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Dynamics of Bond Market Integration between Established and New European Union Countries

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Abstract:

In this paper, we examine the integration of European government bond markets using daily returns over the 1998-2003 period to assess the time-varying level of financial integration. We find evidence of strong contemporaneous and dynamic linkages between the Euro zone bond markets with that of Germany. However, there is much weaker evidence outside of the Euro zone for the three new EU markets of the Czech Republic, Hungary and Poland, and the UK. In general, the degree of integration for these markets is weak and stable, with little evidence of further deepening despite the increased political integration associated with further enlargement of the EU.

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1. Introduction

The political, economic and monetary developments associated with the European Union (EU) have been major catalysts for regional financial market integration. As such, the next historical stage of EU enlargement will also have financial implications. Whilst there is substantial evidence of convergence in the present bond markets within the European Union (EU) (eg., see Galati and Tsatsaronis, 2003), less is known about the extent and dynamics of financial integration between the new and established members. In this study, we focus on integration between government bond markets of three new EU countries, Poland, the Czech Republic and Hungary, as well as a subset of countries already belonging to the EU, Belgium, France, Ireland, Italy, Netherlands, UK and Germany. The choice of sample countries has been determined by data and economic factors. In regards to data, the three new EU countries chosen represent those that have the longest available time series data comparable to the established EU countries. In economic terms these countries represent the largest, most developed economies amongst the new and established member groups, with the largest and most liquid government debt markets.

The concept of financial market integration is integral to international finance and it is natural that financial market integration changes with economic conditions. The economic explanation that is generally accepted is that investors' risk aversion level varies over time, causing them to require varying compensation for accepting a risky payoff from financial assets. For this reason, recent studies have allowed financial integration to vary over time. For government bonds, Ilmanen (1995) provided one of the first assessments on time varying expected returns using an asset pricing model. Extending from this, Barr and Priestley (2004) applied a similar framework to assess international bond market integration by investigating the extent to which bond returns are determined by world risk factors rather than by domestic risk factors. Moreover, both Clare and Lekkos (2000) and Cappiello et al. (2003) have found significant variations in international bond market return comovements. Like Cappiello et al. (2003), Christiansen (2003) has also found some changes in European bond markets since the introduction of the Euro. She provides empirical evidence that regional effects have become dominant over both own country and global effects in EMU bond markets with the introduction of the Euro but not in non-EMU countries where country effect remains strong. Given that Driessen, Melenberg and Nijman (2003) find factors relating to the term structure to explain most of the variations in international excess bond returns, it is conceivable that economic convergence required as part of EU membership has inevitably led to higher levels of bond market convergence. However, this remains to be determined for new EU members, as there is little evidence of the extent, still less the dynamics, of bond market integration.

The attention on comovements across government bond markets in the literature pales in comparison to that on stock markets. Smith (2002) is one of the few studies to have tested for cointegration (long-term relationship) in international government bond markets. They apply the Johansen (1988) and Johansen and Juselius (1990) techniques on monthly mixed maturity bond index returns and detect the existence of cointegrating vectors. However, the literature is scant on the time varying nature of bond market integration in new EU members, despite this having serious implications for policy making in an enlarged EU. This paper attempts to address this void and provide empirical evidence on the dynamic nature of bond market integration amongst the established and new EU countries. This is accomplished by the investigation of the time varying nature of the market integration via three advanced econometric modeling methodologies. Given that yield differences between government bond issues in the European Monetary Union (EMU) are small (through monetary policy co-ordination), we expect EMU bond markets to be more closely integrated overall than with new incoming members, and we aim to investigate the extent to which these new EU government bond markets differ from the existing markets. This is vital for the success of the European Union's next phase of enlargement, which began in May 2004. Barr and Priestley (2004) believe the economic costs and benefits of international bond market integration are likely to be significant, ultimately leading to lower cost of fiscal funding for governments. This suggests that benefits of integration are likely to outweigh the costs.

The major findings of this paper are: i) Although there are strong linkages between established EU bond markets with that of Germany, the three new EU countries' linkages are weaker and show no evidence of growing integration with the EU core in the near term; ii) The UK bond market's linkage with Germany is relatively weaker than those in the Eurozone markets; iii) Of the three new EU countries, the Czech Republic is the least integrated with the established EU bloc.

The remainder of this paper is organized as follows: Section 2 discusses the bond market index data used in this study; Section 3 details the empirical methodologies employed; and the estimation results are discussed in section 4. Lastly, we provide our conclusions in section 5.

2. Data description

The data used in the paper are all-maturity total returns on MSCI Government Bond Indices for the Czech Republic, Hungary, Poland, Belgium, France, Ireland, Italy, Netherlands, the UK and Germany sourced from Thompson Datastream.[1] We have chosen these bond indices on the basis that they are available at a daily frequency for the longest time period for the three new EU countries: Czech Republic, Hungary and Poland. Daily returns provide a more accurate assessment of integration dynamics than lower frequency returns. The bond indices are all denominated in US dollars, and the sample period is 30 June 1998 to

[1] Total return indices account for both price changes and dividends reinvested.

31 December 2003 (yielding 1435 usable observations) to calculate returns as first log differences.[2a,b] In our analyses, we choose to use the German government bond index as the proxy for the established EU bloc due to their benchmark status in the European financial markets. This will also avoid spurious integration results as individual bond markets will not be a composite of the EU regional proxy index. We have included data on the UK as well as the Euro zone countries, as the three countries under investigation are not expected to adopt the Euro for a number of years. Thus, exclusion of the sterling debt market would be unwarranted.

In Table 1, we provide descriptive statistics on the bond returns. In general, bond returns are higher in the new EU countries compared to the existing EU member countries, and this corresponds to generally higher return variances in these countries due to perceived higher levels of credit, political and transfer risks. In addition, it is revealed that the distributions of these bond market returns are statistically non-normal (significant levels of skewness and excess kurtosis). The three new EU countries have larger (in magnitude) skewness than the rest. Interestingly, Hungary and Poland show significant negative skewness while the others show the opposite. Also, the excess kurtosis of these two countries are considerable larger than the other countries. The bond index returns are not serially correlated in the first moment in all cases except Poland. However, significant correlation in the second moments is found in all three new EU countries and the UK which is clear evidence of time varying volatility in these markets. In addition, the significance of the bivariate tests for white noise for each bond market and the German benchmark indicates that the first and second

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[2] a) We follow the existing literature in applying log-changes of total return government bond indices (eg. Bodart and Reding, 1999, Christiansen, 2003 and Driessen et al., 2003).

b) Given that we have used all European countries in our sample, data asynchronicity is not a huge problem with our daily frequency returns as the time difference between Eastern and Western European countries are ±2 hours and government bond market trading hours in our sample countries deviate ±1hour.

moments of all these return series move closely together and that the bivariate nature of these distributions need to be accounted for in the modeling of these daily bond market returns.[3]

3. Dynamic Methodologies

It is vital to consider the time varying nature of financial market integration as economic fundamentals are changing in European economies. The methodologiess we use here expressly allow us to capture this important element. In general, we interpret comovements between new EU government bond markets and the German benchmark as a proxy measure for the extent of financial integration. A high degree of co-movement with the German benchmark would provide indirect evidence that the new EU bond markets are pricing in common regional information in the same manner as the bond markets of existing EU countries, and are therefore relatively well integrated into the EU.

3.1 Dynamic Cointegration

The essence of cointegration is that the series cannot diverge arbitrarily far from each other, implying that there exists a long-term relationship between these series and that they can be written in an Error Correction form. By definition, cointegrated markets thus exhibit common stochastic trends. This, in turn, limits the amount of independent variation between these markets. Hence, from the investors' standpoint, markets that are cointegrated will present limited diversification opportunities. The requirement for assets that are integrated in an economic sense to share common stochastic factors, is an alternative definition of

[3] A bivariate version of the Ljung Box (portmanteau) Q test for serial correlation devised by Hosking (1980) was used on linear and squared market returns.

cointegration, as pointed out in Chen and Knez (1995).

In the literature, two primary methods exist to examine the degree of cointegration among indices.[4] The first is the Engle-Granger methodology (see Engle and Granger (1987)) which is bivariate, testing for cointegration between pairs of indices. The second is the Johansen-Juselius technique (see Johansen (1988) and Johansen and Juselius (1990)), hereafter referred to as the JJ technique which is a multivariate extension and allows for more than one cointegrating vector or common stochastic trend to be present in the data. The advantage of this is that the JJ approach allows testing for the number as well as the existence of these common stochastic trends. In essence, the JJ approach involves determination of the rank of a matrix of cointegrating vectors.

To illustrate, for a given lag length of l, and assuming no deterministic components[5], we can write the Vector Autoregression (VAR) representation of the stock indices in levels as

$$\mathbf{E}_t = \mathbf{A}_1\mathbf{E}_{t-1} + \mathbf{A}_2\mathbf{E}_{t-2} + ... + \mathbf{A}_l\mathbf{E}_{t-l+} + \mu_t \qquad (1)$$

where $\mu_t \approx N(0,\Sigma)$ and E represents an $(n\text{x}1)$ vector of stock equity indices, **A** is an $(n\text{x}n)$ matrix of coefficients. We can represent this relationship more generally in the Vector Error Correction (VECM) format as

$$\Delta\mathbf{E}_t = \prod\mathbf{E}_{t-1} + \Gamma_1\Delta\mathbf{E}_{t-1} + \Gamma_2\Delta\mathbf{E}_{t-2} + ... + \Gamma_{l-1}\Delta\mathbf{E}_{t-l+1} + \Gamma_l\Delta\mathbf{E}_{t-l} + \mu_t \qquad (2)$$

[4] See Enders(1995) for a detailed statistical description of the techniques.

[5] The selection of the lag length is important, but more important again is the treatment of deterministic components. In the presence of deterministic elements the estimation of the VAR and the determination of the cointegration vectors, and thus the rank of the system, becomes complex.

Or

$$\prod \mathbf{E}_{t-1} = \Delta \mathbf{E}_{t-1} - \sum_{i=1}^{l} \Gamma_i \Delta \mathbf{E}_{t-i} - \mu_t \tag{3}$$

Where the right hand side terms of Equation (3) are stationary, it follows that $\prod \mathbf{E}_{t-1}$ is also stationary. The JJ technique endeavors to ascertain the rank, r, of Π. This gives the number of stable cointegrating vectors in the system, as Π can be demonstrated to be equivalent to $\alpha\beta'$ where β' is the vector of cointegrating relationships and α a matrix associated with the equilibrium errors $\beta'\mathbf{E}_t$.[6]

The JJ approach generates two statistics of primary interest. The first is the λ_{trace} statistic, which (in this instance) is a test of the general question of whether there exist one or more cointegrating vectors. An alternative test statistic is the λ_{max} statistic, which allows testing of the precise number of cointegrating vectors. These test statistics can be plotted over time to examine how the nature of market integration is changing over time.[7] This approach is in essence a visual application of the recursive cointegration approach of Hansen and Johansen (1992) that has also been applied in a somewhat different form by Rangvid (2001). The output from the approach which we have taken is twofold: first, the largest value of the λ_{trace} statistic which tests the general hypothesis of no cointegration versus cointegration, and second, the number of cointegrating vectors given by the λ_{max} statistic. A set of series that are in the process of converging should be expected, as in Hansen and Johansen (1992) and Rangvid (2001), to show increasing numbers of cointegrating vectors. Intuitively, this makes

[6] Serletis and King (1997) used this approach to examine European equity market integration, the BENELUX and France in particular were found to be converging to the US market.

[7] Further details regarding the dynamic cointegration approach can be found in Barari and Sengupta (2002). There-in the process is described whereby the investigator can plot over time the values of selected test statistics from the JJ approach. The Barari and Sengupta (2002) paper concentrates on the λ_{trace} statistic.

sense. Consider a set of p series which have n cointegrating vectors, $n<p$. This implies that there are n linear combinations of the p vectors that are stationary. If we later find that we have k vectors, $n<k<p$, there are additional combinations that can be used in the representation of the p data. If we have a static number of cointegrating vectors then recursive estimation will simply lead to an upward trend in the λ_{trace} statistic. It should be noted that in general the λ_{trace} statistic is more powerful and to be preferred to the λ_{max} statistic.

3.2 Haldane and Hall

There are a variety of feasible alternative approaches to the Cointegration methodology. The Haldane and Hall (1991) Kalman Filter based methodology is one that has been used in a number of settings.[8] The Haldane & Hall (hereafter HH) method estimates a simple equation of the following specification

$$\ln\left(\mathbf{E}_{jt} / \mathbf{E}_{Bt}\right) = \alpha + \beta_t \ln\left(\mathbf{E}_{jt} / \mathbf{E}_{Xt}\right) + \varepsilon_{jt} \tag{4}$$

via kalman filter estimation. Here the market subscripted B is the preimposed internal base market and that subscripted X is the preimposed external market. Thus, for example, in testing for integration among SE Asian markets, Manning (2002) imposes the US market as the external market (to which the SE Asian markets are assumed to be converging) and Hong Kong as the dominant local market. Here we set the German bond market as the local base and the UK as the external bond market, and estimate the system. We also invert these

[8] Manning (2002) examines Asian stock market integration taking the Haldane and Hall (1991) approach of specifying time varying coefficients via a Kalman filter.

relationships, as we are not confident as to which market, over the time period of this study, represents the dominant market towards which the system may be converging. There are a number of indicators of convergence or divergence. Negative values of β_t indicate divergence, as does a tendency to move further from zero.

The Kalman filter used in this paper works in the following way. The equation is estimated over an initial period, to initialize the coefficients and related information. Thereafter it is updated with the addition of each daily data point. Let $Y_t = \alpha_t + X_t\beta_t + \varepsilon_t, \mathrm{var}(\varepsilon_t) = \eta_t$ be the measurement equation of interest. If we set β_t as the coefficient of interest at time t, then the transition equation is given by $\beta_t = \beta_{t-1} + \nu_t, \mathrm{var}(\nu_t) = \mathrm{M}_t$. Given the estimate of β_{t-1} from information up to that period ($\beta_{t-1|t-1}$) with the associated covariance matrix Σ_{t-1} , the updated estimate is given by equations (5), (6) and (7).

$$S_t = \Sigma_{t-1} + \mathrm{M}_t \tag{5}$$

$$\Sigma_t = S_t - S_t X_t'(X_t S_t X_t' + \eta_t)^{-1} X_t S_t \tag{6}$$

$$\beta_{t|t} = \beta_{t-1|t-1} + S_t X_t'(X_t S_t X_t' + \eta_t)^{-1}(Y_t - \alpha_{t-1} X_t \beta_{t-1|t-1}) \tag{7}$$

3.3 Dynamic Conditional Correlations

We also utilise the recently developed Dynamic Conditional Correlation model of Engle (2002) to model the volatility of bond market total returns in Germany and other EU members and to derive the time-variations in conditional correlations between them. The DCC model is formulated as a generalization of Bollerslev’s (1990) constant conditional correlation assumption. Hence, the residual vector r_t is specified as

$$r_t|F_{t-1} \sim N(0, H_t) \quad (8)$$

where $H_t=D_tR_tD_t$ and $D_t = diag(\sqrt{h_{1,t}}, \sqrt{h_{2,t}})$ is the diagonal matrix of conditional standard deviations, R_t is the time-varying conditional correlation matrix and F_t is information available to time *t.*[9] In short, the actual H matrix is generated in two steps involving a combination of separate univariate GARCH models for the variances of individual bond market returns and the time varying conditional correlations produced by another GARCH parameterization for the unconditional covariance matrix.

The conditional variances for each individual bond market return process is modeled as a typical univariate GARCH(1,1)[10]

$$h_{i,t} = \omega_i + \alpha_i r_{i,t-1}^2 + \beta_i h_{i,t-1} \quad (9)$$

where α_i represents the ARCH effects (short-run persistence of shocks to bond market return i) and β_i represents the GARCH effects.

Following Engle(2002), the entire covariance matrix is also parameterized directly as a GARCH(1,1) model as shown in the matrix specification

[9] Following the GARCH literature that uses daily returns, we simply used a constant and an error term in the conditional mean equation ie. $Y_t=\mu+r_t$.

[10] The bond market integration literature reports little evidence of asymmetry in volatility and so we have omitted modelling this aspect in the current paper.

$$Q_t = (1-\lambda_1-\lambda_2)Q + \lambda_1\varepsilon_{t-1}\varepsilon'_{t-1} + \lambda_2 Q_{t-1} \tag{10}$$

where Q is the positive definite unconditional covariance matrix used solely to provide the correlation matrix. λ_1 and λ_2 are scalar parameters used to capture the effects of past standardized shocks ($\varepsilon_t = D_t^{-1} r_t$) and past dynamic conditional correlations on current dynamic conditional correlations respectively. In matrix terms, the correlation estimator is derived from the covariance matrix using

$$R_t = \mathrm{diag}[Q_t]^{-1/2}[Q_t]\ \mathrm{diag}[Q_t]^{-1/2} \tag{11}$$

In theory, these parameters can be obtained by maximum likelihood estimation using a joint normal distribution assumption for the vector of residuals. Although the descriptive statistics in Table 1 suggest the residuals follow a non-normal distribution, the use of a normal distributional assumption can still be justified asymptotically by quasi-maximum likelihood (QML) theory. Under suitable regularity conditions, QML estimators are consistent (but inefficient) and asymptotically normal. The log likelihood function can be written as

$$L(\theta,\phi) = \sum_{t=1}^{T} L_t(\theta,\phi) \tag{12}$$

where θ and Φ denote the parameters in D_t and R_t respectively. As shown in Engle (2002), this can be expressed as follows[11]

[11]This expression is to facilitate a two-step maximization process using the volatility and correlation parts of the likelihood function decomposed in Engle(2002). We performed this estimation in RATS v.6.0 using the Broyden, Fletcher, Goldfarb and Shanno (BFGS) algorithm.

$$L(\theta,\phi) = -\frac{1}{2}\sum_{t=1}^{T}[n\log(2\pi) + 2\log|D_t| + r_t' D_t^{-1} D_t^{-1} r_t - \varepsilon_t'\varepsilon_t + \log|R_t| + \varepsilon_t' R_t^{-1}\varepsilon_t] \qquad (13)$$

4. Empirical Results

All bond index returns, in levels, contain a unit root with zero drift[12]. Thus the cointegration analysis is possible, in which we find that on the whole, bond markets in the established EU members are already fully integrated, corroborating with European financial market studies such as Galati and Tsatsaronis (2003), Cappiello et al. (2003) and Baele (2004). However, those in the new EU countries are not as well integrated with the established EU bloc and this is a new result. Moreover, the UK bond market is not as well integrated with the rest of the EU, which perhaps is not surprising given that it is not a member of the EMU. Its' economy has also performed differently, and it has lower government debt levels. This is also consistent with lower unconditional correlations found by Cappiello et al. (2003) between EMU and non-EMU bond markets on a regional level.

We show results for the dynamic cointegration analyses in Figures 1 and 2. Figure 1 shows results for the global, recursive, analysis. The data are initially estimated over the first 500 observations, equating to approximately end-May 2000. Thereafter 20 observations, 4 weeks data, are added each iteration and the data reanalyzed. The trace statistics are normalized to the asymptotic 90% critical values – thus a value greater than 1 implies cointegration and less than 1 no cointegration. It is clear that over the time period in general there is consistent evidence of cointegration indicating that the markets are in a stable relationship: the bond markets of the accession countries and those of the existing countries

[12] Details available on request.

form part of a system[13]. However, the number of cointegrating vectors from the λ_{max} statistic settles at between 3 and 4, again indicating that the system is not integrating further. Recall that in a system of 9 variables full integration would be achieved with 1 or 8 cointegrating vectors. What we find here is perhaps a reflection of the near complete integration of the two sets of countries considered independently with a very weak linkage between the two sets of markets. The local plots are shown in figure 2: the evidence is more favorable to the hypothesis of an integrated system, but again there is little evidence that the system is increasing in convergence.

The Haldane and Hall convergence factors for the three accession countries with the UK and with Germany are shown in Figure 3. It is clear that these bond markets are not in general close to convergence, with the exception of Poland, which has converged to the UK. On a closer examination, we find that the convergence factors to the UK are rising, while the factors to Germany are declining. In so far as there is any evidence it is that the markets are converging more to the UK than to Germany. This has obvious policy implications for monetary integration. In general, this would appear to cast some doubt on the suitability of these new EU countries for moving towards full adoption of the euro.

The results for the bivariate DCC estimations are provided in Table 2. Both the ARCH(α) and GARCH(β) estimates in the conditional variance equation are significant for most bond markets returns in our sample and are consistent with high degrees of persistence and time-varying volatility. The significant ARCH effects are positive and small while the GARCH effects are large and close to one, consistent with their stylized behaviour. More importantly the two DCC parameters are statistically significant for all pairings except the Czech Republic and this is consistent with the DCC plots in Figure 4. The ARCH (λ_1) and GARCH (λ_2)

[13] Although omitted for space, the evidence from an analogous examination of the existing members is that they are multivariate cointegrated, as are, generally, the three accession countries. Details are available on request.

effects in the DCC equation are also consistent with their stylized behaviour in similar specifications. The estimate of λ_2 is close to one which suggests the conditional correlations are highly persistent. Estimated parameters in the conditional variance equations for Germany are dependent on the conditional time varying correlations (ie. Q matrix estimations) in Germany's different pairings with other sample EU markets. For this reason, the German estimates vary from one bivariate DCC model to another.

It is clear from Figure 4 that conditional correlations in EU bond markets are dynamic as there is considerable variation in the conditional correlations and providing empirical evidence that Engle's DCC model has been appropriately used in our investigation. The historical DCC plots suggest that integration between established bond markets in the EU increased rapidly in the late 1990s leading up to the formal inauguration of the European Moneatry Union (EMU) in 1999. However, bond market integration appears to be relatively low in the UK perhaps due to the British government's desire to stay out of the EMU and to maintain a monetary policy stance that was independent of the European Central Bank (ECB). Low integration in the UK government bond market was also found in Barr and Priestley (2004) and they provided low liquidity and an underdeveloped repo market as explanations. Of the three new EU bond markets, the Czech Republic displays the least variation in interdependence with other bond markets in the EU whilst Hungary and Poland showed generally increasing trends as they progressed with formal EU accession. In both Hungary and Poland, the government bond markets became rapidly more interdependent with the established EU bloc from the late 1990s but a correction occurred for both markets during 2001 when the accession talks became more uncertain. Since then, the Polish bond market has again become rapidly interdependent with established bond markets in the EU bloc but the Hungarian bond market has not. In the beginning of our sample period there is a common downward spike in all conditional correlations series between the German government bond market and other sample EU markets (except the UK and Czech Republic) - coinciding with the Russian Crisis of 1998. The magnitude of the percentage decreases in these conditional correlations was much higher for the Hungarian and Polish bond markets (130 and 75% respectively) compared with the more established EU bond markets (11% for Italy, 5% for Ireland, 2% for Belgium and 0.4% for France and the Netherlands). These corrections are in line with the perceived level of default risk associated with these national bond markets and Kaminsky and Schmukler's (2002) finding of stronger outlook changes on bonds during financial crises. German Bundesbank bonds are traditionally deemed to be the benchmark bonds in the EU and so the government bond market is viewed as the least risky. During the Russian Crisis it is likely that greater risk premia were priced into the other EU government bond markets as investors became more risk averse (also less confident) resulting in the sudden divergence in bond returns with Germany. Naturally, this divergence was more extreme in the more illiquid emerging debt markets in Hungary and Poland.

The descriptive statistics for the dynamic conditional correlations are shown in Table 3. The skewness and excess kurtosis of the DCCs indicate a negatively skewed and fat-tailed distribution. The means for established EU bond markets are almost one signifying extreme interdependence whilst those for Hungary (0.721) and Poland (0.336) indicate medium interdependence and higher volatility relative to the established EU bond markets. The Czech Republic appears to be independent of the established EU markets (DCC mean is 0.027) and there is no sign of any changes as it appears to be a very stable process. On the basis of the Ljung Box Q statistics up to 40 lags[14], we find that serial correlations in the conditional variances and correlations of the standardized residuals have been successfully eliminated in all bivariate estimations except with Belgium and Italy. This suggests that our bivariate DCC estimations are robust and adequate.

[14] As $\sqrt{N} = \sqrt{1430} \approx 38$, we test for serial correlation up to 40 lags.

5. Conclusions

We note that previous research on European bond market integration is predominantly focused on established EU markets. This paper has examined the evolving nature of the relationship between the MSCI bond indices of selected new EU and established EU countries, using a variety of dynamic perspectives. We have examined the dynamic nature of the linkages via dynamic cointegration, Haldane and Hall's Kalman filtering method and a bivariate version of Engle's (2002) Dynamic Conditional Correlation model. We provide robust empirical evidence for strong contemporaneous and dynamic linkages between existing EU member country bond markets with that of Germany. For the UK and the three new EU countries of Czech Republic, Poland and Hungary, however, we find such linkages were weak and relatively stable over the sample. Convergence towards the EMU, so far as it exists, appears to be slow. It appears that the pre-accession measures to achieve economic convergence were insufficient to generate rapid bond market integration. Thus, our results suggest that bond market participants believe that the new EU countries are not yet ready to adopt the euro.

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Figure 1: Global Trace and Vector

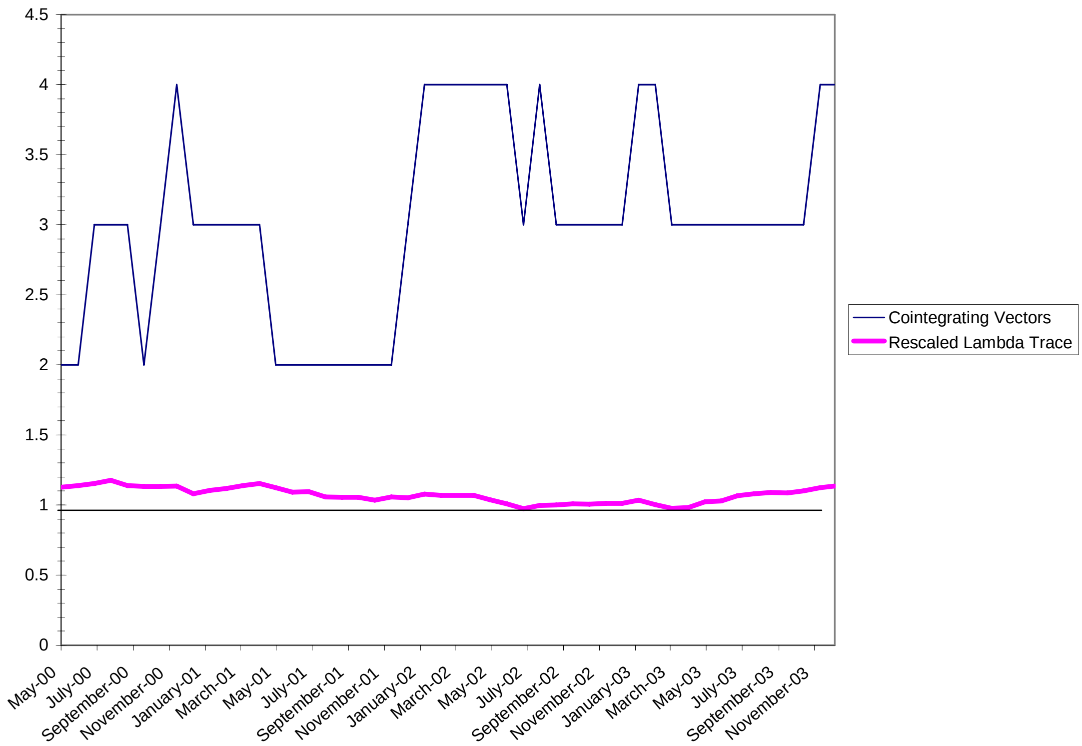

Figure 2: Local Trace and Vector

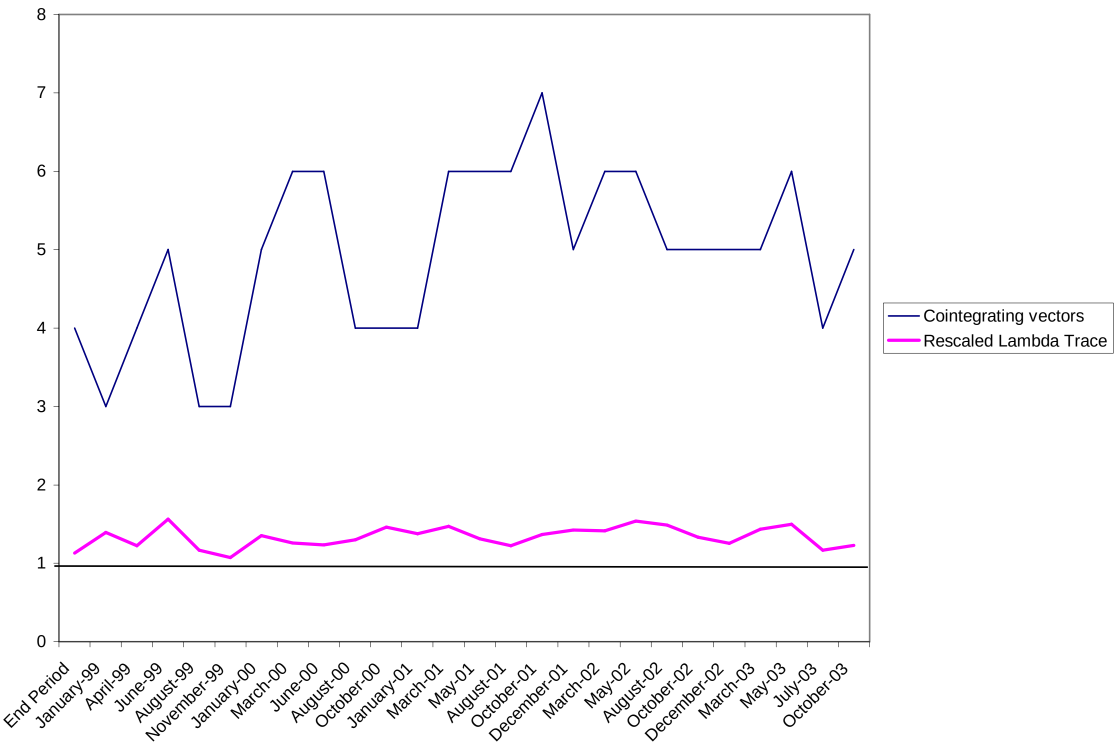

Figure 3: Haldane and Hall convergences

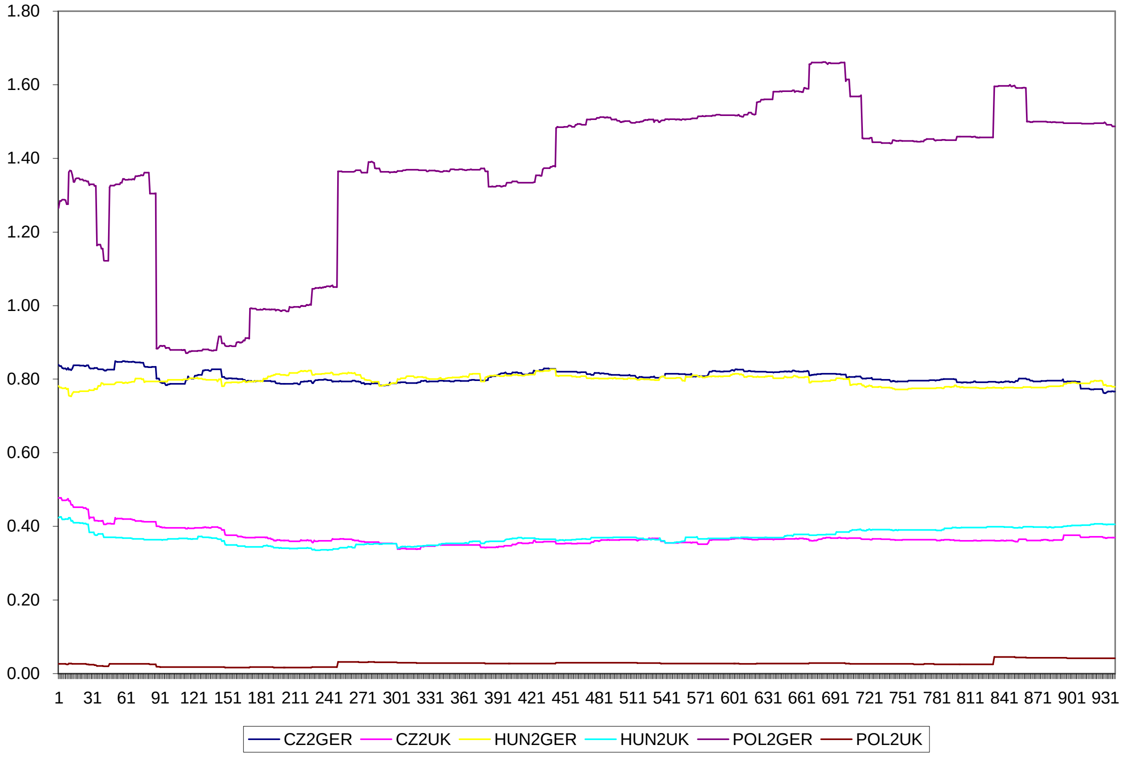

Figure 4. Time-variations in European bond market integration:

1/7/1998-31/12/2003

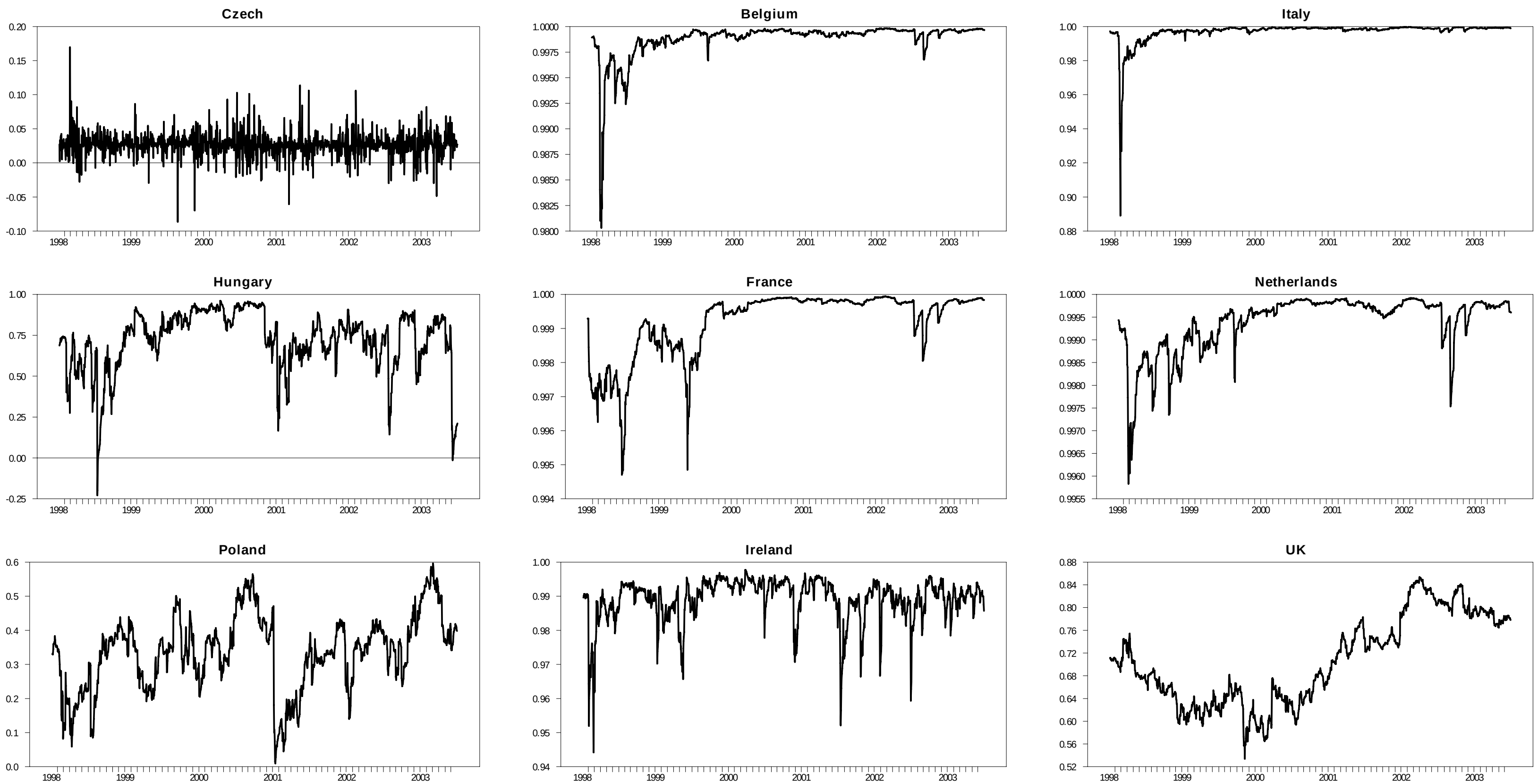

Table 1. Descriptive Statistics on daily MSCI bond index returns (%), 1/7/1998-31/12/2003

This table shows the summary statistics for the bond index returns. Asymptotic p-values are shown in the brackets. *,**,*** denote statistical significance at the 10, 5 and 1% level respectively. Test results for H_0:Skewness=0 and H_0:Excess kurtosis=0 are indicated. Q(40) is the Ljung-Box test statistic for serial correlation up to the 40th order in the return series (since $\sqrt{N=1435} \approx 40$); $Q^2(40)$ is the Ljung-Box test statistic for serial correlation up to the 40th order in the squared returns. $Q_b(40)$ and $Q^2_b(40)$ are the bivariate Ljung-Box tests for joint white noise in the linear and squared returns up to the 40th order.

	Bond Index Return				Test of univariate *iid*		Test of bivariate *iid* (with German benchmark)	
	Mean	Variance	Skewness	Excess Kurtosis	Q(40): $\chi^2(40)$	$Q^2(40)$: $\chi^2(40)$	$Q_b(40)$: $\chi^2(160)$	$Q^2_b(40)$: $\chi^2(160)$
New EU members:								
Czech	0.056	0.543	0.295*** {0.000}	1.033*** {0.000}	45.143 {0.266}	105.839*** {0.000}	140.968 {0.858}	225.174*** {0.001}
Hungary	0.045	0.611	-0.586*** {0.000}	4.837*** {0.000}	45.432 {0.256}	257.530*** {0.000}	113.522 {0.998}	371.959*** {0.000}
Poland	0.052	0.593	-0.377*** {0.000}	3.066*** {0.000}	72.257*** {0.001}	277.988*** {0.000}	127.583 {0.972}	371.230*** {0.000}
Existing EU members and the UK								
Belgium	0.032	0.528	0.161** {0.013}	0.991*** {0.000}	30.211 {0.869}	50.912 {0.116}	298.226*** {0.000}	165.817 {0.360}
France	0.031	0.528	0.173*** {0.007}	1.033*** {0.000}	29.819 {0.880}	48.447 {0.169}	198.438** {0.021}	231.686*** {0.000}
Ireland	0.033	0.557	0.118* {0.068}	1.015*** {0.000}	31.682 {0.823}	47.539 {0.193}	254.932*** {0.000}	125.563 {0.980}
Italy	0.031	0.513	0.137** {0.034}	1.034*** {0.000}	30.473 {0. 862}	50.863 {0.117}	338.878*** {0.000}	334.921*** {0.000}
Netherlands	0.031	0.523	0.178*** {0.006}	1.018*** {0.000}	30.006 {0.875}	49.469 {0.145}	204.418** {0.010}	249.609*** {0.000}
UK	0.028	0.358	0.074 {0.253}	0.942*** {0.000}	42.183 {0. 377}	70.223*** {0.002}	102.000 {0.999}	118.417 {0. 994}
Germany	0.030	0.521	0.173*** {0.007}	1.004*** {0.000}	29.832 {0.880}	50.429 {0.125}		

Table 2. Parameter Estimates and Diagnostic Tests for the DCC-GARCH(1,1) Models: 8/7/1998 to 31/12/2003.

	Conditional Variance			DCC			Univariate	Bivariate
	ω	α	β	λ_1	λ_2	LogL	Q(40): $\chi^2(40)$	$Q_b(40)$: $\chi^2(160)$
Germany	0.505***	-0.006	0.040	0.018	0.000	-	49.513	132.910
	{0.000}	{0.745}	{0.175}	{0.454}	{1.000}	3143.226	{0.144}	{0.942}
Czech	0.025***	0.041***	0.911***				30.943	
	{0.000}	{0.000}	{0.000}				{0.847}	
Germany	0.024***	0.062***	0.898***	0.079***	0.909***	-	38.297	113.819
	{0.008}	{0.000}	{0.000}	{0.000}	{0.000}	2508.127	{0.547}	{0.998}
Hungary	0.020***	0.106***	0.870***				25.350	
	{0.001}	{0.000}	{0.000}				{0.966}	
Germany	0.582	0.011	-0.133	0.023***	0.955***	-	49.834	125.810
	{0.226}	{0.566}	{0.886}	{0.000}	{0.000}	3020.938	{0.137}	{0.979}
Poland	0.061***	0.165***	0.732***				41.252	
	{0.000}	{0.000}	{0.000}				{0.416}	
Germany	0.019***	0.041***	0.922***	0.056***	0.937***	1566.747	34.562	194.132**
	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}		{0.713 }	{0.034}
Belgium	0.019***	0.041***	0.923***				35.117	
	{0.000}	{0.000}	{0.000}				{0.690}	
Germany	0.442***	0.003	0.133***	0.036***	0.962***	1967.037	49.585	147.141
	{0.000}	{0.228}	{0.000}	{0.000}	{0.000}		{0.142}	{0.759}
France	0.573***	0.004	-				48.054	
	{0.000}	{0.170}	0.117***				{0.179}	
			{0.000}					
Germany	0.023	0.035***	0.921***	0.076***	0.869***	-324.042	33.864	115.062
	{0.024}	{0.000}	{0.000}	{0.000}	{0.000}		{0.742}	{0.997}
Ireland	0.025**	0.035***	0.921***				36.709	
	{0.023}	{0.000}	{0.000}				{0.619}	
Germany	0.023***	0.051***	0.901***	0.073***	0.915***	1145.669	36.857	336.615***
	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}		{0.613}	{0.000}
Italy	0.023***	0.053***	0.898***				41.335	
	{0.000}	{0.000}	{0.000}				{0.412}	
Germany	0.486***	0.028**	0.019	0.040***	0.954***	2013.189	50.496	167.194
	{0.000}	{0.034}	{0.487}	{0.000}	{0.000}		{0.124}	{0.332}
Netherlands	0.491***	0.031**	0.005				50.499	
	{0.000}	{0.021}	{0.836}				{0.124}	
Germany	0.381	0.001	0.259	0.011***	0.987***	-	49.496	97.017
	{0.157}	{0.865}	{0.608}	{0.000}	{0.000}	2318.232	{0.144}	{0.999}
UK	0.008***	0.020***	0.958***				42.600	
	{0.000}	{0.000}	{0.000}				{0.360}	

*Notes: P values are shown inside the brackets. *, ** and *** denote significance at the 10, 5 and 1% respectively. Q(40) denotes the test for the null hypothesis of no serial correlation up to 40 lags. The statistic is reported for individual squared standardized residuals (ε_t^2's) and the bivariate test on both standardized residuals to test for the adequacy of the DCC model for variance and correlations. The statistic is asymptotically distributed as $\chi^2(40)$ in the univariate test and $\chi^2(160)$ in the bivariate case.*

Table 3. Descriptive Statistics on DCCs: 8/7/1998 to 31/12/2003.

Country	Mean	Std Error	Skewness	Excess Kurtosis
Czech	0.027	0.017	0.194	9.371
Hungary	0.721	0.184	-1.424	2.601
Poland	0.336	0.110	-0.319	-0.062
Belgium	0.999	0.002	-5.461	39.187
France	0.999	0.001	-1.726	2.652
Ireland	0.989	0.007	-2.249	7.231
Italy	0.997	0.006	-8.565	99.006
Netherlands	0.999	0.001	-2.093	5.117
UK	0.706	0.077	0.151	-1.181