Co-movements in EU banks' fragility: a dynamic factor model approach

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Abstract

We analyse co-movements in the fragility of EU banks and verify to which extent such co-movements have increased in time, following, for example, the completion of Monetary Union and the introduction of the euro. To this end, we provide a measure of co-movements in bank risk by means of a dynamic factor model, which allows to decompose an indicator of bank fragility, the Distance-to-Default, into three main components: an EU-wide, a country-specific and a bank-level idiosyncratic component. Our results show the commonality in bank risk appears to have significantly increased since 1999, in particular if one concentrates on large banks. We also show that co-movements in EU banks' fragility are only in part related to common macro shocks and that a banking system specific component at the EU-wide level appears relevant. This has obvious consequences in terms of systemic stability, but may also have far reaching policy implications with regards to the structuring of banking supervision in Europe (i.e. it increases the scope for supervisory co-operation).

Keywords: Co-movements, dynamic factor models, distance-to-default, Systemic risk
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Introduction

The aim of this paper is to analyse co-movements in the fragility of EU-15 banks and verify to which extent such co-movements have increased in time, following, for example, the completion of Monetary Union and the introduction of the euro.

Essentially, co-movements in bank risk derive from the exposure to common shocks, which may come from different sources. They may be related to common macroeconomic shocks, but they may also stem from common exposures to industries, countries, or individual counterparts, as well as from interbank linkages (see Upper and Worms 2002, Gropp and Vesala 2004).

There are several reasons to believe that common shocks affecting EU banks may have increased. Firstly, as regards common macro shocks at EU wide level, there seems to be sufficient evidence showing their relevance. Forni and Reichlin (2001), among others, show that the variance in output growth displayed by individual EU countries is largely explained by a European component. Secondly, bank linkages stemming from cross-border interbank exposures in the euro area have significantly increased during 1998 and 1999 (Hartmann et. al. 2003, Galati et. al. 2001). Lastly, while retail banking has remained a largely domestic business, there has been a considerable growth in a number of segments (syndicated loans for large corporates, derivatives, country exposures etc.) that may have increased the sources of common shocks to which EU banks are exposed.

Co-movements in banks fragility have obvious consequences in terms of systemic stability, since they clearly increase the likelihood of widespread banking crises. But, they may also have far reaching policy implications with regard to the structuring of banking supervision in Europe, e.g. the split of supervisory competencies between national and supranational or EU-wide authorities. Indeed, finding robust evidence of growing linkages between the fragility of banks located in different national jurisdictions increases the scope for supervisory co-operation at EU-wide level. This would be especially true if such interconnectedness are related not only to common macroeconomic shocks but also to growing EU-wide banking system specific factors (due for example to increased banking integration).

Against this backdrop, we provide a measure of co-movements in bank risk by means of a dynamic factor model (Stock and Watson 1999 and Forni, Hallin, Lippi, Reichlin 2000, 2002), which allows to decompose an indicator of bank fragility, the Distance-to-Default (DD) (Gropp et. al. 2002 and 2004), into three main components: an EU-wide, a country-specific and a bank-level idiosyncratic component.

In addition we measure the influence of common macroeconomic shocks at EU and country level on our fragility indicator. By removing the effects of such common macro shock we identify a banking sector specific source of fragility which is in turn decomposed into the three components specified above.

A further contribution of our paper is that, analysing the data in the frequency domain, we are able to distinguish between short-term, cyclical and long-term co-movements in bank fragility. Whereas the former might be related to large shocks or, eventually, some sort of contagion, the latter might be associated to common cyclical shocks or the fact that banking sectors are becoming increasingly similar (or integrated).

While the idea of co-movements in economic and financial variables is not new in economic literature (see Sargent and Sims 1977) and has recently gained renewed interest, to our knowledge applications to the banking sector are more limited. Indeed, the most recent work has been devoted to measuring co-movements in economic variables, like GDP or inflation, in the context of the business cycle analysis, but there is also vast literature regarding co-movements in financial variables (see for instance, among others, Fama and French (1993), Emiris (2002)).

Hawkesby, Marsh and Stevens (2003 and 2005) provide an application to the banking sector. These authors analyse co-movements in equity returns for a set of US and European Large Complex Financial Institutions (LCFI) by using several statistical techniques amongst which a static factor model. They find a high degree of commonality between asset price developments of most LCFIs. However, their results also show that there is still significant heterogeneity between sub-groups of LCFIs, e.g. according to geography. Increased interconnectedness among banks is also found by De Nicolò and Kwast (2002), who notice a significant rise in stock price correlation for a set of large US banks, which they partly attribute to consolidation in the financial sector.

The analysis of co-movements in risk is also quite connected to credit risk's portfolio analysis. In both cases, in fact, the focus is on default correlations. Within this context, Nickell and Perraudin (1999), for UK banks, and Lehar (2003), for a sample of international banks, examine bank fragility on a portfolio perspective. To this end, they derive banks' default probabilities from observable market data based on the option pricing theory (similarly to us), and calculate the risk of simultaneous weakness in several banks by considering asset return correlations.

Our approach is different from that followed in the papers mentioned above, since we consider the propagation mechanism of common shocks, which, ultimately, are the sources of asset and default correlation. In other words, this means that different banks may be hit by the same shock but with different time delays (and leads), which allows for bank-level heterogeneity. Indeed, this is one of the main advantages of using a dynamic factor model, which enables exploiting much more information than, for instance, a static factor model. In addition, we are able to measure the relative contribution of EU-wide, domestic and idiosyncratic shocks to bank risk, which is the main focus of this paper.

Our results highlight the fact that co-movements in bank fragility are not negligible at EU-wide level. Further, the commonality in bank risk appears significantly increasing since 1999 and that such rise is largely related to the increased relevance of a EU banking system specific component rather than common macroeconomic shocks. Moreover, by analysing co-movements in the frequency domain, we find out that common EU-wide shocks are more relevant at cyclical and/or long-term frequencies, which is in line with the increasing integration in the EU banking system (Cabral et. al. (2002)). However, we notice that co-movements at very high frequencies (i.e. in the very short term) are relevant when one concentrates on large banks, which is consistent with some recent results on bank contagion in Europe (Gropp and Vesala, 2004) and with the idea of tiered structured of the EU banking system.

The paper is structured as follows. We start by describing the methodology underlying our fragility indicator and the data used. We then perform some basic descriptive analyses in order to provide a first rough evidence of how EU banks fragility is interconnected. These descriptive analyses constitute the premises for our dynamic factor model whose description and results are reported in section 3. In section 4 we assess the role of common macroeconomic shocks at national and EU-wide level in explaining the dynamics of banks' fragility. Section 5 concludes and outlines possible lines for future research.

1 The fragility indicator and the data

The fragility indicator

We use the distance to default (DD) as an indicator of bank fragility. The DD is a Merton-based (i.e. option pricing) indicator derived from the Black and Scholes formula (see KMV Corporation 2001).
More specifically, assuming that the market value of a firm's assets follows a stochastic process of the type:

$$\ln V_A^T = \ln V_A + \left(r - \frac{\sigma_A^2}{2} \right) \cdot T + \sigma_A \cdot \sqrt{T} \cdot \varepsilon$$

which expresses the time path of the asset value given its current value (V_A) and a stochastic disturbance normally distributed with zero mean and unit variance ($\varepsilon \approx N(0,1)$).

From this, indicating with D the value of the firm's liabilities, we can define the distance from the default point as follows:

$$d = \ln V_A^T - \ln D = \ln V_A + \left(r - \frac{\sigma_A^2}{2} \right) \cdot T + \sigma_A \cdot \sqrt{T} \cdot \varepsilon - \ln D \Leftrightarrow$$

$$\frac{d}{\sigma_A \cdot \sqrt{T}} = \frac{\ln\left(\frac{V_A}{D}\right) + \left(r - \frac{\sigma_A^2}{2} \right) \cdot T}{\sigma_A \cdot \sqrt{T}} + \varepsilon$$

This yields the formula for the Distance-to-default, which is defined as the number of standard deviations that a firm is from the default point.

$$DD \equiv \frac{d}{\sigma_A \cdot \sqrt{T}} - \varepsilon = \frac{\ln\left(\frac{V_A}{D}\right) + \left(r - \frac{\sigma_A^2}{2} \right) \cdot T}{\sigma_A \cdot \sqrt{T}}$$

We decided to use the DD as fragility indicator since it represents a measure of bank risk with some desirable properties. In particular, Gropp et al. (2002 and 2004) show that this indicator encompasses most elements of bank risk (asset returns, volatility - i.e. asset risk - and leverage) and constitutes a measure not affected by the presence of explicit or implicit safety nets. Further, this indicator, being based on stock market information, is inherently forward-looking and available more frequently than traditional balance-sheet indicators (in principle, it can be calculated on a real-time basis). More importantly, the authors show that this measure is more capable than other market indicators of bank fragility (e.g. subordinated bond spread, or stock returns) to predict a material deterioration in bank's condition (up to 18 months in advance). Hence, the DD may represent a useful indicator to monitor bank fragility that may complement the information provided by other sources (e.g. balance sheets).
However the same authors also highlight some limitations of the DD indicator. In particular, the distance to default can be sensitive to trading irregularities which could be particularly high for banks with low trading volumes (typically small banks or banks in a troubled situation). In the context of this paper this could mean biasing our results towards not finding evidence of co-movements in the fragility of EU banks.

It follows from the formula that the basic ingredients for the calculation of the DD are V_A and σ_A. They can be calculated from observable market value of equity, V_E, equity volatility, σ_E, and the value of liabilities D, by solving the following system of two equations:

$$V_E = V_A \cdot N(d_1) - D \cdot e^{-rT} \cdot N(d_2)$$
$$\sigma_E = \left(\frac{V_A}{V_E} \right) \cdot N(d_1) \cdot \sigma_A$$

where

$$d_1 = \frac{\ln\left(\frac{V_A}{D} \right) + \left(r + \frac{\sigma_A^2}{2} \right)}{\sigma_A \cdot \sqrt{T}}$$
$$d_2 = d_1 - \sigma_A \cdot \sqrt{T}$$

We solved the system of two equations by using the generalised gradient method to yield the values for V_A and σ_A. As observable market value of equity, V_E, we employed the end of week equity market capitalisation from Thomson Financial Datastream. The equity volatility, σ_E, was estimated by taking the standard deviation of weekly equity returns in a rolling one-year window (i.e. 52 weeks). The total liabilities, D, are obtained from the banks published accounts, and as risk free rates we used the interest rates on the one year asset swap. Finally, the maturity of the debt, T, was set to one year, which is a common benchmark assumption without any specific information about the maturity structure of the debt.

Once obtained the DDs for each bank in the sample, we calculated their log first difference, $\ln(\Delta DD)$ at weekly and monthly frequencies[1], in order to partly reduce the noise (which is especially high in financial markets data) that may affect weekly changes but also to better distinguish the short-term from the cyclical and long-term components of co-movements in bank risk.

The sample of banks

The initial sample of banks considered in the paper is represented by 160 listed banks for which stock market data (stock price and market capitalisation) and debt are available during the period from November 1994 to December 2004.

We estimated the dynamic factor model by using a balanced panel. Hence, we had to delete a number of banks for which data were not available for the whole sample period. We ended-up with a sample of 99 banks incorporated in EU-15 countries (new accessed EU countries are not represented), with 529 weekly observations per bank. The list of banks with their total assets and country of incorporation is reported in Table 1.

The banks in the sample are relatively large (the average asset size amounts to slightly more than EUR 100 bln), but there is also a substantial presence of small-mid sized banks. Note on this regard that the median size equals EUR 25 bln euro. The largest bank in the sample is Deutsche Bank (end 2002 total assets of about EUR 760 bln), while the smallest is Union Financière de France Banque with only EUR 186 mln of total assets.

The distribution of the banks by country highlights the relatively high presence of Italian banks (19 banks), while some large countries are relatively underrepresented (there are only 8 French and UK banks). The reduced size of the sample for some countries may constitute a problem when estimating the country component of bank fragility. However, given the approach followed in the paper in estimating the dynamic factor model (i.e. the procedure suggested by Stock and Watson (1999)), the fact of having a large T should preserve the significance of our results (at least as far as the EU-wide component is concerned).[2] Moreover, since our main interest relies in the estimate of the relevance of the EU-wide component, the fact that the measurement of the national component might be distorted by small sample size problems should not constitute a major issue. Nevertheless, this caveat should be borne in mind when interpreting the results obtained in the paper.

2 Preliminary descriptive analyses

In order to provide a first rough evidence of co-movements in bank fragility we conducted a set of preliminary descriptive analyses, as basic premises to our dynamic factor model.

[1] The monthly DDs are obtained as a simple average of the weekly.

[2] Stock and Watson (1999, theorem 1 at pag. 11) show that the approximate dynamic factor model yields estimated factors that are asymptotically efficient in forecasting out of sample for any joint sequences (N,T)$\rightarrow \infty$.

Contemporaneous correlation analyses

We first looked at the contemporaneous correlation in the weekly and monthly changes in banks' DDs. We considered the monthly changes in order to partly reduce the noise (which is especially high in financial markets data) that may affect weekly changes. The correlations were calculated for the sample of 99 banks considering the entire period, and the periods before and after 1 January 1999 in order to check whether in correspondence with the start of the EMU there has been a rise in the degree of co-movements between the fragility of EU banks. Of course the choice of the break-point in the sample is purely arbitrarily, but without any further reference as to where fix it, the EMU starting date becomes a quite natural candidate. It is also clear that finding an increase in correlations between the two sub-periods does not necessarily mean that it has been "caused" by the EMU process. Nevertheless, such a correspondence would certainly be of some interest, e.g. for research purposes (and not only). Results are summarised in Table 2.

In general, correlations in bank risk appear rather low on average (6 % for weekly changes, up to 14 % in the case of monthly changes). Distinguishing between correlations among banks belonging to the same country (domestic correlation), and correlations among banks from other countries (cross-border correlation), it appears that the average domestic correlation, albeit still remaining low, is dominant over the cross-border one: while the average domestic correlation stands at 14% (23% for the monthly changes), the cross-border one equals only 5% (12% for monthly changes). Note, however, that the distinction made is not appropriate because part of what has been labelled domestic correlation may be due to EU-wide shocks. This is one of the reasons why a factor model is particularly useful, since it yields components of banks' fragility which are mutually orthogonal.

Splitting the sample in the two sub-periods there seems to be a slight increase in average pairwise correlations: taking the weekly changes the average correlation equals 4% in the period before 1999 while it goes up to 8%. A similar finding is obtained with the monthly changes.

Nonetheless, these results are not surprising as small and mid sized banks are largely affected by developments in their country of incorporation or by idiosyncratic shocks. Further, as it will be shown in the next section, contemporaneous correlations may not fully capture the transmission of shocks between banks.

We moved then to look at the correlation in bank fragility among a set of large banks, defined somewhat arbitrarily as those with total assets as of end 2002 above 100 bln euro (28 banks belonging to 9 EU countries).
In this case, the average correlations appear significantly larger both considering the weekly (17%) and the monthly changes (35%): in both cases they are, in fact, above the standard threshold $\pm \, {}^{2}\!/\!\sqrt{T}$ (where T is the number of observations) denoting statistically significant correlations. Further there seems to be a material increase in the average correlation in the post 1999 period: taking the weekly changes, the mean correlation goes up to 24% from 10% in the first part of the sample. It is worth noting that the observed increase is largely owing to cross-border correlations which rise to 23% in the post 1999 period from 8% in the first sub sample.

Correlations increase significantly between the two sub-periods also when the monthly changes are considered (from 21% to 42%). Even in this case the rise can be noticeably attributed to cross-border correlations (41% in the post 1999 period from 19% in the earlier part of the sample).

Looking at average correlations, though, may not fully reveal the degree of commonality in bank risk among EU banks. Indeed there could be large pairwise correlations which are then offset by low or even negative correlations. For the analysis of co-movements in bank fragility (and for financial stability purposes) might thus be relevant considering the distribution of such pairwise correlations. One can, in fact, think of that even relatively few large correlations between the riskness of banks incorporated in different countries might be sufficient for having significant cross-border co-movements in bank fragility. Charts 1-4 report the frequency distribution of pairwise correlations between the changes in banks' DDs in the two sample-periods distinguishing among domestic and cross-border correlations as specified above. The charts reinforce the finding previously highlighted of strengthened interconnectedness in the riskness of EU banks. For example, taking the weekly changes (Charts 1 and 2) we do observe a large increase in the number of statistically significant pairwise positive correlations (namely greater than $2/\sqrt{T}$): the number of such significant correlations stands at 1,516 out of 4,851 (i.e. 99*98/2) in the post-1999 period versus 646 in the ante-1999 sample. Adopting a criterion of economic significance, e.g. considering correlations greater or equal than 50% (which are, indeed, very large when if one takes DDs weekly changes), we obtain a similar outcome: the number of economically significant correlations increases from 7 in the 1995-'98 time interval to 48 in the 1999-'04 period. Again, we do find a large increase in the number of statistically and economically significant correlations at the cross-border level. The frequency distribution of correlations on monthly DD changes (Charts 3 and 4) tells a pretty similar story.

To sum up, the results of the correlation analysis in DDs changes provides a first evidence of the fact that co-movements in bank fragility at EU-wide level are not negligible, especially when one concentrates on large banks. In addition, the commonality in bank risk appears significantly increasing since 1999 even at the cross-border level.

Correlations at leads and lags

As a second step we looked at correlations at several leads and lags. This constitutes the basic premises for the dynamic factor model developed in the following section. Indeed, one motivation for the use of a dynamic factor model instead of a static one is the fact that common shocks are not only contemporaneous, but that there exists a propagation mechanism of such shocks which follows a more complex dynamics, which implies the existence of first or higher order auto-correlations and cross-correlations. In addition, this enables to take into account the heterogeneity among banks in the propagation of common shocks.

As before, it is perhaps more interesting to focus on the distributions of the computed pairwise correlations at several leads and lags in weekly and monthly DD changes (we considered 8 leads and lags for the weekly changes and 3 leads and lags for the monthly). Table 3 reports the count of the statistically and economically significant correlations[3]. It shows that the number of such correlations is material suggesting that including leads and lags changes in the factor model may increase its explicative power. Taking for example the lag 1 for the weekly DD changes we find 953 statistically significant positive correlations, around 20% of the total pairwise correlations. Further around 80% of these correlations (i.e. 761) are among banks incorporated in different EU countries. Indeed, considering leads and lags in the DD changes appears relevant to highlight the transmission of common shocks at the cross border level especially between large and mid sized banks. To illustrate we report, as an example, the cross-correlations between a large Italian bank (Capitalia) and a medium size Spanish bank (Banca Pastor): Chart 5 shows that correlations at lags 1 and 2 in the weekly DD changes are significantly higher than the contemporaneous one (equalling respectively 44% and 25% versus 17%).

Dynamic correlations and cohesion

Further interesting insights may come from the analysis of dynamic correlations and cohesion which represent two measures of correlation in the frequency domain proposed by Croux, Forni and Reichlin (2001). Essentially, these measures highlight the frequencies at which cross-correlations between variables are more relevant. Thus, they help in saying whether co-movements are related to common short-term dynamics or if they reflect common cyclical shocks or more long-term tendencies.

Taking two zero-mean real stochastic processes x and y, the dynamic correlation can be defined as follows:

$$\rho_{xy}(\lambda) = \frac{C_{xy}(\lambda)}{\sqrt{S_x(\lambda) \cdot S_y(\lambda)}}$$

where $S_x(\lambda)$ and $S_y(\lambda)$, for $-\pi \le \lambda \le \pi$, are the spectral density functions of x and y, and $C_{xy}(\lambda)$ is the co-spectrum.

Along the same line, the cohesion is a synthetic measure of dynamic correlation when there are more than 2 variables. It simply equals the weighted average of dynamic correlations between all pairs of series.

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3 Statistically significant correlations are those above or below the threshold $\pm\ {}^{2}\!/\!\sqrt{T}$.
Economically significant correlations are defined as those greater than 30% or 50% for the weekly and monthly changes respectively.

In our case, we calculated these measures by using a Bartlett kernel with window width at $T^{1/2}$. Spectra, cross spectra, dynamic correlations and cohesion have then been computed on 128 equally spaced points[4].

In Charts 6 we report the cohesion on weekly changes, for the two sub-periods 1995-1998 and 1999-2004[5]. These charts clearly show the increase in co-movements between the two periods. In addition, we notice that co-movements are concentrated mainly at low frequencies: i.e. bank risk co-moves in the long-term or at cyclical frequencies.

Finally, we ran the exercise for the sample of 28 large banks (Chart 7). The results highlight the larger commonality among this set of banks found in the simple correlation analysis. For this set of banks we also notice a spike in the cohesion calculated on weekly DD changes at a frequency corresponding to a period of two weeks. This results also highlights the difference between the weekly and the monthly DD changes: while weekly DD changes tend to stress co-movements on a very short-term basis, the monthly changes appear more suitable to reflect co-movements related to common cyclical shocks or stemming from common long term tendencies.

To sum up, the analysis on cohesion tends to suggest that cyclical and long-term co-movements in bank risk are more relevant than those at very short-term frequencies (i.e. high frequencies), which is coherent with the increasing integration in the EU banking system (Cabral et. al. (2002)).[6] There is also some evidence of co-movements in the very short-term for large banks. This seems to suggest that in case of common shocks large banks are hit first. Perhaps more importantly, this result could also be indicative of some form of contagion hitting large banks, whose source might be worth of investigation in future research.

3 The dynamic factor model

Model description and estimation procedure

Our basic assumption is that the bank fragility indicator (DD) can be decomposed into three main components: an EU-wide, a country-specific and a bank-specific (i.e. idiosyncratic) component. These three components are, by definition, mutually orthogonal.

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[4] We used the Matlab code provided by Croux, Forni and Reichlin, which is available in the web site www.dynfactor.com. All the other programmes and routines were prepared by the authors.

[5] The charts report the cohesion for frequencies ranging from 0 (low frequencies corresponding to medium to long term cycles) to 3.14 (high frequencies corresponding to very short dynamics). This means that with weekly data having for example 210 observations a frequency of 1.55 corresponds to a cycle of approximately 4 weeks.

[6] These results are also confirmed by a spectral analysis of the three components extracted with the dynamic factor model. We do observe, in particular, that in the short-term (high frequencies), the idiosyncratic component tends to dominate over the other two, while in the long-run the EU-wide component starts to become relevant. For the period 1999-2003, there is also the emergence of a EU-wide factor at cyclical frequencies. In particular, the charts noticeably suggest a cycle of slightly more than two years that can be associated to the industrial cycle in EU countries in the last years. Further, the presence of a national cycle at 4 months frequency in the first sub-sample seems to have been absorbed by the EU component in the second period.

Following Forni and Reichlin (2001) and denoting with DD_t^{ij} the Distance-to-Default of bank i incorporated in country j, we assume that the changes in the DDs can be decomposed as follows

$$\Delta(DD_t^{ij}) = E_t^{ij} + N_t^{ij} + I_t^{ij}$$

where E_t^{ij}, N_t^{ij}, I_t^{ij} are the EU-wide component, the national component and the bank-level component respectively. Each component can, in turn, be written as linear combination of unit variance shocks, which are uncorrelated at all leads and lags. Thus,

$$E_t^{ij} = a^{ij}(L) \cdot e_t$$
$$N_t^{ij} = b^{ij}(L) \cdot n_t^j$$
$$I_t^{ij} = c^{ij}(L) \cdot i_t^{ij}$$

where a^{ij}, b^{ij} c^{ij} are polynomials in the lag operator L, while e_t, n_t^j and i_t^{ij} are the EU-wide, the national and the bank specific shocks respectively.

The model entails the estimation of the three unobserved components, which is done through a sequential procedure. More specifically, the EU-wide component is first estimated by means of an approximate dynamic factor model à-la Stock and Watson[7] (1999) applied to all banks in the sample, which can be written as follows (in matrix notation):

$$\Delta(DD_t) = \Lambda \ F_t + \varepsilon_t$$

The matrix Λ contains the loadings, $F_t = (f_t, f_{t\pm1}...., f_{t\pm q})$ is the matrix of common factors, while ε_t is the matrix of residuals, which in the first step of the procedure is a bundle of the national and idiosyncratic components (i.e. everything which is not common at the EU-wide level). The national component is, in turn, isolated from the idiosyncratic one by running the dynamic factor model on these extracted residuals for groups of banks incorporated in the same country.

As noted, while the estimation of the EU common factor should not constitute a major problem, the size of the sample (i.e. the number of cross-sections/banks) for some countries might not be sufficient to consistently estimate the country component of bank fragility. However, given that the focus of this paper is in measuring the weight of the EU component this should not constitute a major issue.

[7] Nothing prevents the use of a dynamic principal components approach like the one proposed in various papers by Forni, Hallin, Lippi, Reichlin (2000). We resort here to the simpler approach proposed by Stock and Watson and quite common in the literature (Angelini-Henry-Mestre 2001, Camacho-Sancho 2003).

Once the three components have been estimated and given their orthogonality, the decomposition enables to calculate the contribution of each component to the variance of the DD changes.

As regards, in particular, the estimation of the dynamic factor model employed in the paper, it requires a number of choices to be made. The first is the number of factors to be used in estimation, the second is the potential inclusion of lags in the observed series, and the third is the inclusion of leads and lags of the factors in the estimation of the common components.

While the first can be made on the basis of the modified information criteria proposed in Bai-Ng (2002), the second and the third have been performed by Stock and Watson (1999) on the basis of the forecasting ability contribution of the model. In our case we choose on the basis of the amount of variance in the idiosyncratic component (trying to minimise it). Being not particularly interested in forecasting, but the more so in the inherent dynamic structure of the data, we investigated if there are advantages by using a two sided interval (leads and lags for the extracted common factor). After preliminary estimations, a final set up with 1 factor (using the Bai and Ng criteria), no lags in data, and 3 leads and lags in the factors have been chosen for the weekly DD changes[8]. For the monthly changes the Bai and Ng criteria identified two factors and 1 lead and lag in the factors.

Model's results

In table 5 we report the average across banks of the variance explained by the three components for all countries and a set of selected countries in the two sub-periods 1995-1998 and 1999-2004.

Our results show that the degree of commonality is quite clearly growing. The EU-wide and national components altogether go up to 32% since 1999, from 28% in the period 1995-1998 in the case of weekly DD changes. Further, the increase in commonality is in large part due to the EU-wide component, which rises to 19 % since 1999 from 10% before 1999.

Co-movements in bank fragility appear much larger when monthly changes are considered. In such a case, in the post 1999-period, the EU-wide component explains 53% of the variance in monthly DD changes (up from 34% in the before 1999 period). Even in this case the increase in the EU-wide component comes at expenses of the domestic one (down from 49% to 19%). There is also a significant reduction in the share of variance explained by the idiosyncratic component when we move from weekly to monthly changes in the DDs. This probably reflects the reduction in noise implied in the monthly changes vs. the weekly changes.

Looking at the results by country, we find that all countries share the increase in co-movements in the two sub-periods. Considering weekly DD changes, the largest increase is found in Italy (more than 20%), while in Germany the EU-wide component (18% in the post 1999 period) is the smallest (albeit higher than the

[8] See the discussion in Stock and Watson (1998) at pagg. 8 and 23.

average for the whole sample). Similar findings are obtained with the monthly DD changes.

The increase in the weight of the EU-wide component clearly appears from Chart 8, which displays the frequency distribution of the variance explained by the EU-wide component in the two sub-periods (weekly DD changes). While before 1999 the percentage of banks with a variance explained by the EU-wide factor of more than 30% was only 2%, since 1999 such percentage goes up to about 22%. Moreover, for 10 banks in our sample more than 50% of the variance in weekly DD changes is explained by the EU-wide factor. These are clearly those labelled as large banks (total assets higher than EUR 100 bln). Indeed, Table 5 makes it clear that the increase in commonality is largely explained by this set of banks: for them the average variance explained by the EU-wide common factor goes from 17% of the period 1995-1998 to 34% in the period 1999-2004. For some of these banks the EU wide common factor explains a figure close or even higher than 50% of the variance in weekly DD changes (see Table 6).

These results are even more striking when monthly changes are considered. In particular, Chart 9 shows that, in the after-1999 period, for 21 banks the share of variance explained by the EU-wide component is larger than 75%. A similar finding is reported in Table 7 referred to the sample of large banks.

4 Sources of co-movements in banks' fragility: the role of common macro shocks

In the previous section we showed that the commonality in the riskness of EU banks is clearly increasing and that such rise is largely due to the EU-wide component. It is also clear, however, that part of the comovements in banks' fragility may stem from common macro shocks both at national and EU-wide level. It might be thus interesting to make a further step and investigate the role of such macro-shocks in explaining the dynamics of our fragility indicator. To this end we resort again to a factor model and assume that the DD of each bank can be decomposed into the following mutually orthogonal components:

1) a common macroeconomic EU-wide component,
2) a country-specific macroeconomic component
3) a residual component.

In other words, with this procedure we clean the dynamics of the DDs from those influences that may come from macroeconomic shocks. In this way, and provided that the common macro shocks are properly identified, we yield a residual component that could be interpreted as a banking system specific source of risk.

Hence, denoting with DD_t^{ij} the Distance-to-Default of bank i incorporated in country j, we assume that the changes in the DDs can be decomposed as follows

$$\Delta(DD_t^{ij}) = macroEU_t^{ij} + macroN_t^{ij} + e_t^{ij}$$

In turn, similarly as done in the previous section, the residual of the previous equation – the banking sector specific source of risk - can be further decomposed into a EU-wide banking sector, a domestic banking sector and a bank-specific (or idiosyncratic) component, i.e.

$$e_t^{ij} = EU_t^{ij} + N_t^{ij} + I_t^{ij}$$

In order to identify the common macro shocks we took a set of macroeconomic variables at country level, available on a monthly frequency, as industrial output (with sector breakdown), consumer and producer prices (with product and sector breakdown), business and consumer confidence indicators, interest rates, exchange rates (nominal and real effective), etc., for a total of over 700 series. We then ran a factor model on the complete set of macro variables to extract the EU-wide common macro factors. Subsequently, we estimated the common macro factors at national level by running the factor model for each country on the residuals of the first step. For each bank in the sample we then regressed the monthly DD changes on the EU-wide and national common macro factors. As said, the residuals of these regressions should represent the banking sector specific sources of risk. Finally, we applied the sequential procedure used in the previous section in order to decompose the banking sector specific source of risk into the EU-wide, domestic and a bank-specific (or idiosyncratic) components.

In order to remove the influence of macro shocks from the dynamics of the fragility indicator, we tried to include as many as possible macro factors. Once again we used the Bai and Ng modified information criteria to choose the number of factors and we ended up with 9 and 5 factors at the EU-wide and country level respectively.

The results of this exercise (summarised in Table 8) show that the dynamics of monthly DD changes can only in part accounted for by macro factors. They explain on average in the entire sample period 34.3% of the dynamics in monthly DD changes. The variance explained by EU common macro factors seems to dominate over the national one, since on average they account for 25.2% of the total variance in banks' DDs versus 9.1% for domestic macro factors. Taking the two sample periods we do observe a larger share of variance explained by the common macro-factors in the first part of the sample (42%), whilst in the period 1999-2004 the share of variance accounted for by the residuals lifts to 71%.

These results seem then to suggest that common macro shocks are not the sole source of bank risks and that the dynamics of EU banks' fragility is largely accounted for by banking system specific factors and that these factors are becoming increasingly important. Of course this outcome may also be due to the fact that we were unable to correctly identify all macro shocks. For example one may consider the influence of stock market variables (taking for example stock market indexes at sector and country level) and this would probably reduce the weight of the residuals. However, the finding we obtained does not come as a total surprise if one takes into account the fact that in the last three years or so there has been an increasing detachment between the results of banks and the performance of the EU economy: while the latter has progressively stagnated the former have been able to keep their profitability at rather satisfactory levels.

Moving to the decomposition of what we have labelled banking system specific component, the results (Table 8) show that the EU-wide part – now at the banking sector level – remain still relevant and is increasing in time even once we have removed the influence of common macroeconomic shocks. Taking the post-1999 period the EU-wide component accounts on average for 51% of the variance of banking system specific source of fragility (or 36% of the whole dynamics in monthly DD changes) up from 35% in the 1994-1998 time interval. Hence in the second part of the sample EU-wide banking sector common shocks seem to have become more important than common macro shocks in explaining the behaviour of banks' fragility.

5 Conclusions and suggestions for future research

With this paper we aspired at measuring to which extent the fragility of EU banks is subject to common shocks. We did this by resorting to a methodology, which has recently been extensively applied in the analysis of economic cycles, namely the dynamic factor model, which allows to decompose an indicator of bank fragility, the Distance-to-Default, into three main mutually orthogonal components: a EU-wide, a country-specific and a bank-level idiosyncratic component.

The results of our model can be summarised as follows. First, the weight of EU wide shocks appears not negligible since they explain around 42% of the variance in bank risk (as measured by monthly changes in the distance-to-default indicator). The relevance of the EU component is also significantly increasing in time, perhaps reflecting greater banking integration among EU-banks. Second, as one would probably expect, the EU component is much huger for large banks, explaining in a number of cases more than 80% of the variance in bank risk. Further, this set of banks constitutes the transmission channel of common shocks. Third, even once we take into account the influence of common macroeconomic shocks, the dynamics of EU banks' fragility is largely accounted for by banking system specific factors and these factors are becoming increasingly important at a EU-wide level. Fourth, by analysing co-movements in the frequency domain, we found out that common EU-wide shocks are more relevant at cyclical and/or long-term frequencies, which is in line with increasing banking integration. However, we notice that co-movements at very high frequencies (i.e. in the very short term) are relevant for large banks, which might be indicative of some form of contagion.

We believe our results have quite important implications as regards the monitoring of financial stability conducted by central banks and supervisory authorities in Europe. In particular, having found that developments in the fragility of large banks are largely affected by common EU-wide shocks constitutes a clear justification for macro-prudential surveillance at the EU level (at least), a field which has been recently developed by some central banks (like the ECB).

More importantly, our findings provide some indications as to the split of supervisory competencies between national and EU-wide authorities. The large weight of the idiosyncratic component indicates that banking supervision at domestic level is still important. However, its scope should be limited to small-medium sized banks whilst for large banks our results suggest an increased scope for supervisory co-operation at

EU-wide level, which should lead to an exchange of information among national supervisors on individual institutions. This is further motivated by the growing relevance of a banking system specific source of risk at the EU wide level.

The results obtained in the paper lend themselves also to a number of potential extensions and applications. Firstly, having found the emergence of common shocks stemming from EU banking system specific factors brings to investigate the sources of such shocks. This means opening the "black box" and measuring, for instance, to which extent developments in EU wide fragility are related to common exposures and/or interbank exposures. Secondly, a result of the dynamic factor model is the calculation of a EU-wide fragility indicator, which is cleaned from country specific or idiosyncratic shocks. In this respect, a potential application consists of conducting stress testing exercises of the fragility of EU banks by showing what happens to the EU-wide fragility indicator in case of changes in the DD of one bank or a set of banks.

Tables and charts

Table 1 – List of banks in the sample

Nr	Bank name	Country of incorporation	Total assets (EUR mln)*	Nr	Bank name	Country of incorporation
1	Bank für Tirol und Vorarlberg AG	Austria	5,712	51	Union Financière de France Banque	France
2	Bank fuer Kaernten und Steiermark AG - BKS	Austria	3,733	52	Alpha Bank AE	Greece
3	Investkredit Bank AG	Austria	13,479	53	Bank of Attica SA	Greece
4	Oberbank AG	Austria	9,689	54	Piraeus Bank SA	Greece
5	Fortis Bank	Belgium	377,728	55	EFG Eurobank Ergasias SA	Greece
6	KBC Bank NV	Belgium	208,501	56	Egnatia Bank SA	Greece
7	Baden - Wuertt. Bank	Germany	26,058	57	Emporiki Bank of Greece SA	Greece
8	Bankgesellschaft Berlin AG	Germany	173,599	58	General Bank of Greece SA	Greece
9	Bayerische Hypo-und Vereinsbank AG	Germany	678,340	59	National Bank of Greece SA	Greece
10	Commerzbank AG	Germany	421,809	60	Allied Irish Banks plc	Ireland
11	DePfa Deutsche Pfandbriefbank AG	Germany	180,899	61	Bank of Ireland	Ireland
12	Deutsche Bank AG	Germany	758,256	62	Banca Fideuram SpA	Italy
13	DVB Bank AG	Germany	9,389	63	Banca Intesa SpA	Italy
14	Eurohypo AG	Germany	225,833	64	Banca Lombarda e Piemontese SpA	Italy
15	HSBC Trinkaus & Burkhardt KGaA	Germany	11,049	65	Banca Nazionale del Lavoro SpA - BNL	Italy
16	IKB Deutsche Industriebank AG	Germany	36,336	66	Banca Popolare di Intra	Italy
17	Vereins-und Westbank AG	Germany	21,232	67	Banca Popolare di Lodi	Italy
18	Württembergische Hypothekenbank AG	Germany	29,253	68	Banca Popolare di Milano SCaRL	Italy
19	Danske Bank A/S	Denmark	235,870	69	Banca popolare dell'Emilia Romagna	Italy
20	Fionia Bank	Denmark	2,341	70	Banche Popolari Unite - BPU Banca	Italy
21	Jyske Bank A/S	Denmark	20,633	71	Banco di Sardegna SpA	Italy
22	Ringkjobing Bank	Denmark	400	72	Capitalia SpA	Italy
23	Roskilde Bank	Denmark	1,147	73	Credito Bergamasco	Italy
24	Spar Nord Bank	Denmark	4,269	74	Credito Emiliano SpA	Italy
25	Sydbank A/S	Denmark	8,990	75	Credito Valtellinese SCarl	Italy
26	Vestjysk Bank A/S	Denmark	997	76	FinecoGroup SpA	Italy
27	Banco Atlantico	Spain	9,720	77	Mediobanca SpA	Italy
28	Banco de Andalucia	Spain	4,978	78	Reti Bancarie Holding SpA	Italy
29	Banco de Castilla	Spain	2,572	79	San Paolo IMI	Italy
30	Banco de Credito Balear	Spain	1,134	80	UniCredito Italiano SpA	Italy
31	Banco de Galicia	Spain	2,272	81	Kredietbank S.A. Luxembourgeoise KBL	Luxembourg
32	Banco de Valencia	Spain	6,618	82	ABN Amro Holding NV	Netherlands
33	Banco de Vasconia	Spain	1,860	83	ING Bank NV	Netherlands
34	Banco Español de Crédito SA, BANESTO	Spain	49,510	84	Kas Bank NV	Netherlands
35	Banco Guipuzcoano SA	Spain	5,044	85	Banco BPI	Portugal
36	Banco Pastor SA	Spain	8,870	86	Banco Totta & Açores, SA	Portugal
37	Banco Popular Espanol SA	Spain	41,899	87	BANIF SGPS SA	Portugal
38	Banco Santander Central Hispano	Spain	319,030	88	Banco Comercial Português, SA	Portugal
39	Bankinter	Spain	22,542	89	Banco Espirito Santo SA	Portugal
40	Banco Bilbao Vizcaya Argentaria SA	Spain	274,934	90	Skandinaviska Enskilda Banken AB	Sweden
41	Alandsbanken Abp - Bank of Aland Ltd.	Finland	1,813	91	Svenska Handelsbanken	Sweden
42	OKO Bank-OKO Osuuspankkien Keskuspankki Oyj	Finland	12,709	92	Abbey National Plc	United Kingdom
43	Sampo Plc	Finland	25,094	93	Barclays Bank Plc	United Kingdom
44	Banque de la Réunion	France	1,496	94	HBOS plc	United Kingdom
45	BNP Paribas	France	710,305	95	HSBC Bank plc	United Kingdom
46	Crédit Foncier de France	France	43,857	96	Royal Bank of Scotland plc (The)	United Kingdom
47	Crédit Agricole d'Ile-de-France	France	18,537	97	Schroders Plc	United Kingdom
48	Natexis Banques Populaires	France	133,400	98	Singer & Fried.	United Kingdom
49	Société Générale	France	501,265	99	Standard Chartered Plc	United Kingdom
50	Sophia	France	3,407			

** as of end 2002*

Table 2 -Mean correlations in EU banks' DDs

		Weekly changes			Monthly changes		
		Total	Domestic	Cross-border	Total	Domestic	Cross-border
All banks	All sample period	0.06	0.14	0.05	0.14	0.23	0.12
	1995-1998	0.04	0.12	0.03	0.11	0.20	0.10
	1999-2004	0.08	0.16	0.07	0.15	0.26	0.14
Large banks	All sample period	0.17	0.27	0.16	0.35	0.44	0.34
	1995-1998	0.10	0.24	0.08	0.21	0.35	0.19
	1999-2004	0.24	0.28	0.23	0.42	0.47	0.41

Chart 1. Frequency distribution of domestic pairwise correlations (weekly DD changes)

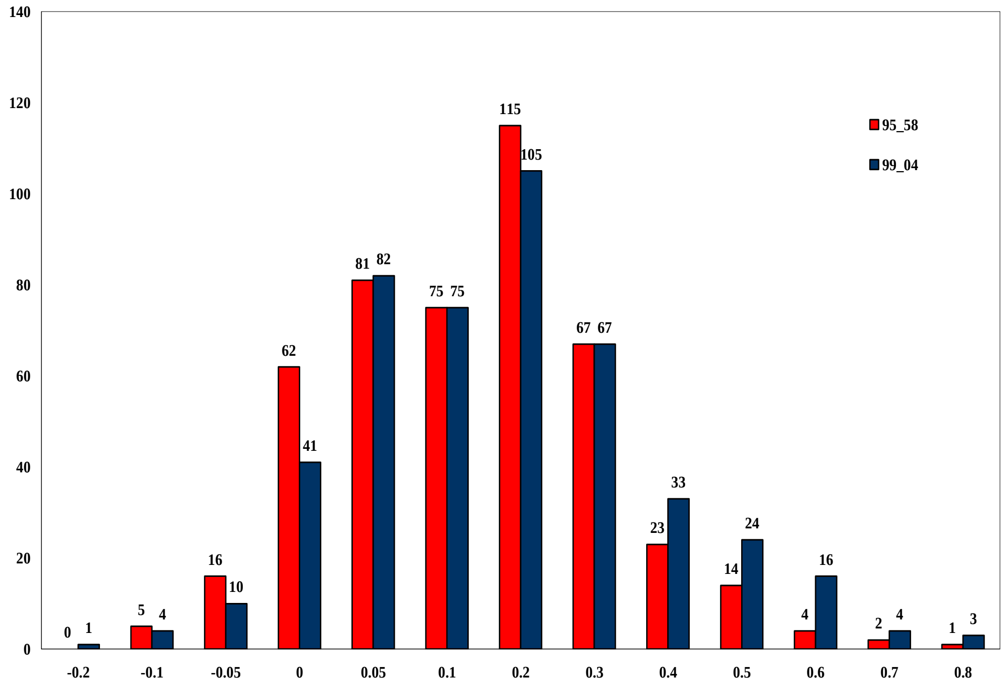


Chart 2: Frequency distribution of cross-border pairwise correlations (weekly DD changes)

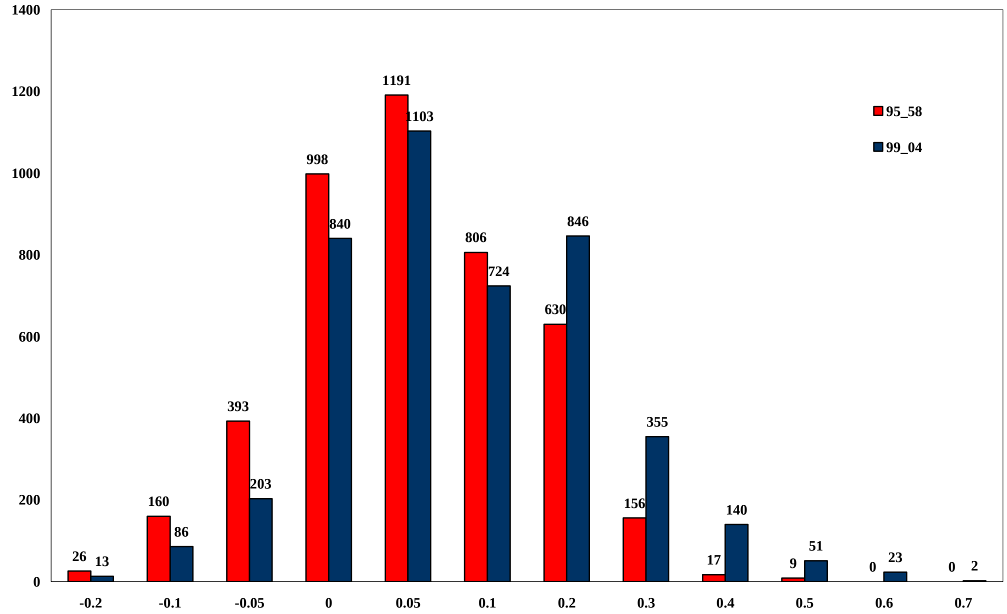


Chart 3: Frequency distribution of domestic pairwise correlations (monthly DD changes)

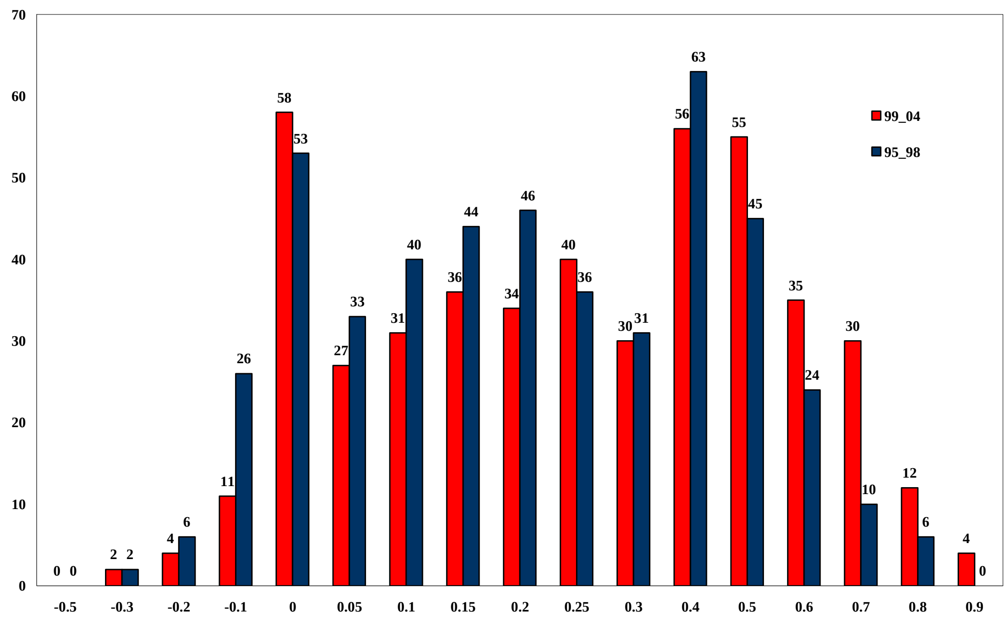


Chart 4: Frequency distribution of cross-border pairwise correlations (monthly DD changes)

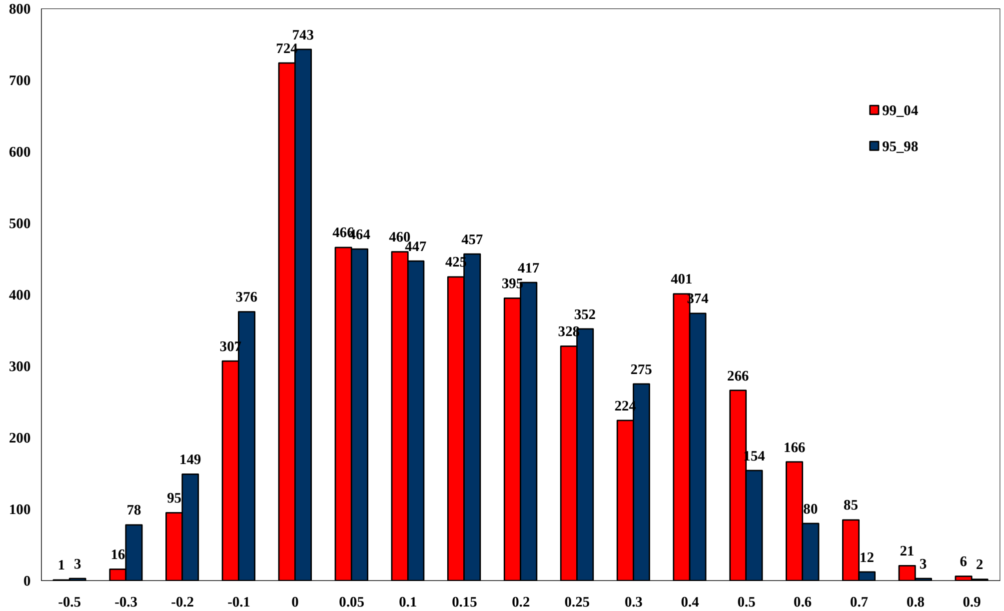


Table 3 –Number of statistically significant correlations in DD changes at several leads and lags*

		Positive correlations		Negative correlations	
		Total	**of which cross-border**	**Total**	**of which cross-border**
		Weekly chages			
Lead	**1**	1035	867	100	88
	2	714	584	90	86
	3	403	353	91	82
	4	317	276	84	68
	5	382	329	63	58
	6	327	277	87	75
	7	335	271	88	83
	8	316	278	85	77
Lag	**1**	953	761	99	88
	2	728	574	73	70
	3	362	298	85	77
	4	295	251	102	89
	5	398	354	75	71
	6	358	320	70	63
	7	377	326	66	59
	8	368	332	74	60
		Monthly chages			
Lead	**1**	1344	1093	57	53
	2	743	639	71	66
	3	560	491	88	77
Lag	**1**	1384	1131	63	62
	2	808	731	59	53
	3	583	526	78	63

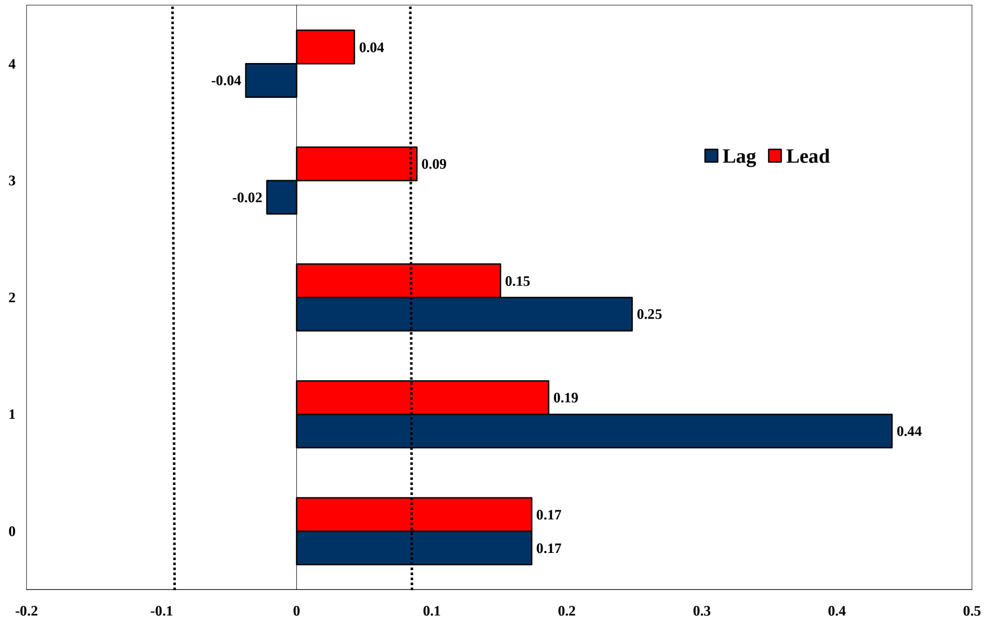
** Statistically significant correlations are those above and below the threshold* $\pm \frac{2}{\sqrt{T}}$

Table 4 –Number of economically significant correlations in DD changes at several leads and lags*

		Positive correlations		Negative correlations	
		Total	of which cross-border	Total	of which cross-border
		Weekly chages			
Lead	1	16	12	1	0
	2	1	0	0	0
	3	2	0	0	0
	4	2	1	2	1
	5	3	3	0	0
	6	0	0	1	1
	7	2	1	0	0
	8	0	0	1	1
Lag	1	15	6	2	1
	2	4	2	2	2
	3	4	4	2	2
	4	0	0	2	1
	5	3	3	2	2
	6	1	1	0	0
	7	0	0	0	0
	8	2	2	2	2
		Monthly chages			
Lead	1	17	1	0	0
	2	2	2	0	0
	3	1	1	0	0
Lag	1	20	4	0	0
	2	0	0	0	0
	3	0	0	0	0

** Economically significant correlations are those above and below the threshold +/- 0.3 +/- 0.5 and for weekly and monthly changes respectively*

Chart 5 –Cross-correlogram in weekly DD changes between Capitalia (Italy) and Banco Pastor (Spain)*



** Dotted lines indicate the threshold* $\pm\, {}^{2}\!/\!\sqrt{T}$

Chart 6 - Cohesion in weekly DD changes

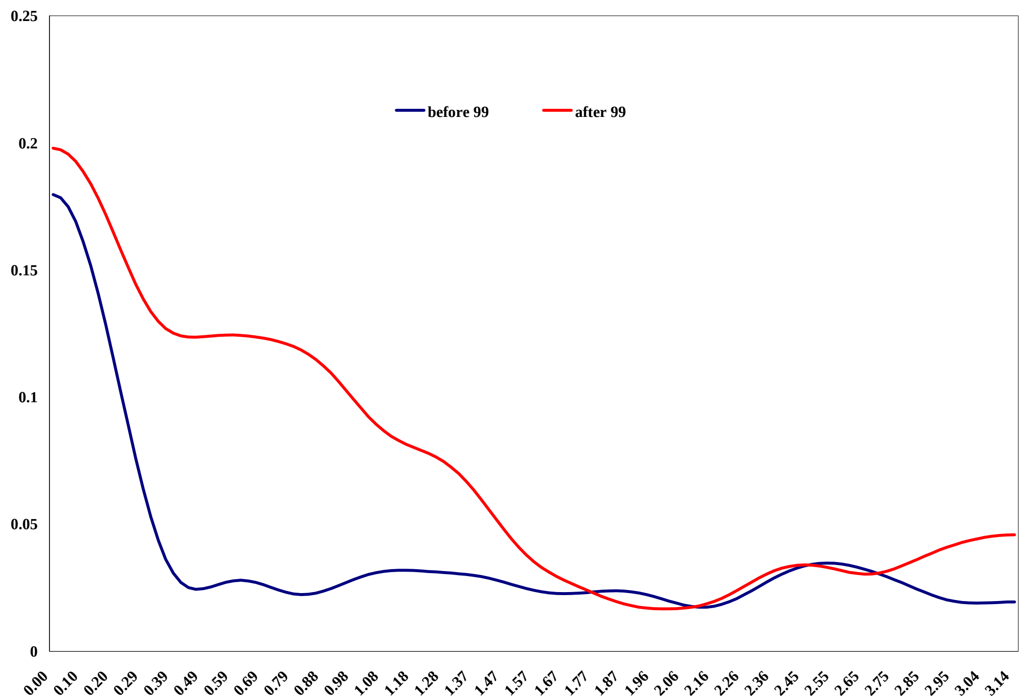


Chart 7 - Cohesion in weekly DD changes
(sample of 28 large banks)

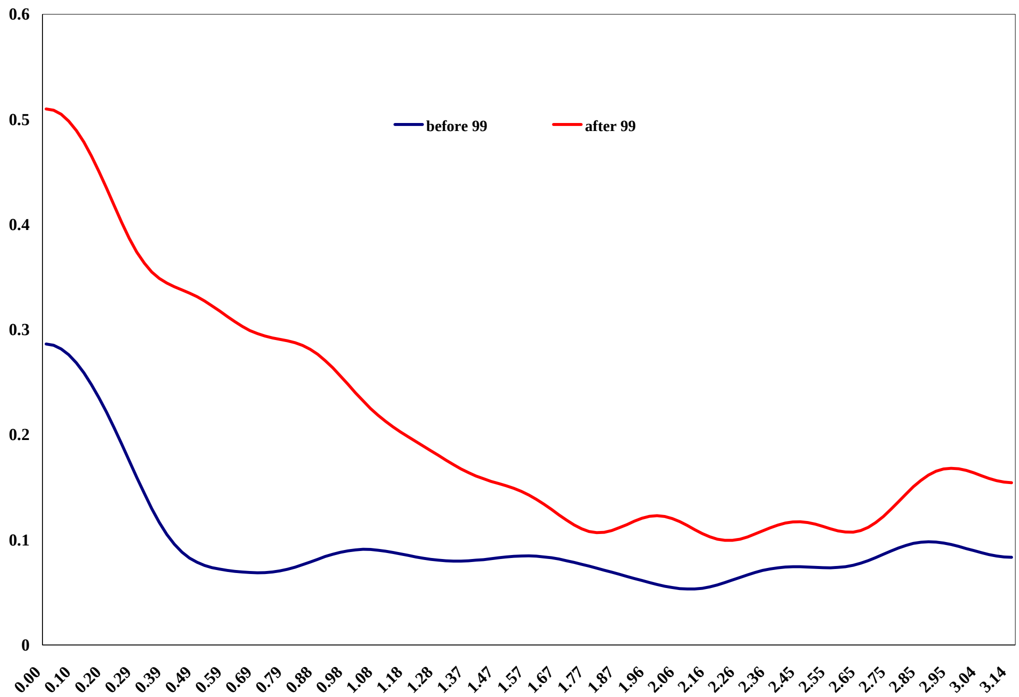


Table 5 - Variance decomposition of DD changes
(Average variance explained by each extracted component)

		Weekly changes		Monthlychanges	
		1995-1998	**1999-2004**	**1995-1998**	**1999-2004**
All countries	EU-wide	0.102	0.188	0.336	0.526
	National	0.180	0.134	0.492	0.191
	Idiosyncratic	0.718	0.678	0.172	0.282
Italy	EU-wide	0.078	0.288	0.349	0.624
	National	0.167	0.074	0.467	0.113
	Idiosyncratic	0.755	0.638	0.184	0.263
Spain	EU-wide	0.117	0.202	0.333	0.513
	National	0.189	0.091	0.527	0.199
	Idiosyncratic	0.694	0.707	0.140	0.288
Germany	EU-wide	0.079	0.180	0.334	0.524
	National	0.191	0.078	0.486	0.158
	Idiosyncratic	0.730	0.742	0.180	0.318
France	EU-wide	0.066	0.216	0.341	0.547
	National	0.208	0.099	0.493	0.139
	Idiosyncratic	0.726	0.685	0.166	0.315
UK	EU-wide	0.173	0.207	0.337	0.531
	National	0.148	0.108	0.507	0.204
	Idiosyncratic	0.679	0.685	0.156	0.265
Large banks	EU-wide	0.167	0.339	0.329	0.687
	National	0.200	0.120	0.510	0.114
	Idiosyncratic	0.634	0.541	0.161	0.199

Chart 8 – Frequency distribution of the variance explained by the EU component (weekly DD changes)

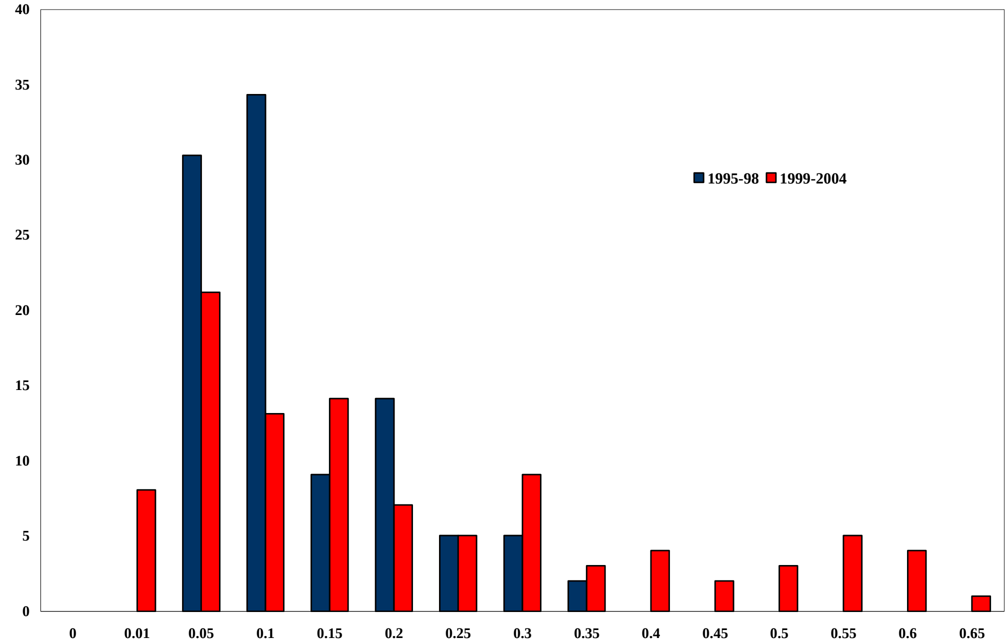


Chart 9– Frequency distribution of the variance explained by the EU component (monthly DD changes)

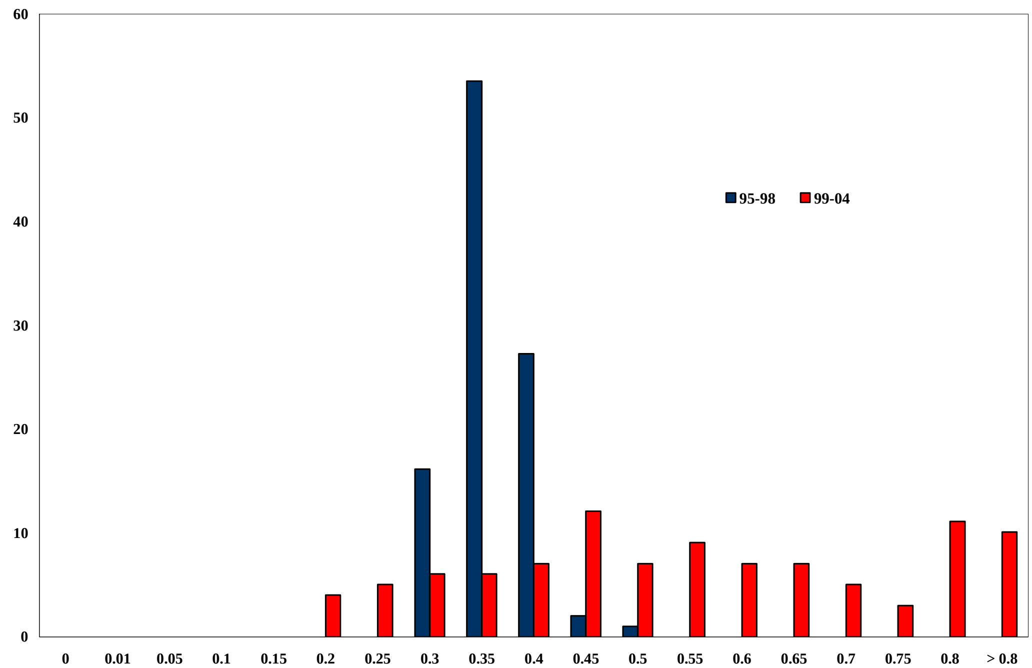


Table 6 - Variance decomposition of weekly DD changes (selected sample of 28 large banks)

		1995-1998			1999-2004		
Bank name	**Country**	**EU-wide**	**National**	**Idiosyncratic**	**EU-wide**	**National**	**Idiosyncratic**
Commerzbank	DE	0.173	0.417	0.411	0.623	0.171	0.207
Banco Santander Central Hispano	ES	0.185	0.055	0.760	0.582	0.131	0.286
Banca Intesa	IT	0.097	0.070	0.833	0.561	0.122	0.317
BBVA	ES	0.265	0.051	0.684	0.560	0.118	0.321
BNP Paribas	FR	0.081	0.714	0.205	0.550	0.221	0.228
ING	NL	0.290	0.061	0.649	0.534	0.072	0.394
Capitalia	IT	0.084	0.297	0.619	0.515	0.077	0.408
San Paolo-IMI	IT	0.079	0.147	0.774	0.505	0.018	0.478
Societe Generale	FR	0.165	0.610	0.224	0.486	0.262	0.252
Fortis Bank	BE	0.309	0.091	0.600	0.484	0.281	0.235
Deutsche Bank	DE	0.205	0.463	0.333	0.442	0.153	0.405
Barclays	UK	0.314	0.112	0.574	0.389	0.094	0.518
UniCredito Italiano	IT	0.180	0.141	0.679	0.375	0.046	0.579
ABN Amro Holding NV	NL	0.160	0.042	0.798	0.354	0.133	0.512
KBC Bank NV	BE	0.261	0.188	0.551	0.348	0.361	0.291
Skandinaviska Enskilda Banken AB	SE	0.178	0.036	0.786	0.308	0.078	0.614
Royal Bank of Scotland	UK	0.157	0.307	0.535	0.290	0.105	0.605
Bayerische Hypo-und Vereinsbank AG	DE	0.162	0.327	0.510	0.275	0.194	0.531
HBOS - MARKET VALUE	UK	0.153	0.177	0.669	0.243	0.279	0.478
Natexis Banques Populaires	FR	0.063	0.099	0.838	0.227	0.046	0.726
HSBC Holdings Plc	UK	0.279	0.106	0.615	0.160	0.048	0.792
Abbey National Plc	UK	0.185	0.195	0.620	0.149	0.173	0.678
Standard Chartered Plc	UK	0.078	0.177	0.745	0.138	0.033	0.829
Bankgesellschaft Berlin AG	DE	0.081	0.051	0.868	0.127	0.054	0.818
Svenska Handelsbanken	SE	0.213	0.030	0.757	0.102	0.035	0.863
Danske Bank A/S	DK	0.162	0.344	0.493	0.093	0.004	0.903
DePfa Deutsche Pfandbrief Bank AG	DE	0.084	0.262	0.655	0.047	0.052	0.901
Eurohypo AG	DE	0.021	0.019	0.960	0.011	0.003	0.986

Table 7: Variance decomposition of monthly DD changes (selected sample of 28 large banks)

		1995-1998			1999-2004		
Bank name	**Country**	**EU-wide**	**National**	**Idiosyncratic**	**EU-wide**	**National**	**Idiosyncratic**
Fortis Bank	BE	0.348	0.561	0.092	0.876	0.043	0.080
Banco Santander Central Hispano	ES	0.346	0.577	0.078	0.852	0.027	0.121
Commerzbank	DE	0.350	0.583	0.067	0.848	0.031	0.121
San Paolo-IMI	IT	0.260	0.413	0.327	0.842	0.036	0.122
Banca Intesa	IT	0.379	0.421	0.200	0.841	0.051	0.108
Deutsche Bank	DE	0.350	0.595	0.054	0.833	0.049	0.118
BBVA	ES	0.327	0.549	0.125	0.811	0.050	0.139
ING	NL	0.336	0.423	0.241	0.795	0.019	0.186
UniCredito Italiano	IT	0.329	0.564	0.107	0.793	0.039	0.168
BNP Paribas	FR	0.352	0.568	0.081	0.788	0.088	0.125
ABN Amro Holding NV	NL	0.306	0.479	0.215	0.787	0.048	0.165
Capitalia	IT	0.361	0.461	0.179	0.783	0.087	0.129
Skandinaviska Enskilda Banken AB	SE	0.307	0.372	0.321	0.783	0.027	0.191
KBC Bank NV	BE	0.345	0.579	0.077	0.777	0.123	0.100
Barclays	UK	0.296	0.513	0.191	0.763	0.071	0.166
Societe Generale	FR	0.352	0.596	0.052	0.763	0.091	0.146
Royal Bank of Scotland	UK	0.327	0.586	0.088	0.694	0.117	0.189
Bayerische Hypo-und Vereinsbank AG	DE	0.293	0.434	0.273	0.686	0.139	0.176
Svenska Handelsbanken	SE	0.285	0.464	0.252	0.675	0.108	0.217
Abbey National Plc	UK	0.339	0.545	0.116	0.609	0.146	0.245
Natexis Banques Populaires	FR	0.391	0.483	0.127	0.550	0.141	0.309
Standard Chartered Plc	UK	0.313	0.581	0.106	0.530	0.231	0.239
HBOS - MARKET VALUE	UK	0.337	0.553	0.110	0.493	0.281	0.226
Danske Bank A/S	DK	0.345	0.572	0.084	0.458	0.133	0.408
DePfa Deutsche Pfandbrief Bank AG	DE	0.346	0.588	0.066	0.456	0.167	0.377
Eurohypo AG	DE	0.268	0.175	0.557	0.448	0.201	0.351
Bankgesellschaft Berlin AG	DE	0.290	0.504	0.206	0.371	0.383	0.246
HSBC Holdings Plc	UK	0.332	0.541	0.127	0.337	0.251	0.412

Table 8 - Variance decomposition of monthly DD changes

	1995-98	**1999-04**
EU macro factors	0.31	0.21
Domestic macro factors	0.11	0.08
Banking sector specific factors	0.58	0.71
- EU wide	0.20	0.36
- Domestic	0.28	0.14
- Bank specific (idiosyncratic)	0.10	0.21

References

Angelini E., J Henry, R. Mestre (2001) "*Diffusion index-based forecasts for the euro area*", ECB Working Paper num. 61, April 2001.

Bai J. and S. Ng (2002) "*Determining the Number of Factors in Approximate Factor Models*", Econometrica, Vol. 70, No. 1, pp 191-221.

Billio M. and L. Pellizzon (2002) "*Contagion and interdependence in stock markets: have they been misdiagnosed ?"*, GRETA Working Paper num 02.08, December

Bongini, P., L. Laeven and G. Majnoni (2002) "*How Good is the Market at Assessing Bank Fragility? A Horse Race between Different Indicators*", Journal of Banking and Finance 26 (5), pp. 1011-1028.

Camacho M. and I. Sancho (2003) *"Spanish diffusion indexes*", Spanish economic review, Vol. 5, No. 3, 2003, pp. 173-203

Cabral I., F. Dierick and J. Vesala (2002) *"Banking Integration in the euro area*", ECB Occasional Paper, num. 6, November

Croux C., M. Forni and L. Reichlin (2001) "*A measure of co-movement in economic variables: theory and empirics*", mimeo

De Bandt O. and P. Hartmann (2000) *"Systemic risk: a survey"*, ECB Working Paper num. 35, November

De Nicolò G. and M. Kwast (2002) *"Systemic risk and financial consolidation: are they related ?"*, Journal of Banking and Finance 26, pp. 861-880

Emiris M. (2002) "*Measuring capital market integration"*, BIS papers num. 12, August

Fama E. and K. French (1993) "Common Risk Factors in the Returns on Stocks and Bonds", Journal of Financial Economics, 33, pp 3-56

Forni M. and L. Reichlin (1998) "*Let's Get Real: A Dynamic Factor Analytic Approach to Disaggregated Business Cycle*", Review of Economic Studies, 65, pp. 453-473

Forni M. and L. Reichlin (2001) "*Federal Policies and Local Economies: Europe and the US*", European Economic Review 45 pp 109-134.

Forni M., M. Hallin, M. Lippi and L. Reichlin (2000) "*The Generalised Dynamic Factor Model: Identification and Estimation*", The Review of economics and statistics 82 pp 540-554

Galati G. and K. Tsatsaronis (2001) "*The impact of the euro on Europe's financial markets"*, BIS Working Papers num. 100, July

Gropp R. and G. Moerman (2003) "*Measurement of contagion in banks' equity prices*", ECB Working Paper num. 297

Gropp R. and J. Vesala (2004) "*Bank Contagion in Europe*", mimeo, Frankfurt am Main

Gropp R., J. Vesala and G. Vulpes (2002) "*Equity and bond market signals as leading indicators of bank fragility*", ECB Working Paper num. 150, June 2002, forthcoming in the Journal of Money Credit and Banking

Gropp R., J. Vesala and G. Vulpes (2004) "M*arket indicators, bank fragility and indirect market discipline*", Federal Reserve Bank of New York Policy Review, vol. 10 num. 2, pp. 53-62

Hawkesby C., I. Marsh and I. Stevens (2003) "*Large complex financial institutions: common influences on asset price behaviour ?",* Financial Stability Review, num. 15, pp. 124-134, Bank of England, December

Hawkesby C., I. Marsh and I. Stevens (2005) "*Comovements in the prices of securities issued by large complex financial Institutions"*, Bank of England Working Paper No. 256

Hartmann P., A. Maddaloni and S. Manganelli (2003) *"The euro-area financial system: structure, integration and policy initiatives",* Oxford Review of Economic Policy, vol. 19, num. 1

KMV (2003) "*Modelling Default Risk*", KMV Corporation, San Francisco

Krainer, J. and J. Lopez (2003) "*Forecasting Bank Supervisory Ratings Using Securities Market Information*" Paper presented at the RTF Workshop on Applied Banking Research, Rome, March

Lehar A. (2003) *"Implementing a portfolio perspective in banking supervision"*, mimeo, University of Vienna, June

Merton, R. (1977) "*An Analytic Derivation of the Cost of Deposit Insurance and Loan Guarantees*", Journal of Banking and Finance 1, pp. 3-11.

Nickell P. and W. Perraudin (2001) "*How much bank capital is needed to maintain financial stability ?"*, mimeo

Pain D. and J. Vesala (2004) "*Driving factors of credit risk in Europe"*, mimeo, European Central Bank

Pesaran M., T. Schuermann, B. Treutler and S. Weiner (2003), "*Macroeconomic Dynamics and Credit Risk: A Global Perspective*", mimeo

Sargent T. J. and C. A. Sims (1977) "*Business Cycle Modelling Without Pretending to Have Too Much a priori Economic Theory*" in C. A. Sims (Ed), New Methods in Business Research (Minneapolis: Federal Reserve Bank of Minneaopolis)

Stock J. and M. Watson (1998), "*Diffusion Indexes*", NBER Working paper No. W6702

Upper C. and A. Worms (2000), "*Estimating bilateral exposures in the German Interbank market: is there a danger of contagion ?"*, mimeo, Deutsche Bundesbank