test statistic that compares their averages is also approximately normally distributed. The upper panel I shows that tail quantiles strongly increase in the crisis period for both continents. But one can also observe that the upward shifts in the eurozone tail risk is not caused by heavier tails because the mean tail index for eurozone banks hardly changes over time. Thus, for eurozone banks, the increase in tail risk seems solely driven by changes in the scaling constants of the bank stock returns. Turning to the cross sectional equality tests in the lower panel II, we see that statistically significant cross-continent differences between tail indices and accompanying tail quantiles only appear for the crisis sample which confirms our observations from Table 1.

[Insert Table 2]

[21] Similar results are found in Straetmans et al. (2008) for the tails of US sectoral stock indices and with the 9/11 terrorist attacks as sample midpoint.

As a complement to our pre-crisis and crisis subsample estimates, we also calculated truly time varying tail risk measures by conditioning on rolling samples. Figure 3 shows the evolution of (average) rolling Hill estimates and (average) rolling expected shortfalls for the US and the Eurozone countries as well as Germany, France and Spain. The figure shows that tail risk measures have been strongly time varying even before the 2007 crisis struck. We see a clear downward trend in the tail index (increased tail risk) for the US and the eurozone banks (top row of the graph) which explains the increase in the expected shortfall measure (bottom row of the graph) for US and eurozone banks; but tail indices again started to rise (and expected shortfalls started to fall) towards the end of the sample. The pictures also clearly show that US tail risk only exceeds eurozone tail risk since the outbreak of the crisis. Within Europe, the tail risk for French banks dominates that of Spanish banks during the banking crisis whereas German banks take some intermediate position. In the pre-crisis sample, Spanish banks are the riskier ones whereas German and French banks exhibit comparable tail riskiness. This may be due to the fact that Spanish banks were less strongly exposed to the US subprime mortgage crisis and the PIIGS sovereign debt crisis if one compares this with German and French banks. Furthermore, the Spanish real estate bubble burst did not yet fully materialize in the considered sample which may also explain the lower tail risk values (EBA, 2011).

[Insert Figure 3]

4.3 Bank Spillover Risk

In this subsection we report results for the multivariate probability indicator $P_{N|1}$ and the multivariate expectation indicator $E\{\kappa\,|\kappa \geq 1\}$ as defined in in equations (3)-(4). We try to address two issues. First, does spillover risk increase over time and if so, for which continent is the change most striking? Second, how does eurozone contagion risk compare to US bank contagion risk? In other words, is one banking system more prone to multivariate bank spillovers than the other one?

[Insert Table 3]

Estimates of these measures are reported in Table 3. The indicators are calculated for the US and the eurozone banking systems as a whole ($N = 15$ banks each) but also for the three main eurozone countries separately (Germany, France, Spain; $N = 3$ banks each). By construction, $1 \leq E\{\kappa|\kappa \geq 1\} \leq 15$ for the eurozone and the US banking system whereas $1 \leq E\{\kappa|\kappa \geq 1\} \leq 3$ for the considered eurozone countries. The lower bound reflects complete tail independence whereas the upper bound can only be reached under complete tail dependence. Point estimates of these multivariate spillover indicators are only comparable across continents or bank sets spanning the same number of banks. In other words, cross-continent (US vs. eurozone) and cross-country (Germany vs. France vs. Italy) comparisons for $E\{\kappa|\kappa \geq 1\}$ or $P_{N|1}$ make sense but comparisons between continental and country outcomes are meaningless because the number of banks for which the country and continental systemic risk indicators are calculated differs.

Panel I of Table 3 contains estimation results for both indicators and for varying sets of banks (continent-wide or separate eurozone countries) whereas panels II and III report the corresponding structural change and cross sectional equality tests to assess whether multivariate contagion risk varies over time or differs across continents and countries, respectively. Equality tests across countries, continents and time are performed using the earlier introduced t-test in (15). The economic interpretation of the point estimates $\hat{E}$ and $P_{N|1}$ is straightforward.[22] For example, the US crisis value $\hat{E} = 4.33$ is not an expected loss given default but it reflects the number of US banks triggered into distress if *at least* one out of 15 US banks is known to be distressed. In other words, more than one quarter of the US banking system risks to become destabilized ($4.33/15 \approx 29\%$) if at least one bank is known to be distressed. As concerns the economic interpretation of the other multivariate measure $P_{N|1}$, consider, e.g., the eurozone crisis value $P_{15|1} = 10.36\%$. This probability implies that if one of the 15 eurozone banks is triggered into distress, there is a 10.36% chance that all 15 banks undergo the same fate. This meltdown probability even equals 22.75% for the US crisis sample which implies that there is a chance of 1 out of 4 that the whole US financial system will collapse if one systemic bank collapses.

Let us now refocus on the earlier mentioned research questions. As concerns the time variation of systemic risk, it is obvious from the Table that all crisis sample estimates of multivariate contagion risk dominate their pre-crisis counterparts irrespective of the considered indicator, continent or country. To clarify this further, we also include the

[22]The conditioning event differs for both measures: whereas the E-indicator conditions on at least one bank being in distress, the P-indicator conditions on one single bank in the system being in distress. However, in both cases, the indicator values are invariant to which banks are actually the conditioning ones.

systemic risk measures' growth rates across the two subsamples. For example, the expected number of joint crashes for the US banking system as a whole has increased from $\hat{E} = 2.94$ in the pre-crisis period to $\hat{E} = 4.33$ in the crisis period (representing a 47% increase). The other US indicator for multivariate bank contagion renders pre-crisis and crisis values of 11.70% and 22.75%, respectively (or an increase by 94%). The relative increase in global eurozone systemic risk is of a similar magnitude. On the eurozone country level, it does not come as a surprise that Spain stands out with the largest increase in systemic risk for both indicators whereas Germany has experienced the smallest increase. France takes on an intermediate position. Finally, notice that the systemic risk increase seems more pronounced when considering the $P_{N|1}$ measure. As a complement to the percentage increase calculations, we also explicitly test for time variation in the multivariate contagion indicators using the t-test in equation (15), see panel II of the Table. Apart from Germany, both systemic risk indicators rise in a statistically significant way for all considered cases.

The second - and in our view more interesting - issue concerns the cross-continent and cross-country differences in systemic risk. First and foremost, the Table 3 shows that the US banking system is more unstable than its eurozone counterpart irrespective of the considered systemic risk indicator or (sub)sample, i.e., $\hat{E}_{US} > \hat{E}_{Eurozone}$ and $\hat{P}_{US} > \hat{P}_{Eurozone}$. The cross sectional equality tests in panel III indeed reveal that multivariate contagion risk always dominates its eurozone counterpart irrespective of the considered indicator or sample. As concerns the eurozone contagion on a country level we observe that $\hat{E}_{Spain} > \hat{E}_{France} > \hat{E}_{Germany}$ and $\hat{P}_{Spain} > \hat{P}_{France} > \hat{P}_{Germany}$ for both the pre-crisis and the crisis sample. However, this divergence in domestic contagion between France, Germany and Spain is only statistically significant for the crisis sample.

In order to better grasp how multivariate spillover risk evolves over time, we show rolling sample estimates of our two multivariate spillover risk indicators for the US, the eurozone, Germany, France and Spain in Figure 4. The top left figure shows the rolling expected number of bank crashes for the US and the eurozone, i.e., $1 \leq E\left\{\kappa \,|\kappa \geq 1\right\} \leq 15$. The bottom left figure contains the rolling expected number of bank crashes for Germany, France and Spain, i.e., $1 \leq E\left\{\kappa \,|\kappa \geq 1\right\} \leq 3$. The two remaining figures show the rolling multivariate contagion probability ($P_{N|1}$) for the US and the eurozone (top right) and for Germany, France and Spain (bottom right). We observe an increase over time for both the expected number of joint bank crashes and the multivariate contagion probability regardless the continent considered. Interestingly, the systemic risk measures are already rising before the start of the financial crisis in 2007. However, the increase in the risk measure is strongest during the crisis. Moreover, systemic risk has increased more strongly in the US as compared to the eurozone. Upon comparing the systemic risk dynamics for the three large European countries, we see that both the expected number of joint bank crashes as well as the multivariate contagion probability stays lowest in Germany.

[Insert Figure 4]

4.4 Extreme Systemic Risk

In this subsection we evaluate the exposure of the banks' equity capital to large adverse movements in "aggregate" shocks. The term "aggregate" in this context refers to a macroeconomic (nondiversifiable) shock. We calculate our indicator of "extreme systematic risk" (or "tail-β") for different candidate-risk factors. First, we use the banking industry sector index and a general stock index for the eurozone and the US, respectively. We also condition on a world-wide banking sector sub-index and a world-wide general stock index. Given that housing busts played a central role in triggering banking gloom at both sides of the Atlantic during the 2007-2009 banking crisis, we also calculate co-crash probabilities of bank stocks conditioned on sharp drops in real estate housing indices. Finally, we assess the impact of the eurozone sovereign debt crisis on the market value of eurozone bank equity capital. To that aim we condition the tail-β on an equally weighted portfolio of the PIIGS countries' sovereign bond total return indices.[23]

Estimates of "tail-β" are obtained via (12) and are summarized in Tables A.4 (US and eurozone; full sample), A.5 (eurozone; pre-crisis and crisis subsamples) and A.6 (US; pre-crisis and crisis subsamples) and for the different conditioning risk factors.

The reported tail-βs in the appendix tables have a straightforward economic interpretation. For example, the pre-crisis value 28.8 in the row "BNP" and column "Eurozone bank" in panel I of appendix Table A.5 implies that a very large downturn in the euro-

[23] Most studies on bond markets and contagion consider cross-country yield spreads as the variable of interest. However, given the fact that we are interested in the impact on bank stock returns, we decide to condition on bond index returns instead of yield spreads. Moreover, and in contrast to bank stock returns, yield spreads exhibit high persistence which may produce erroneous outcomes for our systemic risk indicators.

zone banking index during the pre-crisis era is associated with a 28.8% probability that BNP Paribas Bank faces a daily stock price decline of comparable magnitude. In other words, even before the systemic banking crisis struck, a daily sharp drop in the bank index is expected to coincide with a comparably large drop in BNP Paribas stock nearly one out of three times. Moreover, BNP Paribas' propensity towards co-crashing with the eurozone banking index has nearly tripled to 68.1% during the crisis period (panel II of the same Table).

Going more systematically up and down the columns as well as left and right in the rows in appendix Tables A.4, A.5 and A.6, a number of empirical regularities can be observed. First, nearly all tail-βs spectacularly increase in the crisis period. Second, tail-βs differ quite considerably across banks but are nevertheless remarkably high regardless the subsample or continent. They are higher than in previous studies like Hartmann et al. (2006) or De Jonghe (2010), even for the pre-crisis sample, but this is due to the fact that we impose the tail dependence parameter to be equal to 1. As a result, we get much higher values of tail-β, which may be interpreted as conservative upperbounds to the true value of extreme systematic risk. Third, US bank exposures to non-diversifiable shocks often exceed their European counterparts but are less dispersed than the eurozone bank exposures (as measured by the cross sectional volatility of the tail-βs). Fourth, although we do not explicitly test for the existence of a relation between bank size and systemic risk, bigger banks often seem to exhibit larger tail-βs, see for example the large values of extreme systematic risk for Bank of America, JP Morgan, Citigroup and Wells Fargo in the US or the German, French and Spanish banks in the eurozone. This confirms findings by De Jonghe (2010) who establishes a cross sectional relation between tail-βs and bank size.[24] Fifth, comparing the magnitudes of the tail-βs across different conditioning risk factors, the tail co-movements with the banking portfolio seems strongest but the impact of adverse real estate shocks on the banks' equity capital should also not be underestimated, see also Pais and Stork (2011) for previous evidence on the impact of real estate shocks. Finally, bank exposures to sovereign debt are low prior to the outbreak of the sovereign debt crisis (this is hardly surprising given that pre-crisis market values of

[24] Related to the size hypothesis, Hartmann et al. (2006) find that smaller banks in peripheral eurozone countries (like some of the smaller PIIGS countries Greece, Portugal or Ireland) seem less exposed to extreme systemic risk. Their larger focus on local businesses and resulting absence of international diversification may explain this stylized fact. The current cross section does not contain a sufficient amount of these peripheral banks to enable us to make the same observation.

public debt were nearly flat); but the PIIGS tail-βs doubled or tripled afterwards. Still, their crisis values are much lower than eurozone bank exposures to shocks that propagate via a eurozone banking index.[25]

To assess to what extent the observed differences in tail-β point estimates truly differ across banks or across time, one can implement the same equality test T_{est} (15) as the one employed in the univariate tail risk section because the estimator (12) used to calculate tail-βs is approximately normally distributed in sufficiently large samples. Upon implementing this test, we find that the vast majority of tail-βs increases over time (structural change) and differs across banks and conditioning risk factors (cross sectional equality) in a statistically and economically significant way.

Analogous to what we did for the univariate tail risk measures, we also present the tail-βs and some accompanying test statistics in a more aggregate way for the entire US and eurozone. This makes it even easier to eyeball certain patterns or tendencies in the results. Based on the point estimates in appendix Tables A.4, A.5 and A.6, Table 4 reports estimated tail-β means, medians and standard deviations for the US and the eurozone and for the pre-crisis and crisis episodes separately. The aggregate results show a large time variation and heterogeneity in tail-βs across continents and conditioning risk factors even more clearly than the individual bank results revealed. The table confirms that US tail-βs seem to dominate eurozone tail-βs for most factors. In fact, the pre-crisis magnitudes of US tail-βs are comparable to the crisis magnitudes of eurozone tail-βs. Comparing the tail-βs averages across different conditioning risk factors, one can see that $\beta_{Eurozonebank} > \beta_{Eurozonestock} > \beta_{Globalbank} > \beta_{Globalstock}$ for eurozone banks and a similar inequality seems to hold for US bank outcomes. That tail-βs are most exposed to shocks transmitted via the continental banking index is conform the intuition. Notice also the stronger exposures of US banks to real estate shocks during the crisis period. Finally, just as for the univariate tail risk measures, one also observes that means and medians in Table 4 do not differ much. Table 5 therefore only reports mean equality tests for the tail-β measures and distinguishes between tests for structural change (panel I) and cross sectional equality (panel II). Given the approximate normality of the tail-β estimator (12), the test statistic that compares average tail-βs is also normally distributed. The

[25] Despite the Spanish real estate bubble burst and the perceived large exposures to PIIGs sovereign debt of especially French banks, it is surprising to see this is not reflected in market-based measures of systemic risk like the tail-β.

test statistics confirm that (i) average tail-βs have risen over time for both the US and eurozone (panel I); (ii) the average US exposure to aggregate shocks seems stronger than its eurozone counterparts regardless the sample period (pre-crisis vs. crisis) or conditioning risk factors.

[Insert Table 4 and 5]

Finally, the question arises whether our tail-β results exhibit different information content relative to traditional CAPM-β estimates.[26] To that aim, we compare the financial institutions' rankings according to both systematic risk measures. Whereas the CAPM-β is a linear regression coefficient that is calculated using all the data, the tail-β only reflects tail dependence. Moreover, the latter measure is also able to pick up non-linear return spillovers (if present in the data). Table 6 contains (Spearman) rank correlations between both measures for the US bank panel and the euro area bank panel. Moreover, we distinguish between full sample, pre-crisis and crisis rank correlations. The results clearly show that the ranks are far from invariant across the two systematic risk measures. Especially during the crisis periods, the rank correlations are low which may be due to the fact that non-linear spillovers captured by the tail-β estimates are strongest during this period. But even in the pre-crisis and full sample, the rankings do not seem to be very similar across the two measures. Thus, one can conclude that CAPM-β estimates do not seem suited for judging exposure to extreme macro shocks during crisis times.

[Insert Table 6]

5 Conclusion

In this paper we exploit statistical extreme value analysis in order to estimate alternative indicators of downside bank risk and systemic risk. The indicators are market-based because they use extreme stock market losses as inputs. We compare tail risk and systemic risk estimators across continents (US vs. eurozone) and across time. Tail risk refers to the downside risk in banks' equity value. Given that sharp falls in (the market price of) equity can drive banks into overnight financial distress and near-insolvency, one can also interpret these downside risk measures as capturing the banks' solvency risk. Obviously,

[26] We thank one of the referees for making this point.

banks with more probability mass in the lower equity return tails will also exhibit more solvency risk according to this measure. The proposed systemic risk measures are twofold and either capture extreme spillovers among banks ("contagion risk") or reflect the exposure of banks to extreme systematic shocks ("tail-β"). The contagion risk measures are either defined as multivariate probabilities of joint sharp drops in stock returns or as the expected number of co-crashing banks on a systemic scale given at least one bank crash within the system. The tail-β indicator is defined as the co-crash probability of bank stock returns conditioned on several possible macro factors. The current study can be seen as an extension of the Hartmann et al. (2006) study on cross-Atlantic banking system stability because we use comparable EVT techniques and US and eurozone bank panels. However, we have a much longer sample at our disposal which includes the 2007-2009 systemic banking crisis. This enables us to investigate the stability of tail risk and systemic risk over time (for example, whether the crisis significantly increased risk indicators). The systemic risk indicators also differ from the ones used in previous studies: the tail-β indicator is conditioned on a wider set of non-diversifiable risk factors (we also condition on real estate and sovereign debt risk factors because of their prominent role in triggering the systemic banking crisis). We also apply a new multivariate spillover risk indicator to the entire banking system, see Huang (1992). However, the most important difference between what we do and previous work lies in the fact that the considered systemic risk indicators assume so-called "tail dependence" as an identifying restriction. We argue that tail dependence is an economically meaningful restriction which produces conservative estimates (upperbounds) for the true underlying systemic risk. From the perspective of regulators and supervisors who are supposed to monitor and safeguard financial system stability this seems a desirable property. Turning to the estimation results, the outcomes on the extreme downside risk proxies (tail index, tail-VaR, expected shortfall) for bank stocks indicate that US banks are riskier than their European counterparts. The multivariate bank spillover indicators for the euro area seem to be significantly lower than in the US. As concerns extreme systematic risk, US tail-βs dominate their European counterparts for most of the conditioning risk factors which is in line with the multivariate contagion risk outcomes. Within a given continent, however, we observe a wide heterogeneity in tail- β outcomes across banks and conditioning factors. Nonsurprisingly, bank equity capital is most reactive to shocks transmitted via a continent's bank index, followed by a continent's global stock index, a world-wide bank index and a world-wide stock index. The sovereign debt crisis exercises a smaller impact on the market value of European banks' equity capital than expected. We find the largest impact for banks in the PIIGS countries themselves but most tail-β values for the sovereign debt risk factor are much smaller than for other conditioning risk factors. Nonsurprisingly, structural stability tests for both our univariate downside risk indicators and multivariate banking system risk indicators suggest a general increase in tail risk and systemic risk when taking the start of the financial crisis as sample split. Finally, we argue that our EVT-based systemic risk measures exhibit different information content as compared to linear dependence measures. We illustrate this by ranking financial institutions acccording to their systemic importance using CAPM-βs and tail-βs. Rankings differ quite substantially depending on the chosen indicator (i.e. low rank correlation), especially during crisis periods. This may be due to the fact that tail-βs capture non-linear spillovers during crisis periods whereas the linear CAPM-βs do not.

References

Acharya, V., Pedersen, L., Phillippon, T., Richardson, M., 2010. Measuring systemic risk. New York University Working Paper.

Adrian, T., Brunnermeier, M., 2011. CoVaR. NBER Working Paper No. 17454.

Aizenman, J., Pinto, B., Sushko, V., 2011. Financial sector ups and downs and the real sector: Big hindrance, little help. NBER Working Paper No. 17530.

Allen, F., Gale, D., 2000. Financial contagion. The Journal of Political Economy 108 (1), 1–33.

Allen, L., Bali, T., Tang, Y., 2012. Does systemic risk in the financial sector predict future economic downturns? The Review of Financial Studies 25 (10), 3000–3036.

Bali, T., 2003. An extreme value aapproach to estimating volatility and value at risk. The Journal of Business 76 (1), 83–108.

Bali, T., Neftci, N. S., 2003. Disturbing extremal behavior of spot rate dynamics. Journal of Empirical Finance 10 (4), 455–477.

Bali, T., Tang, Y., Mo, H., 2008. The role of autoregressive conditional skewness and kurtosis in the estimation of conditional VaR. Journal of Banking and Finance 32 (2), 269–282.

Bali, T., Theodossiou, P., 2007. A conditional-SGT-VaR approach with alternative GARCH models. Annals of Operations Research 151 (1), 241–267.

Beirlant, J., Dierckx, G., Goegebeur, Y., Matthys, G., 1999. Tail index estimation and an exponential regression model. Extremes 2 (2), 177–200.

Bisias, D., Flood, M., Lo, A. W., Valavanis, S., 2012. A survey of systemic risk analytics. U.S. Department of Treasury, Office of Financial Research No. 0001.

Brownlees, C., Engle, R., 2012. Volatility, correlation and tails for systemic risk measurement. SSRN Working Paper.

Calomiris, C., Mason, J., 1997. Contagion and bank failure during the great depression: The June 1932 Chicago banking panic. American Economic Review 87 (5), 863–883.

Calomiris, C., Mason, J., 2000. Causes of U.S. bank distress during the depression. NBER Working Paper No. 7919.

Chan-Lau, A. J., 2009. Regulatory capital charges for too-connected-to-fail institutions: A practical proposal. Working Paper, IMF.

Danielsson, J., de Vries, C. G., 1997. Tail index and quantile estimation with very high frequency data. Journal of Empirical Finance 4 (2-3), 241–257.

De Haan, L., Jansen, D. W., Koedijk, K., de Vries, C. G., 1994. Safety first portfolio selection, extreme value theory and long run asset risks. In: Galambos, J., Lechner, J., Simiu, E., Macri, N. (Eds.), Extreme value theory and applications. Kluwer Academic Publishers, Dordrecht, pp. 471–487.

De Jonghe, O., 2010. Back to the basics of banking? A micro-analysis of banking system stability. Journal of Financial Intermediation 19 (3), 387–417.

De Nicolo, G., Kwast, M., 2002. Systemic risk and financial consolidation: Are they related? Journal of Banking and Finance 26 (5), 861–880.

De Vries, C. G., 2005. The simple economics of bank fragility. Journal of Banking and Finance 29 (4), 803–825.

Degryse, H. A., Nguyen, G., 2007. Interbank exposures: An empirical examination of contagion risk in the Belgian banking system. International Journal of Central Banking June, 123–171.

Dekkers, A., de Haan, L., 1989. On the estimation of the extreme value index and large quantile estimation. The Annals of Statistics 17 (4), 1795–1832.

Demirgüc-Kunt, A., Detragiache, E., 1998. The determinants of banking crises in developing and developed countries. IMF Staff Papers 45 (1), 81–109.

Draisma, G., Drees, H., Ferreira, A., de Haan, L., 2004. Bivariate tail estimation: Dependence in asymptotic independence. Bernouilli 10 (2), 251–280.

EBA, 2011. European Banking Authority 2011 EU-wide stress test aggregate report. European Banking Authority.

Embrechts, P., Kluppelberg, C., Mikosch, T., 1997. Modelling extremal events. Springer Verlag, Berlin.

Freixas, X., Parigi, B. M., Rochet, J.-C., 2000. Systemic risk, interbank relations, and liquidity provision by the central bank. Journal of Money, Credit and Banking 32 (3), 611–638.

Giglio, S., Kelly, B., Pruitt, S., Qiao, X., 2013. Systemic risk and the macroeconomy: An empirical evaluation. Chicago Booth Research Paper No. 12-49.

Goldie, C., Smith, R., 1987. Slow variation with remainder: Theory and applications. Quarterly Journal of Mathematics 38 (1), 45–71.

Gonzalez-Hermosillo, B., Pazarbasioglu, C., Billings, R., 1997. Determinants of banking system fragility: A case study of Mexico. IMF Staff Papers 44 (3), 295–314.

Gorton, G., 1988. Banking panics and business cycles. Oxford Economic Papers 40 (4), 751–781.

Gropp, R., Duca, M. L., Vesala, J., 2009. Cross-border bank contagion in Europe. International Journal of Central Banking 5 (1), 97–139.

Gropp, R., Moerman, G., 2004. Measurement of contagion in banks' equity prices. Journal of International Money and Finance 23 (3), 405–459.

Hall, P., Horowitz, J., Jing, B., 1995. On blocking rules for the bootstrap with dependent data. Biometrika 82 (3), 561–574.

Hartmann, P., Straetmans, S., de Vries, C. G., 2003. A global perspective on extreme currency linkages. In: Hunter, W., Kaufman, G., Pomerleano, M. (Eds.), Asset price bubbles: The implications for monetary, regulatory and international policies. MIT Press: Cambridge, MA, pp. 361–383.

Hartmann, P., Straetmans, S., de Vries, C. G., 2004. Asset market linkages in crisis periods. Review of Economics and Statistics 86 (1), 313–326.

Hartmann, P., Straetmans, S., de Vries, C. G., 2006. Banking system stability: A cross-atlantic perspective. In: The risks of financial institutions. Carey, M. and Stulz, R. (Eds.), The University of Chicago Press (Chicago and London), pp. 133–193.

Hartmann, P., Straetmans, S., de Vries, C. G., 2010. Heavy tails and currency crises. Journal of Empirical Finance 17 (2), 241–254.

Hellwig, M., 1994. Liquidity provision, banking, and the allocation of interest rate risk. European Economic Review 38 (7), 1363–1389.

Hill, M. B., 1975. A simple general approach to inference about the tail of a distribution. The Annals of Statistics 3 (5), 1163–1174.

Huang, X., 1992. Statistics of bivariate extreme values. Ph. D. thesis, Tinbergen Institute Research Series 22, Erasmus University Rotterdam.

Jansen, D. W., De Vries, C. G., 1991. On the frequency of large stock returns: Putting booms and busts into perspective. The Review of Economics and Statistics 73 (1), 18–24.

Kelly, B., Jiang, H., 2013. Tail risk and asset prices. Working Paper, University of Chicago.

Kho, B., Lee, D., Stulz, R. M., 2000. US banks, crises, and bailouts: From Mexico to LTCM. American Economic Review Papers and Proceedings 90 (2), 28–31.

Ledford, A., Tawn, J., 1996. Statistics for near independence in multivariate extreme values. Biometrika 83 (1), 169–187.

Longin, F., 1996. The asymptotic distribution of extreme stock market returns. Journal of Business 69, 383–408.

Longin, F., Solnik, B., 2001. Extreme correlation of international equity markets. The Journal of Finance 56 (2), 649–676.

Mandelbrot, B., 1963. The variation of certain speculative prices. Journal of Business 36 (4), 394–419.

Mistrulli, P., 2005. Interbank lending patterns and financial contagion. Banca d'Italia.

Neftci, N. S., 2000. Value at risk calculations, extreme events, and tail estimation. Journal of Derivatives 7 (3), 23–37.

Pais, A., Stork, A. P., 2011. Contagion risk in the Australian banking and property sectors. Journal of Banking and Finance 35 (3), 681–697.

Poon, S., Rockinger, M., Tawn, J., 2004. Extreme value dependence in financial markets: Diagnostics, models, and financial implications. The Review of Financial Studies 17 (2), 581–610.

Quintos, C., Fan, Z., Philips, P., 2001. Structural change tests in tail behaviour and the Asian crisis. The Review of Economic Studies 68 (3), 633–663.

Saunders, A., Wilson, B., 1996. Contagious bank runs: Evidence from the 1929-33 period. Journal of Financial Intermediation 5 (4), 409–423.

Slovin, M., Sushka, M., Polonchek, J., 1999. An analysis of contagion and competitive effects at commercial banks. Journal of Financial Economics 54 (2), 197–225.

Smirlock, M., Kaufold, H., 1987. Bank foreign lending, mandatory disclosure rules, and the reaction of bank stock prices to the Mexican debt crisis. Journal of Business 60 (3), 347–364.

Straetmans, S., 1998. Extreme financial returns and their comovements. Tinbergen Institute Research Series No. 181.

Straetmans, S., 2000. Extremal spill-overs in equity markets. In: Extremes and integrated risk management. Embrechts, P. (ed.), London: Risk Books, pp. 187–204.

Straetmans, S., Verschoor, W. F. C., Wolff, C., 2008. Extreme US stock market fluctuations in the wake of 9/11. Journal of Applied Econometrics 23 (1), 17–42.

Swary, I., 1986. Stock market reaction to regulatory action in the Continental Illinois crisis. Journal of Business 59 (3), 451–473.

Tarashev, N., Borio, C., Tsatsaronis, K., 2010. Attributing systemic risk to individual institutions. BIS Working Paper No. 308.

Upper, A., Worms, C., 2004. Estimating bilateral exposures in the German interbank market: Is there a danger of contagion. European Economic Review 48 (4), 827–849.

van Lelyveld, I., Liedorp, F., 2006. Interbank contagion in the Dutch banking sector: A sensitivity analysis. International Journal of Central Banking June, 99–133.

Wall, L., Peterson, D., 1990. The effect of Continental Illinois' failure on the financial performance of other banks. Journal of Monetary Economics 26 (1), 77–99.

Zhou, C., 2010. Are banks too big to fail? Measuring systemic importance of financial institutions. International Journal of Central Banking 6 (4), 205–250.

Figure 1: Hill Plots for a few Representative US (m=219) and Eurozone (m=120) banks

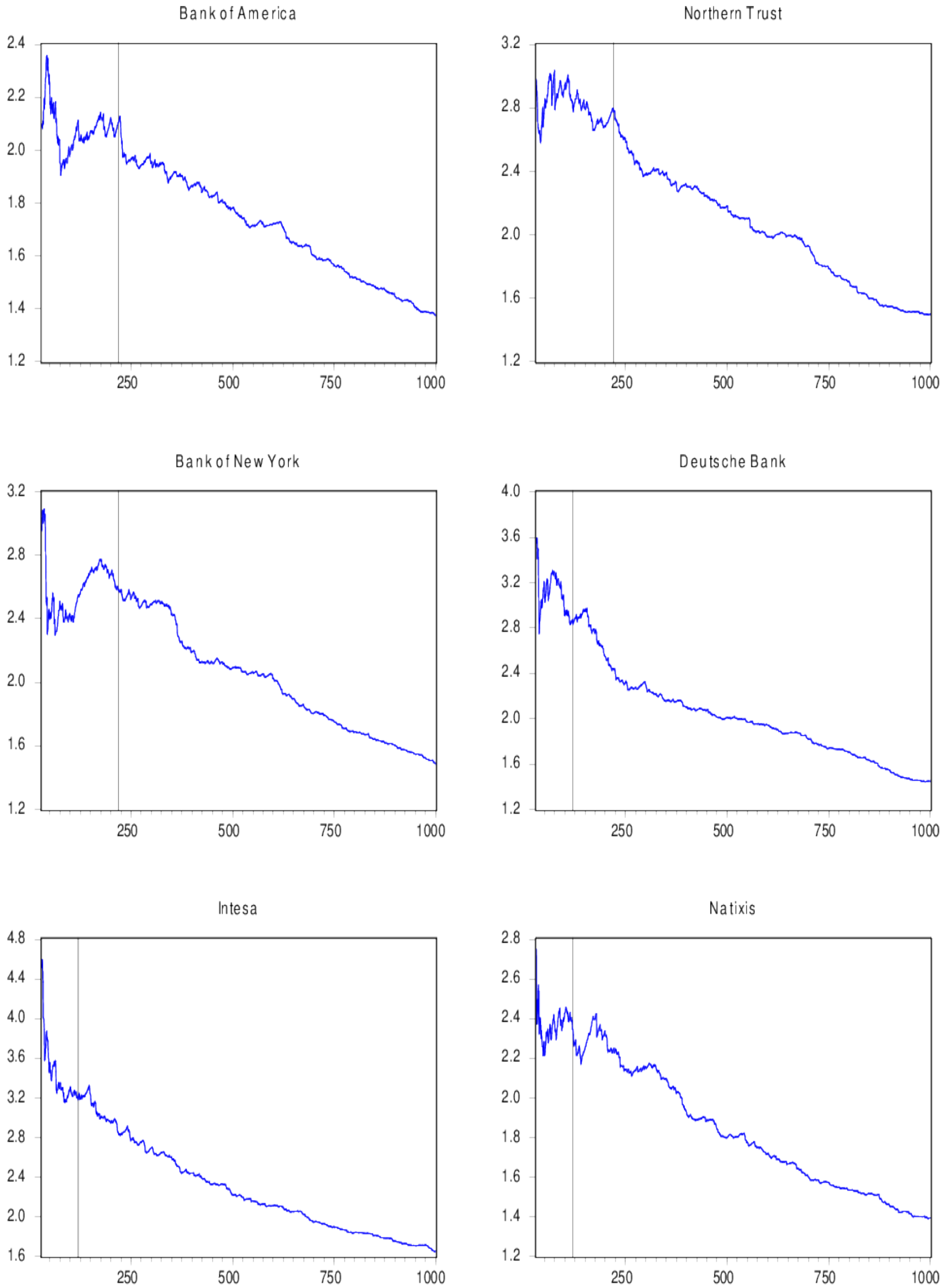

Figure 2: Tail-β Plots for a few Representative US and Eurozone Banks (m=400)

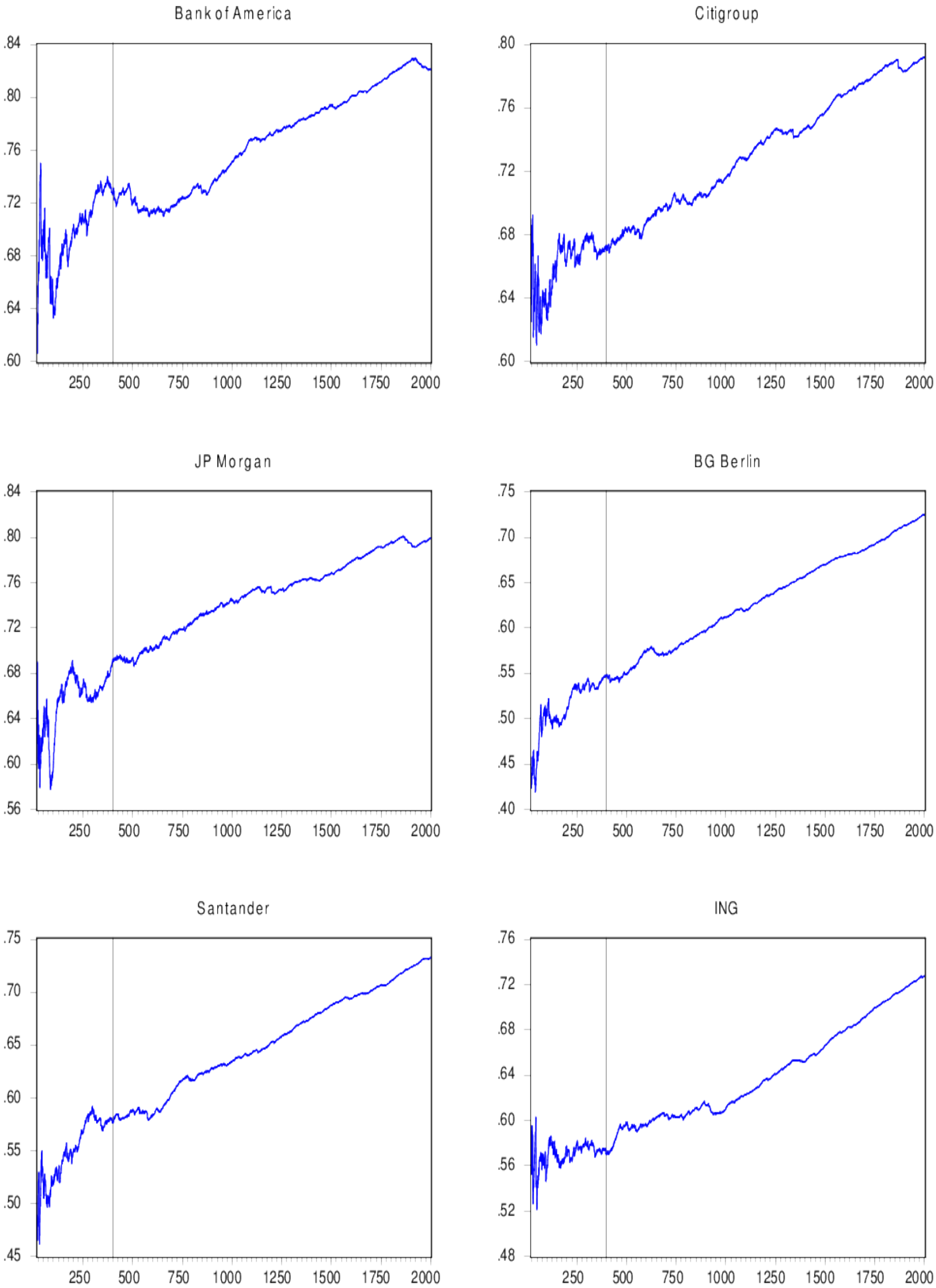

Figure 3: Time Varying Tail Risk: (Rolling) Hill Estimates and Expected shortfalls for US and Eurozone Banks

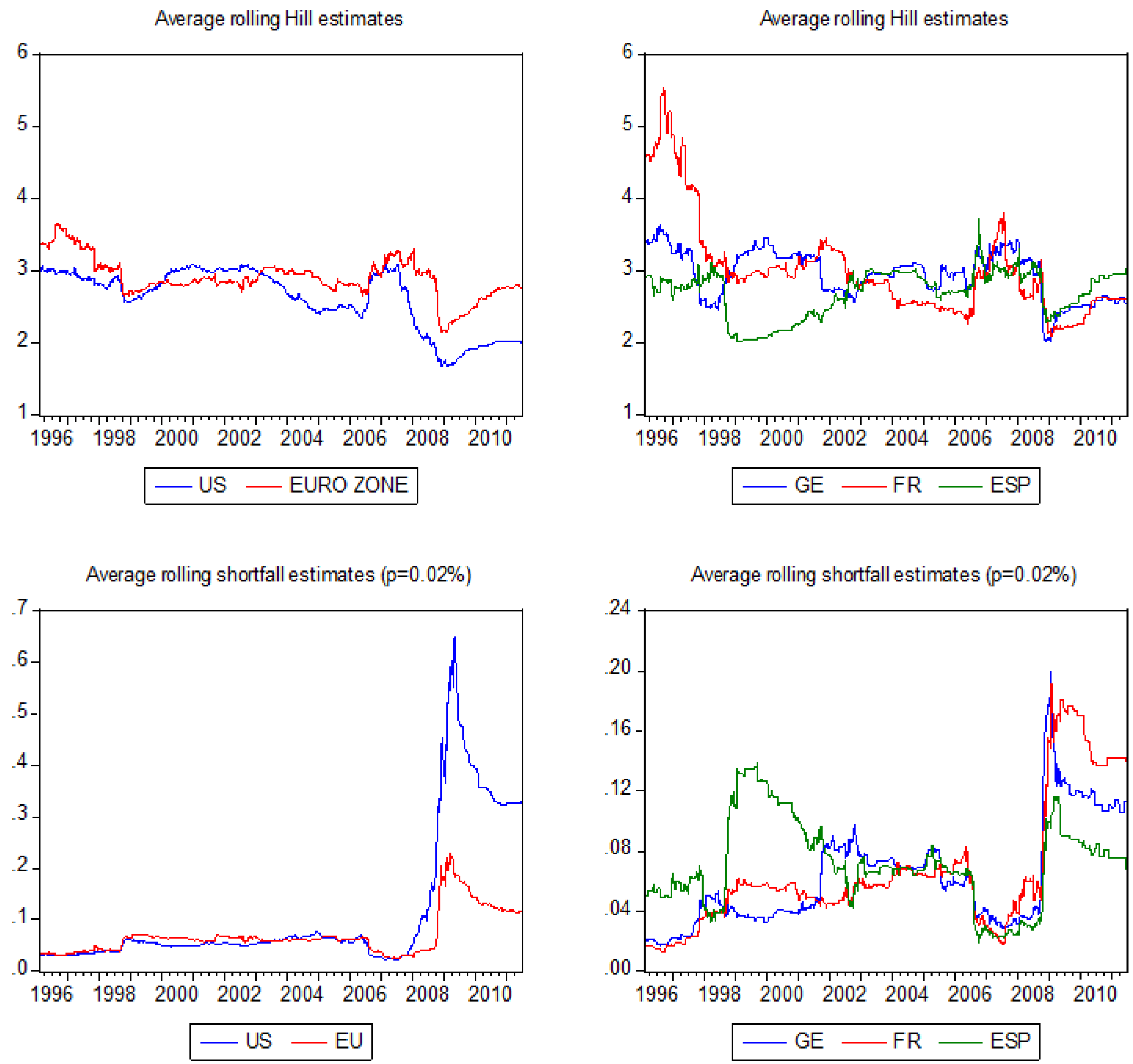

Figure 4: Time Varying Systemic Risk: (Rolling) Expected Co-crash Indicators and Co-crash Probabilities for US and Eurozone Banks

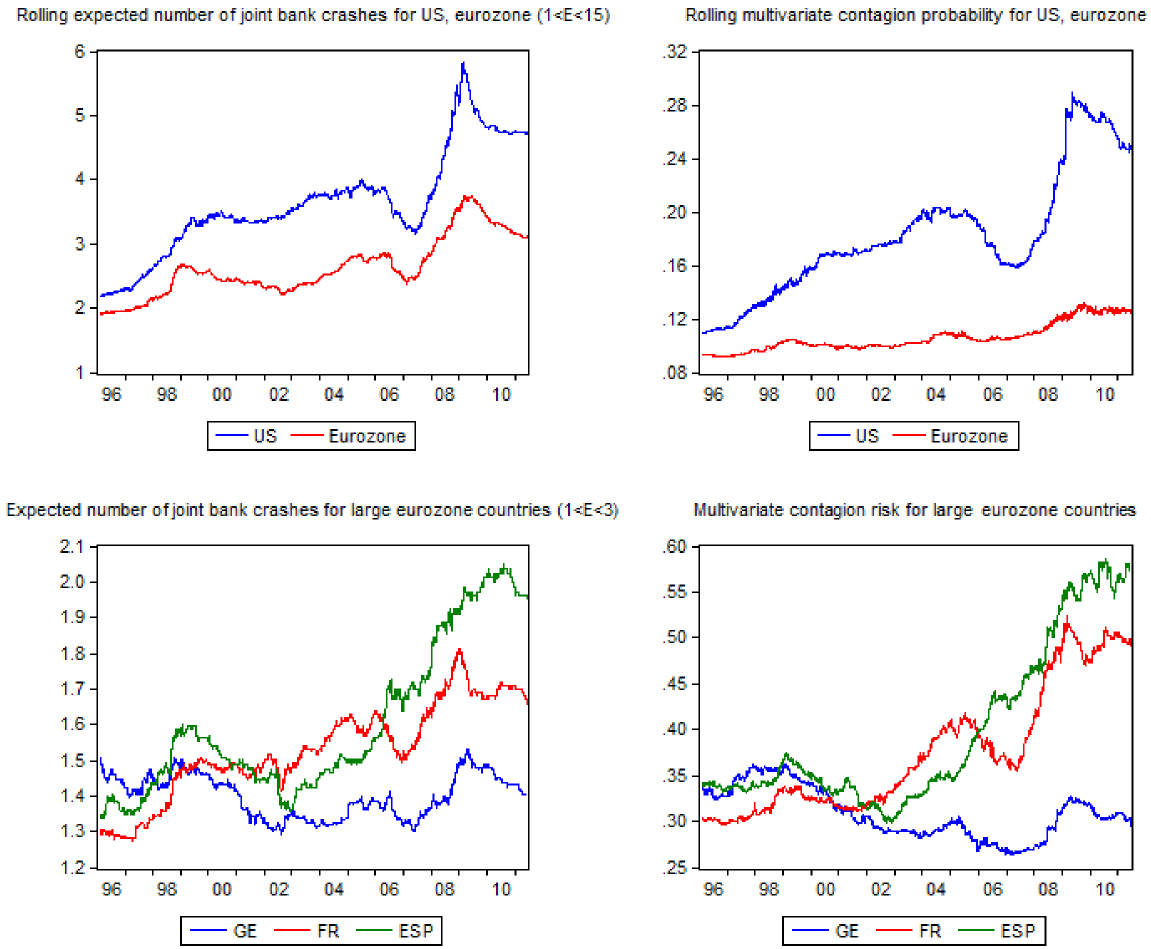

Table 1: Tail Risk Measures for Selected Eurozone and US Banks: Full Sample, Pre-crisis and Crisis

This table reports sample means, medians and standard deviations of the estimators for the tail index α, the tail quantile x_p and the expected shortfall ES across the time series dimension (pre-crisis vs. crisis) and the cross sectional dimension (US vs. eurozone). The disaggregated results that underpin mean and median calculations are reported in Tables A.1, A.2 and A.3 in appendix. The nuisance parameter m equals 120 and 219 for full sample eurozone and US banks. The pre-crisis and crisis m for the eurozone banks is 103 and 41 respectively whereas it is 188 and 75 for the US banks.

Bank	$\widehat{\alpha}$	$\widehat{x}(p)$ *in* %		$ES(X>s)$		$ES(\widehat{x}(p))$ *in* %	
		$p=0.2\%$	$p=0.1\%$	$s=25\%$	$s=50\%$	$p=0.2\%$	$p=0.1\%$
Panel I: Eurozone banks full sample estimates							
Mean	2.8	11.9	15.5	14.6	29.0	7.2	9.6
Median	2.8	11.2	14.2	14.0	28.0	6.0	7.6
S.E.	0.3	3.3	4.8	3.1	6.2	4.0	5.7
Panel II: Eurozone banks pre-crisis estimates							
Mean	2.9	9.0	11.6	13.6	27.0	4.9	6.5
Median	3.0	9.0	11.3	12.7	25.3	4.4	5.5
S.E.	0.4	1.4	2.1	3.0	6.1	1.6	2.4
Panel III: Eurozone banks crisis estimates							
Mean	2.7	18.0	23.5	14.5	29.1	11.3	14.9
Median	2.7	16.3	20.7	14.5	29.0	9.8	12.5
S.E.	0.8	7.9	11.1	3.8	7.7	7.5	10.4
Panel IV: US banks full sample estimates							
Mean	2.3	14.2	19.5	20.4	40.8	12.1	16.7
Median	2.2	13.3	17.9	20.4	40.8	10.9	14.9
S.E.	0.3	3.0	4.8	4.8	9.7	5.4	8.1
Panel V: US banks pre-crisis estimates							
Mean	2.9	8.0	10.2	13.3	26.7	4.3	5.5
Median	3.0	8.0	10.1	12.7	25.5	3.8	4.9
S.E.	0.2	1.0	1.4	1.4	2.7	0.9	1.2
Panel VI: US banks crisis estimates							
Mean	2.0	30.7	43.9	25.7	51.5	32.9	47.2
Median	2.0	29.0	39.3	24.0	48.1	27.3	39.1
S.E.	0.21	8.5	13.5	5.5	10.9	15.9	24.8

Table 2: Univariate Tail Risk Proxies: Testing for Cross Sectional Equality and Structural Change

This table reports t-tests for equal sample means (Hill and quantile estimates). Sample averages are denoted with upper bars. The upper panel compares pre-crisis and crisis sample averages of the Hill estimates and the quantile estimates for each continent separately. The lower panel compares continental averages for the pre-crisis sample and the crisis sample separately. (One-sided) rejections at the 5%, 2.5% and 1% significance level are denoted with *, ** and ****, respectively. The significance level p on which the tail quantile estimator $\widehat{x}_p$ is conditioned equals 0.1%.

Panel I: Structural change tests		
	$\overline{\alpha}_{precrisis} = \overline{\alpha}_{crisis}$	$\overline{x}_{precrisis}(p) = \overline{x}_{crisis}(p)$
Eurozone mean	0.9	-4.0***
US mean	12.5***	-9.6***
Panel II: Cross-sectional equality tests		
	$\overline{\alpha}_{eurozone} = \overline{\alpha}_{US}$	$\overline{x}_{eurozone} = \overline{x}_{US}$
Pre-crisis mean	0.3	2.2**
Crisis mean	3.2***	-4.5***

Table 3: Multivariate Bank Contagion Indicators: Estimation and Testing Results

This table reports estimation results for multivariate spillover risk measures $E[\kappa|\kappa \geq 1]$ and $P_{N|1}$ in Panel I, whereas Panels II and III report the corresponding cross sectional equality tests and structural change tests to assess whether multivariate contagion risk varies over time or differs across continents and countries, respectively. The nuisance parameter m for eurozone and US banks is 200, 150 and 50 for the full sample, the pre-crisis and the crisis, respectively. For German, French and Spanish banks the parameter m is selected as 300, 250 and 100 for the full sample, the pre-crisis and the crisis, respectively. (One-sided) rejections at the 5%, 2.5% and 1% significance level are denoted with *, ** and ****, respectively.

Panel I: Multivariate indicators								
	$\hat{E}\{\kappa\,|\kappa \geq 1\}$				$(\hat{P}_{N|1})$			
	Full	Pre	Crisis	%Δ	Full	Pre	Crisis	%Δ
US (N=15)	3.64	2.94	4.33	47.27	14.31	11.70	22.75	94.44
EU (N=15)	2.41	2.08	2.94	41.35	7.37	6.59	10.36	57.21
GE (N=3)	1.35	1.34	1.41	5.22	24.84	25.67	29.61	15.35
FR (N=3)	1.53	1.39	1.68	20.86	32.72	27.97	49.07	75.44
ESP (N=3)	1.58	1.45	1.97	35.86	35.30	28.81	60.30	109.3

Panel II: Structural change tests (pre-crisis=crisis)		
	$E_{pre} = E_{crisis}$	$P_{pre} = P_{crisis}$
US	-2.66***	-2.90***
EU	-2.66***	-3.32***
GE	-0.75	-0.89
FR	-3.47***	-2.99***
ESP	-5.10***	-3.42***

Panel III: Cross sectional tests				
	E		P	
	Pre-crisis	Crisis	Pre-crisis	Crisis
US=EU	6.41***	3.42***	6.36***	3.41***
FR=GE	1.03	3.24***	1.35	4.37***
ESP=FR	1.28	3.39***	0.45	2.15***
ESP=GE	2.09**	5.99***	1.76	4.21***

Table 4: Extreme Systematic Risk (tail-β's) for Selected Eurozone Banks and US Banks

This table reports sample means, medians and standard deviations for the tail-β estimates across the time series dimension (pre-crisis vs. crisis) and the cross sectional dimension (US vs. eurozone). The tail-β is estimated according to equation (12). The table reports results conditional on different aggregate risk factors (PIIGS tail-β estimates are only calculated for eurozone banks). The disaggregated results that underpin mean and median calculations are reported in Tables A.4, A.5 and A.6 in appendix. The nuisance parameter m equals 400 for full sample eurozone and US banks if the conditioning aggregate risk factor is either bank index or stock index. The parameter m is 300 in case the conditioning aggregate risk factor is the real estate index and it is 65 if the aggregate risk factor is the so-called PIIGS index. The parameter m is determined by the Hill estimator. The pre-crisis and crisis m for the eurozone banks and US banks is 340 and 138, respectively if the conditioning aggregate risk factor is either the bank index or the stock index, and it is 258 and 103 in case of the real estate index as a conditioning aggregate risk factor, and 59 and 17 if the PIIGS index is the conditioning aggregate risk factor.

Bank	Aggregate risk factor (index)					
	Eurozone bank	Eurozone stock	Global bank	Global stock	Real estate	PIIGS
	Panel I: Eurozone banks full sample estimates					
Mean	48.0	45.8	44.4	42.5	32.9	19.7
Median	46.8	44.7	43.4	41.2	36.3	20.1
S.E.	9.0	8.4	8.4	6.9	6.8	2.0
	Panel II: Eurozone banks pre-crisis estimates					
Mean	43.7	42.6	40.2	40.0	32.6	13.8
Median	42.1	41.6	39.5	38.7	33.4	13.7
S.E.	8.2	7.2	6.0	5.8	5.5	0.8
	Panel III: Eurozone banks crisis estimates					
Mean	62.5	58.7	58.4	55.6	44.4	21.3
Median	64.3	60.6	63.1	58.0	42.8	20.8
S.E.	8.5	7.6	7.5	6.5	8.7	2.8
	Panel IV: US banks full sample estimates					
	US bank	US stock	Global bank	Global stock	Real estate	
Mean	63.7	52.1	46.6	45.2	43.2	
Median	62.8	50.8	46.1	44.8	43.1	
S.E.	3.9	2.5	1.9	2.1	1.3	
	Panel V: US banks pre-crisis estimates					
Mean	60.0	49.9	44.9	44.5	36.7	
Median	61.2	49.4	44.8	44.1	36.3	
S.E.	3.3	2.8	1.7	2.1	1.0	
	Panel VI: US banks crisis estimates					
Mean	72.6	63.8	54.5	53.5	61.3	
Median	71.2	63.4	53.8	52.7	61.7	
S.E.	5.1	2.8	2.1	2.1	2.7	

Table 5: Extreme Systematic Risk: Testing for Cross Sectional Equality and Structural Change

This table reports the mean structural change tests for the US and the eurozone conditioning on six (five in case of the US) market factors in panel I. Panel II reports the mean cross-sectional equality tests across US and eurozone for pre-crisis and crisis periods separately conditioning on five different market factors. (One-sided) rejections at the 5%, 2.5% and 1% significance level are denoted with *, ** and ****, respectively.

Panel I: Structural change tests						
	Conditioning aggregate risk factor					
	Bank	Stock	Global bank	Global stock	Real estate	PIIGS
Eurozone mean	-6.2***	-6.0***	-7.3***	-7.0***	-4.5***	-10.0***
US mean	-8.0***	-13.8***	-13.9***	-11.6***	-33.6***	-
Panel II: Cross-sectional equality tests						
Pre-crisis mean	-7.2***	-3.6***	-2.9***	-2.9***	-2.9***	
Crisis mean	-4.0***	-2.4***	2.0*	1.8	-7.2***	

Table 6: Spearman's Rank Correlations of OLS-βs and Tail-βs

This table reports the Spearman's rank correlations for OLS-βs and tail-βs for the full sample, the pre-crisis sample and the crisis sample for eurozone and US banks.

	Full sample	Pre-crisis sample	Crisis sample
Eurozone banks	0.52	0.70	0.20
US banks	0.55	0.43	0.17

6 Appendix

Table A.1: Full Sample Tail Risk Indicators for Eurozone and US banks

This table reports estimations for the tail index α, the tail quantile x_p and the expected shortfall ES for full sample eurozone and US banks, which are given in equations (6), (7) and (8). The nuisance parameter m denoting the number of extreme returns used in estimation equals 120 and 219 for the Eurozone banks and the US banks, respectively.

Bank	$\widehat{\alpha}$	$\widehat{x}(p)$		$\widehat{ES}(X>s)$		$\widehat{ES}(\widehat{x}(p))$	
		$p=0.2\%$	$p=0.1\%$	$s=25\%$	$s=50\%$	$p=0.2\%$	$p=0.1\%$
Panel I: Eurozone banks							
COMMERZ	2.5	12.9	17.0	16.2	32.4	8.4	11.0
DEUTSCHE	2.8	10.9	14.0	13.6	27.3	6.0	7.6
BGBERLIN	3.0	11.3	14.2	12.4	24.8	5.6	7.1
BNP	2.5	11.2	15.7	16.5	29.4	6.6	10.4
SOCGEN	2.8	11.9	15.3	13.9	27.8	6.6	8.5
NATIXIS	2.3	13.0	17.4	18.6	37.1	9.6	12.9
INTESA	3.2	10.6	13.2	11.4	22.8	4.8	6.0
UNICREDIT	2.7	11.6	15.0	14.9	29.8	6.9	8.9
SANTANDER	3.0	10.1	12.7	12.3	24.6	5.0	6.3
BBVA	2.7	10.0	12.9	14.4	28.8	5.8	7.4
ESPANOL	2.8	8.9	11.4	14.0	28.0	5.0	6.4
ING	2.6	14.9	19.4	15.5	31.0	9.2	12.0
ALPHA	3.2	11.0	13.6	11.3	22.7	5.0	6.2
AIBANK	2.1	22.0	30.7	23.0	46.0	20.2	28.2
BCP	3.3	7.9	9.8	11.1	22.2	3.5	4.3
Panel II: US banks							
CITIG	2.2	17.1	23.5	21.5	43.0	14.7	20.2
J MORGAN	2.6	12.3	16.0	15.4	30.7	7.6	9.8
BAMERICA	2.1	16.3	22.6	22.6	45.2	14.7	20.4
FARGO	2.2	13.1	17.9	20.7	41.5	10.9	14.9
BNYORK	2.6	11.8	15.4	15.9	31.8	7.5	9.8
SSTREET	2.4	13.4	17.8	17.6	35.3	9.4	12.5
NTRUST	2.8	10.2	13.0	13.9	27.8	5.6	7.2
BCORP	2.2	13.3	18.3	21.7	43.4	11.5	15.9
PNC	2.5	11.4	15.0	16.8	33.5	7.6	10.1
KEYCO	2.2	15.6	21.3	20.4	40.8	12.7	17.4
SUNTRUST	1.9	17.2	24.8	28.0	56.0	19.3	27.8
COMERICA	2.4	12.4	16.6	17.8	35.6	8.9	11.8
BBT	2.5	10.8	14.3	16.8	33.6	7.3	9.6
53BANCO	1.9	18.8	27.1	28.0	55.9	21.0	30.3
REGION	1.9	19.6	28.4	29.0	58.0	22.7	32.9

Table A.2: Tail Risk Measures for Selected Eurozone Banks: Pre-crisis and Crisis Estimates

This table reports estimations for the tail index α, the tail quantile x_p and the expected shortfall ES for pre-crisis and crisis sample for eurozone banks, which are given in equations (6), (7) and (8). The table distinguishes pre-crisis from crisis estimates (sample splits on August 7, 2007). The nuisance parameter m equals 103 and 41 for the pre-crisis and the crisis samples, respectively.

Bank	$\widehat{\alpha}$	$\widehat{x}(p)$		$ES(X>s)$		$ES(\widehat{x}(p))$	
		$p=0.2\%$	$p=0.1\%$	$s=25\%$	$s=50\%$	$p=0.2\%$	$p=0.1\%$
Panel I: Pre-crisis estimates							
COMMERZ	3.0	9.0	11.3	12.2	24.5	4.4	5.5
DEUTSCHE	3.2	8.4	10.4	11.3	22.5	3.8	4.7
BGBERLIN	2.7	11.4	14.8	14.7	29.4	6.7	8.7
BNP	2.7	9.0	14.8	14.9	26.3	4.7	8.8
SOCGEN	2.9	9.6	12.2	13.2	26.5	5.1	6.4
NATIXIS	3.4	6.6	8.1	10.4	20.8	2.7	3.4
INTESA	3.7	9.1	10.9	9.2	18.4	3.3	4.0
UNICREDIT	3.4	8.3	10.2	10.5	21.1	3.5	4.3
SANTANDER	3.1	9.0	11.3	12.2	24.3	4.4	5.5
BBVA	2.6	9.2	12.1	15.9	31.9	5.9	7.7
ESPANOL	2.3	9.3	12.6	19.8	39.6	7.4	10.0
ING	2.4	11.8	15.8	18.2	36.3	8.6	11.5
ALPHA	3.1	8.7	10.9	12.0	24.1	4.2	5.3
AIBANK	3.0	7.2	9.1	12.7	25.3	3.7	4.6
BCP	2.5	7.6	10.0	16.8	33.6	5.1	6.8
Panel II: Crisis estimates							
COMMERZ	2.7	19.7	25.4	14.5	29.0	11.4	14.7
DEUTSCHE	2.4	18.6	24.7	17.4	34.7	12.9	17.2
BGBERLIN	2.7	14.1	18.4	15.1	30.2	8.5	11.1
BNP	2.7	16.3	21.2	15.1	30.2	9.9	12.8
SOCGEN	3.1	16.3	20.4	12.1	24.2	7.9	9.8
NATIXIS	2.1	27.1	37.8	23.2	46.5	25.2	35.1
INTESA	2.6	15.8	20.7	16.1	32.2	10.2	13.3
UNICREDIT	2.8	17.3	22.2	14.1	28.2	9.8	12.5
SANTANDER	2.9	13.5	17.1	13.1	26.2	7.0	8.9
BBVA	2.8	13.2	16.9	14.3	28.5	7.5	9.6
ESPANOL	3.9	8.5	10.1	8.5	17.0	2.9	3.4
ING	2.4	25.4	33.8	17.3	34.7	17.6	23.4
ALPHA	3.8	13.9	16.6	8.8	17.6	4.9	5.9
AIBANK	0.4	40.4	54.1	18.4	36.7	29.6	39.7
BCP	3.4	10.2	12.5	10.2	20.4	4.2	5.1

Table A.3: Tail Risk Measures for Selected US banks: Pre-crisis and Crisis Estimates

This table reports estimations for the tail index α, the tail quantile x_p and the expected shortfall ES for pre-crisis and crisis sample for US banks, which are given in equations (6), (7) and (8). The table distinguishes pre-crisis from crisis estimates (sample split equals August 7, 2007). The nuisance parameter m equals 188 and 75 for the pre-crisis and the crisis samples, respectively.

Bank	$\widehat{\alpha}$	$\widehat{x}(p)$		$ES(X > s)$		$ES(\widehat{x}(p))$	
		$p = 0.2\%$	$p = 0.1\%$	$s = 25\%$	$s = 50\%$	$p = 0.2\%$	$p = 0.1\%$
Panel I: Pre-crisis estimates							
CITIG	3.0	8.8	11.0	12.2	24.5	4.3	5.4
JP MORGAN	3.0	9.2	11.7	12.5	25.1	4.6	5.9
BAMERICA	2.8	8.7	11.2	14.2	28.4	5.0	6.4
FARGO	3.1	6.9	8.7	12.1	24.2	3.3	4.2
BNYORK	3.2	8.2	10.1	11.3	22.7	3.7	4.6
SSTREET	2.6	10.0	13.1	16.1	32.1	6.4	8.4
NTRUST	2.8	8.4	10.7	13.5	27.0	4.6	5.8
BCORP	2.6	9.0	11.8	16.1	32.3	5.8	7.6
PNC	3.0	7.4	9.4	12.7	25.5	3.8	4.8
KEYCO	2.8	8.0	10.3	14.1	28.3	4.5	5.8
SUNTRUST	2.9	6.8	8.7	13.5	26.9	3.7	4.7
COMERICA	3.0	7.3	9.2	12.7	25.5	3.7	4.7
BBT	2.8	7.0	8.9	13.7	27.3	3.8	4.9
53BANCO	3.0	7.3	9.2	12.5	25.1	3.7	4.6
REGION	3.0	7.0	8.9	12.6	25.2	3.5	4.5
Panel II: Crisis estimates							
CITIG	1.8	43.9	65.1	32.8	65.6	57.7	85.5
JP MORGAN	2.1	24.8	34.9	23.9	47.7	23.7	33.3
BAMERICA	1.6	46.9	71.5	39.1	78.1	73.2	111.8
WELLS FARGO	1.9	31.3	45.4	29.0	58.0	36.3	52.7
BNYORK	2.1	23.2	32.2	22.6	45.3	21.0	29.2
SSTREET	1.9	29.8	43.1	28.5	57.0	34.0	49.2
NTRUST	1.9	22.8	32.6	26.9	53.8	24.5	35.1
BCORP	1.9	25.6	36.7	26.7	53.3	27.3	39.1
PNC	2.1	23.1	31.9	21.9	43.8	20.2	28.0
KEYCO	2.1	34.1	47.7	23.7	47.3	32.3	45.2
SUNTRUST	2.3	29.0	39.3	19.6	39.1	22.7	30.7
COMERICA	2.0	27.6	38.8	24.0	48.1	26.6	37.3
BBT	2.5	18.9	25.0	17.1	34.2	12.9	17.1
53BANCO	1.9	42.8	61.9	28.3	56.6	48.5	70.0
REGIONS	2.1	36.5	50.5	22.0	44.0	32.2	44.5

Table A.4: Extreme Systematic Risk (Tail-βs) for Selected Eurozone Banks and US Banks: Full Sample Results

This table reports results conditional on different aggregate risk factors (results conditional to the PIIGS factor are only calculated for eurozone banks). The nuisance parameter m denoting the number of extreme returns used in estimation equals 400 for both the Eurozone banks and the US banks.

Bank	Aggregate risk factor (index)					
	Eurozone/US bank	Eurozone/US stock	Global bank	Global stock	Real estate	PIIGS
		Panel I: Eurozone banks				
COMMERZ	54.7	52.1	50.6	49.3	22.6	33.0
DEUTSCHE	56.5	53.5	53.1	50.7	23.1	32.2
BGBERLIN	34.4	33.9	32.3	32.8	22.8	35.6
BNP	28.6	28.8	27.9	27.8	25.8	35.0
SOCGEN	56.6	52.4	50.6	47.2	38.8	33.1
NATIXIS	44.2	41.4	43.0	39.7	39.1	33.5
INTESA	46.8	44.7	42.8	40.6	35.1	33.2
UNICREDIT	48.8	45.9	44.9	41.2	37.0	33.0
SANTANDER	57.7	55.8	51.6	49.6	39.1	33.4
BBVA	58.4	56.6	52.4	50.5	38.0	33.1
ESPANOL	44.8	41.8	41.2	39.3	36.3	35.8
ING	57.0	55.3	53.5	49.3	38.7	32.1
ALPHA	40.2	38.7	37.7	37.4	35.9	34.5
AIBANK	46.3	43.8	43.4	42.2	36.7	34.2
BCP	44.5	41.7	40.5	39.8	25.0	25.0
		Panel II: US banks				
CITIG	67.0	55.0	50.4	48.9	44.7	
J MORGAN	69.2	57.9	50.0	48.8	43.0	
BAMERICA	72.7	53.6	48.4	45.9	43.1	
FARGO	62.8	49.8	44.0	42.7	44.3	
BNYORK	61.4	53.3	46.1	45.5	41.4	
SSTREET	59.9	53.8	45.9	47.7	43.1	
NTRUST	58.2	54.7	45.4	47.5	42.3	
BCORP	61.0	50.5	45.1	43.5	41.8	
PNC	64.1	50.8	44.8	44.0	42.9	
KEYCO	63.8	50.5	46.3	44.5	43.6	
SUNTRUST	66.1	50.8	48.2	44.9	42.6	
COMERICA	64.7	52.1	46.8	44.4	46.0	
BBT	62.6	50.5	45.6	43.1	43.4	
53BANCO	59.8	49.1	44.7	42.4	40.9	
REGION	61.4	48.8	47.3	44.8	44.5	

Table A.5: Extreme Systematic Risk (Tail-βs) for Selected Eurozone Banks: Pre-crisis vs. Crisis Results

This table reports results conditional on different aggregate risk factors. The table distinguishes pre-crisis estimates form crisis estimates (sample mid-point equals August 7, 2007; the sample split for the PIIGS tail-βs equals December 15, 2009). The nuisance parameter m equals 340 and 138 for pre-crisis and crisis samples, respectively.

Bank	Aggregate risk factor (index)					
	Eurozone bank	Eurozone stock	Global bank	Global stock	Real estate	PIIGS
Panel I: Pre-crisis estimates						
COMMERZ	50.3	49.2	44.7	44.5	35.3	13.2
DEUTSCHE	54.3	50.7	47.8	47.5	35.6	13.4
BGBERLIN	35.4	35.0	32.6	33.2	30.6	14.1
BNP	28.8	29.6	28.6	28.5	25.7	15.1
SOCGEN	50.8	47.6	45.3	43.7	33.5	12.8
NATIXIS	37.6	37.3	36.5	36.0	33.3	14.1
INTESA	42.1	41.1	39.5	38.7	32.5	14.2
UNICREDIT	44.8	42.8	38.7	37.6	34.5	13.7
SANTANDER	53.7	51.4	47.9	46.4	40.1	13.6
BBVA	53.6	52.2	47.4	47.7	38.9	13.1
ESPANOL	38.3	36.6	36.5	36.4	36.1	15.5
ING	51.1	50.5	45.6	45.9	33.0	13.1
ALPHA	35.1	36.0	35.4	36.3	36.5	14.4
AIBANK	41.2	41.6	40.8	40.9	23.6	13.7
BCP	38.1	37.5	35.7	36.6	24.2	13.1
Panel II: Crisis estimates						
COMMERZ	61.9	58.5	65.8	61.9	55.1	25.4
DEUTSCHE	63.4	61.1	63.4	61.7	52.1	18.1
BGBERLIN	41.5	40.6	40.8	40.2	35.3	17.8
BNP	68.1	61.9	63.1	58.0	33.7	20.8
SOCGEN	65.8	60.3	63.4	57.1	52.6	19.8
NATIXIS	61.1	58.8	63.7	58.5	54.8	19.6
INTESA	66.1	63.7	56.6	55.0	48.2	25.1
UNICREDIT	68.4	63.7	59.5	58.3	51.3	24.0
SANTANDER	73.5	67.4	63.1	59.8	42.8	19.2
BBVA	73.9	68.4	64.6	61.7	40.6	21.0
ESPANOL	64.3	60.6	58.5	56.9	41.4	20.5
ING	66.4	64.3	64.0	60.3	54.3	19.2
ALPHA	52.3	49.9	47.0	46.4	41.1	21.6
AIBANK	54.2	50.8	50.2	49.2	32.2	20.8
BCP	56.2	51.0	52.7	48.8	31.2	27.1

Table A.6: Extreme Systematic Risk (Tail-βs) for Selected US Banks: Pre-crisis vs. Crisis results

This table reports results conditional on different aggregate risk factors. The table distinguishes pre-crisis estimates form crisis estimates (sample mid-point equals August 7, 2007). The nuisance parameter m equals 340 and 138 for pre-crisis and crisis samples, respectively.

Bank	Aggregate risk factor (index)				
	US Bank	US stock	Global bank	Global stock	Real Estate
			Panel I: Pre-crisis estimates		
CITIG	62.5	55.2	47.4	47.6	36.2
JP MORGAN	63.9	55.5	48.3	48.6	37.1
BAMERICA	65.0	49.0	45.9	44.8	36.8
FARGO	57.8	47.0	43.3	42.3	35.8
BNYORK	62.0	51.4	45.8	44.9	38.1
SSTREET	57.5	51.1	44.8	45.8	35.7
NTRUST	57.5	51.8	45.0	48.0	37.4
BCORP	55.0	47.6	42.4	42.3	35.8
PNC	61.2	48.5	44.0	43.4	36.1
KEYCO	62.2	49.4	45.2	44.6	38.0
SUNTRUST	63.6	50.5	44.5	43.5	36.3
COMERICA	61.6	49.4	45.6	44.1	38.8
BBT	59.0	47.9	44.7	43.3	36.6
53BANCO	55.6	46.5	42.1	42.1	36.0
REGION	56.0	47.2	44.1	42.5	35.8
			Panel II: Crisis estimates		
CITIG	73.1	63.4	57.6	57.1	59.9
JP MORGAN	82.7	69.8	57.3	54.8	67.0
BAMERICA	80.8	66.7	58.5	58.5	63.3
WELLS FARGO	80.3	63.1	53.5	52.7	61.7
BNYORK	66.4	65.2	51.4	52.3	62.5
SSTREET	66.1	66.4	54.0	54.2	61.7
NTRUST	69.4	64.9	51.5	51.9	61.7
BCORP	75.5	66.1	54.6	54.8	66.1
PNC	70.1	60.3	53.8	52.5	58.9
KEYCO	70.1	59.8	53.3	50.4	58.9
SUNTRUST	72.0	61.1	55.9	52.7	58.3
COMERICA	71.2	64.0	53.8	53.5	60.7
BBT	73.1	61.7	53.5	52.1	62.1
53BANCO	68.7	61.4	52.9	52.3	58.3
REGIONS	70.1	63.1	55.3	52.5	58.9