TAIL RISK AND SYSTEMIC RISK OF US AND EUROZONE FINANCIAL INSTITUTIONS IN THE WAKE OF THE GLOBAL FINANCIAL CRISIS

S. STRAETMANS AND S. CHAUDHRY

Abstract. We evaluate multiple market-based measures for US and eurozone individual bank tail risk and banksystemic 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 ("contagion 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. We also assess to what extent magnitudes of tail risk and systemic risk have been altered by the global financial crisis. Using both US and eurozone banks allows one to make a cross-atlantic comparison of the financial systems' riskiness and financial stability. For Europe we assess the relative importance of cross-border bank spillovers as compared to domestic bank spillovers. The results suggest, inter alia, that both tail risk and systemic risk in the US are higher than in the eurozone. We cannot generally conclude that domestic eurozone spillover risk dominates cross-border eurozone spillover risk. Finally, tail risk and systemic risk have increased over time on both sides of the Atlantic.

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

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

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 situations of financial instability 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. Whereas 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 by e.g. taking into account a bank's inter-linkages with other banks. 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 e.g. be used as a basis to impose taxes or capital surcharges on systemically important financial institutions (provided one reaches consensus over what systemic risk exactly is), see e.g. Acharya et al. (2010).

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 paper will mainly focus on comparing the financial stability of the US and eurozone financial systems. We believe such a cross-atlantic comparison makes sense because of the perception that banking consolidation and financial deregulation has been stronger in the US than in the eurozone during the last 10 to 15 years. More specifically, while there has been considerable bank consolidation within individual industrialized nations in recent years, cross-border bank mergers and acquisitions (for example within Europe) have generally been less frequent (Group of Ten, 2001). On the one hand, the removal of US regulatory barriers to universal and cross-state banking has led to the emergence of large and complex banking organizations (LCBOs) that have not only become "too big to fail" but also "too complex" to fail. The European banking market, on the other hand, still seems more fragmented despite the introduction of the single currency.[2] Eurozone

[2]Usign a comparable methodology to ours, Hartmann et al. (2006) were unable to identify structural breaks in their systemic risk indicators around the introduction of the single currency (1999). We will therefore not test for a euro effect in this

retail banking is generally far less integrated than wholesale banking and banks' capital market-related activities. Also, cross-border bank consolidation (M&A activity) has been relatively modest as compared to the US. This relatively lower degree of European banking market integration may be due to cross-country legal and tax barriers, differing national supervisory rules, cultural differences or geographic distance, see e.g. Berger et al. (2003) or Heuchemer and Kleimeier (2009). It will be interesting to see whether and to what extent this differing degree of banking market integration across the two continents is also reflected into indicators of systemic risk. Next to making a cross-atlantic comparison, we also identify bank spillover (contagion) likelihoods within and across the European countries in our sample.[3] As to date, European banks are still supervised by national regulators which implies cross-country differences in regulation and supervision may explain differences in domestic bank spillovers. Thus, this justifies an evaluation of spillover likelihoods on both a continent level as well as a country level. In addition, we are also interested in comparing eurozone domestic spillover effects with eurozone cross-border spillover effects: if systemic risk is related to the degree of European banking integration, we expect countries with strong banking ties to exhibit comparable intensities of domestic and cross-border spillover; whereas cross-border contagion is expected to be lower for country pairs with banking sectors that do not have much involvement. If domestic and cross-border contagion likelihoods are found to be of comparable magnitude throughout the eurozone, this would further strengthen the argument in favor of a more eurozone-wide financial regulatory and supervisory framework, e.g. an EU Banking Union.[4]

The fact that supposed triggers of systemic instability like e.g. the degree of interbank interconnectedness, the location of banks within

paper. However, this does not necessarily imply that the single currency did not impact financial integration and systemic risk. Monetary integration has been a gradual process spread out over half a decade preceding 1999 which makes it likely that the effects on systemic risk have also been spread out over time. Structural change tests probably lack sufficient statistical power to detect breakpoints when shifts are so gradual. Alternatively, it is of course possible that monetary integration did not impact systemic risk: stronger cross-border crisis propagation mechanisms resulting from the introduction of a eurozone-wide money market could have been neutralized by better risk sharing and a better ability of a deeper market to absorb shocks (i.e. the same or even lower systemic risk).

[3]In this paper we use the terms "spillover" and "contagion" interchangeably.

[4]The EU's banking union plans seek to place eurozone banks under the overarching supervision of the ECB, followed by the creation of a bank resolution scheme for the bloc and, eventually, a common deposit scheme.

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" indicators of systemic risk. In particular, all kinds of co-movement measures for bank equity returns have been applied. Probably 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, see e.g. Swary (1986), Wall and Peterson (1990) or Slovin, Sushka and Polonchek (1999). Other authors applied various regression approaches to link abnormal bank stock returns to asset-side risks, including those related to aggregate shocks, see e.g. Smirlock and Kaufold (1987) or Kho, Lee and Stulz (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 and Vesala (2004) 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 (2010)) and Marginal Expected Shortfall (Acharya et al. (2010) or Brownlees and Engle (2011)).[5] Whereas the literature described above mainly focused on identifying contagion-type bank equity spillovers, other papers argued that banking crises are related to macro shocks on an aggregate level. 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

[5]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 by e.g. Saunders and Wilson (1996) and Calomiris and Masson (1997, 2000). A more recent literature tries to related bank contagion risk to central bank data on interbank exposures, see e.g. Upper and Worms (004), Degryse and Nguyen (2004), Lelyveld and Liedorp (2004) or Mistrulli (2005). Purely theoretical models of bank contagion have been proposed by e.g. Allen and Gale (2000) or Freixas et al. (2002). Bisias et al. (2012) provide a a comprehensive survey of 21 systemic risk indicators that have been proposed through time (both market-based and others).

multi-country evidence. Hellwig (1994) suggests that the fact that deposit contracts are noncontingent on the state of the macro economy may also partly explain their vulnerability towards aggregate shocks. The systemic risk indicators we are going to work with in this paper complement both the contagion literature as well as the literature on aggregate macro shocks destabilizing the banking system.

This paper partly builds on the statistical extreme value (EVT) approach followed by e.g. 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" indicators 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-$\beta's$"). Notice the proposed risk indicators are also market-based indicators because they make use of banks' equity returns. More specifically, the EVT approach presupposes that bank stocks are efficient in the sense that large daily losses in bank stocks are not sunspots but fundamentals-based and reflect that banks are financial distressed. Moreover, joint sharp falls in bank stocks reflect the risk of a problem in one bank spreading to other banks ("contagion" 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 of an individual bank to aggregate shocks.[7]

The probabilistic spillover measures that we also refer to as "spillover" risk or "contagion" risk in this paper are related to a large body of

[6]Other applications of multivariate EVT towards assessing asset market linkages during stress periods include Longin and Solnik (2001) and Poon et al. (2004) for stock markets, Hartmann et al. (2003a/b) for currency linkages and Hartmann et al. (2004) for stock-bond linkages.

[7]Market-based indicators of tail risk or systemic risk also have their limitations. First, by definition they are unsuited to evaluate the systemic risk contribution of non-listed banks (and one knows that some of the non-listed banks can be quite big and potentially systemically important indeed). Another point of discussion is that market-based indicators 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. However, some of the mentioned information like interbank interconnectedness is not publically available. Also, balance sheet risks have been increasingly shifted off the balance sheet partly due to financial deregulation. Thus, the presumption that bank stocks

literature on theoretical and empirical financial contagion. Several definitions of bank "contagion" co-exist in this literature but Hartmann et al. (2006) summarize five identification criteria: (i) bad news about one financial institution adversely affects other financial institutions or a decline in an asset price leads to declines in other asset prices ; (ii) the interdependence between asset price declines during stress periods differs from those observed in normal times (regular "interdependence"); (iii) the co-movements between bank stocks are in excess of what can be explained by economic fundamentals; (iv) the events constituting contagion are negative "extremes", such as bank failures or bank equity capital meltdowns, so that they correspond to crisis situations; (v) bank stock co-movements are the result of propagations over time rather than being caused by the simultaneous effects of common shocks. Most empirical strategies to identify contagion only reflect the first criterion (i) and widely differ on the other points. The crucial distinction between our EVT approach and previous approaches to measuring systemic risk is that we strongly emphasize criterion (iv), i.e. we focus on events that are severe enough to basically always be of concern for regulators and supervisors caring about financial stability.[8] Some of the other mentioned criteria have their own rationale, but more regular shock transmission is not necessarily something regulators or policymakers need to care about if financial stability is their main concern. The shock propagation criterion (v) is certainly interesting to investigate but dynamic spillovers are virtually non-existent in daily

are efficiently priced and that market-based indicators may therefore be forward-looking is probably a too strong 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.

[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, cf. criterion (iv) to identify contagion.

return data and one probably needs to use high frequency data in order to identify intra day bank contagion. We leave this for future research.

The current study contributes to existing studies on banking system stability in different dimensions. First, and as a "prequel" to studying bank risk spillovers, we estimate extreme downside risks of single financial institutions' bank capital as a "summary statistic" of these institutions' overall risk-taking behavior. We distinguish between the tail index, tail quantiles and expected shortfalls as measures of extreme downside risk for bank equity capital. Although so-called integrated risk management is increasingly important, different types of bank risks are still too often separately monitored or managed. However, when bank stocks are efficiently priced, it is reasonable to assume that different types of bank risk (credit risk, liquidity risk, operational risk, interest rate risk or trading risk) should be jointly reflected in the evolution of the market value of bank equity. Thus, when news is revealed about one of these risk sources, we assume it is directly discounted in the market value of the bank equity capital. Poorly monitored traders in dealing rooms of big international banks accumulating huge trading losses constitute only one example. Furthermore, we know that huge losses arising from one of these bank risks could even drive financial institutions into overnight financial distress, see e.g. Danielsson and de Vries (1997) for examples. We use the resulting sharply negative stock market reactions as price information to identify our downside risk indicators. Second, we perform a cross-atlantic comparison of systemic risk over time (we earlier motivated why a cross-atlantic comparison would make sense from an economic point of view). There are hardly any papers that compare the two continents in terms of systemic risk apart form 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 data were actually tail dependent. Moreover, imposing tail dependence is a reasonable assumption given the interconnectedness of banks via interbank markets and via their common asset exposures, see e.g. de Vries (2005). The tail dependence assumption is not only statistically convenient but also economically relevant 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 that are primarily used for "prudential" motives of regulatory and supervisory bodies. Fourth, our indicator of extreme systematic risk can be conditioned on many different sources of non-diversifiable risk. Previous studies typically conditioned the tail-β on an index for bank stocks or a general stock market index, see e.g. Straetmans et al. (2008). Given the fact that real estate and sovereign debt played a key role in the recent systemic banking crisis, we condition the tail-β both on traditional factors like a banking and general stock market index but also on a real estate and sovereign debt country index.[9] Fifth, we apply Huang's (1992) expectational linkage measure in a banking context as an indicator of multivariate contagion risk.[10] The indicator reflects the expected number of banks jointly triggered into distress when at least one bank in the system is distressed or failed. To our knowledge, we are the first to apply this multivariate measure of extreme co-movement to banking. Last but not least, the performed tail risk and tail co-movement analysis is performed for an extended sample encompassing the demise of Lehman Brothers as well as the eurozone sovereign debt crisis up to June 2011. This enables us to compare pre-crisis and crisis estimates of downside risk and systemic risk indicators as well as to compare our results with previous cross-atlantic comparisons like in Hartmann et al. (2006) that do not use the crisis data.[11]

The used data are daily bank stock returns in euro area countries and the United States between April 1992 and June 2011. We choose 15 banks per continent based on the criteria of balance-sheet size and involvement in interbank lending. Our sample represents the systemically most relevant financial institutions, but neglects a large number of smaller banks. Several selected banks were financially distressed during parts of the sample and also global markets were characterized by severe episodes of stress: the systemic banking crisis that developed after the Lehman debacle and the ongoing eurozone sovereign debt crisis constitute the most notorious episodes in our sample. All in all, we have about 5,000 stock price observations per financial institution.

[9] Co-crash probabilities of bank equity capital can be conditioned on virtually any factor of interest provided the conditioning factor's data frequency and availability is identical to that of the bank's equity prices. As such, these types of extreme probabilities can also be seen as a device for macro stress tests.

[10] 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).

Anticipating our results, 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, upon "dissecting" the multivariate spillover risks into bivariate spillover risk probabilities for pairs of US banks and pairs of eurozone banks separately, we find that US contagion probabilities dominate both eurozone domestic and cross-border contagion probabilities. Domestic contagion dominates cross-border contagion for Italy and Spain but not for Germany and France. The highest spillover found is also the cross-border spillover between Italy and Spain. The domestic vs. cross-border contagion outcomes are such that we cannot generally conclude that domestic eurozone contagion dominates cross-border eurozone contagion (or vice versa). Fourth, 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, which illustrates the relevance of aggregate risks for banking system stability. 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. Last but not least, upon comparing pre-crisis estimates with crisis estimates, both our indicators of 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.[12] Our results partly confirm the outcomes of the preceding studies like Hartmann et al. (2006), Acharya et al. (2010) and Gorton (2010) but there are also some striking discrepancies which will be discussed more in-depth when going through the empirical results.

[12]Insofar as equality tests aim to detect structural change, candidate-break dates are chosen exogenously, 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 e.g. 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 dependence parameter and not on the systemic risk indicators themselves. Given that we restrict the tail dependence parameter to be equal to 1 ($\alpha = 1$), this type of endogenous structural change test would not make sense for the current paper.

The paper is structured as follows. The next section discusses indicators of downside bank risk (2.1) and systemic risk (2.2). We distinguish tail-VaR and expected shortfall indicators for banks' equity capital downside risk measures. For systemic risk, we both consider multivariate spillover (or contagion) indicators as well as an aggregate tail-β indicator. 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 euro area and the US. The extreme systematic risk measure (tail-β) is conditioned on a multitude of factors including real estate and sovereign debt indices. We also assess whether the downside risk and systemic risk indicators significantly differ across continents and across time. The final section concludes. All individual bank outcomes are provided in appendix.

2. Indicators of downside risk and systemic risk

We introduce extreme downside risk ("tail risk") measures for financial institutions. Next, several systemic risk indicators are considered that either reflect multivariate bank contagion or individual banks' sensitivity to system-wide non-diversifiable shocks.

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. Provided financial markets process information in a more or less efficient way, problems with e.g. the credit portfolio, interbank liquidity constraints or failing asset-liability management will 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 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 fat tails in financial markets. Let S_t stand for the dividend-corrected 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):

$$P\{X > x\} \approx \mathcal{L}(x)\, x^{-\alpha}, \quad x \text{ large,} \tag{2.1}$$

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., $E[X^r]$, $r > \alpha$, are unbounded. In contrast, all statistical moments exist (and are thus bounded) for e.g. the thin-tailed normal distribution , i.e., $E[X^r] < \infty$, $\forall r$. Popular distributional models like the Student-t, the class of symmetric stable distributions or the Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model all exhibit fat tails. The exceedance probability in (2.1) 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 $(X > x_p)$. However, it can be easily shown that the expected shortfall is closely related to VaR:

$$E\left(X - x_p \,|X > x_p\right) = \frac{x_p}{\alpha - 1}, \tag{2.2}$$

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.

2.2. **Systemic risk indicators.** In line with the downside risk measures introduced in the previous subsection, the systemic risk indicators we introduce are market-based in the sense that they require the input

[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 $\lim_{x \longrightarrow \infty} \mathcal{L}(tx) / \mathcal{L}(x) = 1$ and $t > 0$.

of extreme stock price movements. Extreme co-movements, as measured by co-crash (or co-distress) probabilities between stock returns of individual banks, are meant to capture "spillover" or "contagion" risk. The co-crash probabilities can be evaluated for bank pairs (bivariate spillover risk) but also for more than two banks (multivariate spillover risk). We will therefore consider both options. 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. In what follows, we define the contagion measures (spillover probabilities between bank stocks) and the tail-β in more detail.

Starting with the contagion measures, consider a banking system consisting of N banks (either referring to the same country or continent). As previously, the upper tail observations for X_i $(i = 1, \cdots, N)$ reflect bank i's stock return losses. For sake of convenience, the "crisis" levels or quantiles Q_i $(i = 1, \cdots, N)$ are chosen such that the corresponding tail probabilities are equal across banks:

$$P\{X_1 > Q_1\} = \cdots = P\{X_i > Q_i\} = \cdots = P\{X_N > Q_N\}. \tag{2.3}$$

The inverse marginal quantile functions $Q_i = (1 - F_i)^{-1}(p)$ relate the excess probability $p = P\{X_i > Q_i\}$ to the corresponding return quantile Q_i. Keeping the significance level p equal across risky positions makes sense because it allows one to rank banks according to the extreme downside risk of the banks' equity capital. The crisis barriers Q_i generally differ across banks, because the marginal distribution functions $P\{X_i > Q_i\} = 1 - F_i(Q_i)$ are bank specific. The crisis levels Q_i can be interpreted as Value-at-Risk (VaR) levels that will on average only be exceeded once in $1/p$ time periods, i.e., once in p^{-1} days if the data frequency is daily.[15] Suppose now that 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

[15]Most financial institutions also calculate Value-at-Risk (VaR) levels for the (same) 5% and 1% significance levels. This makes the riskiness of different banks' positions comparable provided the risk calculations are made public.

of $L < N$ banks. Elementary probability calculus learns that

$$P_{N|L} = P\left\{\bigcap_{i=L+1}^{N} X_i > Q_i(p) \middle| \bigcap_{i=1}^{L} X_i > Q_i(p)\right\}$$

$$= \frac{P\left\{\bigcap_{i=1}^{N} X_i > Q_i(p)\right\}}{P\left\{\bigcap_{i=1}^{L} X_i > Q_i(p)\right\}}, \tag{2.4}$$

see Hartmann et al. (2003a, 2003b, 2006) who provide earlier applications of this multivariate contagion measure to evaluate the breadth of currency crisis and the systemic risk in the banking sector, respectively. Taking into account that the marginal probabilities obey (2.3), statistical independence of bank stock returns is sufficient to reduce the indicator to p^{N-L}. This provides a lower bound against which the dependent cases can be judged. We limit ourselves to calculating two special cases of this indicator in the empirical section. First, we calculate 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:

$$P_{N|1} = P\left\{\bigcap_{i=2}^{N} X_i > Q_i(p) \,|X_1 > Q_1(p)\right\}$$

$$= \frac{1}{p} P\left\{X_1 > Q_1(p), \cdots, X_i > Q_1(p), \cdots, X_N > Q_N(p)\right\} \tag{2.5}$$

Notice the bank contagion measure stays invariant to the choice of the conditioning bank because of the marginal probability equality assumption in (2.3). For conditioning sets $L > 1$, this would no longer be the case because the denominator probability $P\left\{\bigcap_{i=1}^{L} X_i > Q_i(p)\right\}$ in (2.4) depends on the banks included in the L-dimensional set. Bilateral ($N = 2$ and $L = 1$) bank contagion probabilities constitute a second special case of (2.4). We will compare eurozone domestic and cross-border bank contagion by averaging the bilateral domestic and cross-border contagion probabilities.

The main advantage of the bank contagion measure (2.4) is that one can condition on specific banks depending on e.g. size, leverage, geographical location. This may bring more clarity as to which banks are more often at the origin of widespread systemic crises. 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 obvious what the relevant conditioning set of banks should be. Moreover, one would like to limit the dimensionality of the estimation problem by not having to calculate so many contagion probabilities. The probabilistic measure (2.4) simply leaves too many degrees of freedom in that respect. The multivariate generalization of the two-dimensional "conditional expectation indicator" presented in Hartmann et al. (2004) constitutes an attractive alternative as contagion 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 in the financial system given at least one distressed bank. The "crash" number κ is defined as the sum of N indicator variables:

$$\kappa = \sum_{i=1}^{N} \mathbf{1}\left\{X_i > Q_i(p)\right\}, \tag{2.6}$$

where $\mathbf{1}\left\{\cdot\right\}$ equals one for a financially distressed bank and zero otherwise. As before, we assume that the marginal distribution functions of the individual bank return losses satisfy the equality condition (2.3).

Elementary probability theory (definition of conditional expectation) leads to the chain of equalities:

$$E[\kappa|\kappa \geq 1] = \frac{E\left[\kappa\right]}{P\left\{\kappa \geq 1\right\}} = \frac{\sum_{i=1}^{N} P\{X_i > Q_i(p)\}}{P\left\{\bigcup_{i=1}^{N} X_i > Q_i(p)\right\}}, \tag{2.7}$$

and where the denominator of (2.7) is defined as

$$P\left\{\bigcup_{i=1}^{N} X_i > Q_i\right\} = 1 - P\left\{X_1 \leq Q_1, \ \cdots X_i \leq Q_i \cdots, \ X_N \leq Q_N\right\},$$

see e.g. Straetmans (1998) or Hartmann et al. (2004) for further details. In contrast to the previous contagion indicator (2.4), the expectations measure in (2.7) is not conditioned on specific distressed banks: the event that at least one of the banks gets distressed constitutes the conditioning event (but one does not need to specify which bank that is to calculate the conditional expectation).[16] Indicator (2.7) summarizes systemic risk in one single number. Taking into account the restriction

[16]This "invariance" poperty is also characteristic for e.g. the Bae et al. (2003) multinomial logit approach towards identifying financial contagion but the latter approach does not enable evaluating true tail co-comovements deep into the distributional tail.

in (2.3), the conditional expectation indicator further specializes to:

$$E[\kappa|\kappa \geq 1] = \frac{Np}{P\left\{\bigcup_{i=1}^{N} X_i > Q_i(p)\right\}}, \tag{2.8}$$

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 $E[\kappa|\kappa \geq 1] = Np \Big/ \left(1-(1-p)^N\right)$ which acts as a lower bound to the true degree of bank contagion.[17]

Up to now, we considered indicators that measure the likelihood that distressed banks trigger other banks into distress as in some domino "cascade". A second class of banking system risk indicators is a bivariate version of (2.4), with $(L, N) = (1, 2)$ and where the conditioning set refers to extreme downturns of a "market portfolio" X_M 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 Hartman et al. (2006) and Straetmans et al. (2008). Denote the (log) return losses on the market portfolio by X_M and let p be the common tail probability, then the multivariate probability measure in (2.5) reduces to:

$$P\left\{X_2 > Q_2(p) \,|X_M > Q_M(p)\right\} = \frac{P\left\{X_1 > Q_1(p), X_M > Q_M(p)\right\}}{p}. \tag{2.9}$$

The indicator reflects how likely it is that an individual bank's equity capital drops sharply overnight, if there is an extreme negative systematic shock. Under the special case of statistical dependence, the tail-β reduces to $p^2/p = p$ which acts as a lower bound to the true value of extreme systematic risk. Our analysis of extreme aggregate 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

When asking different people, consensus will probably not arise on what extreme and systemic events are. On the other hand, most would probably agree that the recent (or current?) banking and financial

[17] 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.

crisis has a systemic character which implies that the frequency (a few times a century?) and severity of such systemic events is sufficiently important to justify its measurement and monitoring. 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. First, we discuss semi-parametric estimators of extreme downside risk (tail indices, tail quantiles and conditional expected shortfalls) before turning to estimation procedures for the systemic risk indicators. We end the section with some testing procedures for testing the null hypotheses of no structural change and absence of cross sectional differences in tail risk and systemic risk.

3.1. **Estimating downside bank risk.** We earlier noticed that bank stock returns - like all other financial returns - exhibit heavy tails:

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

with x large and where $\mathcal{L}\left(tx\right)/\mathcal{L}\left(x\right)$ converges to 1 for large x and $t > 0$. Under some mild extra conditions this class of distributions obeys the following 2nd order expansion for large x:

$$P\left\{X > x\right\} \simeq ax^{-\alpha}\left(1 + bx^{-\beta} + o\left(x^{-\beta}\right)\right), \tag{3.1}$$

as $x \rightharpoonup \infty$ and $\alpha, \beta, a > 0$, see de Haan and Stadtmüller (1996).[18] We are now interested in estimating the quantile x for extremely low values of $p \equiv P\left\{X > x\right\}$. An intuitive derivation of such a quantile estimator proceeds as follows (see de Haan et al. (1994) and Danielsson and de Vries (1997) for the original references). Let $\widetilde{p} > 1/n$ but close to $1/n$, and $p < 1/n$, where n is the sample size and $\widetilde{p}$, p stand for the in sample and out of sample tail probabilities, respectively. We want to estimate

[18]The scaling constant a together with the second order term $bx^{-\beta}$ leads to an approximation of the slowly varying function $\mathcal{L}(x) \approx a\left(1 + bx^{-\beta}\right)$ which converges to a for large x; but the convergence goes quicker for larger β. Higher values of β imply that the second order tail expansion comes closer to a pure Pareto-type tail decline.

the out of sample quantile x_p by using the empirical counterpart of the in sample quantile $x_{\widetilde{p}}$. By using the above expansion, we get:

$$p \simeq a\left(x_p\right)^{-\alpha}\left[1 + bx_p^{-\beta}\right] \quad \text{and } \widetilde{p} \simeq a\left(x_{\widetilde{p}}\right)^{-\alpha}\left[1 + bx_{\widetilde{p}}^{-\beta}\right].$$

Division of p and q and rearranging renders

$$x_p \simeq x_{\widetilde{p}}\left(\frac{\widetilde{p}}{p}\right)^{1/\alpha}\left(\frac{1 + bx_p^{-\beta}}{1 + bx_{\widetilde{p}}^{-\beta}}\right)^{1/\alpha}.$$

Ignore the second term and replace $x_{\widetilde{p}}$ by its empirical counterpart $X_{n-m,n}$ $(X_{1,n} \leq \cdots \leq X_{n-m,n} \leq \cdots \leq X_{n,n})$ for which m/n is closest to $\widetilde{p}$. The "tail cut-off point" $X_{n-m,n}$ is the lower bound of the set of upper order extreme returns used to identify the tail quantile with m the number of extremes used in estimation. The extreme quantile estimator then becomes:

$$\widehat{x}_p \simeq X_{n-m,n}\left(\frac{m}{np}\right)^{1/\alpha}. \tag{3.2}$$

De Haan et al. (1994) establish consistency and asymptotic normality of the estimator. The tail-VaR estimator $\widehat{x}_p$ extends the empirical distribution function outside the domain of the sample by means of its asymptotic Pareto tail from (2.1).[19] The quantile estimator requires an estimate 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:

$$\widehat{\alpha} = \left(\frac{1}{m}\sum_{j=0}^{m-1}\ln\left(\frac{X_{n-j,n}}{X_{n-m,n}}\right)\right)^{-1}, \tag{3.3}$$

where m has the same value and interpretation as in (3.2). 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, an estimator for the expected equity capital loss given a sharp fall in the equity capital (previously denoted as "expected shortfall") easily follows by imputing the Hill statistic

[19] The quantile estimator (3.2) can be seen as the 1rst order Taylor approximation of (2.1) with $\frac{m}{n}\left(X_{n-m,n}\right)^{\widehat{\alpha}}$ an estimator of the constant term in the slowly varying function $\mathcal{L}(x)$. How good this approximates the true tails has been previously studied by e.g. Danielsson and de Vries (1997). We performed our own simulation study for a variety of data generating processes and found that the performance of the quantile estimator is quite satisfactory. Details of the simulation studies are available from the authors upon request.

(3.3) and the quantile estimator (3.2) in the definition of the expected shortfall (2.2):

$$\widehat{E}\left(X-\widehat{x}_p\left|X>\widehat{x}_p\right.\right)=\frac{\widehat{x}_p}{\widehat{\alpha}-1}. \tag{3.4}$$

Notice the Hill statistic (3.3) and the quantile estimator (3.2) 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 $\widehat{\alpha}=\widehat{\alpha}\left(m\right)$ as well as implementing the Beirlant et al. (1999) algorithm to minimize a sample equivalent of the AMSE.

3.2. **Estimating the systemic risk indicators.** Whereas the probability measures in (2.4)-(2.5)-(2.9) require estimation of multivariate probabilities defined on the *intersection* of sets, i.e.,

$$P\left\{\bigcap\nolimits_{i=1}^{N}X_i>Q_i\right\}=P\left\{X_1>Q_1,\cdots X_i>Q_i,\cdots,X_N>Q_N\right\},$$

the multivariate probability in the denominator of expectational linkage measure (2.8) is defined on a *union* of sets, i.e.,

$$P\left\{\bigcup\nolimits_{i=1}^{N}X_i>Q_i\right\}=1-P\left\{X_1\leq Q_1,\ \cdots X_i\leq Q_i\cdots,\ X_N\leq Q_N\right\}.$$

These differing conditioning probability spaces also require different estimation approaches. In order to estimate multivariate probabilities of the first type $P\left\{\bigcap\nolimits_{i=1}^{N}X_i>Q_i\right\}$, we follow Ledford and Tawn's (1996) approach (see also Poon et al. (2004), Hartmann et al. (2006) and Straetmans et al. (2008) for other applications in financial economics and banking). 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 (e.g. 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 e.g. correlation-based measures that are still influenced by the differences in marginal distribution shapes. We decided to map the bank stock returns $(X_1, \cdots, X_i, \cdots, X_N)$ to unit Pareto marginals (see Draisma et al., 2001):

$$\widetilde{X}_i = \frac{1}{1 - F_i(X_i)}, \; i = 1, \cdots, N,$$

with $F_i(\cdot)$ representing the marginal cumulative distribution function (cdf) for X_i.[20] Since the marginal cdfs are unknown, we have to replace them with their empirical counterparts. For each X_i this leads (with a small modification to prevent division by 0) to:

$$\widetilde{X}_i = \frac{1}{1 - R_{X_i}/(n+1)}, \; i = 1, \cdots, N, \tag{3.5}$$

where $R_{X_i} = rank(X_{il}, l = 1, \cdots, n)$. This variable transform allows one to rewrite the joint tail probability occuring in (2.4), (2.5) and (2.9) to exhibit a common exceedance quantile q:

$$P\left\{\bigcap\nolimits_{i=1}^{N} X_i > Q_i(p)\right\} = P\left\{\bigcap\nolimits_{i=1}^{N} \widetilde{X}_i > q\right\} \; ,$$

and where $q = 1/p$. The common quantile q enables one to reduce the multivariate estimation problem to a univariate exceedance probability by taking the cross-sectional minimum of the N (transformed) bank return series:

$$P\left\{\bigcap\nolimits_{i=1}^{N} \widetilde{X}_i > q\right\} = P\left\{\min_{i=1}^{N}\left(\widetilde{X}_i\right) > q\right\} = P\left\{\widetilde{X}_{\min} > q\right\} \; . \tag{3.6}$$

This marginal tail probability can be calculated assuming that the auxiliary variable's tail inherits the original bank returns' fat tail property. In other words, we assume that

$$P\left\{\widetilde{X}_{\min} > q\right\} \approx \mathcal{L}(q) q^{-\alpha}, \tag{3.7}$$

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 $P\left\{\bigcap\nolimits_{i=1}^{N} X_i > Q_i\right\}$. The auxiliary variable's tail index α is therefore also dubbed the "tail dependence" parameter that governs the dependence structure of the original returns. The case $\alpha = 1$ is of particular interest. One can easily see why by substituting (3.7) back into systemic risk measures (2.5)-(2.9)-(2.4). Starting with the simplest case of a *single* conditioning asset as in (2.5)-(2.9), substituting (3.7) into these co-crash probability measures

[20] Ledford and Tawn (1996) transform the marginal distributions to identical unit Fréchet marginals. Draisma et al. (2001) propose the alternative Pareto transform and demonstrate that these two differing transformations lead to almost the same outcomes for the joint dependence structure and joint probabilities.

renders $\mathcal{L}(q)q^{1-\alpha}$. This *conditional* probability stays bounded away from zero when q grows large provided $\alpha = 1$.[21] When conditional co-crash probabilities like $\mathcal{L}(q)q^{1-\alpha}$ do not vanish when $q \to \infty$, the corresponding return vectors for which the co-crash probabilities are defined are classified as "tail dependent". In general, the tail index α of the auxiliary variable $\widetilde{X}_{\min}$ reflects whether the original return vector components $(X_1, \cdots, X_i, \cdots, X_N)$ exhibit tail dependence ($\alpha = 1$) or tail independence ($\alpha > 1$). For *multiple* conditioning assets as in (2.4), the multivariate co-crash probabilities in denominator and numerator can be identified by means of (3.7) which renders the expression

$$\left(\frac{\mathcal{L}_1(q)}{\mathcal{L}_2(q)}\right) q^{\alpha_2 - \alpha_1}. \tag{3.8}$$

The above discussion on tail dependence vs. tail independence makes clear that tail dependence in (2.4) requires $\alpha_1 = \alpha_2 = 1$.

Whether return series exhibit tail dependence or not ultimately remains an empirical issue. Hartmann et al. (2004) test the null hypothesis of tail dependence for pairs of stock and bond return indices. They found that 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. For 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 (3.8) makes clear that the corresponding systemic risk indicator becomes independent from the crisis level q upon assuming tail dependence (q disappears from the expression). This invariance is convenient because it makes a discussion on the required extremity of the threshold q redundant. Most importantly,

[21] Conform with the second order expansion in (3.1), $\mathcal{L}(q) \approx a\left(1 + bq^{-\beta}\right)$ which implies that $\mathcal{L}(q)$ approaches a when q grows large.

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.

The steps (3.5), (3.6) and (3.7) imply that the estimation of multivariate probabilities can be reduced to a univariate estimation problem that is well-known. Univariate tail probabilities for fat-tailed random variables - like in (3.6) - can be estimated by using the semi-parametric probability estimator from de Haan et al. (1994):

$$\widehat{p}_q = \widehat{P}\left\{\widetilde{X}_{\min} > q\right\} = \frac{m}{n}\left(C_{n-m,n}\right)^{\alpha} q^{-\alpha}, \tag{3.9}$$

where the "tail cut-off point" $C_{n-m,n}$ is the $(n-m)$-th ascending order statistic from the cross-sectional minimum series $\widetilde{X}_{\min}$. This is the inverse of the quantile estimator (3.2) for calculating the tail-VaR in the univariate section.

An estimator of the multivariate spillover risk indicator in (2.5) easily follows by using (3.9) and dividing with p:

$$\begin{aligned} P_{N|1} &= \frac{\widehat{p}_q}{p} \\ &= \frac{m}{n}\left(C_{n-m,n}\right)^{\alpha} q^{1-\alpha}, \end{aligned} \tag{3.10}$$

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.

The alternative systemic risk measure in (2.4) is defined on another type of failure region which implies it cannot be estimated by using the Ledford and Tawn approach (1996). Under fairly general conditions the joint probability in the denominator of (2.4) can be expressed as a function of the marginal tail probability p:

$$P\left\{\bigcup_{i=1}^{N} X_i > Q_i\right\} \approx \ell\left(p, \cdots, p, \cdots, p\right) \tag{3.11}$$

and with $\ell(\cdot)$ being the so called "Stable Tail Dependence Function" or tail copula $STDF$. This tail copula is formally defined as

$$\ell\left(p,\cdots,p,\cdots,p\right)=\lim_{t\to 0}\frac{1}{t}P\left\{\bigcup\nolimits_{i=1}^{N}X_i>Q_i(tp)\right\},\tag{3.12}$$

see Huang (1992). The curvature of $\ell(\cdot)$ completely determines the dependence structure between the X_i components in the tail area. A basic property of $\ell(\cdot)$ constitutes the inequality

$$p\leq\ell\left(p,\cdots,p,\cdots,p\right)\leq Np.$$

Equality holds on the left-hand side if the bank stock returns are completely mutually dependent in the tail area, while equality on the right hand side obtains if the return series are mutually independent in the tail area.

The estimation of (3.11) either requires adopting a specific functional form for the $STDF$, like in Longin and Solnik (2000), or nonparametric estimation. Since a unique parametrization for the $STDF$ does not exist, we prefer a semi-parametric estimation method based on the highest order statistics. Semi-parametric estimation exploits the linear homogeneity property of the tail copula function: $\ell\left(\lambda p,\cdots,\lambda p\right)=\lambda\ell\left(p,\cdots,p\right)$, $\lambda>1$. For a sufficiently large scaling factor λ,the quantiles Q_i $(i=1,\cdots,N)$ in (3.12) are shifted inside the observable return data sample and the joint probability can be estimated using the empirical distribution function (i.e. by counting the exceedances). Exploiting linear homogeneity with $\lambda=1/p>1$ and replacing the joint probability in the denominator of (2.8) by its tail copula approximation renders:

$$\begin{aligned}E[\kappa|\kappa\ \geq\ 1]&=\frac{Np}{P\left\{\bigcup_{i=1}^{N}X_i>Q_i(p)\right\}}\\&\approx\frac{Np}{\ell\left(p,\cdots,p,\cdots,p\right)}\\&\approx\frac{N}{\ell\left(1,\cdots,1,\cdots,1\right)}.\end{aligned}\tag{3.13}$$

The denominator can be further rewritten using the STDF definition (3.12). Set $t=k/n<1$ and $p=1$ in (3.12). Upon substituting (3.12) into (3.13) one obtains

$$E[\kappa|\kappa\geq 1]\approx\frac{N}{\frac{n}{k}P\left\{\bigcup_{i=1}^{N}X_i\geq Q_i\left(\frac{k}{n}\right)\ \right\}}.$$

Clearly, the quantiles $Q_i\left(\frac{k}{n}\right)$ are inside the sample boundaries of the historical return data which enables estimation of $E[\cdot]$ in a nonparametric way. In order to turn this expression into an estimator, we replace P, Q_1 and Q_2 by their empirical counterparts:

$$E[\kappa|\kappa \geq 1] \approx \frac{N}{\frac{n}{k}\frac{1}{n}\sum_{i=1}^{n} \mathbf{I}\left\{\bigcup_{i=1}^{N} X_i > X_{i,n-k}\right\}}, \tag{3.14}$$

and where the denominator is an estimator of the stable tail dependence function $\ell(1,\cdots,1,\cdots,1)$. The upper order statistic $X_{i,n-k}$ estimates the quantile $Q_i\left(\frac{k}{n}\right)$ and $\mathbf{I}\{\cdot\}$ stands for the indicator function. The threshold parameter k plays a similar role as the parameter m in the Hill estimator (3.3): it determines how many extreme returns are used in estimating $E[\kappa|\kappa \geq 1]$. Just like the multivariate spillover risk indicator in (3.10), the estimator (3.14) is invariant to changes in p (or, alternatively, to choices in the crisis quantiles Q_i). The homogeneity property of the l-function in (3.13) indeed implies that p disappears 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 (3.10) or (3.14) 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 $\widehat{\ell}(1,\cdots,1,\cdots,1)$. Such a minimum should exist because of the bias-variance trade-off that is characteristic for this estimator. Alternatively, we determine k by calculating (3.14) over a whole range of k and looking at the curvature of the corresponding plots $\widehat{E} = \widehat{E}(k)$.

3.3. **Hypothesis testing.** We like to know whether tail risk and systemic risk of banking systems significantly change over time ("structural" change) but we also like to make cross-atlantic comparisons between these different risk measures over a common sample period (cross sectional equality). For $m/n \to 0$ as $m, n \to \infty$, it has been shown that the tail index statistic $\sqrt{m}\left(\widehat{\alpha} - \alpha\right)$ and tail quantile statistic $\frac{\sqrt{m}}{\ln\left(\frac{m}{pn}\right)}\left[\ln\frac{\widehat{q}(p)}{q(p)}\right]$ are asymptotically normal, see Haeusler and Teugels (1985) and de Haan et al. (1994) for a derivation of these respective results. Asymptotic normality also holds for the tail probability estimator (3.9) we use for calculating multivariate spillover risk measures like (2.4)-(2.5) as well as tail-βs in (2.9) because all these estimators make use of the de Haan et al. (1994) quantile estimator. Finally, for

$k/n \to 0$ as $k, n \to \infty$, Huang (1992) derived the asymptotic normality of the stable tail dependence function statistic $\sqrt{k}\left(\widehat{l} - l\right)$ for tail dependent random vectors.[22] Given the mentioned estimators' asymptotic normality property, 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:

$$T_{est} = \frac{\widehat{est}_1 - \widehat{est}_2}{s.e.\left(\widehat{est}_1 - \widehat{est}_2\right)}, \tag{3.15}$$

with s.e. $[\cdot]$ denoting the standard deviation of the estimation difference. The estimator $\widehat{est}$ either stands for the Hill statistic (3.3), the tail quantile estimator (3.2), the tail probability estimator (3.9) or the tail dependence function estimator (3.14). Given the consistency and asymptotic normality properties of $\widehat{est}$, the test statistic T is approximately standard normally distributed in sufficiently large samples.[23]

The question arises how the standard error s.e.[.] in the denominator of (3.15) is calculated. Given the temporal dependence in the data (serial correlation and above all volatility clustering in bank stock returns) as well as cross sectional dependence, the denominator's standard error $s.e.\left(\widehat{est}_1 - \widehat{est}_2\right)$ 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 extreme value application.

Given the enormous amount of possible comparisons that can be made (pre-crisis vs. crisis and cross-continent) for 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 US and 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, 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 e.g. Hartmann et al. (2006), implemented endogenous

[22]For random vectors that exhibit tail independence, the limiting distribution of the stable tail dependence function estimator becomes degenerate.

[23]One can safely assume that T comes sufficiently close to normality for empirical sample sizes as the ones used in this paper (see our own simulations that are available upon request).

stability tests like the Quintos et al. (2001) procedure. However, the former test is designed to investigate the temporal stability of the tail index (or, alternatively, the tail dependence parameter). Given that our framework restricts 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

We first discuss the data selection and some descriptive statistics. Second, we investigate the tail risk properties of individual banks like the tail index, the tail quantile and expected shortfall of the banks' equity capital. Multivariate bank spillover probabilities are considered in the 3rd subsection. Finally, we consider indicators of extreme systematic risk (or "tail-βs") for different conditioning risk factors. We further distinguish between US banks and eurozone banks and try to assess which continent is the riskier one, either in terms of tail risk or systemic risk. We also assess whether and to what extent tail risk and systemic risk have shifted through time (and more specifically after the outbreak of the financial crisis). We therefore consider rolling, pre-crisis and crisis estimates of our tail risk and systemic risk indicators. Subsample estimates are complemented with test statistics assessing cross sectional and time series differences of the considered risk measures. August 7, 2007 is taken as the starting point of the crisis but our conclusions remain robust (i.e. subsample estimates hardly alter) upon considering the Lehman debacle as the start of the crisis. As for the pre-crisis and crisis tail-βs with respect to a PIIGS sovereign debt index, we took December 15, 2009 as start of the eurozone sovereign debt crisis.

4.1. **Data and descriptive statistics.** We collect daily stock price data from Datastream (dividend-corrected total return indices) for 15 euro area 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. The 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. This marks the 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.

Table A.1 in Appendix A report standard descriptive statistics (return average, standard deviation, skewness and kurtosis) for the 30 individual bank stock return series. We further distinguish sample moments for the full sample period, pre-crisis and crisis episodes. Means and standard deviations are expressed in percentages. As starting point of the crisis, we select August 7, 2007.[24]

Full sample mean returns are basically zero, as one would expect, whereas full sample standard deviations of returns tend to be around 2. Upon comparing pre-crisis and crisis estimates, however, all crisis mean returns fall sharply below their pre-crisis levels (they all become negative) whereas the opposite holds for the crisis variances. Comparing sample means and variances across both sides of the Atlantic, one cannot conclude that one continent dominates the other one either in terms of average return or volatility: the full sample US mean and volatility dominate their euro area counterparts but this outcome is not robust for the subsamples. Also, the full sample and pre-crisis results indicate little skewness but strong leptokurtosis. Nonsurprisingly, skewness and kurtosis seem to have increased during the crisis in the majority of cases. We also performed some hypothesis tests (not included in the table) on the subsample moment estimates. Sample averages significantly dropped and variances significantly increased during the crisis: the majority of shifts is even statistically significant a the 1% level. The Jarque-Bera normality test rejects the null hypothesis of normality for all considered samples although statistical rejections seem strongest for the crisis sample. The testing results are available upon requests but are omitted for sake space considerations.

4.2. **Downside risk estimates of individual bank equity capital.** The high kurtosis of bank stock returns reflects that they are non-normally distributed or "heavy tailed". We exploit this property

[24]Break results are robust to choosing other economically relevant breakpoint like e.g. the Lehman debacle. The same holds true for other breakpoint tests considered throughout the paper.

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 Tables A.2 (US and eurozone; full sample), A.3 (eurozone; pre-crisis and crisis samples) and A.4 (US; pre-crisis and crisis samples) estimates of the tail index $\widehat{\alpha}$ and corresponding values of Tail-VaR and expected shortfall. A graphical summary of these results are provided in Figure 1. The banks are named on the horizontal axis. Eurozone and US results are reported in the left and right columns of the figure matrix, respectively. The results on tail indices, tail quantiles and expected shortfalls correspond with the upper, middle and lower row of the figure matrix, respectively.

[insert Figure 1]

Extreme quantiles are calculated for p-values equal to 0.2% and 0.1%. The corresponding tail-VaR's 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-VaR's or on crisis barriers $s = 25\%$ or 50%. Given the extreme quantile estimates $\widehat{x}_p$ nearly always fall below s, expected shortfalls conditioned on the threshold s are the more extreme expected shortfall measure.[25]

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. Tables A.2, A.3 and A.4 and Figure 1 also 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

[25]One may argue that this is still not at the very extreme end of the tail. Indeed, previous research often estimated extreme quantiles much further into the left tail of bank stock returns: Hartmann et al. (2006) conditioned extreme quantiles on p-values of 0.05% and 0.02% (producing tail-VaR's that are expected to be violated every 7,5 and 19 years, respectively). However, the tail-VaR estimator (3.2) is unbounded from above which implies that estimates above 100% cannot be ruled out. Such a quantile estimate would be pretty meaningless from an economic point of view indicating that one can lose more than the initial investment. The extreme quantile indeed exceeds its economically meaningful upperbound of 100% when one tries to calculate tail-VaR's on the 2007-2010 crisis sample for p-values below 0.05%. This is why we conditioned on higher p-values for the univariate downside risk analysis.

behavior of eurozone Hill estimates is less straightforward: some eurozone bank tails even seem to 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 (this invalidates the use of traditional risk measures such as standard deviations or CAPM-$\beta' s$ which require the existence of the secnd moment or $\alpha > 2$). For Allied Irish Banks we even observe a crisis value $\widehat{\alpha} = 0.8 < 1$ signifiying that even the population mean of the bank return series does no longer exist. Nonsurprisingly, 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.[26] Bank of America's tail risk is also noteworthy: it played an active role in rescuing other financial institutions. Bank of America bought ailing financial institutions like Countrywide Financial (mortgages) and Merril Lynch (the acquisition of Merril Lynch being financially supported by the US government). However, huge trading losses at Merill Lynch nearly brought down Bank of America themselves in 2009.[27]

Upon comparing the tail quantiles (middle row in Figure 1) and expected shortfalls (bottom row in Figure 1) 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. A more elaborate discussion of the statistical and economic significance of these differences in point estimates is provided below.

[26]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 aid or other rescue packages. The crisis tail risk of 18.6% is nevertheless substantial 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.

[27]Nonsurprisingly, 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.

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. Nonsurprisingly, 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.

Upon comparing pre-crisis and crisis values for tail risk, the point estimates for α, x_p and $E(X - x_p | X > x_p)$ change quite dramatically indeed. To assess whether the crisis altered the tail risk properties in a statistically and economically significant way, we applied the equality test statistic T_{est} (3.15) to test the null hypothesis of structural change (time variation) or cross sectional equality of the tail index and the corresponding tail-VaR on the individual bank level. We find that Tail-VaR differences across time and across individual banks differ in a statistically and economically 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.[28]

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 Tables A.2, A.3 and A.4, Table 1 reports estimated means, medians and standard deviations for the US and the eurozone and for the pre-crisis and crisis episodes separately. The Table reveals that US tail risk measures exceed their European counterparts for the full sample as well as for the crisis sample but extreme downside risk seems of comparable magnitude in the pre-crisis periods. Upon comparing tail risk for pre-crisis and crisis samples, we see that tail indices

[28]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.

decline and accompanying tail risk increases for both continents. Finally, notice that mean and median estimates are nearly 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 (3.3)-(3.2) ensures that the test statistic based on their averages also exhibits normal critical values. 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 eurozone tail risk is not caused by fatter tails because the mean tail indices for European banks hardly change over time. Thus, for European 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 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 Tables 1, 2]

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 2 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 euro area 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 2]

4.3. **Bank contagion risk.** In this subsection we distinguish between three different bank contagion measures: the multivariate probability and expectation indicators in eqs. (2.5)-(2.8) as well as the bivariate contagion probabilities for bank pairs based on co-crash probability (2.9). The latter bilateral co-crash probability indicator requires replacing the conditioning non-diversifiable risk factor in the tail-β formula (2.9) by capital losses on individual bank stocks, i.e. $X_M = X_1$. We try to address three main issues. First, does contagion 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? Finally, how large is eurozone bank contagion risk within (i.e. "domestic" contagion) and across (i.e. "cross-border" contagion) the eurozone countries? Whether domestic bank spillovers dominate cross-border bank spillovers within the eurozone is relevant for the ongoing debate whether eurozone financial regulation and supervision can stay organized at the national level or not.

[insert table 3]

The multivariate spillover risk measures $E\{\kappa\,|\kappa \geq 1\}$ and $P_{N|1}$ as defined in (2.8)-(2.5) can already shed some light on the first two issues. Estimates of these measures are reported in Table 3. The indicators are calculated for the US and 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 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. Obviously, the $E\{\kappa\,|\kappa \geq 1\}$ indicators are only comparable across continents or countries provided they span the same number of banks. The same holds for the $P_{N|1}$ indicator. In other words, cross continent (US vs. euro area) 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:

the number of banks for which the country and continental systemic risk indicators are calculated are not the same.

Panel I of Table 3 contains estimation results for both indicators and for varying sets of banks (continent-wide or separate European 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 can be performed using the earlier introduced T-test in (3.15).The economic interpretation of the point estimates $\widehat{E}$ and $\widehat{P}_{N|1}$ is straightforward.[29] For example, the US crisis value $\widehat{E} = 4.33$ reflects the expected 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 threatens to be 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 $\widehat{P}_{N|1}$, 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 1out of 4 that the whole US financial system will collapse if one systemic bank collapses.

Let us now refocus on the three research questions earlier mentioned. 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 systemic risk measures' growth rates across the two subsamples (%Δ column). For example, the expected number of joint crashes for the US banking system as a whole has increased from $\widehat{E} = 2.94$ in the pre-crisis period to $\widehat{E} = 4.33$ 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

[29]The conditioning event differs for both measures: whereas the E-indicator conditions on at least one bank being in distress, the $P_{N|1}$-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.

smallest increase. France takes on an intermediate position. Finally notice that the systemic risk increase seems more pronounced when considering the $\widehat{P}_{N|1}$ 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 (3.15), 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 issue we want to clarify concerns the cross-continent and cross-country differences in systemic risk. First and foremost, the table shows that the US banking system seems more fundamentally unstable than its eurozone counterpart irrespective of the considered systemic risk indicator or (sub)sample, i.e. $E_{US} > E_{EU}$ and $P_{US} > P_{EU}$. 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 time period. As concerns eurozone contagion on a country level we observe that $E_{Spain} > E_{France} > E_{Germany}$ and $P_{Spain} > P_{France} > P_{Germany}$ for both the pre-crisis and the crisis sample. However, these domestic contagion differences between France, Germany and Spain are only statistically significant for the crisis sample.

The remaining question of interest is to know how important eurozone cross-border contagion is as compared to eurozone domestic contagion. In case of segmented (or poorly integrated) national banking sectors, domestic bank contagion is expected to dominate cross-border contagion. On the other hand, the exposures of Northern European banks to Southern European PIIGS debt is expected to have raised cross-border contagion effects. Notice that the impact of PIIGS countries bank distress on overall eurozone financial instability has already implicitly been taken into account in the calculation of the eurozone-wide values of E and P in Table 3; but these multivariate indicators do not provide information on the magnitudes of *bilateral* domestic and cross border eurozone contagion linkages. To that aim, we first calculate bivariate bank contagion probabilities $P\left\{X_2 > Q_2(p)\,|X_1 > Q_1\left(p\right)\right\}$ for all possible $C_{15}^2 = 105$ eurozone bank pairs that can be drawn from our eurozone bank sample. Next, we calculate sample averages across these 105 bank co-crash probabilities in order to obtain domestic contagion effects per country (average across bank pairs of the same country) and cross-country contagion effects (average across country pairs). Table 4 summarizes these contagion probability averages. The left panel contains averages of the bilateral co-crash probabilities for the domestic pairs per country.[30] The middle panel contains cross-border co-crash probability averages per country pair (lower middle panel) and per country (upper middle panel). The right panel reports US bilateral bank contagion results as a benchmark of comparison with the eurozone results.

The economic interpretation of the numbers is relatively straightforward. For example, the 59.5% Spanish domestic contagion probability for the crisis sample is the average of 3 bilateral co-crash probabilities defined on the bank trio Banco Santander,BBVA and Banco Espanol; whereas the pre-crisis value of 21% for the GE-FR country pair is obtained by averaging the joint crash probabilities for all 9 pairs of German and French banks; the pre-crisis cross-border value of 26.3% for Germany is obtained by averaging all 36 bilateral contagion probabilities between German and non-German banks etc.

[insert table 4]

First of all, we see that US contagion probabilities usually dominate their eurozone counterparts. Domestic eurozone contagion probabilities only dominate cross-border eurozone contagion probabilities for Italy and Spain. For Germany, domestic and cross-border contagion effects seem of comparable magnitude and for France cross-border contagion even slightly exceeds domestic contagion! The central role German and French banks play within the eurozone financial system may explain this outcome. The cross-border contagion probabilities for different country pairs (lower middle panel) enable one to compare contagion for PIIGS country pairs, non-PIIGS country pairs and "mixed" pairs between PIIGs and non-PIIGS banks. The highest cross-border contagion value is between the two biggest PIIGS countries Italy and spain (average value of 60.2%). Also, Germany and France seem to exhibit stronger contagion linkages with Italy and Spain than with each other. But cross-border contagion linkages of Germany and France with Greece and Portugal remain relatively small. Finally, cross-border contagion effects from smaller PIIGS countries Greece, Ireland and Portugal to the rest of Europe seem modest. Summarizing, it is difficult to draw general conclusions about domestic eurozone contagion dominating cross-border eurozone contagion (or vice versa) because the magnitudes of domestic contagion and cross-border contagion seem to large

[30]Obviously, domestic contagion probabilities are only identifiable for countries that have at least two banks in the sample. This is only the case for Germany, France, Italy and Spain. As for Ireland, Greece, the Netherlands and Portugal, they are represented by a single bank in the sample which implies that domestic contagion is nonidentifiable.

depend on the considered countries and country pairs. This observation differs from Hartmann et al. (2006) who found evidence that domestic eurozone contagion still dominates cross-border eurozone contagion.

In order to better grasp how multivariate contagion risk evolves over time, we show rolling sample estimates of our two multivariate systemic risk indicators for the US, the eurozone, Germany, France and Spain in Figure 3. The top left figure shows the rolling expected number of bank crashes for the US and the eurozone, i.e., $1 \leq E\{\kappa \,|\kappa \geq 1\} \leq 15$.The bottom left figure contains the rolling expected number of bank crashes for Germany, France and Spain, i.e., $1 \leq E\{\kappa \,|\kappa \geq 1\} \leq 3$. 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 a temporal increase for both the expected number of joint bank crashes as well as the multivariate contagion probability regardless the continent considered. The risk measures are time varying even before the start of the financial crisis in 2007. However, the increase in the risk measure is very high after the crisis. Moreover, the systemic risk measures for the US are much higher than for the eurozone. Comparing systemic risk for the three large European countries reveals that both the expected number of joint bank crashes as well as the multivariate contagion probability is the lowest in Germany.

[Insert Figure 3]

4.4. **Aggregate banking system 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 macro economic shock that should be sufficiently global in nature such that it is non-diversifiable. 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 euro area 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, 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 euro area bank equity capital. To that aim we condition the tail-β on an equally weighted average portfolio of the PIIGS countries' sovereign bond total return indices.[31]

Estimates of tail-β are obtained via (3.10) and are summarized in Tables A.5 (US and eurozone; full sample), A.6 (eurozone; pre-crisis and crisis subsamples) and A.7 (US; pre-crisis and crisis subsamples) and for the different conditioning risk factors. A graphical summary of tail-β results is provided in the bar graph panels of Figure 4. As in Figure 1, the banks are named on the horizontal axis and eurozone and US results are reported in the left and right columns of the figure matrix, respectively. The tail-βs in the top row, middle row and bottom row are conditioned on a continental bank index, a continental stock market index and a world bank index, respectively.

[Insert Figure 4]

The reported tail-βs in the Appendix tables and Figure 4 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 table A.6 means that a very large downturn in the euro area banking index during the pre-crisis era is associated with a 28.6% 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's 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 tables A.5-A.6-A.7, a number of empirical regularities can be observed. First, nearly all tail-βs spectacularly increase in the crisis period, see also Figure 4? 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 coefficient to be equal to 1. As a result, we get much higher values of tail-β that may be seen as conservative upperbounds to the

[31] 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.

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 relative 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.[32] 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 (2010) 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 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.[33]

To assess to what extent the observed differences in tail-β estimates truly differ across banks or across time, we implement the same equality test T_{est} (3.15). The quantile estimator (3.10) used to calculate tail-βs is approximately normally distributed in sufficiently large samples. 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.[34]

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

[32]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 aggregate 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.

[33]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.

[34]We omitted the individual testing outcomes due to the large amount of testing results but they are available upon request from the authors.

even easier to eyeball certain patterns or tendencies in the results. Based on the point estimates in Tables A.5, A.6 and A.7, Table 5 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. The table confirms that US tail-βs dominate eurozone tail-βs for most factors. In fact, the pre-crisis magnitudes of US tail-βs are comparable to the crisis magnitudes of euro zone tail-βs. Comparing the tail-β averages across different conditioning risk factors, one can see that $\beta_{eurobank} > \beta_{eurostock} > \beta_{worldbank} > \beta_{worldstock}$ 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 (the pre-crisis exposures are of similar magnitude) which should not surprise given that the subprime mortgage crisis originated in the US. Finally, and just as for the univariate tail risk measures, one also observes that means and medians in Table 5 do not differ much. Table 6 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 (3.10), the test statistic that compares average tail-βs is also normally distributed. The 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 5, 6]

5. Conclusions

In this paper we exploit techniques borrowed from multivariate extreme value analysis in order to measure alternative indicators of downside bank risk and systemic risk. The indicators are market-based because they use stock market (extreme) returns as input. We compare tail risk and systemic risk estimators across continents (US vs. eurozone) and across time (i.e. did tail risk and systemic risk change over time in an economically and statistically significant way?). 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, 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 two-fold 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 defined as multivariate probabilities of joint sharp drops in the market value of bank equity capital and are both evaluated across bank pairs as well as in a purely multivariate fashion, i.e. for the US and eurozone banking system as a whole. The tail-β indicator is defined as a co-crash probability of individual bank equity capital and conditioning macro factors including a banking stock index, a general stock index, a real estate index and an equally weighted government bond portfolio consisting of Portuguese, Italian, Irish, Greek and Spanish (PIIGS) debt. Conditioning on sharp drops in the real estate index enables one to identify the banks' exposure to real estate bubble bursts. Conditioning on sharp falls in the PIIGS index produces exposures of the eurozone banks to fluctuations in the market value of PIIGS debt (US bank exposures to PIIGS shocks have not been considered). 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. We have, however, a much longer price history at our disposal including 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 (for example, we also condition on real estate and sovereign debt risk factors as they played a prominent role in triggering the most recent banking crisis). We also apply a new multivariate spillover risk indicator to the entire banking system, see Huang (1992) for earlier applications on other financial assets. 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 estimates that act as upperbounds for the true underlying systemic risk. From the perspective of regulators and supervisors, this seems a desirable property as they are supposed to monitor and safeguard financial system stability.

Turning to the estimation results, we distinguish between univariate results on downside bank risk and multivariate results on systemic risk. The outcomes on the extreme downside risk proxies (tail index, tail quantile, tail conditionally 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. Domestic (bilateral) linkages in the euro area also fall below extreme (bilateral) linkages among US banks. We cannot generally conclude that domestic (bilateral) eurozone linkages dominate cross-border (bilateral) eurozone linkages or vice versa. In fact, we observe a large heterogeneity in domestic and cross-border eurozone contagion depending on the considered countries or country pairs. As concerns the second indicator of systemic 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. Also, the impact of adverse shocks in real estate is considerable for both eurozone and US banks. The sovereign debt crisis exercises a smaller impact on the equity capital of European banks than expected. We find the largest impact for banks in the PIIGS countries themselves but most of the tail-β values conditioned on the sovereign debt risk factor are only half of the values we find for other conditioning risk factors. Finally, 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. Overall, one may conclude there is a strong need for both continents to fine-tune existing micro-prudential and macro-prudential regulations and supervision. How this will materialize is the subject of ongoing discussion and lobbying.

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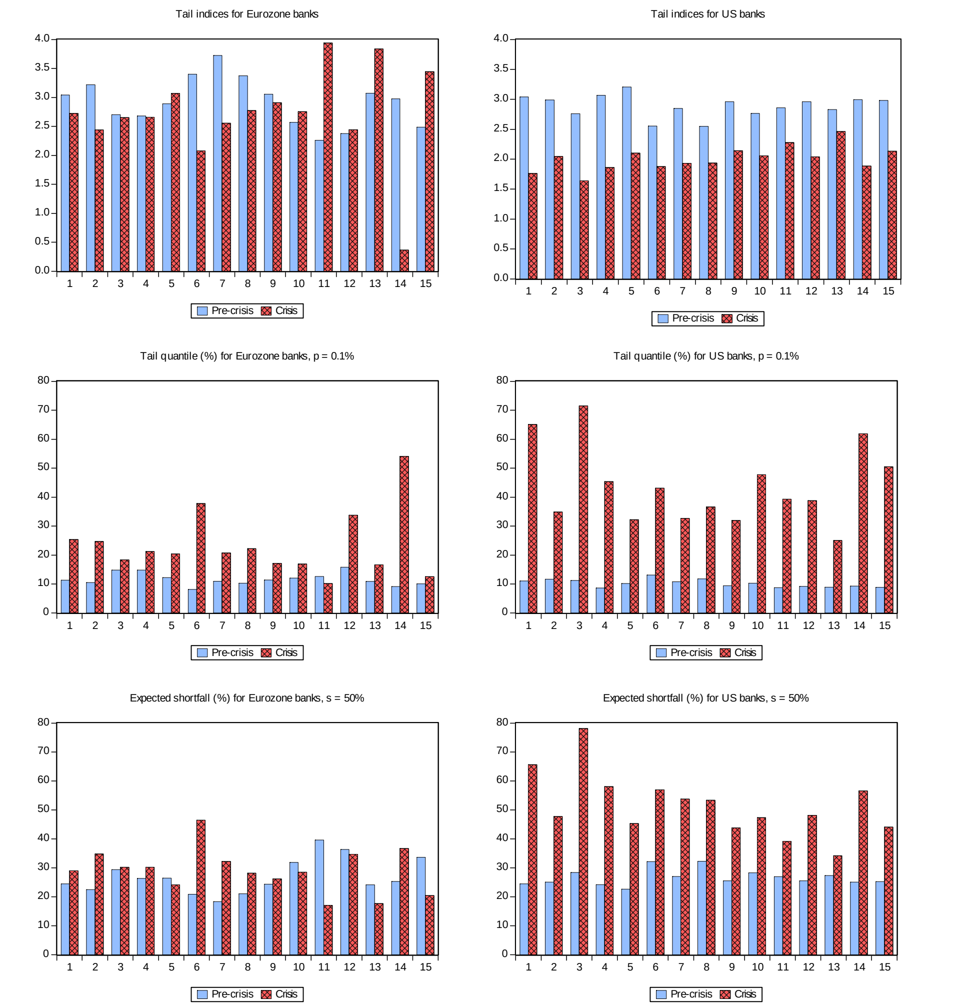
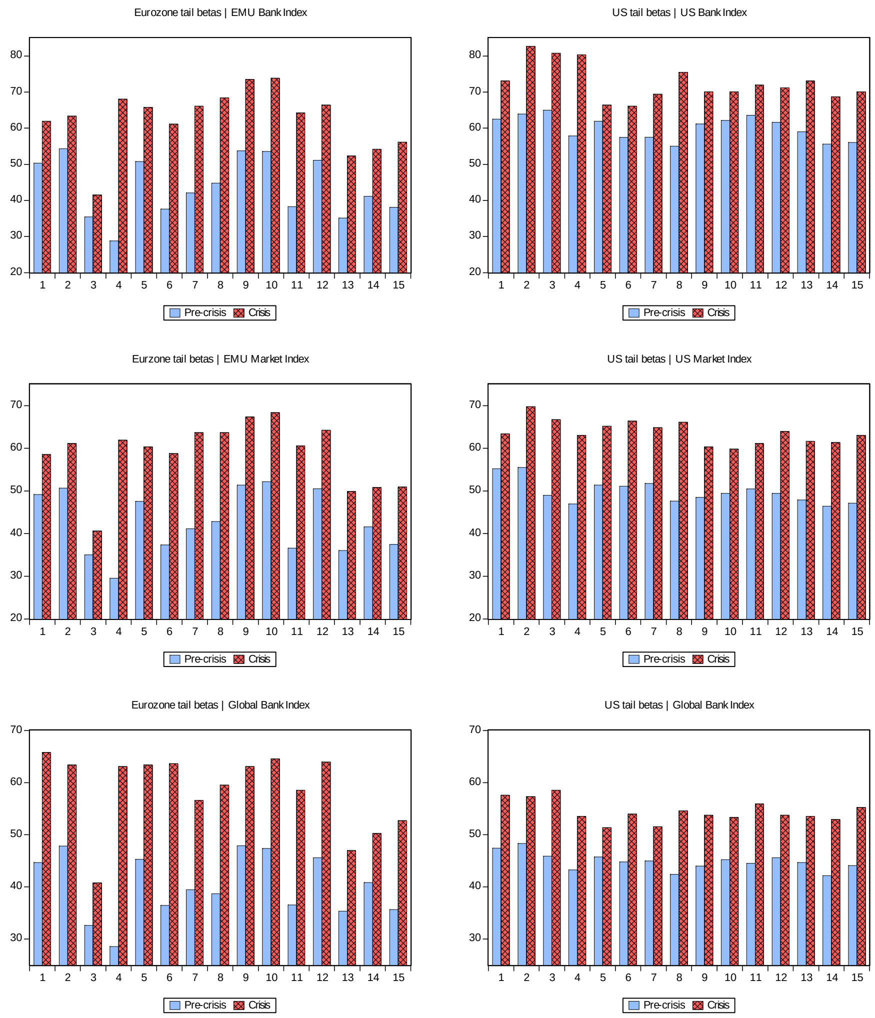
FIGURE 1. Univariate tail risk measures (tail indices, tail quantiles and expected shortfalls) for US and eurozone banks: pre-crisis vs. crisis results



Note: For Eurozone banks 1 to 15 in the bottom axis represent Commerzbank, Deutsche, BGBerlin, BNP Paribas, SocGen, Natixis, Intesa, Unicredit, Santander, BBVA, Espanol, ING, Alpha, AIB and BCP respectively. For US banks 1 to 15 represent Citi, JPMorgan, BoA, WellsFargo, BNY, SStreet, Ntrust, USBanc, PNC, Keyco, SunTrust, Commerica, BBT, Fifth3rd and Region respectively.

FIGURE 2. Extreme systematic risk for US and eurozone banks: pre-crisis vs. crisis results and different conditioning risk factors



Note: For Eurozone banks 1 to 15 in the bottom axis represent Commerzbank, Deutsche, BGBerlin, BNP Paribas, SocGen, Natixis, Intesa, Unicredit, Santander, BBVA, Espanol, ING, Alpha, AIB and BCP respectively. For US banks 1 to 15 represent Citi, JPMorgan, BoA, WellsFargo, BNY, SStreet, Ntrust, USBanc, PNC, Keyco, SunTrust, Commerica, BBT, Fifth3rd and Region respectively.

FIGURE 3. Time varying tail risk: (rolling) Hill estimates and expected shortfalls for US and eurozone banks

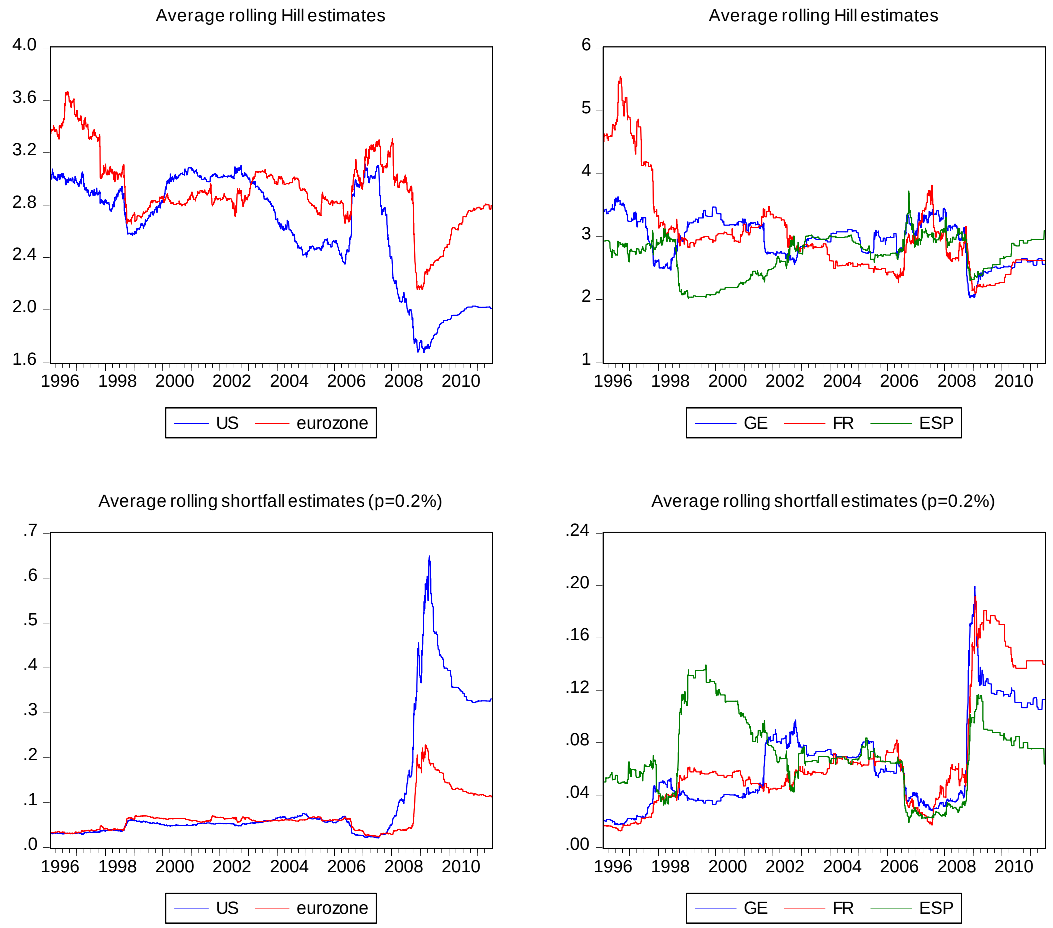


FIGURE 4. Time varying systemic risk: (rolling) expected co-crash indicators and co-crash probabilities for US and eurozone banks

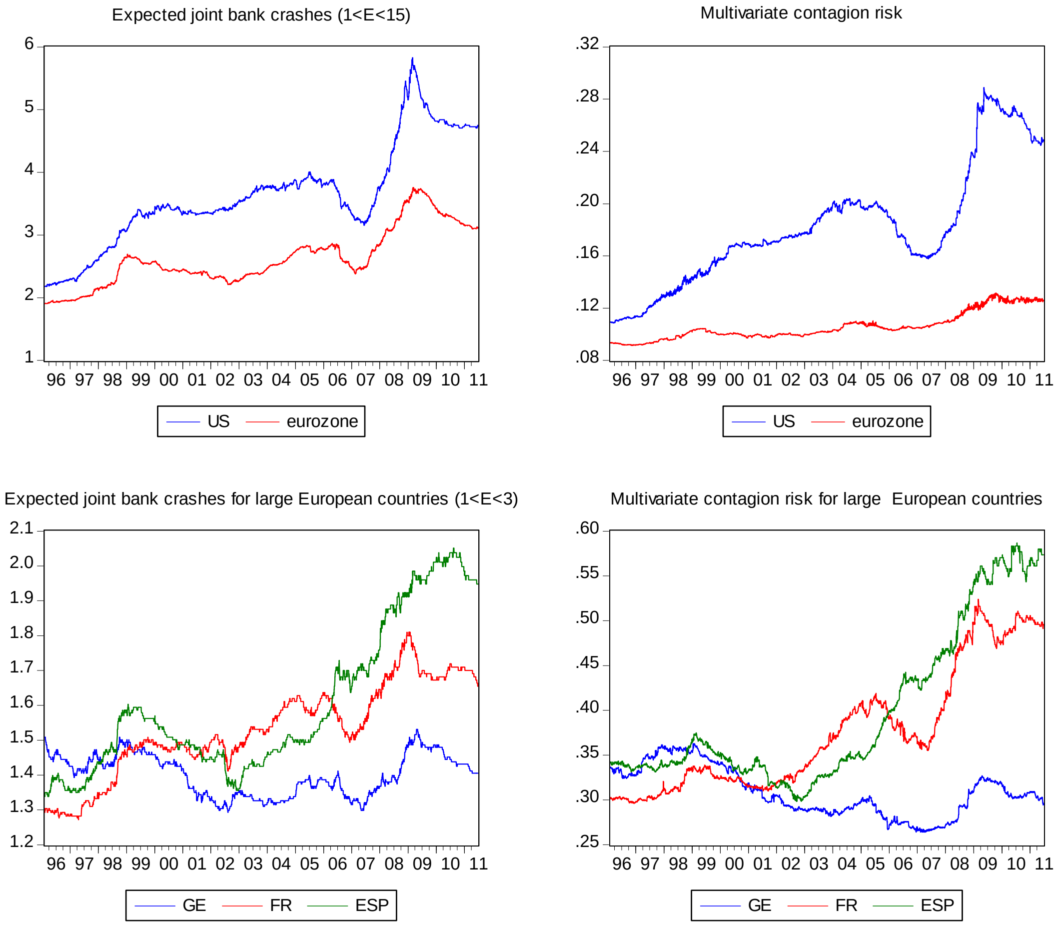


FIGURE 5.

TABLE 1. Tail risk masures for selected eurozone and US banks: full sample, pre-crisis and crisis

Bank	$\widehat{\alpha}$	$\widehat{q}\,(p)$		$ES\,(X > s)$		$ES\,(\widehat{q}\,(p))$	
		$p = 0.2\%$	$p = 0.1\%$	$s = 25\%$	$s = 50\%$	$p = 0.2\%$	$p = 0.1\%$
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

Note: Sample means, medians and standard deviations for the tail index α, the tail quantile x_p and the expected shortfall ES are reported 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.2, A.3 and A.4 in Appendix. The nuisance parameter m equals 120 and 219 for full sample eurozone and US banks (median values across US and eurozone). 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.

Table 2. Univariate tail risk proxies: testing for cross sectional equality and structural change

	Panel I: Structural change tests	
	$\overline{\alpha}_1 = \overline{\alpha}_2$	$\overline{x}_1\,(p) = \overline{x}_2\,(p)$
US mean	12.5***	-9.6***
eurozone mean	0.9	-4.0***
	Panel II: Cross-sectional equality tests	
	$\overline{\alpha}_{US} = \overline{\alpha}_{EU}$	$\overline{x}_{US} = \overline{x}_{EU}$
Pre-crisis mean	0.3	2.2**
Crisis mean	3.2***	-4.5***

Note: the table reports t-tests for equal sample means (Hill and quantile estimates) and is approximately normally distributed. 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%

Table 3. Indicators of multivariate bank spillover risk

panel I: Multivariate indicators								
	$E\{\kappa\,|\kappa \geqslant 1\}$				Multiprob ($P_{N|1}$).			
	full	pre	crisis	%Δ	full	pre	crisis	%Δ
United States (N=15)	3.64	2.94	4.33	47.27	14.31	11.70	22.75	94.44
eurozone (N=15)	2.41	2.08	2.94	41.35	7.37	6.59	10.36	57.21
Germany (N=3)	1.35	1.34	1.41	5.22	24.84	25.67	29.61	15.35
France (N=3)	1.53	1.39	1.68	20.86	32.72	27.97	49.07	75.44
Spain (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)		
	$E_{pre} = E_{crisis}$	$P_{pre} = P_{crisis}$
US	-2.66***	-2.90***
eurozone	-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=eurozone	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***

Note: Panel I reports estimation results for multivariate spillover risk measures for $E\kappa|\kappa = 1$ and $P_{N|1}$ 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.

Table 4. Bilateral extreme bank linkages: comparing US with eurozone

eurozone								US			
Domestic (per country)				cross-border (per country)							
country	full	pre	crisis	pairs	full	pre	crisis		full	pre	crisis
GE	27.2	28.1	31.6	GE	26.3	24.2	30.5	CITIG	42.4	32.3	49.0
FR	16.7	13.9	19.5	FR	22.7	18.6	26.3	J MORGAN	42.9	32.3	55.4
IT	42.6	28.1	60.9	IT	31.0	20.4	38.7	BAMERICA	49.6	33.0	51.8
ESP	44.6	31.8	59.5	ESP	30.7	22.4	38.4	FARGO	45.7	31.5	55.1
				cross-border (per country pair)				BNYORK	39.4	32.2	47.4
				GE-FR	21.9	21.0	25.5	SSTREET	40.5	33.1	44.3
				GE-IT	34.9	28.1	46.3	NTRUST	37.7	32.6	48.2
				GE-ESP	35.9	30.0	45.5	BCORP	43.0	31.1	52.4
				GE-NL	36.0	14.0	39.7	PNC	43.3	36.1	53.2
				GE-GR	17.1	37.9	21.3	KEYCO	47.9	35.7	48.4
				GE-IRE	20.4	14.9	29.8	SUNTRUST	46.5	37.8	51.3
				GE-POR	21.6	19.8	19.0	COMERICA	47.2	35.8	52.7
				FR-IT	29.6	21.2	40.2	BBT	43.2	31.3	49.7
				FR-ESP	30.6	22.9	39.5	53BANCO	43.8	30.7	46.4
				FR-NL	40.9	24.7	42.7	REGION	45.6	35.0	43.7
				FR-GR	20.3	13.6	24.5				
				FR-IRE	25.4	16.1	27.5				
				FR-POR	19.8	16.6	19.3				
				IT-ESP	43.6	30.0	60.2				
				IT-NL	39.8	31.2	51.0				
				IT-GR	17.8	13.7	23.4				
				IT-IRE	23.8	17.5	25.8				
				IT-POR	24.2	18.3	22.7				
				ESP-NL	39.3	33.6	48.1				
				ESP-GR	20.4	14.7	26.8				
				ESP-IRE	23.5	20.2	28.3				
				ESP-POR	25.6	21.6	30.5				
				NL-GR	23.0	17.2	28.0				
				NL-IRE	28.0	24.1	29.8				
				NL-POR	28.8	26.0	27.5				
				GR-IRE	26.5	16.9	22.2				
				GR-POR	24.1	15.3	24.2				
				IRE-POR	23.5	19.1	18.4				

Note: Each cell is a sample average of co-crash probabilities for bank pairs. The panel "domestic" contains averages of all bilateral co-crash probabilities for bank pairs within Germany, France , Italy and Spain (we only consider the eurozone countries that have more than one bank in the sample). Cross-border contagion can either be calculated per eurozone country pair or per eurozone country. The panel "cross-border (per pair)" reflects averages of cross-border co-crash probabilities between bank pairs originating from the indicated eurozone country pair. The panel "cross-border (per country)" reports averages of cross-border co-crash probabilities between bank pairs of the indicated country with all other foreign eurozone banks. The "US" panel reports averages of bilateral linkage probabilities between each of the 15 US banks with respect to each other. The nuisance parameter m for the full sample, the pre-crisis and the crisis is 200, 172 and 69, respectively for all pairs.

Table 5. extreme systematic risk for selected eurozone banks and US banks: full sample, pre-crisis and crisis

	Aggregate risk factor (index)					
	Bank	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	

Note: Sample means, medians and standard deviations for the tail-β estimates are reported across the time series dimension (pre-crisis vs. crisis) and the cross sectional dimension (US vs. eurozone). The tail-β is estimated according to (3.10). 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.5, A.6 and A.7 in Appendix. The nuisance parameter m equals 400 for full sample eurozone and US banks if the conditioning aggregate risk factor is either a bank index or stock index. The parameter m is 300 in case the conditioning aggregate risk factor is a 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.

Table 6. Extreme systematic risk: testing for cross sectional equality and structural change

	Conditioning aggregate risk factor					
	bank	stock	global bank	global stock	real estate	PIIGS
	Panel I: structural change tests					
US mean	-8.0***	-13.8***	-13.9***	-11.6***	-33.6***	-
eurozone mean	-6.2***	-6.0***	-7.3***	-7.0***	-4.5***	-10.0***
	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***	

Note: This table reports the structural change tests and the cross-sectional equality tests for extreme systemic risk. Panel I reports the mean structural change tests for the US and the eurozone conditioning on six (five in case of the US) market factors. 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.

TABLE A.1. US and eurozone bank stock returns: descriptive statistics

	full sample				pre-crisis				crisis			
	μ	σ	S	K	μ_1	σ_1	S_1	K_1	μ_2	σ_2	S_2	K_2
Panel I: eurozone banks												
COMMERZ	-0.016	2.4	-0.2	15.9	0.033	1.9	0.1	9.9	-0.208	3.8	-0.2	10.7
DEUTSCHE	0.013	2.2	0.2	13.4	0.035	1.8	-0.1	7.6	-0.074	3.3	0.4	10.7
BGBERLIN	-0.007	2.3	-0.6	28.9	0.000	2.3	-1.1	34.6	-0.035	2.6	0.6	14.6
BNP	0.031	2.3	0.3	10.7	0.050	2.1	0.1	7.3	-0.033	3.2	0.4	10.0
SOCGEN	0.030	2.4	0.05	9.7	0.064	2.0	0.05	7.5	-0.103	3.5	0.1	7.3
NATIXIS	0.007	2.4	0.7	23.4	0.035	1.6	0.4	10.2	-0.105	4.2	0.6	11.3
INTESA	0.026	2.4	0.2	8.6	0.056	2.3	0.3	6.8	-0.095	2.9	0.01	10.2
UNICREDIT	0.023	2.4	0.6	12.1	0.060	2.1	1.0	13.2	-0.126	3.4	0.3	7.9
SANTANDER	0.043	2.1	0.1	10.3	0.061	1.9	-0.1	9.0	-0.031	2.8	0.5	9.4
BBVA	0.041	2.0	0.2	10.2	0.067	1.8	0.02	9.5	-0.066	2.6	0.5	8.8
ESPANOL	-0.007	2.1	-12.1	509.9	0.014	2.1	-15.3	639.9	-0.088	2.1	0.2	5.8
ING	0.029	2.7	-0.03	21.1	0.062	2.0	-0.1	11.7	-0.100	4.4	0.1	12.3
ALPHA	0.027	2.5	0.3	9.3	0.079	2.1	0.5	14.0	-0.179	3.6	0.2	4.0
AIBANK	-0.032	3.5	-2.8	93.7	0.070	1.6	-0.3	10.7	-0.435	7.2	-1.5	27.1
BCP	-0.009	1.7	0.01	11.7	0.038	1.5	-0.1	14.9	-0.196	2.4	0.3.	6.4
average	0.014	2.36			0.048	1.94			-0.125	3.47		
Panel II: US banks												
CITIG	0.013	3.1	-0.4	43.0	0.078	2.0	0.1	8.6	-0.241	5.6	-0.3	19.5
J MORGAN	0.038	2.5	0.3	15.1	0.049	2.1	0.1	9.3	-0.007	3.9	0.3	10.8
BAMERICA	0.012	2.8	-0.3	33.2	0.050	1.7	-0.2	6.8	-0.140	5.2	-0.1	13.6
FARGO	0.046	2.4	0.8	28.5	0.062	1.6	0.1	6.0	-0.014	4.4	0.7	12.8
BNYORK	0.040	2.4	-0.04	19.5	0.063	1.9	0.1	8.7	-0.051	3.7	-0.03	14.5
SSTREET	0.038	2.8	-6.1	212.2	0.059	1.9	-0.2	10.5	-0.044	5.0	-5.4	108.7
NTRUST	0.040	2.2	0.4	16.5	0.057	1.8	0.6	10.3	-0.030	3.2	0.2	13.2
BCORP	0.053	2.2	0.2	19.8	0.070	1.8	0.5	22.3	-0.016	3.5	0.03	10.5
PNC	0.030	2.4	-1.4	71.0	0.041	1.6	-0.2	8.8	-0.010	4.1	-1.2	36.9
KEYCO	0.004	2.8	-0.5	44.2	0.041	1.6	0.1	7.2	-0.140	5.2	-0.3	16.5
SUNTRUST	0.016	2.5	-0.4	28.6	0.047	1.5	-0.1	7.3	-0.106	4.8	-0.2	10.6
COMERICA	0.025	2.3	-0.2	16.5	0.040	1.6	-0.6	15.9	-0.035	4.0	0.05	7.4
BBT	0.039	2.1	0.2	21.2	0.055	1.5	0.5	9.6	-0.027	3.6	0.1	10.9
53BANCO	0.014	3.1	-0.3	67.4	0.045	1.6	0.3	6.2	-0.107	6.2	-0.2	21.9
REGION	0.003	3.0	-0.6	51.8	0.042	1.5	0.3	9.9	-0.150	5.8	-0.3	16.9
average	0.027	2.57			0.053	1.71			-0.074	4.55		

Note: The (full) sample mean, standard deviation, skewness and kurtosis are denoted by μ, σ, S and K. Subsample moments indexed with 1 and 2 represent pre-crisis and crisis values. Sample means and standard deviations are expressed in percentages. August 7, 2007 is taken as starting point of crisis.

TABLE A.2. Full sample tail risk indicators for eurozone and US banks

Bank	α	$q(p)$		$ES(X>s)$		$ES(q(p))$	
		$p=0.2\%$	$p=0.1\%$	$s=25\%$	$s=50\%$	$p=0.2\%$	$p=0.1\%$
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

Note: Estimators for the tail index α, the tail quantile x_p and the expected shortfall ES are given in eqs. (3.3), (3.2) and (3.4). 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.

TABLE A.3. Tail risk indicators for selected eurozone banks: pre-crisis and crisis estimates

Bank	α	$q(p)$		$ES(X>s)$		$ES(\widehat{q}(p))$	
		$p=0.2\%$	$p=0.1\%$	$s=25\%$	$s=50\%$	$p=0.2\%$	$p=0.1\%$
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

Note: Estimators for the tail index α, the tail quantile x_p and the expected shortfall ES are given in (3.3), (3.2) and (3.4). 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.

Table A.4. Tail risk indicators for selected US banks: pre-crisis and crisis estimates

Bank	α	$q(p)$		$ES(X>s)$		$ES(q(p))$	
		$p=0.2\%$	$p=0.1\%$	$s=25\%$	$s=50\%$	$p=0.2\%$	$p=0.1\%$
Panel I: pre-crisis estimates							
CITIG	3.0	8.8	11.0	12.2	24.5	4.3	5.4
J 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

Note: Estimators for the tail index α, the tail quantile x_p and the expected shortfall ES are given in (3.3), (3.2) and (3.4). 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.

Table A.5. Extreme systematic risk for selected eurozone banks and US banks: full sample results

Bank	Aggregate risk factor (index)					
	bank	stock	world bank	world 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	

Note: The tail-β estimator is given by (3.10). The 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.

Table A.6. Extreme systematic risk for selected euro-zone banks: pre-crisis vs. crisis results

Bank	Aggregate risk factor (index)					
	bank	stock	world bank	world 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

Note: The tail-β estimator is given by (3.10). The 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 equals $m = 340$ and $m = 138$ for pre-crisis and crisis samples, respectively.

TABLE A.7. Extreme systematic risk for selected US banks: pre-crisis vs. crisis results

Bank	Aggregate risk factor (index)				
	bank	stock	world bank	world 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

Note: the tail-β estimator is given by (3.10). The 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 equals $m = 340$ and $m = 138$ for pre-crisis and crisis samples, respectively.

Current address: Stefan Straetmans, Maastricht University (School of Business and Economics), P.O.Box 616, 6200 MD Maastricht, The Netherlands
E-mail address: `s.straetmans@maastrichtuniversity.nl`

Current address: Sajid Chaudhry, Birmingham Business School, Edgbaston Park Road, B15 2TY, Birmingham, United Kingdom
E-mail address: `s.m.chaudhry@bham.ac.uk`