Project funded under the Socio-economic Sciences and Humanities

European Commission

Working Paper D.1.1d

The Financial Integration of the European Union: Common and Idiosyncratic drivers

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January 2009

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February 27, 2009

Abstract

The purpose of this paper is to establish how far the process of financial integration has gone in the European Union. There is growing evidence that the appearance of the Euro has accelerated the integration of a number of financial markets among those countries who have adopted the Euro. We identify the growth in financial integration as the process by which idiosyncratic factors at the national level become less and less important for the behaviour of particular markets. While the Euro plays an important part because it eliminates currency risk, financial integration will still emerge between other European countries as long as the institutional and legal barriers are removed.

*Financial support from the European Commission (7th Framework Programme, Grant Agreement No.217266) is gratefully acknowledged.

1 Introduction

Financial integration is a key goal of the Single Market Programme within the European Union, where it is expected to aid allocative efficiency and the efficacy of monetary and fiscal policy[1]. The hope is that broad and deep capital markets should allow sovereign debt to be financed at minimum cost and assist the even transmission of monetary policy to all parts of the Euro Area. Baele et al (2004) measure the state of financial integration in the Euro area, for 5 classes of asset: money, government bonds, corporate bonds, credit and equity. These measures are based on the idea that full integration is achieved when all participants in financial markets face the same rules and have equal access to the services provided by financial intermediation. Operationally this means that the return or yield on equivalent assets in different countries should be driven by common factors[2], and be relatively immune to local shocks.

Globally, financial integration has increased substantially over the last twenty years, following the abolition of capital controls, financial innovation, and new technologies, and this has implications for the potential for portfolio diversification. The literature suggests that developed equity markets worldwide, including the major European markets, are now closely integrated[3]. But the evidence of financial integration in some of the smaller European equity markets is more mixed. Here,

[1] The major institutional driving force for financial integration is the Financial Services Action Plan drawn up as part of the Lisbon Agreement in 2000.

[2] International stock markets sharing a common trend are perfectly correlated over long horizons, thus implying that there are no gains to be made from international portfolio diversification (von Furstenberg and Jeon (1989)). Full stock market integration would imply that risk-adjusted stock returns denominated in a common currency are equal in all countries. Consequently, economic interdependence among the subject countries may emerge as an additional explanatory factor; common stochastic trends in stock markets of those countries potentially mirror their economic fundamentals that are related significantly with one another. Kasa (1992) provided one of the first studies - using cointegration methods - that examined whether there are long-run benefits from international equity diversification. The results indicated the presence of a single common trend driving stock markets in a number of major economies. Corhay et al. (1993) found a common stochastic trends among five major European stock markets over the period 1975-1991. Rangvid (2001) identified an increasing number of cointegrating relationships between European stock markets in the last three decades and concluded that the markets have experienced a process of convergence. Lence and Falk (2005) argue that there need not be a connection between financial integration, where similar assets in different countries display the same risk adjusted expected returns, market efficiency, where asset prices fully reflect all information, and cointegration. They argue that in a dynamic general equilibrium asset pricing model the relationship between these three concepts depends on fundamental similarities in technology, preferences and endowments.

[3] A non exhaustive list of papers on the subject includes Abbot and Chow (1992), Darbar and Deb (1997), Francis and Leachman (1998), Hardouvelis et al. (2006) Meric and Meric (1997), Serletis and King (1997), Malliaris, A.G. and Urrutia (1996), Geersing et al. (2008).

idiosyncratic factors still play a significant role for stock prices. Worthington et al. (2003) found that the Euro-11 equity markets are highly integrated, both before and after the transition to the single currency. However, this process of long-term integration appears to be unaffected by the actual transition to the euro, and is indicative of the decade-long process of economic convergence following from the 1992 Maastricht Treaty. Furthermore, they find that the level of financial integration within non-euro participating Member States and non-EU members has also increased over this period, especially for the period after the introduction of the single currency.

Equity markets provide a demanding setting for testing financial integration. In contrast to purer financial securities such as gilts and a short-term money, equities are securities written on complex real assets. Some equity markets are international in that they are dominated, in value terms, by foreign companies to which they have given a listing (for example London and Amsterdam). But generally equity markets are national, in the sense that they trade local businesses, some of which, in turn may be multinational, embodying the performance of overseas real assets. Different national equity markets have different sectoral compositions and the fundamentals of the local economy, given the sector - growth rates, labour costs, competitiveness, institutional setting including taxation - may or may not display euro-related convergence. While the Euro eliminates currency risk, even without the Euro, financial integration will still emerge between other European countries as long as the institutional and legal barriers are removed. Liberalization of financial markets worldwide and the increasing role of the market in corporate assets as a mechanism for cross border merger and acquisition is likely to increase financial integration over and above the effect of a common currency.

In this paper we examine convergence in equity markets in the European Union, using the time-varying factor model of Phillips and Sul (2008). They propose a method to capture convergence allowing for a wide range of possible time paths and heterogeneity across countries. The model has both common and individual specific components and is formulated as a nonlinear time varying factor model. These time varying factor loads allow us to identify the process by which financial market integration takes place. The time varying formulation is particularly suitable for our analysis as it may be that the integration process proceeds at different speeds and to different extents in different countries. Our tests reject the hypothesis of overall convergence in the equity markets we consider. These results are perhaps not surprising in the context of the whole of the European Union, in which a number of members have only been in the EU from a comparatively short space of time. However we find a lack of overall convergence even when the analysis is restricted to the countries in the Euro Area.

Arguably, global convergence reflects too narrow a definition of integration.

It requires that, normalised for an initial period, equity markets will converge to the same stochastic process asymptotically. In the language of the cointegration literature this requires not only the presence of a single common factor, or $N-1$ cointegrating relations (asymptotically), but also that these cointegrating relations are of the form $(1,-1)$. Therefore we also use the Phillips and Sul method to test the weaker requirement that there is convergence in clusters. We identify three distinct clusters among the members of the European Union: 1. those stock markets that outperform the EU average, which are predominantly the new markets; 2. those equity markets that are concentrated around the average for the European economy as a whole; 3. mature markets (mostly EMU). We relate these three clusters to the underlying economic performance of their economies. The fastest growing economies also experience fastest growing equity markets, and the slowest growing economies the slowest growth in equity markets.This is consistent with Lence and Falk (2005) who show, using a simple dynamic general equilibrium asset pricing model, that the process of financial integration - a situation in which similar assets in different countries display the same risk adjusted expected returns - clearly depends on fundamental similiarities in technology, preferences and endowments among countries. In order to control for the effect of different market composition (Heston and Rouwenhorst, 1994, and Dutt and Mihov, 2008) we also report the results for more disaggregated indexes at the sectoral level. These results confirm what we find for the aggregate equity markets.

The paper is organised as follows. Sections 2 describes the methodology used in the paper and relates it to the analysis of cointegration. Section 3 details the data used in the analysis. Section 4 presents the empirical results and relates them to the existing literature on financial market integration. Section 5 concludes. The Appendix considers the relationship between market efficiency, financial integration and cointegration.

2 Econometric Framework

Models with a time varying factor structure have been popular for some time in finance. Most of the empirical literature focuses on the return and a standard exercise is to decompose the return into its aggregate and idiosyncratic component. Our interest, however, is in long run convergence so we analyse the level rather than the change in stock prices. Stock prices as returns have a standard common factor representation, the main difference lies in the fact that here at least one of the fundamentals is a common trend driving the long run component of stock prices. For instance, Menzly, Santos and Veronesi (2002) develop a general equilibrium model where asset prices are given by a linear function of a stochastic trend in dividends plus a second term that reflects deviations from this trend. Cointegration and common stochastic trends in international stock markets imply that the long-run paths of stock market prices in these markets are driven by some shared economic growth factors underlying earnings and dividends (Crowder & Wohar, 1998). Essentially, there are fewer assets available to investors than a simple count of the number of markets would suggest, and therefore implying a more limited role for long-run gains from diversification (Chen et al.,2002; Hassan and Naka, 1996).

Specifically, consider the $N-$dimension panel of stock prices X_t, the i-th element, X_{it}, has a standard factor representation

$$X_{it} = \boldsymbol{\lambda}_{it}'\mathbf{f}_t + u_{it} \tag{1}$$

where $\mathbf{f}_t$ is a $k-$ dimensional vector of common factors at time t, $\boldsymbol{\lambda}_{it}$ is the vector of corresponding loadings, which are allowed to be time varying[4], and u_{it} is a stationary idiosyncratic component.

Estimating (1) directly is impossible without imposing some restrictions on (1) since the number of unknowns in the model exceeds the number of observations. This is why it has often been found convenient to assume that the time varying loading coefficients are constant over short time periods. Nevertheless, Phillips and Sul (2007) note that a possible pattern of convergence of X_{it} can be easily analyzed without the need to directly estimate (1). Specifically, they suggest a different specification of (1) allowing for time variation in the factor loadings as follows

$$\begin{aligned} X_{it} &= \delta_{it}\mu_t \\ &= \left(\sum_{j=1}^{k} \lambda_{it}^{j} \frac{f_{jt}}{\mu_t} + \frac{u_{it}}{\mu_t} \right) \mu_t \end{aligned} \tag{2}$$

where the common factors are replaced by a unique factor μ_t and the loadings δ_{it} have a random component, which absorbs u_{it}. If the common factor μ_t also captures the stochastic common trend in the data, the time dependence of the loadings δ_{it} depends only on the original loadings $\boldsymbol{\lambda}_{it}$. It is not necessary to assume that there is a dominant common factor for this representation to hold. Global convergence occurs if $\lambda_{it}^{j} \to \lambda^{j}\ \forall i, j$ as $t \to \infty$. Then in this case $\delta_{it} \to \delta\ \forall i$ as $t \to \infty$. Moreover, if this condition holds for certain subgroups, then the X_{it} diverge overall but the panel may be decomposed into specific convergent clusters.

[4] Menzly et al. (2002) derive a similar structure from a DSGE model, where the loadings on the stochastic trend and actual dividends vary with the business cycle, increasing during peaks and decreasing during troughs.

2.1 Relation to the cointegration literature

Much of the previous literature looking at long run convergence in stock markets regards cointegration as evidence of convergence. In this section we review the relation between the cointegration hypothesis and the Phillips and Sul test of relative convergence and we highlight the difference between relative and absolute convergence.

Equity markets will exhibit relative convergence if $X_{it}/X_{jt} \to 1$, this definition is accomplished if $\delta_{it} \to \delta \ \forall i$ as $t \to \infty$. Relative convergence implies that in the long run, equity markets share a common trend which can be stochastic or deterministic. If the common trend $\boldsymbol{\lambda}_{it}'\mathbf{f}_t$ is a stochastic trend, then the indices for any pair of countries i and j are cointegrated in the long run with a cointegrating vector $(1, -1)$. This convergence concept does not require that $\delta_{it} = \delta_{jt}$ in any finite sample, but only $\delta_{it} \to \delta \ \forall i$ asymptotically. Notice that absolute convergence, defined as $X_{it} - X_{jt} \to 0$, also requires that the speed of divergence of μ_t is slower than the speed of convergence of δ_{it}.

On the other hand, if X_{it} and X_{jt} are cointegrated, then the ratio X_{it}/X_{jt} typically converges to a constant or a random variable, the former occurring when the series have a nonzero deterministic drift. In this sense, the definition of relative convergence places an additional restriction on the (asymptotic) cointegrating vector. However, the clustering procedure based on the relative convergence measure allows us to disentangle asymptotic cointegration in situations where the cointegration test has low power. Suppose that there are 2 groups $\delta_{it} \to \delta_a \ \forall i \in G_a$ and $\delta_{it} \to \delta_b \ \forall i \in G_b$. Then any pair of equity indices in each of the two subgroups are asymptotically cointegrated with cointegrating vector $(1; -1)$. Whereas any pair of equity indices in opposite groups are asymptotically cointegrated with the cointegrating vector $(1; -\delta_a/\delta_b)$.

2.2 Phillips and Sul (2007)

Phillips and Sul (2007) suggest a modeling approach based on the following relative measure:

$$h_{it} = \frac{X_{it}}{N_t^{-1}\sum_{i=1}^{N_t} X_{it}} = \frac{\delta_{it}}{N_t^{-1}\sum_{i=1}^{N_t} \delta_{it}} \tag{3}$$

which eliminates the common growth component by scaling and measures the transition element δ_{it} for unit i relative to the cross section average. Here we consider the case of an unbalanced panel, where the number of cross sections, N_t, varies over time. Over time, the variable h_{it} traces out an individual trajectory for each i relative to the average, so we call this the 'transition path'. At the same time, h_{it} measures unit i's relative departure from the common steady state growth path μ_t. Thus, any divergences from μ_t are reflected in the transition paths

h_{it}.

Phillips and Sul (2007) model the time varying factor loadings δ_{it} in a semi-parametric form - implying non-stationary transitional behaviour - in the following way

$$\delta_{it} = \delta_i + \sigma_{it}\xi_{it}, \qquad \sigma_{it} = \frac{\sigma_i}{L_i(t)t^{\alpha_i}}, \qquad t \geq 1, \ \sigma_i > 0 \text{ for all } i \tag{4}$$

where δ_i is fixed, ξ_{it} is $iid(0,1)$ across i and weakly dependent over t, and $L_i(t)$ is a slowly varying function, for example $L_i(t) = \log^{\beta_i} t$, so that $L_i(t) \to \infty$ for all i, as $t \to \infty$. Obviously, for all idiosyncratic decay rates $\alpha_i \geq 0$ the loadings δ_{it} converge to δ_i, allowing us to carry out a hypothesis test for convergence or divergence of the observed panel of time series X_{it}. Notice that this formulation allows for general flexibility in modelling the idiosyncratic transitional path, so it encompasses most cases of practical interest - the most important extension being to allow for individual rate effects α_i. One role for the slowly varying component $L_i(t)$ in (4) is to ensure that convergence holds even when $\alpha_i = 0$ for some i, although possibly at a very slow rate. This formulation accommodates some interesting empirical possibilities where there is slow transition and slow convergence.

When there is common (limiting) transition behaviour across units, we have $h_{it} = h_t$ across i; and when there is ultimate convergence in the growth pattern of stock indices we have

$$h_{it} \to 1, \text{ for all } i, \qquad \text{as } t \to \infty$$

In this case, in the long run, the cross sectional variance of h_{it} converges to zero, so that we have

$$\lim_{t\to\infty} H_t = \lim_{t\to\infty} \left[N_t^{-1} \sum_{i=1}^{N_t} (h_{it} - 1)^2 \right] = 0$$

where H_t provides a quadratic distance measure for the panel from the common limit. This is the property used to test the null hypothesis of convergence (and to group economies into convergence clusters). We discuss how to test for global convergence and classify clusters of convergent subgroups in the next section.

2.3 Global Convergence

Phillips and Sul (2007) propose a simple regression-based procedure to test the null of convergence in the non-linear factor model (1). The null hypothesis of convergence may be written as

$$H_0 : \delta_i = \delta \qquad \& \qquad \alpha_i \geq 0 \ \forall i$$

The test involves the weak inequality $\alpha_i \geq 0$ and has power against divergence in terms of different δ_i as well as divergence if $\alpha_i = 0$. Indeed, the alternative hypothesis is given by

$$H_A : \left\{ \begin{array}{c} \delta_i = \delta \ \forall i \text{ with } \alpha_i < 0 \text{ for some } i \\ \delta_i \neq \delta \text{ for some } i \text{ with } \alpha_i \geq 0 \text{ or } \alpha_i < 0 \end{array} \right\}$$

The alternative hypothesis includes straightforward divergence but more importantly also includes the possibility of club convergence. The null implies that the cross sectional variance of h_{it} converges to zero. Phillips and Sul (2007) show that the null can be easily tested as a one-sided t test on the coefficient b, $t_{\widehat{b}}$, in following regression[5]

$$\begin{array}{rcl} \log\left(\dfrac{H_1}{H_t}\right) - 2\log L(t) & = & a + b\log(t) + e_t \\ \text{for} \qquad t & = & [rT], [rT]+1, ..., T \qquad \text{with } r > 0 \end{array}$$

where the t test makes use of HAC consistent standard errors. Furthermore, they show that $b = 2\underline{\alpha}$, where $\underline{\alpha}$ is the lower bound of the support rate of the decay rates a_i. Notice that the regression starts at $[rT]$, the integer part of rT for some fraction $r > 0$ (Phillips and Sul recommend that the fraction be set to $r = 0.3$).

This is a test for the global convergence of a series, but the regression test has power against cases of club convergence, so we can expect that the null hypothesis of convergence will be rejected for data in which there is evidence of club convergence. However, the $\log t$ test can also be used as a test for cluster convergence when the cluster are exogenously chosen. In the application with equity markets, possible clusters arise from the introduction of the Euro. Equally, with the same indices in the same country, when the common stochastic component is country specific or the indices could be clustered by sector for different countries when the common stochastic trend component is sector specific. Possible subclusters among the broad categories just outlined are also allowed. The next section describes how a clustering mechanism test procedure can be employed which relies on the following stepwise and cross section recursive application of $\log t$ regression tests.

[5] Notice that here we consider the case where heterogeneity in the transitional path is given by the decaying rate a_i, this is the most interesting case for empirical applications. The function $L(t) = \log(t)$ is to be preferred in terms of asymptotic power, as argued by Phillips and Sul (2007).

2.4 Cluster Selection

A detailed analysis of the clustering procedure is given in Phillips and Sul (2007). The steps needed to implement the procedure are as follows.

Step 1 (Cross section ordering by final observation): Order the members in the panel according to values in the last period[6].

Step 2 (Form a core primary group of r^* countries): Selecting the first r highest members in the panel to form the subgroup G_r for some $N > r \geq 2$, run the $\log t$ regression and calculate the convergence test statistic $t_r = t_{\widehat{b}}(G_r)$ for this subgroup. Then the core group size r is chosen by maximizing $t_{\widehat{b}}(G_r)$ over r under the condition that the min $\left\{t_{\widehat{b}}(G_r)\right\} > -1.65$. If the condition min $\left\{t_{\widehat{b}}(G_r)\right\} > -1.65$ does not hold for $r = 2$, then the first unit is dropped and the same procedure is performed for remaining units. There is no convergence clusters in the panel if the same condition does not hold for every subsequent pair of units. Otherwise, a core group can be detected.

Step 3 (Sieve the data for new club members): Once a core convergence group is identified separately evaluate additional individuals for membership of this group, i.e. run $t_{\widehat{b}}$ adding one index at a time to the original core group. If the corresponding test statistic $t_{\widehat{b}}$ exceeds some chosen critical value ς, then the unit is included in the current subgroup[7]. After forming the subgroup the $\log t$ test is run for the whole subgroup. If $t_{\widehat{b}}(G_r) > -1.65$, the forming of the subgroup is complete, otherwise the critical value ς is raised and the procedure is repeated.

Step 4 (Stopping Rule): Once the first cluster has been detected, $t_{\widehat{b}}$ is applied to the complementary set, i.e. all remaining units are jointly tested for convergence. If this group satisfies the convergence test then we conclude that there are only two clusters. Otherwise we repeat steps 1-3 for remaining units. If no other subgroups are detected the remaining indices do not contain a convergence subgroup and so they are classified as divergent.

3 Data description

We analyse the convergence pattern of stock market indices for the 26 countries[8] in the European Union, since 1985[9]. The dataset is composed of monthly stock price

[6] In cases in which there is considerable volatility in the observations Phillips and Sul (2007) recommend the use of the average over a window in the later part of the sample.

[7] The evidence from the Monte Carlo experiments in Phillips and Sul (2007) suggest the use of 50% critical values (i.e. sign test). In the empricical application we choose a conservative position with $\varsigma = 0.3$.

[8] Estonia is excluded from the analysis given the limited data availability.

[9] The construction of these indices ignores recent trends towards the merging of stock markets. In 2000 Euronext arose out of the merger of the stock exchanges of Amsterdam, Brussels and

indices including the aggregate stock prices and the sector specific stock prices for each country[10]. All stock indices are denominated in euros, this is to offset possible divergence due to divergence in the bilateral exchange rate between countries. The US stock indices are also included as a control for global factors in the dataset.

The index are standardized to zero for a series specific base year. Therefore the first issue in the construction of the dataset is to transform series to a common base year. The issue is complicated by the fact that the series have different starting times and the dataset is a highly unbalanced panel. Furthermore, the base year has to be chosen at the beginning of the sample so as to avoid the problem that the convergence pattern is influenced by the standardisation. We choose as the base date January 1981, and then discarded the first 8 years of observations to get rid of the base year initialisation. Specifically, we fill in the dataset as suggested by Stock and Watson (2002, Appendix A) with an EM algorithm that make use of the factor structure of the dataset. This imputation strategy requires that the missing data can be considered missing at random (MRA)[11]. This condition that is hardly satisfied in our case. However, we use this imputation of the missing data only for the reconstruction of the base year, and the empirical analysis uses only the actual data. In this sense we believe that the computed base year for the standardisation should not affect the empirical analysis.

This procedure requires us to choose the number of factors to be used in the factor models. Altering the number of factors does not have strong implications for the test of relative convergence, though it might have some effect when testing for the formation of different clusters. In the empirical exercise we follow an agnostic procedure. We update the dataset with the number of factors varying between 1 and 6 and then we average among the different results. This approach should be robust to the possible misspecification in the number of factors. Phillips and Sul (2007) observe that the small sample property of the convergence test and clustering procedure is greatly enhanced when the data are filtered and the procedure is applied to the trend, accordingly we use the HP filter[12] to extract the trend component of the series.

The aggregate equity market indices are shown in figure 1. Clearly there are 2 distinct outliers. Slovakia which is well below and Bulgaria which is well above. Table 1 shows the average cross sectional correlation for the European markets for 3 sub-periods. Partly because of the steady addition of new members there is no obvious pattern of convergence in either levels or returns. Tables 2a and 2b report the average cross sectional correlation of each country with the EU as

Paris. In 2001 the Portuguese exchanges joined Euronext

[10] An additional appendix with data details, coverage and mnemonics is available from the authors upon request.

[11] See Rubin (1976) for some discussion of this implication of the MRA condition.

[12] The smoohting parameter is set to 14400, the standard value with monthly series.

a whole in both levels and returns for the 3 sub-periods. For both levels and returns, the majority of countries that were members in the first period (1981-91) had increased their correlations by the second period (1992-98) but this did not in general continue into the last period (1999-2007). For returns, all countries that joined in the second period had also increased their correlation by the 3 period (Cyprus started with a negative correlation in returns), but this was not the case in levels, with some countries increasing correlations and some experiencing a decline.

4 Results.

4.1 Relative Convergence tests

In this section we apply the convergence analysis introduced by Phillips and Sul (2007) to the stock market price indices in the European Union. Possible changes in convergence patterns due to the adoption of the single currency for countries in the euro area are investigated by splitting the sample for these countries into a pre-euro period and a post-euro period. If the euro has fostered convergence among equity markets of the euro zone this would in principle imply a stronger convergence pattern, and should result in lower values for the $t_{\widehat{b}}$ statistic and in a higher value for $\underline{\alpha}$, the lower bound of the support of the decay parameter. The Monte Carlo experiments in Phillips and Sul (2007) suggest that the properties of the test should be preserved in small samples, so we can analyse the two subsamples separately.

Table 3 summarises the results when the tests are applied to all EU countries using both the aggregate stock market index and the sectoral indices. We analyse sectoral indices since the different composition of the aggregate market might prevent aggregate stock market indices converging (see also Heston and Rouwenhorst, 1994, and Dutt and Mihov, 2008). The only market for which there are signs of stable convergence are "Metal, iron and steel" and "Industrials". These sectors operate in markets that are increasingly international (partly by cross-border merger and acquisition) and country specific factors have become less important. Furthermore, the tests indicate that a reduction in the dispersion of stock market indices can be observed in many markets when the analysis is confined to the last decade. This suggest that globalisation is playing an increasing role as one of the main drivers of real and financial integration between markets. Figure 2a shows the cross sectional covariance of the converging markets, whereas figure 2b shows the same measure for non converging markets[13].

[13]The fact that the panel in the analysis is unbalanced and when new countries enter the analysis this might be very far from the average of the countries already present in the analysis might cause an increase (jump) in the cross sectional variance which might seriously reduce the

Table 4 reports results of the tests applied to countries that joined the euro in 1999. In this case we have a larger number of markets for which convergence is detected. Beside "Metal, iron and steel" and "Industrials", convergence is now detected for "Chemicals", "Electronic and Electric Goods", "Industrial Transport", "Financial", "Pharmaceutical & Bio" and "Health". Furthermore, in the latter part of the sample there seems to be signs of convergence of aggregate stock market indices among EMU countries. Moreover, in the latter subsample for the Euro area countries there is evidence of an even number of markets where relative convergence is detected. Figures 3a and 3b plot the cross sectional covariance for the EMU countries. Not surprisingly the magnitude of the cross sectional dispersion of stock indices is much smaller for the countries in the currency union. These results mainly reflect an higher degree of similarity of the markets in the European Union, and a process of integration between markets in the area that has been fostered by a common effort to create a single common market.

In summary, the analysis of the EU or EMU finds that in the latter part of the sample some evidence of convergence in a number of markets. However, it is important to note that from figure 2 and 3 it is clear that these reflect a reverse of the divergence pattern that started in the middle of the 1990s. Furthermore, the turnaround occurs well after the introduction of the euro - usually around 2002-2003. Therefore, it is not clear whether the evidence of increased convergence in the last subsample is to be regarded as a reflection of the introduction of the common currency. Indeed, the increase inintegration among markets in the last part of the sample seems to be shared by all countries in the European Union. Perhaps, the faster degree of convergence and lower dispersion found among the Euro Area countries might be attributed to similarities among countries and the fact that most of the Euro Area countries have been part of the common market area for a longer period.

The magnitude of the $\underline{\alpha}_i$s suggest that even when some convergence is detected, the speed of convergence remain always very low. This suggests that global convergence, if it is to be observed at all, is going to be very slow.

4.2 Cluster analysis

The rejection of relative convergence does not rule out the presence of (asymptotic) cointegration between subsets of equity markets. Specifically, equity markets can share the same common trend, but with loadings that are different for subgroups of markets. Indeed, the null hypothesis of the $\log(t)$ test of Phillips and Sul is robust to the presence of club convergence between countries.

We perform the analysis of cluster convergence for all equity markets. The

power of the test. This seems to be the case for the "Pharmaceutical and Bio" sector.

general finding is that there are usually one or two countries which show a pattern of divergence, whereas all the others tend to group into two to four clusters. Therefore, for most of the markets the indices seems to share a common stochastic trend[14], therefore asymptotic cointegration of the indices is detected. Table 5 summarises the findings of the clustering analysis[15].

Table 6 shows the results of the cluster analysis applied to aggregate stock market indices. Inspection of Figure 1 suggests a common stochastic trend for countries in the European Union, with the exception of Bulgaria and Slovakia[16]. In Figure 4 we plot the average of each of the 3 clusters against against the S&P 500 index (converted into Euros), the average of the EU as a whole and the average of the EMU countries.The first convergence club is formed by markets that in the whole sample have generally outperformed the EU average, divergence has increased since the mid 1990s The second cluster is generally formed by small countries, whose markets are the more volatile and their average fluctuates around the EU average throughout all the sample. The third club is formed by the large economies, with the exception of Poland and the UK, this group includes most of the large Euro area countries. Interestingly this second group has followed the EU average very closely throughout the sample, but it seems to have decoupled around 1998, and settled at a slower growth rate[17].

Figure 5 shows the common factors of the EU, the Euro countries, the 3 identified clusters and the S&P500 index (converted into Euros). Clearly the indices seem to share the same common factor, even though differences between markets are clear. This is confirmed by a look at cross correlations between the series as shown in Table 7. The Euro Area average is not too different from the EU average, pointing to the homogeneity of equity markets between the countries in the EU. Nevertheless, the Euro area markets seem to be heading towards a lower loading to the aggregate factor, with a decupling sometime around 2002, as stressed above. The differences with the US seems to mainly reflect the accumulated loss in the first part of the sample, from 1981 to 1986.

4.3 Macroeconomic fundamentals and convergence in equity markets

Since the seminal work of Campbell and Shiller (1988) the relation between stock markets and their fundamentals have been widely documented in the literature.

[14]We perform ADF tests for a unit root of the cross sectional average of each market and for all of them there is evidence in favour of a unit root with drift.

[15]Detailed tables for all the markets are available from the authors on request.

[16]We consider Slovakia as an outlier even though the clustering procedure of Phillips and Sul (2007) would include it in the second convergence group.

[17]This result is not influenced by the inclusion of Poland.

In this section we give a sketch of how financial integration might be the natural result of deeper integration in the economies of a currency area when free capital mobility is allowed.

Consider the relation between the stock prices and some macroeconomic fundamentals[18], x_{it}

$$s_{it} = b_i x_{it} + e_{it} \tag{5}$$

where $e_{it} \sim I(0)$. Stacking the vector of indices, this can be rewritten as

$$s_t = Bx_t + e_t \tag{6}$$

where B is a diagonal matrix. Notice that this relation can be derived from the optimizing behavior of a maximizing agent, therefore, the b_i reflect agent's preferences over risk. If the macroeconomic fundamentals themselves have a common factor structure then

$$x_t = \gamma F_t + \epsilon_t \tag{7}$$

where F_t represent the common factors, if F_t is nonstationary and $\epsilon_t \sim I(0)$ then the macroeconomic fundamentals are cointegrated. This is usually the case in the standard DSGE model (Lence and Falk, 2005) framework.where the long run properties of the system are driven by common supply shocks (i.e. total factor productivity has a common trend). Substituting this expression back into the expression for equity prices we obtain

$$s_t = B\gamma F_t + B\epsilon_t + e_t \tag{8}$$

If we consider the particular case of a single common factor, then $B\gamma$ is an $n \times 1$ vector whose generic i element is $b_i\gamma_i$. Convergence in this setting requires that

$$b_{it}\gamma_{it}/b_{jt}\gamma_{jt} \to 1 \tag{9}$$

Perhaps, the most trivial example is the case of two countries with the same preference over risk, and who share a common trend with equal loading (therefore, with convergence in the fundamentals).

In the empirical analysis we also consider the possibility of clustering among stock market indices. The clusters are defined such that market indices in the same cluster are converging to the same long run value. The relation between markets in different clusters is such that a linear combination of two equity prices

[18] To simplify notation in this section we drop the time index in the relations' coefficients.

is stationary. This can be expressed as

$$\begin{array}{rclr} b_{it}\gamma_{it}/b_{jt}\gamma_{jt} & \to & 1 & i,j\in G_1 \\ b_{it}\gamma_{it}/b_{jt}\gamma_{jt} & \to & \kappa & i\in G_1, j\in G_2 \end{array} \qquad (10)$$

for a constant κ, this constant may reflect both differences in the loadings, γs (different technology absorption capabilities) or different bs (different preferences of agents, where these might reflect for instance different level of liquidity of markets).

Equity markets will be driven by underlying fundamentals so there will only be convergence if there is convergence in the basic drivers of profits and dividends. This relationship between underlying economic performance and equity markets is brought out in Figure 5. First we plot in the top panel the average of each of the country clusters *relative* to the EU average. The first cluster (solid line)is always well above the EU average. The second cluster (dashed line) starts above average, spends some time below average and then moves above average in the last few years. The 3rd cluster generally remains below average over all of the sample though it is very close to average around the year 2000. In the second panel we carry out a similar exercise but now for accumulated real growth rates in GDP. For each cluster we calculate the average growth rate in each year and accumulate it and plot it relative to the accumulated average of the EU. Although the results are not completely clear cut, there is a strong suggestion that relative movements in stock markets are related to relative movements in aggregate output.

5 Summary and conclusions

Whether the countries in the European Union are experiencing a process of financial integration is a question of broad interest. In this paper we report evidence that seem to confirm the view that a process of integration is under way even though these seem to be rather slow. Furthermore, this process seem to be shared by most of the countries of the European Union and not only those that are already part of the Euro zone. In this sense our analysis supplement and generalized previous findings (see e.g. Rangvid (2001) and Worthington et al. (2003)) that with mixed enthusiasm confirm this results for a subset of countries in the European Union. The fact that the process is shared among all the countries and not only those that adopted the single currency suggest that this phenomenon cannot be solely attributed to the recent adoption of the single currency.

Whereas financial integration and the adoption of a common currency should be associated with convergence in short term and long term interest rates on sovereign bonds, this need not necessarily be so in equity markets. Differences in the performance of equity markets can persist if there are differences in the underlying drivers of profitability and dividends. Only when there is convergence in the fundamental drivers of economic growth will equity markets converge. We find in this paper that an examination of equity markets in the 25 countries of the European Union reveals three clusters that reflect differences in underlying growth rates. Therefore, the process of integration seem to reflect a more deep process of economic convergence among the countries.

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6 Cointegration, common trends and market efficiency

The study of market interdependence and portfolio diversification can be traced back to Grubel (1968), Granger and Morgenstern (1970) and Levy and Sarnat (1970). These early studies employ correlation analysis to examine short-run inter-market relationships. Another branch has concentrated on examining financial links amongst stock markets by using either bivariate or multivariate cointegration methodology. These studies have typically either used the Engle and Granger (1987) or Johansen (1988) method of testing for cointegration.

Efficiency and integration are key issues in the study of financial markets. But early on in the application of cointegration methods to these questions an apparent paradox was identified. According to Granger (1986) if a pair of asset prices are I(1) and are efficiently priced they cannot be cointegrated[19]. If two variables are cointegrated then there must be Granger causality in at least one direction so one variable can be used to forecast the other. Thus, if two asset prices are priced efficiently they cannot be cointegrated because ot herwise one could be used to forecast the other, thereby violating the efficient pricing assumption. This has provided the basis for a number of studies of market efficiency (MacDonald and Taylor 1989, Coleman, 1990, Baillie and Bollerslev, 1989). However, the assertion has also been challenged (Levich, 1985, Dwyer and Wallace, 1992, Engel, 1996).

Consider a set of equity market indices. In the bivariate case let two equity market indices follow a random walk with drift:

$$\begin{aligned} s_{1t} &= \alpha_1 + s_{1t-1} + \varepsilon_{1t} \\ s_{2t} &= \alpha_2 + s_{2t-1} + \varepsilon_{2t} \end{aligned} \tag{11}$$

with starting values s_{10} and s_{20}. A multivariate unobserved components model can be set up in the form

$$\mathbf{s}_t = \mathbf{a} + \boldsymbol{\mu}_t + \mathbf{e}_t \tag{12}$$

$$\boldsymbol{\mu}_t = \boldsymbol{\beta} + \boldsymbol{\mu}_{t-1} + \boldsymbol{\eta}_t \tag{13}$$

With $\mathbf{e}_t \sim NID(\mathbf{0}, \boldsymbol{\Sigma}_e)$, similarly $\boldsymbol{\eta}_t \sim NID(\mathbf{0}, \boldsymbol{\Sigma}_\eta)$. The two indexes have a common stochastic trend if $\boldsymbol{\Sigma}_\eta$ is singular. The model can then be rewritten in its common trend representation

$$\mathbf{s}_t = \mathbf{a} + \Theta\mu_t + \mathbf{e}_t \tag{14}$$

$$\mu_t = \beta + \mu_{t-1} + \eta_t \tag{15}$$

[19]See also Richards (1995) and Caporale and Pittis(1998).

with $\eta_t \sim NID(0, \sigma_\eta)$. with Θ a 2×1 matrix of factor loadings, normalized such that $\Theta = (1; \theta)$; $\mu_0 = 0$.

Now let us derive the random walk with drift representation from this unobservable components model:

$$\begin{aligned} s_{1t} &= \mu_t + a_1 + e_{1t} \\ &= \beta + \mu_{t-1} + \eta_{1t} + a_1 + e_{1t} \\ &= \beta + s_{1t-1} - a_1 - e_{1t-1} + \eta_{1t} + a_1 + e_{1t} \\ &= \beta + s_{1t-1} + \eta_{1t} + \Delta e_{1t} \end{aligned} \tag{16}$$

this implies that

$$s_{1t} = s_{10} + \underbrace{\beta t}_{\text{deterministic trend}} + \underbrace{\sum\nolimits_{\tau=1}^{t} \eta_{1\tau}}_{\textit{stochastic trend}} + e_{1t}$$

and for the other stock index we have:

$$\begin{aligned} s_{2t} &= \theta\beta + s_{2t-1} + \theta\eta_{2t} + \Delta e_{2t} \\ &= s_{20} + \theta\beta t + \theta \sum\nolimits_{\tau=1}^{t} \eta_{2\tau} + e_{2t} \end{aligned} \tag{17}$$

Therefore, the random walk specification (11) above implicitly imposes 2 restrictions. First, that the error terms have a common factor representation, where the permanent component is constrained to be common to both markets:

$$\boldsymbol{\varepsilon}_t = \Theta\eta_t + \Delta\mathbf{e}_t$$

and secondly that the intercepts are proportional (and the deterministic drifts are the same)

$$\begin{aligned} \alpha_1 &= \beta \\ \alpha_2 &= \beta\theta \end{aligned}$$

and the starting values are:

$$\begin{aligned} s_{10} &= a_1 \\ s_{20} &= a_2 \end{aligned}$$

Convergence is observed if the loadings on the two series are the same , i.e. if $\theta = 1$. Notice that if the loadings are the same this implies that the linear combination

$y_{1t} - \frac{1}{\theta} y_{2t}$ is stationary (i.e. the cointegrating vector is 1;-1); this then implies that

$$s_{1t} - \frac{1}{\theta} s_{2t} = (a_1 - \frac{1}{\theta} a_2) + e_{1t} - \frac{1}{\theta} e_{2t} \tag{18}$$

therefore strictly speaking convergence requires also that the initial values are the same.

Given that the Granger-Engle representation theorem ensures that if there is cointegration between two indices so they share a common stochastic trend, there is an equivalent error correction representation. For s_{1t} and s_{2t} these are:

$$\Delta s_{1t} = \gamma_1 - \frac{1}{\theta}(\theta s_{1t-1} - s_{2t-1}) + \epsilon_{1t} \tag{19}$$

and

$$\Delta s_{2t} = \gamma_2 - \theta(\frac{1}{\theta} s_{2t-1} - s_{1t-1}) + \epsilon_{2t} \tag{20}$$

where:

$$\begin{aligned} \gamma_1 &= \beta + a_1 - \frac{1}{\theta} a_2 \\ \gamma_2 &= \theta\beta + a_2 - \theta a_2 \\ \epsilon_{1t} &= e_{1t} + \eta_{1t} - \frac{1}{\theta} e_{2t-1} \\ \epsilon_{2t} &= e_{2t} + \theta\eta_{2t} - \theta e_{1t-1} \end{aligned}$$

The next question is whether the assumption of cointegration between the two markets violates the efficient market assumption by making one market predictable by the other. The conditional expectation of s_1 at period $t+1$ is:

$$E_t(s_{1t+1}|\Omega_t) = s_{1t} + \gamma_1 - \frac{1}{\theta}(\theta s_{1t} - s_{2t}) = \gamma_1 + \frac{1}{\theta} s_{2t} \tag{21}$$

We can also compute the conditional expectation of s_{2t+1} as:

$$E_t(s_{2t+1}|\Omega_t) = \gamma_2 + \theta s_{1t} \tag{22}$$

which is also a linear function of s_{1t}. Since they are been priced simultaneously arbitrage ensures that there is no predictability but there is cointegration. The no arbitrage condition is given by the expectation of equation (18). So

$$E_t(s_{1t+1}|\Omega_t) = \frac{1}{\theta}(\theta s_{1t} - \theta\alpha_1 - \alpha_2) + \beta + \alpha_1 - \frac{1}{\theta}\alpha_2 = \beta + s_{1t} \tag{23}$$

and

$$E_t(s_{2t+1}|\Omega_t) = \theta\beta + s_{2t} \tag{24}$$

Much of the empirical literature on convergence looks at returns (and sometimes excess returns over the riskless rate of return). Given the no arbitrage condition, the conditional expectation of the two returns is:

$$E_t(\Delta s_{1t+1}|\Omega_t) = \beta \tag{25}$$

and

$$E_t(\Delta s_{2t+1}|\Omega_t) = \theta\beta \tag{26}$$

The expected return on each of the markets is the deterministic increment to productivity. Thus equity markets are ultimately driven by fundamentals and should converge if $\theta = 1$.[20]

[20] Granger (1986) explicitly considers the case of gold and silver prices. Here we would not expect to find a common stochastic trend, so if they were found to be cointegrated that would contradict market efficiency.

TABLE 1: AVERAGE CROSS SECTIONAL CORRELATIONS

	1981-1991	1992-1998	1999-2007
$LEVEL$	0.623	0.725	0.590
$RETURN$	0.346	0.428	0.412

TABLE 2a: AVERAGE CROSS SECTIONAL CORRELATIONS (returns)			
	1981-1991	1992-1998	1999-2007
AU	0.248	0.479	0.438
BE	0.379	0.531	0.464
BU	—	—	0.071
CY	—	-0.167	0.193
CZ	—	0.345	0.423
DE	0.228	0.522	0.526
FI	0.123	0.434	0.433
FR	0.384	0.544	0.585
GE	0.431	0.493	0.579
GR	0.094	0.414	0.436
HU	—	0.378	0.514
IR	0.451	0.480	0.464
IT	0.292	0.405	0.548
LA	—	—	0.238
LT	—	—	0.275
LU	—	0.396	0.422
MA	—	—	0.186
NE	0.464	0.537	0.574
PL	—	0.415	0.512
PR	—	0.426	0.513
RM	—	—	0.279
SK	—	—	0.147
SL	—	—	0.229
SP	0.573	0.491	0.561
SW	0.410	0.529	0.565
UK	0.424	0.476	0.551

TABLE 2b: AVERAGE CROSS SECTIONAL CORRELATIONS (LEVEL)			
	1981-1991	1992-1998	1999-2007
AU	0.718	0.571	0.603
BE	0.790	0.835	0.679
BU	—	—	0.650
CY	—	0.473	0.396
CZ	—	0.104	0.601
DE	0.717	0.833	0.707
FI	-0.324	0.757	0.473
FR	0.767	0.803	0.673
GE	0.744	0.829	0.580
GR	0.353	0.761	0.595
HU	—	0.762	0.655
IR	0.774	0.800	0.717
IT	0.706	0.722	0.667
LA	—	—	0.492
LT	—	—	0.539
LU	—	0.833	0.618
MA	—	—	0.511
NE	0.769	0.810	0.476
PL	—	0.592	0.733
PR	—	0.825	0.605
RM	—	—	0.556
SK	—	—	0.316
SL	—	—	0.497
SP	0.525	0.837	0.748
SW	0.776	0.819	0.686
UK	0.779	0.817	0.559

TABLE 3: EU 27 Countries

	Jan 1989-Dec 2007	Jan 1989-Dec 1999	Jan 1999-Dec 2007
Total Market	-0,9965	**-0,0598**	-0,1776
	(-8,1409)	**(-0,9029)**	(-6,1309)
Oil	-0,3912	-0,5409	-0,1972
	(-14,5407)	(-5,3215)	(-17,1493)
Basic Material	-0,2606	-0,2393	-0,3619
	(-12,0411)	(-6,1247)	(-22,7036)
Chemicals	-0,7747	-0,7958	**0,0434**
	(-6,3815)	(-24,4314)	**(0,8466)**
Metal, Iron & Steel	**0,2230**	-0,1022	**0,5011**
	(1,6300)	(-3,5724)	**(5,6344)**
Industrials	**-0,1422**	-0,3447	**0,2214**
	(-1,4906)	(-3,8691)	**(2,4266)**
Construction	-0,2851	-0,3903	**-0,0785**
	(-3,8284)	(-3,5618)	**(-1,0858)**
Industrial Machinery	-0,6318	**-0,0567**	-0,2259
	(-10,6933)	**(-0,9486)**	(-6,6771)
Electronic and Electric Goods	-0,5272	-0,1497	-0,2837
	(-7,1786)	(-6,4032)	(-16,8939)
Consumption Goods	-0,2728	-0,4974	**-0,0225**
	(-4,6875)	(-6,9807)	**(-0,3799)**
Industrial Transport	-0,4011	-1,4501	**0,0386**
	(-2,0442)	(-15,6113)	**(0,4215)**
Utilities	-0,4450	-0,7142	**0,0475**
	(-4,5774)	(-6,9359)	**(0,8781)**
Financials	-0,7626	**-0,0102**	-0,3987
	(-12,3820)	**(-0,2868)**	(-24,5372)
Food and Beverage	-0,2202	-0,9107	-0,1050
	(-6,9203)	(-5,7441)	(-2,5967)
Pharmaceutical & Bio	-1,0600	-0,4838	**0,4782**
	(-6,5505)	(-4,3916)	**(5,0493)**
Health	-0,3560	**-0,1334**	-0,1560
	(-5,3190)	**(-1,1883)**	(-2,8488)

The table 1 reports the value of $\underline{\alpha}$, where $\underline{\alpha}$ is the lower bound of the support rate of the decay rates a_i. Notice that the regression starts at $[rT]$, the integer part of rT for some fraction $r > 0$ (Phillips and Sul recommend that the fraction be set to $r = 0.3$).

The value in parenthesis is the t value for the $\log t$ test. Bold carachters indicates that the value is significant at the 5% critical value.

TABLE 4: EMU 11 Countries

	Jan 1989-Dec 2007	Jan 1989-Dec 1999	Jan 1999-Dec 2007
Total Market	-0,5667	-0,1323	**0,0204**
	(-7,5118)	(-2,3440)	**(0,4630)**
Oil	-0,1337	-0,5576	-0,2900
	(-4,8313)	(-5,2940)	(-17,9268)
Basic Material	-0,1602	**-0,0897**	-0,2131
	(-6,4790)	**(-1,3782)**	(-8,2021)
Chemicals	**0,1079**	-0,4663	-0,1417
	(4,7627)	(-8,5208)	(-6,9474)
Metal, Iron & Steel	**0,0509**	-0,2446	**0,3412**
	(0,4784)	(-4,9756)	**(3,6270)**
Industrials	**-0,0068**	-0,2031	**0,2748**
	(-0,0681)	(-2,4675)	**(2,2024)**
Construction	-0,2375	-0,1358	-0,1349
	(-5,2424)	(-6,0486)	(-1,8222)
Industrial Machinery	-0,4682	**-0,0703**	-0,2836
	(-6,1071)	**(-1,0448)**	(-3,2711)
Electronic and Electric Goods	**0,3564**	-0,1022	-0,3528
	(5,6149)	(-3,0599)	(-5,0570)
Consumption Goods	-0,3878	-0,5740	-0,1876
	(-4,1626)	(-3,9291)	(-2,2613)
Industrial Transport	**-0,1171**	-0,5209	**-0,0352**
	(-1,5686)	(-10,4103)	**(-0,4401)**
Utilities	-0,1382	**-0,0325**	**0,0065**
	(-3,0427)	**(-0,7103)**	**(0,3481)**
Financials	**-0,1613**	**0,6485**	-0,6840
	(-0,9022)	**(6,9469)**	(-6,3304)
Food and Beverage	-0,3036	-1,0012	**0,0180**
	(-5,0423)	(-5,2332)	**(0,3014)**
Pharmaceutical & Bio	**0,1392**	-0,3434	-0,1171
	(8,4137)	(-3,3312)	(-5,3100)
Health	**0,1918**	**-0,0474**	**0,0040**
	(4,8802)	**(-0,2948)**	**(0,1081)**

See notes Table 1

TABLE 5: Cluster Analysis Summary

	No. of clubs	Divergence Countries
Total Market	3	BU (SL, possible outlier)
Oil	2	LU
Basic Material	2	LU
Chemicals	1	CZ, RM
Construction	1	CY, FI, SP
Industrial Machinery	4	none
Electronic and Electric Goods	1	CY
Consumption Goods	2	none
Industrial Transport	3	AU, CZ
Utilities	4	none
Financials	2	(CZ, possible outlier)
Food and Beverage	3	none
Pharmaceutical & Bio	2	none
Health	3	GR

TABLE 6: CLUB CONVERGENCE IN EQUITY MARKETS

Name	t value Step 1	Step 2	Club	$\log t$ test	Name	t value Step 1	Step 2	Club	$\log t$ test
BU		Outlier[ç]							
LA	Base	Core	S_1						
GR	2.278	Core	S_1	$t_{S_1} = 0.784$					
FI	2.729	Core	S_1						
DE	1.272	1.272	S_1						
LT	0.073	0.188							
HU	0.856	2.470	S_1						
SL	0.156	-0.373							
MA	0.126	0.828	S_1						
CY		-2.484							
RM		-2.331			LT	Base	Core	S_2	
SP		1.891	S_1		SL	2.135	Core	S_2	
CZ		-0.148			CY	2.655	Core	S_2	
IR		1.562	S_1		RM	2.467	2.467	S_2	$t_{S_2} = -0.426$
SW		0.899	S_1		CZ	1.550	2.472	S_2	
AU		-1.383			AU	1277	0.540	S_2	
IT		-1.948			IT		-0.129	S_3	
PL		-2.656			PL		0.009	S_3	
BE		-1.857			BE		-0.678	S_3	
LU		-2.284			LU		-0.768	S_3	
PR		-2.658		$t_{S_1^C} = -5.491$	PR		-0.963	S_3	$t_{S_3} = 4.402$
FR		-0.926			FR		-0.507	S_3	
NE		-1.591			NE		-0.992	S_3	
UK		-3.197			UK		-1.952	S_3	
GE		-2.286			GE		-5.275	S_3	
SK		-4.245			SK		1.419[§]	S_2	

[ç] The value of the log t test for the group Bulgaria and Latvia is -8.676.

[§] From inspection of the data Slovakia appears as a possible outlier, the clustering procedure would include it in both cluster 2 and 3.

TABLE 7a: GLOBAL FACTORS CORRELATIONS (level)

1991-1998	S&P500 (in US$)	S&P500 (in Euro)	EU	EuroArea	Cluster 1	Cluster 2
EU	0.852	0.748				
EuroArea	0.900	0.817	0.989			
Cluster 1	0.902	0.822	0.988	0.996		
Cluster 2	0.303	0.227	0.561	0.507	0.548	
Cluster 3	0.894	0.798	0.988	0.990	0.988	0.529
1999-2007	S&P500 (in US$)	S&P500 (in Euro)	EU	EuroArea	Cluster 1	Cluster 2
EU	0.681	0.820				
EuroArea	0.901	0.763	0.856			
Cluster 1	0.777	0.758	0.967	0.920		
Cluster 2	0.535	0.826	0.960	0.721	0.869	
Cluster 3	0.897	0.695	0.769	0.984	0.849	0.622

TABLE 7b: GLOBAL FACTORS CORRELATIONS (return)

1991-1998	S&P500 (in US$)	S&P500 (in Euro)	EU	EuroArea	Cluster 1	Cluster 2
EU	-0.034	-0.237				
EuroArea	-0.039	-0.258	0.919			
Cluster 1	-0.019	-0.237	0.945	0.919		
Cluster 2	0.090	-0.092	0.714	0.639	0.631	
Cluster 3	-0.079	-0.299	0.893	0.911	0.847	0.567
1999-2007	S&P500 (in US$)	S&P500 (in Euro)	EU	EuroArea	Cluster 1	Cluster 2
EU	0.088	0.019				
EuroArea	0.143	0.097	0.923			
Cluster 1	0.101	0.050	0.959	0.918		
Cluster 2	0.000	-0.073	0.802	0.594	0.688	
Cluster 3	0.127	0.070	0.917	0.983	0.891	0.602

FIGURE 1: TOTAL MARKET INDEX EUROPEAN UNION

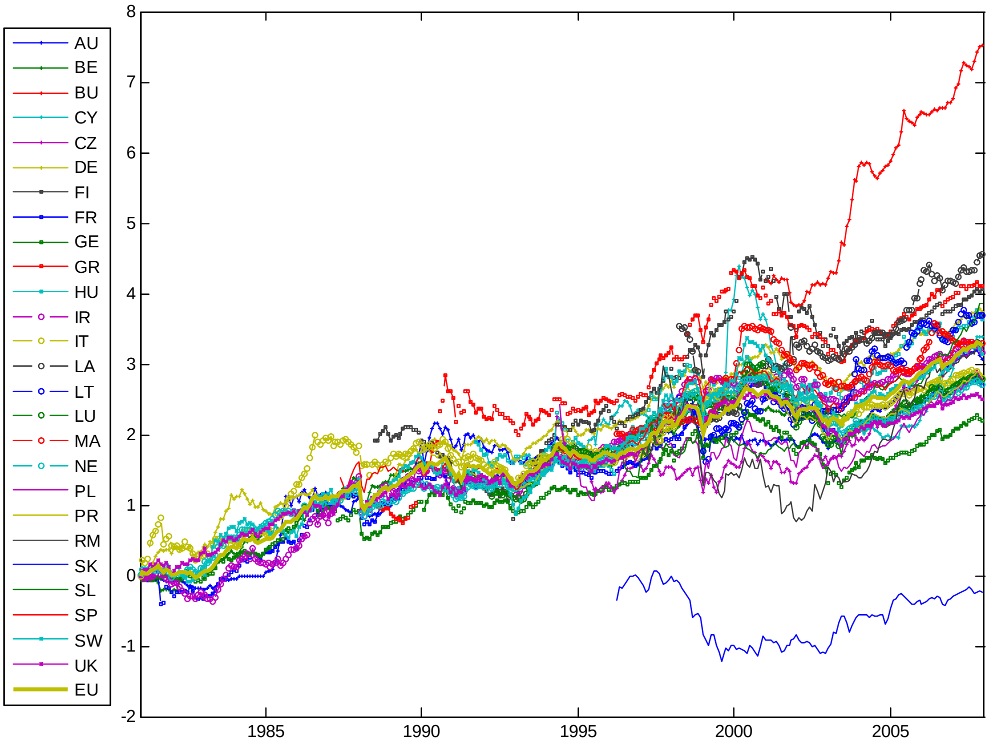


FIGURE 2a: Cross-sectional covariance of convergent groups EU

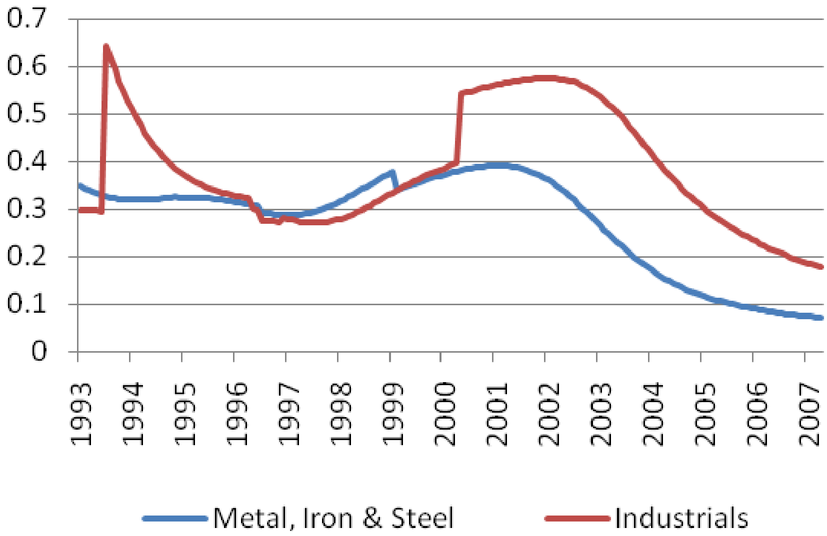


FIGURE 2b: Cross-sectional covariance of convergent groups EU

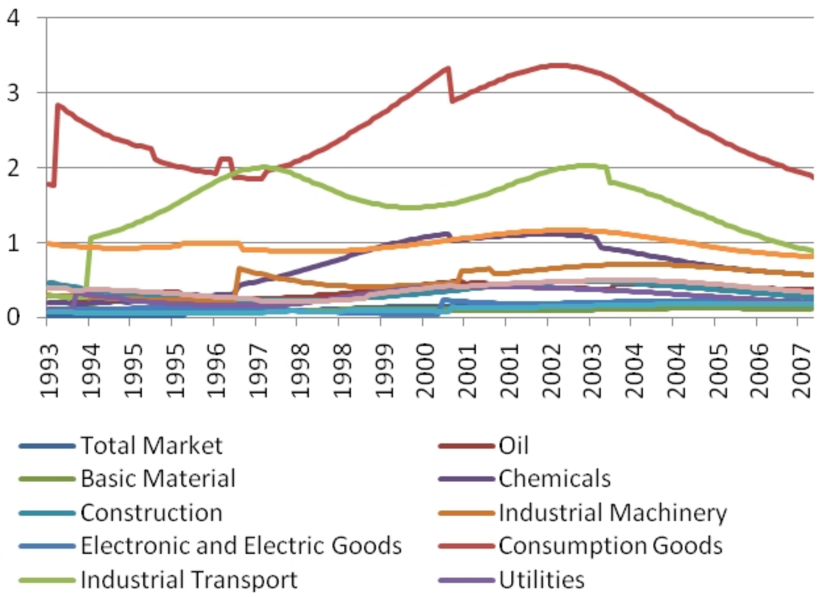


FIGURE 3a: Cross-sectional covariance of convergent groups EMU

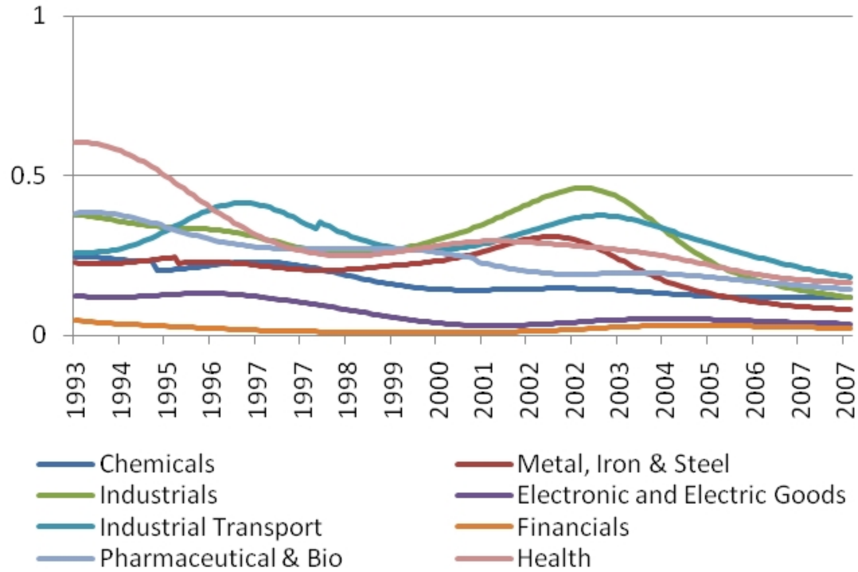


FIGURE 3b: Cross-sectional covariance of non convergent groups EMU

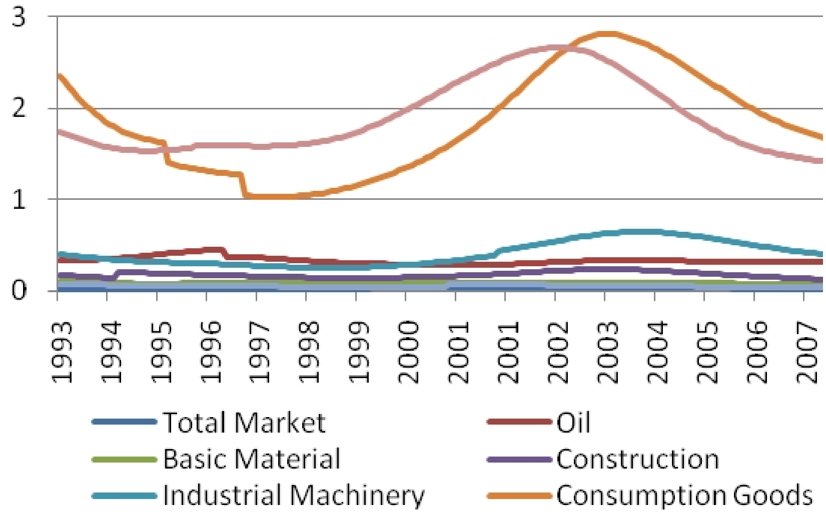


FIGURE 4: CLUSTERS

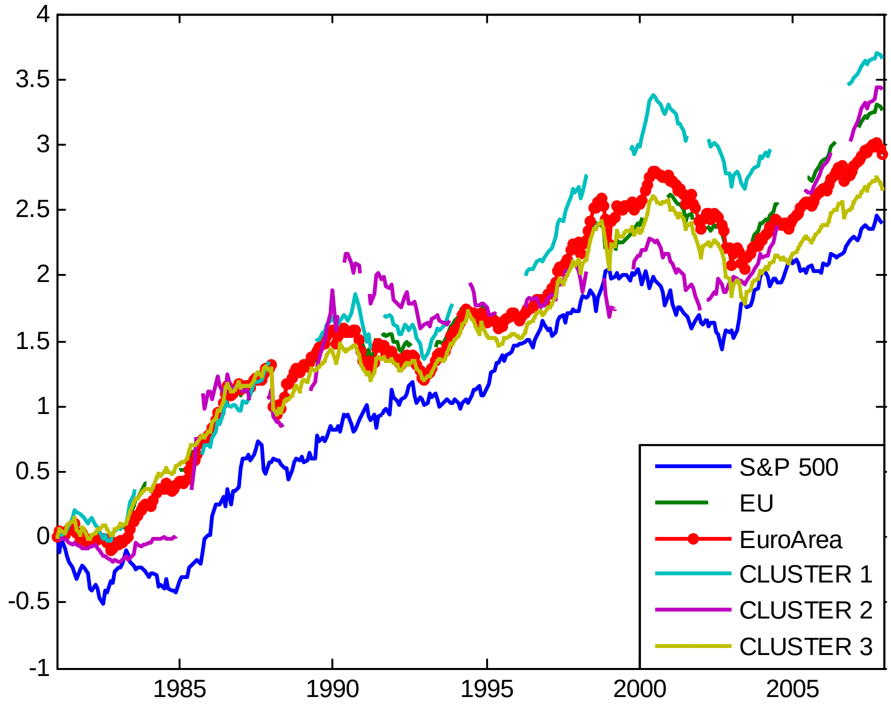
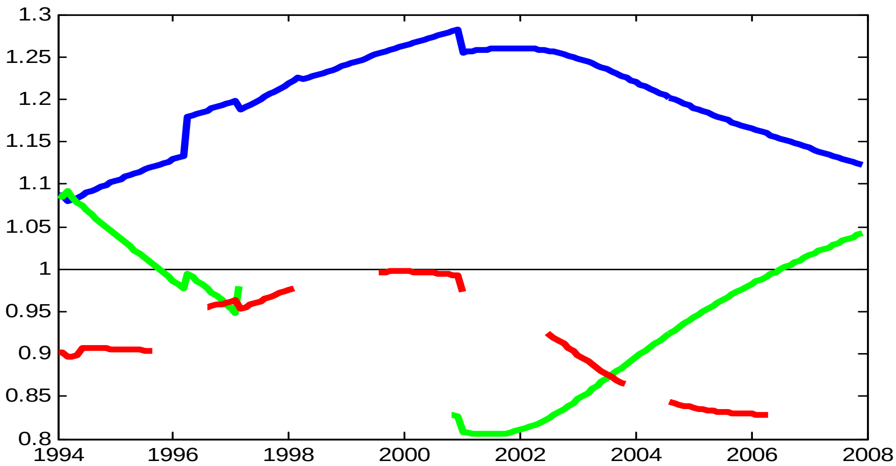


Figure 5: CLUSTER CONVERGENCE AND ECONOMIC FUNDAMENTALS

Convergence Paths of Clusters



Cumulated real GDP Growth

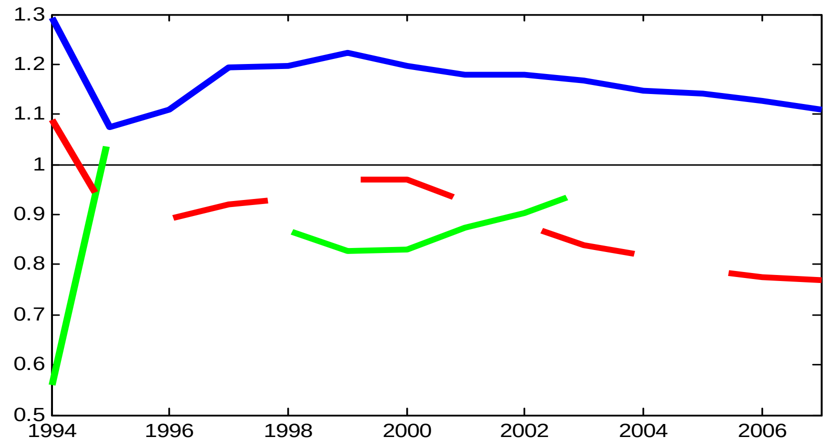


Figure 5. The top panel shows the cluster convergence paths with respect to the EU average. The bottom panel reports the similar figures caluculated on the cumulated annual growth rates (datasource: the Conference Board and Groningen database). The blue continuous line (—–) refers to cluster 1, the green dashed line (- - - -) refers to cluster 2, whereas the dotted red line (· · · · · ·) refers to cluster 3.