BANKING SYSTEM STABILITY: A CROSS-ATLANTIC PERSPECTIVE

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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.

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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 or the existence of contagion risk 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 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 country 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 and exchange 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 more regular propagations or changes in them are not necessarily a concern for policies that aim at the stability of financial systems.[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]

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[1] Less extreme spillovers might still indicate some form of microeconomic inefficiencies but not necessarily widespread destabilization.

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 supervisory authorities 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).

A recent central banking literature attempts to assess the importance of contagion risk by simulating chains of failures from (incomplete and mostly confidential) national information about interbank exposures. See, e.g., Furfine (2003), Lehar and Summer (2002), Upper and Worms (2004), Degryse and Nguyen (2004) or Lelyveld and Liedorp (2004).

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 Swary (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 (2002) relate changes in correlations between bank stock prices over time to banking consolidation. Gropp and Moerman (2004) measure conditional co-movements of abnormal bank stock returns and of equity-derived distances to default at the 5 and 95 percentile. Gropp and Vesala (2004) take out aggregate factors from these equity-based distances to default using factor analysis and apply an ordered logit approach to estimate the effect of shocks at other banks on them.[3]

In this paper we also use bank equity prices as indicators of contagion/banking system risks. Compared to the previous literature, we 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. While EVT has been applied to general stock indices before, it has not yet been used to assess the

[3]Other market indicators used in the literature to assess bank contagion include bank debt risk premia (see, in particular, Saunders (1986) and Cooperman, Lee and Wolfe (1992)).

A number of approaches that do not rely on market indicators have also been developed in the literature. Grossman (1993) and Hasan and Dwyer (1994) measure autocorrelation of bank failures after controlling for macroeconomic fundamentals during various episodes of US banking history. Saunders and Wilson (1996) study deposit withdrawals of failing and non-failing banks during the Great Depression. Calomiris and Mason (1997) look at deposit withdrawals during the 1932 banking panic and ask whether also ex ante healthy banks failed as a consequence of them. Calomiris and Mason (2000) estimate the survival time of banks during the Great Depression, with explanatory variables including national and regional macro fundamentals, dummies for well known panics and the level of deposits in the same county (contagion effect).

Chen (1999), Allen and Gale (2000) and Freixas, Parigi and Rochet (2002) develop the theoretical foundations of bank contagion.

extreme dependence between bank stock returns with the aim to measure banking system risk. Second, we cover both European countries and the United States to compare banking system stability internationally. We are not aware of any other study that tries to compare banking system risk between these major economies. 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. Again, whereas a few other papers addressed the changing interdependence between bank stock returns before, none focused on the extreme interdependence we are interested in in the present paper.

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 co-movements 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-β" proposed by Straetmans, Verschoor and Wolf (2003).[4] The tail-β is measured by conditioning our co-crash probability on a general stock index or a banking sector sub-index rather than on individual banks' stock prices. Therefore, in some respects it reflects the tail equivalent to standard asset pricing models. In this paper we further extend the analysis of tail β by also using highy-yield bond spreads as measures of aggregate risk. Based on the estimated individual co-crash probabilities and tail-βs, 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.

[4]Some authors point out that most banking crises have been related to aggregate fluctuations rather than to prevalent contagion. Gorton (1988) provides ample historical evidence for the US, Gonzalez-Hermosillo et al. (1997) also find related evidence for the Mexican crisis of 1994-1995 and Demirgüc-Kunt and Detragiache (1998) add substantial further support for this hypothesis using a large multi-country panel dataset.

Hellwig (1994) argues that the observed vulnerability of banks to macroeconomic shocks may be explained by the fact that deposit contracts are not conditional on aggregate risk. Chen (1999) models, inter alia, how macro shocks and contagion can reinforce each other in the banking system.

Our data are daily bank stock excess returns in euro area countries and the United States between April 1992 and February 2004. 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. Several of the banks selected faced failure-like situations during our sample period. All in all, we have about 3,100 observations per bank.

Our present results still undergo further robustness checks and should therefore be interpreted cautiously. It turns out so far that the degree of multivariate extreme linkage between US banks is much higher than between European banks. In other words, bank contagion risk might be higher among the major US banks than the case among the major euro area banks. Second, the lower contagion risk among European banks is entirely related to their extreme cross-border linkages. Domestic linkages in France, Germany and Italy, for example, are of the same order as domestic US linkages. One interpretation of this results is that further banking integration in Europe could lead to higher cross-border contagion risk in the future, with the more integrated US banking system providing a benchmark. Third, when looking at cross-border spillovers as compared to domestic spillovers in Europe, our contagion risk indicator tends to be larger for the latter, but only for a few countries this difference is statistically significant. For example, among the banks from larger countries – such as France, Germany, Italy, the Netherlands and Spain – extreme cross-border linkages are statistically indistinguishable from domestic linkages. In contrast, the effects of banks from these larger countries on the main banks from some smaller countries – including particularly Finland and Greece, and sometimes also Ireland or Portugal – tend to be significantly weaker than the effects of their own banks. Hence, those smaller countries located around the center of Europe seem to be more insulated from European cross-border contagion. Fourth, estimated tale βs are similar for the euro area and the US, and they illustrate the relevance of aggregate risks for banking system stability. While stock market indices perform well as indicators of aggregate risk, we find that high-yield bond spreads capture extreme systematic risk for banks relatively poorly, both in Europe and the US. Fifth, structural stability tests for both our indicators suggest that systemic risk has increased in Europe and in the US. While gradual developments may be behind those breaks, statistically the changes tend to occur during the second half of the 1990s. The introduction of the euro in January 1999, however, did not seem to have had any significant additional effect on cross-border contagion risk beyond what was already under way in Europe in terms of banking integration before.

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-β measure for stock returns. 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 (using, inter alia, balance-sheet information), provides some standard statistics for the individual bank and index returns, and gives some information about the occurrence of negative extremes for individual banks and the related events. 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-βs 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. We have four appendices. The first one (appendix A) discusses small sample properties of estimators and tests. Appendix B lists the banks in our sample and the abbrevations used for them across the paper. Appendix C presents some balance-sheet information about the banks. The last appendix (appendix D) contains the standard statistics for our return data and for yield spreads.

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, conditioning 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-β") 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 minus the risk-free interest rate by the random variables X_i $(i = 1, \cdots, N)$. Thus, X_i describes a bank i's excess return. To study simultaneous sharp 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 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 Q_i 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 measure the propagation of severe problems through, e.g., the European and US banking sectors by calculating the probability of joint collapse in an arbitrarily large set of N bank stocks, conditional on the collapse of a subset $M < N$ banks:

(2.1)
$$P_{N|M} = P\left\{\bigcap_{i=1}^{N} X_i > Q_i(p) \,\middle|\, \bigcap_{j=1}^{M} X_j > Q_j\,(p)\right\} = \frac{P\left\{\bigcap_{i=1}^{N} X_i > Q_i(p)\right\}}{P\left\{\bigcap_{j=1}^{M} X_j > Q_j(p)\right\}} \ .$$

[5]Notice that from 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.

Clearly, the right-hand side immediately follows from the definition of conditional probability. 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-βs": 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 market portfolio.[7] This "tail-β" 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 excess return on the market portfolio (e.g. using a stock market index) and p again our common tail probability, then this measure can be written as:

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

This measure captures how likely it is that an individual bank's value declines dramatically, if there is an extreme negative systematic shock. We extend the analysis of extreme aggregate risk in this paper by also experimenting with high-yield bond spreads as a measure M of systematic shocks.[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 techniques. However,

[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.

[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.

if one makes the wrong distributional assumptions, the linkages estimates may be severely biased due to misspecification. As there is no clear evidence that all stock returns follow the same distribution, we want to avoid very specific assumptions for bank stock returns. We rather prefer 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 different original excess returns to ones with 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 versus 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 excess 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 $F_i\left(\cdot\right)$ representing the marginal cumulative distribution function (cdf) for X_i. However, 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:

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

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 $s = 1/p$.[9] The multivariate estimation problem can now be reduced to estimating a univariate exceedance probability for the cross-sectional minimum of the N bank excess return series, i.e., it is always true that:

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

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 $\widetilde{X}_{\min}$. Ledford and Tawn (1996) impose a regularly varying (or heavy) tail for the auxiliary variable $\widetilde{X}_{\min}$ in a bivariate framework.[10] This assumption can be justified by referring to the empirical stylized fact of heavy-tailed bank stock returns (see tables 1 and 2 in section 5). 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 often consider more than two dimensions.

Assuming that $\widetilde{X}_{\min}$ exhibits heavy tails with tail index α 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:

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

with s large (p small). The estimation of the joint probabilities in the denominator and numerator of equation (2.1) and the joint tail probability in the numerator of equation (2.2) can now simply be reduced to estimating a Pareto tail like in (3.3). For example, applying the

[9] The multivariate probability stays invariant under the variable transformation $(X_1, \cdots, X_i, \cdots, X_N) \to \left(\widetilde{X}_1, \cdots, \widetilde{X}_i, \cdots, \widetilde{X}_N\right)$, because the determinant of the Jacobian matrix can be shown to be equal to 1.

[10] Equation (3.2) requires a common quantile s. This can, however, be easily generalized to the case where s differs across the marginals. Assume that we both allow the quantiles of the original distribution function Q_1 and Q_2 and the corresponding marginal probabilities p_1 and p_2 to be different from each other. For the bivariate case this would imply, for example, that

$$P\left\{X_1 > Q_1(p_1), X_2 > Q_2(p_2)\right\} = P\left\{\widetilde{X}_1 > s_1, \widetilde{X}_2 > s_2\right\} ,$$

with $s_i = 1/p_i$ ($i = 1, 2$). By multiplying $\widetilde{X}_2$ with s_1/s_2 the above joint probability again reduces to a probability with a common quantile s_1 and we are back to the framework described above where the loading variable $\widetilde{X}_{\min}$ can be calculated.

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:

$$\begin{aligned}
\frac{P\left\{X_1 > Q_X\left(p\right), M > Q_M\left(p\right)\right\}}{p} &= \frac{P\left\{\widetilde{X}_1 > p^{-1}, \widetilde{M} > p^{-1}\right\}}{p} \\
&= \frac{P\left\{\min\left(\widetilde{X}_1, \widetilde{M}\right) > p^{-1}\right\}}{p} \\
&\approx dp^{\alpha-1} ,
\end{aligned}$$

where d is a constant that depends on the specific joint probability distribution of $\widetilde{X}_1$ and $\widetilde{M}$. Hence, the conditional probability is strongly related to the tail index α. We can now estimate the tail dependence by means of the popular Hill (1975) estimator:

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

where $\widehat{\eta}$ is the estimated parameter of tail dependence and m is the number of higher order extremes that enter the estimation. The higher $\widehat{\eta}$ the more dependent are $\widetilde{X}_1$ and $\widetilde{M}$ far out in their joint tail. Hall (1982) showed that the statistic $\sqrt{m}\left(\widehat{1/\eta}\left(m\right)\eta - 1\right)$ is asymptotically standard normally distributed when the number of highest order extremes grows suitably slowly (as $m, n \to \infty$, $m/n \to 0$), which will prove convenient for the tests discussed in the next section. Further details can be found in Jansen and De Vries (1991), for example, and in the monograph by Embrechts et al. (1997).

The optimal choice of the threshold parameter m is hotly debated in the extreme value theory literature. Goldie and Smith (1987) suggest to select m so as to minimize the asymptotic mean-squared error. A widely used heuristic procedure plots the tail estimator as a function of m and selects m in a region where $\widehat{\eta}$ is more or less constant. Double bootstrap techniques based upon this idea have been developed recently (e.g. Danielsson et al., 2001), but these are only advisable for sample sizes that are larger than the ones we have available for this paper. For simplicity and in accordance with the minimization criterion of Goldie and Smith (1987), we select $m = \kappa n^{\gamma}$.[11] Finally, we provide in

[11] We further impose the parameter restrictions $\gamma = 2/3$ and $\kappa = 0.1\left(200\right)^{1/3}$. They imply, e.g., that 10% of the extremes will be used for a sample of size 200.

appendix A.1 below a discussion of the properties of our tail dependence parameter in small samples.

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 extreme systematic risk (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 dependence parameter η is constant or not. We study the occurrence of upward and downward swings in η with newly developed structural stability tests for the Hill statistic (3.4).

Quintos, Fan and Phillips (2001) introduce a recursive, rolling and sequential test for identifying single unknown breaks in estimated tail indexes $\widehat{\alpha}$, using subsample estimates of a recursive and rolling nature as inputs. As our estimation approach allows to map the multivariate dependence problem we are interested in into a univariate problem, we can simply rewrite their test procedures in terms of our tail dependence parameter η. Let t denote the endpoint of a subsample of size $w_t < n$. The *recursive* estimator is calculated for subsamples $[1;t] \subset [1;n]$ and reads as a special case of (3.4):

$$\widehat{\eta}_t = \frac{1}{m_t} \sum_{j=0}^{m_t-1} \ln\left(\frac{X_{t-j,t}}{X_{t-m_t,t}}\right), \tag{4.1}$$

(This will be the initial sample size for the endogenous break test to be implemented later on.) The monotonicity condition for the selection of m guarantees asymptotic normality and consistency of the Hill statistic. Moreover, it can be shown that minimizing the asymptotic mean-squared error for the Hill estimator by balancing bias and variance renders a nonlinear selection rule like the one mentioned above. Imposing common restrictions on γ and κ is called for, as in this paper we are particularly interested in cross-sectional comparisons and tests.

with $m_t = \kappa t^{2/3}$. The *rolling* estimator is conditioned on a fixed subsample of size $w^* = \gamma_0 n$ such that $m_{w^*} = 0.1w^*$:

$$\widehat{\eta}_t^* = \frac{1}{m_{w^*}} \sum_{j=0}^{m_{w^*}-1} \ln\left(\frac{X_{w^*-j,w^*}}{X_{w^*-m_{w^*},w^*}}\right). \tag{4.2}$$

Finally, the *sequential* estimator (denoted by $\widehat{\eta}_{2t}$) is basically the same as the recursive estimator in (4.1), but it is calculated by "reversing" calendar time, i.e., by using the extremes of more recent subsamples first.

The values of the three test statistics equal the suprema of the following time series:

$$Y_n^2(t) = \left(\frac{tm_t}{n}\right)\left(\frac{\widehat{\eta}_n}{\widehat{\eta}_t} - 1\right)^2, \tag{4.3}$$

$$V_n^2(t) = \left(\frac{w^* m_{w^*}}{n}\right)\left(\frac{\widehat{\eta}_n}{\widehat{\eta}_t^*} - 1\right)^2, \tag{4.4}$$

$$Z_n^2(t) = \left(\frac{tm_t}{n}\right)\left(\frac{\widehat{\eta}_{2t}}{\widehat{\eta}_t} - 1\right)^2. \tag{4.5}$$

Expressions (4.3) and (4.4) compare the change in the recursive and rolling values of the estimated tail parameter (3.4) to their full sample counterpart $\widehat{\eta}_n$, whereas the sequential test uses (4.5) to compare the fluctuations of the recursive with the reverse recursive estimator. The null hypothesis of interest is that the tail dependence parameter does not exhibit any temporal changes. More specifically, let η_t be the dependence in the left tail of X.[12] The null hypothesis of constancy then takes the form

$$H_0 : \eta_{[nr]} = \eta, \quad \forall r \in R_\tau,$$

with the alternative hypothesis $H_A : \eta_{[nr]} \neq \eta$ for some $r \in R_\tau$. In line with Quandt's (1960) pioneering work on endogenous breakpoint

[12]For practical reasons the above tests are calculated over compact subsets of $[0;1]$, i.e., t equals the integer part of nr for $r \in R_\tau = [\tau; 1-\tau]$ and for small $\tau > 0$. Sets like R_τ are often used in the construction of parameter constancy tests (see, e.g., Andrews, 1993). The restricted choice of r implies that $\tau n \leq t \leq (1-\tau)\,n$.When the lower bound would be violated the recursive and rolling estimates might become too unstable and inefficient because of too small subsample sizes. On the other hand, the tests will never find breaks for t equal to or very close to n, because the testing values in (4.3), (4.4) and (4.5) are close to zero in that latter case. Thus, for computational efficieny one might stop calculating the tests beyond the upper bound of $(1-\tau)\,n < n$. In the empirical applications we set the smallest recursive sample size equal to 200, i.e., $\tau = 200/n$.

determination in linear time series models, the candidate breakdate r can be selected so as to maximize the value of the sequences of test statistics in (4.3), (4.4) and (4.5), because at these dates in time the constancy hypothesis is most likely to be violated.

Asymptotic critical values can be derived for the sup-values of the three testing procedures. However, if data are temporally dependent, the test sequences Y_n^2, V_n^2 and Z_n^2 need to be scaled in order to guarantee convergence to the same limiting distribution function as in the case of absence of temporal dependence. It is well known that financial returns exhibit nonlinear dependencies like ARCH effects (volatility clustering). This ARCH dependence is likely to be (at least partly) present in the loading variable $\widetilde{X}_{\min}$, which was defined in the previous section as the cross sectional minimum of the bank stock returns (transformed using their proper empirical distribution function). Loosely speaking, the stronger the volatility clustering, the larger the scaling factor has to be. More details on the ARCH robust procedure in general and how the scaling factor can be consistently estimated are provided in Quintos et al. (2001). One now selects r for, e.g., the recursive test such that $Y_n^2(t)$ - appropriately scaled - is maximal:

$$Q_{r\in R_\tau} = \sup \widehat{\sigma}_t^{-1} Y_n^2(t), \tag{4.6}$$

with $\widehat{\sigma}_t$ the estimate of the time varying scaling factor. The null of parameter constancy is rejected if the sup-value exceeds the asymptotic critical values.

Quintos et al. also provide a Monte Carlo study of small sample power, size and bias properties of the break date estimator. Again applying their results to our problem of tail dependence, the simulated breaks under the alternative hypothesis both comprise situations where the tails become more ($\eta_1 < \eta_2$) or less ($\eta_1 > \eta_2$) dependent. The three tests exhibit only small size distortions, which implies that the asymptotic critical values can still be used in samples of only moderate size. Small sample power crucially depends on the sign of the change in the tail dependence parameter under the alternative hypothesis. The recursive and rolling tests are able to satisfactorily identify an increase in η. The power, however, of the rolling test is much larger in detecting a decrease in η. This outcome can be understood by observing that (4.1) is based on the m largest extremes, 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. The dominance of the initially selected extremes when $\eta_1 > \eta_2$ does not happen for the rolling test, since the impact of extremal behavior in the initial sample on $\widehat{\eta}$ gradually disappears when the rolling window is moved through the total sample. The sequential test seems to perform poorly, although the power differs quite a lot depending on the location of the break and the direction of the change in η.

The recursive test's poor power record under the alternative of a declining η is more an apparent than a real problem. The recursive test can be performed by applying equations (4.3)-(4.6) in calendar time (forward recursive test) and by inversing the sample (backward recursive test) in order to identify increases and decreases in η, respectively. Because of it's ability to test against a one-sided alternative - which is more interesting from an economic point of view, as we can identify rises and falls in systemic risk instead of unspecified "changes" - we prefer to work with Quintos et al.'s recursive test instead of the rolling or sequential test.

Appendix A.2 below addresses the small-sample properties of the structural break test.

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 $\widehat{\eta}$ referred to above enables some straightforward hypothesis testing. A test for the equality of tail dependence parameters between, e.g., Europe and the United States can thus be based on the following T-statistic:

$$T = \frac{\widehat{(1/\eta)}_1\,(m_1) - \widehat{(1/\eta)}_2\,(m_2)}{\sqrt{\frac{c_1\left(\widehat{1/\eta_1}\right)^2}{m_1} + \frac{c_2\left(\widehat{1/\eta_2}\right)^2}{m_2} - \frac{2c_3 cov\left(\widehat{1/\eta_1},\widehat{1/\eta_2}\right)}{m_1 m_2}}} \to^d N(0,1), \tag{4.7}$$

which converges to a standard normal distribution in large samples.[13] Note that the weighting in the denominator of the statistic takes non-linear dependence into account, so that the test is robust to GARCH effects in the data. One can safely assume that η and T 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).

[13]The analytical expressions for c_1, c_2 and c_3 can be found in Quintos et al. (2001). In the empirical application of the T-test (4.7) further below, we simplify by setting the covariance term in the denominator equal to zero. In the revised version of the paper, we intend to replace those expressions in the denominator of T by expressions derived from a block-bootstrap procedure.

5. Data and descriptive statistics

We collected daily stock prices (excluding dividends) for 25 euro area banks and 25 US banks. Excess returns are constructed by taking log first differences of the prices and deducting 3-month LIBOR rates (adjusted linearly to derive daily from annual rates). The market risk factor or aggregate shocks to the euro area and US banking systems, respectively, are proxied by three different measures: A banking sector sub-index, a general stock market index and the spread between below-investment-grade and treasury bond yields. All series, except one, start on 2 April 1992 and end on 27 February 2004, giving 3,106 return observations per bank. The euro area high-yield bond spread is only available from 1998 onwards. All price and index series are downloaded from Datastream (total returns), whose source for high-yield bond spreads is Merril Lynch.[14] The stock indices are the ones calculated by the data provider.

The following sub-section provides detailed information about how those 50 banks were chosen based on balance sheet items for European and US banks. The subsequent section discusses the return data in greater depth, referring to the typical host of standard descriptive statistics.

5.1. **Bank selection and balance sheet information.** The time dimension of this dataset was very much constrained by the unavailaility of longer stock price series for European banks. Before the 1990s fewer large European banks were privately quoted on stock exchanges and also many banks disappeared as a consequence of mergers. 10 out of 12 euro area countries have banks in our sample. There is no Austrian bank, as we could not construct a long enough stock price series for any of the two largest banks from this country. We deliberately excluded banks from Luxembourg, as they are considerably smaller than the larger banks from all other euro area countries. Roughly in proportion to the sizes of their economies in terms of GDP and the sizes of their banking systems in terms of assets, we have 6 banks from Germany, 4 banks from France, 4 banks from Italy, 3 banks from Spain, 2 banks each from the Netherlands and from Belgium and one bank from Finland, Greece, Ireland and Portugal, respectively. Appendix B contains the full list of banks, the abbreviations used in the tables and their country of origin.

[14]See de Bondt and Marques (2004) for an in-depth discussion of high-yield bond spreads.

Apart from the above constraints, banks were chosen on the basis of two main criteria: First, their size (as measured mainly by assets and deposits) and, second, their involvement in interbank lending (as measured by interbank loans, amounts due to and due from other banks and total money market funding). The necessary balance-sheet information was taken from Bureau van Dijk's Bankscope database (considering end of year values between 1992 and 2003). For the United States, the choice of banks was double-checked on the basis of the Federal Reserve Bank of Chicago commercial bank and bank holding company databases.

We used this balance-sheet information to identify the "systemically most important" banks all across the twelve years. By using several criteria, naturally some choices had to be made. This is illustrated in Appendix C, which reports data for one size (total assets) and one interbank trading ("due from banks") measure, all expressed in US dollars. Table C.2 displays the assets of all 25 US banks over the sample period, by declining order of average size. The corresponding table for "due from banks" is C.4. It turns out that the most important US bank according to the latter criterion is State Street, although in terms of assets it only comes at number 13. Similar phenomena can also be observed for other "clearing banks", such as Northern Trust (5th by interbank linkages and only 24th by assets), Bank of New York and Mellon, whose sizes are relatively poor indicators for their role in interbank relationships. We were particularly careful to have these banks that are most active in clearing and settlement in our sample. The justification for this is that failures of one or several main clearing banks may consitute a particular source of contagion risk, even though they may not be very large compared to other players.[15] Interestingly, as one can see by comparing tables C.1 and C.3 size and interbank activity are much more aligned for euro area banks.

Moreover, by comparing table C.1 with table C.2 we can see that the banks chosen for the euro area and the ones chosen for the US are of comparable size, even though - not too surprisingly - the aggregate balance sheet of the euro area banks is overall larger than the US aggregate. The same similarity, however, does not apply to the "due from banks" measure of interbank relations, which is significantly larger in Europe than in the US (see tables C.3 and C.4). It will be interesting to verify below whether this aggregate information from balance sheets

[15]For example, the failure of Continental Illinois in 1983-84 and the computer problem of Bank of New York in 1985 raised major concerns and were accompanied by public action in order to prevent those incidents from spreading through the banking system.

is informative about the relative importance of systemic risk in the euro area as compared to the US banking system.

5.2. **Descriptive statistics for stock returns and yield spreads.** Appendix D presents the typical host of standard descriptive statistics for our 50 bank stock return series and the three indices capturing aggregate factors. Tables D.1 and D.2 report on the left-hand side mean excess returns, standard deviations, skew and kurtosis as well as on the right-hand side correlations between the individual bank stock returns and the three aggregate risk factors for the euro area and the United States, respectively. Mean returns are basically zero, as one would expect, whereas standard deviations of returns tend to be around 2. Naturally, the volatility of the two stock indices is significantly lower than the one of the individual bank stocks. While there are little signs of skew, except for the troubled bank Banesto (see next sub-section for details) that shows some right skew, most series are leptokurtic.

As regards the correlations between bank stocks and aggregate risk factors, they are pretty high for the two stock indices, as could have been expected. Many correlation coefficients (though not all) reach levels of the order of 0.6 or higher, and plausibly the banking sector sub-index tends to be slightly more related to the individual stocks than the general stock market index. The picture is different for correlations between individual stock returns and the high-yield bond spread. First of all, correlation coefficients tend to be very low, varying between 0 and 0.05 in absolute value. Moreover, many of the US correlations have the "wrong" sign (a small positive correlation coefficient). This provides first evidence that the high-yield bond spread might not be a good predictor of aggregate banking system risk.

We complete the discussion of standard return statistics with the correlation matrices of individual bank stock returns. Table D.3 shows the correlation matrix for the euro area. Euro area bank returns seem to be generally positively correlated, with correlation coefficients varying between 0.05 and 0.77. For the US, table D.4 provides a similar picture, although correlation coefficients appear to be more uniform (varying only between 0.32 and 0.66) and on average slightly higher.

For the purpose of the present paper, we are particularly interested in extreme negative returns. The left-hand sides of tables 1 and 2 report the three largest negative excess returns (in absolute value) for all the banks in the sample and for the two banking sector stock indices. Starting with Europe, the largest stock price decline in the sample (a massive daily collapse of 85%) happens for Banesto (Banco Espanol de Credito) in February 1994. Around that time, this Spanish bank faced major difficulties, even leading to a form of bailout. Another bank in major difficulties during our sample period is Berliner Bankgesellschaft from Germany. This is reflected in two consecutive stock price "crashes" of 38% and 27% during the summer of 2001. Ultimately, also this bank was saved. As regards the United States, the largest daily stock price slump happens to Unionbancal Corporation. The market value of this troubled Californian bank declined in June 2000 by as much as 36%. The next most significant corrections of just above 20% occur for Comerica Inc. and AmSouth Bancorporation.[16]

[Insert table 1 about here]

Extreme negative returns of stock indices are obviously smaller than the ones for individual banks. Many of them happen around a number of well-known crisis episodes. In contrast to the stock returns, the high-yield bond spreads reported at the bottom of tables 1 and 2 are maxima, as extreme positive values indicate a situation of high risk. One can see that in times of stress non-investment grade corporate debt can trade at yields more than 10% above government debt.

There is also some first evidence of clustering in extreme bank stock declines. For example, a significant number European and US-based banks faced record downward corrections around the end of the summer 1998. This is the infamous episode related to the Long Term Capital Management (LTCM) collapse (and perhaps also to the Russian default). Another similar episode, very much limited to US banks, happened in spring and summer 2000, potentially related to the burst of the technology bubble. Finally, some American and European banks were hit significantly by the onset of the Asian crisis in fall 1997.

[Insert table 2 about here]

Both tables also display the estimated tail indexes $\widehat{\alpha}$ for individual banks and for the stock indices. It turns out that the tail indexes vary around 3, further illustrating the non-normality of bank stock returns and the non-existence of higher-order moments.[17] If anything, the tails of a number of European banks seem to be slightly fatter

[16]As we work with individual return data from Datastream, we screened our dataset for the problems described in Ince and Porter (2004). As one could probably expect for the relatively large banks we are looking at, we did not find any signs of erroneous returns. For example, tables 1 and 2 suggest that stock splits or re-denominations did not artificially generate any huge returns.

[17]The non-normality of stock returns in general is a well-known fact in financial economics since at least the fundamental work by Mandelbrot (1963). For a related discussion of non-normality and the difficulty of parametric distributions to accurately capture the behaviour of large bank stock returns for a wider cross-section of European banks, see Gropp and Moerman (2004).

(smaller α) than the ones of US banks. The right-hand sides of tables 1 and 2 show the estimated quantiles for all the banks, when assuming a common percentile (or crash probability). In this paper, we experiment with percentiles between 0.02% and 0.05%, as for these values the implied crisis levels tend to be close to or slightly beyond the historical extremes (see left-hand side). In other words, there cannot be any doubt about the fact that the phenomona considered constitute critical situations for banks. Finally, it is worthwhile noting that the extreme quantiles implied by the common crash probability p exhibit some variation across banks, as was expected.

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 for macroprudential surveillance and for 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 6.1 and the latter in sub-section 6.2. 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). We also abstract here from potential changes of contagion risk over time, which is addressed in section 8.

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 η parameter governing the extreme dependence (see columns $\widehat{P}$ and $\widehat{\eta}$). To keep the amount of information manageable, 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 France (upper middle panel), from Italy (lower middle panel) and from France (lower panel).

For example, the value 0.17 in the row "Germany" and the column "$\widehat{P}_1$" 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 a few cells down, the value 0.08 describes the probability that Banco Santander Central Hispano (the largest Spanish 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 (in particular through the columns for more than one conditioning bank crash), it turns out that cross-border contagion risk tends to be smaller than domestic contagion risk in the euro area banking system, indeed. To pick just another example, the probability that the largest French bank (BNP Paribas) faces an extreme stock price slump given that the second (Crédit Agricole) and third largest French bank (Societé Générale) have experienced one is a non-negligible 70% (see column $\widehat{P}_2$, bottom panel, France). The same probability for the largest Italian bank (Banca Intesa) is 46% (see column $\widehat{P}_2$, bottom panel, row Italy). The probabilities in the first row of each panel are very often higher than the probabilities in the rows underneath. There are also some exceptions, in particular among the bivariate probabilities reflecting linkages between two large banks (column $\widehat{P}_1$). This is not too surprising, as the largest players will have more extensive international operations, implying greater cross-border contagion risk relative to domestic contagion risk. (Of course, the estimated values of the η parameter, which determines the extreme dependence, leads to the same conclusions.)

[Insert table 3 about here]

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. Something similar, but to a lesser extent can be observed for Ireland and Portugal. Apparently, smaller banking systems located more in the periphery of the euro area can be more insulated from contagion risk than larger systems in the center. Overall, the level of contagion probabilities seem to be economically relevant, both domestically and across borders, in particular when more than one large bank faces a stock price crash. Contagion risk for single crashes tend, however, to be markedly lower.

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.[18] The test statistics partly qualify the interpretation of the contagion probabilities in table 3. Extreme cross-border linkages between Belgian, Dutch, French, German, Italian and Spanish banks are not (statistically) significantly different from domestic linkages within the major countries. In contrast, for the remaining smaller countries (Finland, Greece, Ireland and Portugal) the null hypothesis is rejected in a non-negligible number of cases. So, severe problems of larger French, German and Spanish banks may create similar problems for other large banks at home, but often would do much less so for the largest banks of those smaller countries.[19]

[Insert table 4 about here]

Another observation from table 3 is that contagion risk in Europe tends to increase with an increasing number of conditioning banks that crash. Using a different methodology, Gropp and Vesala (2004) find a similar phenomenon for a larger sample of European banks. 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, 2003, figures 1 to 7). While the results in table 3 suggest that most contamination functions in European banking are monotonuously increasing (as for currencies), there are also some exceptions. Witness, for example, the exposure of Banco Commercial Portugues (the largest Portuguese bank) to problems of German banks. 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 banks to put them in good banks. Such behaviour has been referred to by Kaufman (1988) in relation to US banking history, and Saunders

[18]The t-statistics result from comparing cross-border η-values with domestic η-values (ceteris paribus the number of conditioning banks) from table 3. For example, the t-statistic in row Netherlands and column T_1 in table 4 results from testing whether the η-value for the largest Dutch bank (ABN AMRO) w.r.t. the 2nd largest German bank (HypoVereinsbank) significantly differs from the domestic η-value of the largest German bank (Deutsche Bank) w.r.t. the 2nd largest German bank (HypoVereinsbank).

[19]We detected that the strength of this result is somewhat sensitive to some of the test parameters. In some cases the speciality of Finland, Greece, Ireland and Portugal comes out relatively systematically, in other cases - like the one reported in table 4 - results tend to be slightly more mixed. Further robustness checks are necessary here.

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 further robustness checks, for surveillance of the banking system and 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. For example, Gropp and Vesala (2004) find interbank exposures at the country level to be a variable explaining part of spillovers in default risk between European banks. One implication of the finding is that macroprudential surveillance and banking supervision need to have a cross-border dimension in the euro area. This is currently happening through the Eurosystem monitoring banking developments, through the application of the home-country principle (the home supervisor considers domestic and foreign operations of a bank), through the existence of various bilateral memoranda of understanding between supervisory authorities and now also through the newly established "Lamfalussy Committees" in banking. The results, if confirmed, could provide some arguments in favour of an increasing degree of centralization in macroprudential surveillance and European supervisory structures over time.

It is also interesting to see that in some smaller and less central countries in the area cross-border risk is more contained. 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 eliminate any contagion risk among the larger players from some key countries in the area to levels that are so low that they can be simply ignored. 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 of these large players happens in international markets that are highly interlinked.

6.2. **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 η that governs the estimate of the multivariate contagion risk measure (2.1). Notice that for each continent η_{US} and η_{EA} are derived from all the extreme stock return linkages between the respective N=25 banks, following the estimation procedure described in section 3. As indicated in table 5, we obtain $\widehat{\eta}_{US} = 0.50$ and $\widehat{\eta}_{EA} = 0.22$. While multivariate extreme dependence is not very strong, this still means that in relative terms overall contagion risk in the US banking system is much higher than contagion risk among euro area banks.[20]

[Insert table 5 about here]

Is this difference statistically significant? We apply the GARCH-robust cross-sectional stability test (4.7) described in sub-section 4.2, with the following null hypothesis:

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

It turns out that the t-statistic reaches t=3.54. In other words our indicators and tests suggest that the difference in systemic risk between the US and the euro area is highly statistically significant (way beyond the 1% confidence level).

One explanation could be that in a much more integrated banking system, such as the one of the United States, area-wide systemic risk is higher, as banking business is much more interconnected. We examine this hypothesis by also estimating the multivariate contagion risk for individual European countries. If the explanation above was true, then overall systemic risk should not be lower within France, Germany or Italy than it is in the US.[21] The bottom part of table 5 shows that this is actually the case. Overall domestic contagion risk in France and Germany is about the same as in the US; in Italy it is even larger than in the US. Our cross-sectional test cannot reject parameter equality between France and the US or between Germany and the US, but it rejects it between Italy and the US (as Italy is even more risky). In other words, the low overall contagion risk in Europe is explained by the quite weak extreme cross-border linkages. Looking ahead, this analysis suggests that - as the European banking system integrates

[20]The $\widehat{P}$ values in the table describe the probability that all 25 banks in the euro area or the US crash, given that any of them crashes. They illustrate that overall systemic risk related to the crash of a single bank is very low. Of course, multivariate contagion risk increases for multiple bank crashes.

[21]We thank Christian Upper for suggesting this exercise to us.

further over time - it could become more similar to the US system in terms of contagion risk.

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. Across this section we assume stability of estimated "tail-βs" over time. Structural breaks of extreme systematic banking system risk are considered in section 8.

The results are summarized in table 6, both for the euro area and the US. "Tail-βs" are denoted as $\widehat{P}$ and the corresponding bivariate extreme dependence parameters as η. We distinguish two measures of aggregate risk, a general stock index and the high-yield bond spread. The former captures market risk, as in traditional asset pricing theory. The high-yield bond spread is also a measure of aggregate risk. For example, Gertler and Lown (1999) have shown that it can be a good predictor of the business cycle, at least in the US. Some might also regard it is a particularly suitable indicator for crisis situations.

To take an example, the value 0.14 in the bottom row "IRBAN" means that a very large downturn in the euro area stock index is usually associated with a 14% probability that Allied Irish Banks, a large Irish bank, faces an extreme stock price decline. The value 0.44 in row "BNPPAR" suggests that the same probability for the largest French bank is substantially higher. Going more systematically up and down the $\widehat{P}$ columns, one can see that "tail-βs" can be quite different across banks, both in Europe and in the US. For example, a number of banks from some more peripheral and smaller euro area countries or smaller banks from large euro area countries can have quite low "tail-βs". One interpretation of this result is that the more local business of the latter banks exposes them less to aggregate euro area risk. Similar cases can be found for the US. For example, some players focussing on regional or local retail business, such as e.g. a savings&loans association like Washington Mutual, have relatively low "tail-βs" (7% in this specific case). Overall, "tail-βs" in Europe and in the US are of similar order of magnitude, although the US βs might be slightly less variable. (Similar results can be found for other measures of aggregate risk, such as a banking-sector sub-index.)

[Insert table 6 about here]

When turning to extreme systematic risk associated with high-yield bond spreads, the results are somewhat different. Most importantly, "tail-βs" for spreads are extremely small. (Also the tail dependence parameters η are smaller than the ones for stock indices.) Extreme positive levels of spreads on average do not seem to be associated with a high likelihood of banking problems. Quite the contrary, the probabilities are almost zero. We conclude from this that the spreads are not very informative about aggregate banking system risk.

8. Has systemic risk increased?

A crucial issue for macroprudential surveillance and 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 (4.3)-(4.6) in a recursive way to the extreme tail dependence parameter η. 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 euro area block $\widehat{\eta}_{EA}$ (as in sub-section 6.2, table 5) and test for structural change. The same we do for Germany, France and Italy, separately. The results are reported on the left-hand side of table 7. The table also exhibits on the right-hand side estimated sub-sample values for η and for the probability that all banks crash, given that one crashes $\widehat{P}$. Finally, the middle of table 7 also displays the results of an exogenous structural stability test (T_{EMU}), in which the break point is chosen to be January 1999.

[Insert table 7 about here]

In all cases the Quintos et al. test strongly rejects the null hypothesis, indicating an increase of multivariate contagion risk. The strongest break found for the euro area happens August 1997 (test value of 5.27) and for the US in July 1998 (test value of 77.77).[22] In all cases the

[22]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). For the cases at hand, the thresholds for significance at the 1% level are 2.58, respectively.

common η-value is larger in the second period. The European multivariate tail dependence parameter increases from 0.16 to 0.25 and its US counterpart from 0.18 to 0.63. 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, the US even more so than 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 interpret it as a sign of increasing systemic risk.[23] 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, slightly earlier than in our case, as they find most correlation changes during 1996 and perhaps 1997. Nevertheless, banking consolidation cannot be ruled out as a possible explanation.

In order to get a better view of the evolution of multivariate contagion risk over time, we plot in figure 1 the recursive estimates of η for the euro area, the US, France, Germany and Italy. From the dashed line at the bottom of the figure we can see the smaller and gradual character of the increase in contagion risk in the euro area. Notice the consistency of this evolution with a slowly advancing integration process. The US also exhibits a gradualist pattern, although it is starting later than the euro area and then advancing at a faster pace. Contrast this with Italy, where banks have much higher tail dependence and where the change in risk is relatively abrupt.

[Insert figure 1 about here]

Figure 2 shows then the recursive statistics of the cross-sectional tests comparing US multivariate contagion risk with euro area, French, German and Italian contagion risk. The solid lines describe the difference in η between the first country (always the US) and the second area or country. The straight dashed lines describe two standard deviation confidence intervals. So, when a solid curve moves out of a confidence interval, then the test rejects the equality of multivariate tail dependence parameters between the two countries. If a curve is above the confidence interval, then the first country is more susceptible to contagion. In the opposite case, the second country is the more risky one. We can immediately see from the upper left-hand chart in

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

figure 2 that the US is more risky than the euro area. The lower right-hand chart illustrates that Italy is more risky than the US. We can also see that the highly volatile period during 1997 and 1998 is somewhat special, as the general increase in noise seems to have had a temporary reductionary effect on the ratio of multivariate US contagion risk and risk in other countries. This episode, however, is not sustained enough to generally change the relative proportions of overall contagion risk across countries.

[Insert figure 2 about here]

Finally, we turn to the results of the exogenous EMU break test in table 7. From the t-statistics reported their it is clear that neither the euro area countries as a group nor Germany or Italy alone experience any change in multivariate contagion risk associated with the introduction of the euro. In none of these three cases the test rejects the null of an identical extreme dependence between bank stock returns before and after the start of Stage Three of EMU. Paradoxically, only France experiences a domestic increase in risk around that time. So, overall the euro does not seem to have had any detrimental effect on contagion risk in Europe beyond the developments that were already well under way much earlier, despite e.g. the creation of a common money market that could act, inter alia, as a transmissional channel for banking instability spilling across borders. Similar to us, Gropp and Vesala (2004) also find an increase in bank contagion risk in Europe, using a different methodology, but they pin down the break point at the introduction of the euro.

8.2. **Time variation of "tail-βs".** Now we apply the structural stability test to extreme systematic risk. Table 8 reports the results for the euro area and table 9 for the United States. Each table shows for the respective banks the estimated break points (if any, with test value in parentheses). Whether the forward or backward version of the recursive Quintos et al. test has been used is indicated by F and B, respectively. Tests are performed for all three aggregate risk measures on which we condition the tail-βs.

[Insert table 8 about here]

The general result is that extreme systematic risk has increased over time.[24] 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. In addition, in the case of stock indices, as measures of aggregate risk, the increase is economically significant. This applies, for

[24]Asymptotic critical values for the tests are 1.78 and 2.54 at the 95% and 99% significance levels, respectively (see e.g. Quintos et al., 2001).

example, to the largest US banks (Citigroup and JP Morgan Chase). The βs of important clearing banks, such as Bank of New York, State Street or Northern Trust, changed by even more than those. Similarly significant changes can also be observed for the euro area.[25]

[Insert table 9 about here]

In Europe the timing of the break points is about 1997 for the stock indices, in many occasions around the onset of the Asian crisis; in the US it is 1996-1997. For Europe this is roughly in line with contagion risks (see the previous sub-section), for the US the tail-β breaks happen somewhat earlier than the contagion breaks.[26]

Both in Europe and in the US there are also breaks in tail-βs for yield spreads. They happen, however, with surprising regularity in 2000, the time of the burst of the technology bubble. In any case, given the very low extreme systematic risk associated with yield spreads, not too much importance should be given to this result.

Finally, a caveat needs to be spelled out. Following the discussion in Poon et al. (2004), we did some preliminary testing for structural stability of tail-βs after having cleaned the return time series from GARCH effects. In the cases considered the structural breaks disappeared or became much weaker. While it seems that for the questions we are interested in the GARCH-uncorrected approach is more advisable, this finding still raises some issues of how to interpret the factors behind the increases in extreme systematic risk we observe.

9. Conclusions

In this paper we made a new attempt to assess banking system risk, by applying recent multivariate extreme-value estimators and tests to excess returns of the major banks in the euro area and the United States. We distinguish two types of measures, one capturing extreme spillovers among banks (which we denote as contagion) and another capturing the exposure of banks to extreme systematic risk (which we denote as tail-β). We compare the importance of those forms of systemic risk across countries and over time.

[25]We do not report the estimated sub-sample βs in the tables to save space. They are available from the authors on request.

[26]Notice that these results are different from the ones by de Nicolo and Kwast (2002) from standard market model βs 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.

Our results so far suggest that bank contagion risk in the euro seems to be significantly lower than in the US. As domestic linkages in the euro area are comparable to extreme linkages among US banks, this finding seems to be related to weak cross-border linkages in Europe. For example, the largest banks of some smaller countries at the periphery of the area seem to be more protected from cross-border contagion risk than some of the major European banks originating from some central European countries. Extreme systematic risk to banks seems to be roughly comparable across the Atlantic. In contrast to stock indices, high-yield bond spreads do not seem to be very informative about aggregate banking risks. Structural stability tests for both our banking system risk indicators suggest an increase in systemic risk taking place over the second half of the 1990s, both in Europe and the US. We do not find, however, that the introduction of the euro had any significant additional effect on banking system risk, beyond what was already under way before. Overall, the increase of risk in the euro area as a whole seems to have happened extremely gradually, as one would expect from the slow integration of traditional banking business.

While our results are still preliminary and should be interpreted cautiously until confirmed by further robustness checks, they still provide some interesting perspectives on the ongoing debate on financial stability policies in Europe. For example, the benchmark of the US seems to indicate that cross-border risks may further increase in the future, as banking business becomes better integrated. At the same time, it should be recognised that the direction of this process is not unique to Europe. Nevertheless, the results in this paper underline the importance of macroprudential surveillance that takes a cross-border perspective, in particular in Europe. They also encourage further thinking about the best institutional structures for supervision in a European banking system that slowly overcomes the barriers imposed by national borders. While important steps have already been taken in this regard, if one thinks for example of the newly established Lamfalussy Committees in banking, it is nevertheless important to prepare for a future that may be different from the status quo.

References

[1] Acharya, V., and T. Yorulmazer (2003), 'Information contagion and interbank correlation in a theory of systemic risk', CEPR Discussion Paper, no. 3743, February.

[2] Agenor, P.-R., M. Miller, D. Vines and A. Weber (1999), *The Asian Financial Crisis: Causes, Contagion and Consequences* (Cambridge, UK: Cambridge University Press).

[3] Aharony, J., and I. Swary (1983), 'Contagion effects of bank failures: evidence from capital markets', *Journal of Business*, 56(3), 305-317.

[4] Allen, F., and D. Gale (2000), 'Financial contagion', *Journal of Political Economy*, 108(1), 1-33.

[5] Andrews, D. (1993), 'Tests for parameter stability and structural change with unknown change point', *Econometrica*, 59, 817-858.

[6] Bae, K., A. Karolyi and R. Stulz (2003), 'A new approach to measuring financial contagion', *Review of Financial Studies*, 16(3), 717-763.

[7] Bekaert, G., C. Harvey and A. Ng (forthcoming), 'Market integration and contagion', forthcoming in 2005 in *Journal of Business*, 78(1).

[8] Blavarg, M., and P. Nimander (2002), 'Interbank exposures and systemic risk', *Risk Measurement and Systemic Risk - Proceedings of the Third Joint Central Bank Research Conference* (Basel, Bank for International Settlements), 287-305.

[9] Boyer, B., M. Gibson, M. Loretan (1997), 'Pitfalls in tests for changes in correlation', International Finance Discussion Paper, no. 5-97, Board of Governors of the Federal Reserve System, December.

[10] Calomiris, C., and J. Mason (1997) 'Contagion and bank failures during the Great Depression: the June 1932 Chicago banking panic', *American Economic Review*, 87(5), 863-883.

[11] Calomiris, C. and J. Mason (2000), 'Causes of U.S. bank distress during the Depression', NBER Working Paper, no. 7919, September.

[12] Campbell, J., M. Lettau, B. Malkiel and Y. Xu (2001), 'Have individual stocks become more volatile? An empirical exploration of idiosyncratic risk', *Journal of Finance*, 56(1), 1-43.

[13] Chen, Y. (1999), 'Banking panics: the role of the first-come, first-served rule and information externalities', *Journal of Political Economy*, 107(5), 946-968.

[14] Cooperman, E., W. Lee and G. Wolfe (1992), 'The 1985 Ohio thrift crisis, the FSLIC's solvency, and rate contagion for retail CDs', *Journal of Finance*, 47(3), 919-941.

[15] Cornell, B., and A.C. Shapiro (1986) 'The reaction of bank stock prices to the international debt crisis', *Journal of Banking and Finance*, 10, 55-73.

[16] Danielsson, J., L. de Haan, L. Peng and C. de Vries (2001), 'Using a bootstrap method to choose the sample fraction in tail index estimation', *Journal of Multivariate Analysis*, 76, 226-248.

[17] De Bandt, O., and P. Hartmann (2000), 'Systemic risk: a survey', ECB Working Paper, no. 35, November.

[18] de Bondt, G., and D. Marques (2004), 'The high-yield segment of the corporate bond market: A diffusion modelling approach for the United States, the United Kingdom and the euro area', ECB Working Paper, no. 313, February, forthcoming in the *Journal of Financial Markets Research*.

[19] De Nicolo, G. and M. Kwast (2002), 'Systemic risk and financial consolidation: Are they related?', *Journal of Banking and Finance*, 26, 861-880.

[20] Degryse, H., and G. Nguyen (2004), 'Interbank exposures: An empirical examination of systemic risk in the Belgian banking system', paper presented

at the Symposium of the ECB-CFS research network on 'Capital Markets and Financial Integration in Europe', European Central Bank, Frankfurt am Main, 10-11 May.

[21] Demirgüc-Kunt, A., and E. Detragiache (1998), 'The determinants of banking crises in developing and developed countries', *IMF Staff Papers*, 45, 81-109.

[22] Diamond, D., and P. Dybvig (1983), 'Bank runs, deposit insurance, and liquidity', *Journal of Political Economy*, 91(3), 401-419.

[23] Docking, D., M. Hirschey and E. Jones (1997), 'Information and contagion effects of bank loan-loss reserve announcements', *Journal of Financial Economics*, 43(2), 219-240.

[24] Draisma, G., H. Drees, A. Ferreira and L. de Haan (2001), 'Tail dependance in independance', EURANDOM report 2001-014.

[25] Dungey, M., R. Fry, B. Gonzalez-Hermosillo and V. Martin (2002), 'International contagion effects from the Russian crisis and the LTCM near-collapse', IMF Working Paper, no. 02/74, April.

[26] Eichengreen, B., A. Rose and C. Wyplosz (1996), 'Contagious currency crises: first tests', *Scandinavian Journal of Economics*, 98, 463-484.

[27] Elsinger, H., A. Lehar and M. Summer (2002), 'Risk assessment for banking systems', Oesterreichische Nationalbank, Working Paper, no. 79, October.

[28] Embrechts, P., C. Klüppelberg and T. Mikosch (1997), *Modelling Extremal Events* (Berlin: Springer).

[29] Forbes, K., and R. Rigobon (2002), 'No contagion, only interdependence: measuring stock market comovements', *Journal of Finance*, 57, 2223-2262.

[30] Freixas, X., B. Parigi and J.-C. Rochet (2002), 'Systemic risk, interbank relations and liquidity provision by the central bank', *Journal of Money, Credit, and Banking*, 32(3/2), 611-640.

[31] Furfine, C. (2003), 'Interbank exposures: Quantifying the risk of contagion', *Journal of Money, Credit, and Banking*, 35(1), 111-128.

[32] Gertler, M., and C. Lown (1999), 'The information in the high-yield bond spread for the business cycle: Evidence and some implications', Oxford Review of Economic Policy, 15(3), 132-150.

[33] Goldie, C., and R. Smith (1987), 'Slow variation with remainder: Theory and applications', *Quarterly Journal of Mathematics*, 38, 45-71.

[34] Gonzalez-Hermosillo, B., C. Pazarbasioglu and R. Billings (1997), 'Banking system fragility: Likelihood versus timing of failure - An application to the Mexican financial crisis', *IMF Staff Papers*, 44(3), 295-314.

[35] Gorton, G. (1988), 'Banking panics and business cycles', *Oxford Economic Papers*, 40, 751-781.

[36] Gropp, R., and G. Moerman (2004), 'Measurement of contagion in banks' equity prices ', in I. Hasan and J. Tarkka (eds.), *Banking, Development and Structural Change*, Special Issue of the *Journal of International Money and Finance*, 23(3), 405-459.

[37] Gropp, R., and J. Vesala (2004), 'Bank contagion in Europe', paper presented at the Symposium of the ECB-CFS research network on 'Capital Markets and Financial Integration in Europe', European Central Bank, Frankfurt am Main, 10-11 May.

[38] Grossman, R. (1993), 'The macroeconomic consequences of bank failures under the National Banking System', *Explorations in Economic History*, 30, 294-320.

[39] Haan, L. de, Jansen, D.W., Koedijk, K. and C.G. de Vries (1994), 'Safety first portfolio selection, extreme value theory and long run asset risks', in J. Galambos, J. Lechner and E. Simiu (eds.), *Extreme Value Theory and Applications* (Dordrecht: Kluwer Academic Publishers), 471-487.

[40] Hall, P. (1982), 'On some simple estimates of an exponent of regular variation', *Journal of the Royal Statistical Society B*, 44(1), 37-42.

[41] Hall, P., and A.H. Welsh (1985), 'Adaptive estimates of parameters of regular variation', *The Annals of Statistics*, 13, 331-341.

[42] Hartmann, P., A. Maddaloni and S. Manganelli (2003), 'The euro area financial system: structure, integration and policy initiatives', *Oxford Review of Economic Policy*, 19(1), 180-213.

[43] Hartmann, P., S. Straetmans and C.G. de Vries (2003a), 'A global perspective on extreme currency linkages', in W. Hunter, G. Kaufman and M. Pomerleano (eds.), *Asset Price Bubbles: The Implications for Monetary, Regulatory and International Policies* (Cambridge (MA): MIT Press), 361-382.

[44] Hartmann, P., S. Straetmans and C.G. de Vries (2003b), 'The breadth of currency crises', paper presented at the Center for Financial Studies/Wharton School conference on 'Liquidity concepts and financial instabilities', Eltville, June.

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

[46] Hasan, I., and G. Dwyer (1994), 'Bank runs in the free banking period', *Journal of Money, Credit, and Banking*, 26, 271-288.

[47] Hellwig, M. (1994), 'Liquidity provision, banking, and the allocation of interest rate risk', *European Economic Review*, 38(7), 1363-1389.

[48] Hill, B. (1975), 'A simple general approach to inference about the tail of a distribution', *The Annals of Statistics,* 3(5), 1163-1173.

[49] Ince, O., and R. Porter (2004), 'Individual equity return data from Thomson Datastream: Handle with care!', University of Florida Working Paper, March.

[50] Jansen, D., and C. de Vries (1991), 'On the frequency of large stock returns: putting booms and busts into perspective', *Review of Economics and Statistics*, 73, 19-24.

[51] Jondeau, E. and M. Rockinger (2003), 'Testing for differences in the tails of stock-market returns', *Journal of Empirical Finance*, 10, 559-581.

[52] Kaminsky, G. and C. Reinhart (2000), 'On crises, contagion and confusion', *Journal of International Economics*, 51, 145-168.

[53] Kaufman, G. (1988), 'Bank runs: causes, benefits and costs', *Cato Journal*, 7(3), 559-587.

[54] Kho, B.-C., D. Lee and R. Stulz (2000), 'U.S. banks, crises, and bailouts: from Mexico to LTCM', *American Economic Review Papers and Proceedings*, 90(2), 28-31.

[55] Ledford, A., and J. Tawn (1996), 'Statistics for near independence in multivariate extreme values', *Biometrika*, 83(1), 169-187.

[56] Lelyveld, I. van, and F. Liedorp (2004), 'Intebank contagion in the Dutch banking sector', De Nederlandsche Bank Working Paper, no. 005, July.

[57] Longin, F., and B. Solnik (2001), 'Extreme correlation of international equity markets', *Journal of Finance*, 56, 649-676.

[58] Mandelbrot, B. (1963), 'The variation of certain speculative prices', *Journal of Business*, 36, 394-419.

[59] Morgenstern, D. (1956), 'Einfache Beispiele zweidimensionaler Verteilungen', *Mitteilungsblatt fur Mathematische Statistik*, 8, 234-235.

[60] Musumeci, J. and J. Sinkey (1990), 'The international debt crisis, investor contagion, and bank security returns in 1987: the Brazilian experience', *Journal of Money, Credit, and Banking*, 22(2), 210-233.

[61] Poon, S.-H., M. Rockinger and J. Tawn (2004), 'Extreme value dependence in financial markets: Diagnostics, models, and financial implications', *Review of Financial Studies*, 17(2), 581-610.

[62] Pritsker, M. (2001), 'The channels for financial contagion', in S. Claessens and K. Forbes (eds.), *International Financial Contagion* (Dordrecht: Kluwer Academic Publishers), 67-95.

[63] Quintos, C., Z. Fan and P. Phillips (2001), 'Structural change tests in tail behaviour and the Asian crisis', *Review of Economic Studies, 68, 633-663.*

[64] Saunders, A. (1986), 'An examination of the contagion effect in the international loan market', *Studies in Banking and Finance*, 3, 219-247.

[65] Saunders, A., and B. Wilson (1996), 'Contagious bank runs: evidence from the 1929-33 period', *Journal of Financial Intermediation*, 5(4), 409-423.

[66] Slovin, M., M. Sushka and J. Polonchek (1999), 'An analysis of contagion and competitive effects at commercial banks', *Journal of Financial Economics*, 54, 197-225.

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

[68] Starica, C. (1999), 'Multivariate extremes for models with constant conditional correlations', *Journal of Empirical Finance*, 6, 515-553.

[69] Straetmans, S. (2000), Extremal spill-overs in equity markets, in P. Embrechts (ed.), *Extremes and Integrated Risk Management* (London: Risk Books), 187-204.

[70] Staetmans, S., W. Verschoor and C. Wolff (2003), 'Extreme US stock market fluctuations in the wake of 9/11', paper presented at the 2004 American Finance Assocation Meetings, Maastricht University, March.

[71] Swary, I. (1986), 'Stock market reaction to regulatory action in the Continental Illinois crisis', *Journal of Business*, 59(3), 451-473.

[72] Upper, C., and A. Worms (2004), 'Estimating bilateral exposures in the German interbank market: Is there a danger of contagion?', *European Economic Review*, 48(4), 827-849.

[73] Wall, L., and D. Peterson (1990) 'The effect of Continental Illinois' failure on the financial performance of other banks', *Journal of Monetary Economics*, 26, 77-99.

Table 1. Historical minima, tail indexes and quantile estimates for excess stock returns of euro area banks

Bank	Extreme negative returns in %, absolute values			$\widehat{\alpha}$	$\widehat{Q}(p)$ %, absolute values	
	$X_{1,n}$ (date)	$X_{2,n}$ (date)	$X_{3,n}$ (date)		$p = 0.05\%$	$p = 0.02\%$
DEUTSCHE	12.37 (09/11/01)	11.98 (03/09/00)	10.06 (09/19/01)	2.7	16.90	23.68
HYPO	17.31 (10/23/02)	14.30 (09/30/02)	11.52 (09/11/01)	2.5	22.50	32.32
DRESDNER	11.13 (10/28/97)	9.93 (07/22/02)	9.74 (03/09/00)	2.8	18.36	25.44
COMMERZ	13.25 (09/11/01)	13.13 (09/20/01)	13.08 (10/23/02)	2.8	16.03	22.14
BGBERLIN	37.86 (08/30/01)	26.99 (09/10/01)	17.08 (01/17/94)	2.4	24.46	36.13
DEPFA	16.46 (11/29/00)	10.40 (10/08/98)	10.29 (07/23/02)	2.7	16.37	23.00
BNPPAR	12.46 (09/30/98)	11.24 (09/30/02)	10.97 (10/04/02)	3.0	15.62	21.30
CA	19.57 (11/19/01)	12.37 (07/12/01)	10.46 (09/12/02)	2.4	13.87	20.44
SGENERAL	12.50 (09/10/98)	11.56 (09/30/02)	10.35 (07/19/02)	2.8	17.29	23.92
NATEXIS	13.58 (10/08/97)	10.79 (09/25/96)	10.62 (03/25/94)	3.5	9.72	12.60
INTESA	12.67 (11/07/94)	12.19 (09/20/01)	11.59 (10/28/97)	3.4	15.40	20.18
UNICREDIT	10.90 (07/20/92)	10.25 (09/10/98)	9.92 (10/21/92)	3.3	14.11	18.70
PAOLO	9.85 (12/04/00)	9.74 (09/10/98)	9.54 (09/20/01)	3.4	13.74	17.97
CAPITA	18.24 (03/07/00)	12.01 (10/01/98)	11.49 (06/20/94)	3.1	18.23	24.60
SANTANDER	15.87 (10/01/98)	12.82 (01/13/99)	11.38 (07/30/02)	2.9	16.34	22.41
BILBAO	14.54 (01/13/99)	11.77 (09/10/98)	10.65 (09/24/92)	2.8	15.84	22.07
BANESP	84.84 (02/02/94)	18.91 (11/27/02)	15.53 (08/28/98)	2.2	20.51	31.40
ING	16.12 (10/15/01)	13.98 (10/02/98)	13.91 (09/11/01)	2.2	25.55	38.48
ABNAMRO	12.57 (09/14/01)	11.90 (09/11/01)	11.26 (09/30/02)	2.3	22.00	32.90
FORTIS	10.99 (08/01/02)	10.60 (09/30/02)	10.59 (09/11/01)	2.8	16.34	22.66
ALMANIJ	8.70 (11/26/99)	8.02 (04/30/92)	6.17 (08/01/02)	3.3	11.01	14.51
ALPHA	9.37 (04/27/98)	9.35 (09/09/93)	9.08 (01/13/99)	3.0	15.17	20.70
BCP	17.12 (10/23/02)	9.88 (02/25/03)	9.07 (04/16/99)	2.5	14.13	20.41
SAMPO	20.65 (08/17/92)	18.25 (12/21/92)	15.60 (08/26/92)	2.3	28.08	41.70
IRBAN	18.22 (02/06/02)	10.29 (10/08/98)	10.13 (10/28/97)	3.0	11.99	16.24
BANK INDEX	6.86 (09/11/01)	6.70 (10/01/98)	6.32 (09/10/98)	2.6	11.06	15.84
STOCK INDEX	6.34 (09/11/01)	5.33 (10/28/97)	4.96 (09/14/01)	3.0	8.19	11.11
YIELD SPREAD	16.58 (10/02/01)	16.49 (10/03/01)	16.28 (10/01/01)	9.1	22.33	24.69

Note: X(1,n), X(2,n) and X(3,n) are the three smallest daily excess returns in the sample for each bank or each index. The last line describes the largest values (maxima) for high-yield bond spreads. Dates in parentheses are denoted XX/YY/ZZ, where XX=month, YY=day and ZZ=year. alpha is the estimated tail index. Q(p) is the estimated quantile (crisis level) for each bank, as implied by the estimated tail index and the assumed percentile (crisis probability). The quantiles are calculated for two percentiles p that correspond to an in-sample quantile (p=0.05%) and an out-of-sample quantile (p=0.02%). Data are from 2 April 1992 to 27 February 2004.

Table 2. Historical minima, tail indexes and quantile estimates for excess stock returns of US banks

Bank	Extreme negative returns in %, absolute values			$\widehat{\alpha}$	$\widehat{Q}(p)$ %, absolute valu	
	$X_{1,n}$ (date)	$X_{2,,n}$ (date)	$X_{3,n}$ (date)		$p = 0.05\%$	$p = 0.02$
CITIG	17.12 (07/23/02)	11.66 (07/22/02)	11.54 (10/27/97)	3.3	13.8	18.2
JP MORGAN	19.98 (07/23/02)	10.84 (09/03/98)	10.10 (09/13/00)	3.3	14.4	19.1
BAMERICA	11.55 (10/14/98)	10.68 (10/27/03)	9.09 (06/16/00)	3.1	14.0	19.0
WACHOVIA	9.16 (11/14/00)	9.05 (05/25/99)	8.95 (01/27/99)	3.3	11.8	15.6
FARGO	9.21 (06/16/00)	7.54 (06/08/98)	7.32 (04/14/00)	3.7	9.6	12.3
BONE	25.76 (08/25/99)	11.44 (11/10/99)	9.47 (10/27/97)	3.1	12.7	17.0
WASHING	11.69 (10/17/01)	10.32 (09/04/98)	9.27 (12/09/03)	3.2	13.6	18.0
FLEET	11.19 (07/16/02)	10.19 (02/21/95)	8.01 (07/23/02)	3.6	11.9	15.2
BNYORK	16.86 (12/18/02)	13.89 (07/16/01)	11.10 (10/03/02)	3.3	13.2	17.6
SSTREET	19.66 (04/14/93)	12.11 (03/21/03)	11.93 (10/12/00)	2.8	16.4	22.9
NTRUST	10.57 (10/03/02)	9.11 (04/14/00)	8.52 (05/25/00)	3.4	12.2	16.0
MELLON	12.97 (10/27/97)	10.56 (01/22/03)	9.77 (03/08/96)	3.2	13.1	17.4
BCORP	17.43 (10/05/01)	15.88 (06/30/92)	10.69 (10/04/00)	2.8	15.1	21.0
CITYCO	9.46 (04/14/00)	8.15 (10/27/97)	7.65 (02/04/00)	2.9	12.2	16.7
PNC	16.06 (07/18/02)	10.31 (10/17/02)	9.83 (01/29/02)	3.2	12.6	15.4
KEYCO	8.93 (08/31/98)	8.26 (03/07/00)	8.19 (06/30/00)	3.2	12.0	16.0
SOTRUST	10.55 (04/26/93)	10.28 (01/03/00)	9.65 (03/17/00)	3.0	12.5	17.0
COMERICA	22.70 (10/02/02)	9.10 (04/17/01)	9.05 (04/14/00)	3.2	11.5	15.4
UNIONBANK	36.41 (06/16/00)	15.50 (03/17/00)	10.85 (12/15/00)	2.7	16.6	23.3
AMSOUTH	20.93 (09/22/00)	14.96 (06/01/99)	6.92 (01/10/00)	3.5	9.4	12.2
HUNTING	18.26 (09/29/00)	10.43 (01/18/01)	9.95 (08/31/98)	2.9	14.1	19.3
BBT	8.17 (01/21/03)	7.21 (06/15/00)	6.97 (04/14/00)	3.3	11.3	13.7
53BANCO	8.53 (11/15/02)	7.28 (01/14/99)	6.97 (04/14/00)	3.7	9.9	12.7
SUTRUST	10.17 (07/20/98)	9.51 (04/14/00)	8.86 (06/16/00)	3.2	10.6	14.1
REGIONS	11.17 (12/15/03)	9.06 (08/31/98)	8.47 (06/15/00)	3.4	10.6	13.9
BANK INDEX	7.02 (04/14/00)	6.79 (07/23/02)	6.65 (10/27/97)	3.1	10.6	13.5
STOCK INDEX	7.04 (08/31/98)	6.82 (04/14/00)	6.81 (10/27/97)	3.5	6.6	8.6
YIELD SPREAD	10.78 (10/10/02)	10.72 (10/09/02)	10.65 (10/11/02)	15.8	12.1	12.9

Note: X(1,n), X(2,n) and X(3,n) are the three smallest daily excess returns in the sample for each bank. The last line describes the largest values (maxima) for high-yield bond spreads. Dates in parentheses are denoted XX/YY/ZZ, where XX=month, YY=day and ZZ=year. alpha is the estimated tail index. Q(p) is the estimated quantile (crisis level) for each bank, as implied by the estimated tail index and the assumed percentile (crisis probability). The quantiles are calculated for two percentiles p that correspond to an in-sample quantile (p=0.05%) and an out-of-sample quantile (p=0.02%). Data are from 2 April 1992 to 27 February 2004.

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

Largest bank	$\widehat{\eta}_1$	$\widehat{P}_1$	$\widehat{\eta}_2$	$\widehat{P}_2$	$\widehat{\eta}_3$	$\widehat{P}_3$	$\widehat{\eta}_4$	$\widehat{P}_4$	$\widehat{\eta}_5$	$\widehat{P}_5$
Conditioning banks: German										
Germany	0.831	0.171	0.657	0.688	0.945	0.723	0.624	0.849	0.511	0.921
Netherlands	0.857	0.191	0.880	0.628	0.813	0.660	0.609	0.703	0.528	0.720
France	0.909	0.159	0.741	0.521	0.870	0.482	0.595	0.629	0.454	0.668
Spain	0.786	0.076	0.775	0.465	0.851	0.514	0.566	0.649	0.477	0.646
Italy	0.842	0.106	0.774	0.348	0.795	0.416	0.552	0.525	0.442	0.580
Belgium	0.912	0.191	0.876	0.529	0.931	0.529	0.567	0.590	0.478	0.636
Ireland	0.819	0.078	0.776	0.296	0.634	0.202	0.521	0.420	0.451	0.499
Portugal	0.863	0.110	0.920	0.404	0.697	0.226	0.551	0.463	0.453	0.503
Finland	0.527	0.001	0.527	0.088	0.690	0.171	0.458	0.209	0.360	0.394
Greece	0.645	0.009	0.541	0.155	0.492	0.111	0.440	0.178	0.427	0.432
Conditioning banks: French										
France	0.958	0.164	0.909	0.701	0.638	0.743				
Germany	0.876	0.085	0.863	0.647	0.524	0.570				
Netherlands	0.836	0.111	0.930	0.748	0.619	0.701				
Italy	0.874	0.076	0.799	0.463	0.512	0.493				
Belgium	1.040	0.294	0.966	0.599	0.608	0.644				
Ireland	0.628	0.006	0.611	0.239	0.565	0.418				
Portugal	0.513	0.002	0.693	0.383	0.530	0.435				
Finland	0.398	0.000	0.452	0.060	0.523	0.327				
Greece	0.332	0.000	0.459	0.118	0.382	0.230				
Conditioning banks: Italian										
Italy	0.588	0.019	0.750	0.527	0.792	0.679				
Germany	0.709	0.037	0.753	0.453	0.720	0.550				
Netherlands	0.781	0.075	0.743	0.449	0.766	0.569				
France	0.909	0.143	0.777	0.444	0.741	0.516				
Belgium	0.811	0.061	0.667	0.415	0.709	0.488				
Ireland	0.824	0.066	0.831	0.294	0.680	0.348				
Portugal	0.874	0.081	0.787	0.297	0.706	0.329				
Finland	0.702	0.0202	0.703	0.242	0.465	0.144				
Greece	0.990	0.109	0.657	0.153	0.382	0.048				
Conditioning banks: Spanish										
Spain	0.843	0.290	0.619	0.697						
Germany	0.862	0.175	0.567	0.462						
Netherlands	0.980	0.396	0.497	0.411						
France	0.707	0.081	0.557	0.399						
Italy	0.841	0.113	0.586	0.416						
Belgium	0.833	0.123	0.490	0.393						
Ireland	0.870	0.093	0.443	0.254						
Portugal	0.810	0.086	0.523	0.314						
Finland	0.681	0.015	0.566	0.264						
Greece	0.827	0.044	0.574	0.242						

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 5 for Germany (upper panel), 1 to 3 for France, 1 to 3 for Italy and 1 to 2 for Spain (bottom panel). 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 (top panel), France (second panel), Italy (third panel) and Spain (bottom panel). Estimates of the respective Pareto exponents $\widehat{\eta} = 1/\widehat{\alpha}$ that govern the multivariate tail dependence are also reported.

	Cross-sectional t-test statistic				
Largest bank	T_1	T_2	T_3	T_4	T_5
	Conditioning banks: German				
Germany	-	-	-	-	-
Netherlands	-0.31	1.00	0.36	0.45	0.10
France	-0.37	1.37	0.08	0.29	0.48
Spain	-0.89	0.68	-0.35	0.50	-0.02
Italy	0.36	0.06	-1.13	0.20	0.15
Belgium	-0.52	0.70	-0.14	0.02	-0.44
Ireland	-0.22	-0.62	-1.52	0.53	0.61
Portugal	-0.02	0.85	-0.23	0.34	0.43
Finland	-1.96**	-1.31	-2.16**	0.62	0.31
Greece	-1.87*	-2.13**	-2.60**	-0.98	-1.17
	Conditioning banks: French				
France	-	-	-		
Germany	-1.11	-0.02	-0.18		
Netherlands	0.02	0.37	-0.54		
Italy	-0.96	-0.68	-0.11		
Belgium	0.25	0.55	-0.15		
Ireland	-2.51***	-2.83***	-1.38		
Portugal	-2.00**	-1.28	0.18		
Finland	-4.30***	-3.41***	-1.81*		
Greece	-3.76***	-2.87***	-2.30**		
	Conditioning banks: Italian				
Italy	-	-	-		
Germany	0.13	0.17	0.23		
Netherlands	0.89	0.07	0.24		
France	0.56	0.56	0.64		
Belgium	-0.73	-0.19	-0.26		
Ireland	-0.21	0.53	-0.22		
Portugal	-0.13	0.53	-0.43		
Finland	-0.73	-0.01	-0.61		
Greece	-0.47	-0.60	-1.25		
	Conditioning banks: Spanish				
Spain	-	-			
Germany	-1.60	-0.69			
Netherlands	-0.77	-0.30			
France	-0.27	-0.05			
Italy	-0.24	-0.57			
Belgium	-1.40	-0.62			
Ireland	-1.60	-0.91			
Portugal	-0.59	-0.77			
Finland	-2.61***	-1.05			
Greece	-2.75***	-1.29			

Note: The table reports testing values for the cross sectional test in eq. (4.7). 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-statistic reflects whether the differences between domestic and cross-border values of η 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 the upper panel compares the degree of domestic contagion risk within the German banking sector - as measured by the exponent η - with the contagion risk from Germany to the Netherlands. Insignificant t-statistics imply that the domestic and cross-country contagion risks are indistinguishable; whereas a significant rejection implies that cross-country contagion risk is statistically smaller than its domestic counterpart. Asterisks *, ** and *** indicate rejections of the null hypothesis at 10%, 5% and 1% significance.

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

Country/Area	Estimation	
	$\widehat{\eta}$	$\widehat{P}$
United States (N=25)	0.497	8.84E-5
Euro area (N=25)	0.224	6.21E-13
Germany (N=6)	0.441	3.29E-5
France (N=4)	0.509	2.94E-4
Italy (N=4)	0.732	0.022

TABLE 5. Multivariate contagion risk in the euro area and the United States

TABLE 6. Extreme systematic risk (tail betas) of euro area and US banks for stock indices and yield spreads

Euro area					United States				
	Stock index		Yield spread			Stock index		Yield spread	
Bank	$\widehat{\eta}$	$\widehat{P}$	$\widehat{\eta}$	$\widehat{P}$	Bank	$\widehat{\eta}$	$\widehat{P}$	$\widehat{\eta}$	$\widehat{P}$
DEUTSCHE	0.857	0.247	0.561	2.41E-3	CITIG	0.908	0.300	0.629	6.51E-3
HYPO	0.805	0.135	0.615	5.51E-3	JPMORGAN	0.863	0.216	0.717	0.024
DRESDNER	0.912	0.285	0.509	4.49E-4	BOA	0.766	0.100	0.641	6.82E-3
COMMERZ	0.942	0.366	0.697	0.017	WACHO	0.843	0.155	0.688	0.015
BGBERLIN	0.635	0.012	0.629	8.66E-3	FARGO	0.827	0.120	-	-
DEPFA	0.824	0.100	0.479	3.10E-4	BONEC	0.856	0.181	0.652	0.009
BNPPAR	1.000	0.440	0.541	1.17E-3	WASHMU	0.782	0.067	0.553	1.66E-3
CA	0.871	0.123	0.516	0.001	FLEET	0.798	0.121	0.706	0.020
SGENERAL	0.908	0.314	0.561	0.002	BNYORK	0.850	0.168	0.694	0.017
NATEXIS	0.751	0.045	0.472	1.96E-4	STATEST	0.900	0.244	0.626	0.007
INTESA	0.893	0.186	0.641	8.91E-3	NOTRUST	0.869	0.206	0.644	0.010
UNICREDIT	0.861	0.155	0.698	0.018	MELLON	0.918	0.271	0.633	0.008
PAOLO	0.905	0.270	0.556	2.25E-3	USBANC	0.758	0.069	0.618	0.006
CAPITA	0.850	0.146	0.675	0.014	CITYCO	0.793	0.107	0.688	0.014
SANTANDER	0.918	0.341	0.573	3.19E-3	PNC	0.903	0.225	0.681	0.013
BILBAO	0.981	0.458	0.538	1.74E-3	KEYCO	0.844	0.147	0.574	0.002
BANESP	0.684	0.020	0.524	6.24E-4	SUNTRUST	0.846	0.166	0.646	0.008
ING	0.977	0.516	0.587	4.27E-3	COMERICA	0.820	0.136	0.713	0.020
ABNAMRO	0.942	0.411	0.619	6.02E-3	UNIONBAN	0.741	0.047	0.532	1.17E-3
FORTIS	0.859	0.236	0.546	1.52E-3	AMSOUTH	0.747	0.066	0.628	0.006
ALMANIJ	0.826	0.125	0.522	1.10E-3	HUNTING	0.837	0.119	0.605	0.004
ALPHA	0.704	0.029	0.456	1.36E-4	BBT	0.772	0.079	0.596	0.003
BCP	0.931	0.231	0.492	5.53E-4	53BANCO	0.787	0.092	0.599	0.004
SAMPO	0.756	0.047	0.519	7.32E-4	SOTRUST	0.751	0.061	0.601	0.004
IRBAN	0.848	0.141	0.508	6.36E-4	RFCORP	0.795	0.104	0.594	0.004

Note: The table shows the estimates of extreme systematic risk (tail betas and the related extreme dependence coefficients eta). The left panel contains the results for the euro area and the right panel for the United States. Both are split in the cases where the aggregate risk factor is measured by the respective general stock index and where it is measured by the respective high-yield bond spread. Note that the euro-area spread is only available for six years, from 1998 to 2004, whereas the US spread is available for the full sample. (Results for the bank sub-index are not reported, but are available on request.)

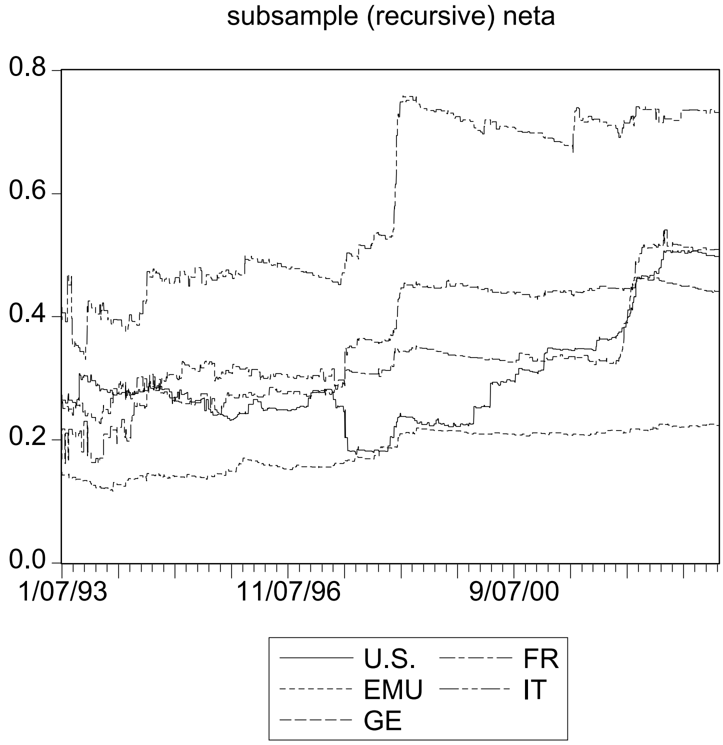

FIGURE 1

Country/Area	Break test results		Subsample estimations			
	Endog. break test T	Exog. T_{EMU}	$\widehat{\eta}_1$	$\widehat{P}_1$	$\widehat{\eta}_2$	$\widehat{P}_2$
United States (N=25)	07/20/98 (77.77)	-	0.181	1.81E-15	0.634	2.48E-3
Euro area (N=25)	08/14/97 (5.27)	0.062	0.155	3.39E-19	0.246	1.46E-11
Germany (N=6)	08/06/97 (13.08)	0.320	0.273	2.91E-9	0.522	3.94E-4
France (N=4)	06/03/02 (20.09)	2.710***	0.323	1.51E-7	0.843	0.107
Italy (N=4)	09/30/97 (10.02)	-0.492	0.452	8.27E-5	0.837	0.080

TABLE 7. Structural stability of multivariate contagion risk in the euro area and the United States: Tests and estimations

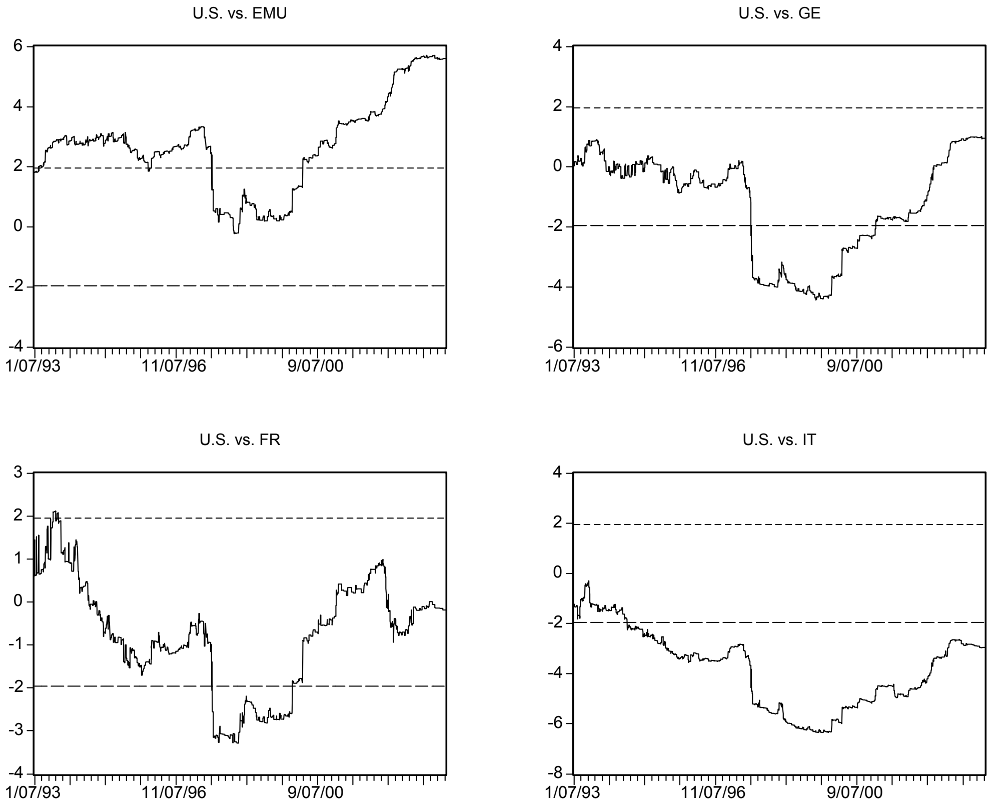
U.S. vs. EMU
6
4
2
0
-2
-4
1/07/93
11/07/96
9/07/00
U.S. vs. GE
4
2
0
-2
-4
-6
1/07/93
11/07/96
9/07/00
U.S. vs. FR
3
2
1
0
-1
-2
-3
-4
1/07/93
11/07/96
9/07/00
U.S. vs. IT
4
2
0
-2
-4
-6
-8
1/07/93
11/07/96
9/07/00

Figure 2

Bank	Aggregate risk measure		
	Bank index	Stock index	Yield spread
DEUTSCHE	8/21/97 (13.57)	3/17/97 (10.83)	9/28/00 (251.19)
HYPO	6/27/97 (15.92)	10/22/97 (16.70)	10/17/00 (265.88)
DRESDNER	8/1/97 (12.51)	8/1/97 (14.26)	10/4/00 (163.12)
	pre (B): 7/6/94 (5.01)		
COMMERZ	10/22/97 (17.40)	8/21/97 (17.27)	10/3/00 (485.36)
	post (B): 12/13/02 (3.16)		
BGBERLIN	3/31/97 (4.13)	10/22/97 (3.30)	1/4/01 (361)
DEPFA	3/1/96 (36.78)	12/5/96 (25.78)	9/20/00 (158.21)
BNPPAR	10/22/97 (40.41)	10/22/97 (33.84)	10/25/00 (168.15)
CA	2/18/02 (62.57)	2/18/02 (55.86)	9/29/00 (232.59)
SGENERAL	10/22/97 (41.51)	10/22/97 (36.96)	10/25/00 (171.36)
NATEXIS	3/19/97 (26.55)	12/3/96 (24.78)	10/12/00 (187.91)
	post (B):12/4/02 (7.65)	post (B): 12/4/02 (3.60)	
INTESA	7/31/97 (29.19)	10/8/97 (21.47)	11/6/00 (296.24)
UNICREDIT	10/8/97 (30.54)	8/1/97 (14.74)	10/2/00 (310.36)
		pre (B): 10/6/94 (3.40)	
PAOLO	8/6/97 (30.86)	8/7/97 (20.36)	10/4/00 (244.84)
	pre (F): 9/6/93 (3.36)		
	post (B): 1/20/03 (2.91)		
CAPITA	10/8/97 (14.65)	9/10/97 (11.54)	9/28/00 (328.64)
	(B) 3/11/03 (4.91)	B: 3/25/03 (2.64)	
SANTANDER	7/23/97 (23.41)	7/18/97 (33.25)	9/19/00 (275.00)
	post (B):1/14/99 (5.73)	post (B): 1/14/99 (3.83)	
BILBAO	10/16/97 (52.21)	10/22/97 (65.68)	9/25/00 (160.86)
		post (B): 2/23/99 (3.94)	
BANESP	5/27/97 (12.12)	10/8/97 (5.09)	9/28/00 (427.76)
	post (B): 12/4/98 (6.44)	post (B); 12/4/98 (11.75)	
ING	3/14/97 (59.54)	3/17/97 (39.06)	10/4/00 (165.79)
ABNAMRO	8/8/97 (42.81)	3/12/97 (34.31)	9/27/00 (165.03)
FORTIS	3/14/97 (21.06)	4/15/98 (18.57)	10/4/00 (166.48)
	post (F): 9/5/01 (3.23)		
ALMANIJ	3/17/97 (34.93)	1/23/97 (40.68)	10/4/00 (144.73)
	B:5/22/03 (2.46)	B:5/22/03 (4.27)	
ALPHA	2/27/97 (14.37)	2/27/97 (9.16)	10/2/00 (131.02)
	pre (B): 2/28/95 (5.61)	pre (B): 1/10/95 (12.89)	
	post (B): 4/2/99 (4.83)	post (B): 4/17/00 (4.96)	
BCP	8/1/97 (30.78)	7/9/97 (23.54)	11/6/00 (204.66)
	pre (F): 6/15/93 (6.96)		
SAMPO	10/24/97 (19.09)	10/24/97 (25.92)	9/27/00 (143.84)
IRBAN	3/19/97 (12.57)	10/22/97 (17.66)	10/2/00 (125.49)

TABLE 8. Structural stability of extreme systematic risk (tail betas) in the euro area

Bank	Aggregate risk measure		
	Bank index	Stock index	Yield spread
CITIG	F:3/7/96 (8.70)	12/15/95 (7.92)	11/9/00 (124.92)
	-		
JPMORGAN	F:3/12/97 (9.81)	2/20/96 (21.66)	10/17/00 (116.97)
	-		
BOA	3/12/97 (4.53)	3/7/96 (17.43)	10/25/00 (69.46)
WACHO	7/20/98 (3.08)	3/12/97 (15.82)	10/20/00 (114.14)
FARGO	3/12/97 (7.39)	11/2/93 (8.10)	(B) 4/4/03 (16.23)
BONEC	2/20/96 (14.23)	3/12/97 (10.00)	10/20/00 (138.77)
WASHMU	3/11/97 (2.99)	3/11/97 (10.74)	12/1/00 (42.79)
FLEET	10/24/97 (5.23)	4/22/98 (16.31)	6/6/01 (88.80)
BNYORK	1/4/96 (4.42)	1/8/96 (16.95)	10/9/00 (115.41)
STATEST	12/15/95 (15.73)	12/11/95 (27.41)	10/9/00 (88.47)
NOTRUST	12/3/96 (11.34)	12/5/96 (21.16)	9/29/00 (184.63)
MELLON	10/24/97 (3.91)	3/7/96 (13.02)	10/16/00 (86.08)
USBANC	2/25/97 (14.99)	1/23/97 (22.41)	3/13/01 (86.75)
CITYCO	12/2/96 (4.85)	12/11/96 (14.71)	3/19/01 (119.03)
PNC	3/12/97 (15.70)	2/20/96 (32.79)	10/5/00 (118.91)
KEYCO	2/28/97 (4.30)	2/20/96 (20.16)	10/4/00 (54.29)
			(B) 4/1/03 (7.34)
SUNTRUST	1/3/96 (15.82)	1/3/96 (18.73)	7/5/01 (80.89)
	pre: (B) 6/8/93 (3.83)		
COMERICA	7/20/98 (3.20)	12/13/95 (6.59)	10/10/00 (91.44)
UNIONBAN	1/5/98 (38.54)	7/17/97 (20.07)	7/13/01 (26.47)
AMSOUTH	3/12/97 (3.50)	1/8/96 (7.17)	11/14/00 (76.98)
HUNTING	1/22/97 (9.70)	3/12/97 (24.96)	10/5/00 (77.21)
	pre (B) 1/20/95 (7.31)		
BBT	7/20/98 (12.76)	F:7/20/98 (22.31)	9/5/01 (48.89)
	-		(B) 4/17/03 (9.31)
53BANCO	1/3/96 (4.48)	F:12/13/95 (14.32)	11/15/00 (61.11)
	pre (B) 11/5/93 (4.57)		(B) 4/14/03 (23.93)
SOTRUST	2/26/97 (14.16)	F:3/12/97 (21.26)	10/10/00 (105.93)
			(B) 5/26/03 (9.54)
RFCORP	2/19/97 (7.12)	F:3/7/96 (8.15)	11/10/00 (35.20)
			(B) 5/8/03 (8.26)

TABLE 9. Structural stability of extreme systematic risk (tail betas) in the United States

Appendix A. Small sample properties of estimators and tests

A.1. **Small sample properties of the tail beta estimator.** In this section we investigate the small sample properties of the tail beta estimator and the dependence parameter. Three different data generating processes are investigated: The bivariate Pareto distribution, the bivariate Morgenstern distribution (1956) with Pareto marginals and the bivariate standard normal distribution. The first two distributions both have Pareto marginals, but only the first distribution exhibits asymptotic dependence (in case which $\eta = 1$). The bivariate normal is also asymptotically independent (as long as $|\rho| \neq 1$). The normal distribution has a dependence parameter η which varies with the correlation coefficient, and we investigate different configurations. The precise specifications of the distributions are as follows:

1/ Bivariate Pareto

$$\begin{aligned}
F(x,y) &= 1 - x^{-\alpha} - y^{-\alpha} + (x+y-1)^{-\alpha} \\
\rho &= 1/\alpha \text{ for } \alpha > 2 \\
\eta &= 1.
\end{aligned}$$

2/ Bivariate Morgenstern distribution with Pareto marginals

$$\begin{aligned}
F(x,y) &= (1-x)^{-\alpha}\left(1-y^{-\alpha}\right)\left(1+\gamma x^{-\alpha}y^{-\alpha}\right), \qquad 0 \leq \gamma \leq 1 \\
\rho &= \gamma\alpha(\alpha-2)(2\alpha-1)^{-2} \text{ for } \alpha > 2 \\
\eta &= 1/2.
\end{aligned}$$

3/ Bivariate normal with correlation coefficient ρ and dependence parameter

$$\eta = \frac{1+\rho}{2}$$

The three specific distributions have the advantage that they allow us to calculate the true value of η and the tail beta τ_β. Thus the estimation bias and AMSE can be calculated explicitly. The true value of the tail beta's are (where $p = P\{X > x\}$):

$$\begin{aligned}
\tau_\beta &= \left(2 - p^{1/\alpha}\right)^{-\alpha} \quad \text{(bivariate Pareto)} \\
\tau_\beta &= (1+\gamma)\,p - 2\gamma p^2 + \gamma p^3 \quad \text{(bivariate Morgenstern)} \\
\tau_\beta &= \frac{\Phi(-x,-x,\rho)}{p}, \quad \text{(bivariate standard normal)}
\end{aligned}$$

In the tables below we evaluate the tail betas and dependence parameter at the boundary of the sample, ie at $p = 1/n$. Two different sample sizes are considered, a true small sample of 200 observations and a larger sample of 3106, corresponding to the actual sample size. We start with an evaluation for the bivariate Morgenstern distribution.

	$\widehat{\eta}$			$\widehat{\tau}_{\beta}$			τ_{β}
$(\alpha;\gamma)$	aver.	bias	s.e.	aver.	bias	s.e.	
			panel A: n=200				
$(2;0)$	0.496	-3.57E-3	9.79E-2	9.95E-3	4.95E-3	1.61E-2	0.005
$(3;0)$	0.498	-1.55E-3	9.57E-2	9.95E-3	4.95E-3	1.57E-2	0.005
$(4;0)$	0.499	-1.35E-3	9.72E-2	1.01E-2	5.15E-3	1.63E-2	0.005
$(2;0.5)$	0.526	2.58E-2	9.94E-2	1.66E-2	9.12E-3	2.25E-2	7.47E-3
$(3;0.5)$	0.524	2.38E-2	0.100	1.65E-2	8.99E-3	2.25E-2	7.47E-3
$(4;0.5)$	0.526	2.65E-2	9.92E-2	1.66E-2	9.15E-3	2.34E-2	7.47E-3
$(2;0.9)$	0.537	3.66E-2	9.88E-2	2.11E-2	1.16E-2	2.76E-2	9.45E-3
$(3;0.9)$	0.537	3.75E-2	9.92E-2	2.13E-2	1.18E-2	2.72E-2	9.45E-3
$(4;0.9)$	0.537	3.74E-2	9.91E-2	2.13E-2	1.18E-2	2.84E-2	9.45E-3
			Panel B: n=3,106				
$(2;0)$	0.499	-2.97E-4	4.16E-2	4.92E-4	1.70E-4	5.89E-4	3.22E-4
$(3;0)$	0.499	-1.97E-4	4.20E-2	4.99E-4	1.77E-4	6.01E-4	3.22E-4
$(4;0)$	0.499	-5.67E-5	4.27E-2	5.08E-4	1.86E-4	6.53E-4	3.22E-4
$(2;0.5)$	0.518	1.77E-2	4.20E-2	9.50E-4	4.67E-4	9.69E-4	4.83E-4
$(3;0.5)$	0.517	1.71E-2	4.16E-2	9.36E-4	4.53E-4	9.77E-4	4.83E-4
$(4;0.5)$	0.517	1.76E-2	4.22E-2	9.58E-4	4.75E-4	1.05E-3	4.83E-4
$(2;0.9)$	0.525	2.49E-2	4.16E-2	1.31E-3	7.03E-4	1.32E-3	6.11E-4
$(3;0.9)$	0.524	2.43E-2	4.20E-2	1.30E-3	6.93E-4	1.28E-3	6.11E-4
$(4;0.9)$	0.525	2.46E-2	4.16E-2	1.31E-3	6.97E-4	1.33E-3	6.11E-4

TABLE A.1. Small sample behavior of tail beta's for bivariate Morgenstern distribution

Note that the dependence parameter is quite well estimated even in the small samples. Since tail betas are so small, not much can be concluded, except that the order of magnitude is correctly captured.

	$\widehat{\eta}$			$\widehat{\tau}_{\beta}$			τ_{β}
	aver.	bias	s.e.	aver.	bias	s.e.	
			panel A: n=200				
$\alpha = 2$	0.790	-0.209	0.129	0.179	-0.089	0.126	0.269
$\alpha = 3$	0.722	-0.278	0.129	0.109	-5.40E-2	9.55E-2	0.163
$\alpha = 4$	0.675	-0.325	0.126	7.47E-2	-3.62E-2	7.43E-2	0.111
			Panel B: n=3,106				
$\alpha = 2$	0.875	-0.125	6.13E-2	0.166	-8.78E-2	7.59E-2	0.254
$\alpha = 3$	0.794	-0.206	6.05E-2	7.05E-2	-6.85E-2	3.99E-2	0.139
$\alpha = 4$	0.735	-0.265	5.94E-2	3.53E-2	-4.67E-2	2.34E-2	0.082

TABLE A.2. Small sample behavior of tail beta's for bivariate Pareto distribution

In contrast to the previous table, there now appears a considerable downward bias in the dependence parameter. Note that the true value is at the boundary, so that in any empirical exercise one expects at least some downward bias. The tail betas also exhibit a downward bias. Lastly, we consider the bivariate normal distribution.

	est.						full	
	$\widehat{\eta}$			$\widehat{\tau}_\beta$			τ_β	η
	aver.	bias	s.e.	aver.	bias	s.e.		
	panel A: n=200							
$\rho = 2/3$	0.749	-8.45E-2	0.118	0.175	-2.47E-2	0.119	0.200	5/6
$\rho = 1/2$	0.685	-6.46E-2	0.116	9.82E-2	-1.40E-3	8.28E-2	9.96E-2	0.75
$\rho = 1/3$	0.623	-4.31E-2	0.113	5.22E-2	7.52E-3	5.37E-2	4.47E-2	2/3
$\rho = 0$	0.495	-4.52E-4	9.78E-2	9.90E-3	4.90E-3	1.65E-2	0.005	1/2
	Panel B: n=3,106							
$\rho = 2/3$	0.780	-5.36E-2	5.37E-2	9.38E-2	-9.09E-3	4.53E-2	0.103	5/6
$\rho = 1/2$	0.707	-4.34E-2	5.32E-2	3.42E-2	-1.61E-3	2.14E-2	3.58E-2	0.75
$\rho = 1/3$	0.636	-3.06E-2	5.03E-2	1.07E-2	2.76E-4	8.20E-3	1.04E-2	2/3
$\rho = 0$	0.500	5.96E-4	4.20E-2	5.07E-4	1.85E-4	6.07E-4	3.22E-4	1/2

TABLE A.3. Small sample behavior of tail beta's for bivariate normal distribution

For the normal distribution the estimators appear to behave quite reasonably. Comparing this last table to the previous, one notes that it may be difficult to distinguish the normal distribution from the bivariate Pareto just on basis of say the dependence parameter estimate. To this end it would be helpful to investigate the tail properties of the marginals as well.

A.2. **Small sample properties of the endogenous break test.** In this part of the annex we investigate the small sample properties of the recursive test for a single endogenous break in η. This is done through a simulation study in which we use the bivariate normal as the DGP. Recall that $\eta = (1+\rho)/2$. By changing the correlation coefficient, we can easily change the dependence parameter η. This break is engineered at the r-th part of the sample. Three different combinations of η's are considered. The sample size was chosen to be 3,000. The table shows that the test has more difficulty locating the break if the break is close to the start or towards the end of the sample. The reason is that in these cases one has fewer observations available for one of the two regimes. The standard errors are quite sizable. The difference between the dependence parameters was twice as large in the second configuration studied, and this affects the standard errors favorably, effectively halving the standard errors.

	Estimated breakpoints (standard error)				
$(\eta_1;\eta_2)$	r=1/4	r=1/3	r=1/2	r=2/3	r=3/4
$(0.5;0.7)$	0.368 (0.192)	0.364 (0.190)	0.514 (0.166)	0.607 (0.181)	0.637 (0.202)
$(0.5;0.9)$	0.268 (0.101)	0.264 (0.095)	0.485 (0.078)	0.636 (0.092)	0.705 (0.120)
$(0.7;0.9)$	0.395 (0.208)	0.394 (0.209)	0.508 (0.172)	0.587 (0.194)	0.616 (0.220)

TABLE A.4. Simulated breakpoints

Appendix B List of banks in the sample

Table B.1 List of banks in the sample

Euro area

Bank name	Abbreviation	Country
Deutsche Bank	DEUTSCHE	Germany
Bayerische Hypo- und Vereinsbank	HYPO	Germany
Dresdner Bank	DRESDNER	Germany
Commerzbank	COMMERZ	Germany
Bankgesellschaft Berlin	BGBERLIN	Germany
DePfa Group	DEPFA	Germany
BNP Paribas	BNPPAR	France
Crédit Agricole	CA	France
Societe Generale	SGENER	France
Natexis Banques Populaires	NATEXIS	France
Banca Intesa	INTESA	Italy
UniCredito Italiano	UNICRED	Italy
Sanpaolo IMI	PAOLO	Italy
Capitalia	CAPITA	Italy
Banco Santander Central Hispano	SANTANDER	Spain
Banco Bilbao Vizcaya Argentaria	BILBAO	Spain
Banco Espagnol de Credito	BANESP	Spain
ABN AMRO	ABNAM	Netherlands
ING Bank	ING	Netherlands
Fortis	FORTIS	Belgium
Almanij	ALMANIJ	Belgium
Sampo Leonia	SAMPO	Finland
Alpha Bank	ALPHA	Greece
Allied Irish Banks	IRBAN	Ireland
Banco Commercial Portugues	BCP	Portugal

US

Bank name	Abbreviation	Country
Citigroup	CITIG	US
JP Morgan Chase	JPMORGAN	US
Bank of America BOA	BOA	US
Wachovia Corporation	WACHO	US
Wells Fargo and Company	FARGO	US
Bank One Corporation	BONEC	US
Washington Mutual Inc	WASHMU	US
Fleet Boston Financial Corporation	FLEET	US
Bank of New York	BNYORK	US
State Street	STATEST	US
Northern Trust	NOTRUST	US
Mellon	MELLON	US
US Bancorp	USBANC	US
National City Corporation	CITYCO	US
PNC Financial Services Group	PNC	US
Keycorp	KEYCORP	US
Sun Trust	SUNTRUST	US
Comerica Incorporated	COMERICA	US
Unionbancal Corporation	UNIONBA	US
AmSouth Bancorp	AMSOUTH	US
Huntington Bancshares Inc	HUNTING	US
BBT Corporation	BBT	US
Fifth Third Bancorp	53BANCO	US
Southtrust	SOTRUST	US
Regions Financial Corporation	REGIONS	US

Appendix C: Balance sheet data

[MUS$]

Table C.1: Total assets of euro area banks

Bank Name	TA 2003	TA 2002	TA 2001	TA 2000	TA 1999	TA 1998	TA 1997	TA 1996	TA 1995	TA 1994	TA 1993	TA 1992	TA AVG	TA AVG 1998-2003	TA AVG 1992-1997
Deutsche Bank AG	934434	730301	641826	647186	569127	555446	419892	386645	461180	352740	308790	297200	525397	679720	371075
BNP Paribas	988881	744867	727318	644886	700675	378990	339817	355299	325880	271640	250440	275310	500334	697603	303064
Crédit Agricole CA	1105378	609055	496421	498433	441524	455781	419971	477591	387130	328130	282870	292090	482864	601099	364630
ABN Amro Holding NV	707801	583073	526450	505419	460000	504122	414655	343699	340640	290800	252990	246980	431386	547811	314961
Bayerische Hypo-und Vereinsbank AG	597584	552068	631216	646016	485099	521336	453909	n/a	203960	173600	151150	134300	413658	572220	223384
Société Générale	681216	525789	451660	424198	437558	447486	410655	339586	326670	277550	259790	251320	402790	494651	310929
Dresdner Bank AG	602461	433489	446238	449036	397944	424620	372779	n/a	330340	252180	215190	199820	374918	458965	274062
Commerzbank AG	481653	442333	441510	422867	371134	374896	294671	n/a	275700	217640	162120	142130	329696	422399	218452
ING Bank NV	684004	500326	390725	378149	351234	326813	190269	179933	154050	125330	105880	109540	291354	438542	144167
Banca Intesa SpA	327353	290917	275967	308334	309719	330138	158597	163712	n/a	n/a	n/a	n/a	270592	307071	161154
Fortis Bank	536857	396107	327451	309011	330835	333608	n/a	n/a	19650	16690	14220	14520	229895	372312	16270
Banco Bilbao Vizcaya Argentaria SA	356921	288311	269208	272225	236802	235799	214978	213680	115820	98820	81420	87640	205969	276544	135393
UniCredito Italiano SpA	300652	226638	188380	188565	169705	175346	161206	n/a	n/a	n/a	n/a	n/a	201499	208214	161206
Bankgesellschaft Berlin AG	191936	182046	165227	189389	192212	217785	195372	206377	34060	20650	n/a	n/a	159505	189766	114115
Banco Santander Central Hispano	250904	188024	159505	160325	n/a	n/a	n/a	n/a	135060	113920	73120	61310	142771	189689	95853
Capitalia SpA	159915	146148	115815	123504	134397	142745	114969	140831	n/a	n/a	n/a	n/a	134790	137087	127900
Almanij	327898	265080	228521	202453	187390	198213	187745	740	3300	2810	2370	1310	133986	234926	33046
DePfa ACS Bank	219708	152944	159425	n/a	n/a	n/a	n/a	n/a	103580	76800	62850	56150	118779	177359	74845
Natexis Banques Populaires	171646	139891	97254	105268	94861	49558	49972	110159	n/a	n/a	n/a	n/a	102326	109746	80066
Allied Irish Banks plc	98699	87717	76551	72516	65548	61439	52815	43105	37810	32200	29430	29940	57314	77078	37550
Banco Español de Crédito SA, BANESTO	72923	51919	39384	41296	39958	42800	36606	42715	41760	43120	53210	61750	47287	48047	46527
Banco Comercial Português, SA	85483	64861	55479	57552	35211	33955	29662	n/a	36170	13960	10900	10370	39418	55423	20212
Sampo Bank Plc	21454	18255	15126	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	18278	18278	n/a
Alpha Bank AE	38902	30123	26052	28420	25445	16372	12409	11680	9250	7130	5610	5020	18034	27552	8517
Banque Sanpaolo	8807	7073	5586	6133	5375	6056	5163	4791	4643	4100	3729	4608	5505	6505	4506
Sum	9953470	7657353	6958293	6681182	6041753	5833304	4536112	3020543	3346653	2719810	2326079	2281308	5638347	7348608	3641882

Comment: BNP PARIBAS: Until 1995, BNP

Source: Bankscope

Appendix C: Balance sheet data

[MUS$]

Table C.2: Total assets of US banks

Bank Name	**TA 2003**	**TA 2002**	**TA 2001**	**TA 2000**	**TA 1999**	**TA 1998**	**TA 1997**	**TA 1996**	**TA 1995**	**TA 1994**	**TA 1993**	**TA 1992**	**TA AVG**	**TA AVG 1998-2003**	**TA AVG 1992-1997**
Citigroup Inc	1264032	1097190	1051450	902210	716937	668641	n/a	n/a	220110	210487	175712	163846	647062	950077	192539
J.P. Morgan Chase & Co.	770912	758800	693575	715348	406105	365875	365521	336099	184879	154917	133888	102941	415738	618436	213041
Bank of America Corporation	736445	660458	621764	642191	632574	617679	264562	185794	163398	147670	136693	133449	411890	651852	171928
Bank One Corporation	326563	277383	268954	269300	269425	261496	115901	101848	n/a	n/a	n/a	n/a	236359	278854	108875
Wells Fargo & Company	387798	349259	307569	272426	218102	202475	88540	80175	50316	53374	52513	52537	176257	289605	62909
Wachovia Corporation	401032	341839	330452	74032	67353	64123	65397	46886	44964	39171	36514	33356	128760	213138	44382
FleetBoston Financial Corporation	200356	190589	203638	179519	190692	104554	85690	85555	11037	9757	8246	8288	106493	178225	34762
US Bancorp	189286	180027	171390	87336	81530	76438	71295	36489	31865	21784	21458	20773	82473	131001	33944
National City Corporation	113934	118258	105817	88535	87122	88246	54684	50856	36199	32114	31068	28964	69649	100318	38981
KeyCorp	84147	84710	80400	87165	83344	79966	73625	67688	66339	66798	32648	25457	69357	83289	55426
PNC Financial Services Group Inc	68193	66410	69570	69916	75428	77232	75101	73174	73507	64221	61945	51523	68852	71125	66578
Bank of New York	89258	74948	78019	74266	71795	60078	56154	52121	42712	39287	36088	36644	59281	74727	43834
State Street Bank and Trust Company	80435	79621	65410	64644	56226	43185	37450	31390	25785	21744	18720	16490	45092	64920	25263
Southtrust Bank	51885	50570	48850	45170	43203	38054	30715	13339	n/a	n/a	n/a	n/a	40223	46288	22027
BB&T Corporation	90467	80217	70870	59340	43481	34427	29178	21247	15992	9179	7794	6256	39037	63134	14941
Fifth Third Bancorp	91143	80899	71026	45857	41590	28922	21375	20549	17057	14973	11981	10232	37967	59906	16028
Mellon Bank NA	20839	26841	27813	41974	39619	42235	38802	37339	40734	38716	36050	31541	35209	33220	37197
Comerica Bank	52684	39643	37256	33697	31243	29375	28936	27052	28394	27044	24935	22364	31885	37317	26454
Regions Financial Corporation	48881	47939	45383	43688	42714	36832	23034	18930	13709	12839	10476	7881	29359	44240	14478
UnionBanCal Corporation	42488	40193	36078	35170	33685	32301	30612	29304	19518	16761	16391	16844	29112	36652	21572
AmSouth Bancorporation	45670	40598	38622	38968	43427	19919	18657	18440	17740	16845	12584	9790	26772	37867	15676
Washington Mutual Bank	29327	26723	31639	34715	35036	32466	26070	21241	21633	18458	15827	n/a	26649	31651	20646
Huntington Bancshares Inc	30566	27702	28497	28599	29037	28296	26731	20852	20255	17771	17619	16247	24347	28783	19912
Northern Trust Company (The)	33403	31974	32758	29709	23500	23304	21185	18127	15231	14736	13538	11907	22448	29108	15787
Sun Trust Capital Markets Inc	n/a	4638	3991	3459	3504	3478	2292	n/a	46472	42534	40728	36647	18774	3814	33735
Sum	5249743	4777430	4520789	3967235	3366670	3059596	1651505	1394493	1207844	1091179	953416	843975	2879044	4157546	1350913

Comment:Comerica: until 1995 Comerica Detroit

Source: Bankscope

Appendix C: Balance sheet data

[MUS$]

Table C.3: Due from banks for euro area banks

Bank Name	DfB 2003	DfB 2002	DfB 2001	DfB 2000	DfB 1999	DfB 1998	DfB 1997	DfB 1996	DfB 1995	DfB 1994	DfB 1993	DfB 1992	DfB AVG	DfB AVG 1998-2003	DfB AVG 1992-1997
BNP Paribas	205797	153641	164469	121536	160510	83169	82147	103735	96870	77920	72780	87370	117495	148187	86804
Deutsche Bank AG	180570	147226	136059	135624	134235	124204	100119	99183	77060	63300	54860	56490	109078	142986	75169
Crédit Agricole CA	119534	70083	56052	61259	62275	79898	78699	112656	98490	78040	68290	63250	79044	74850	83237
Dresdner Bank AG	154862	92666	68276	83419	56934	77022	68836	n/a	55910	40830	29470	32300	69139	88863	45469
Société Générale	76133	56999	56004	50409	55263	77499	89485	66669	72850	66720	61240	62910	66015	62051	69979
ABN Amro Holding NV	74261	43964	43729	45205	47419	71047	69495	68983	81860	73220	65820	65080	62507	54271	70743
Commerzbank AG	65191	56900	55770	69266	50026	67994	49210	n/a	59180	44880	32660	23250	52212	60858	41836
Bayerische Hypo-und Vereinsbank AG	66489	60068	78634	84804	56089	67207	68637	0	25000	17000	18050	12910	50444	68882	28319
Fortis Bank	105699	87860	57640	60307	82766	68522	n/a	n/a	2150	2620	2530	2570	47266	77132	2468
Banca Intesa SpA	36657	31916	35400	44249	44398	64423	33975	34586	n/a	n/a	n/a	n/a	40701	42841	34281
Almanij	47735	39979	34662	28575	27128	43366	53842	n/a	n/a	n/a	n/a	n/a	39327	36907	53842
ING Bank NV	77115	47905	47662	41087	42126	59516	26071	21783	22000	16850	13840	16320	36023	52568	19477
Bankgesellschaft Berlin AG	35502	32286	29606	35579	36738	45972	43037	43984	14340	6710	n/a	n/a	32375	35947	27018
UniCredito Italiano SpA	41404	30915	23319	23173	20100	27181	35089	n/a	n/a	n/a	n/a	n/a	28740	27682	35089
Banco Bilbao Vizcaya Argentaria SA	12129	12371	8691	19582	22621	31674	41493	43787	35430	31930	27030	24580	25943	17845	34042
Banco Santander Central Hispano	35994	35630	29007	25513	n/a	n/a	n/a	n/a	28570	20990	17390	12470	25695	31536	19855
Natexis Banques Populaires	54015	38767	14694	14853	23422	7821	8874	20808	n/a	n/a	n/a	n/a	22907	25595	14841
Capitalia SpA	21622	21410	17360	15500	18592	23072	23793	26081	n/a	n/a	n/a	n/a	20929	19593	24937
DePfa ACS Bank	23323	14117	12373	n/a	n/a	n/a	n/a	n/a	4170	4320	3540	4620	9495	16604	4163
Banco Español de Crédito SA, BANESTO	5461	2521	1804	4663	4965	7802	6486	8069	10470	8410	7920	6940	6293	4536	8049
Allied Irish Banks plc	4069	5198	5828	4312	4122	6186	6270	4645	3950	4070	3740	2980	4614	4953	4276
Banco Comercial Português, SA	4724	3515	4104	5531	2376	3568	5951	n/a	7720	4140	2690	1500	4165	3970	4400
Alpha Bank AE	2130	1728	2563	5399	4239	3338	1592	2449	1540	1340	290	390	2250	3233	1267
Sampo Bank Plc	1284	2707	1790	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	1927	1927	n/a
Banque Sanpaolo	2323	1681	1262	1528	863	1690	1391	1233	1356	1226	1298	1577	1453	1558	1347
Sum	1454021	1092053	986757	981372	957208	1042172	894490	658649	698916	564516	483438	477507	956035	1105375	790906

Comment: BNP PARIBAS: Until 1995, BNP

Source: Bankscope

Appendix C: Balance sheet data
[MUS$]
Table C.4: Due from banks for US banks

Bank Name	DfB 2003	Dfb 2002	DfB 2001	DfB 2000	DfB 1999	DfB 1998	DfB 1997	DfB 1996	DfB 1995	DfB 1994	DfB 1993	DfB 1992	DfB AVG	DfB AVG 1998-2003	DfB AVG 1992-1997
State Street Bank and Trust Company	21628	28133	20306	21289	16902	12008	10076	7562	5975	4847	5148	4803	13223	20044	6402
Citigroup Inc	19777	16382	19216	17274	13429	13425	n/a	n/a	9256	7201	7137	6249	12935	16584	7461
J.P. Morgan Chase & Co.	10175	8942	12743	8333	28076	7212	2886	8344	1986	1362	1221	1516	7733	12580	2886
Bank of America Corporation	8051	6813	5932	5448	4838	6750	2395	1843	5899	6771	2956	2779	5040	6305	3774
Northern Trust Company (The)	8766	8267	6954	5191	2291	3264	2282	2060	1567	1865	2090	1860	3871	5789	1954
Bank One Corporation	3093	1503	1030	5210	6645	4642	n/a	n/a	n/a	n/a	n/a	n/a	3687	3687	n/a
Bank of New York	7154	4418	5924	4949	6208	4134	1343	809	644	854	652	672	3147	5464	829
Wachovia Corporation	2308	3512	6875	3239	1073	2916	710	316	451	7	13	190	1801	3321	281
Mellon Bank NA	2770	1768	4089	2349	657	991	925	790	553	433	889	992	1434	2104	764
FleetBoston Financial Corporation	2695	3679	3744	2826	1772	444	76	858	0	1000	0	0	1425	2527	322
UnionBanCal Corporation	235	279	64	74	183	210	629	1131	505	1030	1200	1201	562	174	949
PNC Financial Services Group Inc	493	518	413	380	207	174	570	145	139	149	233	695	343	364	322
National City Corporation	592	615	120	49	129	141	49	282	51	97	543	1234	325	274	376
Sun Trust Capital Markets Inc	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	29	56	476	695	314	n/a	314
Wells Fargo & Company	988	352	206	95	421	113	47	1238	10	7	0	0	290	363	217
US Bancorp	n/a	434	625	200	897	76	238	50	11	7	33	46	238	446	64
Comerica Bank	23	14	43	24	13	8	1	26	1	377	897	1231	221	21	422
KeyCorp	186	112	83	34	35	20	531	217	45	381	14	141	150	78	221
Regions Financial Corporation	n/a	304	667	3	10	144	30	33	47	0	11	0	114	226	20
BB&T Corporation	271	148	115	39	71	5	27	1	1	4	7	n/a	63	108	8
Fifth Third Bancorp	58	198	152	109	82	51	27	31	1	11	1	1	60	108	12
Huntington Bancshares Inc	34	37	21	5	7	103	40	2	284	3	13	134	57	34	79
Washington Mutual Bank	17	16	28	18	15	15	n/a	n/a	n/a	n/a	n/a	n/a	18	18	n/a
AmSouth Bancorporation	7	28	12	61	24	29	0	0	1	1	1	0	14	27	0
Southtrust Bank	5	4	6	1	0	1	0	0	n/a	n/a	n/a	n/a	2	3	0
Sum	89325	86476	89369	77200	83984	56875	22881	25736	27458	26460	23534	24437	57064	80650	27677

Comment:Comerica: until 1995 Comerica Detroit
Source: Bankscope

Appendix D: Return and spread data

Table D.1: Moments of euro area returns and correlations with aggregate risk factors

Bank	Average	SD	Skewness	Kurtosis	Correlation, local bank sector index	Correlation, local stock market index	Correlation, 6 year local Yield spread	Correlation, 12 year local Yield spread
deutsche	0.012%	1.96%	-0.12	4.04	0.77	0.69	-0.03	n.a.
hypo	-0.006%	2.38%	0.11	6.08	0.66	0.57	-0.05	n.a.
dresalianz	0.012%	2.15%	0.17	5.88	0.67	0.59	-0.03	n.a.
commerz	0.002%	2.03%	0.15	6.92	0.68	0.62	-0.05	n.a.
bgberlin	-0.057%	2.39%	-1.39	32.76	0.20	0.18	-0.05	n.a.
depfa	0.050%	1.95%	0.17	6.22	0.31	0.30	-0.05	n.a.
bnppar	0.033%	2.18%	0.14	3.72	0.70	0.64	-0.01	n.a.
cagr	0.023%	1.40%	-0.79	21.26	0.30	0.26	-0.03	n.a.
sgener	0.039%	2.18%	0.06	3.86	0.73	0.66	-0.02	n.a.
natexis	0.005%	1.65%	0.32	6.32	0.35	0.34	-0.03	n.a.
intesa	0.023%	2.53%	0.33	2.93	0.55	0.49	-0.03	n.a.
unicredi	0.035%	2.32%	0.93	8.54	0.57	0.52	-0.01	n.a.
sanpaolo	0.002%	2.25%	0.22	2.06	0.65	0.60	-0.04	n.a.
capitalia	-0.041%	2.61%	0.33	5.17	0.51	0.46	-0.05	n.a.
santander	0.040%	2.11%	-0.13	5.07	0.74	0.69	-0.02	n.a.
bilbao	0.045%	1.99%	0.03	5.47	0.77	0.71	-0.01	n.a.
espcredito	-0.023%	2.36%	-14.48	543.24	0.23	0.20	-0.06	n.a.
ing	0.044%	2.20%	-0.12	7.52	0.77	0.74	-0.03	n.a.
abnamro	0.043%	1.98%	-0.08	5.31	0.78	0.72	-0.01	n.a.
fortis	0.031%	1.96%	0.24	8.41	0.68	0.63	-0.01	n.a.
almanij	0.030%	1.65%	0.40	5.11	0.48	0.45	-0.02	n.a.
alpha	0.033%	2.12%	0.38	3.70	0.23	0.24	-0.06	n.a.
bcport	0.001%	1.51%	-0.24	12.23	0.39	0.38	-0.05	n.a.
sampo	0.066%	2.79%	0.26	7.68	0.26	0.28	-0.03	n.a.
Alliedirish	0.051%	1.72%	-0.36	7.41	0.45	0.43	0.01	n.a.
POOLED Euroarea	0.020%	2.12%	-0.71	41.18				
INDEX:Bank sector	0.018%	0.50%	-0.23	5.65				
INDEX:Stockmarket	0.017%	0.46%	-0.29	3.50				
INDEX:Yield spreads 6 years	8.047%	3.18%	0.60	-0.74				

Comment: Excess return for indeces are calculated without subtracting the risk-free rate

Source: Datastream

Appendix D: Return and spread data

Table D.2: Moments of US returns and correlations with aggregate risk factors

Bank	Average	SD	Skewness	Kurtosis	Correlation, local bank sector index	Correlation, local stock market index	Correlation, 6 year local Yield spread	Correlation, 12 year local Yield spread
citigroup	0.080%	2.24%	0.06	4.31	0.80	0.69	-0.01	0.00
jpmorgan	0.040%	2.27%	0.10	5.01	0.81	0.67	-0.02	-0.01
wachovia	0.030%	1.76%	-0.05	2.92	0.78	0.58	0.01	0.02
fargo	0.053%	1.72%	0.10	2.24	0.74	0.54	0.00	0.01
bankone	0.017%	1.94%	-0.62	13.01	0.75	0.57	0.01	0.02
washingt	0.057%	2.09%	0.28	3.80	0.53	0.40	0.01	0.02
fleet	0.036%	2.03%	0.50	6.52	0.76	0.60	-0.01	0.00
bnyork	0.054%	2.11%	-0.01	4.68	0.77	0.60	-0.03	-0.02
sstreet	0.049%	2.08%	-0.18	6.71	0.68	0.57	-0.01	-0.01
ntrust	0.046%	1.97%	0.64	6.48	0.68	0.58	-0.03	-0.03
mellon	0.047%	1.99%	0.07	3.67	0.76	0.60	-0.02	-0.01
usbancorp	0.066%	1.95%	0.46	16.42	0.62	0.46	-0.01	0.01
natcityco	0.039%	1.60%	-0.05	2.99	0.76	0.56	0.01	0.03
pnc	0.027%	1.78%	-0.18	4.97	0.77	0.59	0.00	0.00
keycorp	0.028%	1.74%	0.09	3.46	0.76	0.57	0.00	0.02
suntrust	0.038%	1.59%	-0.05	3.52	0.80	0.61	0.00	0.02
comerica	0.033%	1.73%	-0.66	12.05	0.74	0.57	-0.02	-0.01
unionban	0.058%	2.09%	-1.74	33.33	0.48	0.36	0.00	0.02
amsouth	0.036%	1.60%	-0.60	14.45	0.65	0.48	0.01	0.03
huntington	0.033%	1.86%	0.09	9.61	0.60	0.47	0.01	0.03
bbt	0.048%	1.61%	0.49	5.91	0.68	0.53	0.00	0.02
53banco	0.048%	1.73%	0.25	2.63	0.66	0.53	-0.01	0.01
southtrust	0.054%	1.73%	0.02	3.96	0.64	0.49	0.01	0.04
regions	0.032%	1.65%	-0.04	3.24	0.66	0.51	0.01	0.04
bamerica	0.038%	1.91%	-0.17	2.78	0.83	0.59	0.01	0.02
POOLED US	0.044%	1.88%	-0.05	8.12				
INDEX:Bank sector	0.026%	0.61%	0.06	3.37				
INDEX:Stockmarket	0.019%	0.46%	-0.14	4.15				
INDEX:Yield spreads 6 years	6.184%	1.85%	0.43	-0.85				
INDEX:Yield spreads 12 years	5.409%	1.71%	0.97	0.09				

Comment: Excess return for indeces are calculated without subtracting the risk-free rate

Source: Datastream

Appendix D: Return and spread data

Table D.3: Correlations of euro area bank returns

	Deutsche	Hypo	dresalianz	commerz	bgberlin	depfa	bnppar	cagr	sgener	natexis	intesa	unicredi	sanpaolo	capitalia	santander	bilbao	espcredito	ing	abnamro	fortis	almanij	alpha	bcport	sampo	Alliedirish
Deutsche	1.00	0.61	0.68	0.65	0.17	0.25	0.49	0.20	0.53	0.24	0.34	0.36	0.43	0.32	0.48	0.49	0.13	0.56	0.56	0.48	0.34	0.17	0.28	0.17	0.27
Hypo	0.61	1.00	0.56	0.62	0.15	0.21	0.41	0.22	0.43	0.20	0.33	0.30	0.40	0.29	0.40	0.42	0.10	0.48	0.47	0.42	0.28	0.15	0.26	0.14	0.24
dresalianz	0.68	0.56	1.00	0.61	0.14	0.21	0.43	0.19	0.44	0.22	0.32	0.28	0.37	0.25	0.42	0.44	0.14	0.50	0.50	0.44	0.31	0.15	0.26	0.17	0.24
commerz	0.65	0.62	0.61	1.00	0.16	0.24	0.42	0.22	0.44	0.21	0.33	0.32	0.40	0.31	0.43	0.46	0.12	0.52	0.50	0.45	0.28	0.15	0.26	0.16	0.25
bgberlin	0.17	0.15	0.14	0.16	1.00	0.12	0.12	0.03	0.12	0.07	0.09	0.09	0.09	0.08	0.14	0.12	0.03	0.12	0.10	0.09	0.08	0.07	0.10	0.09	0.13
depfa	0.25	0.21	0.21	0.24	0.12	1.00	0.19	0.11	0.22	0.14	0.14	0.16	0.16	0.11	0.19	0.21	0.06	0.24	0.23	0.22	0.18	0.09	0.14	0.13	0.19
bnppar	0.49	0.41	0.43	0.42	0.12	0.19	1.00	0.25	0.66	0.31	0.35	0.37	0.43	0.34	0.50	0.51	0.17	0.54	0.53	0.46	0.30	0.14	0.25	0.19	0.30
cagr	0.20	0.22	0.19	0.22	0.03	0.11	0.25	1.00	0.25	0.12	0.15	0.10	0.19	0.11	0.20	0.22	0.05	0.28	0.25	0.26	0.16	0.05	0.10	0.06	0.12
sgener	0.53	0.43	0.44	0.44	0.12	0.22	0.66	0.25	1.00	0.30	0.34	0.39	0.44	0.33	0.51	0.52	0.15	0.57	0.55	0.49	0.33	0.17	0.25	0.20	0.34
natexis	0.24	0.20	0.22	0.21	0.07	0.14	0.31	0.12	0.30	1.00	0.17	0.18	0.21	0.13	0.24	0.26	0.10	0.27	0.28	0.22	0.15	0.11	0.16	0.13	0.19
intesa	0.34	0.33	0.32	0.33	0.09	0.14	0.35	0.15	0.34	0.17	1.00	0.46	0.49	0.48	0.36	0.38	0.11	0.40	0.38	0.37	0.24	0.12	0.20	0.15	0.22
unicredi	0.36	0.30	0.28	0.32	0.09	0.16	0.37	0.10	0.39	0.18	0.46	1.00	0.50	0.48	0.36	0.39	0.12	0.40	0.41	0.35	0.24	0.09	0.18	0.14	0.22
sanpaolo	0.43	0.40	0.37	0.40	0.09	0.16	0.43	0.19	0.44	0.21	0.49	0.50	1.00	0.48	0.46	0.48	0.12	0.49	0.48	0.41	0.27	0.12	0.24	0.17	0.26
capitalia	0.32	0.29	0.25	0.31	0.08	0.11	0.34	0.11	0.33	0.13	0.48	0.48	0.48	1.00	0.34	0.37	0.09	0.35	0.33	0.31	0.20	0.06	0.16	0.14	0.21
santander	0.48	0.40	0.42	0.43	0.14	0.19	0.50	0.20	0.51	0.24	0.36	0.36	0.46	0.34	1.00	0.77	0.22	0.55	0.56	0.47	0.30	0.17	0.30	0.19	0.31
bilbao	0.49	0.42	0.44	0.46	0.12	0.21	0.51	0.22	0.52	0.26	0.38	0.39	0.48	0.37	0.77	1.00	0.21	0.56	0.56	0.49	0.33	0.18	0.31	0.19	0.31
espcredito	0.13	0.10	0.14	0.12	0.03	0.06	0.17	0.05	0.15	0.10	0.11	0.12	0.12	0.09	0.22	0.21	1.00	0.12	0.13	0.11	0.06	0.05	0.11	0.06	0.09
ing	0.56	0.48	0.50	0.52	0.12	0.24	0.54	0.28	0.57	0.27	0.40	0.40	0.49	0.35	0.55	0.56	0.12	1.00	0.74	0.65	0.42	0.19	0.30	0.22	0.36
abnamro	0.56	0.47	0.50	0.50	0.10	0.23	0.53	0.25	0.55	0.28	0.38	0.41	0.48	0.33	0.56	0.56	0.13	0.74	1.00	0.59	0.40	0.18	0.28	0.19	0.34
fortis	0.48	0.42	0.44	0.45	0.09	0.22	0.46	0.26	0.49	0.22	0.37	0.35	0.41	0.31	0.47	0.49	0.11	0.65	0.59	1.00	0.45	0.17	0.24	0.19	0.30
almanij	0.34	0.28	0.31	0.28	0.08	0.18	0.30	0.16	0.33	0.15	0.24	0.24	0.27	0.20	0.30	0.33	0.06	0.42	0.40	0.45	1.00	0.12	0.20	0.16	0.24
alpha	0.17	0.15	0.15	0.15	0.07	0.09	0.14	0.05	0.17	0.11	0.12	0.09	0.12	0.06	0.17	0.18	0.05	0.19	0.18	0.17	0.12	1.00	0.14	0.13	0.14
bcport	0.28	0.26	0.26	0.26	0.10	0.14	0.25	0.10	0.25	0.16	0.20	0.18	0.24	0.16	0.30	0.31	0.11	0.30	0.28	0.24	0.20	0.14	1.00	0.13	0.19
sampo	0.17	0.14	0.17	0.16	0.09	0.13	0.19	0.06	0.20	0.13	0.15	0.14	0.17	0.14	0.19	0.19	0.06	0.22	0.19	0.19	0.16	0.13	0.13	1.00	0.20
Alliedirish	0.27	0.24	0.24	0.25	0.13	0.19	0.30	0.12	0.34	0.19	0.22	0.22	0.26	0.21	0.31	0.31	0.09	0.36	0.34	0.30	0.24	0.14	0.19	0.20	1.00

Source: Datastream

Appendix D: Return and spread data

Table D.4: Correlations of US bank returns

	citigroup	jpmorgan	wachovia	fargo	bankone	washingt	fleet	bnyork	sstreet	ntrust	mellon	usbancorp	natcityco	pnc	keycorp	suntrust	comerica	unionban	amsouth	huntington	bbt	53banco	southtrust	regions	bamerica
citigroup	1.00	0.65	0.56	0.52	0.53	0.38	0.56	0.56	0.52	0.51	0.55	0.41	0.53	0.54	0.53	0.56	0.52	0.34	0.46	0.41	0.50	0.47	0.45	0.44	0.61
jpmorgan	0.65	1.00	0.59	0.55	0.57	0.39	0.61	0.61	0.53	0.52	0.61	0.43	0.56	0.58	0.57	0.58	0.56	0.34	0.48	0.44	0.50	0.48	0.46	0.49	0.65
wachovia	0.56	0.59	1.00	0.57	0.60	0.40	0.60	0.57	0.50	0.52	0.59	0.49	0.61	0.62	0.62	0.64	0.59	0.38	0.51	0.49	0.55	0.52	0.49	0.52	0.66
fargo	0.52	0.55	0.57	1.00	0.53	0.41	0.55	0.57	0.51	0.49	0.57	0.46	0.58	0.60	0.58	0.63	0.56	0.34	0.49	0.43	0.53	0.51	0.49	0.50	0.60
bankone	0.53	0.57	0.60	0.53	1.00	0.41	0.55	0.56	0.50	0.49	0.56	0.45	0.58	0.59	0.57	0.61	0.55	0.35	0.47	0.45	0.50	0.48	0.46	0.49	0.60
washingt	0.38	0.39	0.40	0.41	0.41	1.00	0.39	0.41	0.39	0.41	0.42	0.35	0.44	0.44	0.45	0.44	0.42	0.27	0.38	0.34	0.42	0.42	0.42	0.40	0.41
fleet	0.56	0.61	0.60	0.55	0.55	0.39	1.00	0.60	0.51	0.53	0.60	0.49	0.61	0.60	0.59	0.63	0.60	0.37	0.52	0.47	0.54	0.51	0.49	0.52	0.59
bnyork	0.56	0.61	0.57	0.57	0.56	0.41	0.60	1.00	0.58	0.59	0.63	0.49	0.58	0.62	0.59	0.64	0.60	0.36	0.51	0.47	0.55	0.52	0.48	0.52	0.60
sstreet	0.52	0.53	0.50	0.51	0.50	0.39	0.51	0.58	1.00	0.60	0.58	0.45	0.51	0.54	0.51	0.56	0.52	0.34	0.47	0.44	0.46	0.49	0.44	0.47	0.52
ntrust	0.51	0.52	0.52	0.49	0.49	0.41	0.53	0.59	0.60	1.00	0.55	0.48	0.52	0.55	0.53	0.54	0.53	0.37	0.48	0.47	0.50	0.52	0.47	0.50	0.50
mellon	0.55	0.61	0.59	0.57	0.56	0.42	0.60	0.63	0.58	0.55	1.00	0.49	0.59	0.63	0.60	0.64	0.58	0.37	0.52	0.45	0.54	0.50	0.51	0.53	0.60
usbancorp	0.41	0.43	0.49	0.46	0.45	0.35	0.49	0.49	0.45	0.48	0.49	1.00	0.50	0.51	0.49	0.50	0.49	0.33	0.46	0.44	0.49	0.43	0.45	0.46	0.46
natcityco	0.53	0.56	0.61	0.58	0.58	0.44	0.61	0.58	0.51	0.52	0.59	0.50	1.00	0.62	0.63	0.66	0.61	0.37	0.55	0.49	0.54	0.53	0.53	0.54	0.61
pnc	0.54	0.58	0.62	0.60	0.59	0.44	0.60	0.62	0.54	0.55	0.63	0.51	0.62	1.00	0.64	0.66	0.62	0.37	0.53	0.48	0.56	0.53	0.52	0.54	0.62
keycorp	0.53	0.57	0.62	0.58	0.57	0.45	0.59	0.59	0.51	0.53	0.60	0.49	0.63	0.64	1.00	0.66	0.63	0.37	0.53	0.51	0.57	0.54	0.53	0.56	0.59
suntrust	0.56	0.58	0.64	0.63	0.61	0.44	0.63	0.64	0.56	0.54	0.64	0.50	0.66	0.66	0.66	1.00	0.64	0.40	0.56	0.49	0.57	0.55	0.54	0.57	0.65
comerica	0.52	0.56	0.59	0.56	0.55	0.42	0.60	0.60	0.52	0.53	0.58	0.49	0.61	0.62	0.63	0.64	1.00	0.38	0.54	0.50	0.56	0.54	0.51	0.56	0.59
unionban	0.34	0.34	0.38	0.34	0.35	0.27	0.37	0.36	0.34	0.37	0.37	0.33	0.37	0.37	0.37	0.40	0.38	1.00	0.37	0.32	0.36	0.32	0.37	0.35	0.38
amsouth	0.46	0.48	0.51	0.49	0.47	0.38	0.52	0.51	0.47	0.48	0.52	0.46	0.55	0.53	0.53	0.56	0.54	0.37	1.00	0.46	0.51	0.46	0.49	0.52	0.50
huntington	0.41	0.44	0.49	0.43	0.45	0.34	0.47	0.47	0.44	0.47	0.45	0.44	0.49	0.48	0.51	0.49	0.50	0.32	0.46	1.00	0.49	0.47	0.48	0.48	0.46
bbt	0.50	0.50	0.55	0.53	0.50	0.42	0.54	0.55	0.46	0.50	0.54	0.49	0.54	0.56	0.57	0.57	0.56	0.36	0.51	0.49	1.00	0.53	0.52	0.52	0.53
53banco	0.47	0.48	0.52	0.51	0.48	0.42	0.51	0.52	0.49	0.52	0.50	0.43	0.53	0.53	0.54	0.55	0.54	0.32	0.46	0.47	0.53	1.00	0.49	0.49	0.49
southtrust	0.45	0.46	0.49	0.49	0.46	0.42	0.49	0.48	0.44	0.47	0.51	0.45	0.53	0.52	0.53	0.54	0.51	0.37	0.49	0.48	0.52	0.49	1.00	0.52	0.49
regions	0.44	0.49	0.52	0.50	0.49	0.40	0.52	0.52	0.47	0.50	0.53	0.46	0.54	0.54	0.56	0.57	0.56	0.35	0.52	0.48	0.52	0.49	0.52	1.00	0.51
bamerica	0.61	0.65	0.66	0.60	0.60	0.41	0.59	0.60	0.52	0.50	0.60	0.46	0.61	0.62	0.59	0.65	0.59	0.38	0.50	0.46	0.53	0.49	0.49	0.51	1.00

Source: Datastream

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