# BANKING SYSTEM STABILITY: A CROSS-ATLANTIC PERSPECTIVE BASED ON EXTREME VALUE ANALYSIS (PRELIMINARY AND INCOMPLETE DRAFT NOTES; PLEASE DO NOT QUOTE!)

P. HARTMANN, S. STRAETMANS, AND C.G. DE VRIES

Abstract. This paper derives indicators of the severity and structure of banking system risk from asymptotic interdependencies between banks' equity prices. We use new tools available from multivariate extreme value theory to estimate individual banks' exposure to each other (contagion risk) and to systematic risk. Moreover, by applying structural break tests to those measures we study whether capital markets indicate changes in the importance of systemic risk over time. Using data for the United States and the euro area, we can also compare banking system stability between the two largest economies in the world. Finally, for Europe we assess the relative importance of cross-border contagion risk as compared to domestic contagion risk.

## 1. Introduction

Contagion is widely perceived as a principal force in the unfolding of many financial crises. Academic scholars, policy makers and market participants pointed to the occurrence of contagion phenomena in various crises episodes during the 1990s, such as the Asian crisis of 1997 (see e.g. Agenor et al., 1999) and the Russian crisis as well as the near-failure of Long Term Capital Management in fall 1998 (see e.g. Dungey et al., 2002). In the more recent Argentinean crisis that broke out in December 2001, domestic banking problems were observed to spill over

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to Uruguay. On this basis, an active literature has developed examining which phenomena constitute financial contagion and how they can be identified empirically. In our reading, the main criteria proposed so far to identify contagion are that (i) a problem at a financial institution adversely effects other financial institutions or that a decline in an asset price leads to declines in other asset prices; (ii) the relationships between failures or asset price declines must be different from those observed in normal times (regular "interdependence"); (iii) the relationships are in excess of what can be explained by economic fundamentals; (iv) the events constituting a contagion episode are negative "extremes", such as full-blown institution failures or market crashes, so that they correspond to crisis situations; (v) the relationships are the result of propagations over time rather than being caused by the simultaneous effects of common shocks.

Most empirical approaches proposed in the recent literature how to measure contagion capture the first criterion, but this is where the agreement usually ends, as different authors put emphasis on different features. Forbes and Rigobon (2002) stress statistically significant changes in correlations over time as a contagion indicator and illustrate how it works with emerging country equity markets. Shiller (1989), Pindyck and Rotemberg (1993) and Bekaert, Harvey and Ng (forthcoming) emphasise "excess co-movements" between stock markets and stock prices, beyond what is explained in various forms of regressions by dividends, macroeconomic fundamentals or asset pricing "factors". Eichengreen, Rose and Wyplosz (1996) estimate probit models to examine whether the occurrence of a balance-of-payments crisis in one country increases the probability of a balance-of-payments crisis in other countries, conditional on macroeconomic fundamentals. Bae, Karolyi and Stulz (2003) propose the logit regression model to estimate probabilities that several stock markets experience large negative returns, given that a smaller number of stock markets experience large negative returns (conditional on interest rates). Longin and Solnik (2001) estimate bivariate extreme equity market correlations, also assuming the logistic distribution. Hartmann, Straetmans and de Vries (2003a/b, 2004) stress that market co-movements far out in the tails ("asymptotic dependence") may be very different from regular dependence in multivariate distributions. Based on extreme value theory (EVT), they estimate semi-parametrically for stocks, bonds and currencies the likelihood of widespread market crashes conditional on contemporaneous and lagged other market crashes. The reason why we particularly focus on criterion (iv) above is that they allow us to concentrate on events that are severe enough to be basically always of a concern for policy. Other criteria are also interesting and have their own justifications, but often one may have doubts whether more regular propagations or changes in them are really a concern for policy.[1]

A particular important part for the stability of financial systems is the banking sector. Banks play a central role in the money creation process and in the payment system. Moreover, bank credit is an important factor in the financing of investment and growth. Faltering banking systems have been associated with hyperinflations and depressions in economic history. Hence, to preserve monetary and financial stability central banks and supervisory authorities have a special interest in assessing banking system stability, including the risk of bank contagion. A complication in this task is that, in contrast to other elements of the financial system such as securities values, interbank relationships that can be at the origin of contagion phenomena or the values of and correlations between loan portfolios are particularly hard to monitor and measure.[2]

For this reason most of the published bank contagion literature has resorted to more indirect market indicators. In particular, spillovers in bank equity prices have been used for this purpose. Pioneered by Aharony and Swary (1983 and 1986) a series of papers have applied the event study methodology to the effects of specific bank failures or bad news for certain banks on other banks' stock prices (see e.g. also Wall and Petersen, 1990; Docking, Hirschey and Jones, 1997; Slovin, Sushka and Polonchek, 1999). In another series of papers various regression approaches are used in order to link abnormal bank stock returns to asset-side risks (see e.g. Cornell and Shaphiro, 1986; Smirlock and Kaufold, 1987; Musumeci and Sinkey, 1990; or Koo, Lee and Stulz, 2000). De Nicolo and Kwast (1999) relate changes in correlations between bank stock prices over time to banking consolidation.[3]

In this paper we also use bank equity prices as indicators of contagion/banking system risks. Compared to the previous literature, we

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[1] De Bandt and Hartmann (2000) provide a more complete survey of the market and banking contagion literature. Pritsker (2001) discusses different channels of contagion.

[2] Even central banks and supervisors usually do not have continuous information about interbank exposures. For the Swedish example of a central bank monitoring interbank exposures at a quarterly frequency, see Blavarg and Nimander (2002).

[3] Other empirical approaches have been proposed by Grossman (1993), Hasan and Dwyer (1994), Calomiris and Mason (1997 and 2000), as well as Saunders and Wilson (1997).

Chen (1999), Allen and Gale (2000) or Freixas, Parigi and Rochet (2000) develop the theoretical foundations of bank contagion.

want to make three main contributions. First, we use our new multivariate extreme value techniques (Hartmann et al., 2003a/b and 2004) to estimate the strength of those risks. In particular, we distinguish conditional co-crash probabilities between banks from crash probabilities conditional on aggregate shocks. Second, we cover both European countries and the United States to compare banking system stability internationally. Third, we extend the new GARCH-robust test of structural stability for tail indexes by Quintos, Fan and Phillips (2001) to the multivariate case of extreme linkages and assess changes in banking system stability over time with it.

The idea behind our approach is as follows. We assume that bank stocks are efficiently priced, in that they reflect all publicy available information about (i) individual banks' asset and liability side risks and (ii) relationships between different banks' risks (be it through correlations of their loan portfolios, interbank lending or other channels). We identify a critical situation of a bank with a dramatic slump of its stock price. We identify the risk of contagion with extreme negative comovements between individual bank stocks, the conditional "co-crash" probability in our earlier stock, bond and currency papers. In addition, we identify the risk of banking system destabilization through aggregate shocks with the help of the "tail-$\beta$" proposed by Straetmans, Verschoor and Wolf (2003).[4] The tail-$\beta$ is measured by conditioning our co-crash probability on a general stock index rather than on individual banks' stock prices. Therefore, in some respects it reflects the tail equivalent to standard asset pricing models. Based on the estimated individual co-crash probabilities and tail-$\beta$s, we can then test for the equality of banking system risk between the US and the euro area and for changes in systemic risk over time.

Our data are daily bank stock prices in euro area countries and the United States between January 1992 and November 2003. For each area or country we choose 25 banks based on two main criteria, size and involvement in interbank lending. So, our sample represents the systemically most relevant financial institutions, but neglects a large number of smaller banks. All in all, we have about 3,000 observations per bank.

Our first results are very preliminary and should not be taken at face value. It turns out so far that the degree of multivariate extreme linkage between US banks is much higher than between European banks. In

[4]Some authors point out that most banking crises have been related to aggregate shocks rather than to prevalent contagion. See e.g. Gorton (1988) for historical evidence in the US. Chen (1999) models, inter alia, how macro shocks and contagion can interact in the banking system.

other words, bank contagion risk might be higher among the major US banks than presently the case among the major euro area banks. Second, when looking at cross-border spillovers as compared to domestic spillovers in Europe, our contagion risk indicator is consistently larger for the latter, but not for all countries this difference is statistically significant. For example, among the banks from larger countries − such as France, Germany and the Netherlands, maybe including also Italy and Spain − extreme cross-border linkages are indistinguishable from domestic linkages. In contrast, the effects of banks from these larger countries on the main banks from some smaller countries − including e.g. Finland, Greece, Ireland and Portugal − tend to be significantly weaker than the effects of their own banks. Third, both our indicators suggest that systemic risk has increased in Europe and in the US. Interestingly, for the US banking system the strongest contagion risk break point seems to occur around the time of the Russian and LTCM crises of late summer/fall 1998. Regarding the measure of systematic risk, most of the increase in tail-$\beta$s in Europe occurs around the time of the Asian financial crisis. Finally, extreme systematic risk varies a lot across banks and continents and systematic differences between Europe and the US are very small.

The paper is structured as follows. The next section describes our theoretical indicators of banking system stability, distinguising the multivariate spillover or contagion measure from the aggregate tail-$\beta$ measure for stock prices. Section 3 outlines the estimation procedures for both measures; and section 4 presents two tests, one looking at the stability of contagion and systematic risk over time and the other looking at the stability of both measures across countries and continents (cross-sectional stability). Section 5 summarizes the data set we use, in particular how we selected the banks covered, and gives some information about the occurrence of negative extremes for individual banks. Section 6 then presents the empirical results on bank contagion risk. For both the euro area and the US we estimate the overall multivariate extreme dependence in the banking sector and we test whether one is larger than the other. Moreover, for Europe we assess whether domestic contagion risk is stronger or weaker than cross-border contagion risk. Section 7 turns to the empirical results for aggregate banking system risk on both continents. We estimate tail-$\beta$s for European banks and for US banks. Section 8 then asks the question whether contagion or systematic risk has changed over time or not. The final section concludes.

## 2. Indicators of banking system stability

Our indicators of banking system stability are based on extreme stock price movements. They are constructed as conditional probabilities, coniditioning single or multiple bank stock price "crashes" on other banks' stock price crashes or on crashes of the market portfolio. Extreme co-movements as measured by multivariate conditional probabilities between individual banks' stock prices are meant to capture the risk of contagion from one bank to another. Extreme co-movements between individual banks's stock prices and a general stock market index (the so-called "tail-$\beta$") are used to assess the risk of banking system instability through aggregate shocks. The two forms of banking system instability are theoretically distinct, but in practice they may sometimes interact. Both have been extensively referred to in the theoretical and empirical banking literature. In what follows we describe them in more precise terms.

2.1. **Multivariate extreme spillovers: a measure of contagion risk.** Let us start with the measure of contagion risk. The measure can be expressed in terms of marginal (univariate) and joint (multivariate) exceedance probabilities. Consider an $N$-dimensional banking system, i.e., a set of $N$ banks from e.g. the same country or continent. Denote the log first differences of the price changes in bank stocks by the random variables $X_i$ $(i = 1, \cdots, N)$. To study simultaneous sharpe falls in stock prices we adopt the convention to take the negative of stock returns so that we can define all used formulae in terms of upper tail returns. For sake of convenience, the crisis levels or extreme quantiles $Q_i$ $(i = 1, \cdots, N)$ are chosen such that the tail probabilities are equalized across banks, i.e.,

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

Obviously, even with the significance level in common, crisis levels $x$ will generally not be equal across banks because the marginal dfs $P\{X_i > Q_i\} = 1 - F_i(Q_i)$ are bank specific. The crisis levels can be interpreted as "barriers" that will on average only be broken once in $1/p$ time periods, i.e., $p^{-1}$ days if the data frequency is daily, $p^{-1}$ weeks if the data frequency is weekly etc.[5] Suppose now that we want to

[5]Notice that from e.g. a risk management point of view ($X_i$ could then be thought of as referring to portfolios of bank stocks) a common significance level makes the different open portfolio positions comparable in terms of their degree of downside risk. Moreover, we argue later on that our bivariate and multivariate probability measures that use the common tail probability as an input will solely reflect dependence information.

measure the propagation of severe problems through e.g. the European and US banking sectors by calculating the probability of joint collapse in a set of $N$ bank stocks conditional on the collapse of a subset $M < N$ banks:

(2.1)

$$P_{N|M} = P\left\{\bigcap_{i=1}^{N} X_i > Q_i(p) \middle| \bigcap_{j=1}^{M} X_j > Q_j(p)\right\} = \frac{P\left\{\bigcap_{i=1}^{N} X_i > Q_i(p)\right\}}{P\left\{\bigcap_{j=1}^{M} X_j > Q_j(p)\right\}}.$$

Clearly, the right-hand side immediately follows from the definition of conditional probability. This measure is defined by the probability that an arbitrarily large number of bank stocks decline dramatically together, given that a specifically chosen set of bank stocks decline dramatically. Notice that the conditioning banks do not necessarily have to be a subset of the bank set at the left hand side of (2.1). Moreover the conditioning random variables could also be others than just bank stock prices.[6]

2.2. **"Tail-$\beta$s": a measure of aggregate banking system risk.** Our second measure of banking system risk is from a methodological point of view a bivariate "variant" of (2.1), in which $N$=1 and the conditioning set is limited to extreme downturns of the world market portfolio.[7] This "tail-$\beta$" measure is inspired by portfolio theory and has been used before by Straetmans et al. (2003) to examine the intraday effects of the September 11 catastrophe on US stocks. Let $M$ be the value of the market portfolio (e.g. a broad stock market index) and $p$ again our common tail probability, then this measure can be written as:

$$\begin{aligned} P\{X_1 > Q_1(p) | M > Q_M(p)\} &= \frac{P\{X_1 > Q_1(p), M > Q_M(p)\}}{P\{M > Q_M(p)\}} \\ &= \frac{P\{X_1 > Q_1(p), M > Q_M(p)\}}{p}. \end{aligned} \tag{2.2}$$

[6]In Hartmann, Straetmans and de Vries (2003b) we applied an analogous measure to assess the systemic breadth of currency crises.

[7]Technically, it is also possible to derive this measure for $N$>1, but we do not do this in the present paper.

This measure captures how likely it is that an individual bank's value declines dramatically, if there is an extreme negative systematic shock.[8]

## 3. Estimation of the indicators

How can we estimate (2.1) and (2.2)? As all marginal probabilities are set equal to $p$ it suffices to estimate the joint probabilities in the denominators of (2.1) and (2.2). Within the framework of a parametric probability law, the calculation of the proposed multivariate probability measures is straightforward, because one can estimate the distributional parameters by, e.g., Maximum Likelihood (ML) techniques. However, if one estimates the linkage measures on the basis of the wrong distributional assumptions, the estimates may be severely biased due to misspecification. We therefore decided to renege from making very specific distributional assumptions for bank stock returns and to implement the semi-parametric EVT approach proposed by Ledford and Tawn (1996) and Draisma et al. (2001). Loosely speaking their approach consists of generalizing some "best practice" in univariate extreme value analysis, based on the Pareto law behaviour of the minima and maxima of the relevant distributions for financial market returns, to the bivariate case. So, they derive the tail probabilities that occur in measures (2.1) and (2.2) for the bivariate case. We go a step further by generalizing their approach to the multivariate case.

Before proceeding with the modelling of the extreme dependence structure, however, we need to remove any possible influences of marginal aspects on the joint tail probabilities by transforming the original variables to a common marginal distribution, see e.g. Ledford and Tawn (1996) and Draisma et al. (2001). After such a transformation, differences in joint tail probabilities across banking systems, e.g. Europe vs. US, can be solely attributed to difference in the tail dependence structure of the extremes. Thus our dependence measures, unlike e.g. correlation, are no longer influenced by the differences in marginal distribution shapes.

In this spirit we transform the bank stock returns $(X_1, \cdots, X_i, \cdots, X_N)$ to unit Pareto marginals:

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

with $F_i(\cdot)$ representing the marginal cumulative distribution function (cdf) for $X_i$. However, since the marginal cdfs are unknown, we have to

[8]In the present paper we limit ourselves to these two measures of banking system risk. In future research, the approach could be extended by also including further economic variables in the conditioning set, such as interest rates or exchange rates.

replace them with their empirical counterparts. For each $X_i$ this leads (with a small modification to prevent division by 0) to:

$$\widetilde{X}_i = \frac{n+1}{n+1-R_{X_i}}, \ i = 1, \cdots, N, \tag{3.1}$$

where $R_{X_i} = rank(X_{ij,}j = 1, \cdots, n)$. Using this variable transform, we can rewrite the joint tail probability that occurs in (2.1) and (2.2):

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

where $s = 1/p$. The multivariate estimation problem can now be reduced to estimating a univariate exceedance probability for the cross-sectional minimum of the $N$ bank stock return series, i.e., it is always true that:

$$P\left\{\bigcap\nolimits_{i=1}^{N} \widetilde{X}_i > s\right\} = P\left\{\min_{i=1}^{N}\left(\widetilde{X}_i\right) > s\right\} = P\left\{T_{\min} > s\right\} \ . \tag{3.2}$$

The marginal tail probability at the right-hand side can now be easily calculated by making an additional assumption on the univariate tail behavior of $T_{\min}$. Ledford and Tawn (1996) impose a regularly varying (or heavy) tail for the auxiliary variable $T_{\min}$ in a bivariate framework. This assumption can be justified by referring to the empirical stylized fact of heavy-tailed bank stock returns. Consequently, the transformed series $\widetilde{X}_i$ and the time series of the cross-sectional minima should inherit this property. Notice, however, that in contrast to Ledford and Tawn (1996) we consider more than two dimensions.

Assuming that $T_{\min}$ exhibits heavy tails with tail index $\alpha$ then the regular variation assumption for the auxiliary variables implies that the univariate probability in (3.2) exhibits a tail descent of the Pareto type :

$$P\left\{T_{\min} > s\right\} \approx s^{-\alpha}, \tag{3.3}$$

with $s$ large ($p$ small). The estimation of the joint probabilities in the denominator and numerator of eq. (2.1) and the joint tail probability in the numerator of eq. (2.2) can now simply be reduced to estimating a Pareto tail like in (3.3). For example, applying the three steps (3.1), (3.2) and (3.3) of the Ledford/Tawn approach to the co-crash probability with respect to the market portfolio (2.2) leads to the following:

$$\frac{P\left\{X_1 > Q_X(p), M > Q_M(p)\right\}}{p} = \frac{P\left\{\widetilde{X}_1 > p^{-1}, \widetilde{M} > p^{-1}\right\}}{p}$$

$$
\begin{aligned}
&= \frac{P\left\{\min\left(\widetilde{X}_1, \widetilde{M}\right) > p^{-1}\right\}}{p} \\
&\approx p^{\alpha-1} .
\end{aligned}
$$

This expression is conditional upon the tail index $\alpha$. We estimate the tail index by means of the popular Hill (1975) estimator:

$$
\frac{1}{\widehat{\alpha}} = \frac{1}{m}\sum_{j=0}^{m-1} \ln\left(\frac{T_{n-j,n}}{T_{n-m,n}}\right) = \widehat{\eta}, \tag{3.4}
$$

where $m$ is the number of higher order extremes and $\widehat{\alpha} = 1/\widehat{\eta}$ stands for the estimated tail index. Further details are provided in Jansen and De Vries (1991) and, e.g., the monograph by Embrechts, Klüppelberg and Mikosch (1997).

## 4. Hypothesis testing

In this section we introduce two tests that can be used to assess various hypotheses regarding the evolution and structure of systemic risk in the banking system. The first one allows to test for the structural stability of the amount of risk found with our two indicators. The second test allows us to compare systemic risk across countries and continents.

4.1. **Time variation.** The multivariate linkage estimator (2.1) and its bivariate counterpart in (2.2) were presented so far assuming stationarity of tail behavior over time. From a policy perspective, however, it is important to know whether systemic risk in the banking system, either in terms of contagion risk (2.1) or in terms of systemic risk associated with aggregate shocks (2.2), has changed over time. As the discussion of the Ledford and Tawn approach toward estimating (2.1) or (2.2) has shown, the structural (in)stability of systemic risk will critically depend on whether the tail index parameter $\alpha = 1/\eta$ in (3.3) is constant or not.

Recently, Quintos, Fan and Phillips (2001) proposed a recursive, rolling and sequential procedure for testing the stability of $\widehat{\alpha}$. They derived asymptotic theory for the test statistics and study their small sample performance. If the tail index decreases over time ($\alpha_1 > \alpha_2$) they conclude that the recursive test outperforms the rolling and sequential test in terms of power and ability to locate the (unknown) breakpoint; but under the opposite alternative hypothesis ($\alpha_1 < \alpha_2$) the recursive test has an inferior performance. The latter result can be understood by observing that eq. (3.4) is based on the $m$ largest observations so that extremal returns occurring in the initial recursive sample will partly remain in the selection of the $m$ highest order statistics when the sample size is increased. This initial extremes dominance when $\alpha_1 < \alpha_2$ does not occur for the rolling test since the influence on $\widehat{\alpha}$ of extremal behavior that occurs in the initial sample gradually drops out when the rolling window is shifted through the total sample. Finally, the sequential test is consistent because it is constructed from the sum of the recursive and reverse recursive estimator, each of which is consistent in opposite directions. Notice, however, that the described "lack of power" problem of the recursive test when the true tail index is increasing over time is more apparent than real. Indeed, applying the recursive test on the "inverse" sample with reversed time, i.e., for recursive subsamples $(T, T-1, ..., T-t)$, solves the problem.

Because of its superior performance, we opt to work with Quintos' single breakpoint recursive test in this paper. (In the next version, we may add a procedure to also discover several break points.) The recursive test is performed using the expression

$$Y_T^2(t) = \left(\frac{tm_t}{T}\right)\left(\frac{\widehat{\alpha}_t}{\widehat{\alpha}_T} - 1\right)^2 , \tag{4.1}$$

where $t$ represents a fraction $r$ of the sample size $T$, i.e., $t = [rT]$. Eq. (4.1) compares Hill's estimator on subsamples $(\widehat{\alpha}_t)$ against the estimator on the whole sample $(\widehat{\alpha}_T)$. As such it reflects a sequence of test statistics as a function of candidate breakdates. Conform with Quandt's (1960) seminal work on structural change tests we select the candidate-breakpoint where the constancy hypothesis is most likely to be violated, i.e., select $r$ such that $Y_T^2(t)$ is maximal:[9]

$$Q_{r\in[0,1]} = \sup Y_T^2(t), \quad t = [rT] . \tag{4.2}$$

It can now be shown that

$$Q_{r\in[0,1]} \to^d \sup_{r\in[0,1]} \bar{W}(r)^2 , \tag{4.3}$$

where $\bar{W}(r) = W(r) - rW(1)$, $W(r)$ is a standard Wiener process and where $\to^d$ stands for convergence in distribution (Quintos et al.,

[9]Quintos et al. show how to make the breaks test robust to nonlinear dependencies in the data caused by e.g. GARCH effects. One has to rescale the test statistic $Y_T^2(t)$ with a time varying factor that depends on the GARCH parameters. For space considerations we do not present an indepth discussion of this scaling factor and how it has to be etimated, but the testing results reported in the empirical section are effectively rescaled to take account of GARCH effects.

2001). The same authors tabulated critical values ($\xi$) for this limiting distribution.

If one lacks prior knowledge on the direction of the jump in the tail index, the recursive test can be performed by applying eqs. (4.1)-(4.2) in calendar time (forward recursive test) and by inversing the sample (backward recursive test). A decrease of the tail index should be signaled by the forward test whereas an increase should be signaled by the backward test. Quintos et al. (2001) have shown that the size distortion of the structural breaks test for sample sizes like the one we are facing ($n \approx 3,000$) is acceptably small so that we can safely use the tabulated asymptotic critical values from their paper. The above procedure can now be performed using both the recursive (forward) and reverse recursive (backward) test independently. This allows for detecting increases (backward test) as well as decreases (forward test) in $\alpha$.

4.2. **Cross-sectional variation.** Apart from testing whether systemic banking risk measures are stable over time, we would also like to know whether cross-sectional differences between between different banking systems, say between the US and Europe or between different European countries, are statistically and economically significant. The asymptotic normality of the estimators enables some straightforward hypothesis testing. Hall (1982) proved that the Hill statistic in (3.4) converges in distribution when the number of highest order extremes grows suitably slowly with the sample size, i.e., for $m/n \to 0$ as $m, n \to \infty$ the statistic $\sqrt{m}\left(\frac{\widehat{\alpha}(m)}{\alpha} - 1\right)$ is asymptotically standard normally distributed. A test for the equality of tail indices between e.g. US and Europe can thus be based on the following $T$-statistic:

$$T = \frac{\widehat{\alpha}_1(m_1) - \widehat{\alpha}_2(m_2)}{\sqrt{\frac{c_1(\widehat{\alpha}_1)^2}{m_1} + \frac{c_2(\widehat{\alpha}_2)^2}{m_2} - \frac{2c_3 cov(\widehat{\alpha}_1, \widehat{\alpha}_2)}{m_1 m_2}}}, \tag{4.4}$$

which converges to a standard normal distribution in large samples. Note that the weighting in the denominator of the statistic takes non-linear dependence into account, so that the test is robust to GARCH in the data. One can safely assume that the Hill estimator and accompanying T-statistic lie sufficiently close to a normal distribution for empirical sample sizes as the one used below (see e.g. Hall, 1982, or Embrechts et al., 1997).

## 5. Data and descriptive statistics

We collected daily stock prices (excluding dividends) for 25 euro area banks and 25 US banks from the Datastream database. We added the corresponding series for the Datastream world stock market index. The series start on 1 January 1992 and end on 27 November 2003, about 3000 observations per bank. (The time dimension of this dataset was very much constrained by the unavailaility of longer stock price series for European banks, partly related to mergers.)

The banks were chosen according to two main criteria: First, their size (as measured mainly by assets and deposits) and their involvement in interbank lending (as measured by interbank loans/money market financing). The necessary balance-sheet information was taken from Bureau van Dijk's Bankscope database (considering end of year values between 1995 and 2002). So, the institutions in our sample cover the "systemically most important" banks all across the twelve years. By using several criteria to identify the "systemically important banks" naturally some choices had to be made. In particular, we tried to make sure that we cover the banks that are most active in clearing and settlement, even though some of them have smaller balance sheets than other banks. The justification for this is that the main "clearing banks" may consitute a particular source of contagion risk in a crisis. Appendix A contains the full list of banks, the abbreviations used in the tables and their country of origin. In the next version of the paper, we plan to extend the data to the second half of the 1980s.

The left-hand sides of tables 1 and 2 report the quantiles associated with the three common crash probabilities we employ in this paper. The three probabilities are chosen at the sample boundary $p = (100/n)\%$ and slightly to the left ($p = 0.05\%$) and to the right ($p = 0.02\%$) of this level. By chosing these low probabilities, and by using extreme-value theory, we ensure that there cannot be any doubt about the fact that the phenomona considered consitute crisis situations. By looking at several values for $p$, we can check the robustness of our results. Focusing on $p = 0.05\%$, for example, we can see that this corresponds to a 30% one-day stock price decline for Bankgesellschaft Berlin, a German bank that faced considerable difficulties towards the end of the sample period, and an 8% decline for IKB Deutsche Industriebank. The largest and smallest returns for the US are 15% for Unionbancal Corporation and 9% for Wells Fargo and Company. For the world stock market index this crash level is of course lower, namely about 4% (see the top of table 1).

## 6. Contagion risk in banking

In this section we report the results from our multivariate bank spillover measure. We are trying to answer two main sets of questions. 1) How large is bank contagion risk in euro area countries? And, in particular, what do our stock market indicators suggest about the relative importance of the risk of domestic contagion as compared to the risk of cross-border contagion? Answers to the latter question are particularly important in relation to the ongoing debate about supervisory co-operation and the structure of supervisory authorities in Europe. 2) What do our indicators say about the relative size of bank contagion risk when comparing the euro area with the United States? Is one banking system more at risk than the other? The former set of questions is addressed in sub-section 5.1 and the latter in sub-section 5.3. (In the next version of the paper we may add a sub-section 5.2 about the structure of domestic contagion risk in the US.) In the present section we still abstract from extreme systematic risk for the euro area and US banking system, as this is addressed in the following section (section 7).

6.1. **Europe.** In order to assess contagion risk in the euro area, as derived from banks' extreme stock price co-movements, we report in table 3 the estimation results for our measure (2.1) and for the $\eta$ parameter governing the extreme dependence (see culomns $\widehat{P}$ and $\widehat{\eta}$). To keep the amount of information managable, we only display in the table the contagion to the largest banks of the countries listed on the left-hand side. We calculate the co-crash probabilities conditional on the second, second and third, second, third and fourth and so on largest banks from Germany (upper panel), from Spain (middle panel) and from Italy (lower panel).

For example, the value 0.21 in the row "Germany" and the culomn "$\widehat{P}_1$" in the upper panel, refers to the probability that Deutsche Bank (the largest German bank) faces an extreme spillover from HypoVereinsbank (the second largest German bank). Going one cell down, the value 0.10 describes the probability that ABN AMRO (the largest Dutch bank) faces an extreme spillover from HypoVereinsbank. The difference between these two values would suggest that the likelihood of cross-border contagion could only be half of the likelihood of domestic contagion. When going through the table more systematically, it turns out that cross-border contagion risk seems smaller than domestic contagion risk in the euro area banking system, indeed. To pick just another example, the probability that the largest Spanish bank (Banco Santander Central Hispano) faces an extreme stock price slump given that the second (Banco Bilbao Vizcaya Argentaria) and third largest Spanish bank (Banco Espagnol de Credito) have experienced one is a non-negligible 67% (see column $\widehat{P}_2$, middle panel, row Spain). The same probability for the largest Portuguese bank (Banco Commercial Portugues) is only 8% (see column $\widehat{P}_2$, middle panel, row Portugal). The probabilities in the first row of each panel are systematically higher than the probabilities in the rows underneath. (Of course, the estimated values of the $\eta$ parameter, which determines the extreme dependence, leads to the same conclusions.)

Another observation from table 3 is that the main Finnish and Greek banks, located in two countries next to the outside "border" of the euro area, tend to be least affected by problems of large banks from other euro area countries.

The test results presented in table 4 show whether the differences between domestic and cross-country contagion risk described above are statistically significant or not. Rows and columns refer to the same banks as in table 3, but the cells now show t-statistics of the cross-sectional test described in sub-section 4.2. The null hypothesis is that domestic contagion risk equals cross-border contagion risk.[10] The test statistics partly qualify the interpretation of the contagion probabilities in table 3. Extreme cross-border linkages between Dutch, French, German and Spanish banks are not significantly different from domestic linkages within those countries. In contrast, for most of the remaining smaller countries (Belgium, Finland, Greece, Ireland and Portugal) the null hypothesis is rejected. So, severe problems of German, Italian and Spanish banks may create similar problems for other banks at home, but usually would not do so for the largest banks of those smaller countries.

Another interesting observation from table 3 is that contagion risk in Europe does not necessarily increase with an increasing number of conditioning banks that crash. (We need to double check this finding!) In our previous paper on currencies, we have denoted this relationship between the probability of crisis and the number of conditioning events as "contamination function" (see Hartmann, Straetmans and de Vries,

[10]The t-statistics result from comparing the $\eta$-values in table 5 with the domestic $\eta$-value (ceteris paribus the number of conditioning banks). For example, the t-statistic of -1.119 for the Netherlands in table 6 results from testing whether the $\eta$-value of 0.8066 for the Netherlands (ABN AMRO) w.r.t. the 2nd largest German bank (HYPO) significantly differs from the "domestic" $\eta$-value (0.8686) of the largest German bank (Deutsche bank) w.r.t. the 2nd largest German bank (HYPO).

2003, figures 1 to 7). The results in table 3 illustrate that contamination functions in banking do not need to be monotonuously increasing. One potential explanation for this phenomenon is "flight to quality", "flight to safety" or "competitive effects". Some banks may benefit from the troubles at other banks, as e.g. depositors withdraw their funds from the bad bank to put them in good banks. Such behaviour has been referred to by Kaufman (1988) in relation to US banking history, and Saunders and Wilson (1996) provided some evidence for it during two years of the Great Depression. For a more recent time period, Slovin, Sushka and Polonchek (1999) find regional "competitive effects" in response to dividend reduction and regulatory action announcements.

The finding of similar contagion risk between major euro area banks within and between some large countries could be important, if confirmed by robustness checks, also for supervisory policies. One explanation for it may be the strong involvement of those banks in the unsecured euro interbank market. As these large players interact directly with each other, and in large amounts, one channel of contagion risk could be the exposures resulting from such trading. (In the next version of the paper, we plan to test whether the relative importance of cross-border contagion risk compared to domestic contagion risk has changed with EMU.) One implication of the finding is that banking supervision needs to have a cross-border dimension in the euro area. This is currently happening through the application of the home-country principle (the home supervisor considers domestic and foreign operations of a bank) and by the existence of various bilateral memoranda of understanding between supervisory authorities. The results, if confirmed, could provide further arguments in favour of an increasing degree of centralization in European supervisory structures over time.

It is also interesting to see that in some smaller and less central countries in the area domestic contagion risk is still larger than cross-border risk. This could suggest that even the larger players from those countries are still less interlinked with the larger players from the bigger countries.

Overall, one could perhaps conclude that the results so far suggest that the still relatively limited cross-border integration of banking in the euro area does not seem to constrain contagion risk among the larger players from some key countries in the area. One explanation for this finding could be that while bank mergers have been mainly national and traditional loan and deposit business of banks are only to a very limited extent expanding across national borders (see e.g. the recent evidence provided in Hartmann, Maddaloni and Manganelli

(2003, figures 10 and 11), much of the wholesale business happens in international markets that are highly interlinked.

6.2. **United States.** [Add a section on the structure of domestic contagion risk in the US? Does it make sense to look at the relative size of within-state vs. cross-state contagion and compare the results to Europe?]

6.3. **Cross-Atlantic comparison.** Our final step to examine contagion risk consists of comparing it between the euro area and US banking systems. To do so, we calculate for each system the tail dependence parameter $\eta$ that governs the estimate of the multivariate contagion risk measure (2.1). Notice that for each continent $\eta_{US}$ and $\eta_{EUR}$ are derived from all the extreme stock prices linkages between the respective $N$=25 banks, following the estimation procedure described in section 3. We obtain $\widehat{\eta}_{US} = 0.377298$ and $\widehat{\eta}_{EUR} = 0.14017359$. This would mean that overall contagion risk in the US banking system is almost three times higher than contagion risk in the euro area.

Is this difference statistically significant? We apply the GARCH-robust cross-sectional stability test (4.4) described in sub-section 4.2, with the following null hypothesis:

$$H_0 : \eta_{US} = \eta_{EUR} \ .$$

It turns out that the t-statistic reaches the level t=8.24. In other words our indicators and tests suggest that the difference in systemic risk between the US and the euro area is not only sizable but also highly statistically significant. One explanation could be that in a much more highly integrated banking system, such as the one of the US, systemic risk is much higher, as banking business is much more interconnected.

## 7. Aggregate banking system risk

Next we turn to the analysis based on our measure of extreme systematic risk. We are interested in assessing to which extent individual banks are vulnerable to an aggregate shock, as captured by an extreme downturn of the market risk factor. Sub-section 7.1 focuses on the euro area and sub-section 7.2 on the United States. (In the next version we plan to add another sub-section testing for differences in extreme systematic risk between the euro area and the US.)

7.1. **Europe.** The right-hand side of table 1 reports the results for the "tail-$\beta$s". The middle column describes the $\eta$ extreme dependence parameter entering this bivariate measure and the three columns on the right contain the probability that a given euro area bank faces an extreme downturn in its equity value given that the world market index faces an extreme downturn. To check robustness, three common percentiles around the sample boundary are distinguished. For example, teh value 0.15 in row "SGENER" and column "$p$=0.05%" means that a 4.4% or larger downturn in the world market index is usually associated with a 15% probability that Societe General, a large French bank, faces an extreme downturn of 11.4% or larger. Going to the right in the same row indicates that for even higher common crash levels extreme systematic risk for this bank is slightly lower but not much so.

Going more systematically up and down these columns, one can see that "tail-$\beta$s" can be quite different across banks, ranging between 0.05% and 15% for the higher common percentile and between 0.02% and 13% for the lower percentile. Some large banks from relatively large and central countries in the euro area have the higher "tail-$\beta$s", whereas some main banks from some more peripheral smaller countries can have quite low "tail-$\beta$s". One interpretation of this result is that the more local business of the latter banks exposes them less to aggregate world market risk.

7.2. **United States.** The results for the US displayed on the right-hand side of table 2 are actually quite similar to the ones from Europe. Some large players with global business, such as e.g. Citygroup, JP Morgan Chase or State Street, have relatively large "tail-$\beta$s", whereas a large savings&loans association like Washington Mutual that has more local retail business has a relatively low "tail-$\beta$". Across banks the range is between 2% and 18% for the higher percentile and between 1% and 16% for the lower percentile.

7.3. **Cross-Atlantic comparison.** Tables 1 and 2 suggest that "tail-$\beta$s" in the euro area and in the US are relatively similar. Note that they are comparable, as they are both conditioned on the same world market index for the same crash levels. The very slightly higher range of values for the US is unlikely to be statistically signifcant. (In the next version of the paper we plan to provide a test comparing the euro area with the US.)

## 8. Has systemic risk increased?

A crucial issue for supervisory policies is whether banking system risks change over time. In particular, it would be important to know whether they may have increased lately. Therefore, we apply in the present section our multivariate extension of the structural stability test by Quintos, Fan and Phillips (2001; see sub-section 4.2) to the estimators of multivariate contagion and systematic risk (sub-sections 8.1 and 8.2, respectively).

8.1. **Time variation of contagion risk.** We apply the structural stability test described in equations (4.1)-(4.2) in a recursive way to the extreme tail dependence parameter $\eta = 1/\alpha$. The null hypothesis for each continent is

$$H_0 : \eta_1 = \eta_2$$

for any decomposition of the sample in two periods. So, we calculate the tail dependence parameter value that spans the whole US block $\widehat{\eta}_{US}$ and the whole European block $\widehat{\eta}_{EUR}$ and test for structural change.

In both cases the test rejects the null hypothesis. The strongest break found for the euro area happens on 3 December 1996 (test value of 4.97) and for the US on 20 July 1998 (test value of 10.21).[11] In both cases the common $\eta$-value is larger in the second period. In sum, we detect a statistically significant increase of multivariate contagion risk both in the euro area and in the US banking system. Both systems seem to be more vulnerable to contagion risk today than they have been in the early 1990s. (In the next version of the paper we will be allowing for more than one break point in each case. Preliminary tests - not reported here - suggest that the introduction of the euro had only a very weak effect on contagion risk in the euro area.)

The increase of contagion risk found for the US is consistent with the findings of de Nicolo and Kwast (2002), who detect an upward trend of regular correlations between US large and complex banking organizations (LCBOs) during the period 1988 to 1999 and interprete it as a sign of increasing systemic risk.[12] The authors estimate that part of the increase is likely to be related to consolidation among LCBOs. The timing of structural change in de Nicolo and Kwast's paper is, however, somewhat different from ours, as they find most correlation changes during 1996 and perhaps 1997. Our break point, in contrast, is very close to the Russian debt default and also not very far from the LTCM bailout. (In the revised version of the paper we would like to discuss possible explanations why the events of late summer/early fall 1998 may have changed contagion risk in US banking. We also want

[11]Both results are highly significant, way beyond the 99% confidence level. Quintos et al. (2001) report critical values in the table of their appendix A (p. 662).

[12]Within the group of about 22 LCBOs, however, most of the increase in correlations is concentrated among the less complex banks.

to address what could explain an increase in European contagion risk at the end of 1996.)

8.2. **Time variation of "tail-$\beta$s".** Now we apply the structural stability test of extreme systematic risk. Table 5 reports the results for the euro area and table 6 for the United States. Each table shows columns – going from left to right – for the respective banks, the estimated break points (if any, with test value in parentheses), the $\eta$ parameter value before the break, the tail-$\beta$ value before the break, the $\eta$ parameter value after the break and the tail-$\beta$ value after the break.

The resounding result is that extreme systematic risk has increased almost across the board.[13] In other words, both the euro area and the US banking system seem to be more exposed to aggregate shocks today than they were in the early 1990s. While this increase is in line with what happend with contagion risks (see the previous sub-section), the break points are somewhat different. In Europe, most of the break points occur in the second half of 1997, often relatively close to onset of the Asian financial crisis. While this is also the case for some US banks, most of the US institutions experience their breaks somewhat earlier, namely in the second half of 1996.[14]

- Asian crisis is the recurring statistically significant break for nearly all banks, both Europe and US; this is also reflected in the strong rise in estimated tail beta's if one estimates the tail beta's across the subsamples determined by the break dates.

## 9. Conclusions

[To be written.]

## Appendix A. List of banks in the sample

US banks: Citygroup (CITYG), JP Morgan Chase (JPMORGAN), Bank of America (BOA), Wachovia Corporation (WACHO), Wells Fargo and Company (FARGO), Bank One Corporation (BONEC), Washington Mutual Inc. (WASHMU), Fleet Boston Financial Corporation (FLEET), Bank of New York (BNYORK), State Street (STATEST),

[13]Only in the cases of Banco Espirito Santo from Portugal and Okobank from Finland the test does not find any break.

[14]Notice that these results are different from the ones by de Nicolo and Kwast (2002) from standard market model $\beta$s among US LCBOs. They do not identify any increase of the impact of the general market index on LCBO stock returns between 1992 and 1999. They only observe an increase of the impact of a special sectoral LCBO index in late 1992/early 1993, conditional on the general market index.

Northern Trust (NOTRUST), Mellon (MELLON), US Bancorp (USBANC), National City Corporation (CITYCO), PNC Financial services Group (PNC), Keycorp (KEYCORP), Sun Trust (SUNTRUST), Comerica Incorporated (COMERICA), Unionbancal Corporation (UNIONBA), Bank of Hawaii Corporation (HAWAII), Huntington Bancshares Inc. (HUNTING), BBT Corporation (BBT), Fifth Third Bancorp (53BANCO), Southtrust (SOTRUST), Regions Financial Corporation (REGIONS).

Euro area banks: Deutsche Bank (DEUTSCHE, Germany), Bayerische Hypo-und Vereinsbank (HYPO, Germany), ABN AMRO (ABNAM, Netherlands), Societe Generale (SGENER, France), ING Bank (ING, Netherlands), Banco Santander Central Hispano (SANTANDER, Spain), Banca Intesa (INTESA, Italy), Banca Bilbao Vizcaya Argentaria (BILBAO, Spain), Commerzbank (COMMERZ, Germany), Bankgesellschaft Berlin (BGBERLIN, Germany), UniCredito Italian (UNICRED, Italy), KBC Bank (KBC, Belgium), DePfa Group (DEPFA, Germany), Natexis Banques Populaires (NATEXIS, France), Allied Irish Banks (IRBAN, Ireland), Bank of Ireland (BOIRE, Ireland), Banco Commercial Portugues (BCPOR, Portugal), Banco Espagnol de Credito (BESCRE, Spain), Banco Espirito Santo (ESPSAN, Portugal), Sampo Leonia (SAMPO, Finland), IKB Deutsche Industriebank (IKB, Germany), Banco Popular Espanol (POPESP, Spain), Alpha Bank (ALPHA, Greece), Banco Populare di Milano (MILANO, Italy), Okobank (OKO, Finland).

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TABLE 1. Univariate crash levels and extreme systematic risk (tail betas) of euro area banks

| bank | $\widehat{Q}(p)$ % | | | $\widehat{\eta}$ | $\widehat{P} = p^{1/\widehat{\eta}-1}$ | | |
|---|---|---|---|---|---|---|---|
| | | $p$ | | | | $p$ | |
| | 0.05% | $(100/n)$% | 0.02% | | 0.05% | $(100/n)$% | 0.02% |
| WORLD M | 4.37 | 4.88 | 5.48 | - | - | - | - |
| DEUTSCHE | 12.14 | 13.65 | 15.48 | 0.84306 | 0.15070 | 0.13884 | 0.12707 |
| HYPO | 17.18 | 19.71 | 22.86 | 0.74466 | 0.05298 | 0.04555 | 0.03869 |
| ABNAM | 12.16 | 13.51 | 15.13 | 0.83144 | 0.14059 | 0.12858 | 0.11675 |
| SGENER | 11.42 | 12.51 | 13.80 | 0.85242 | 0.15231 | 0.14113 | 0.12997 |
| ING | 14.22 | 15.76 | 17.61 | 0.83512 | 0.13826 | 0.12675 | 0.11538 |
| SANTAN | 13.25 | 15.00 | 17.16 | 0.84270 | 0.15024 | 0.13839 | 0.12662 |
| INTESA | 12.49 | 13.78 | 15.32 | 0.75841 | 0.05513 | 0.04792 | 0.04117 |
| BILBAO | 12.23 | 13.70 | 15.48 | 0.82696 | 0.13643 | 0.12442 | 0.11263 |
| COMMERZ | 13.00 | 14.66 | 16.70 | 0.82528 | 0.12111 | 0.11033 | 0.09975 |
| BGBERLIN | 29.84 | 36.92 | 46.48 | 0.61462 | 0.00662 | 0.00502 | 0.00372 |
| UNICRED | 10.34 | 11.11 | 12.00 | 0.74826 | 0.04051 | 0.04050 | 0.03451 |
| KBC | 8.55 | 9.27 | 10.11 | 0.75497 | 0.05585 | 0.04842 | 0.04148 |
| DEPFA | 13.50 | 15.50 | 17.98 | 0.71098 | 0.02841 | 0.02375 | 0.01957 |
| NATEXIS | 10.51 | 12.30 | 14.57 | 0.66190 | 0.01434 | 0.01145 | 0.00898 |
| IRBANKS | 15.07 | 17.93 | 21.64 | 0.73203 | 0.04418 | 0.03761 | 0.03159 |
| BOIRE | 9.90 | 10.94 | 12.20 | 0.76804 | 0.06487 | 0.05679 | 0.04919 |
| BAPOR | 14.22 | 16.99 | 20.60 | 0.80954 | 0.08541 | 0.07700 | 0.06884 |
| BESPCRE | 21.44 | 26.42 | 33.11 | 0.60243 | 0.00563 | 0.00421 | 0.00308 |
| ESPSAN | 19.67 | 23.21 | 27.76 | 0.49680 | 0.00047 | 0.00030 | 0.00019 |
| SAMPO | 19.36 | 21.97 | 25.20 | 0.64561 | 0.01221 | 0.00959 | 0.00738 |
| IKB | 7.52 | 8.57 | 9.88 | 0.63858 | 0.009661 | 0.00753 | 0.00572 |
| POPESP | 8.58 | 9.58 | 10.80 | 0.75766 | 0.05459 | 0.04742 | 0.04072 |
| ALPHA | 12.37 | 13.80 | 15.52 | 0.64026 | 0.01134 | 0.00886 | 0.00678 |
| MILANO | 14.57 | 16.96 | 19.97 | 0.70057 | 0.02802 | 0.02322 | 0.01894 |
| OKO | 14.93 | 16.91 | 19.35 | 0.50694 | 0.00069 | 0.00045 | 0.00028 |

Note: The table's left panel reports univariate quantiles (crisis levels) for the different bank stocks. The quantiles are calculated for three values of the significance level p that correspond with an in-sample quantile (p=0.05%), a boundary sample quantile (p=inverse of the sample size) and an out-of-sample quantile (p=0.02%). The table's right panel reports the probability that inidividual bank stocks crash given a crash in the market portfolio. The probabilities are evaluated for the three significance levels used in the left panel.

TABLE 2. Univariate crash levels and extreme systematic risk (tail betas) of US banks

| bank | $\widehat{Q}_1(p)$ | | | $\widehat{\eta}$ | $\widehat{P}=p^{1/\widehat{\eta}-1}$ | | |
|---|---|---|---|---|---|---|---|
| | $p$ | | | | $p$ | | |
| | 0.05% | $\frac{100}{n}$% | 0.02% | | 0.05% | $p=\frac{100}{n}$% | 0.02% |
| CITYG | 12.95 | 14.68 | 16.82 | 0.84239 | 0.15794 | 0.14711 | 0.13457 |
| JPMORGAN | 12.69 | 14.28 | 16.21 | 0.83640 | 0.15471 | 0.14195 | 0.12933 |
| BAMERICA | 10.95 | 12.21 | 13.75 | 0.75441 | 0.06360 | 0.05511 | 0.04719 |
| WACHOVIA | 10.06 | 11.21 | 12.62 | 0.77970 | 0.07940 | 0.07011 | 0.06129 |
| FARGO | 8.72 | 9.68 | 10.84 | 0.69951 | 0.03164 | 0.02618 | 0.02134 |
| BANKONE | 13.48 | 15.64 | 18.36 | 0.80460 | 0.10209 | 0.09174 | 0.08172 |
| WASHING | 10.74 | 11.90 | 13.31 | 0.67145 | 0.01948 | 0.01570 | 0.01244 |
| FLEET | 10.59 | 11.75 | 13.16 | 0.79372 | 0.09529 | 0.08499 | 0.07510 |
| BNYORK | 13.00 | 14.85 | 17.16 | 0.82367 | 0.12252 | 0.11150 | 0.10070 |
| SSTREET | 14.20 | 16.32 | 18.98 | 0.87113 | 0.18304 | 0.17150 | 0.15984 |
| NTRUST | 10.08 | 11.16 | 12.46 | 0.83327 | 0.13999 | 0.12819 | 0.11654 |
| MELLON | 11.69 | 13.16 | 14.96 | 0.79661 | 0.10456 | 0.09345 | 0.08275 |
| BANCORP | 13.29 | 15.29 | 17.80 | 0.72054 | 0.04191 | 0.03533 | 0.02937 |
| CITYCO | 8.47 | 9.33 | 10.35 | 0.75193 | 0.05934 | 0.05132 | 0.04386 |
| PNC | 10.07 | 11.31 | 12.83 | 0.78694 | 0.08643 | 0.07672 | 0.06744 |
| KEYCO | 9.41 | 10.43 | 11.65 | 0.75641 | 0.06347 | 0.05508 | 0.04725 |
| SUNTRU | 9.87 | 11.21 | 12.87 | 0.78124 | 0.08049 | 0.07115 | 0.06227 |
| COMERICA | 10.63 | 12.12 | 13.96 | 0.77042 | 0.07348 | 0.06445 | 0.05592 |
| UNIONBAN | 15.26 | 17.73 | 20.85 | 0.70508 | 0.03196 | 0.02659 | 0.02179 |
| HAWAII | 10.39 | 11.78 | 13.50 | 0.72957 | 0.04520 | 0.03840 | 0.03218 |
| HUNTING | 12.07 | 13.76 | 15.84 | 0.76776 | 0.06401 | 0.05603 | 0.04851 |
| BBT | 8.91 | 9.96 | 11.22 | 0.73433 | 0.04875 | 0.04157 | 0.03499 |
| 53BANCO | 8.61 | 9.52 | 10.62 | 0.72308 | 0.04192 | 0.03541 | 0.02951 |
| SOUTH | 10.23 | 11.51 | 13.07 | 0.72543 | 0.04108 | 0.03477 | 0.02904 |
| REGIONS | 12.30 | 14.34 | 16.39 | 0.74860 | 0.05574 | 0.04808 | 0.04098 |

Note: The table's left panel reports univariate quantiles (crisis levels) for the market portfolio and the different bank stocks. The quantiles are calculated for three values of the significance level p that correspond with an in-sample quantile (p=0.05%), a boundary sample quantile (p=inverse of sample size) and an out-of-sample quantile (p=0.02%). The table's right panel reports the probability that inidividual bank stocks crash given a crash in the market portfolio. The probabilities are evaluated for the three significance levels used in the left panel.

Table 3. Domestic versus cross-border contagion risk in the euro area: estimations

| Largest bank | $\widehat{\eta}_1$ | $\widehat{P}_1$ | $\widehat{\eta}_2$ | $\widehat{P}_2$ | $\widehat{\eta}_3$ | $\widehat{P}_3$ | $\widehat{\eta}_4$ | $\widehat{P}_4$ |
|---|---|---|---|---|---|---|---|---|
| | | | | Conditioning banks: German | | | | |
| Germany | 0.8686 | 0.2100 | 0.7643 | 0.1715 | 0.5367 | 0.7401 | 0.4531 | 0.6156 |
| Netherlands | 0.8066 | 0.0999 | 0.7337 | 0.0914 | 0.5130 | 0.3140 | 0.3347 | 0.4357 |
| France | 0.7707 | 0.0578 | 0.6892 | 0.0477 | 0.5146 | 0.3081 | 0.3086 | 0.0549 |
| Spain | 0.7621 | 0.0508 | 0.6931 | 0.0506 | 0.5015 | 0.2132 | 0.2916 | 0.0135 |
| Italy | 0.7420 | 0.0371 | 0.6775 | 0.0372 | 0.4992 | 0.1811 | 0.2783 | 0.0037 |
| Belgium | 0.7468 | 0.0419 | 0.6643 | 0.0309 | 0.5175 | 0.3178 | 0.3136 | 0.0806 |
| Ireland | 0.6625 | 0.0117 | 0.5670 | 0.0045 | 0.4429 | 0.0286 | 0.2683 | 0.0014 |
| Portugal | 0.6955 | 0.0178 | 0.5515 | 0.0032 | 0.4451 | 0.0309 | 0.2690 | 0.0015 |
| Finland | 0.5275 | 0.0008 | 0.4841 | 0.0005 | 0.4239 | 0.0130 | 0.2593 | 0.0005 |
| Greece | 0.5910 | 0.0032 | 0.5077 | 0.0010 | 0.4147 | 0.0086 | 0.2403 | 5E-5 |
| | | | | Conditioning banks: Spanish | | | | |
| Spain | 0.9764 | 0.4934 | 0.6326 | 0.6714 | 0.5097 | 0.4358 | - | - |
| Germany | 0.8102 | 0.0960 | 0.5179 | 0.0450 | 0.4336 | 0.0281 | - | - |
| Netherlands | 0.8843 | 0.1949 | 0.5296 | 0.0633 | 0.4517 | 0.0561 | - | - |
| France | 0.8530 | 0.1459 | 0.5302 | 0.0684 | 0.4694 | 0.1083 | - | - |
| Italy | 0.6955 | 0.0229 | 0.4732 | 0.0124 | 0.3942 | 0.0053 | - | - |
| Belgium | 0.7332 | 0.0370 | 0.4866 | 0 .0188 | 0.4325 | 0.0263 | - | - |
| Ireland | 0.6918 | 0.0194 | 0.4969 | 0.0224 | 0.4279 | 0.0198 | - | - |
| Portugal | 0.6987 | 0.0216 | 0.5460 | 0.0832 | 0.4409 | 0.0333 | - | - |
| Finland | 0.5791 | 0.0027 | 0.4669 | 0.0086 | 0.4136 | 0.0105 | - | - |
| Greece | 0.6002 | 0.0040 | 0.4691 | 0.0088 | 0.4077 | 0.0074 | - | - |
| | | | | Conditioning banks: Italian | | | | |
| Italy | 0.7422 | 0.0454 | 0.6154 | 0.1871 | - | - | - | - |
| Germany | 0.7362 | 0.0361 | 0.5606 | 0.0562 | - | - | - | - |
| Netherlands | 0.7010 | 0.0243 | 0.5678 | 0.0692 | - | - | - | - |
| France | 0.6989 | 0.0228 | 0.5796 | 0.0853 | - | - | - | - |
| Belgium | 0.7279 | 0.0308 | 0.5705 | 0.0661 | - | - | - | - |
| Ireland | 0.6167 | 0.0055 | 0.5106 | 0.0140 | - | - | - | - |
| Portugal | 0.6342 | 0.0069 | 0.5195 | 0.0176 | - | - | - | - |
| Finland | 0.6098 | 0.0046 | 0.4457 | 0.0019 | - | - | - | - |
| Greece | 0.5374 | 0.0009 | 0.4331 | 0.0010 | - | - | - | - |

Note: The table reports conditional co-crash probabilities $P_i$ for the largest bank stock in each country conditional upon a set of banks from either the same country or other countries. We use the extended Ledford-Tawn estimation approach applied to measures like in eq. (2.1). The number of conditioning banks $i$ varies from 1 to 4 for Germany (panel A), from 1 to 3 for Spain and from 1 to 2 for Italy. For example, the $\widehat{P}_2$ column stands for the crash probability of the largest bank in each country conditional on a crash in the 2nd and 3rd largest bank in Germany (Panel A), Spain (panel B), or Italy (Panel C). Estimates of the respective Pareto exponents $\widehat{\eta} = 1/\widehat{\alpha}$ that govern the multivariate tails are also reported.

TABLE 4. Domestic versus cross-border contagion risk in the euro area: tests

| Largest bank | Cross sectional t-test stats | | | |
|---|---|---|---|---|
| | Conditioning banks: German | | | |
| Netherlands | -1.119 | -0.632 | -0.239 | -0.929 |
| France | -0.414 | -0.499 | -0.207 | -0.404 |
| Spain | -1.084 | -1.765 | 0.436 | -0.995 |
| Italy | -1.521 | -2.225 | -1.851 | -1.856 |
| Belgium | -1.680 | -1.766 | -1.103 | -2.568 |
| Ireland | -2.462 | -4.024 | -0.957 | -1.916 |
| Portugal | -1.040 | -1.723 | -0.317 | -2.453 |
| Finland | -5.387 | -5.639 | -3.373 | -3.456 |
| Greece | -5.294 | -6.022 | -2.514 | -3.209 |
| | Conditioning banks: Spanish | | | |
| Germany | -1.184 | -0.769 | -1.667 | - |
| Netherlands | -0.693 | -1.487 | -1.315 | - |
| France | -0.816 | -1.400 | -2.227 | - |
| Italy | -2.752 | -1.196 | -3.055 | - |
| Belgium | -3.012 | -3.167 | -2.310 | - |
| Ireland | -3.975 | -2.635 | -2.033 | - |
| Portugal | -2.788 | -1.603 | -3.033 | - |
| Finland | -6.502 | -3.840 | -3.089 | - |
| Greece | -5.765 | -4.226 | -1.347 | - |
| | Conditioning banks: Italian | | | |
| Germany | -0.758 | -0.735 | - | - |
| Netherlands | -0.841 | -0.792 | - | - |
| France | 0.331 | -0.347 | - | - |
| Belgium | -0.354 | -0.558 | - | - |
| Ireland | -2.555 | -2.811 | - | - |
| Portugal | -2.825 | -2.074 | - | - |
| Finland | -2.229 | -3.831 | - | – |
| Greece | -3.842 | -3.838 | - | - |

Note: The table reports testing values for the cross sectional test in eq. (4.4). Within each panel we compare the degree of domestic contagion with the degree of cross-country contagion for a given fixed number of conditioning banks. So each t-stat reflects whether the differences between domestic and cross border values of $\eta$ within each column (keeping the number of conditioning banks fixed) of the previous table are statistically significant. For example, the test statistics in the "Netherlands" row for Panel A compares the degree of domestic contagion within the German banking sector - as measured by the exponent $\eta$ - with the contagion effect from Germany to the Netherlands. Insignificant t-stats imply that the domestic and cross country contagion effects are indistinguishable; whereas a significant rejection implies that cross country contagion is much smaller than it's domestic counterpart.

Table 5. Structural change in extreme systematic risk of euro area banks: estimation and test results

| bank | breakdate (sup) | Subsample estimates | | | |
|---|---|---|---|---|---|
| | | $\widehat{\eta}_{pre}$ | $\widehat{P}_{pre}$ | $\widehat{\eta}_{post}$ | $\widehat{P}_{post}$ |
| DEUTSCHE | 31/7/97 (56.90) | 0.65381 | 0.01587 | 0.79171 | 0.10598 |
| HYPO | 31/7/97 (69.52) | 0.56821 | 0.00412 | 0.70234 | 0.03627 |
| ABNAM | 4/7/96 (41.42) | 0.59984 | 0.00745 | 0.80817 | 0.12054 |
| SGENER | 22/10/97 (35.05) | 0.65794 | 0.01579 | 0.84886 | 0.16417 |
| ING | 1/8/97 (60.55) | 0.61263 | 0.00875 | 0.83102 | 0.14426 |
| SANTANDER | 16/10/97 (41.51) | 0.61543 | 0.00863 | 0.83261 | 0.15760 |
| INTESA | 8/10/97 (20.48) | 0.58623 | 0.00461 | 0.75534 | 0.06541 |
| BILBAO | 8/10/97 (34.42) | 0.65612 | 0.01701 | 0.82479 | 0.14758 |
| COMMERZ | 21/8/97 (61.36) | 0.60605 | 0.00795 | 0.74683 | 0.06619 |
| BGBERLIN | 5/12/96 (15.62) | 0.51892 | 0.00140 | 0.56777 | 0.00317 |
| UNICRED | 8/10/97 (17.19) | 0.60794 | 0.00678 | 0.77167 | 0.07634 |
| KBC | 20/6/97 (90.99) | 0.53658 | 0.00193 | 0.76370 | 0.06453 |
| DEPFA | 11/8/97 (31.06) | 0.58611 | 0.00447 | 0.68517 | 0.02295 |
| NATEXIS | 27/8/97 (16.22) | 0.48015 | 0.00048 | 0.70909 | 0.03546 |
| IRBAN | 22/10/97 (16.31) | 0.65378 | 0.01724 | 0.72495 | 0.04337 |
| BOIRE | 8/10/97 (24.09) | 0.71416 | 0.03459 | 0.75509 | 0.05933 |
| BCPOR | 17/7/97 (48.50) | 0.52101 | 0.00114 | 0.76467 | 0.06746 |
| BESPCRE | 22/10/97 (2.99) | 0.55381 | 0.00287 | 0.64119 | 0.01281 |
| ESPSAN | - | - | - | - | - |
| SAMPO | 18/12/97 (12.54) | 0.57031 | 0.00351 | 0.73376 | 0.04456 |
| IKB | 3/9/97 (12.38) | 0.52773 | 0.00148 | 0.67697 | 0.02040 |
| POPESP | 24/10/97 (19.94) | 0.61490 | 0.00862 | 0.76555 | 0.06717 |
| ALPHA | 26/2/97 (66.55) | 0.43094 | 0.00013 | 0.61221 | 0.00829 |
| MILANO | 23/1/97 (46.32) | 0.51039 | 0.00098 | 066858 | 0.02122 |
| OKO | - | - | - | - | - |

Note: The table's left panel contains test results on the break date. The 1st column reports estimated break dates using the forward version of our recursive testing procedure. Calendar dates are in continental notation (dd/mm/yy). The Sup-values correspond with the value of the test statistic at the break dates. Asymptotic critical values for Q are 1.78 and 2.54 at the 95% and 99% significance levels, respectively, see e.g. Quintos et al. (2001). Subsample (pre-and post-break) estimates of the tail dependence coefficients and corresponding extreme systematic risk (tail betas) are reported in the right panel of the table.

Table 6. Structural change in extreme systematic risk of US banks: estimation and test results

| bank | break date(sup) | Subsample estimates | | | |
|---|---|---|---|---|---|
| | | $\widehat{\eta}_{pre}$ | $\widehat{P}_{pre}$ | $\widehat{\eta}_{post}$ | $\widehat{P}_{post}$ |
| CITYG | 26/6/96 (30.61) | 0.61235 | 0.01117 | 0.86321 | 0.20576 |
| JPMORGAN | 16/10/97 ( 23.60) | 0.68967 | 0.02780 | 0.77550 | 0.10476 |
| BOA | 4/7/96 (26.98) | 0.58499 | 0.00671 | 0.76443 | 0.07425 |
| WACHO | 25/2/97 (21.46) | 0.63117 | 0.01226 | 0.75063 | 0.06635 |
| FARGO | 21/8/97 (8.63) | 0.67204 | 0.02177 | 0.73091 | 0.05147 |
| BONEC | 2/1/96 (25.97) | 0.63362 | 0.01246 | 0.78040 | 0.09024 |
| WASHMU | 15/10/97 (11.48) | 0.65938 | 0.01624 | 0.67111 | 0.02235 |
| FLEET | 8/1/98 (37.62) | 0.63809 | 0.01379 | 0.77860 | 0.09462 |
| BNYORK | 10/12/96 (26.16) | 0.64431 | 0.01599 | 0.78971 | 0.09773 |
| STATEST | 10/12/96 (42.37) | 0.65829 | 0.01710 | 0.79098 | 0.10853 |
| NOTRUST | 5/12/96 (48.74) | 0.60076 | 0.00757 | 0.77440 | 0.09206 |
| MELLON | 4/7/96 (20.71) | 0.64229 | 0.01503 | 0.80809 | 0.12359 |
| USBANC | 20/8/97 (31.21) | 0.59882 | 0.00724 | 0.70908 | 0.04018 |
| CITYCO | 2/12/96 (25.98) | 0.62185 | 0.01027 | 0.75476 | 0.06510 |
| PNC | 24/10/95 (32.03) | 0.47069 | 0.00066 | 0.80439 | 0.11056 |
| KEYCO | 2/12/96 (26.00) | 0.61134 | 0.00929 | 0.71927 | 0.04657 |
| SUNTRUST | 24/10/95 ( 32.30) | 0.52893 | 0.00242 | 0.72236 | 0.04733 |
| COMERICA | 4/7/96 (20.19) | 0.59513 | 0.00719 | 0.76785 | 0.08012 |
| UNIONBAN | 29/10/97 (7.40) | 0.63028 | 0.01048 | 0.69968 | 0.03497 |
| HAWAII | 22/10/97 (24.06) | 0.65341 | 0.01592 | 0.70589 | 0.03853 |
| HUNTING | 24/10/97 (33.81) | 0.61921 | 0.00842 | 0.77235 | 0.07682 |
| BBT | 24/6/98 (23.75) | 0.60421 | 0.00732 | 0.77941 | 0.09205 |
| 53BANCO | 10/12/96 (24.58) | 0.62362 | 0.01041 | 0.69011 | 0.03019 |
| SOTRUST | 17/9/97 (29.00) | 0.59664 | 0.00610 | 0.71408 | 0.04272 |
| RFCORP | 28/8/97 (16.82) | 0.68372 | 0.02398 | 0.73843 | 0.05591 |

Note: The table's left panel contains test results on the break date. The 1st column reports estimated break dates using the forward version of our recursive testing procedure. Calendar dates are in continental notation (dd/mm/yy). The Sup-values correspond with the value of the test statistic at the break dates. Asymptotic critical values for Q are 1.78 and 2.54 at the 95% and 99% significance levels, respectively, see e.g. Quintos et al. (2001). Subsample (pre-and post-break) estimates of the tail dependence coefficients and corresponding extreme systematic risk (tail betas) are reported in the right panel of the table.

*Current address*: Philipp Hartmann, European Central Bank and CEPR, DG Research, Kaiserstraß e 29, 60311 Frankfurt, Germany
*E-mail address*: philipp.hartmann@ecb.int
*URL*: http://papers.ssrn.com/sol3/cf_dev/AbsByAuth.cfm?per_id=229414

*Current address*: Stefan Straetmans, Limburg Institute of Financial Economics (LIFE), Economics Faculty, Maastricht University, P.O.Box 616, 6200 MD Maastricht, The Netherlands
*E-mail address*: s.straetmans@berfin.unimaas.nl
*URL*: http://www.fdewb.unimaas.nl/finance/faculty/straetmans/

*Current address*: Casper G. de Vries, Erasmus Universiteit Rotterdam, Economics, P. O. Box 1738, 3000 DR Rotterdam, The Netherlands
*E-mail address*: cdevries@few.eur.nl
*URL*: http://www.few.eur.nl/people/cdevries/