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. 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 at EU-wide level).

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Introduction

The aim of this paper is to 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.

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.

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 this context, we follow a recent paper by Pain and Vesala (2004), who examine the drivers of credit risk in a sample of EU non-financial corporates. To this end, they use an approximate dynamic factor model, similar to the one employed here, to decompose the Moody's-KMV Expected Default Frequency into a EU-wide, country, sector and firm specific components.

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) 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 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. In addition, we find the presence of some regional clusters of correlations, namely the fact that banks in some countries appear more closely interconnected with banks in certain other countries. 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 commonality in economic cycles among EU countries, but also 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).

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 conduct some robustness checks to the methodology employed in the paper, while section 5 concludes and suggests 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 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).

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.

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

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, 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 88 listed banks for which stock market data (stock price and market capitalisation) and debt are available during the period from 25 November 1994 to 16 January 2004.

We estimated the dynamic factor model by using first 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 57 banks incorporated in 13 EU countries (Luxembourg and Austria are not represented), with 481 weekly observations per bank. We also estimated the dynamic factor model with an unbalanced panel in order to increase the number of cross-sections considered. To this end, we reconstructed backwards and forwards the times series for those banks with missing data by means of the EM algorithm (Engle and Watson (1983), Stock and Watson (1998)). The list of banks with their total assets, country of incorporation and the indication of whether they belong to the balance or unbalanced sample case is reported in Table 1.

The banks in the sample are relatively large (the average asset size amounts to about EUR 150 bln), but there is also a discrete presence of small-mid sized banks. The largest bank in the sample is Deutsche Bank (end 2002 total assets of about EUR 760 bln), while the smallest is Banque Worms with slightly more than EUR 1 bln of total assets.

The distribution of the banks by country highlights the relatively high presence of Italian banks (13 banks in the balanced sample, 19 banks in the unbalanced), while some large countries are relatively underrepresented (there are only 3 French banks in the balanced sample). 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).[1] 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.

In any event, in section 4 we conduct a robustness check on the extraction procedure of the three unobserved components by using a different approach, i.e. partly following the strategy suggested by Forni and Reichlin (2001).

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.

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

[1] 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 $(N,T) \rightarrow \infty$.

changes[2]. The correlations were calculated for the balanced sample of 57 banks considering the entire period, and the periods before and after 1 January 1999. Results are summarised in Table 2.

In general, the average correlation in bank risk does not appear particularly high (18% for weekly changes, which goes up to 22% 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 is dominant over the cross-border one: while the average domestic correlation stands at 37% (both for the weekly and the monthly changes), the cross-border one equals only 14% (19% for monthly changes). Note, however, that the distinction made is not fully 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.

Nonetheless, this result was somehow expected as small and mid sized banks are largely affected by developments in their country of incorporation or by idiosyncratic shocks. In other words, this result would suggest that only a set of (large) banks is being exposed to EU-wide shocks.

However, the results also highlight two basic facts. First, the increase in correlation since 1999, which suggests that the degree of commonality is growing. Second, the rise in cross border correlation in the same period. The average cross-border correlation in the period 1995-1998 is 11% (14% for monthly changes), while in the period 1999-2003 it goes up to 17% (24% for monthly changes)[3].

From the correlation analysis the presence of some regional clusters of correlation also emerges, namely the fact that banks in some countries appear more closely interconnected with banks in certain other countries. For instance, the average correlation of DDs changes between Dutch banks and Belgian banks (39%) appears even higher than the domestic correlation observed for the Dutch banks only (34%). This is probably due to the proximity of the two countries, but also to the fact that the Dutch and Belgian banks in our sample are rather large compared to the size of their countries, which means that such banks undertake extensive cross-border activities. Once again, the cross-country correlation tends to increase since 1999.

We also looked at the correlation in bank fragility among a set of large banks defined as those with total assets as of end 2002 above 100 bln euro (26 banks belonging to 9 EU countries). In this case, the correlation appears significantly higher and patterns of cross-country correlation clearly emerge. Again, the average correlation in bank fragility between Belgian and Dutch banks appears relatively high (44% but it goes up to 52% since 1999), but also the correlations among large Dutch and Spanish banks

[2] Weekly changes are very informative when the focus is on contagion. It must be said that even monthly changes may contain a lot of noise, however considering quarterly or yearly changes introduces non-stationarity in the DD changes.

[3] A t-test on the mean difference between the cross-border correlations in the two sample periods highlights the fact that the correlation in the second period is significantly higher than the correlation in the first period.

(50%, up to 67% since 1999), and, to a lesser extent, among Italian and Spanish banks (35% up to 47% since 1999) appear relevant.

Finally, there are several cases in which the correlation in bank fragility appears particularly high even at the cross-border level. To name just a few of them (taking the after 1999 period and focusing on weekly correlations): the correlation among Societè Generale (France) and ABN AMRO (The Netherlands), 61%; the one among Banco Santander (Spain) and ING (The Netherlands), 74%; the correlation among Commerzbank (Germany) and Banca Intesa (Italy), 56%. We believe that even these correlations are important for the analysis of co-movements in bank fragility (and for financial stability purposes). Indeed, one can easily demonstrate that, under certain conditions, even a single large correlation between the riskness of two banks incorporated in different countries might be sufficient for having significant cross-border co-movements in bank fragility.

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

Correlations at leads and lags and dynamic correlations

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. In addition, this enables to take into account the heterogeneity among banks in the propagation of common shocks.

In Table 3 are reported the average correlations at several leads and lags (we considered 3 leads and lags) between weekly and monthly DD changes. When calculated on the weekly changes they appear lower than the contemporaneous correlations, but in a number of cases they appear significant, especially at the cross border level.[4]
The average cross-correlations are higher when referred to the monthly changes. At lead 1 and lag 1 they appear as large as the contemporaneous ones, but they look significant also at other leads and lags. This would suggest that including leads and lags of DD changes in the factor model increases its explicative power.

These results also highlight 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.

[4] This is true in particular when considering the correlations in the DD changes between large and mid-sized banks. For example cross-correlations in the weekly DD changes between UniCredit (a large Italian bank) and Banco Pastor (a Spanish mid-size bank) are much larger at leads and lags than the contemporaneous ones.

Such difference also emerges by considering 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.

In the same way, 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.

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[5].

In Charts 1 we report the cohesion on weekly changes, for the two sub-periods 1995-1998 and 1999-2003 (sample of 57 banks) [6]. These charts clearly show the increase in co-movements between the two periods. In addition, while before 1999, co-movements are concentrated only at low frequencies (i.e. bank risk co-moves only in the long-term), after 1999 there is evidence of co-movements even at cyclical frequencies. This picture clearly emerges by calculating cohesion on the monthly DD changes, which enables to get a clearer picture of cycles at medium and low frequencies (not reported). In particular, in the post 1999 period there is a noticeable peak in cohesion at frequencies corresponding to two and a half months and 18 months.

Finally, we ran the exercise for the sample of 26 large banks (Chart 2). 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.

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

[5] 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.
[6] 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). Since use weekly data for about 210 observations this means that a frequency of for example 1.55 corresponds to a cycle of approximately 4 weeks.

(i.e. high frequencies), which is coherent with the commonality in economic cycles among EU countries found in literature, but also with the increasing integration in the EU banking system (Cabral et. al. (2002)).[7] 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.

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

[7] 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.

estimated by means of an approximate dynamic factor model à-la Stock and Watson[8] (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.

While the estimation of the EU common factor should not constitute a major problem, the extraction of the national component may be more problematic given the limited number of cross-sections (banks) for each country in the balanced panel. For this reason, we increased the size of the cross-sections employed in the model by means of the EM algorithm (Engle and Watson (1983), Stock and Watson (1999)). Essentially, this algorithm consists of an iterative maximization procedure of the likelihood function, which is done in two steps. In the first step an estimation of missing observations is carried out, conditional on parameters calculated on the available information. The model is, then, re-estimated on the basis of the enlarged data set. The two steps are repeated until convergence is achieved (namely, until the improvement in the likelihood function gained in each iteration is above a certain threshold).

However, even after this procedure the size of the sample for some countries might not be sufficient to consistently estimate the country component of bank fragility. In essence, because of the limited size of the sample for some countries, this means that the idiosyncratic component might not be completely washed out. As noted, given that the focus of this paper is in measuring the weight of the EU component this should not constitute a major issue.

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.

[8] 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).

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[9]. For the monthly changes the Bai and Ng criteria identified two factors.

Model's results

In tables 4 and 5 we report the average across banks of the variance explained by the three components for the whole sample and a set of selected countries in the two sub-samples 1995-1998 and 1999-2003 (weekly DD changes and monthly changes respectively). The tables also display separately the results for the balanced and unbalanced samples.

Our results show that the degree of commonality is quite clearly growing. The EU-wide and national components altogether go up to 35% since 1999, from 27% in the period 1995-1998 in the case of weekly DD changes. Further, the increase in commonality is completely due to the EU-wide component, which rises to 22.2% since 1999 from 12.2% before 1999.

Co-movements in bank fragility appear larger when monthly changes are considered. In such a case, in the post 1999-period, the EU-wide component explains 40% of the variance in monthly DD changes (up from 25.4% in the before 1999 period). 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 DDs. This probably reflects the reduction in noise implied in the monthly changes vs. the weekly changes.

Results do not differ significantly when the balanced sample is considered instead of the unbalanced one, which is rather comforting as regards the consistency of the EM algorithm procedure. The only significant difference in the results between the two samples is found for French banks. In this case, the share of variance explained by the EU factor in the period 1999-2003 drops from 57% to 37% (monthly DD changes – Table 7b) in the balanced and unbalanced samples respectively. This is attributable to the fact that the there are only 3 (relatively large) French banks in the balanced sample, against 10 in the unbalanced, which tends to amplify the EU wide component.

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 (19.4%) is the smallest. Similar findings are obtained with the monthly DD changes.

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

The increase in the weight of the EU-wide component clearly appears from Chart 3, 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 slightly less than 10%, since 1999 such percentage goes up to about 42%. Moreover, for 14.3% of the 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 4 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 17.2% of the period 1995-1998 to 37.9% in the period 1999-2003. 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).

Again, these results are even more striking when monthly changes are considered. In particular, Chart 4 shows that, in the after-1999 period, for about 14% of the banks in the sample 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.
The results obtained for this set of banks tend to confirm, as also found in the cohesion analysis, a propagation mechanism of common shocks, which goes from large to smaller banks.

4 Robustness checks

A different extraction procedure of the unobserved components

The decomposition of the DD changes by means of the dynamic factor model estimated in the previous section is based on a sequential procedure, which yields, in the first instance, the EU-wide common factor, and secondly the extraction of the national component from the residuals obtained in the first step. As noted, one critical element of this extraction procedure resides in the relatively small size of the sample, which may constitute a problem when estimating the national component of bank fragility.

In order to verify to which extent this small sample size issue affects our results, we proceeded to extract the three unobserved components by resorting to a different procedure. In this case, we adopted in part the strategy suggested by Forni and Reichlin (2001). Basically, this method entails a procedure which is the reverse of the one employed in the previous section. Hence, the idiosyncratic components of bank fragility are washed out first, and subsequently the national and EU-wide components are extracted.

More specifically, we isolate the idiosyncratic components from the national and EU-wide ones by running the dynamic factor model for each set of banks incorporated in the same country. The component obtained is therefore a bundle of national and EU-wide factors.

We then take this extracted component and, applying the factor model to it, we yield the EU-wide common factor. The national component is, therefore, simply given by the residuals of this second step.

In Table 8 we report the results of this exercise (only for monthly DD changes referred to the period 1999-2003). By comparing them with those obtained in the previous section, the contribution of the EU-wide component to the total variance of monthly DD changes appears significantly lower (27.2% vs. 40.4%). This result is clearly owing to the procedure used, suggesting that a portion of the EU component (non national) is absorbed by the idiosyncratic one in the first step of the procedure. In other words this tends to suggests that, because of the relatively low number of banks in each country, the idiosyncratic is not completely washed out, indicating that the procedure used in the previous section provides a less biased decomposition of the DD changes variance since it is not as much affected by this small sample size issues (at least as far as the estimation of the EU wide factor is concerned).

Nevertheless, even with this alternative extraction procedure the EU component appears not negligible and clearly dominates over the national one. Further, it is confirmed the ranking of the countries in terms of contribution of the EU component to DD changes variance.

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 40% 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 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 up to 80% of the variance in bank risk. Further, this set of banks constitutes the transmission channel of common shocks. Third, 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 the commonality in economic cycles among EU countries. However, we notice that co-movements at very high frequencies (i.e. in the very short term) are relevant for large banks, which could 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 limited to small-medium sized banks whilst for large banks our results suggest at minimum 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 fact that, as noted, our results could point to some form of contagion among this set of banks.

The results obtained in the paper lend themselves also to a number of potential extensions and applications. Firstly, having found that EU banks are subject to common shocks 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 EU macro shocks and to which extent there is something else that could explain its dynamics. 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 – Description of the sample

Nr	Bank name	Country of incorporation	Total assets (EUR mln)*	Balanced / Unbalanced	Nr	Bank name	Country of incorporation	Total assets (EUR mln)*	Balanced / Unbalanced
1	Bank Austria AG	Austria	128,470	Unbalanced	45	Banca Popolare di Intra	Italy	4,451	Balanced
2	Creditanstalt AG (1)	Austria	34,040	Unbalanced	46	Banca Popolare di Lodi	Italy	35,911	Balanced
3	Erste Bank	Austria	121,222	Unbalanced	47	Banca Popolare di Milano SCaRL	Italy	32,520	Balanced
4	Bank Brussel Lambert / ING Belgium	Belgium	114,865	Unbalanced	48	Banca Popolare di Sondrio SCarl	Italy	10,185	Unbalanced
5	Dexia Banque Belgique	Belgium	209,150	Unbalanced	49	Banco Desio - Banco di Desio e della Brianza SpA	Italy	3,678	Unbalanced
6	Fortis Bank	Belgium	377,728	Balanced	50	Banco di Napoli (2)	Italy	30,443	Unbalanced
7	KBC Bank NV	Belgium	208,501	Balanced	51	Capitalia SpA	Italy	140,916	Balanced
8	Danske Bank A/S	Denmark	235,870	Balanced	52	Credito Valtellinese SCarl	Italy	9,430	Balanced
9	Jyske Bank A/S (Group)	Denmark	20,633	Balanced	53	Credito Emiliano SpA	Italy	18,996	Balanced
10	OKO Bank-OKO Osuuspankkien Keskuspankki Oyj	Finland	12,709	Balanced	54	Rolo Banca 1473 S.P.A. (2)	Italy	50,428	Unbalanced
11	Sampo Plc	Finland	25,094	Balanced	55	San Paolo IMI	Italy	199,351	Balanced
12	BNP Paribas	France	710,305	Balanced	56	UniCredito Italiano SpA	Italy	213,339	Balanced
13	Compagnie Parisienne de Reescompte - CPR (2)	France	4,709	Unbalanced	57	ABN Amro Holding NV	Netherlands	556,018	Balanced
14	Credit Agricole	France	580,795	Unbalanced	58	ING Bank NV	Netherlands	477,111	Balanced
15	Credit Lyonnaise	France	244,886	Unbalanced	59	Kas Bank NV	Netherlands	6,463	Balanced
16	Entenial	France	13,372	Unbalanced	60	Van Lanschot	Netherlands	11,289	Unbalanced
17	Crédit Foncier de France	France	43,857	Unbalanced	61	Banco BPI (2)	Portugal	23,575	Balanced
18	Natexis Banques Populaires	France	133,400	Balanced	62	Banco Comercial Português, SA	Portugal	61,851	Balanced
19	Société Générale	France	501,265	Balanced	63	Banco Espirito Santo SA	Portugal	41,234	Balanced
20	Banque Worms	France	1,277	Unbalanced	64	Banco Totta & Açores, SA	Portugal	26,864	Unbalanced
21	Baden - Wuertt. Bank	Germany	26,058	Balanced	65	Banco Español de Crédito SA, BANESTO	Spain	49,510	Balanced
22	Bankgesellschaft Berlin AG	Germany	173,599	Balanced	66	Banco Guipuzcoano SA	Spain	5,044	Balanced
23	Bayerische Hypo-und Vereinsbank AG	Germany	678,340	Balanced	67	Banco Pastor SA	Spain	8,870	Balanced
24	Commerzbank AG	Germany	421,809	Balanced	68	Banco Popular Espanol SA	Spain	41,899	Balanced
25	DePfa Deutsche Pfandbriefbank AG (2)	Germany	180,899	Balanced	69	Banco Santander Central Hispano	Spain	319,030	Balanced
26	Deutsche Bank AG - IAS	Germany	758,256	Balanced	70	Banco Zaragozano SA	Spain	5,826	Unbalanced
27	Dresdner Bank AG - IAS	Germany	413,375	Unbalanced	71	Banco Bilbao Vizcaya Argentaria SA	Spain	274,934	Balanced
28	HSBC Trinkaus & Burkhardt KGaA - IAS	Germany	11,049	Balanced	72	Foereningssparbanken - Swedbank	Sweden	99,981	Unbalanced
29	IKB Deutsche Industriebank AG	Germany	36,336	Balanced	73	Skandinaviska Enskilda Banken AB	Sweden	128,457	Balanced
30	ING BHF-BANK AG	Germany	58,687	Unbalanced	74	Svenska Handelsbanken	Sweden	134,328	Balanced
31	Alpha Bank AE	Greece	28,725	Balanced	75	HBOS plc	United Kingdon	488,385	Unbalanced
32	Emporiki Bank of Greece SA	Greece	16,891	Balanced	76	Abbey National Plc	United Kingdon	270,925	Balanced
33	Allied Irish Banks plc	Ireland	83,647	Balanced	77	Alliance & Leicester PLC	United Kingdon	63,400	Unbalanced
34	Anglo Irish Bank Corporation Plc	Ireland	19,339	Balanced	78	Bank of Scotland	United Kingdon	318,302	Unbalanced
35	Bank of Ireland	Ireland	84,128	Balanced	79	Barclays Bank Plc	United Kingdon	608,238	Balanced
36	First active	Ireland	6,976	Unbalanced	80	Close Brothers Limited	United Kingdon	3,908	Balanced
37	Banca Intesa SpA	Italy	277,418	Balanced	81	HSBC Bank plc	United Kingdon	330,635	Balanced
38	Banca Monte dei Paschi di Siena	Italy	128,730	Unbalanced	82	Lloyds TSB Bank Plc	United Kingdon	321,489	Unbalanced
39	Banca Lombarda e Piemontese SpA	Italy	30,022	Balanced	83	National Westminster Bank Plc - NatWest	United Kingdon	264,193	Unbalanced
40	Banca Nazionale del Lavoro SpA - BNL	Italy	83,033	Balanced	84	Northern Rock PLC	United Kingdon	50,207	Unbalanced
41	Banca Popolare di Bergamo - Credito Varesino SpA	Italy	42,337	Unbalanced	85	Royal Bank of Scotland plc (The)	United Kingdon	364,567	Balanced
42	Banca Popolare Commercio e Industria SpA	Italy	20,363	Unbalanced	86	Schroders Plc	United Kingdon	3,778	Balanced
43	Banco Popolare di Verona e Novara	Italy	48,202	Balanced	87	Singer & Fried.	United Kingdon	3,218	Balanced
44	Banca popolare dell'Emilia Romagna	Italy	36,091	Balanced	88	Standard Chartered Plc	United Kingdon	107,766	Balanced

** as of end 2002*

Table 2 -Mean correlations in EU banks' DDs (Balanced sample of 57 banks)

		Weekly changes			Monthly changes		
		Total	Domestic	Cross-border	Total	Domestic	Cross-border
All banks	All sample period	0.18	0.37	0.14	0.22	0.39	0.19
	1995-1998	0.14	0.33	0.11	0.17	0.33	0.14
	1999-2003	0.20	0.39	0.17	0.27	0.43	0.24
Large banks	All sample period	0.29	0.50	0.25	0.35	0.56	0.30
	1995-1998	0.20	0.43	0.15	0.22	0.44	0.17
	1999-2003	0.35	0.53	0.31	0.46	0.63	0.43

Table3 -Mean correlations in DD changes at several leads and lags (Balanced sample of 57 banks)

		Weekly changes	Monthly changes
Lag	**1**	0.086	0.204
	2	0.070	0.167
	3	0.037	0.127
Lead	**1**	0.075	0.199
	2	0.072	0.164
	3	0.025	0.090

Chart 1 - Cohesion in weekly DD changes
(sample of 57 banks)

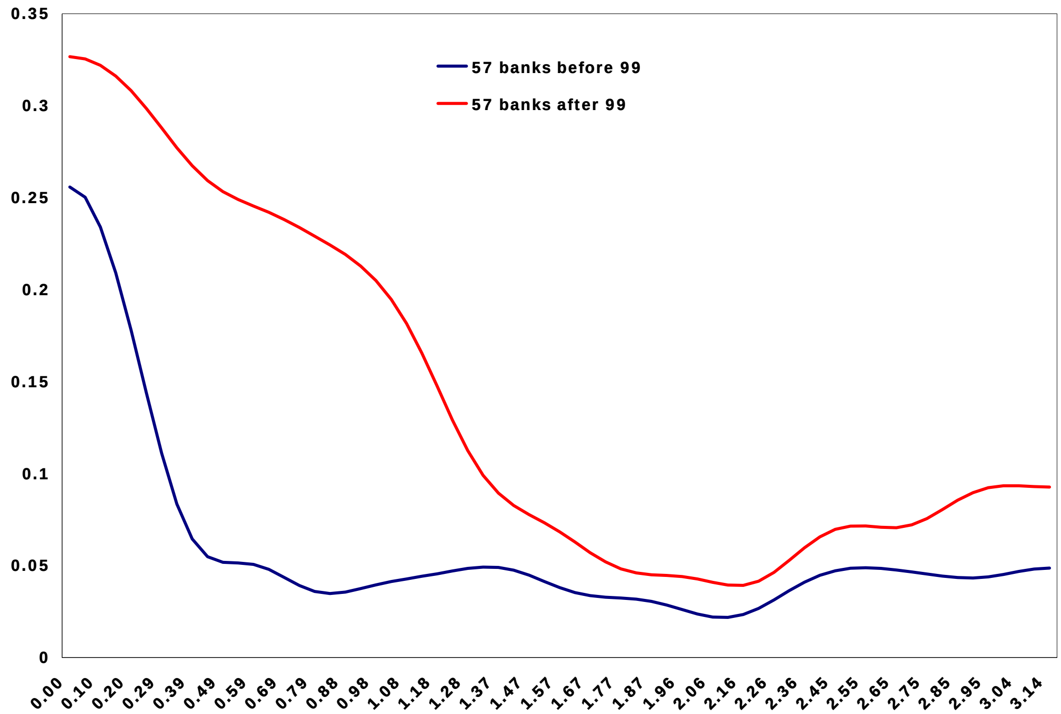

Chart 2 - Cohesion in weekly DD changes
(sample of 26 large banks)

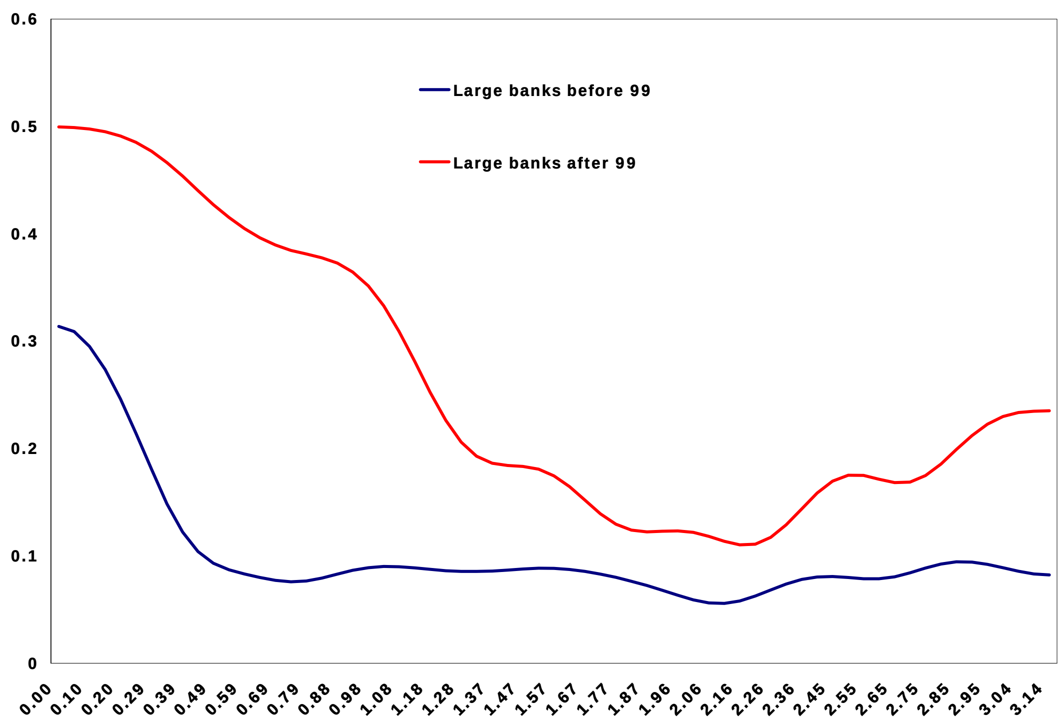

Table 4 - Variance decomposition of weekly DD changes
(Average variance explained by each extracted component)

		Balanced sample		Unbalanced sample	
		1995-1998	**1999-2003**	**1995-1998**	**1999-2003**
All countries	EU-wide	0.128	0.281	0.125	0.227
	National	0.165	0.121	0.146	0.120
	Idiosyncratic	0.707	0.599	0.729	0.654
Italy	EU-wide	0.064	0.328	0.060	0.271
	National	0.194	0.109	0.162	0.092
	Idiosyncratic	0.742	0.563	0.778	0.636
Spain	EU-wide	0.122	0.307	0.110	0.266
	National	0.208	0.181	0.184	0.165
	Idiosyncratic	0.670	0.511	0.706	0.569
Germany	EU-wide	0.116	0.232	0.123	0.194
	National	0.222	0.140	0.247	0.117
	Idiosyncratic	0.662	0.628	0.631	0.690
France	EU-wide	0.137	0.405	0.125	0.212
	National	0.043	0.085	0.072	0.095
	Idiosyncratic	0.820	0.510	0.802	0.693
UK	EU-wide	0.163	0.293	0.139	0.234
	National	0.120	0.090	0.135	0.169
	Idiosyncratic	0.717	0.617	0.726	0.597
Large banks	EU-wide	0.172	0.379	0.172	0.379
	National	0.195	0.107	0.195	0.107
	Idiosyncratic	0.632	0.513	0.632	0.513

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

		Balanced sample		Unbalanced sample	
		1995-1998	**1999-2003**	**1995-1998**	**1999-2003**
All countries	EU-wide	0.286	0.465	0.254	0.404
	National	0.301	0.189	0.272	0.184
	Idiosyncratic	0.413	0.346	0.473	0.413
Italy	EU-wide	0.192	0.521	0.184	0.452
	National	0.329	0.138	0.282	0.152
	Idiosyncratic	0.478	0.341	0.534	0.396
Spain	EU-wide	0.301	0.518	0.284	0.466
	National	0.334	0.145	0.347	0.145
	Idiosyncratic	0.365	0.337	0.369	0.390
Germany	EU-wide	0.268	0.391	0.287	0.335
	National	0.351	0.242	0.342	0.211
	Idiosyncratic	0.380	0.367	0.371	0.453
France	EU-wide	0.281	0.570	0.243	0.368
	National	0.289	0.090	0.190	0.140
	Idiosyncratic	0.431	0.340	0.568	0.492
UK	EU-wide	0.353	0.503	0.288	0.455
	National	0.258	0.180	0.244	0.235
	Idiosyncratic	0.389	0.317	0.468	0.310
Large banks	EU-wide	0.330	0.569	0.330	0.569
	National	0.294	0.145	0.294	0.145
	Idiosyncratic	0.376	0.286	0.376	0.286

Chart 3 – Frequency distribution of the variance explained by the EU component (weekly DD changes)

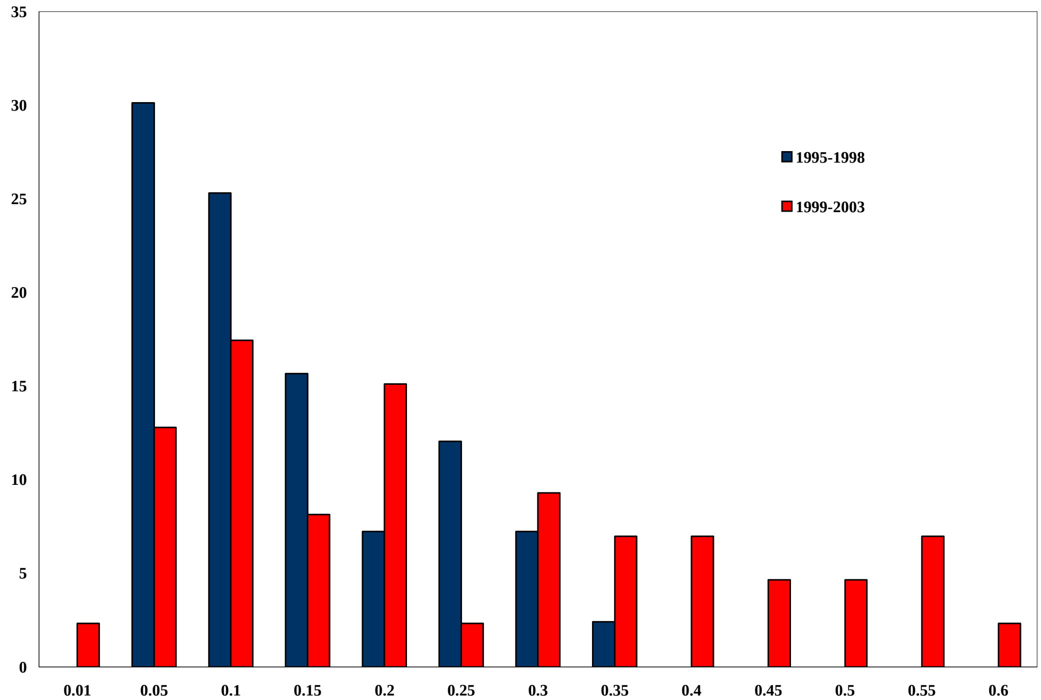

Chart 4– Frequency distribution of the variance explained by the EU component (monthly DD changes)

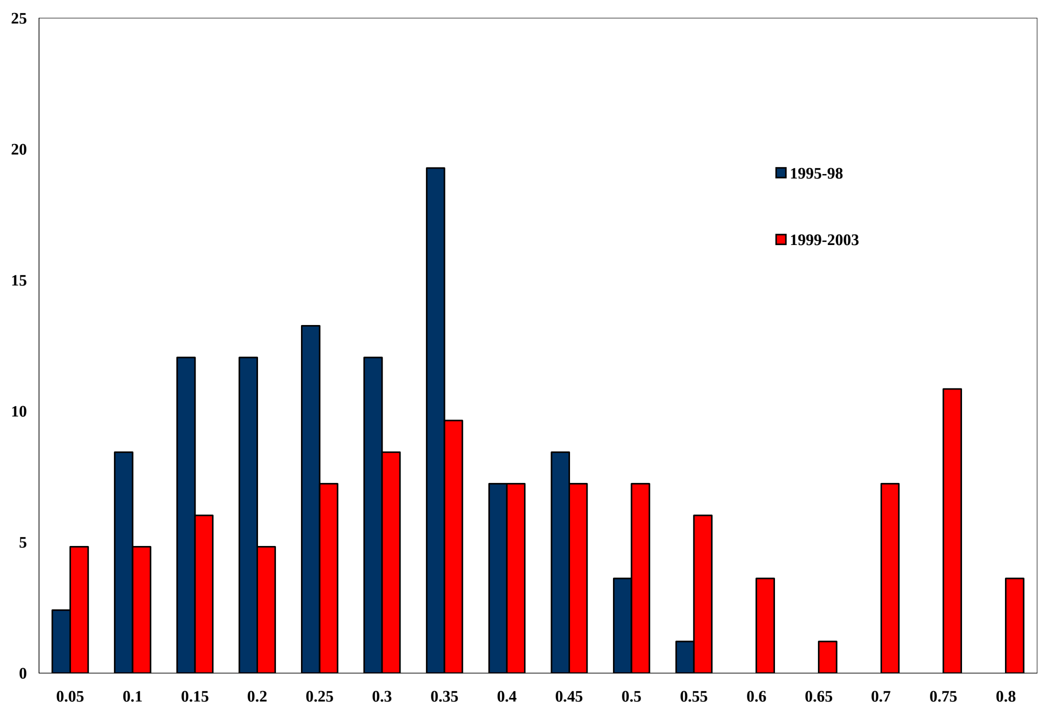

Table 6: Variance decomposition of weekly DD changes (selected sample of 26 large banks)

		1995-1998			1999-2003		
Bank name	**Country**	**EU-wide**	**National**	**Idiosyncratic**	**EU-wide**	**National**	**Idiosyncratic**
Fortis Bank	BE	0.281	0.029	0.690	0.552	0.020	0.429
Commerzbank	DE	0.204	0.421	0.375	0.551	0.029	0.420
Banco Santander Central Hispano	ES	0.196	0.308	0.495	0.545	0.306	0.149
Capitalia	IT	0.065	0.174	0.761	0.529	0.171	0.300
Banca Intesa	IT	0.082	0.064	0.854	0.516	0.142	0.342
ING	NL	0.321	0.039	0.640	0.511	0.109	0.381
San Paolo-IMI	IT	0.088	0.166	0.746	0.509	0.059	0.431
BBVA	ES	0.207	0.374	0.419	0.505	0.323	0.172
UniCredito Italiano	IT	0.170	0.142	0.687	0.490	0.103	0.407
BNP Paribas	FR	0.127	0.052	0.821	0.488	0.126	0.387
Barclays	UK	0.313	0.254	0.433	0.446	0.078	0.477
Royal Bank of Scotland	UK	0.148	0.198	0.654	0.440	0.032	0.529
Deutsche Bank	DE	0.264	0.453	0.283	0.435	0.014	0.551
Societe Generale	FR	0.202	0.039	0.759	0.431	0.118	0.451
Skandinaviska Enskilda Banken AB	SE	0.171	0.538	0.291	0.377	0.248	0.374
ABN Amro Holding NV	NL	0.175	0.115	0.710	0.349	0.083	0.568
Standard Chartered Plc	UK	0.091	0.042	0.867	0.339	0.021	0.640
KBC Bank NV	BE	0.202	0.072	0.725	0.324	0.043	0.633
Bayerische Hypo-und Vereinsbank AG	DE	0.207	0.227	0.567	0.300	0.037	0.662
Natexis Banques Populaires	FR	0.081	0.039	0.880	0.297	0.011	0.691
HSBC Holdings Plc	UK	0.208	0.162	0.630	0.253	0.070	0.678
Abbey National Plc	UK	0.207	0.165	0.628	0.180	0.065	0.755
Danske Bank A/S	DK	0.103	0.215	0.681	0.165	0.041	0.794
Svenska Handelsbanken	SE	0.190	0.567	0.243	0.159	0.446	0.395
Bankgesellschaft Berlin AG	DE	0.049	0.097	0.853	0.124	0.004	0.872
DePfa Deutsche Pfandbrief Bank AG	DE	0.122	0.127	0.751	0.050	0.092	0.858

Table 7: Variance decomposition of monthly DD changes (selected sample of 26 large banks)

		1995-1998			1999-2003		
Bank name	**Country**	**EU-wide**	**National**	**Idiosyncratic**	**EU-wide**	**National**	**Idiosyncratic**
Banco Santander Central Hispano	ES	0.358	0.323	0.322	0.795	0.143	0.062
UniCredito Italiano	IT	0.289	0.212	0.472	0.794	0.010	0.184
Commerzbank	DE	0.339	0.350	0.303	0.739	0.086	0.176
Banca Intesa	IT	0.138	0.459	0.412	0.733	0.146	0.119
BNP Paribas	FR	0.282	0.352	0.373	0.730	0.086	0.189
BBVA	ES	0.465	0.336	0.206	0.729	0.178	0.088
Capitalia	IT	0.106	0.279	0.620	0.720	0.115	0.157
Deutsche Bank	DE	0.485	0.292	0.226	0.713	0.010	0.267
ABN Amro Holding NV	NL	0.277	0.298	0.422	0.709	0.050	0.245
San Paolo-IMI	IT	0.286	0.200	0.523	0.707	0.106	0.183
ING	NL	0.339	0.331	0.328	0.705	0.101	0.190
Skandinaviska Enskilda Banken AB	SE	0.362	0.527	0.116	0.680	0.124	0.189
Societe Generale	FR	0.423	0.273	0.303	0.678	0.072	0.252
Barclays	UK	0.427	0.351	0.222	0.676	0.152	0.177
Fortis Bank	BE	0.329	0.244	0.449	0.671	0.177	0.151
Standard Chartered Plc	UK	0.523	0.135	0.347	0.564	0.142	0.297
Royal Bank of Scotland	UK	0.376	0.069	0.558	0.560	0.197	0.249
KBC Bank NV	BE	0.411	0.157	0.433	0.482	0.301	0.217
Bayerische Hypo-und Vereinsbank AG	DE	0.305	0.130	0.564	0.481	0.115	0.402
HSBC Holdings Plc	UK	0.288	0.520	0.201	0.396	0.267	0.347
Abbey National Plc	UK	0.409	0.243	0.359	0.331	0.241	0.434
Natexis Banques Populaires	FR	0.138	0.240	0.569	0.302	0.113	0.589
Svenska Handelsbanken	SE	0.390	0.480	0.131	0.285	0.423	0.295
Danske Bank A/S	DK	0.283	0.534	0.246	0.269	0.316	0.418
Bankgesellschaft Berlin AG	DE	0.233	0.169	0.640	0.238	0.019	0.748
DePfa Deutsche Pfandbrief Bank AG	DE	0.308	0.150	0.566	0.113	0.073	0.817

Table 8 - Variance decomposition of monthly DD changes 1999-2003
Comparison of the two alternative procedures

		From the EU component to the idiosyncratic	**From the idiosyncratic component to the EU**
All countries	EU-wide	0.404	0.272
	National	0.184	0.086
	Idiosyncratic	0.411	0.641
Italy	EU-wide	0.452	0.359
	National	0.152	0.062
	Idiosyncratic	0.388	0.578
Spain	EU-wide	0.466	0.323
	National	0.145	0.060
	Idiosyncratic	0.388	0.617
Germany	EU-wide	0.335	0.146
	National	0.211	0.115
	Idiosyncratic	0.453	0.732
France	EU-wide	0.368	0.193
	National	0.140	0.058
	Idiosyncratic	0.494	0.751
UK	EU-wide	0.455	0.314
	National	0.235	0.064
	Idiosyncratic	0.309	0.625

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