Annex 10 - Financial Integration Measure and Factor Analysis of European country and sector-based stock indexes

1 Introduction

In this paper we aim at measuring financial integration in Europe over the last decade. More precisely we want to measure the impact of the European convergence process on the dynamics of stock markets. It is of course essential to propose a dynamic measure of integration in order to investigate as precisely as possible the changes in the integration process over time. We do not compare integration over subperiods, but rather examine the continuous changes at a daily frequency. At each date, the integration measure is a function of the values of the observed returns over a period of one (respect. three) year (s) before this date. The volatility of the measure depends obviously of the rolling window which is retained for the recursive estimation. We look for the integration by considering the daily returns of different country or sector-based indexes. The integration measure is linked to the common part of the risk that the different returns share and that we identify through a relevant Factorial Analysis. We do not choose to explain the dynamics of the returns of a set of individual stocks as Hamelink et al. (2001). However, we aim at giving an integration measure which is more precise than the one proposed by Fratzsher (2001) who analyzes the dynamics of country-based indexes only. Indeed, equity returns are known to be strongly influenced not only by country but also sector effects, among others.

Moreover a key issue is to be able to disentangle those various effects from another, in particular when portfolio allocation strategies are at hand. We do not exactly answer to the question whether

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diversification obtained through a sector-based allocation is more efficient than the one allowed by a country-based strategy. However, our analysis give some indications about how diversification opportunities have evolved over time.

The plan of the paper is as follows. Section 2 is devoted to the presentation of the methodology we adopt to measure integration by referring mainly to Chamberlain and Rothshild (1983). In section 3, we present the data, the statistical procedure and comment the results obtained about the integration process and the contributions of the countries and sectors to this process. In Section 4 we compare the specific contributions of countries and sectors to co-movements of the European indexes in order to shed light on how diversification opportunities have changed over time. The last section concludes and lists some expectations for further research.

2 Modeling the integration measure and the diversification opportunities

In order to investigate both properties of integration and diversification, we choose to use a factorial description of a set of returns. So, we first refer to the theoretical framework proposed by Chamberlain and Rothshild (1983) and next to the practical strategy of extracting factors in dynamic frameworks, as proposed by Stock and Watson (1998).

2.1 The Arbitrage model of Chamberlain and Rothshild (1983)

Beforehand, it is worth emphasizing that the empirical analysis presented in this paper is not implemented to validate or invalidate the Arbitrage theory formalized by these authors. We just adopt the principles of analyzing the risk of financial returns, through a factor model which is decomposes the risk into a well-diversified market-priced component and an idiosyncratic diversified part.

More precisely, N returns are supposed to share a systematic (market) risk represented by a limited number of factors. The risk corresponding to the N idiosyncratic components is diversified for a relevant composition of the portfolio this risk can be eliminated.

The asset market is said to have a strict K-factor structure if the return of the i^{th} asset is generated by:

$$R_i = ER_i + \sum_{h=1}^{K} \beta_{ih} f_h + u_i$$

where the factors f_h are uncorrelated with the idiosyncratic disturbances u_i,which are in turn uncorrelated with each other.

Thus, the covariance matrix Σ_N can be decomposed into a matrix of rank K and a diagonal matrix:

$$\Sigma_N = B_N B_N' + Diag(Var(u_i))$$

with B_N denoting a NxK matrix of factor loadings.

Accordingly, the variance of the return of a portfolio $\alpha = Vec\left\{\alpha_i\right\}_{1 \leq i \leq N}$ can be decomposed into two parts:

$$Var(\sum_{i=1}^{N} \alpha_i R_i) = \alpha' B_N B_N' \alpha + \sum_{i=1}^{N} \alpha_i^2 Var(u_i)$$

The strict factorial structure can be extended by supposing only that the eigenvalues of the variance matrices $Var(u^{(N)})$ are uniformly bounded for every set of N returns, whatever N considered. This factorial structure is thus said to be a weak factorial structure, or is also called an approximate factor model.

In both cases, if the quantity $\sum_{i=1}^{N} \alpha_i^2$ tends to zero when N tends to infinity, one can prove that the idiosyncratic risk also tends to zero, by using relevant hypothesis excluding any arbitrage opportunity. Thus, the so-called diversified part of the risk $u^{(N)}$ is eliminated by diversification. Accordingly, $\sum_{i=1}^{N} \alpha_i^2$ is interpreted as a measure of the diversification opportunities offered by the portfolio. This measure is proved to be a function of $\overline{\lambda} = \sup_N \lambda_u^{(N)} < \infty$ (Chamberlain (1983)).

Assuming a weak factorial structure to describe the dynamics allows to derive the (approximative) multi-beta relationships (Chamberlain and Rothshild (1983)):

$$\exists \alpha_0, \exists \{\tau_k\}_{1 \leq k \leq K} \ /\forall i, \ ER_i \approx \alpha_0 + \sum_{k=1}^{K} \beta_{ik} \tau_k$$

where α_0 denotes the return of a riskless asset, if it exists, β_{ik} the beta coefficient of the i^{th} asset relative to the k^{th} factor and τ_k the risk premium of the k^{th} factor.

There exist sufficient conditions for the Data Generating Process (DGP) obeying to a weak K-factor structure [1]. The problem with such conditions is that they are difficult to test, because one has to look for maxima over N, whose value is of course fixed in practice.

For a practical purpose, we choose to refer to the empirical strategy proposed by Stock and Watson (1998) who investigate the common-dynamic- features of a large number of series.

2.2 Dynamic Factorial Analysis by Stock and Watson (1998)

The idea is to look for a factorial representation of the joint dynamics of the N returns of country&sector-based indexes. The analysis is therefore conducted for a set of 11 countries and 10 sectors for each country in the euro area (resp. 10 and 10 for the rest of the world). N should be therefore equal to 110 (resp.100). In fact, due to missing data, there are 77 and 83 returns respectively.

N is large enough to justify arguments derived from the application of the law of large numbers as in Ross (1977): the residual part of the risk can be approximately eliminated by choosing the α coefficients of order $\frac{1}{N}$ provided the cross-sectional correlations between the residual components are low enough. From now on, i and j will denote respectively a country and a sector index, the factorial model is the following:

$$R_{ij,t} - \overline{R_{ij,T}} = \sum_{k=1}^{K} \Lambda_{ij,k} F_{kt} + \varepsilon_{ij,t}$$

where i and j denote respectively country and sector-based indexes and $\overline{R_{ij,T}}$ is the historical mean of the return of the j sector in the i country. Note that one can always find a reparametrization with constant loadings over time (See Appendix).

[1] Note that a sufficient condition for the DGP obying to a weak K-factor structure is given by:

$$\sup_N \lambda_K^{(N)} \to \infty, \ \sup_N \lambda_{K+1}^{(N)} < \infty \ \inf_N \lambda_N^{(N)} > 0$$

if the eigenvalues of the matrix $Var(R^{(N)})$ for a given N, are ordered according to:

$$\lambda_1^{(N)} > \lambda_2^{(N)} > ... > \lambda_N^{(N)}$$

The factors must summarize as precisely as possible the cross sectional correlations between the different returns. But when the number N is too large, it is not possible to maximize the likelihood to estimate the factors identified by such a property. However, when N is large, one can prove that the space spanned by the factorial directions defined as above is identical to the space spanned by the Principal Components, provided that the DGP has a strict factor structure.

Chamberlain and Rothshild (1983) also suggest to use principal component analysis, which is computational and conceptually simpler than factor analysis, to extract the eigenvectors of Σ_N. Indeed, they remark that examining the eigenvectors of Σ_N relative to any positive-definite matrix leads to the same approximate factor structure, because this structure is unique.

In what follows, we implement a Dynamic Factorial Analysis (DFA) in the lines of Stock and Watson (1998), mainly based on the principles of a Principal Component Analysis. The computational strategy is the one used by Connor and Korajczyk (1986, 1993) (See appendix). The main contribution of Stock and Watson (1998) has been to prove the consistency of the estimates of factors obtained in this way when both the panel (N) and the time (T) dimensions tend to infinity at relevant rates. For example, both N and T are taken to tend to infinity but $\frac{T}{N} \to 0$. The latter condition is not so simple to verify in practice and in particular in this paper, but practical applications of the DFA by Stock and Watson very often forget checking the convergence rate condition.

Compared to the framework of Chamberlain and Rotshild (1983), the model is no longer static. Time is explicitly introduced in the analysis. The dynamics of a set of N returns is described by a strict factorial structure, according to:

$$R_t = \Lambda_t F_t + u_t \tag{1}$$

where R_t denotes the corresponding N-dimensional vector of returns, F_t the Kx1 dimensional factor component, u_t the Nx1 dimensional vector of idiosyncratic residuals and Λ_t the Nxr matrix of loadings.

Notice that, in the previous equation, the dynamics can be introduced in three ways:

1. the factors are assumed to evolve according to a time series (multivariate) process which is not observable,
2. the factors can enter with lags (or even with leads),
3. the error terms are correlated over time.

The approach we adopt is quasi static because we look for the principal components which explain the maximal part of the variance shared by contemporaneous variables (the returns at a same date). However, we implement a rolling DFA and so a recursive estimation of factors and loadings with a window of three (respectively) one years(s). To implement such a recursive estimation,we need a window which is wide enough to provide sufficient observations to refer to asymptotic inference results. But it must not be too wide because it could hire the volatility of the integration measure. Note however that the experiments corresponding to a window of three and one year (s) respectively provide the same kind of results concerning the main features of the dynamics of the integration measure.

It is also worth noting that dynamic features are explicitly taken into account in the factorial analysis when we investigate the effects of serial correlations between daily returns on the integration measure.

In order to identify the common factorial part of the returns, as opposed to the residual part, we first use Information criteria recently proposed by Bai and Ng (2002) in the framework of Stock and Watson (1998). These criteria allow us to identify the number of common factors.

Once the identification of the number of common factors is achieved, we distinguish two steps in our analysis.

1. We examine integration properties from synthetic measures derived from correlations between returns, without referring to any (financial) pricing model. Thus our investigation is twofold.

    - We aim at comparing the global integration measure we propose in the Euro area and in what we call the rest of the world. It is indeed worth detecting a specific impact of the European convergence on the integration of the stock markets, if it exists, compared to the globalization effects.
    - We try to disentangle the influences of the countries and the sectors on the integration process, first for the financial purposes outlined in Introduction and also in the perspective of an economic analysis of European integration which is left for further research. Indeed, if financial benefits are usually expected from low correlations among asset classes, and particularly among equity markets, the sources driving correlations remain controversial. Low correlations may be du to differences in economic conditions across national borders, like regulatory environment, economic policies and growth rates. Low correlations among equity markets may also be explained by the specific composition of each country.

2. We focus more specifically on how to draw some indications about changes in the diversification opportunities offered by the countries compared to the ones offered by the sectors.

The latter step justifies the choice made in this paper to investigate integration by using a DFA. Indeed, we could have implemented a regression of the about initial returns over the European returns of the different indexes, in the lines of Hamelink et al. (2001) and thus estimate the contribution of the sectors (resp. the countries) to the determination of equity prices in the Euro area, at each date, as the (cross-sectional) average (weighted by market capitalization) value of the coefficients associated with the indicator variables associated with the sectors (resp. the countries). However, such an analysis does not provide an empirical characterization of common and idiosyncratic risk. contrary to DFA which is precisely used in pricing financial risks according to the Arbitrage Theory introduced by Ross (1977).

3 The Data and the statistical procedures to measure financial integration

In this section, we describe the different empirical procedures we propose to analyze financial integration in Europe by examining the dynamics of returns of stock indexes, first from a global point of view, in order to identify a specific behavior in the European area as opposed to the rest of the world, second by examining the relative contributions of sectors and countries within Europe. Let us first consider the data we use.

3.1 Data and transformations

We observe the returns of different country and sector-based indexes, in the Euro (Belgium, France, Germany, Italia, Spain, Netherland, Austria, Greece, Ireland, Finland and Portugal) area as well as "in the rest of the world" (USA, Canada, Japan, Australia, Sweden, United Kingdom, Denmark, Switzerland, Norway and Asian area excluding Japan), that is 77 and 83 returns respectively. The data source is DATASTREAM. First, we choose to measure integration excluding the contribution of the exchange rate. Accordingly, the prices are expressed in Euro for the countries and sectors of the Euro area (before introduction of Euro, we refer to the dynamics of the ECU). For the rest of the world the returns are expressed in US dollar. Using area-denominated returns has the effect of lumping nominal currency influences. This measure is closer from the view of financial investors, who try to make sure that their positions are covered against the exchange risk. Note that, for the rest of the world, we find that the integration measure is not significantly affected when the returns are expressed in local currencies.

The frequency is daily. The period of observation is [1990:01, 2002:08]. The returns are defined as the ratio of the prices of two successive days. The fundamental part (fundamental variables as dividend, size, ...) has not be substracted, but it only contributes to a significative explanation of the returns for lower frequencies, typically monthly frequencies and not so much at the daily frequency (usually, a very small part of the variance). One also has to focus on the part of the returns that can be explained by past returns, because it might be a measure of inefficiency rather than a measure of integration as outlined by Fratzscher (2000).

When one just regresses the current return of a country or sector-based index on the corresponding return of the previous day, this has not a clear impact on the integration measure we propose. In any case, the past information contributes poorly to the explanation of the dynamics: the returns are very weakly intertemporally correlated (see Appendix 1). Note however that returns from European countries can be correlated with lagged returns from the rest of the world, due to differences in the opening hours of the markets.

As explained latter, we conduct principal component analysis of correlation matrices, because the maximal eigenvalue is the sum of the squared correlation coefficients between the common factor and the different returns. Accordingly, an integration measure based on this eigenvalue, is directly related to the comovements of the returns. Thus, the normalization used to get correlation matrices is obtained by considering the conditional volatility as estimated, each day, on the basis of the set of observations of the associated window. It would be interesting to investigate normality of the so reduced returns, because serial non-correlation is thus equivalent to independency. This analysis and more generally the careful investigation of all non-standard properties of the returns has been partially conducted. At this stage, just note that the usual transformations of the returns that we experimented[2] do not deeply modify the main features of the dynamics of the integration measure(s) we propose.

3.2 Integration features as revealed by a test procedure

Bai and Ng (2002) have proposed some information criteria to identify the relevant number of common factors, as extracted from a factorial analysis in the lines of Stock and Watson (1998). We use, here, two of these information criteria which are:.

$$\begin{aligned} IC1 &= \ln(V) + K \times \frac{\ln(\frac{NT}{N+T})}{\frac{NT}{N+T}} \\ IC2 &= \ln(V) + K \times \frac{\ln(\max(N,T))}{\frac{NT}{N+T}} \end{aligned}$$

where $V = \frac{1}{NT}\sum_{i=1}^{N}\sum_{t=1}^{T}(X_t - \Lambda F_t)^2$ and K is the number of factors

[2] Results are available upon request

We look at the factorial model to describe the returns $R_{ij,t}$

$$R_{ij,t} - \overline{R_{ij,T}} = \sum_{k=1}^{K} \Lambda_{ij,k} F_{kt} + \varepsilon_{ij,t}$$

and we want to identify K. By implementing these information criteria recursively, along with the dynamic factorial analysis, we find that the number of common factors is decreasing over time indicating an increasing integration in the European area. In particular, we observe two main regimes, a first one before mid 98, where the number of common factors varies between 4 -at the beginning, that is before mid-94- and 3 and a second one, from 1998 until 2002, where the number of common factors is almost always equal to 2.

[insert figure 1]

In what follows, we focus on factorial analysis of different returns, by retaining just one factor to describe the common movements of the returns.

3.3 Global integration measure obtained by a Principal component analysis of the correlation matrix

As announced previously, at each date, we implement a Factorial Analysis in the lines of Stock and Watson (1998) (See appendix for more details), that is a recursive principal component analysis of the correlation matrix. The analysis is not strictu sensu dynamic because one focuses on contemporaneous returns. However, the estimation is conducted recursively with a rolling window of three years (or one year) as detailed in the previous sections.

For the panel of the countries limited to the Euro area, we find that the first factor is the only one which displays dynamic features. So we decide to retain only the first factor to summarize the evolutionary co-movements, that is:.

$$R_{ij,t} - \overline{R_{ij,T}} = \Lambda_{ij,1} F_{1t} + \varepsilon_{ij,t}. \qquad ((1))$$

Then, we check that the cross sectional correlations of the residuals $\varepsilon_{ij,t}$ are significantly lower than the cross sectional correlations of the returns, as measured by the associated squared maximal eigenvalue, which is the sum of the squared correlation coefficients between the residuals and the common factor.

[insert figure 2]

Keeping just one common factor, we define a global integration measure as the squared maximal eigenvalue of the correlation matrix of the returns, with the correlation matrix estimated from the observations of the current window. This measure can be expressed as:

$$I_t^{(G)} = \sum_{i=1}^{I} \sum_{j=1}^{J_i} \widehat{r}^2 \left(R_{ij,t}, \widehat{F_{1t}} \right)$$

with $\widehat{r}^2 \left(R_{ij,t}, \widehat{F_{1t}} \right) = \frac{\sum_{s=T-t}^{t} R_{ij,s}, \widehat{F_{1s}}}{\sqrt{\sum_{s=T-t}^{t} \left(R_{ij,s} - \overline{R_{ij}} \right)^2} \sqrt{\sum_{s=T-t}^{t} F_{1s}^2}}$ where T denotes the number of observations of the window. $\widehat{F_{1t}}$ is the first common factor .

[insert figure 3]

We use a rolling window of, successively, three years and one year; Figure (2) displays $I_t^{(G)}$ for both the euro area and the rest of the world. Not surprisingly, integration is higher for the euro area. This property could be partly explained by the fact that the markets of the rest of the world are not synchronized. Moreover, one observes that the integration decreases from 1993 until 1996, with a tendency to increase from this date, first slowly and then, from 1998 to January 1999, very sharply. The introduction of the single currency has obviously boosted the integration process. A significant increase follows the announcement of the EMU members around May 1998, and this increasing tendency is clearly intensified over the second part of the year 1998 until introduction of the Euro in January 1999. Afterwards, the integration decreases likely due to the crisis in the new technology sector and, at the end of the period, the measure is around its initial level. The feature of the curve over the last year suggests that the integration might increase again. With a rolling window of three years, the integration measure or the rest of the world is always below the European integration measure and the differential between both measures is significantly increased since 1998. The Euro convergence process has obviously boosted integration over 1998-1999. One also observes that the sectors have a clear impact on the integration: for example, the measure sharply decreases during 2000 undoubtedly because of the intensified heterogeneity of the investment opportunities (in the new technologies for example) during this period .The one year rolling window is particularly useful to highlight this impact. Note this fact is observed overall the world.

Compared to the results obtained by Fratzscher (2001), the results we obtain are broadly speaking similar especially after 1995. The only noticeable difference is over the year 1993 which displays a stable low integration level in Fratzscher, of the same order as the one observed over 1992. This author interprets this feature as resulting from the economic crisis (recession period) in Europe during theses years, but he also mentions that integration seems to have increased between the Asian stock markets during the 1997-1998 crisis. So, the impact of a crisis on integration is uncertain. Here, we observe a decrease of the integration measure from 1993 to 1995. It could be representative of the delayed impact of the economic recession observed during 1992-1993, but not so synchronized over the different countries of the Euro area. Moreover, it is worth emphasizing that the integration measure we build is a function of the returns of country and sector-based indexes, while Fratzscher only works with country-based indexes.

Finally, it is worth emphasizing that until 1993, the stock market turnover is extremely small compared to the one which can has been observed afterwards. The volume effect is clearly at hand and it must be kept in mind because all price series are quite similar and this proximity should not be interpreted in terms of integration. So, it is better to focus on the recent period 1996-2002 to investigate the financial integration in the new (European) regime (1998-2002), in contrast with the comovements observed before (1995-1998). Accordingly, the differences between our results and the ones obtained by Fratzsher (2001) are not so worth being commented.

Now, we look at the differences or similarities in the contributions of the sectors and countries to the comovements of the returns.

3.4 Relative contributions of sectors and countries to the financial integration process

We conduct successively a DFA on the panel of the returns of the country-based indexes and on the sector-based indexes. Of course, the conditions required to have the consistency properties of the estimates of the factors in the lines of Stock and Watson (1998) are not satisfied because the panel dimension is too low. Anyway, as for the global DFA, one just retains the first factor of the PCA of the correlation matrix to build the two corresponding integration measures, because the associated squared maximal eigenvalue captures all dynamic features of the comovements.

First, for the countries:

$$R_{it}^{c} - \overline{R_{iT}^{c}} = \Lambda_{i1}^{c} F_{1t}^{c} + \varepsilon_{it}^{c}; 1 \leq i \leq I \tag{(2)}$$

where R_{it}^{c} (resp. $\overline{R_{iT}^{c}}$) denotes the return of the index of country i (resp. the corresponding historical mean over period $[0, T]$) and F_{1t}^{c} is the first factor of the PCA conducted for the set of the country-based returns). The corresponding integration measure is given by:

$$I_t^c = \sum_{i=1}^{I} \widehat{r}^2 \left(R_{it}^c, \widehat{F_{1t}^c} \right)$$

[insert figure 4]

Then for the sectors:

$$R_{j,t}^{s} - \overline{R_{j,T}^{s}} = \Lambda_{j,1}^{s} F_{1t}^{s} + \varepsilon_{jt}^{s}; 1 \leq j \leq J \tag{(3)}$$

where $R_{j,t}^{s}$ (resp. $\overline{R_{j,T}^{s}}$) denotes the return of the index of country i (resp. the corresponding historical mean over period $[0, T]$) and F_{1t}^{s} is the first factor of the Principal Component Analysis (PCA) conducted for the set of the sector-based returns. Accordingly, the sector-based integration measure is:

$$I_t^s = \sum_{j=1}^{J} \widehat{r}^2 \left(R_{jt}^s, \widehat{F_{1t}^s} \right).$$

[insert figure 5]

Note that I_t^c and I_t^s, which are linear combinations of respectively country-based returns R_{it}^c and sector-based returns R_{jt}^s , are also linear combinations of the initial returns $R_{ij,t}$. Accordingly, the factors extracted from the partial PCAs, are constrained linear combinations of the initial returns used in the global PCA. So, they explain a lower part of the variance of all returns $R_{ij,t}$. The results are displayed in figures 4 and 5.

One observes that the dynamics of I_t^c only behave quite similarly to the global integration measure $I_t^{(G)}$, except during the second regime: the decreasing movement is not so sharp and deep for the countries because the effects of sectors are not directly at work and in particular the bubble and crisis of the new technologies sector. If one looks at the difference between the country-based integration measures of the euro area and the rest of the world, one observes that there are two regimes with the break at the middle of 1998 as mentioned before. Indeed the difference is almost constant over the two regimes, emphasizing the effect of the introduction of euro. Concerning the sectors, the integration measure they provide is constantly decreasing, except at the end of the whole period, where one observes a slight tendency of the integration measure to increase again. One remarks the persistency in the dynamics of this measure. Note also that this dynamics a similar features in the Euro area and the rest of the world.

From now on, we focus on the Euro area. Note that one can not compare the two partial integration measures because the factorial analysis are not conducted on nested panels. However, considering the two measures successively, it is possible to characterize the evolution of the common risk, that is the evolution of the variance explained by the factor, or, equivalently, of the comovements measured by the sum $\sum_{i=1}^{I}\widehat{r}^2\left(R_{it}^c,\widehat{F_{1t}^c}\right)$, (resp. $\sum_{j=1}^{J}\widehat{r}^2\left(R_{jt}^s,\widehat{F_{1t}^s}\right)$). In particular, one observes that the common part of the risk shared by the country-based returns is higher over the second regime than over the first one (around 0.40 versus 0.55), indicating a deeper integration. Concerning the sectors, the common risk is constantly decreasing over time -except at the very end of the period. But it is worth emphasizing that one can recognize two regimes of integration around 1999, when integration is measured through sector-based returns: these returns have a higher dispersion after than before.

To compare more precisely the relative contributions of the sectors and countries to financial integration in Europe we examine the determinants of the global factor. We regress this factor over the European country-based returns. The factor as well as the returns of the different indexes are linear combinations of the initial returns. But the latter is not observed contrary to the former. So we are faced with an error- in -the variable problem in the definition of the endogenous variable. Apart from this problem, the inference is quite standard as all variables are stationary. The regression is the following:

$$\widehat{F_{1t}} = \alpha^c + \sum_{i=1}^{I}\delta_i^c R_{it}^c + u_t^c. \tag{(4)}$$

By focusing on the coefficients R^2 of the regression at each date, we observe that this coefficient is approximately constant over time and quite near to 1, except in the very recent period where it decreases slightly. Accordingly, it appears that the country-based indexes capture the main part of the common risk of the returns R_{ij} over the whole period. The higher value of R^2coefficients is striking, but one can check, by regression that F_1 can be mimicked by a European market portfolio,which accordingly appear as well-diversified: the correlation between the global factor and the return of the European global index is constantly quite near to 1. Thus, it is not surprising to find that the sector-based indexes also capture the main part of the common risk of the returns[3].

If one implements the regression:

$$\widehat{F_{1t}} = \alpha^s + \sum_{j=1}^{J}\delta_j^s R_{jt}^s + u_t^s \tag{(5)}$$

one can comment the features of the coefficients $\delta_i^c$and δ_j^s where δ^s denote the coefficients which measure the relative contribution of the sectors to the global factor.

[3] $\widehat{F_{1t}} \approx \alpha^c + \sum_{i=1}^{I}\delta_i^c R_i^c \approx \alpha^c + \sum_{i=1}^{I}\frac{c_i^c}{c_E}R_i^c$ where c_i^c denotes the capitalization of the i^{th} country in the european market, whose global capitalization is denoted c_E . Accordingly, $\widehat{F_{1t}}$ can be rewritten as:

$$\begin{aligned}\widehat{F_{1t}} &\approx \alpha^c + \sum_{i=1}^{I}\frac{c_i^c}{c_E}\sum_{j=1}^{J}\frac{c_{ij}}{c_i^c}R_{ij} \\ &= \alpha^c + \sum_{i=1}^{J}\frac{c_j^s}{c_E}\sum_{j=1}^{I}\frac{c_{ij}}{c_j^s}R_{ij} \\ &= \alpha^c + \sum_{i=1}^{J}\frac{c_j^s}{c_E}R_j^s\end{aligned}$$

The following figures report the dynamics of the estimates of the δ_i^c and the δ_j^s which show the evolutionary contributions of the different returns to the factor. We note that the δ^c coefficients display a higher (cross-sectional) dispersion before 1998. There exist clearly two regimes, before and after the single currency (with a structural break around 1998, corresponding to the announcement of the EMU members). Since this date, all countries have nearer contributions to the common part of the risk shared by the $ij-$returns; in that sense, a convergence process has occurred. As the integration is estimated over a rolling window of three years, we can exclude that the convergence is solely due to a mechanic effect of the exchange rate.

[insert figure 6]

Concerning the δ^s coefficients, one also observes a convergence process in the sense of a decreasing dispersion.

[insert figure 7]

In the next section, we aim at comparing the specific contributions of the country-based and sector-based stock indexes. to the co-movements summarized by the first global factor.

4 Specific contributions of the sector- and country based indexes to the fist global factor

One usually admits that an increasing -and major- part of managers of the European equity markets currently believe in the superiority of portfolio allocation strategies based on sectors. Although the benefits of international diversification arising from low correlations among equity markets are well documented, the main sources driving correlations remain controversial.

It is interesting to refer to Hamelink et al (2001) who identify turbulence periods by focusing on the monthly cumulative cross sectional dispersion among pure country and pure sector factors according to their terminology. In September 2000 the sectors were twice as volatile as country returns and three times in February 2001. However, most of the time the dispersion of the country returns is much higher than sector returns. Moreover, over the overall period, the dispersion of country returns is 0.25% per month while it is as low as 0.19% for sector returns. Accordingly, the country-based allocations seem to offer higher diversification opportunities. However, by considering the average correlation among country and sector pure factors over time (resp. between 7% and 17% and -5% and -2%), the authors conclude that sector factors seem to offer slightly higher diversification benefits.

Let us also mention the study by Griffin and Karolyi (1998) who examine the extent to which gains of diversification are due to differences in industrial structure across countries. They refer to a popular computation of the proportion of the variance of a single representative firm's stock that can be reduced by combining this stock with other stocks randomly selected from the total population. To assess diversification benefits, they examine the covariances between stocks based on their industrial and country memberships as a percentage of the average stock variance. They find that randomly combining securities across different industries into large portfolios within each country can reduce the variance to 21.9% of the variance of the individual stock. By contrast, diversification across countries even within a single industry can achieve almost 8.4% of the average individual stock variance, which is close to the unrestricted limit of 7.06% .

In investigating integration properties and more precisely the contributions of sector and country-based indexes to integration, we have found that the countries always share a weaker common part as compared to the sectors, with a clear difference between the beginning and the end of the period under study: the sectors appear more integrated before than after contrary to the countries and both sector-based and country-based indexes display similar integration properties over the most recent period. In terms of correlations, country-based returns are always less correlated than sector-based ones but the difference is not so sharp over the most recent period.

Moreover, we have found that the global actor F_1 can be obtained as a linear combination of the returns of the country-based indexes only, or, equivalently sector-based indexes up to a residual whose variance is extremely low and constant over time. So the main part of the variances of the initial 77 returns can be explained by both kinds of indexes taken separately. As the next factors only explain a few percents of the variance and as the cross-sectional correlations between the residuals are low, one can claim that the factor F_1, whose structure is very closed to the one of a European Stock index mainly contributes to the common well-diversified part of all returns. Accordingly, we can interpret the residual variance as measuring the non-diversified part of the risk, which can be eliminated by choosing a relevant portfolio allocation.

If one accepts this interpretation, it is interesting to look at the residual part $\varepsilon_i^c$of the risk identified for the country-based returns from regression (2). More precisely, one can run a recursive PCA on the correlation matrix of these residuals. The corresponding dynamic "integration measure" gives indications on the correlations between the idiosyncratic parts of the returns and accordingly on the diversification opportunities offered by country-based portfolio allocation strategies.

One observes that cross-correlations of the residuals ε_i^c are approximately constant over time. Indeed the cross-correlation measure:

$$I_t^{(\varepsilon)c} = \sum_{i=1}^{I} \widehat{r}^2 \left(\varepsilon_{it}^c, \widehat{F_{1t}^{(\varepsilon)c}} \right)$$

is approximately constant over time around 0.40 This property is not found for the sector-based returns ($I_t^{(\varepsilon)s}$). The corresponding cross-correlation measure changes over time and is constantly decreasing from 0.78 to about 0.38.

[insert figure 8]

Note that the latter results may have been affected by the bubble and the crisis of new technologies, which can have weakened the cross-correlations.

According to these observations, if the common global factor F_1summarizes the well-diversified -and priced- part of the risk, one should conclude that the country-based portfolio allocation strategies seem to offer more interesting diversification opportunities. However, to confirm such a conclusion, it would be necessary to test how many factors should be retained to explain the common -well-diversified risk and more generally to test for multi-beta pricing in the lines of APT. This analysis is left for further research.

5 Conclusion

In this paper we aimed at investigating the financial integration process in Europe compared to the rest of the world over the last past decade, as potentially revealed by the dynamics of the daily returns of about 90 country and sector-based indexes in Europe as well as in the rest of the world.

First, we have observed that the relevant number of common factors -as identified by implementing Bai and Ng's test- is decreasing over time, indicating an increasing integration in the Euro area.

Then, we have proposed to measure the integration level as the part of the variance explained by the first factor, as extracted from a Factorial Analysis of all sector- and country-based returns in the lines of Stock and Watson (1998). Indeed, the first factor explains the main part of the comovements of all returns. Moreover, it is the only one which displays clear dynamic features among all factors, which explain a few percents of the variance. Finally, the cross sectional correlations among the residuals of the Factorial Analysis with only one factor are significantly lower than the ones of the returns. The interpretation of this measure is rather a measure of the common risk shared by the different indexes than an integration measure as meant when one refers to the principle of a unique price.

With this interpretation in mind, it is worth emphasizing that the countries appear to play a dominant role in driving the common part of the risk shared by all returns, as compared to the sectors. Indeed, contrary to the sector-based integration measure, the dynamics of the country-based measure displays two regimes -before and after 1998-, with a significant higher integration level over the second regime. The European integration process appears clearly to be at work in 1998, just before the introduction of the single currency, where the measure increases sharply, similarly influenced by countries and sectors. A mechanic (and exclusive) exchange rate effect can be excluded because the integration measure is estimated over a rolling window of three years. Afterwards, one can observe the effects of the bubble and crisis of the new technologies around 2001, through a decreasing movement of the integration measure, mainly driven by the sector-based indexes. It is interesting to note that the sector-based and country-based integration measures reach a similar level at the very end of the period, which tends to prove that integration has occurred in the Euro area across borders: one can think that integration is now mainly driven by economic forces.

Moreover, the common risk as captured by this measure appears to be lower for the rest of the world even after correcting for effects of non-synchronization of the markets.

Our analysis can not give any precise indication on the diversification opportunities offered by country-based portfolio allocation strategies as compared to the ones offered by sector-based ones. One can just notice that the former seem not to have much changed over time contrary to the latter. Indeed, it appears to be easier to diversify the idiosyncratic risk of the sector-based returns after 2000 than before with a quite similar level of diversification offered by both types of strategies. But such a conclusion highly depends on the hypothesis that the first global factor which we have estimated summarizes the whole part of the common well-diversified risk. Only a complete APT analysis of the risk could give reliable indications for portfolio managers. This is left for further research.

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A The dynamic factor structure DFA in the lines of Stock and Watson (1998)

A.1 The main assumptions

Let y_t denote a scalar series, and X_t be a N-dimensional multiple time series which will be used to forecast y_t. The factor structure is as follows:

$$X_t = \Lambda_t F_t + u_t \tag{2}$$

where the dimensions are respectively : $N \times 1$, $N \times r$, $r \times 1$ and $N \times 1$. The common part X_t of is ΛF_t and u_t denotes its idiosyncratic part. Note that, in the previous model, the dynamics are introduced in three ways:

1. The factors are assumed to evolve according to a time series (multivariate) process which is not observable.
2. The idiosyncratic error terms are serially correlated.
3. The factors can enter with lags (or even with leads).

In the static factor model , the factor loadings are constant ($\Lambda_t = \Lambda_0$), the idiosyncratic terms are serially uncorrelated , F_t and u_{jt} are mutually uncorrelated and are *i.i.d.*. The model becomes approximately static if the idiosyncratic disturbances are weakly correlated across series (for different j) ; for example, see Chamberlain and Rothshild (1983). The factor structure is used to estimate $E(y_t/X_t)$ where y_t denotes the series of interest:

$$y_{t+1} = \beta_t' F_t + \varepsilon_{t+1} \tag{3}$$

The disturbance ε is supposed to be such that:

$$E(\varepsilon_{t+1}/\underline{X_t}; \underline{y_t}; \underline{\beta_t}) = 0 \tag{4}$$

where $\underline{Z_t}$ denotes the set of the variables $Z_{t-i}, i \geq 0$, for any process Z.

A.2 Constant loadings

By the suitable redefinition of the factors and the idiosyncratic disturbances, the dynamic factor model can be rewritten such that Λ_t is constant. If the factor model states:

$$\begin{aligned} X_{it} &= \sum_{j=0}^{p} \sum_{h=1}^{r} \alpha_{ij,h} f_{h,t-j} + u_{it} \text{ for } i = 1, ...N \\ u_{it} &= \sum_{j=1}^{q} \phi_j u_{it-j} + \eta_{it} \end{aligned}$$

one can describe the $Nq \times 1$ dimensional vector $Z_t = (X_t', X_{t-1}', ..., X_{t-q+1}')'$ according to the factor structure :

$$Z_t = \Lambda F_t + v_t$$

where the factor component $F_t = (f_t', f_{t-1}', ..., f_{t-p}', ..., f_{t-q}', f_{t-q+1}', ..., f_{t-q-p+1}')'$ has the dimension $(p+1)qr \times 1$, because the model has r factors : $f_t = (f_{1t}, ..., f_{rt})'$. The factor loading Λ is $Nq \times (p+q)r$ and the idiosyncratic term is the $Nq \times 1$ dimensional vector:

$$v_t = (u_t', u_{t-1}', ..., u_{t-q+1}')'$$

where $A_j = (\alpha_{1j}', ..., \alpha_{Nj}')'$is a Nxr dimensional matrix with $\alpha_{ij} = (\alpha_{ij,1}, ..., \alpha_{ij,r})$[4]. Accordingly, Λ is a $Nq \times (p+1)qr$-dimensional matrix. So one is led to extract dynamic factors using contemporaneous as well as lagged values of X_t. Note that, if one is ready to accept that the residuals terms are serially correlated in the factor structure, one can write the factor model with constant parameters, as follows :

$$Z_t = \Lambda F_t + u_t$$

where $Z_t = X_t$, $u_t = v_t$ are $N-$dimensional vectors, while the factor $F_t = (f_t', f_{t-1}', ..., f_{t-p}')'$and the factor loading $\Lambda = (A_0, ..., A_p)$ have the dimensions $r \times (p+1)$ and $N \times (p+1)r$ respectively. So the factors can be extracted by using contemporaneous values of X only.

A.3 Estimation of the parameters of the factor model

We examine the cases of balanced panels.

The strong parametric assumptions are the following : (i) $\Lambda_t = \Lambda_0$ and, (ii) the disturbances u_t are i.i.d. independent across series, normally distributed so that the covariance matrix Σ of the vector of residuals $u = (u_1, ..., u_T)$ is diagonal. (Its seems to be possible to allow a weak correlation structure between the u_{jt} for any date t (Chamberlain and Rothshild (93)).

$F = (F_1', ..., F_T')'$ is treated as a $T \times r$ dimensional non random vector of parameters to be estimated. The estimator of (Λ_0, F) solves the non-linear least squares problem with the objective function [5]:

$$V_{NT}(\Lambda_0, F) = \frac{1}{NT} \sum_{i=1}^{N} \sum_{t=1}^{T} I_{it}(X_{it} - \lambda_{i0} F_t)^2 \qquad (5)$$

[4] More precisely, Λ is expressed has follows:

$$\Lambda = \begin{bmatrix} A_0 & A_1 & ... & A_p & 0 & ... & 0 \\ 0 & A_0 & ... & ... & A_p & ... & 0 \\ . & & & & & & \\ . & & & & & & \\ . & & & & & & \\ 0 & ... & ... & A_0 & A_1 & ... & A_p \end{bmatrix}$$

[5] Note that these estimators are not Maximum Likelihood estimators, even under the normality assumption.(contrary to what is claimed in the NBER working paper by Stock and Watson (1998). Indeed, the log-likelihood is:

$$-\frac{NT}{2} - \frac{T}{2} \sum_{i=1}^{N} \log(\sigma_i^2) - \frac{1}{2} \sum_{i=1}^{N} \frac{1}{\sigma_i^2} \sum_{t=1}^{T} (X_{it} - \lambda_{i0} F_t)^2$$

where $I_{it} = 1$ if the variable is observed at time t and equal to 0, otherwise.

For given Λ_0, F_t^* must satisfy the first order condition (which gives the usual OLS estimator of F_t, in the regression of X_t on $\Lambda_0 = (\lambda'_{10}, ..., \lambda'_{n0})'$ with $\lambda_{i0} = (\lambda_{i0}^{(1)}, ..., \lambda_{i0}^{(r)})$:[6]

$$F_t^* = \left(\sum_{i=1}^{N} I_{it} \lambda'_{i0} \lambda_{i0} \right)^{-1} \left(\sum_{i=1}^{N} I_{it} \lambda'_{i0} X_{it} \right) \tag{6}$$

and, conversely, for given F_t, Λ_0^* must satisfy the first order condition (which gives the usual OLS estimator of Λ_0 in the regression of X_t on F) :

$$\lambda_{i0}^{*\prime} = \left(\sum_{t=1}^{T} I_{it} F_t F'_t \right)^{-1} \left(\sum_{t=1}^{T} I_{it} F_t X_{it} \right) \tag{7}$$

Thus, the optimal values, $F_t^*$and Λ_0^* jointly solve the two previous equations.

In what follows, one supposes that all observations are available. Accordingly, the optimal value for F is obtained by reporting (7) in (5), and by solving an eigenvalue problem;

$$Min_F V_{NT}(F, \Lambda_0^*) = Min_F \left\{ \left(\frac{1}{NT} \sum_{i=1}^{N} \underline{X}'_i \underline{X}_i \right) - \frac{1}{NT} \left(\sum_{i=1}^{N} \underline{X}'_i P_F \underline{X}_i \right) \right\} \tag{8}$$

where $\underline{X}_i = (X_{i1}, ..., X_{iT})$ and $P_F = F(FF')^{-1}F'$ denotes the orthogonal projector on the subspace generated by the columns of $F = (F^{(1)}, ..., F^{(r)})$, with $F^{(h)} = (F_{1h}, ..., F_{Th})'$ under the normalization condition:$\frac{1}{N}\Lambda'\Lambda = I_{dr}$

These r eigenvectors are the first r principal components of X_t. The previous analysis is a standard principal component analysis (with the only difference being that dynamic features are taken into account). Up to now, the number of factors r is supposed to be given. Recently, Bai and Ng (2000) have proposed to use relevant information criteria to determine the number of factors in the S&P framework.

[6] cf. $\forall t, F_t^* = (\Lambda'_0\Lambda_0)^{-1}\Lambda'_0 X_t$, according to Zellner's theorem

B Graphics.

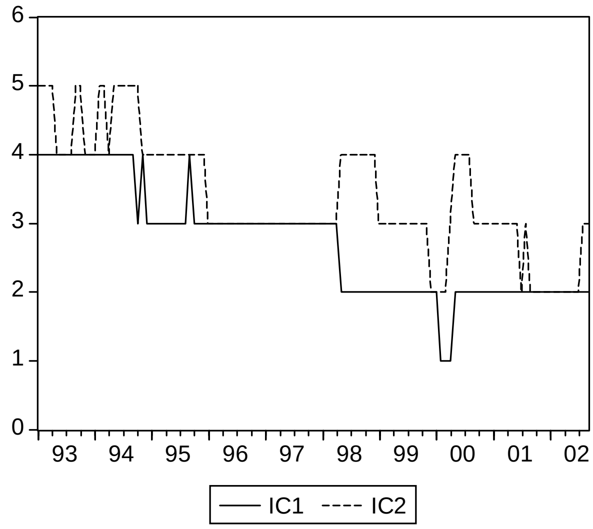

Figure 1: Bai & Ng's criteria

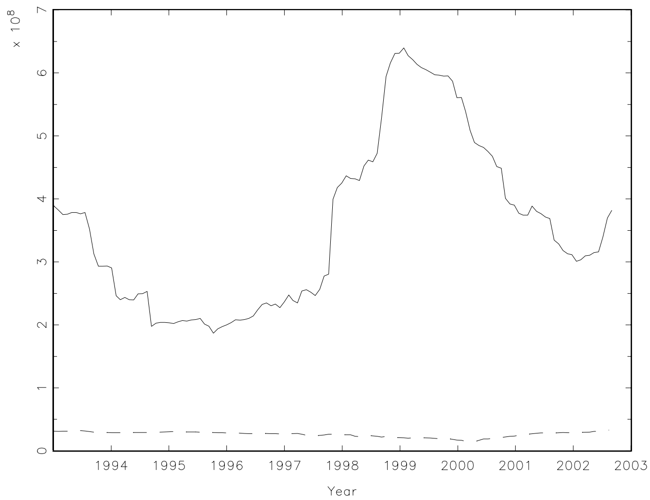

Figure 2: Maximum squared eigenvalues (Euro area).

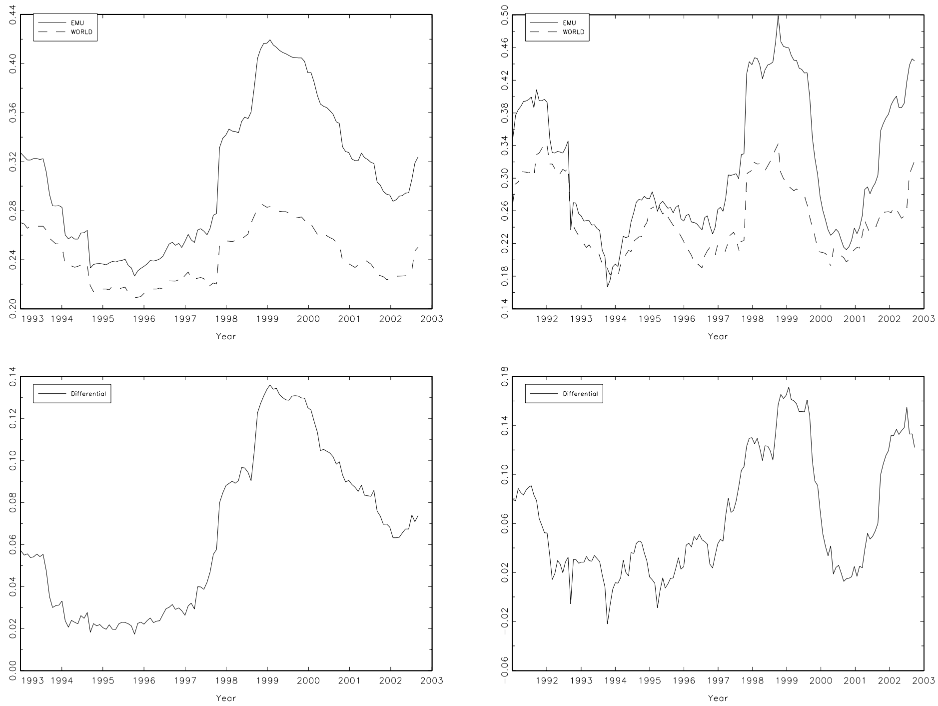

Figure 3: Rolling window of three years (left) and one year (right), global integration measures in the euro area and the rest of the world and their difference.

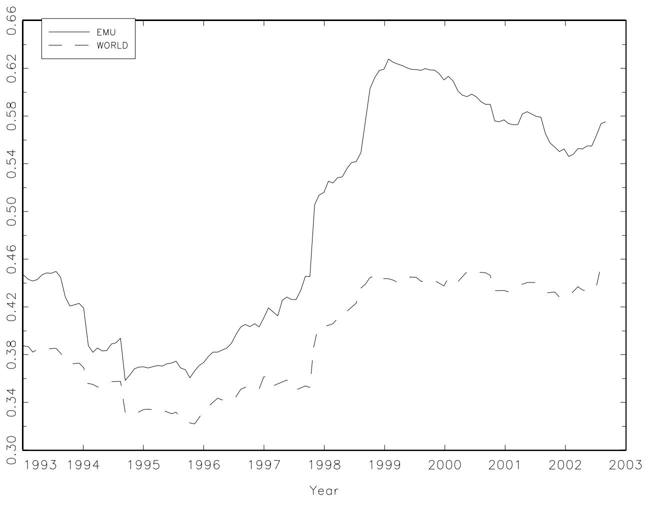

Figure 4: Country-based integration measure (rolling window of three years).

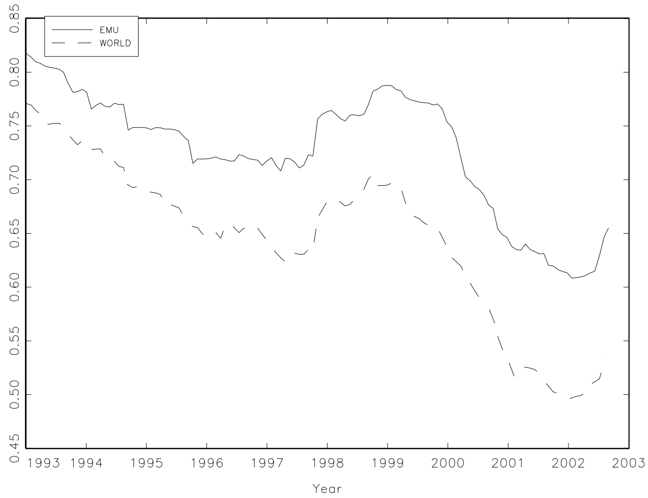

Figure 5: Sector-based integration measure (rolling window of three years).

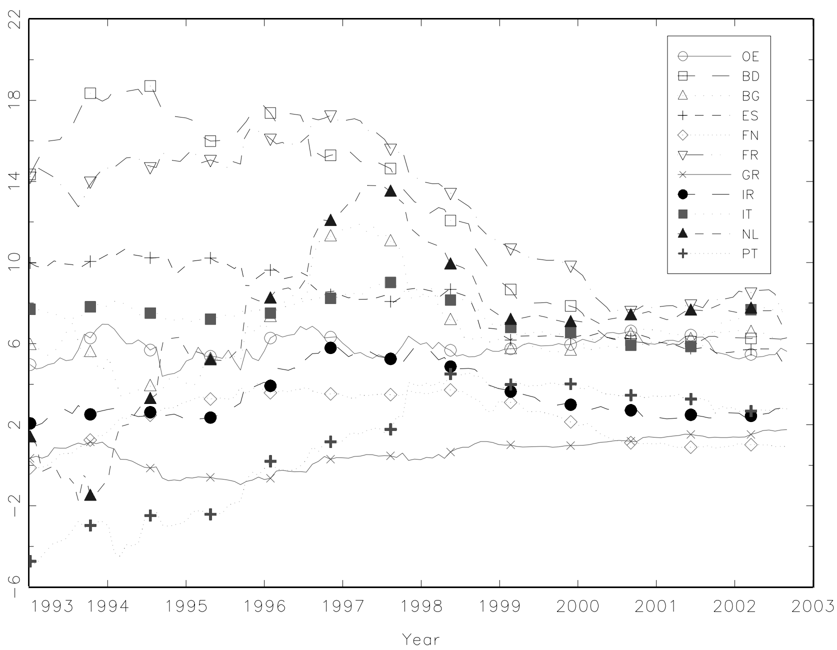

Figure 6: Rolling estimates of the δ^c coefficients with three years window (Euro area).

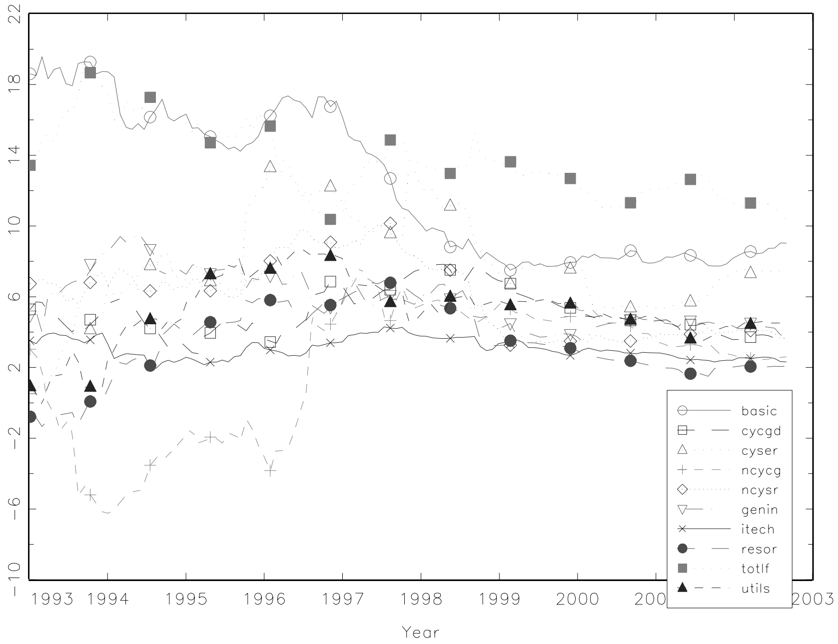

Figure 7: Rolling estimates of the γ^s coefficients with three years window (Euro area).

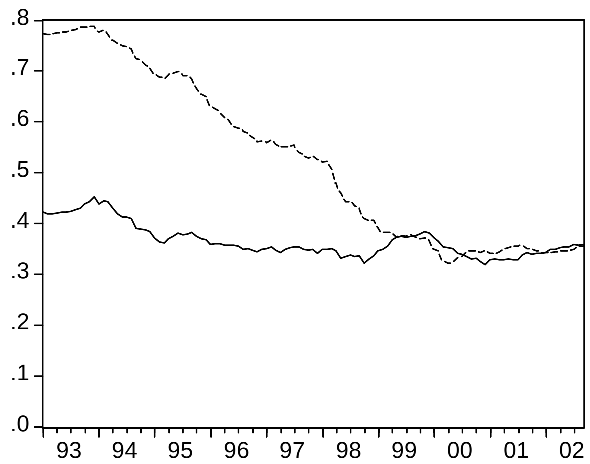

Figure 8: Cross-correlations of the residuals ε_i^c (solid) and ε_i^c (dashed).

C Tables.

Table 1 displays the sector classification from the FTSE Globlal Classification System (Level 3). Table 2 provides the name of the countries use in this paper. Tables 3 and 4 display the most contribution of the country and sector-based indexes to the first factor and, also provide the contribution of these indexes to each of the four other factors.

	LEVEL 3 SECTORS[a]
BASIC	*Basic Industries*
GENIN	*General Industrial*
CYCGD	*Cyclical Consumer Goods*
NCYCG	*Non-Cyclical Consumer Goods*
CYSER	*Cyclical Services*
NCYSR	*Non-Cyclical Services*
UTILS	*Utilities*
ITECH	*Information Technology*
TOTLF	*Financials*
RESOR	*Ressources*
TOTMK	*Total Market*

[a] Level 3 is from the FTSE Globlal Classification System and is equivalent to Economic Groups.

Table 1: Mnemonics of the sectors

	EMU		*WORLD*
OE	*Austria*	AJ	*Asia*
BD	*Germany*	AU	*Australia*
BG	Belgium	DK	*Denmark*
ES	*Spain*	CN	*Canada*
FN	*Finland*	NW	*Norway*
FR	*France*	JP	*Japan*
GR	*Greece*	SD	*Sweden*
IR	*Ireland*	SW	*Switzerland*
IT	*Italia*	US	*United States*
NL	*Netherland*	UK	*United Kingdom*
PT	*Portugal*		

Table 2: Mnemonics of the countries

		F1	***F2***	***F3***	***F4***	***F5***
BASIC	***BD***	1.96%	1.20%	0.04%	0.46%	0.74%
GENIN	***BD***	2.46%	0.17%	0.49%	0.07%	0.69%
CYCGD	***BD***	2.18%	0.67%	0.00%	0.15%	0.39%
NCYCG	***BD***	1.73%	1.48%	0.20%	0.20%	0.37%
CYSER	***BD***	1.92%	0.55%	0.11%	0.01%	0.59%
NCYSR	***BD***	1.57%	0.46%	2.44%	0.00%	0.31%
TOTLF	***BD***	2.34%	0.50%	0.04%	0.16%	0.33%
BASIC	***BG***	1.65%	1.98%	0.24%	0.15%	0.05%
GENIN	***BG***	1.32%	2.14%	0.15%	0.11%	0.01%
TOTLF	***BG***	2.00%	0.92%	0.01%	0.92%	0.12%
BASIC	***ES***	1.64%	0.05%	0.58%	0.62%	0.69%
GENIN	***ES***	1.41%	0.17%	0.01%	0.02%	0.67%
NCYSR	***ES***	1.83%	1.35%	1.08%	0.39%	0.51%
UTILS	***ES***	1.58%	0.03%	1.21%	2.61%	0.87%
TOTLF	***ES***	2.38%	0.04%	0.07%	0.87%	0.82%
BASIC	***FR***	2.26%	0.00%	0.31%	1.47%	0.01%
GENIN	***FR***	2.46%	0.16%	0.45%	1.79%	0.13%
CYCGD	***FR***	2.28%	0.03%	0.14%	1.27%	0.05%
NCYCG	***FR***	2.00%	0.01%	0.04%	4.69%	0.17%
CYSER	***FR***	2.32%	0.76%	2.13%	0.26%	0.03%
NCYSR	***FR***	1.74%	1.88%	2.96%	0.83%	0.02%
ITECH	***FR***	2.08%	1.36%	4.28%	0.01%	0.00%
TOTLF	***FR***	2.51%	0.00%	0.02%	1.74%	0.25%
BASIC	***IT***	1.52%	2.93%	6.96%	2.56%	0.02%
GENIN	***IT***	1.76%	5.33%	2.51%	1.99%	0.00%
CYCGD	***IT***	1.65%	3.87%	5.89%	1.33%	0.03%
CYSER	***IT***	1.51%	5.11%	0.17%	1.38%	0.00%
NCYSR	***IT***	1.80%	6.55%	1.13%	0.69%	0.01%
TOTLF	***IT***	2.16%	4.13%	4.59%	0.62%	0.00%
BASIC	***NL***	1.49%	1.37%	0.09%	0.63%	0.02%
GENIN	***NL***	1.85%	0.40%	4.10%	0.04%	0.09%
NCYCG	***NL***	1.40%	1.18%	0.77%	2.08%	0.00%
CYSER	***NL***	2.25%	0.01%	0.71%	0.25%	0.10%
NCYSR	***NL***	1.61%	0.82%	2.61%	0.04%	0.01%
ITECH	***NL***	1.56%	0.42%	4.17%	0.14%	0.08%
TOTLF	***NL***	2.51%	0.04%	0.17%	0.97%	0.07%

Table 3: The main contibutions of variables related to the fisrt global-factor extracted from the EMU database over 1990-2002.

		F1	*F2*	*F3*	*F4*	*F5*
BASIC	***SD***	1.85%	0.78%	0.83%	0.00%	0.13%
GENIN	***SD***	2.11%	1.06%	0.85%	0.00%	0.06%
CYCGD	***SD***	1.41%	0.55%	0.68%	0.02%	0.17%
CYSER	***SD***	1.26%	0.55%	0.60%	0.03%	0.01%
TOTLF	***SD***	1.47%	0.72%	0.79%	0.00%	0.09%
GENIN	***AJ***	1.66%	0.50%	0.35%	8.62%	2.13%
CYSER	***AJ***	1.68%	0.42%	0.49%	7.54%	1.49%
NCYSR	***AJ***	1.33%	0.33%	0.33%	4.10%	1.11%
TOTLF	***AJ***	1.57%	0.41%	0.37%	8.44%	1.77%
BASIC	***SW***	1.91%	1.76%	0.67%	0.08%	0.00%
GENIN	***SW***	2.23%	1.48%	0.75%	0.06%	0.10%
CYCGD	***SW***	1.38%	0.72%	0.49%	0.02%	0.08%
NCYCG	***SW***	1.75%	2.25%	0.71%	0.14%	0.01%
CYSER	***SW***	1.81%	1.15%	0.52%	0.03%	0.06%
TOTLF	***SW***	2.19%	1.91%	1.07%	0.12%	0.04%
BASIC	***US***	1.31%	3.02%	0.22%	0.88%	0.01%
GENIN	***US***	1.86%	3.99%	0.25%	0.93%	0.03%
CYCGD	***US***	1.38%	3.38%	0.24%	0.64%	0.04%
NCYCG	***US***	1.23%	2.32%	0.21%	0.87%	0.02%
CYSER	***US***	1.81%	4.03%	0.26%	0.98%	0.04%
ITECH	***US***	1.38%	2.66%	0.10%	0.28%	0.21%
TOTLF	***US***	1.67%	3.87%	0.19%	0.94%	0.03%
BASIC	***UK***	1.92%	1.29%	0.67%	0.02%	0.03%
GENIN	***UK***	1.82%	1.07%	0.75%	0.01%	0.17%
CYSER	***UK***	2.26%	1.44%	1.01%	0.00%	0.26%
NCYSR	***UK***	1.33%	1.18%	1.15%	0.00%	0.40%
ITECH	***UK***	1.51%	0.24%	0.73%	0.00%	0.49%
TOTLF	***UK***	1.99%	1.52%	0.98%	0.01%	0.17%
BASIC	***JP***	1.42%	0.65%	8.70%	0.77%	0.02%
GENIN	***JP***	1.79%	0.29%	7.97%	0.86%	0.12%
CYCGD	***JP***	1.58%	0.33%	7.21%	0.78%	0.04%
NCYCG	***JP***	1.23%	0.86%	7.96%	1.18%	0.04%
CYSER	***JP***	1.50%	0.58%	9.03%	1.05%	0.05%
ITECH	***JP***	1.54%	0.09%	5.69%	0.42%	0.26%
TOTLF	***JP***	1.24%	0.39%	7.62%	0.79%	0.00%
GENIN	***DK***	1.46%	0.11%	0.29%	0.07%	0.02%
NCYCG	***DK***	1.46%	0.36%	0.33%	0.05%	0.25%
CYSER	***DK***	1.46%	0.30%	0.30%	0.05%	0.04%
NCYSR	***DK***	1.22%	0.12%	0.37%	0.00%	0.01%
TOTLF	***DK***	1.43%	0.46%	0.27%	0.06%	0.11%
CYSER	***AU***	1.44%	0.83%	0.14%	0.91%	7.12%
TOTLF	***AU***	1.29%	0.40%	0.24%	1.55%	13.29%

Table 4: The main contibutions of variables related to the fisrt global-factor extracted from the World database over 1990-2002.