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Banking System Stability
A Cross-Atlantic Perspective

Philipp Hartmann, Stefan Straetmans, and
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4.1 Introduction

A particularly important sector 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.

This is a particularly complex task in very large economies with highly developed financial systems, such as the United States and the euro area. Moreover, structural changes in the financial systems of both these economies make it particularly important to track risks over time. In Europe,

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gradually integrating financial systems under a common currency increase the relationships between banks across borders. This development raises the question of how banking systems should be monitored in a context where banking supervision—in contrast to monetary policy—remains a national responsibility. In the United States, tremendous consolidation as well as the removal of regulatory barriers to universal and cross-state banking has led to the emergence of large and complex banking organizations (LCBOs), whose activities and interconnections are particularly difficult to follow. For all these reasons we present a new approach in this paper of how to assess banking system risk, and apply it to the euro area and the United States.

A complication in assessing banking system stability is that, in contrast to other elements of the financial system, such as securities values, interbank relationships that can be at the origin of bank contagion phenomena or the values of and correlations between loan portfolios are particularly hard to measure and monitor.[1] Hence, a large part of the published banking stability 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), a series of papers has examined the effects of specific bank failures or bad news for certain banks on other banks' stock prices (see also Wall and Petersen 1990, or Docking, Hirschey, and Jones 1997).[2] In another series of papers various regression approaches are used in order to link abnormal bank stock returns to asset-side risks (e.g., Smirlock and Kaufold 1987, Musumeci and Sinkey 1990). In fact, some authors point out that most banking crises have been related to macroeconomic fluctuations rather than to prevalent contagion (e.g., Gorton 1988, Demirgüç-Kunt and Detragiache 1998).[3]

An issue in the previously noted literature is that any form of stock market reaction is considered. The extreme-value approach for assessing banking system risk advocated in this paper also employs equity prices, but focuses only on crisis propagations, that is, relationships between extremely large negative returns. We want to make three main contributions compared to the previous literature. First, we use the novel multivariate extreme value techniques applied by Hartmann, Straetmans, and de Vries (2003a, 2003b, and 2004) and Poon, Rockinger, and Tawn (2004) to esti-

1. 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).

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

3. 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.

For a comprehensive survey of the theoretical and empirical contagion and systemic risk literature, see De Bandt and Hartmann (2000). We list the most recent contributions in the accompanying working paper (Hartmann, Straetmans, and de Vries 2005).

mate the strength of banking system risks. In particular, we distinguish conditional co-crash probabilities between banks from crash probabilities conditional on aggregate shocks. While extreme value theory (EVT)—both univariate and multivariate—has been applied to general stock indices before, it has not yet been used to assess the extreme dependence between bank stock returns with the aim to measure banking system risk. Second, we cover both euro area countries and the United States to compare banking system stability internationally. We are not aware of any other study that tries to compare systemic risk in these major economies. Third, we apply the 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 earlier papers addressed the changing correlations between bank stock returns (e.g., de Nicoló and Kwast 2002), 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 publicly available information about (1) individual banks' asset and liability side risks and (2) relationships between different banks' risks (be it through correlations of their loan portfolios, interbank lending, or other channels). We identify the risk of a problem in one or several banks spilling over to other banks (contagion risk) with extreme negative comovements between individual bank stocks (similar to 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). The tail-β is measured by conditioning our co-crash probability on a general stock index (or another measure of systematic risk) 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 high-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 United States and the euro area and for changes in systemic risk over time.

Our work is also related to the broader literature examining which phenomena constitute financial contagion and how they can be empirically identified. In our reading, the main criteria proposed so far to identify contagion are that (1) a problem at a financial institution adversely affects other financial institutions or that a decline in an asset price leads to declines in other asset prices (e.g., Bae, Karolyi, and Stulz 2003); (2) the relationships between failures or asset price declines must be different from those observed in normal times (regular interdependence; see Forbes and Rigobon 2002); (3) the relationships are in excess of what can be explained by economic fundamentals (Pindyck and Rotemberg 1993, and Bekaert, Harvey, and Ng, forthcoming); (4) the events constituting contagion are negative extremes, such as full-blown institution failures or market crashes, so that they correspond to crisis situations (Longin and Solnik 2001, and Hartmann et al. 2004); (5) 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 on how to measure contagion capture the first criterion (1), but this is where the agreement usually ends. Authors differ in their views of which of the other criteria (2) through (5) are essential for contagion. The reason why we particularly focus on criterion (4) is that it allows us to concentrate on events that are severe enough to always be 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.

The data we use in this work 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 chose twenty-five banks based on the criteria of balance-sheet size and involvement in interbank lending. So, our sample represents the most systemically relevant financial institutions, but neglects a large number of smaller banks. During our sample period several of the banks selected faced failure-like situations; also, global markets passed through several episodes of stress. All in all, we have about 3,100 observations per bank.

Our results suggest that the risk of multivariate extreme spillovers between U.S. banks is higher than between European banks. Hence, despite the fact that available balance-sheet data show higher interbank exposures in the euro area, the U.S. banking system seems to be more prone to contagion risk. The lower spillover risk among European banks is mainly related to relatively weak cross-border linkages among a certain number of countries. Domestic linkages in France, Germany, and Italy, for example, are of the same order as domestic U.S. linkages. One interpretation of this result is that further banking integration in Europe could lead to higher cross-border contagion risk in the future, with the more integrated U.S. banking system providing a benchmark. Second, cross-border spillover probabilities tend to be smaller than domestic spillover probabilities, but only for a few countries is this difference statistically significant. For example, among the banks from a number of larger countries—such as France, Germany, 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 Finland and Greece in particular, and sometimes Ireland or Portugal—tend to be significantly weaker than the effects on their domestic banks. Hence, those smaller countries located further away from the center of Europe seem to be more insulated from European cross-border contagion.

Third, the effects of macro shocks emphasized by the estimated tail-βs are similar for the euro area and the United States, 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 United States. Fourth, structural stability tests for our indicators suggest that systemic risk, both in the form of interbank spillovers and in the form of aggregate risk, has increased in Europe and in the United States. Our tests detect the break points during the second half of the 1990s, but graphic illustrations of our extreme dependence measures show that this was the result of developments spread out over time. In particular in Europe the process was very gradual, in line with what one would expect during a slowly advancing financial integration process. Interestingly, the introduction of the euro in January 1999 seems to have had a reductionary or no effect on banking system risk in the euro area. This may be explained by the possibility that stronger cross-border crisis transmission channels through a common money market could be offset by better risk sharing and the better ability of a deeper market to absorb shocks.

The paper is structured as follows. The next section describes our two theoretical indicators of banking system stability. Section 4.3 briefly outlines the estimation procedures for both measures; section 4.4 sketches the tests for their stability over time and across countries and continents. Section 4.5 describes the data we employ. Section 4.6 then presents the empirical results on extreme bank spillover risks; section 4.7 turns to the empirical results for aggregate banking system risk (tail-βs). Section 4.8 asks the question whether systemic risk has changed over time. The final section concludes. We have five appendices. Appendix A describes in greater depth our estimation procedures and appendix B the structural stability test. Appendix C discusses small sample properties of estimators and tests. Appendix D lists the banks in our sample and the abbreviations used for them in the paper. Finally, appendix E discusses the relevance of volatility modeling for financial stability policy-oriented research and examines the importance of volatility clustering for extreme dependence in bank stock returns.

4.2 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 comovements, as measured by multivariate conditional probabilities between individual banks' stock returns, are meant to capture the risk of contagion from one bank to another. Extreme comovements between individual banks' stock returns and the returns of a general stock market index or another measure of nondiversifiable risk (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.

4.2.1 Multivariate Extreme Spillovers: A Measure of Bank Contagion Risk

Let us start by describing the measure of multivariate extreme bank spillovers. The measure can be expressed in terms of marginal (univariate) and joint (multivariate) exceedance probabilities. Consider an N-dimensional banking system, that is, a set of N banks from, for example, 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 $X_i (i = 1, \ldots, N)$. Thus, X_i describes a bank i's excess return. 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. The crisis levels or extreme quantiles $Q_i (i = 1, \ldots, N)$ are chosen such that the tail probabilities are equalized across banks; that is,

$$P(X_1 > Q_1) = \ldots = P(X_i > Q_i) = \ldots = P(X_N > Q_N) = p.$$

With the probability level in common, crisis levels Q_i will generally not be equal across banks, because the marginal distribution functions $P(X_i > Q_i) = 1 - F_i(Q_i)$ are bank specific. The crisis levels can be interpreted as "barriers" that will on average only be broken once in $1/p$ time periods, that is, p^{-1} days if the data frequency is daily. Suppose now that we want to measure the propagation of severe problems throughout the European and U.S. 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 $L < N$ banks:

$$(1) \qquad P_{N|L} = P\left[\bigcap_{i=1}^{N} X_i > Q_i(p) \;\middle|\; \bigcap_{j=1}^{L} X_j > Q_j(p)\right]$$

$$= \frac{P[\cap_{i=1}^{N} X_i > Q_i(p)]}{P[\cap_{j=1}^{L} X_j > Q_j(p)]}.$$

Clearly, the right-hand side immediately follows from the definition of conditional probability. With independence the measure reduces to p^{N-L}. This provides a benchmark against which the dependent cases are to be judged.

Equation (1) is very flexible in terms of the conditioning set on the right-hand side. For example, the conditioning banks do not necessarily have to be a subset of the bank set on the left-hand side. Moreover, the conditioning random variables could also be other than just bank stock prices.[4]

4.2.2 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 equation (1), in which $N = 1$ and the conditioning set is limited to extreme downturns of the market portfolio or another indicator of aggregate risk ($L = 1$).[5] This tail-β measure is inspired by portfolio theory and has been used before by Straetmans, Verschoor, and Wolff (2003) to examine the intraday effects of the September 11 catastrophe on U.S. stocks. Let X_M be the excess return on the market portfolio (e.g., using a stock market index) and let p be the common tail probability; then this measure can be written as:

$$(2) \qquad P[X_k > Q_k(p) \mid X_M > Q_M(p)] = \frac{P[X_k > Q_k(p), X_M > Q_M(p)]}{P[X_M > Q_M(p)]} = \frac{P[X_k > Q_k(p), X_M > Q_M(p)]}{p}.$$

The measure captures how likely it is that an individual bank's (k) value declines dramatically if there is an extreme negative systematic shock. Analogous to the multivariate spillover probability (1), the tail-β (2) reduces to $p^2/p = p$ under the benchmark of independence. We extend the analysis of extreme aggregate risk in this paper by also experimenting with high-yield bond spreads as a measure X_M of systematic shocks.[6]

4.3 Estimation of the Indicators

The joint probabilities in (1) and (2) have to be estimated. 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 (for example) maximum likelihood techniques. However, if one makes the wrong distributional assumptions, the linkage estimates may be severely biased due to misspecification. As there is no clear evidence that all stock returns follow the same distribution—even less so for the crisis situations we are interested in here—we

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

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

6. In the present paper we limit ourselves to the measures (1) and (2) 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.

want to avoid very specific assumptions for bank stock returns. Therefore, we implement the semiparametric EVT approach proposed by Ledford and Tawn (1996; see also Draisma et al. 2001, and Poon, Rockinger, and Tawn 2004, for recent applications). Loosely speaking, their approach consists of generalizing some "best practice" in univariate extreme value analysis.

After a transformation of the return data to unit Pareto marginals, which removes any influence of the marginal distributions on the probabilities of interest, we can rewrite the joint tail probability that occurs in equations (1) and (2):

$$P\left[\bigcap_{i=1}^{N} X_i > Q_i(p)\right] = P\left[\bigcap_{i=1}^{N} \tilde{X}_i > q\right].$$

$\tilde{X}_i$ is the excess return of X_i after the transformation, and $q = 1/p$. We describe the details of this step in appendix A. The consequence is that differences in joint tail probabilities across different banking systems (e.g., United States versus Europe) can now be attributed solely to differences in the tail-dependence structure of the extremes.

The multivariate estimation problem is thus reduced to estimating a univariate exceedance probability for the cross-sectional minimum of the N bank excess return series; that is, it is always true that

$$(3) \qquad P\left[\bigcap_{i=1}^{N} \tilde{X}_i > q\right] = P[\min_{i=1}^{N} (\tilde{X}_i) > q] = P[\tilde{X}_{\min} > q].$$

The estimation exploits the fact that under fairly general conditions the auxiliary variable $\tilde{X}_{\min}$ has a regularly varying tail (Ledford and Tawn 1996).[7] Assuming that the tail index of $\tilde{X}_{\min}$ is $\alpha = 1/\eta$, the univariate probability in equation (3) exhibits a tail descent of the Pareto type:

$$(4) \qquad P(\tilde{X}_{\min} > q) \approx q^{-1/\eta}, \eta \leq 1,$$

with q large (p small). The higher η the more dependent are the components $(\tilde{X}_1, \ldots, \tilde{X}_i, \ldots, \tilde{X}_N)$ from (3) far out in their joint tail. As we argue in appendix A, if the return series $\tilde{X}_i$ are asymptotically dependent then $\eta = 1$, and if they are asymptotically independent then $\eta < 1$.

We estimate equation (4) with the semiparametric probability estimator from de Haan et al. (1994):

$$(5) \qquad \hat{P}(\tilde{X}_{\min} > q) = \frac{m}{n}\left(\frac{C_{n-m,n}}{q}\right)^{1/\eta},$$

7. A function $F(x)$ is said to have a regularly varying left tail if

$$\lim_{u\to\infty} F(-ux)/F(-u) = x^{-\alpha}$$

for any $x > 0$ and tail index $\alpha > 0$.

where n is the sample size and the "tail cut-off point" $C_{n-m,n}$ is basically the $(n-m)$-th largest return from the cross-sectional minimum series $\tilde{X}_{\min}$. Equation (5) extends the empirical distribution function of $\tilde{X}_{\min}$ for more extreme returns q than the ones observed in the sample. It is conditional upon the tail dependence parameter η and a choice of the threshold parameter m.

To estimate η we use the popular Hill (1975) estimator for the index of regular variation:

$$\hat{\eta} = \frac{1}{m}\sum_{j=0}^{m-1}\ln\left(\frac{C_{n-j,n}}{C_{n-m,n}}\right) = \frac{1}{\hat{\alpha}}. \tag{6}$$

m is the number of most extreme returns that enter the estimation. Appendix A contains a discussion on how it is chosen optimally. Draisma et al. (2001) derive asymptotic normality of $\sqrt{m}(\hat{\eta}/\eta - 1)$ under fairly general conditions. The asymptotic normality will prove convenient for the tests implemented later on. We discuss small-sample properties of our tail-dependence estimator $\hat{\eta}$ in the first section of appendix C.

4.4 Hypothesis Testing

In this section we introduce some 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. In the first subsection we present the rationale for using this test and the intuition of how it works. Appendix B contains a more detailed technical exposition. The second test in subsection 4.4.2 allows us to compare systemic risk across countries and continents.

4.4.1 Time Variation

The multivariate linkage estimator (1) and its bivariate counterpart in (2) were presented so far as 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 (1) or in terms of extreme systematic risk (2)—has changed over time. As the discussion of the Ledford and Tawn approach toward estimating (1) or (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 a recently developed structural stability test for the Hill statistic (6).

Quintos, Fan, and Phillips (2001) present a number of tests for identifying single unknown breaks in the estimated tail index $\hat{\alpha}$. As our estimation approach allows us to map the multivariate dependence problem into a univariate estimation problem, we can choose from them the best test procedures for our tail dependence parameter η. Balancing the prevention of type I and type II errors, we opt for their recursive test.

This test takes a window of the data at the start of the sample and estimates the respective $\hat{\eta}$. It then reestimates the tail dependence parameter, successively increasing the data window until the end of the sample is reached. One calculates the (appropriately scaled) ratios of the subsample ηs and the full sample equivalent and chooses the date with the maximum ratio as a candidate break point. The null hypothesis of the test is that there is no change in η over time. The alternative hypothesis is that asymptotic dependence has either increased or decreased at some point in time.

Asymptotic critical values of the suprema of the ratio series have been derived by Quintos, Fan, and Phillips (2001). They are 1.46, 1.78, and 2.54 for the 10 percent, 5 percent, and 1 percent significance levels, respectively. If the data exhibit nonlinear intertemporal dependencies, such as the well-known autoregressive conditional heteroskedasticity (ARCH) effects (volatility clustering) in financial returns, then some additional scaling of the test statistic is needed to avoid erroneous inference. In contrast to Quintos, Fan, and Phillips, we estimate the asymptotic variance of the dependence parameter that is used for the scaling with a block bootstrap, which accounts for more general dependencies than ARCH. If the supremum of the scaled ratio exceeds the critical values, the test rejects the null hypothesis of constant extreme dependence.

Quintos, Fan, and Phillips report a Monte Carlo study that indicates good small sample power, size, and bias properties of the recursive break test. Only in the case of a decrease of extreme tail dependence under the alternative hypothesis ($\eta_1 > \eta_2$) do they detect less-acceptable power properties. We solve this problem by executing the recursive test both in a "forward" version and a "backward" version. The forward version calculates the subsample ηs in calendar time, and the backward version in reverse calendar time. If a downward break in η occurs and the forward test does not pick it up, then the backward test corrects for this. The second section of appendix C provides a further Monte Carlo study of the small-sample properties of the recursive structural break test.

4.4.2 Cross-sectional Variation

We would also like to know whether cross-sectional differences between various groups of banks or different banking systems, say between the United States and Europe or between different European countries, are statistically and economically significant. The asymptotic normality of $\hat{\eta}$ referred to earlier enables some straightforward hypothesis testing. A test for the equality of tail-dependence parameters (null hypothesis) is based on the following T-statistic:

$$T = \frac{\hat{\eta}_1 - \hat{\eta}_2}{\text{s.e.}(\hat{\eta}_1 - \hat{\eta}_2)}, \tag{7}$$

which converges to a standard normal distribution in large samples.[8] Accordingly, the asymptotic critical values are 1.65, 1.96, and 2.58 for the 10 percent, 5 percent, and 1 percent significance levels, respectively. In the following empirical applications, the asymptotic standard error in the test's denominator (7) is estimated using a block bootstrap.[9] Similar to the previous structural stability test, we opt for bootstrapping in blocks because of the nonlinear dependencies that might be present in the return data.

4.5 Data and Descriptive Statistics

We collected daily stock price data (total return indexes including dividends) for twenty-five euro area banks and twenty-five U.S. banks. Excess returns are constructed by taking log first differences and deducting three-month London Interbank Offered Rate (LIBOR) rates (adjusted linearly to derive daily from annual rates). They are expressed in local currency so that they do not vary directly with exchange rates. The market risk factor or aggregate shocks to the euro area and U.S. banking systems are proxied by several measures, with an eye toward some sensitivity analysis. First, we employ a general stock index and the banking sector subindex for the euro area and the United States, respectively. Second, we use the spread between below-investment-grade and treasury bond yields for each of these economies. Finally, we use a global stock index and the global banking sector subindex.

All series, except one, start on 2 April, 1992, and end on 27 February, 2004, rendering 3,106 return observations per bank. The euro area high-yield bond spread is only available from 1 January, 1998, onward, yielding 1,497 observations. All series are downloaded from Datastream, whose source for high-yield bond spreads is Merrill Lynch.[10] The stock indices are the total return indexes calculated by the data provider.

The following subsection provides information about how the fifty banks were chosen, based on balance sheet items for European and U.S. banks. The subsequent section discusses the return data, in particular their negative extremes.

8. One can safely assume that T comes sufficiently close to normality for empirical sample sizes as the one used in this paper (see, e.g., Hall 1982, or Embrechts, Klüppelberg, and Mikosch 1997).

9. As for the test of time variation (see appendix B), we follow Hall, Horowitz, and Jing (1995) and set the optimal block length equal to $n^{1/3}$.

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

4.5.1 Bank Selection and Balance Sheet Information

The time dimension of this dataset was very much constrained by the unavailability of longer stock price series for European banks. Before the 1990s fewer large European banks were privately quoted on stock exchanges; also, many banks disappeared as a consequence of mergers.[11] Roughly in proportion to the sizes of their economies in terms of gross domestic product (GDP) and the sizes of their banking systems in terms of assets, we have six banks from Germany, four banks from France, four banks from Italy, three banks from Spain, two banks each from the Netherlands and from Belgium, and one bank from Finland, Greece, Ireland, and Portugal, respectively. Appendix D contains the full list of banks, the abbreviations used in the tables, and their country of origin.

Apart from those 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 across all the twelve years. By using several criteria, some choices naturally had to be made. We showed the data and discussed the choices in detail in the accompanying working paper (see subsection 4.5.1 and appendix C in Hartmann, Straetmans, and C. de Vries 2005). Here we just list two interesting observations from this: (1) while in Europe bank size and interbank lending activity are quite aligned, in the United States a number of smaller banks (such as State Street, Northern Trust, Bank of New York, or Mellon) have very large interbank exposures. We are careful to have these clearing banks in our sample of twenty-five U.S. banks, as the failure of one or several of them may constitute a particularly severe source of contagion risk,[12] and (2) the sizes of euro area and U.S. banks chosen are similar, but the data also show much larger interbank exposures among European than among U.S. banks. To our knowledge, this difference has not been noted in the literature on banking system

11. Ten out of twelve 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.

12. 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.

risk before. It will be interesting to subsequently verify whether it translates into larger systemic risk in the European banking system.

4.5.2 Stock Returns and Yield Spreads

The accompanying working paper presents an extensive discussion of the typical host of descriptive statistics for our fifty bank stock return series and the factors capturing aggregate risk (see subsection 4.5.2 and appendix D in Hartmann, Straetmans, and C. de Vries 2005). As the results are pretty standard, we list here only two observations: (1) while individual bank stock returns are highly correlated with stock indices, the same does not apply to high-yield bond spreads. This provides first evidence that yield spreads might not be a good predictor of aggregate banking system risk, and (2) correlations between individual bank stock returns are generally positive and of similar order of magnitude in the euro area and in the United States. For the United States, however, correlation coefficients appear to be much more uniform across bank pairs.

For the purpose of the present paper, we are particularly interested in extreme negative returns. The left-hand sides of tables 4.1 and 4.2 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 percent) happens for Banco Espanol de Credito (Banesto) in February 1994. Around that time, this Spanish bank faced major difficulties and was rescued by an initial public intervention in December 1993. 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 percent and 27 percent during the summer of 2001. Ultimately this bank was also saved by the federal state of Berlin. As regards the United States, the largest daily stock price slump happens to Unionbancal Corporation. The market value of this troubled California bank declined in June 2000 by as much as 36 percent, as a consequence of credit quality problems. The next most significant corrections of just above 20 percent occur for Comerica Inc. and AmSouth Bancorporation. These examples illustrate that we have a number of individual bank crises in the sample.

In contrast to the stock returns, the high-yield bond spreads reported at the bottom of tables 4.1 and 4.2 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 of more than 10 percent above government debt.

There is also some first evidence of clustering in extreme bank stock declines, as many of them happen around a number of well-known crisis episodes. For example, a significant number of European and U.S.-based banks faced record downward corrections around the end of the summer

Table 4.1 **Historical minima, tail indexes and quantile estimates for excess stock returns of euro area banks (%)**

	|Extreme negative returns|				|$\hat{Q}(p)$|	
Bank	$X_{1,n}$ (date)	$X_{2,n}$ (date)	$X_{3,n}$ (date)	$\hat{\alpha}$	$p = 0.05$	$p = 0.02$
DEUTSCHE	12.4 (09/11/01)	12.0 (03/09/00)	10.1 (09/19/01)	3.3	13.8	18.2
HYPO	17.3 (10/23/02)	14.3 (09/30/02)	11.5 (09/11/01)	3.1	17.9	24.0
DRESDNER	11.1 (10/28/97)	9.9 (07/22/02)	9.7 (03/09/00)	3.2	16.1	21.5
COMMERZ	13.3 (09/11/01)	13.1 (09/20/01)	13.1 (10/23/02)	2.9	15.9	21.9
BGBERLIN	37.9 (08/30/01)	27.0 (09/10/01)	17.1 (01/17/94)	2.	23.4	34.2
DEPFA	16.5 (11/29/00)	10.4 (10/08/98)	10.3 (07/23/02)	3.2	13.4	17.6
BNPPAR	12.5 (09/30/98)	11.2 (09/30/02)	11.0 (10/04/02)	3.0	15.4	20.8
CA	19.6 (11/19/01)	12.4 (07/12/01)	10.5 (09/12/02)	2.4	13.3	19.4
SGENERAL	12.5 (09/10/98)	11.6 (09/30/02)	10.4 (07/19/02)	2.7	17.1	23.6
NATEXIS	13.6 (10/08/97)	10.8 (09/25/96)	10.6 (03/25/94)	3.6	9.6	12.3
INTESA	12.7 (11/07/94)	12.2 (09/20/01)	11.6 (10/28/97)	3.9	13.7	17.4
UNICREDIT	10.9 (07/20/92)	10.3 (09/10/98)	9.9 (10/21/92)	3.6	12.9	16.7
PAOLO	9.9 (12/04/00)	9.7 (09/10/98)	9.5 (09/20/01)	3.5	13.3	17.3
CAPITA	18.2 (03/07/00)	12.0 (10/01/98)	11.5 (06/20/94)	3.3	16.7	24.6
SANTANDER	15.9 (10/01/98)	12.8 (01/13/99)	11.4 (07/30/02)	3.0	15.8	21.4
BILBAO	14.5 (01/13/99)	11.8 (09/10/98)	10.7 (09/24/92)	2.6	17.4	24.8
BANESP	84.8 (02/02/94)	18.9 (11/27/02)	15.5 (08/28/98)	2.2	20.1	30.6
ING	16.1 (10/15/01)	14.0 (10/02/98)	13.9 (09/11/01)	2.4	23.4	34.4
ABNAMRO	12.6 (09/14/01)	11.9 (09/11/01)	11.3 (09/30/02)	2.5	19.6	28.3
FORTIS	11.0 (08/01/02)	10.6 (09/30/02)	10.6 (09/11/01)	3.1	14.6	19.7
ALMANIJ	8.7 (11/26/99)	8.0 (04/30/92)	6.2 (08/01/02)	3.8	0.7	12.4
ALPHA	9.4 (04/27/98)	9.4 (09/09/93)	9.1 (01/13/99)	3.1	14.4	19.3
BCP	17.1 (10/23/02)	9.9 (02/25/03)	9.1 (04/16/99)	2.5	13.8	19.8
SAMPO	20.7 (08/17/92)	18.3 (12/21/92)	15.6 (08/26/92)	2.6	23.8	33.7
IRBAN	18.2 (02/06/02)	10.3 (10/08/98)	10.1 (10/28/97)	2.9	12.7	17.4
Bank index	6.9 (09/11/01)	6.7 (10/01/98)	6.3 (09/10/98)	2.5	11.2	16.1
Stock index	6.3 (09/11/01)	5.3 (10/28/97)	5.0 (09/14/01)	3.2	7.7	10.2
Yield spread	16.6 (10/02/01)	16.5 (10/03/01)	16.3 (10/01/01)	9.1	22.3	24.7

Source: The source of raw data is Datastream.

Notes: Returns and quantiles are reported in absolute values and therefore positive. $X_{1,n}$, $X_{2,n}$, 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. $\hat{\alpha}$ is the tail index, estimated with the method by Hill (1975). $\hat{Q}(p)$ 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. See table 4D.1 for list of abbreviations.

of 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 U.S. banks, happened in spring and summer 2000, potentially related to the burst of the technology bubble. Interestingly, record bank stock crashes around 11 September, 2001—the time of the New York terrorist attack—are registered for a num-

Table 4.2 **Historical minima, tail indexes, and quantile estimates for excess stock returns of U.S. banks (%)**

	|Extreme negative returns|				$\|\hat{Q}(p)\|$	
Bank	$X_{1,n}$ (date)	$X_{2,n}$ (date)	$X_{3,n}$ (date)	$\hat{\alpha}$	$p = 0.05$	$p = 0.02$
CITIG	17.1 (07/23/02)	11.7 (07/22/02)	11.5 (10/27/97)	3.3	13.7	18.0
JP MORGAN	20.0 (07/23/02)	10.8 (09/03/98)	10.1 (09/13/00)	3.7	12.9	16.6
BAMERICA	11.6 (10/14/98)	10.7 (10/27/03)	9.1 (06/16/00)	3.6	12.0	15.5
WACHOVIA	9.2 (11/14/00)	9.1 (05/25/99)	9.0 (01/27/99)	3.5	10.9	14.1
FARGO	9.2 (06/16/00)	7.5 (06/08/98)	7.3 (04/14/00)	3.7	9.6	12.3
BONE	25.8 (08/25/99)	11.4 (11/10/99)	9.5 (10/27/97)	3.0	13.5	18.4
WASHING	11.7 (10/17/01)	10.3 (09/04/98)	9.3 (12/09/03)	3.5	12.7	16.5
FLEET	11.2 (07/16/02)	10.2 (02/21/95)	8.0 (07/23/02)	3.7	11.7	15.0
BNYORK	16.9 (12/18/02)	13.9 (07/16/01)	11.1 (10/03/02)	3.4	12.6	16.5
SSTREET	19.7 (04/14/93)	12.1 (03/21/03)	11.9 (10/12/00)	3.0	14.8	20.0
NTRUST	10.6 (10/03/02)	9.1 (04/14/00)	8.5 (05/25/00)	3.5	11.8	15.4
MELLON	13.0 (10/27/97)	10.6 (01/22/03)	9.8 (03/08/96)	3.3	12.7	16.7
BCORP	17.4 (10/05/01)	15.9 (06/30/92)	10.7 (10/04/00)	2.9	14.4	19.8
CITYCO	9.5 (04/14/00)	8.2 (10/27/97)	7.7 (02/04/00)	3.1	11.3	15.2
PNC	16.1 (07/18/02)	10.3 (10/17/02)	9.8 (01/29/02)	3.4	10.9	14.3
KEYCO	8.9 (08/31/98)	8.3 (03/07/00)	8.2 (06/30/00)	3.4	11.4	14.9
SOTRUST	10.6 (04/26/93)	10.3 (01/03/00)	9.7 (03/17/00)	3.1	12.0	16.2
COMERICA	22.7 (10/02/02)	9.1 (04/17/01)	9.1 (04/14/00)	3.4	10.7	14.0
UNIONBANK	36.4 (06/16/00)	15.5 (03/17/00)	10.9 (12/15/00)	3.0	15.1	20.6
AMSOUTH	20.9 (09/22/00)	15.0 (06/01/99)	6.9 (01/10/00)	3.5	9.4	12.2
HUNTING	18.3 (09/29/00)	10.4 (01/18/01)	10.0 (08/31/98)	3.1	13.2	17.8
BBT	8.2 (01/21/03)	7.2 (06/15/00)	7.0 (04/14/00)	3.4	10.1	13.2
53BANCO	8.5 (11/15/02)	7.3 (01/14/99)	7.0 (04/14/00)	3.8	9.6	12.3
SUTRUST	10.2 (0720/98)	9.5 (04/14/00)	8.9 (06/16/00)	3.2	10.6	14.2
REGIONS	11.2 (12/15/03)	9.1 (08/31/98)	8.5 (06/15/00)	3.5	10.2	13.2
Bank index	7.0 (04/14/00)	6.8 (07/23/02)	6.7 (10/27/97)	3.4	9.1	12.0
Stock index	7.0 (08/31/98)	6.8 (04/14/00)	6.8 (10/27/97)	3.7	6.3	8.0
Yield Spread	10.8 (10/10/02)	10.7 (10/09/02)	10.7 (10/11/02)	15.8	12.1	12.9

Source: The source of raw data is Datastream.
Notes: See table 4.1.

ber of European banks, but not for U.S. banks.[13] Finally, some American and European banks were hit significantly by the onset of the Asian crisis in fall 1997. These examples illustrate, first, that our sample covers a number of stress situations in global and national markets,[14] and second, that they also indicate the relevance of systematic shocks for banking stability, which motivates our tail-β indicator.

13. The less extreme reactions of U.S. bank stocks may, however, also have to do with a four-day suspension of trading at the New York Stock Exchange.
14. The presence of single and aggregate crisis situations in our sample is reassuring, as the focus of our paper is financial stability. At the same time, however, we would like to note that extreme-value methods do not require the presence of individual or aggregate failures in the

We also report in tables 4.1 and 4.2 the estimated tail indexes $\hat{\alpha}$ for individual banks and for the stock indices. It turns out that they vary around 3, which is in line with the evidence presented in Jansen and de Vries (1991), illustrating the well known nonnormality of stock returns and the nonexistence of higher-order moments. If anything, the tails of a number of European banks seem to be slightly fatter (smaller α) than the ones of U.S. banks. In addition to the larger interbank lending in Europe referred to earlier, this observation raises again the issue of whether systemic risk on the European side of the Atlantic is more pronounced than on the other. Another observation is that the yield spreads have much thinner tails than stock index returns.

The right-hand sides of tables 4.1 and 4.2 show the estimated quantiles for all the banks when assuming a common percentile (or crash probability). In this paper, we experiment with percentiles p between 0.02 percent and 0.05 percent (explicitly reporting results for the latter), 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 phenomena considered constitute critical situations for banks. In terms of sensitivity analysis, all our qualitative results reported subsequently are robust to varying the crash probability p, at least within this range.

4.6 Bank Contagion Risk

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 spillovers between banks as compared to the risk of cross-border spillovers? Answers to the latter question are particularly important for macroprudential surveillance and for the ongoing debate about supervisory cooperation 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 subsection 4.6.1 and the latter in subsection 4.6.2. In the present section we still abstract from extreme systematic risk for the euro area and U.S. banking system, as this is addressed in the following section (section 4.7). For expositional reasons, we also abstract here from changes of spillover risk over time, which are addressed in section 4.8.

sample. In contrast to fully nonparametric and parametric approaches, our semiparametric approach allows us to estimate reliably extremal behavior even beyond the sample boundaries.

4.6.1 Euro Area

In order to assess the exposure of euro area banks to each other, as derived from their extreme stock price comovements, we report in table 4.3 the estimation results for our measure (1). To keep the amount of information manageable, we do not show the extreme dependence parameters η that enter in the estimation of (1), and we only display the spillovers to the largest banks of the countries listed on the left-hand side. We calculate the co-crash probabilities conditional on the second (column $\hat{P}_1$), second and third (column $\hat{P}_2$), second, third, and fourth (column $\hat{P}_3$), and so on largest banks from Germany (upper panel), from Spain (upper middle panel), from Italy (lower middle panel) and from France (lower panel). All probabilities refer to the crisis levels (extreme quantiles) reported in table 4.1 for $p = 0.05$ percent.

For example, the value 22.4 percent in the row "Germany" and the column "$\hat{P}_1$" 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 11.2 percent 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 is indeed generally estimated to be smaller than domestic contagion risk in the euro area banking system. 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 (Société Générale) have experienced one is a nonnegligible 35.9 percent (see column $\hat{P}_2$, upper middle panel, row "France"). The same probability for the largest Italian bank (Banca Intesa) is 7.5 percent (see column $\hat{P}_2$, upper middle 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 $\hat{P}_1$). This is not too surprising, as the largest players will have more extensive international operations, implying more scope for cross-border contagion. In particular, Algemene Bank Nederland-Amsterdam Roterdam (ABN AMRO)—the largest Dutch bank—is more affected by problems of HypoVereinsbank than Deutsche Bank (26.5 percent > 22.4 percent). Actually, the linkages between Dutch and German banks tend to be among the largest cross-border linkages in our sample. Other important cross-border linkages exist between the top banks of France, Germany, the Netherlands,

Table 4.3 **Domestic versus cross-border extreme spillover risk among euro area banks: Estimations**

Largest bank	$\hat{P}_1$	$\hat{P}_2$	$\hat{P}_3$	$\hat{P}_4$	$\hat{P}_5$
	Conditioning banks: German				
Germany	22.4	65.1	74.3	72.7	55.4
The Netherlands	26.5	54.1	70.1	43.0	34.2
France	8.2	25.2	35.8	31.0	16.2
Spain	11.2	17.4	24.2	44.1	40.3
Italy	7.5	13.6	12.9	7.5	10.8
Belgium	16.1	44.2	42.6	28.5	9.2
Ireland	4.0	5.5	5.4	24.7	16.5
Portugal	7.7	13.6	21.7	25.1	18.0
Finland	0.9	1.7	2.3	4.0	4.5
Greece	0.9	1.4	1.3	1.3	2.1
	Conditioning banks: French				
France	2.9	35.9	76.6		
Germany	3.1	23.9	69.5		
The Netherlands	8.2	48.7	71.8		
Italy	1.5	7.5	13.1		
Spain	3.3	27.4	70.1		
Belgium	6.7	38.0	56.3		
Ireland	1.0	1.8	6.9		
Portugal	2.5	6.5	26.5		
Finland	0.0	0.2	0.7		
Greece	0.2	0.3	0.6		
	Conditioning banks: Italian				
Italy	9.6	16.4	16.6		
Germany	5.1	12.4	18.8		
The Netherlands	7.2	16.1	18.0		
Spain	4.6	11.7	14.6		
France	5.2	7.3	8.6		
Belgium	4.7	12.0	11.4		
Ireland	1.6	2.6	5.1		
Portugal	1.8	2.5	3.3		
Finland	1.9	3.2	2.5		
Greece	0.8	0.8	0.7		
	Conditioning banks: Spanish				
Spain	45.4	31.6			
Germany	22.4	13.9			
The Netherlands	26.5	15.6			
France	25.8	21.6			
Italy	8.3	9.0			
Belgium	13.7	5.6			
Ireland	4.1	3.3			
Portugal	6.2	6.5			
Finland	1.1	1.4			
Greece	1.7	1.1			

Notes: The table reports estimated extreme spillover probabilities between banks, as defined in (1). Each column $\hat{P}_j$ shows the spillover probabilities for the largest bank of the country mentioned on the left-hand side conditional on a set of banks j from either the same country

Table 4.3 (continued)

or other countries. The number of conditioning banks varies from one to five for Germany (top panel), one to three for France (upper middle panel), one to three for Italy (lower middle panel), and one to two for Spain (bottom panel). For example, the $\hat{P}_2$ column contains probabilities for a stock market crash of the largest bank in each country, conditional on crashes of the second and third largest bank in Germany, France, Italy, or Spain. All probabilities are estimated with the extension of the approach by Ledford and Tawn (1996) described in section 4.3 and reported in percentages. Univariate crash probabilities (crisis levels) are set to p = 0.05 percent.

and the top Spanish bank. Moreover, as in the case of BNP Paribas, Crédit Agricole, and Société Générale, the largest institutions of a country must not always be very strongly interlinked in the home market. As a consequence, the French panel shows that ABN AMRO and Fortis—the largest Belgian bank—are more exposed to the second and third largest French bank than is BNP Paribas. The fact that Belgian and Dutch banks are associated with the largest cross-border spillover risks is also intuitive, since the banking sectors of these countries are dominated by a small number of very large international financial conglomerates. Also, the results of Degryse and Nguyen (2004) and van Lelyveld and Liedorp (2004) suggest their special exposure to cross-border risk.

Another observation from table 4.3 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, with exceptions, for Portugal. Apparently, smaller banking systems located more in the periphery of the euro area are more insulated from foreign spillovers than larger systems in the center. Overall, the level of spillover risk seems 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 tends, however, to be markedly lower.

An interesting exception is Italy. While being a larger core country in the euro area, it is much less affected by problems in French, German, or Spanish banks than other core countries. This is also consistent with the findings of Mistrulli (2005). In addition, spillovers from the largest Italian banks to other main banking systems in Europe seem also quite limited. One explanation for this phenomenon could be the low penetration of the Italian banking system from abroad and the limited number of acquisitions by Italian banks in other European countries.[15]

The test results in table 4.4 show whether the differences between domestic and cross-country contagion risk are statistically significant or not.

15. This must, however, not remain like this, as the recent acquisition of HypoVereinsbank by UniCredito suggests.

Table 4.4 **Domestic versus cross-border extreme spillover risk among euro area banks: Tests**

Largest bank	T_1	T_2	T_3	T_4	T_5
			Conditioning banks: German		
The Netherlands	–1.01	0.00	–0.50	0.66	0.59
France	1.61	1.58	1.20	0.83	1.52
Spain	0.98	2.51**	2.19**	0.50	0.21
Italy	1.56	2.58***	3.10***	2.59***	1.91*
Belgium	0.12	0.26	0.83	0.98	1.86*
Ireland	2.08**	–2.15**	3.78***	1.36	1.51
Portugal	1.28	2.9**	1.90*	0.91	1.17
Finland	3.93***	4.82***	4.32***	3.09***	2.62***
Greece	3.61***	4.47***	4.44***	3.28***	2.66***
			Conditioning banks: French		
Germany	–0.31	0.86	–0.39		
The Netherlands	–2.50**	–1.11	–0.75		
Spain	–0.24	0.48	0.08		
Italy	1.03	2.75***	1.92*		
Belgium	–1.85*	–0.51	0.37		
Ireland	1.32	3.20***	2.58***		
Portugal	0.11	2.36**	1.04		
Finland	3.56***	3.96***	3.93***		
Greece	2.56**	3.73***	3.65***		
			Conditioning banks: Italian		
Germany	1.11	0.42	–0.09		
The Netherlands	0.41	–0.17	–0.56		
Spain	1.33	0.45	–0.01		
France	0.96	1.27	–0.09		
Belgium	1.01	0.31	–0.36		
Ireland	2.50**	2.52**	1.46		
Portugal	2.70***	2.57**	2.07**		
Finland	2.33**	2.10**	2.16**		
Greece	3.90***	3.59***	3.34***		
			Conditioning banks: Spanish		
Germany	1.41	1.04			
The Netherlands	0.89	1.00			
France	0.68	0.31			
Italy	2.83***	1.51			
Belgium	1.83*	1.91*			
Ireland	4.21***	3.00***			
Portugal	3.47***	2.05**			
Finland	5.40***	3.92***			
Greece	4.58***	3.39***			

Notes: The table reports the statistics for the cross sectional test (4.4.1). Within each panel the degree of extreme domestic spillover risk is compared with the degree of extreme cross-border spillover risk for a given fixed number of conditioning banks. So, each T-statistic describes whether the differences between domestic and cross-border values of η that entered the estimations in table 4.3 are statistically significant. For example, in the top panel the test statistic in the row "The Netherlands" and the column T_1 indicates whether the difference between the η for the spillover probability between ABN AMRO and HypoVereinsbank and the η be-

Table 4.4 (continued)

tween Deutsche Bank and HypoVereinsbank is statistically significant. The null hypothesis is that the respective two ηs are equal. Insignificant *T*-statistics imply that the domestic and cross-border spillover risks are indistinguishable. A significant rejection with positive sign implies that cross-border spillover risk is statistically smaller than its domestic counterpart; a rejection with negative sign implies that cross-border risk is larger than domestic risk. The critical values of the test are 1.65, 1.96, and 2.58 for the 10 percent, 5 percent, and 1 percent levels, respectively.

***Indicates rejection of the null hypothesis at 1 percent significance.

**Indicates rejection of the null hypothesis at 5 percent significance.

*Indicates rejection of the null hypothesis at 10 percent significance.

Rows and columns refer to the same banks as in table 4.3, but the cells now show *T*-statistics of the cross-sectional test described in subsection 4.4.2. The null hypothesis is that domestic spillovers equal cross-border spillovers.[16] The test statistics partly qualify the interpretation of some of the contagion probabilities in table 4.3. Extreme cross-border linkages between Belgian, Dutch, French, German, and Spanish banks are not (statistically) significantly different from domestic linkages within the major countries. In contrast, for Finland and Greece the null hypothesis is rejected in all cases. Moreover, the same happens in many cases for Ireland and Portugal. So, severe problems of larger French, German, Italian, and Spanish banks may create similar problems for other large banks at home or in other central euro area countries, but often would do much less so for the largest banks of those smaller countries close to the outside border of the euro area. Hence, for the latter countries the tests of table 4.4 confirm the impression from the estimations in table 4.3.

The *T*-tests also confirm the special situation of Italy among the larger euro area countries. In many cases the exposure of Italian banks to foreign problems is significantly lower than domestic exposures in the other main countries. In addition, the greater exposure of ABN AMRO to Crédit Agricole (cross-border) than BNP Paribas to Crédit Agricole (domestic) is statistically significant at the 1 percent level. And, similarly, the greater exposure of Fortis to Crédit Agricole (cross-border) than BNP Paribas to Crédit Agricole (domestic) is significant at the 10 percent level.

The probabilities in table 4.3 allow one to derive a relationship between

16. The *T*-statistics result from comparing cross-border η-values with domestic η-values (ceteris paribus the number of conditioning banks), as used for the spillover probabilities of table 4.3. The estimation of tail dependence parameters η have been described in equation (7). For example, the *T*-statistic in row Netherlands and column T_1 in table 4.4 results from testing whether the η-value for the largest Dutch bank (ABN AMRO) with respect to the second largest German bank (HypoVereinsbank) significantly differs from the domestic η-value of the largest German bank (Deutsche Bank) with respect to the second largest German bank (HypoVereinsbank).

the likelihood of a bank crash as a function of the number of other banks crashing. In our previous paper on currencies, we have denoted this relationship between the probability of crises and the number of conditioning events as "contamination function" (see Hartmann, Maddaloni, and Manganelli 2003, figs. 1 to 7). Bae, Karolyi, and Stulz (2003) speak in their international equity market contagion paper of "co-exceedance response curves." Gropp and Vesala (2004) apply the latter concept to European banks. While the results in table 4.3 suggest that most contamination functions in European banking are monotonously increasing (as for currencies), at least over certain ranges of conditioning events, there are also some exceptions. Witness, for example, the exposure of Banco Commercial Portugues (the largest Portuguese bank) to problems of German banks. Going from $\hat{P}_4$ to $\hat{P}_5$ implies a reduction in the crash probability of BCP.

Potential explanations for this phenomenon are "flight to quality," "flight to safety," or "competitive effects." Some banks may benefit from the troubles at other banks, as, for example, depositors withdraw their funds from the bad banks to put them in good banks. Such behavior has been referred to by Kaufman (1988) in relation to U.S. banking history, and Saunders and Wilson (1996) provide 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. Nonmonotonicity of contamination functions might also occur for the curse of dimensionality, as very few observations may enter the joint failure area for more than two banks.

The finding of statistically similar spillover risk between major euro area banks within and between some large countries could be important 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 similarity of domestic and cross-border spillover risks for some countries 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 of 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, through multilateral "colleges" of supervisors for specific groups, and now also through the newly established "Lamfalussy Committees" in banking. The results could provide some arguments in favor of an increasing European-wide component in macroprudential surveillance and 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. The existence of significant differences in the degree of cross-border risks between different groups of European countries could make the development of homogenous supervisory structures more complicated.

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 to levels that are so low that they can be simply ignored. This conclusion is also consistent with Degryse and Nguyen (2004) and Lelyveld and Liedorp (2004), whose analyses of interbank exposures suggest that risks from abroad may be larger than domestic risks in the Belgian and Dutch banking systems. One explanation for the relevance of cross-border bank risks 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, figs. 10 and 11), much of the wholesale business of these large players happens in international markets that are highly interlinked.

4.6.2 Cross-Atlantic Comparison

The next step in examining interbank spillovers consists of comparing them between the euro area and U.S. 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 (1). Notice that for each continent η_{US} and η_{EA} are derived from all the extreme stock return linkages (bilateral and multilateral) between the respective N = twenty-five banks, following the estimation procedure described in section 4.3.

As indicated in table 4.5, we obtain $\hat{\eta}_{US} = 0.39$ and $\hat{\eta}_{EA} = 0.17$. The evidence thus suggests that overall contagion risk in the U.S. banking system is higher than contagion risk among euro area banks (about two times).[17] Moreover, knowing that for the case of independence $\eta = 1/N = 0.04$, the amount of multivariate linkage is of economically relevant magnitude. The $\hat{P}$ values in the table describe the probability that all twenty-five banks in the euro area or the United States crash, given that any of them crashes. These probabilities illustrate that overall systemic risk related to the crash

17. Strictly speaking, this and subsequent related statements in the main text make the plausible assumption that the dependence structure is sufficiently similar on both sides of the Atlantic for the slowly varying function $\ell(q)$ described in appendix A not to have a large impact on relative probabilities.

Table 4.5 **Multivariate extreme spillover risk among euro area and U.S. banks**

	Estimations		
Country/Area	$\hat{\eta}$	$\hat{P}$	Cross-sectional test T
United States ($N = 25$)	0.39	2.8E-4	$H_0 : \eta_{\text{U.S.}} = \eta_{\text{EA}}$
Euro area ($N = 25$)	0.17	6.7E-15	$T = 7.25$
Germany ($N = 6$)	0.42	1.5E-3	
France ($N = 4$)	0.48	1.4E-2	
Italy ($N = 4$)	0.62	0.6	

Notes: The table reports in the column $\hat{\eta}$ the coefficient that governs the multivariate extreme tail dependence for all the banks of the countries/areas detailed on the left-hand side. In the column $\hat{P}$ it shows the probability that all banks of a specific country/area crash given that one of them crashes. Both statistics are estimates of systemwide extreme spillover risks. Univariate crash probabilities (crisis levels) are set to $p = 0.05$ percent. The right-hand column describes the cross-sectional test (4.4.1) for the whole United States and euro area banking system. A positive (negative) test statistic indicates that the United States (euro area) η is larger than the euro area (United States) η. The critical values of the test are 1.65, 1.96, and 2.58 for the 10 percent, 5 percent, and 1 percent levels, respectively. Note that η values for countries/areas with different numbers of banks may not be comparable.

of a single bank is extremely low. Of course, multivariate contagion risk increases for multiple bank crashes.

Is this difference between the United States and the euro area statistically significant? We apply the cross-sectional stability test (7) described in subsection 4.4.2, with the following null hypothesis:

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

It turns out that the T-statistic reaches $T = 7.25$. In other words, our indicators and tests suggest that the difference in systemic spillover risk between the United States and the euro area is statistically significant, way beyond the 1 percent confidence level.

One explanation could be that in a much more integrated banking system, such as that of the United States, areawide 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 previous explanation was true, then overall systemic spillover risk should not be lower within France, Germany, or Italy than it is in the United States.[18] The bottom part of table 4.5 shows that this is actually the case. Overall, domestic spillover risk in France and Germany is about the same as in the United States; in Italy it is even larger than in the United States (see also fig. 4.1 in subsection 4.8.1). Our cross-sectional test cannot reject parameter equality between France and the United States or between Germany and the United States, but it rejects it between Italy

18. We thank Christian Upper for suggesting this exercise to us.

and the United States (as Italy is even more risky). In other words, the lower overall spillover risk in Europe is explained by the quite weak extreme cross-border linkages.

Having said this, we note that there is some structural instability in the extreme dependence of bank stock returns on both sides of the Atlantic. As we will discuss in depth in section 4.8 following, the risk of spillovers has quite generally increased in the course of our sample period. We will, however, also show that all our conclusions here are robust for taking structural instability into account. The only caveat we have to keep in mind is that the probabilities in table 4.3 represent averages across the whole sample period, so that they tend to overestimate the risk of spillovers at the start of the sample and underestimate it towards the end of the sample.

Looking ahead, the analysis in the present section suggests that—as the European banking system integrates further over time—it could become more similar to the U.S. system in terms of contagion risk. In other words, the ongoing and gradual integration process should be accompanied by appropriate changes in macroprudential surveillance and supervisory structures.

4.7 Aggregate Banking System Risk

Next we turn to the analysis based on our measure of extreme systematic risk. We are interested in assessing the extent to which individual banks and banking systems are vulnerable to an aggregate shock, as captured by an extreme downturn of the market risk factor or an extreme upturn of high-yield bond spreads. Across this section we assume stability of estimated tail-βs over time. The same caveat applies as in the previous section, as structural breaks of extreme systematic banking system risk are only considered in section 4.8.

The results are summarized in tables 4.6 and 4.7 for the euro area and the United States, respectively, and for all measures of aggregate risk listed in subsection 4.5.2. The different stock indexes capture market risk, as in traditional asset pricing theory. The high-yield bond spread is also tested as 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 United States, and fluctuations in economic activity are the most important determinant of banks' asset quality. Some might also regard high-yield spreads as a particularly suitable indicator for crisis situations.

The upper part of the tables report tail-βs for individual banks. To take an example, the value 12.1 in the row "IRBAN" and column "stock index" of table 4.6 means that a very large downturn in the general euro area stock index is usually associated with a 12 percent probability that Allied Irish Banks, a top Irish bank, faces an extreme stock price decline. The value 30.2 in row "BNPPAR" and column "stock index" suggests that the same

Table 4.6 Extreme systematic risk (tail-βs) of euro area banks

	Aggregate risk factor				
Bank	Bank index	Stock index	Global bank	Global stock	Yield spread
DEUTSCHE	51.1	35.0	25.6	13.0	3.8E-5
HYPO	22.3	20.8	9.3	5.5	0.1
DRESDNER	37.9	27.7	19.1	11.6	0.3
COMMERZ	39.5	30.8	15.2	13.9	0.2
BGBERLIN	2.8	1.6	0.8	0.7	0.8
DEPFA	6.2	7.3	3.0	2.9	3.4E-2
BNPPAR	42.1	30.2	23.2	13.2	2.7E-2
CA	9.2	6.7	1.6	2.0	0.4
SGENERAL	45.8	30.0	22.7	16.0	6.9E-2
NATEXIS	1.8	1.9	2.2	1.7	9.1E-3
INTESA	19.1	11.2	7.2	5.9	0.4
UNICREDIT	14.5	9.5	10.5	5.0	0.3
PAOLO	36.7	28.5	15.2	10.2	0.3
CAPITA	16.5	9.3	9.4	6.4	0.3
SANTANDER	36.4	33.4	17.4	14.5	0.6
BILBAO	41.6	31.1	20.4	13.4	0.6
BANESP	2.6	1.2	1.4	0.6	2.7E-3
ING	61.7	46.0	23.1	14.1	0.5
ABNAMRO	50.3	46.3	23.7	13.9	0.2
FORTIS	48.5	36.3	11.8	10.9	0.1
ALMANIJ	11.9	11.1	7.4	4.5	0.2
ALPHA	3.7	4.1	1.5	1.2	8.0E-3
BCP	17.0	11.9	9.3	7.5	0.3
SAMPO	2.7	2.2	3.4	1.4	2.1E-2
IRBAN	13.9	12.1	6.9	4.6	0.1
Average	25.4	19.4	11.6	7.8	0.2
Standard deviation	18.8	14.5	8.3	5.3	0.2

Note: The table exhibits the estimates of extreme systematic risk (2; tail-βs) for individual euro area banks and for the euro area banking system as a whole. The entries show the probability that a given bank crashes given that a market indicator of aggregate risk crashes (or in the case of the yield spread, booms). Results are reported for five different aggregate risk factors: the euro area banking sector subindex, the euro area stock index, the world banking sector subindex, the world stock index, and the euro area high-yield bond spread. Data for the euro area yield spread are only available from 1998 to 2004. All probabilities are estimated with the extension of the approach by Ledford and Tawn (1996) described in section 4.3 and reported in percentages. Univariate crash probabilities (crisis levels) are set to $p = 0.05$ percent. The average and the standard deviation at the bottom of the table are calculated over the twenty-five individual tail-βs in the upper rows, respectively. See table 4D.1 for list of abbreviations.

probability for the largest French bank is substantially higher. Going more systematically up and down the columns as well as moving to the right and left in the rows, one can see (1) that tail-βs can be quite different across banks, both in Europe and in the United States, and (2) that the relative sizes of tail-β seem to be quite similar for different measures of aggregate risk. For example, a number of banks from some more peripheral and

Table 4.7 **Extreme systematic risk (tail-βs) of U.S. banks**

	Aggregate risk factor				
Bank	Bank index	Stock index	Global bank	Global stock	Yield spread
CITIG	41.1	26.5	16.5	17.4	0.3
JPMORGAN	39.4	18.0	15.2	16.4	1.3
BOA	37.7	12.4	6.4	7.1	0.2
WACHO	27.2	9.6	8.6	9.3	0.5
FARGO	17.1	7.1	4.5	3.8	2.4E-2
BONEC	31.0	14.0	9.7	10.0	0.4
WASHMU	9.5	2.8	4.7	1.8	0.1
FLEET	38.8	13.1	10.6	10.1	0.6
BNYORK	25.2	12.9	10.9	11.3	1.0
STATEST	26.8	19.0	10.9	18.3	1.0
NOTRUST	26.7	17.4	12.0	10.0	0.9
MELLON	29.4	16.4	10.6	10.4	0.8
USBANC	19.6	6.6	7.8	4.8	0.3
CITYCO	32.3	8.9	7.4	6.7	0.2
PNC	25.8	12.7	10.2	8.9	0.3
KEYCO	24.9	8.4	6.1	6.1	0.2
SUNTRUST	32.0	11.7	8.9	7.8	0.3
COMERICA	24.0	13.5	7.1	7.1	0.5
UNIONBAN	11.2	3.9	5.9	3.8	0.1
AMSOUTH	15.1	7.5	8.7	6.4	0.3
HUNTING	17.5	7.0	8.3	6.0	0.1
BBT	19.9	6.6	5.3	5.4	0.2
53BANCO	21.7	8.6	4.9	3.6	0.2
SOTRUST	33.3	7.3	6.8	4.4	0.3
RFCORP	26.5	11.6	8.4	7.8	0.2
Average	26.2	11.3	8.6	8.2	0.4
Standard deviation	8.5	4.4	3.0	4.2	0.3

Notes: The table exhibits the estimates of extreme systematic risk (2; tail-βs) for individual U.S. banks and for the U.S. banking system as a whole. The entries show the probability that a given bank crashes given that a market indicator of aggregate risk crashes (or in the case of the yield spread, booms). Results are reported for five different aggregate risk factors: the U.S. banking sector subindex, the U.S. stock index, the world banking sector subindex, the world stock index, and the U.S. high-yield bond spread. All probabilities are estimated with the extension of the approach by Ledford and Tawn (1996) described in section 4.3 and reported in percentages. Univariate crash probabilities (crisis levels) are set to $p = 0.05$ percent. The average and the standard deviation at the bottom of the table are calculated over the twenty-five individual tail-βs in the upper rows, respectively. See table 4D.1 for list of abbreviations.

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 United States in table 4.7. For example, some players focusing on regional or local retail business, such as a savings and loans association like Washington Mutual, have relatively low tail-βs (in this specific case, 3 percent for the U.S. stock index as aggregate risk factor). In contrast, large and geographically broad banks—such as Deutsche Bank, BNP Paribas, Citigroup, or JP Morgan Chase—exhibit larger tail-βs, as they are much more diversified.

The bottoms of tables 4.6 and 4.7 report the means and standard deviations of tail-βs across the twenty-five banks for each continent. Overall, tail-βs in Europe and in the United States are of similar order of magnitude, although the U.S. tail-βs tend to be slightly less variable (except for yield spreads). We can use a cross-sectional T-test to compare aggregate banking risk across the Atlantic. Table 4.8 shows the average extreme dependence parameters $\bar{\eta}$ derived from the individual η parameters governing the tail-βs of the twenty-five banks on each continent. It also shows the T-values for a test with the following null hypothesis:

$$H_0 : \bar{\eta}_{\mathrm{US}} = \bar{\eta}_{\mathrm{EA}}$$

The equality of extreme dependence between stock returns and the market risk factor in Europe and the United States cannot be rejected.

When turning to extreme systematic risk associated with high-yield

Table 4.8 **Comparisons of extreme systematic risk across different banking systems**

	Aggregate risk factor				
Banking system	Bank index	Stock index	Global bank	Global stock	Yield spread
$\bar{\eta}_{US}$	0.87	0.79	0.78	0.77	0.55
$\bar{\eta}_{EA}$	0.86	0.83	0.80	0.76	0.53
$\bar{\eta}_{FR}$	0.85	0.82	0.79	0.76	0.50
$\bar{\eta}_{GE}$	0.86	0.84	0.80	0.76	0.53
$\bar{\eta}_{IT}$	0.88	0.83	0.82	0.78	0.57
Null hypothesis					
$\bar{\eta}_{US} = \bar{\eta}_{EA}$	0.19	–0.94	–0.44	0.21	0.30
$\bar{\eta}_{US} = \bar{\eta}_{FR}$	0.34	–0.59	–0.32	0.14	1.18
$\bar{\eta}_{US} = \bar{\eta}_{GE}$	0.20	–1.05	–0.47	0.30	0.48
$\bar{\eta}_{US} = \bar{\eta}_{IT}$	–0.08	–0.63	–0.81	–0.16	–0.48

Notes: The table exhibits the average tail dependence parameters η that govern the tail-β estimates reported in tables 4.6 and 4.7 for the United States, euro area, French, German, and Italian banking system (upper panel) and the statistics of tests examining differences in extreme systematic risk between the United States and euro area banking systems (lower panel). Each $\bar{\eta}$ is calculated as the mean of tail-β dependence parameters across all the banks in our sample for the respective country/area. The tests are applications of the cross-sectional test (7). The null hypothesis is that extreme systematic risk in the U.S. banking system is the same as in the other banking systems. A positive (negative) test statistic indicates that extreme systematic risk in the U.S. banking system (in the respective euro area banking system) is larger than in the respective euro area (United States) banking system. The critical values of the test are 1.65, 1.96, and 2.58 for the 10 percent, 5 percent, and 1 percent levels, respectively. All results are reported for the five different aggregate risk factors: the euro area/United States banking sector subindex, the euro area/United States stock index, the world banking sector subindex, the world stock index, and the euro area/United States high-yield bond spread. Univariate crash probabilities (crisis levels) are set to $p = 0.05$ percent.

bond spreads (see the right-hand side of tables 4.6 and 4.7), the results are different. Tail-βs for spreads are extremely small. 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. This also confirms the simple correlation analysis referred to in subsection 4.5.2.

Accordingly, the tail dependence parameters $\bar{\eta}$ for spreads in table 4.8 are much smaller than the ones for stock indexes. Note that the mean dependence parameters for yield spreads are all estimated to be quite close to the level associated with asymptotic independence for this two-dimensional measure, $\eta_{\text{indep}} = 1/N = 0.5$. Thus, it is no surprise that the T-tests show that—as for the market risk factor—the level of extreme aggregate risk in the United States and in the euro area is statistically indistinguishable.

We conclude from this that high-yield bond spreads are not very informative about extreme aggregate banking system risk on both sides of the Atlantic. This finding could mean, for example, that credit spreads are a less-good predictor of business cycle fluctuations—in particular of severe ones—than previously thought. It could also mean that the banks in our sample hold only a very limited amount of loans from borrowers that are rated below investment grade. Still, future research could address whether they have at least some incremental explanatory value for banking problems when other variables are controlled for as well.

4.8 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 application of the structural stability test by Quintos, Fan, and Phillips (2001; see subsection 4.4.2) to the estimators of multivariate spillovers and systematic risk (see subsections 4.8.1 and 4.8.2, respectively).

4.8.1 Time Variation of Bank Contagion Risk

We apply the recursive structural stability test described in subsection 4.4.1 and equations (B.1) through (B.4) of appendix B to the extreme tail dependence parameters η that govern the spillover probabilities reported in table 4.3. The null hypothesis of constancy of η for the cases in the table is given by equation (B.3). The test results are reported in table 4.9, with the different cases structured in the same way as in tables 4.3 and 4.4.

Each entry first shows the endogenously estimated break point, if any, and then the value of the test statistic in parentheses. It turns out that the forward version of the recursive test discovers a significant upward break

Table 4.9 **Domestic and cross-border extreme spillover risk among euro area banks: Time variation**

Largest bank	$\hat{\eta}_1$	$\hat{\eta}_2$	$\hat{\eta}_3$	$\hat{\eta}_4$	$\hat{\eta}_5$
		Conditioning banks: German			
Germany	3/31/97 (43.5)	8/1/97 (62.0)	4/2/97 (38.4)	8/15/97 (7.2)	7/23/97 (17.3)
The Netherlands	3/31/97 (81.1)	4/2/97 (77.9)	4/2/97 (66.2)	8/21/97 (16.9)	4/2/97 (7.3)
France	7/23/97 (25.6)	8/1/97 (37.5)	9/9/97 (41.2)	7/23/97 (19.3)	8/15/97 (8.4)
Spain	7/21/97 (68.8)	5/27/97 (39.7)	5/29/97 (55.9)	7/23/97 (18.9)	8/14/97 (5.5)
Italy	7/21/97 (49.2)	9/9/97 (46.2)	9/9/97 (41.4)	8/21/97 (20.2)	8/21/97 (9.3)
Belgium	8/21/97 (62.2)	4/2/97 (50.1)	3/27/97 (56.7)	7/23/97 (25.9)	6/12/98 (6.9)
Ireland	8/20/97 (43.0)	10/16/97 (24.3)	8/15/97 (21.9)	8/14/97 (11.3)	8/15/97 (4.7)
Portugal	9/9/97 (27.5)	1/14/94 (37.1)	1/25/94 (50.1)	7/23/97 (23.2)	7/23/97 (7.5)
Finland	10/16/97 (30.5)	10/16/97 (26/3)	5/23/94 (37.2)	8/22/97 (23.6)	7/23/97 (9.6)
Greece	3/27/97 (64.0)	3/27/97 (58.8)	4/2/97 (47.8)	3/27/97 (18.8)	8/15/97 (7.4)
		Conditioning banks: French			
France	2/15/02 (25.3)	9/19/00 (32.8)	6/17/94 (22.5)		
Germany	10/9/00 (52.6)	11/21/00 (36.3)	5/21/96 (4.4)		
The Netherlands	10/10/00 (54.4)	9/20/00 (44.9)	10/22/97 (39.0)		
Italy	1/11/02 (20.1)	1/31/01 (37.8)	10/22/97 (32.5)		
Spain	10/10/00 (34.3)	9/19/00 (40.6)	10/13/97 (32.1)		
Belgium	9/1/00 (47.7)	11/27/01 (52.4)	6/9/98 (40.8)		
Ireland	9/20/00 (13.8)	11/21/00 (19.4)	12/7/01 (12.2)		
Portugal	1/25/02 (24.8)	1/29/02 (30.4)	10/22/97 (20.4)		
Finland	4/14/00 (6.1)	5/31/94 (26.0)	11/4/96 (27.5)		
Greece	6/11/98 (15.5)	2/28/97 (32.5)	2/28/97 (19.2)		
		Conditioning banks: Italian			
Italy	9/30/97 (5.4)	9/25/97 (9.0)	9/30/97 (3.6)		
Germany	7/25/97 (23.9)	7/25/97 (31.7)	10/8/97 (18.8)		
The Netherlands	10/7/97 (16.6)	8/1/97 (27.7)	8/7/97 (18.7)		
Spain	6/27/97 (7.6)	7/14/97 (19.9)	9/9/97 (12.1)		
France	10/8/97 (9.9)	10/22/97 (8.3)	9/9/97 (7.9)		
Belgium	7/31/97 (25.8)	8/1/97 (44.8)	10/8/97 (30.2)		
Ireland	8/22/97 (4.9)	10/8/97 (7.0)	8/7/97 (6.7)		
Portugal	8/1/97 (9.1)	8/1/97 (18.2)	8/7/97 (13.6)		
Finland	—	7/25/97 (8.5)	10/24/97 (5.9)		
Greece	9/9/97 (15.3)	10/17/97 (19.2)	8/15/97 (13.4)		
		Conditioning banks: Spanish			
Spain	7/16/97 (33.1)	7/16/97 (4.0)			
Germany	3/17/97 (88.0)	5/21/97 (9.0)			
The Netherlands	7/21/97 (39.0)	7/3/97 (7.3)			
France	10/22/97 (34.6)	5/27/97 (5.4)			
Italy	7/28/97 (33.2)	6/18/97 (3.8)			
Belgium	7/17/97 (47.7)	2/25/97 (12.4)			
Ireland	7/16/97 (22.7)	—			
Portugal	6/16/97 (42.7)	3/31/97 (12.8)			
Finland	10/24/97 (21.3)	7/23/97 (3.9)			
Greece	6/2/97 (37.9)	3/27/97 (12.4)			

Notes: The table reports the results of tests examining the structural stability of the extreme spillover risks documented in table 4.3. This is done by testing for the constancy of the η tail-dependence param-

Table 4.9 (continued)

eters (null hypothesis) that govern the spillover probabilities in table 4.3. Applying the recursive test (B1) through (B4) by Quintos, Fan, and Phillips (2001) described in appendix B and subsection 4.4.1, each cell shows the endogenously found break date and the test value in parentheses. Dates are denoted XX/YY/ZZ, where XX = month, YY= day, and ZZ = year. The critical values of the test are 1.46, 1.78, and 2.54 for the 10 percent, 5 percent, and 1 percent levels, respectively. A test value exceeding these numbers implies an increase in extreme dependence over time. The absence of a break over the sample period is marked with a dash.

in spillover risk in almost every case, be it a domestic linkage or a cross-border linkage. For spillovers conditioned on German, Italian, and Spanish banks, almost all increases in risk occur sometime during the year 1997. If crashes of French banks are the conditioning events, breaks tend to occur somewhat later, most often around the year 2000. While there have been economic events in the vicinity of the break point times found by the test that could have contributed to increases in spillover risks (e.g., the Asian financial crisis, the end of the technology boom), we would not pay too much attention to the exact dates. The reason is that further evidence, presented subsequently, suggests that changes in risk exhibit fairly gradual patterns, so that just singling out the most important break point could be misleading.

These results suggest that there was also an increase in systemwide spillover risks. We examine this question in table 4.10. We first calculate the 25-dimensional (N = 25) tail-dependence parameter values that span the whole U.S. block $\hat{\eta}_{US}$ and the whole euro area block $\hat{\eta}_{EA}$ (as in subsection 4.6.2, table 4.5) and test for structural change. We do the same for Germany (N = 6), France (N = 4), and Italy (N = 4), separately. The null is again as in equation (B3). Table 4.10 shows on the left-hand side break points and test statistics for the full sample; in the middle of table 4.10 estimated subsample values for the different ηs are reported. Finally, the right-hand side of the table also displays the results of two further structural stability tests, limited to the second half of the sample after the first endogenous break. The first test is another Quintos, Fan, and Phillips endogenous stability test, and the second an exogenous stability test (T_{EMU}), in which the break point is chosen to be 1 January, 1999, the start of economic and monetary union in Europe.

The tests indicate a significant upward break in euro area systemic risk around mid-1996 (test value 4.9) and in U.S. systemic risk at the end of 1995 (test value 18.5). These breaks are both slightly earlier than the lower-dimensional ones in table 4.9.[19] The extreme dependence parameter $\hat{\eta}_{US}$ increases from 0.20 to 0.41, and parameter $\hat{\eta}_{EA}$ from 0.13 to 0.20. Gropp and

19. One explanation for the earlier increase in fully systemic risk could be that the (many) cases not covered in table 4.9 have earlier breaks than the ones shown.

Table 4.10 Multivariate extreme spillover risk among euro area and U.S. banks: Time variation

Country/Area	Full sample break test	Subsample estimates $\hat{\eta}_1$	Subsample estimates $\hat{\eta}_2$	Second subsample break tests: Endogenous	Second subsample break tests: Exogenous
United States (N = 25)	11/22/95 (18.5)	0.20	0.41	3/11/97 (2.2)	n.a.
Euro area (N = 25)	12/5/96 (4.9)	0.13	0.20	(B) 1/18/99 (3.2)	(1.4)
Germany (N = 6)	7/23/97 (17.6)	0.24	0.52	—	(1.9)
	(B) 4/2/97 (2.1)			(B) 1/22/99 (3.9)	
France (N = 4)	6/17/94 (21.9)	0.19	0.52	12/7/01 (12.8)	(–3.0)
	(B) 5/21/96 (4.3)			(B) 2/24/97 (3.0)	
Italy (N = 4)	09/30/97 (3.4)	0.45	0.72	(B) 4/11/03 (2/2)	(2.1)

Notes: The table reports tests and estimations assessing time variation in the multivariate spillover probabilities of table 4.5. The column on the left displays estimated break dates and values from the recursive Quintos, Fan, and Phillips (2001) test (B.1) through (B.4) described in appendix B and subsection 4.4.1 applied to the η parameter governing the extreme tail dependence of the banks located in the countries/areas displayed on the extreme left. Dates are denoted XX/YY/ZZ, where XX = month, YY = day, and ZZ = year. The forward recursive version of the test is used, unless marked otherwise. (B) marks the backward recursive version of the test. The critical values of the test are 1.46, 1.78, and 2.54 for the 10 percent, 5 percent, and 1 percent levels, respectively. The middle columns show pre- and postbreak estimates for η. The columns on the right display two tests that assess the occurrence of further breaks in the second half of the sample. The first one is the same as the one on the left-hand side. The second one is a simple differences-in-means test based on (7). The exogenous break point is chosen to be 1/1/99, the time of the introduction of the euro. Critical values for this test are 1.65, 1.96, and 2.58 for the 10 percent, 5 percent, and 1 percent significance levels. Note that η values for countries/areas with different numbers of banks may not be comparable.

Vesala (2004) also find an increase in bank spillover risk in Europe, using a different methodology, but they impose the break point at the time of the introduction of the euro. For France, Germany, and Italy, our test also indicates strong domestic upward breaks, but in addition France and Germany experience a (weaker) downward break (as indicated by the backward version of the test). In sum, we detect a significant increase of multivariate spillover risk both in the euro area and in the U.S. banking system. Both systems seem to be more vulnerable to contagion risk today than they have been in the early 1990s, the United States even more so than the euro area.

The increase of spillover risk found for the United States is consistent with the findings of de Nicoló and Kwast (2002), who detect an upward trend of regular correlations between U.S. LCBOs during the period 1988 to 1999 and interpret it as a sign of increasing systemic risk.[20] The authors estimate that part of the increase is likely to be related to consolidation among LCBOs. The timing of structural change in de Nicoló and Kwast's

20. Within the group of about twenty-two LCBOs, however, most of the increase in correlations is concentrated among the less-complex banks.

paper is not exactly the same as in ours but quite similar, as they find most correlation changes during 1996 and perhaps 1997. Mistrulli (2005) argues that some increase in domestic contagion risk in the Italian banking sector has been caused by new interbank lending structures that emerged from consolidation. And the risk seems to pick up around 1997, similar to our break points. Hence, banking consolidation may be one important explanation for a higher contagion risk *within* the countries discussed. It is, however, a less likely explanation for the increase in η for the euro area banking system as a whole. The reason is that cross-border bank mergers are still relatively rare in Europe (see, e.g., Hartmann, Maddaloni, and Manganelli 2003, figure 10).

In order to get a better view of the evolution of multivariate contagion risk over time, we plot in figure 4.1 the recursive estimates of η for the euro area, the United States, France, Germany, and Italy. In addition to unfiltered results (solid lines), we also display results for GARCH-filtered return data (dotted lines). For the reasons given in the first subsection of appendix E, however, one should focus on the unfiltered results. Comparing the two upper panels of the figure, we can see the smaller and gradual character of the increase in spillover risk in the euro area. Notice the consistency of this evolution with a slowly advancing integration process. Multivariate risk in the United States starts at a higher level and begins to rise later, but at a much faster pace. The lower panels of the figure confirm the results discussed in subsection 4.6.2, insofar as general spillover risk within France, Germany, and Italy is higher than in the euro area as a whole and, on average, of a similar order of magnitude as within the United States. (The results are qualitatively the same for filtered data, although the strength of changes is sometimes muted.[21]) All these findings are consistent with the hypothesis advanced in section 4.6—that banks are more exposed to each other within a country than across borders. So far, this remains true even in the euro area, which shares a common currency and a common interbank market.

Figure 4.2 shows the recursive statistics of the cross-sectional tests comparing U.S. multivariate spillover risk with euro area, French, German, and Italian spillover risk. We would like to learn from this whether the similarities and differences in multivariate risk across those banking systems established in section 4.6 generally hold across our sample period. Each panel exhibits the difference in η between the first country (always the United States) 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

21. A similar phenomenon for general stock market data has already been observed by Poon, Rockinger, and Tawn (2004). In the working paper version of the present paper we display a larger number of the results for filtered data (Hartmann, Straetmans, and C. de Vries 2005, appendix E). The second section of appendix E briefly summarizes them.

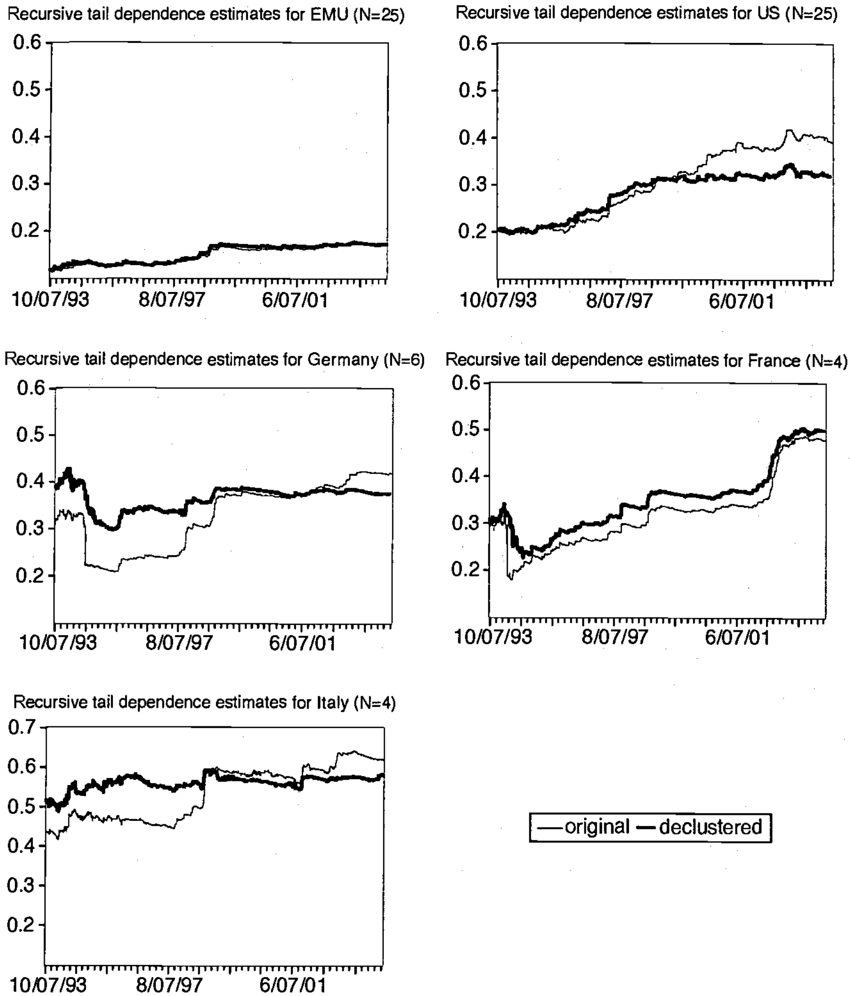

Fig. 4.1 Evolution of multivariate extreme spillover risk among euro area and U.S. banks

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 confirm from the upper left-hand chart in figure 4.2 that the United States is more risky than the euro area, except for the very start of the sample. The lower right-hand chart illustrates that Italy is more risky than the United States.

Finally, we turn to the results of the two structural stability tests for the second half of the sample on the right of table 4.10. Interestingly enough, the endogenous test (backward version) finds a second break point for the

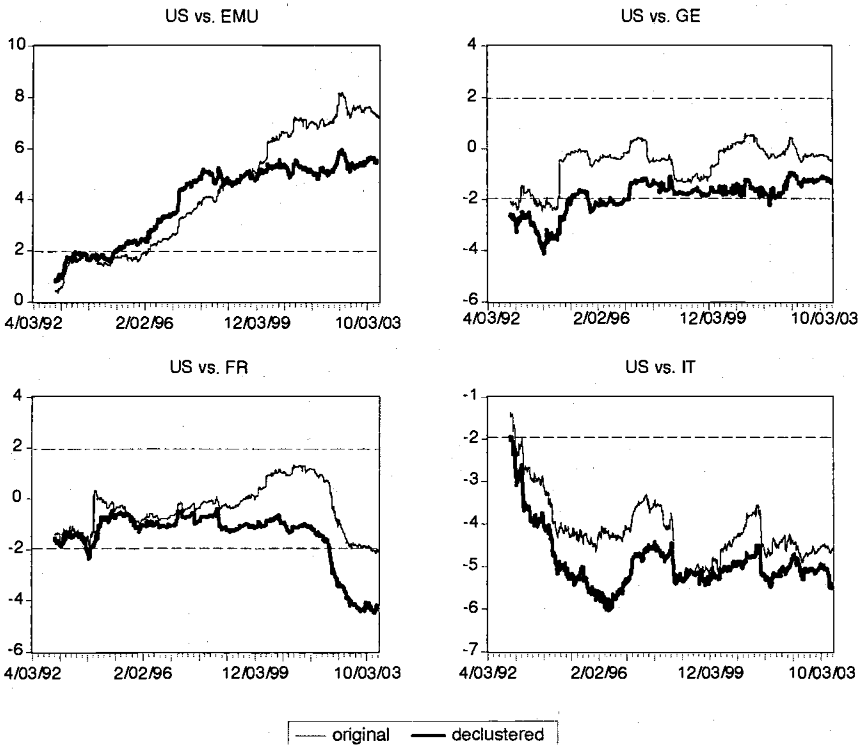

Fig. 4.2 Comparisons of the evolution of extreme bank spillover risk across countries

euro area in January 1999 reducing η (test value 3.2 compared to a critical value of 2.6 for a significant change at the 1 percent level). In other words, it indicates that multivariate contagion risk decreased in parallel with the introduction of the euro. As we are concerned about the validity of the asymptotic properties of the Quintos, Fan, and Phillips test when it is applied in a sequential way, we also conduct an exogenous stability test for which we impose 1 January, 1999, as the break point. This test exploits the asymptotic normality of the tail dependence parameter, as in the case of cross-sectional differences discussed earlier. It confirms that there is some decline in η_{EA} at the time of the euro changeover, but this decline is not statistically significant (test value 1.4 compared to a critical value of 1.9 for a significant change at the 5 percent level).

While it is often assumed that the introduction of the euro with a common money market should have led to an increase in contagion risk in the euro area, our results do not provide any evidence of that actually happening. On the contrary, if anything there was a slight decrease of multivariate extreme dependence between all euro area banks. One explanation for such a development would be as follows. Whereas the introduction of a single currency with a common (and fully integrated) money market could increase the interbank linkages between banks across borders, and thereby the risk of contagion, on the other hand the much larger and more liquid money market as well as the wider access to different contingent claims under a single currency could also increase the money market's resilience against shocks and improve risk sharing. If the latter effects dominate the former, then the banking system could well become less prone to extreme spillovers.

As for the three larger euro area countries, Germany experiences a similar reduction in risk as the area as a whole. But in this case the reduction is also statistically significant for the exogenous break test, at least at the 10 percent level. France and Italy also have some further breaks. While statistically significant, they do not happen in the vicinity of the euro changeover. The United States banking system faces a further increase in multivariate spillover risk at the end of 1997.

We close this subsection with a word of caution. While the evidence supporting increases in multivariate extreme dependencies among banks in both the euro area and the United States seems statistically relatively strong, we should not forget that our sample period extends only over twelve years. This means, first, that we cover only a small number of economic cycles.[22] Since there was a relatively long upturn during the 1990s, there may be a risk that this had an impact on extreme bank stock return dependence. More generally, similar to correlation, extreme dependence can oscillate over time. Obviously, we cannot know whether there was already a period of higher extreme linkages between banks before our sample starts or whether the high linkages observed toward the end of our sample will come down again in the future.

4.8.2 Time Variation of Aggregate Banking System Risk

Lastly, we apply the structural stability test to extreme systematic risk in banking systems. More precisely, we study whether the bivariate extreme dependence parameters η that enter our estimates of tail-βs have changed between 1992 and 2004. Table 4.11 reports the results for each euro area bank in our sample and table 4.12 for each U.S. bank. Each table shows for the respective banks the estimated break points, if any, with test values in parentheses. Tests are performed for all aggregate risk measures on which we condition the tail-βs.

The general result is that extreme systematic risk has increased over time. In other words, both the euro area and the U.S. banking system seem to be more exposed to aggregate shocks today than they were in the early 1990s. We further illustrate this at the systemwide level in figure 4.3, which gives us a better insight into the time evolution of extreme systematic risk.

22. Following the NBER and CEPR business cycle dating programs, we cover at most two full cycles; see http://www.nber.org/cycles.html and http://www.cepr.org/data/Dating/.

Table 4.11 **Extreme systematic risk (tail-βs) of euro area banks: Time variation**

	Aggregate risk factor				
Bank	Bank index	Stock index	Global bank	Global stock	Yield spread
DEUTSCHE	3/12/97 (45.3)	3/12/97 (57.7)	8/15/97 (53.3)	12/5/96 (86.1)	9/14/00 (153.4)
HYPO	7/21/97 (40.1)	10/22/97 (60.0)	9/9/97 (62.8)	10/22/97 (60.5)	10/4/00 (124.1)
DRESDNER	8/1/97 (69.1)	12/5/96 (53.1)	12/5/96 (48.5)	12/5/96 (59.5)	8/22/00 (44.1)
COMMERZ	7/21/97 (22.8)	3/19/97 (34.8)	8/1/97 (30.4)	8/21/97 (70.4)	10/3/00 (142.7)
BGBERLIN	12/3/96 (7.9)	12/3/96 (10.9)	12/5/96 (11.8)	7/3/97 (19.2)	1/4/01 (496.6)
DEPFA	7/5/96 (33.7)	7/15/96 (37.6)	8/21/97 (19.4)	8/12/97 (33.6)	9/13/00 (97.5)
BNPPAR	8/15/97 (34.7)	7/17/97 (41.1)	10/22/97 (27.5)	8/27/97 (34.0)	9/15/00 (77.3)
CA	10/5/00 (50.4)	9/19/00 (52.7)	10/9/00 (26.6)	9/19/00 (31.7)	7/21/00 (127.3)
SGENER	10/22/97 (40.9)	10/22/97 (35.4)	10/22/97 (37.4)	10/22/97 (42.6)	9/21/00 (114.5)
NATEXIS	12/5/96 (6.0)	12/3/96 (8.5)	8/28/97 (11.0)	8/28/97 (21.1)	9/15/00 (155.1)
INTESA	7/31/97 (25.6)	7/28/97 (39.7)	9/9/97 (14.5)	7/31/97 (24.4)	7/24/00 (183.9)
UNICRED	10/8/97 (23.8)	9/25/97 (14.2)	10/8/97 (18.7)	9/9/97 (18.0)	9/11/00 (123.4)
PAOLO	7/28/97 (52.6)	9/25/97 (51.4)	10/24/97 (43.8)	10/8/97 (58.7)	8/17/00 (218.4)
CAPITA	8/12/97 (17.0)	9/10/97 (15.7)	9/9/97 (13.1)	9/9/97 (16.0)	9/15/00 (170.6)
SANTANDER	7/23/97 (60.3)	5/27/97 (64.0)	8/21/97 (28.3)	10/8/97 (51.5)	9/15/00 (207.3)
BILBAO	10/8/97 (54.0)	10/16/97 (58.7)	10/7/97 (36.2)	10/22/97 (68.7)	9/11/00 (209.3)
BANESP	5/16/97 (6.3)	10/16/97 (5.3)	10/22/97 (2.5)	10/22/97 (2.3)	7/21/00 (29.3)
ING	11/26/96 (43.7)	10/22/96 (36.4)	8/21/97 (57.2)	7/5/96 (51.7)	9/20/00 (186.5)
ABNAMRO	11/26/96 (48.1)	12/5/96 (56.3)	7/4/96 (73.9)	7/4/96 (61.6)	9/15/00 (132.5)
FORTIS	3/17/97 (65.4)	12/10/96 (41.1)	12/10/96 (33.0)	7/17/97 (36.7)	9/15/00 (161.2)
ALMANIJ	3/14/97 (59.4)	1/23/97 (56.7)	1/23/97 (54.5)	8/7/97 (77.1)	9/14/00 (238.2)
ALPHA	2/24/97 (52.7)	2/27/97 (64.5)	1/8/97 (36.6)	2/6/97 (66.1)	9/29/00 (80.7)
BCP	6/16/97 (37.8)	7/3/97 (42.2)	8/26/97 (28.7)	7/17/97 (57.6)	9/15/00 (129.0)
SAMPO	10/16/97 (15.2)	10/24/97 (15.6)	10/24/97 (6.0)	10/16/97 (11.5)	8/16/00 (151.6)
IRBAN	8/12/97 (22.4)	3/12/97 (25.2)	8/21/97 (16.5)	8/20/97 (25.3)	9/29/00 (164.7)

Notes: The table reports the results of tests examining the structural stability of the extreme systematic risks of euro area banks documented in table 4.6. This is done by testing the constancy of the η tail-dependence parameters (null hypothesis) that govern the tail-βs in table 4.6. Applying the recursive test (B1) through (B4) by Quintos, Fan, and Phillips (2001) described in appendix B and subsection 4.4.1, each cell shows the endogenously found break date and the test value in parentheses. Dates are denoted XX/YY/ZZ, where XX = month, YY = day, and ZZ = year. The critical values of the test are 1.46, 1.78, and 2.54 for the 10 percent, 5 percent, and 1 percent levels, respectively. A test value exceeding these numbers implies an increase in extreme dependence over time. See table 4D.1 for list of abbreviations.

The lines in the two panels refer to averages of ηs across the twenty-five euro area and twenty-five United States banks, respectively. We choose the general local stock indexes as aggregate risk factors, but the picture is unchanged for other stock indexes. Similar to figure 4.1 for interbank spill-over risk, the η-values entering the figure are calculated recursively. One can see that the increase in aggregate banking system risk is also economically significant, both in the euro area and in the United States.[23] While results corrected for time-varying volatility (GARCH-filtered returns) are

23. Notice that these results are different from the ones by de Nicoló and Kwast (2002) using standard market model βs among U.S. LCBOs. They do not identify any increase of the

Table 4.12 Extreme systematic risk (tail-βs) of U.S. banks: Time variation

	Aggregate risk factor				
Bank	Bank index	Stock index	Global bank	Global stock	Yield spread
CITIG	12/20/96 (28.0)	12/15/95 (17.8)	10/22/97 (34.0)	10/23/97 (30.8)	10/20/00 (93.5)
JPMORGAN	2/25/97 (34.1)	3/11/97 (28.3)	10/13/97 (33.1)	10/16/97 (40.0)	10/17/00 (87.4)
BOA	12/2/96 (27.4)	12/10/96 (27.9)	11/29/96 (33.1)	12/2/96 (38.6)	9/15/00 (64.7)
WACHO	3/10/97 (14.9)	12/10/96 (22.0)	2/26/97 (66.4)	2/26/97 (41.3)	10/10/00 (64.5)
FARGO	1/3/96 (14.4)	12/15/95 (14.7)	2/27/97 (23.4)	2/26/97 (15.6)	10/5/00 (35.4)
BONEC	12/6/95 (23.7)	12/13/95 (32.3)	11/29/96 (47.6)	2/19/96 (40.3)	10/5/00 (98.8)
WASHMU	2/27/97 (8.1)	2/23/96 (10.6)	10/16/97 (20.2)	2/24/97 (9.9)	11/21/00 (33.6)
FLEET	4/22/98 (33.8)	12/10/96 (25.5)	4/17/98 (39.2)	12/10/96 (36.2)	11/30/00 (52.6)
BNYORK	2/19/96 (20.2)	1/8/96 (17.7)	12/11/96 (41.3)	2/6/97 (47.0)	9/19/00 (77.8)
STATEST	3/11/97 (35.8)	12/2/96 (49.4)	12/2/96 (41.7)	10/16/97 (58.2)	10/5/00 (158.3)
NOTRUST	11/29/96 (33.8)	12/2/96 (51.7)	10/22/97 (35.3)	12/5/96 (52.8)	9/29/00 (107.8)
MELLON	12/4/95 (13.4)	12/13/95 (25.4)	10/24/97 (38.3)	10/24/97 (26.0)	10/11/00 (108.6)
USBANC	2/25/97 (40.1)	1/23/97 (48.3)	9/25/97 (57.9)	9/25/97 (39.5)	11/10/00 (37.0)
CITYCO	11/29/96 (26.7)	12/2/96 (28.8)	11/29/96 (45.9)	12/2/96 (44.7)	10/10/00 (38.9)
PNC	12/10/96 (24.3)	12/13/95 (26.3)	12/10/96 (34.6)	3/7/96 (34.5)	11/30/00 (51.6)
KEYCO	12/2/96 (12.1)	12/6/95 (18.1)	12/5/96 (19.5)	12/2/96 (27.3)	9/28/00 (56.7)
SUNTRUST	12/2/96 (29.0)	12/13/95 (38.7)	12/5/96 (31.8)	12/5/96 (31.6)	10/20/00 (40.8)
COMERICA	1/3/96 (11.3)	12/13/95 (17.9)	2/25/97 (27.8)	1/8/96 (23.4)	10/11/00 (64.2)
UNIONBAN	7/21/97 (29.6)	10/24/97 (44.6)	6/26/97 (6.4)	10/23/97 (17.2)	9/26/00 (19.6)
AMSOUTH	12/19/95 (18.4)	1/8/96 (24.9)	12/10/96 (23.8)	1/1/97 (17.5)	9/19/00 (45.4)
HUNTING	2/6/97 (34.2)	1/22/97 (67.3)	10/13/97 (29.9)	10/16/97 (40.9)	10/5/00 (30.3)
BBT	3/28/97 (22.3)	3/28/97 (24.7)	10/22/97 (16.7)	10/29/97 (19.4)	9/19/00 (24.6)
53BANCO	12/2/96 (31.6)	12/2/96 (26.2)	12/5/96 (59.2)	4/9/97 (34.3)	10/16/00 (42.0)
SOTRUST	2/26/97 (47.4)	2/24/97 (36.6)	10/13/97 (35.6)	10/8/97 (44.2)	12/1/00 (41.5)
RFCORP	3/7/96 (36.4)	2/23/96 (40.7)	12/10/96 (23.3)	12/10/96 (33.9)	10/10/00 (24.0)

Notes: The table reports the results of tests examining the structural stability of the extreme systematic risks of U.S. banks documented in table 4.7. This is done by testing for the constancy of the η tail-dependence parameters (null hypothesis) that govern the tail-βs in table 4.7. Applying the recursive test (B1) through (B4) by Quintos, Fan, and Phillips (2001) described in appendix B and subsection 4.4.1, each cell shows the endogenously found break date and the test value in parentheses. Dates are denoted XX/YY/ZZ, where XX = month, YY = day, ZZ = year. The critical values of the test are 1.46, 1.78, 2.54 for the 10 percent, 5 percent, and 1 percent levels, respectively. A test value exceeding these numbers implies an increase in extreme dependence over time. See table 4D.1 for list of abbreviations.

somewhat more muted, qualitatively they are unchanged (see also the second subsection of appendix E). Moreover, the similarity of extreme aggregate banking system risk in the euro area and the United States established in section 4.7 seems to be valid for the entire sample period.

Table 4.11 locates the timing of most European break points for the stock indexes around 1997 and for some cases in 1996. In the United States

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.

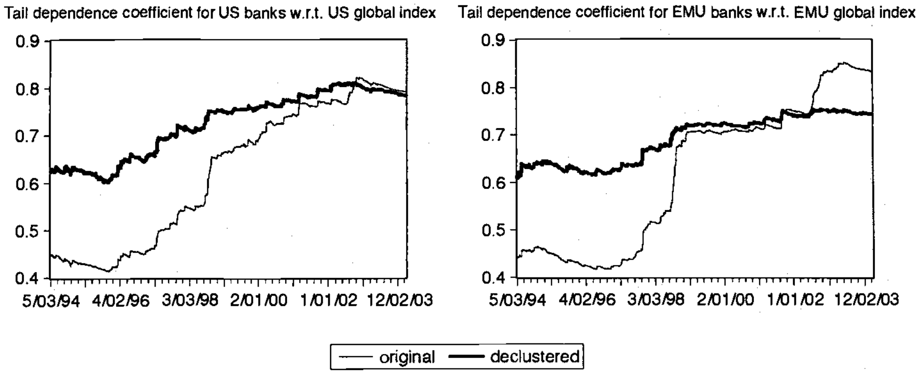

Fig. 4.3 Evolution of extreme systematic risk in the euro area and the U.S. banking systems

they happen somewhat earlier, with many breaks in 1996 (table 4.12). For Europe the timing is roughly in line with, but not identical to, interbank spillover risks (see the previous subsection). For the United States the tail-β breaks happen somewhat later than the contagion breaks. Similar to the spillover risks discussed earlier, the time evolution visible in figure 4.3, however, suggests that not too much importance should be given to the exact break dates.

We just mention that economically relevant tail-β changes occur for some of the most important players, such as the largest U.S. banks (Citigroup and JP Morgan Chase). The βs of important clearing banks, such as Bank of New York, State Street, or Northern Trust, changed as well, sometimes by even more than the former. The main U.S. clearers also have some of the statistically most significant breaks (table 4.12). Similarly significant changes can also be observed for the euro area.

Both in Europe and in the United States 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, the same words of caution about business cycles and time-varying comovements should be kept in mind as for the previous subsection.

4.9 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 (contagion risk) and another capturing the exposure of banks to extreme systematic shocks (which we denote as tail-β). We compare the importance of those forms of systemic risk across countries and over time.

Our results suggest that bank spillover risk in the euro area is significantly lower than in the United States. As domestic linkages in the euro area are comparable to extreme linkages among U.S. banks, this finding appears 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 for banks seems to be roughly comparable across the Atlantic. In contrast to stock indexes, high-yield bond spreads in general do not seem to be very informative about aggregate banking risks. Structural stability tests for both our banking system risk indicators suggest a general increase in systemic risk taking place over the second half of the 1990s, both in Europe and the United States. We do not find, however, that the introduction of the euro had any adverse effect on cross-border banking risks, quite the contrary. 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. For the United States it may be noteworthy that some of the strongest increases in extreme systematic risk seem to be concentrated among the largest players and the main clearing banks.

Our results provide some interesting perspectives on the ongoing debate on financial stability policies in Europe. For example, the benchmark of the United States 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 recognized that the direction of this process is not unique to Europe. And in addition, our twelve-year sample period includes one long economic cycle that may have overemphasized commonality in banking risks. Keeping these caveats in mind, 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 and economic 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.

Appendix A

Estimation of the Indicators of Banking System Stability: Details

In this appendix we discuss a number of more technical issues describing the estimators for (1) and (2) that had to be left out in section 4.3.

The first issue concerns the variable transformation from X_i to $\tilde{X}_i$. It is important to stress that the dependence between two random variables and the shape of the marginal distributions are unrelated concepts. To extract the dependence, given by the copula function, it is convenient to transform the data and remove any possible influences of marginal aspects on the joint tail probabilities. One can transform the different original excess returns to ones with a common marginal distribution (see, e.g., Ledford and Tawn, 1996; Draisma et al., 2001). After such a transformation, differences in joint tail probabilities across banking systems (e.g., Europe versus the United States) can be solely attributed to differences in the tail-dependence structure of the extremes. This is different, for example, from correlation-based measures that are still influenced by the differences in marginal distribution shapes.

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

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

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

$$\text{(A.1)} \qquad \tilde{X}_i = \frac{n+1}{n+1-R_{X_i}}, \; i = 1, \ldots, N,$$

where $R_{X_i} = \text{rank}(X_{il}, l = 1, \ldots, n)$. Using this variable transform, we can rewrite the joint tail probability that occurs in (1) and (2):

$$P\left[\bigcap_{i=1}^{N} X_i > Q_i(p)\right] = P\left(\bigcap_{i=1}^{N} \tilde{X}_i > q\right),$$

where $q = 1/p$.[24]

In this way the multivariate estimation problem can be reduced to estimating a univariate exceedance probability for the cross-sectional minimum of the N bank excess return series:

24. The multivariate probability stays invariant under the variable transformation $(X_1, \ldots, X_i, \ldots, X_N) \rightarrow (\tilde{X}_1, \ldots, \tilde{X}_i, \ldots, \tilde{X}_N)$, because the determinant of the Jacobian matrix can be shown to be equal to 1.

(A.2) $$P\left(\bigcap_{i=1}^{N} \tilde{X}_i > q\right) = P[\min_{i=1}^{N} (\tilde{X}_i > q] = P(\tilde{X}_{\min} > q).$$

The marginal tail probability at the right-hand side can be calculated, provided the following additional assumption on the univariate tail behavior of $\tilde{X}_{\min}$ is made. Ledford and Tawn (1996) argue that the bivariate dependence structure is a regular varying function under fairly general conditions. Peng (1999) and Draisma et al. (2001) give sufficient conditions and further motivation. Therefore, we assume that the auxiliary variable $\tilde{X}_{\min}$ has a regularly varying tail. Notice, however, that in contrast to Ledford and Tawn (1996) we often consider more than two dimensions.[25]

Another issue is the approximate nature of equation (4), as described in section 4.3. Assuming that $\tilde{X}_{\min}$ exhibits heavy tails with tail index $\alpha = 1/\eta$, then the regular variation assumption for the auxiliary variables implies that the univariate probability in equations (3) or (A.2) exhibits a tail descent of the Pareto type:

(A.3) $$P(\tilde{X}_{\min} > q) \approx \ell(q)q^{-1/\eta}, \ \eta \leq 1,$$

with q large (p small) and where $\ell(q)$ is a slowly varying function (i.e., $\lim_{q\to\infty} \ell[xq]/\ell[q] = 1$ for all fixed $x > 0$). As $\ell(q)$ is unlikely to have significant effects on our results, we neglected it in the main body of the paper.

From equations (4) and (A.3) one sees that a higher η implies, ceteris paribus (given the slowly varying function $\ell[q]$), a higher degree of dependence among the components $(\tilde{X}_1, \ldots, \tilde{X}_i, \ldots, \tilde{X}_N)$ from equations (4) or (A.2) far out in their joint tail. We can distinguish the two extreme cases in which the $\tilde{X}_i$, are *asymptotically dependent* and asymptotically independent. In the former case $\eta = 1$ and

$$\lim_{q\to\infty} \frac{P(\tilde{X}_{\min} > q)}{P(\tilde{X}_{\max} > q)} = 0.$$

with $P(\tilde{X}_{\max} > q) = P(\max_{i=1}^{N}[\tilde{X}_i] > q]$. Examples of asymptotically dependent random variables include the multivariate Student-T distribution, for example. For *asymptotic independence* of the random variables $\eta < 1$, we have that

25. Equations (3) and (A.2) require a common quantile q. This can, however, be easily generalized to the case where q differs across the marginals. Assume that we allow both 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

$$P[X_1 > Q_1(p_1), X_2 > Q_2(p_2)] = P(\tilde{X}_1 > q_1, \tilde{X}_2 > q_2),$$

with $q_i = 1/p_i (i = 1, 2)$. By multiplying $\tilde{X}_2$ with q_1/q_2 the above joint probability again reduces to a probability with a common quantile q_1 and we are back to the framework described previously, where the loading variable $\tilde{X}_{\min}$ can be calculated.

$$\lim_{q\to\infty} \frac{P(\tilde{X}_{\min} > q)}{P(\tilde{X}_{\max} > q)} > 0. \tag{A.4}$$

An example of this case is the bivariate standard normal distribution with correlation coefficient ρ. For this distribution $\eta = (1 + \rho)/2$ and the limit (A.4) applies. When the normal random variables are independent ($\rho = 0$), one immediately obtains that $\eta = 1/2$. In general, whenever the $\tilde{X}_i$ are fully independent in the N-dimensional space, $\eta = 1/N$ and $P(\tilde{X}_{\min} > q) = p^N$. But the reverse is not true; that is, there are joint N-dimensional distributions with nonzero pairwise correlation that nevertheless have $\eta = 1/N$. The Morgenstern distribution constitutes an example of this tail behavior. (A bivariate version is employed in a Monte Carlo exercise in appendix C.1.)

The estimation of equation (4) with the de Haan et al. estimator (5) and the Hill estimator (6) has already been sketched in the main text. One may still want to remark that, technically, the "tail cut-off point" $C_{n-m,n}$ in equation (5) is the $(n - m)$-th ascending order statistic from the cross-sectional minimum series $\tilde{X}_{\min}$. Similarly, m is the number of higher-order extremes that enter the estimation of (6). The estimator (5) basically extends the empirical distribution function of $\tilde{X}_{\min}$ outside the domain of the sample by means of its asymptotic Pareto tail from equation (4). An intuitive derivation of the estimator is provided in Danielsson and de Vries (1997). For discussions of alternative estimators and proper convergence behavior, see for example Draisma et al. (2001), Peng (1999), and Beirlandt and Vandewalle (2002). Further details on the Hill estimator can be found in Jansen and de Vries (1991), for example, and in the monograph by Embrechts, Klüppelberg, and Mikosch (1997).

The optimal choice of the threshold parameter m is a point of concern in the extreme value theory literature. Goldie and Smith (1987) suggest to select the nuisance parameter 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 $\hat{\eta}$ from equation (6) is stable. Double bootstrap techniques based upon this idea have been developed recently (see, 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 $m = \kappa n^{\gamma}$ with $\gamma = 2/3$, sample size n, where κ is derived from the widely used Hill plot method.[26]

26. Minimizing the asymptotic mean-squared error for the Hill estimator by balancing bias and variance renders this nonlinear selection rule. For convenience, we impose the parameter restriction $\gamma = 2/3$. While simplifying, it can be shown to hold for a wide variety of distribution functions. Moreover, establishing stable and accurate estimates of γ is notoriously difficult (see, e.g., Gomes, de Hann, and Peng 2002, for a recent example). κ is calibrated by means of the heuristic Hill plot method. Once a value of m^* is selected in a horizontal range of $\hat{\eta} = \hat{\eta}(m)$, the scale factor immediately follows from $\kappa = m^*/n^{2/3}$.

Appendix B

Test for Time Variation in the Indicators of Banking System Stability: Details

In this appendix we discuss a number of more technical issues that had to be left out from the description of the Quintos, Fan, and Phillips recursive structural break test presented in subsection 4.4.1.

Let t denote the endpoint of a subsample of size $w_t < n$. The recursive estimator for the tail-dependence parameter η is calculated from equation (6) for subsamples $[1; t] \subset [1; n]$:

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

with $mt = \kappa t^{2/3}$.[27]

The value of the recursive test statistic equals the supremum of the following time series:

$$Y_n^2(t) = \left(\frac{tm_t}{n}\right)\left(\frac{\hat{\eta}_n}{\hat{\eta}_t} - 1\right)^2. \tag{B.2}$$

Expression (B.2) compares the recursive value of the estimated tail parameter (6) or (B.1) to its full sample counterpart $\hat{\eta}_n$. 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. The null hypothesis of constancy then takes the form

$$H_0 : \eta_{(nr)} = \eta, \quad \forall r \in R_\varepsilon = (\varepsilon; 1 - \varepsilon) \subset (0; 1), \tag{B.3}$$

with $[nr]$ representing the integer value of nr. Without prior knowledge about the direction of a break, one is interested in testing the null against the two-sided alternative hypothesis $H_A : \eta_{(nr)} \neq \eta$. For practical reasons this test is calculated over compact subsets of (0; 1); that is, t equals the integer part of nr for $r \in R_\varepsilon = (\varepsilon; 1 - \varepsilon)$ and for small $\varepsilon > 0$. Sets like R_ε are often used in the construction of parameter constancy tests (see, e.g., Andrews 1993).[28] In line with Quandt's (1960) pioneering work on endogenous breakpoint determination in linear time series models, the candidate break date r can be selected as the maximum value of the test statistic (B.2)

27. See the end of appendix A for a discussion of how to choose m.

28. The restricted choice of r implies that $\varepsilon n \leq t \leq (1 - \varepsilon)n$. When the lower bound would be violated the recursive estimates might become too unstable and inefficient because of too-small subsample sizes. On the other hand, the test will never find a break for t equal or very close to n, because the test value (B.2) is close to zero in that latter case. Thus, for computational efficiency one might stop calculating the tests beyond the upper bound of $(1 - \varepsilon)\, n < n$. We search for breaks in the $[0.15n; 0.85n]$ subset of the total sample, as Andrews (1993) does.

because at this point in time the constancy hypothesis is most likely to be violated.

Asymptotic critical values can be derived for the sup-value of equation (B.2), but if the data are temporally dependent the test sequence Y_n^2 needs 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, for example, ARCH effects (volatility clustering). It is likely that the loading variable $\tilde{X}_{\min}$, previously defined as the cross-sectional minimum of the bank stock returns (transformed using their proper empirical distribution function), partly inherits these nonlinearities. The nonlinear dependence implies that the asymptotic variance of the Hill estimator $1/\hat{\eta}$ is s^2/η^2, with s some scaling factor. If the scaling factor differs from 1 (presence of temporal dependence), the asymptotic critical values of the test statistic will depend on the scaling. Quintos, Fan, and Phillips suggest to premultiply the test statistic with the inverse of the scaling factor in order to let it converge to the same critical values as in the i.i.d. case. However, their scaling estimator is based upon the ARCH assumption for univariate time series. As we do not want to make very specific assumptions on the precise structure of the nonlinear dependence in the marginals, we apply a block bootstrap to the asymptotic variance of the Hill statistic $1/\hat{\eta}$ and thus the scaling factor s.[29] Following Hall, Horowitz, and Jing (1995), the optimal block length is set equal to $n^{1/3}$. One now selects r for the recursive test such that $Y_n^2(t)$—appropriately scaled—is maximal:

$$\Omega_{r \in R_\tau} = \sup \hat{s}^{-1} Y_n^2(t), \tag{B.4}$$

with $\hat{s}$ the estimate of the scaling factor. The null of parameter constancy is rejected if this sup-value exceeds the asymptotic critical values.

Appendix C

Small Sample Properties of Estimators and Tests

Small Sample Properties of the Bivariate Estimator

In this section we investigate the small sample properties of our estimators. We limit our attention to the bivariate version, which could either be a spillover probability between two banks or a tail-β, and the respective de-

29. The scale is estimated by $s = \hat{\eta} m \hat{\sigma}^2 (1/\hat{\eta})$ with $\hat{\sigma}^2$ the block bootstrapped variance of the Hill statistic.

pendence parameter. Without loss of generality, we will always refer to tail-β in the following discussion. Three different data-generating processes are investigated: the bivariate Pareto distribution (C.1), the bivariate Morgenstern distribution (1956) with Pareto marginals (C.2), and the bivariate standard normal distribution (C.3). The first two distributions both have Pareto marginals, but only the first distribution exhibits asymptotic dependence (in which case $\eta = 1$). The bivariate normal is also asymptotically independent (as long as $|\rho| \neq 1$). The normal distribution has a dependence parameter η that varies with the correlation coefficient, and we investigate different configurations. The precise specifications of the distributions are as follows:

Bivariate Pareto

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

Bivariate Morgenstern Distribution with Pareto Marginals

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

Bivariate Normal with Correlation Coefficient ρ *and Dependence Parameter*

$$\eta = \frac{1 + \rho}{2} \tag{C.3}$$

The three specific distributions have the advantage that they allow us to calculate the true value of η and the tail-β (τ_β). Thus, the estimation bias and asymptotic mean-squared error can be calculated explicitly. The true "benchmark" values of the tail-βs are:

$$\tau_\beta = (2 - p^{1/\alpha})^{-\alpha} \quad \text{(bivariate Pareto)},$$

$$\tau_\beta = (1 + \delta)p - 2\delta p^2 + \delta p^3 \quad \text{(bivariate Morgenstern)},$$

$$\tau_\beta = \frac{\Phi(-x, -x, \rho)}{p}, \quad \text{(bivariate standard normal)},$$

where $p = P(X > x)$. In the following tables we evaluate the tail-βs and dependence parameters at $p = 0.05$ percent, which is one of the marginal significance levels we also use in the empirical applications. Two different sample sizes are considered: a truly small sample of 500 observations and a larger sample of 3,106, corresponding to the actual sample size in the empirical application to bank stocks.

The following three tables report true values of τ_β as well as estimates of the average, bias, and standard deviation of η and τ_β for 5,000 Monte Carlo replications. Notice that biases are reported in absolute and not in percentage terms. Back-of-the-envelope calculations of the relative (percentage) biases may nevertheless be handy for the sake of comparing the bias across different parametrizations, but were omitted because of space considerations.[30] Averages, biases, and standard deviations are multiplied by 100 for the sake of convenience. The estimates are conditioned on cutoff points m^* that minimize the Asymptotic Mean Squared error (AMSE). The AMSE is calculated for 5,000 Monte Carlo replications.[31]

We start with an evaluation for the Morgenstern distribution with Pareto marginals (see table 4C.1).

Analytic tail-β values are small, which makes this model the least realistic as a benchmark for comparison with the tail-βs we found in practice. We let both the tail index α and the parameter δ vary. The table shows that the Morgenstern bias in η and τ_β does depend on δ but not on α. This is not surprising, given that α does not enter the analytic expression of the Morgenstern tail-β; that is the tail-β is independent from marginal properties in this case.[32] Biases are small for small δ but become substantial in both absolute and relative terms when δ is large. Also, the estimation accuracy—as reflected by the standard errors s.e.—is found to be higher for small values of δ.

Next, we turn to the results for the Pareto distribution. The results are in table 4C.2. In contrast to table 4C.1, there now appears a considerable downward bias in absolute terms for both η and τ_β. However, the relative (percentage) biases can be shown to be smaller than in the Morgenstern case. Recall that the true value of η is equal to the boundary value of 1 in this case, so that in any empirical exercise one expects at least some downward bias. Moreover, (absolute and relative) biases and standard errors decrease with a decrease in correlation (an increase in α).

Last, we consider the small-sample performance for the bivariate nor-

30. Relative or percentage measures of the bias can be calculated as $100 \times (E[\hat{\eta}] - \eta/\eta)$ and $100 \times (E[\hat{\tau}_\beta] - \tau_\beta)/\tau_\beta$ for the tail dependence parameter and the tail-β, respectively.

31. If two (unit Pareto) random variables are independent, we previously noted that $P(X > q, Y > q) = p^2$ with $p = P(X > q) = P(Y > q)$. This exact Pareto tail allows the use of all extreme observations in estimation because of the unbiasedness of the Hill statistic under the Pareto law, that is, $m^* = n - 1$.

32. It can be easily shown that the analytic expressions for Morgenstern bias and asymptotic mean squared error (AMSE) do not depend on the marginal distributional properties like scale and tail indices.

Table 4C.1 Small sample behavior of tail betas for bivariate Morgenstern distribution

		$\hat{\eta}$			$\hat{\tau}_\beta(\times 100)$			
$(\alpha; \delta)$	m^*	Average	Bias	Standard error	Average	Bias	Standard error	τ_β ($\times$ 100)
				A. n = 500				
(2; 0.0)	499	0.499	–0.001	0.013	0.052	0.002	0.021	0.050
(3; 0.0)	499	0.499	–0.001	0.013	0.052	0.002	0.021	0.050
(4; 0.0)	499	0.499	–0.001	0.013	0.052	0.002	0.021	0.050
(2; 0.5)	150	0.546	0.046	0.034	0.231	0.156	0.190	0.075
(3; 0.5)	150	0.545	0.045	0.034	0.226	0.151	0.189	0.075
(4; 0.5)	150	0.546	0.046	0.034	0.232	0.157	0.198	0.075
(2; 0.9)	134	0.570	0.070	0.036	0.424	0.329	0.338	0.095
(3; 0.9)	134	0.570	0.070	0.037	0.427	0.332	0.349	0.095
(4; 0.9)	134	0.570	0.070	0.037	0.419	0.324	0.327	0.095
				B. n = 3,106				
(2; 0.0)	3,105	0.500	0.000	0.005	0.050	0.000	0.008	0.050
(3; 0.0)	3,105	0.500	0.000	0.005	0.050	0.000	0.008	0.050
(4; 0.0)	3,105	0.500	0.000	0.005	0.050	0.000	0.008	0.050
(2; 0.5)	376	0.532	0.032	0.023	0.152	0.077	0.083	0.075
(3; 0.5)	376	0.532	0.032	0.023	0.151	0.076	0.083	0.075
(4; 0.5)	376	0.532	0.032	0.023	0.148	0.073	0.080	0.075
(2; 0.9)	335	0.543	0.043	0.025	0.225	0.130	0.121	0.095
(3; 0.9)	335	0.543	0.043	0.025	0.224	0.129	0.120	0.095
(4; 0.9)	335	0.543	0.043	0.025	0.225	0.130	0.120	0.095

Notes: The table reports estimated values and true (analytic) values of the tail dependence parameter η and the tail-β (τ_β) for different sample sizes and different parameter configurations (α, δ). Tail-βs and corresponding biases and accuracy are expressed in percentage terms (%). Moreover, the linkage estimates are conditioned on the cutoff point m^* that minimizes the asymptotic mean squared error of $\hat{\eta}$. The conditioning quantiles for the tail-β are chosen such that the corresponding marginal excess probabilities are equal to 0.05 percent.

mal distribution (see table 4C.3). For the normal distribution the estimators appear to behave quite reasonably. Absolute and relative biases are found to be smaller than in the Pareto case. Moreover, it may be difficult to distinguish the normal distribution from the Pareto distribution just on the basis of, say, the dependence parameter estimate. To this end it would be helpful to investigate the tail properties of the marginals as well.

Small-Sample Properties of the Endogenous Break Test

In this part of the appendix 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 data-generating process (see table 4C.4).

Table 4C.2 **Small sample behavior of tail betas for bivariate Pareto distribution**

		$\hat{\eta}$			τ_β (× 100)				
α	m^*	Average	Bias	Standard error	Average	Bias	Standard error	τ_β (× 100)	η
				A. n = 500					
2	31	0.831	–0.169	0.113	15.44	–10.12	13.15	25.56	1
3	26	0.763	–0.237	0.126	8.32	–5.79	9.49	14.11	1
4	22	0.719	–0.281	0.134	5.49	–3.04	7.40	8.53	1
Indep.	499	0.498	–0.002	0.013	0.05	0.00	0.02	0.05	1/2
				B. n = 3,106					
2	89	0.889	–0.111	0.073	19.19	–6.38	8.73	25.57	1
3	45	0.832	–0.168	0.106	10.61	–3.50	7.51	14.11	1
4	42	0.777	–0.223	0.110	6.28	–2.25	5.37	8.53	1
Indep.	3,105	0.500	0.000	0.005	0.05	0.00	0.00	0.05	1/2

Notes: The table reports estimated values and true (analytic) values of the tail-dependence parameter η and the tail-β (τ_β) for different sample sizes and different values of α. Tail-βs and corresponding biases and accuracy are expressed in percentage terms (%). Moreover, the linkage estimates are conditioned on the cutoff point m^* that minimizes the Asymptotic Mean Squared Error of $\hat{\eta}$. The conditioning quantiles for the tail-β are chosen such that the corresponding marginal excess probabilities are equal to 0.05 percent.

Table 4C.3 **Small sample behavior of tail betas for bivariate normal distribution**

		$\hat{\eta}$			$\hat{\tau}_\beta$ (× 100)				
ρ	m^*	Average	Bias	Standard error	Average	Bias	Standard error	τ_β (× 100)	$\eta = \frac{1+\rho}{2}$
				A. n = 500					
3/4	138	0.795	–0.080	0.038	13.55	–4.59	5.11	18.14	0.875
1/2	154	0.684	–0.066	0.038	3.09	–1.12	1.69	4.21	0.75
1/4	233	0.583	–0.042	0.026	0.47	–0.20	0.27	0.67	0.625
0	499	0.499	–0.001	0.013	0.05	0.00	0.02	0.05	0.05
				B. n = 3,106					
3/4	299	0.815	–0.060	0.031	15.74	–2.40	4.10	18.14	0.875
1/2	403	0.699	–0.051	0.027	3.47	–0.74	1.20	4.21	0.75
1/4	574	0.594	–0.031	0.020	0.54	–0.12	0.20	0.66	0.625
0	3,105	0.500	0.000	0.005	0.05	0.00	0.00	0.05	0.5

Notes: The table reports estimated values and true (analytic) values of the tail-dependence parameter η and the tail-β (τ_β) for different sample sizes and different correlations ρ. Tail-βs and corresponding biases and accuracy are expressed in percentage terms (%). Moreover, the linkage estimates are conditioned on the cutoff point m^* that minimizes the Asymptotic Mean Squared Error of $\hat{\eta}$. The conditioning quantiles for the tail-β are chosen such that the corresponding marginal excess probabilities are equal to 0.05 percent.

Table 4C.4 Simulated breakpoints

	Estimated breakpoints (standard error)		
$(\eta_1; \eta_2)$	$r = 1/3$	$r = 1/2$	$r = 2/3$
(0.5; 0.7)	0.364	0.514	0.617
	(0.190)	(0.166)	(0.117)
(0.5; 0.9)	0.264	0.485	0.636
	(0.095)	(0.078)	(0.092)
(0.7; 0.9)	0.394	0.508	0.587
	(0.209)	(0.172)	(0.194)

Notes: Estimated breakpoints are reported for the tail dependence parameter of the bivariate normal df. The break estimates are reported for varying locations of the true breakpoints (r = 1/3, 1/3, 2/3). The number of Monte Carlo replications is set to 1,000. The accompanying sampling errors are reported between brackets. Q-tests are calculated starting with a minimum sample size of 500. For sake of convenience, we set the number of upper-order extremes used in estimating the tail index equal to $2_{n2/3}$.

Recall that in this case $\eta = (1 + \rho)/2$. By changing the correlation coefficient, we can easily change the dependence parameter η.

The breaks are engineered at five different points in the sample (see r-columns in the table). Three different combinations of pre- and postbreak ηs are considered (see rows of the table). The sample size is 3,000. Table 4C.4 shows that the test has more difficulty in accurately locating the break if it is close to the start or the end of the sample. The reason is that in these cases one has fewer observations available for one of the two subsamples. When the change in the dependence parameter is small, then the standard errors tend to be more sizable. For example, the standard errors in the first and third scenario are about twice as large as in the second scenario. In sum, the cases in which we have to be more cautious in interpreting the test results are when the changes in η are small and when they occur close to the boundaries of the sample.

Appendix D

Table 4D.1 List of banks in the sample

Euro area		United States	
Bank name	Abbreviation	Bank name	Abbreviation
Germany		Citigroup	CITIG
Deutsche Bank	DEUTSCHE	JP Morgan Chase	JP MORGAN
Bayerische Hypo- und Vereinsbank	HYPO	Bank of America BOA	BAMERICA
Dresdner Bank	DRESDNER	Wachovia Corporation	WACHOVIA
Commerzbank	COMMERZ	Wells Fargo and Company	FARGO
Bankgesellschaft Berlin	BGBERLIN	Bank One Corporation	BONE
DePfa Group	DEPFA	Washington Mutual, Inc.	WASHING
France		Fleet Boston Financial Corporation	FLEET
BNP Paribas	BNPPAR	Bank of New York	BNYORK
Crédit Agricole	CA	State Street	SSTREET
Societe Generale	SGENER	Northern Trust	NTRUST
Natexis Banques Populaires	NATEXIS	Mellon	MELLON
Italy		US Bancorp	BCORP
Banca Intesa	INTESA	National City Corporation	CITYCO
UniCredito Italiano	UNICREDIT	PNC Financial Services Group	PNC
Sanpaolo IMI	PAOLO	Keycorp	KEYCO
Capitalia	CAPITA	Sun Trust	SUTRUST
Spain		Comerica Incorporated	COMERICA
Banco Santander Central Hispano	SANTANDER	Unionbancal Corporation	UNIONBANK
Banco Bilbao Vizcaya Argentaria	BILBAO	AmSouth Bancorp	AMSOUTH
Banco Espagnol de Credito	BANESP	Huntington Bancshares, Inc.	HUNTING
The Netherlands		BBT Corporation	BBT
ABN AMRO	ABNAMRO	Fifth Third Bancorp	53BANCO
ING Bank	ING	Southtrust	SOTRUST
Belgium		Regions Financial Corporation	REGIONS
Fortis	FORTIS		
Almanij	ALMAIJ		
Finland			
Sampo Leonia	SAMPO		
Greece			
Alpha Bank	ALPHA		
Ireland			
Allied Irish Banks	IRBAN		
Portugal			
Banco Commercial Portugues	BCP		

Appendix E

Volatility Modeling and the Analysis of Banking System Stability

A widely recognized feature of financial market returns is volatility clustering (see, e.g., Bollerslev, Chou, and Kroner, 1992). So a question that comes to mind is to which extent the extreme dependence between bank stock returns and its changes we discover in this paper is associated with persistence and changes in volatility. Before providing some answers to this question, we need to establish first the relationship between the manner in which volatility of bank stock returns is modeled and the objectives of our paper. So, in the first section of this appendix we discuss whether financial stability policy oriented research should focus on conditional volatility modeling or not. In the second section we summarize some results for our indicators of banking system stability when the return data are cleaned for GARCH effects.

How Useful Is Conditional Volatility Modeling for Financial Stability Policy?

The main objective of our work is to measure systemic risk in banking on the basis of market data. The amount of systemic risk in banking is instrumental for the assessment of financial stability and for the design of policies to preserve the stability of financial systems, such as banking regulation and crisis management. The indicators of banking system stability we are using are designed to satisfy the demand by policymakers, who need to have a view about the likelihood of crises and who need to devise the best financial regulations to preserve financial stability.

To assess system stability, banking supervisors need to know the likelihood that one or several banks break down given that other banks break down, or how likely it is that one or several banks break down given that there is an adverse macroeconomic shock. They are not interested in two-sided volatility of bank stock returns per se or in its persistence. In addition, banking regulations are determined in advance for longer periods of time. They cannot be changed within a few days. So, they need to be based on long-term structural risk assessments, not on the likelihood of volatility tomorrow given today's volatility. This is why, for the questions we are interested in, straight returns are preferable to volatility of returns and unconditional modeling is preferable to conditional models. In contrast, conditional models will be preferable for short-term volatility forecasting, as today's volatility is informative for tomorrow's volatility. This type of analysis may be more important for short-term pricing of financial instruments.

Summary of Results for GARCH-Filtered Data

Although the indicators (1) and (2) are the right ones for answering the questions of interest in this paper, we may learn from unclustered return data more about the statistical components of spillover and extreme systematic risk in banking. For example, Poon, Rockinger, and Tawn (2004) argue that conditional heteroskedasticity is an important source of extreme dependence in stock markets in general, but not the only one. Thus, in this section we ask to which extent the extreme dependence of bank stock returns uncovered in the main body of the paper results from univariate volatility clustering or multivariate dependence in volatilities. We do this by filtering our bank excess returns with standard GARCH(1,1) processes and by recalculating the results for our estimators of banking system risk and related tests.

Appendix E.1 in the accompanying working paper (Hartmann, Straetmans, and C. de Vries 2005) reports the results for multivariate spillover probabilities (equation [1]) using the unclustered return data. Tables E.1 through E.5 there reproduce tables 4.3, 4.4, 4.5, 4.9, and 4.10 in the main text here for GARCH-filtered returns. While extreme dependence generally tends to decrease, the qualitative results are quite similar to the ones for plain bank returns. Only very few of the spillover risk changes in Europe (table 4.9) seem to be entirely related to volatility clustering. But clustering plays more of a role in the differences between domestic and cross-border spillovers (table 4.4). Multivariate spillover risk in the United States and Europe, as well as its changes over time, seem little related to volatility clustering (tables 4.5 and 4.10). This is also confirmed by the dotted lines in figures 4.1 and 4.2, which describe the same statistics as the solid lines for GARCH-filtered returns.

Appendix E.2 in the working paper does the same for tail-βs (equation [2]). Tables E.6 through E.10 there reproduce tables 4.6, 4.7, 4.8, 4.11, and 4.12 in the main text here for unclustered returns. As for the previously noted spillover risk, dependencies generally decrease, but none of the qualitative results is fundamentally changed. Again this is also confirmed by the dotted lines in figure 4.3, which illustrate the more muted changes in GARCH-filtered tail-βs and the same direction of their movements.

Overall, we can conclude that in line with the results of Poon, Rockinger, and Tawn (2004) for stock markets in general, part of the extreme dependencies in bank stock returns we find in this paper are related to time-varying volatility and volatility clustering. From the exercises summarized in this appendix we can not ascertain whether this phenomenon is related to the marginal distributions or to multivariate dependence of volatilities. Nevertheless, the primary results that supervisors should pay attention to in order to assess general banking system stability and decide upon regulatory policies are the unadjusted spillover and systematic risk probabilities.

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Comment Anthony Saunders

Introduction

The topic of banking contagion and crash risk has spawned a voluminous literature, exceeding more than 100 papers. Yet despite apparent extreme events, such as September 11th, 2001, the banking systems of Europe and the United States seem robust, and have survived such events in a remarkably intact way. One possible explanation is that central bankers have been highly skilled in using policy instruments—such as the discount window during the September 11th event—to deter contagious runs and crashes. Nevertheless, the possibility remains that there will be an event that overwhelms even the most sophisticated and adaptable policymakers. Thus, the question of what is the probability of a crash occurring in the current United States and euro area banking contexts is of some importance.

This essentially is the focus of this excellent and comprehensive paper by Hartmann, Straetmans, and de Vries.

The Authors' Approach

To date, a large number of approaches have been employed to examine bank contagion risk. These include: (1) event study analysis on stock returns, (2) correlation analysis, (3) fund withdrawal behavior, and (4) logit/probit analysis. This literature is amply reviewed in an earlier paper by De-Bant and Hartmann and I will not go over the strengths and weaknesses of these approaches again here. What has been missing is a detailed examination of the tails of bank failure probability distributions. Put simply, what is the probability that an extreme event (e.g., far worse than September 11th) will have such a strong systematic impact that we will get the long-feared crash of Western banking systems?

The authors' novel approach is to use extreme value theory (EVT)—long used in life insurance to assess extreme claims risk—to examine the probability of extreme banking events, such as a systemic collapse. To paraphrase the authors, they apply EVT to examine dependencies in the extreme tail of bank equity return distributions within countries and between countries with emphasis on the United States and Europe. This extreme risk is measured in two ways: (1) between bank stock returns and (2) between a bank's stock return and bank indexes, so as to examine the home country's systematic exposure to shocks (so-called tail-β [beta] risk). Since the focus is on large bank contagion, the banks analyzed are twenty-five United States and twenty-five European banks, chosen based on two criteria: (1) size and (2) interbank lending market presence. The basic premise—although not one tested directly in the paper—is that a primary route of contagion among banks is through the interbank market in purchased funds. Thus, the branch structures and deposit-raising powers of different banks are not explicitly explored in the paper. For example, a bank with the same interbank borrowing exposure as another bank, but with a more extensive branch network (and thus core deposit base) would likely be less susceptible to interbank market propagation of shocks. Of course, one could think of many more sample conditioning variables (see later), but to my mind the authors' focus on size and interbank lending seems a reasonable first approximation.

The Authors' Major Findings

The paper has a large number of empirical results and findings. I will leave technical issues such as their choice of tail indicator measure and estimation approaches to others to evaluate, but the choice of an appropriate estimator is not without controversy, especially in regards to parametric versus nonparametric methods of estimation (the authors apply a semiparametric method of estimation). Contingent on their choice of estimator, the authors most important findings are that the risk of a bank contagion spillover in the euro area is lower than in the United States. In addition, they find that banks in smaller countries on the periphery of the euro area, such as Finland and Greece, have lower cross-country contagion risk than those in larger, "central" euro area countries (possibly due to weaker cross-country linkages in small countries). Finally, they find that a structural increase in bank contagion risk has taken place in both the U.S. and European banking markets.

Remaining Issues

No paper can address all the issues relating to large bank contagion, although this paper comes very close to doing this. What remains to be done?

EVT and Capital Requirements

The focus of the paper is on the correlation between banks' extreme (negative) tail risks and the probability of joint crashes. The reader—or at least one interested in bank regulation—thinks about the adequacy of bank capital requirements such as those under Basel I and Basel II. There is little or no discussion of the probability of current or proposed bank capital requirements withstanding the size of the EVT-based co-crash probabilities found in the paper. For example, perhaps there is a structural increase in contagion risk—but what is the probability of joint failure under a Basel I 8 percent rule? Importantly, it should be noted that the issue of the optimum size of a systematic component to bank capital relative to the size of the bank-specific (unsystematic) component remains a relatively underresearched area. Since there seems to be a clear potential linkage between co-crash banks' EVT-measured risk and the optimal size of bank systematic risk capital, this issue could have been explored by the authors.

Interbank Loans

I'm still not convinced that interbank lending exposure as measured in the Hartman, Straetmans, and de Vries paper is really the best way (along with size) to select the samples of euro area and U.S. banks. For example, I still have a hard time convincing myself that State Street Bank or Northern Trust belong in the same contagion risk league as Citicorp. Their inclusion appears to be, in part, dependent on their prominent clearing and settlement activities. However, much of this activity is in securities markets and not the fed funds market or on the clearing house interbank payments system (CHIPS), which are most relevant for interbank lending in the United States. This suggests that additional sample conditioning variables may be worth exploring, such as branch networks, or the scope of geographic diversification of funds, both of which would provide some form of risk mitigation in the presence of a run in the interbank market.

Mergers and Acquisitions

While the authors take note of the growth in merger and acquisition (M&A) activity in enhancing interbank correlations, my feeling is that its current and future importance is somewhat underplayed in the paper. For example, the high rate of bank M&As in the United States following the passage of the Riegle-Neal Interstate Banking Act in 1994 may well explain a significant component of the higher relative contagion risk in the United States versus the euro area in the later 1990s. This is especially so in view of the relatively slow cross-border bank M&A in the euro area to date (notwithstanding the Single Capital Market legislation). In addition, the existence of M&A activity raises some important implications in terms of sample selection bias, including (1) the use of bank asset size and (2) survivorship bias over a twelve-year sample period. My feeling is that these issues are not sufficiently confronted in the paper.

Other Conditioning Variables

The authors focus on conditioning systematic risk on either general bank indexes or high-yield spreads. Thus, unsystematic bank risk is the residual excess return after such conditioning. This unsystematic risk will include all other risk effects after controlling for market indexes or yield spreads. As is well known, one- or two-factor models potentially leave a lot of systematic risk unexplained. Indeed, when I think of extreme events, my natural inclination is to think of disasters or catastrophes (including reputational), which are often put under the general rubric of "operational" risk. Indeed, one interesting EVT question is that after controlling for all reasonable systematic risk factors—including market and macro-factors—what are the co-crash probabilities across banks' operational or "extreme event" risks? While the authors have not extended their research in this direction, there is one recent working paper by Allen and Bali of Baruch College, CUNY that explores this issue by analyzing correlations across residual stock returns after controlling for a large array of market and macro-factors. In sum, one is not quite sure what remaining tail risks the Hartmann, Straetmans, and de Vries paper explores.

Good News Contagion

The focus of this paper, as in much of the bank contagion literature, is on contagion due to bad news or negative events. This is, of course, natural, given the "specialness" of banks and the downside macro-risk and externalities from systemic failure. Nevertheless, there is often good news, such as an individual bank announcing record earnings that may well (also) favorably impact other banks' stock return distributions. For example, is bank-specific good news sufficiently contagious across banks that it enhances the safety and soundness of the banking system overall? For example, in good-news periods banks may exploit the higher stock returns associated with such news by issuing more equity to bolster capital reserves against bad times. To my knowledge upside contagion or extreme positive event risk is a relatively unexplored area.

Conclusion

This is an excellent paper. The authors should be commended for proposing and employing a novel way of thinking about event and co-crash risk across banks. As noted earlier, the results of the paper have important implications for policymakers, encompassing M&A, cross-border policy, capital requirements, and safety net design in general. I'm sure that there will be many future papers extending the Hartmann, Straetmans, and de Vries EVT methodology, including ones analyzing developing banking systems such as those in Asia, Africa, and elsewhere.

Discussion Summary

René Stulz opened the general discussion by asking whether what the authors measure as contagion simply reflects an increase in volatility of a factor that affects the equity returns of all banks. *Philipp Hartmann* noted that results of some preliminary robustness checks employing GARCH models imply that this is not the whole story, but even if it is, the vulnerability of the banking system to extreme shocks is of interest. This issue is now discussed in detail in the revised version of the paper. *Jan Krahnen* asked about the experience of healthy versus unhealthy banks, and Hartmann replied that extreme moves appear to be larger for the latter.

Eric Rosengren suggested segmenting the sample by market-makers versus other banks, rather than using geography, as the relative vulnerability of the major dealer banks is of considerable interest. *Hashem Pesaran* suggested systematic pairwise comparison of banks in the sample, to see if most of the average results are coming from a few banks. *Philipp Hartmann* noted that a pairwise approach would not capture higher-order dependencies, which are captured by the authors' method.

In response to a query about practitioner use of extreme value theory, *Ken Abbott* noted that although the methods used by risk managers generally have to be understandable by nonspecialists, and EVT does not yet meet that standard, he intends to train his staff to understand EVT.