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Abstract

In this paper, we examine the financial integration process amongst 17 EMU countries from January 2002 to June 2013 over a normal period as well as for the Global Financial Crisis (GFC) and Eurozone Debt Crisis (EDC) periods. We classify the economies in three groups (A, B and C) based on their GDP to examine whether the economic size influences financial integration. Seven indicators are used for the purpose, namely, Beta Convergence, Sigma Convergence, Variance Ratio, Asymmetric DCC, Dynamic Cointegration, Market Synchronisation Measure and Common Components Approach. The results suggest that large sized EMU economies (termed as Group A) exhibit strong financial integration. Moderate financial integration is observed for middle-sized EMU economies with old membership (termed as Group B). Small sized economies (termed as Group C) economies seemed to be least integrated within the EMU stock market system. The findings further suggest presence of contagion effects as one moves from normal to crisis periods, which are specifically stronger for more integrated economies of Group A. We recommend institutional, regulatory and other policy reforms for Group B and especially Group C to achieve higher level of integration.

JEL Classification: C22, E44, F36, G14, G15

Keywords: EMU, Global Financial crisis, Eurozone Debt Crisis, Stock Market integration, Time-varying financial integration, Beta Convergence, Sigma Convergence, Variance Ratio, Asymmetric DCC, Rolling Cointegration, Carhart four factor model, Markov Regime Switching Model.

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1. Introduction

The recent twin crises seem to have hobbled the dream of an integrated Europe. After World War II, the European economies took deliberate political and economic policy measures to prevent protectionism, fragmentation and war. The creation of European Monetary Union (EMU) and introduction of a single currency-euro was shown to be positively promoting financial integration in the region (Bartram *et al.* 2007; Kim *et al.* 2005). However, in the changed economic landscape post-crisis, many researchers have uncovered a setback in the integration process (see e.g., Battistini *et al.* 2013; Philippas & Siriopoulos 2013). In the aftermath of crisis, the recent debate on the degree and direction of the financial integration process in EMU needs immediate attention as it has wide implications for return differentials, diversification benefits, risk sharing and hence, portfolio construction (Bartram and Dufey 2001). Further, it has implications for other regions aspiring to adopt a single currency as well as for policy makers in general, as integrated financial market operations have the potential of creating serious disequilibrium during crisis. On one hand, while, financial integration is considered to be an important catalyst for region's economic development (see Baele *et al.* 2004; Pagano 1993), the recent crisis revealed the risk of cross-border financial contagion due to intensified financial linkages (see Beirne & Fratzscher 2012; Samitas & Tsakalos 2013). Claessens *et al.* (2010) maintained that integration is the factor uncommon to the other crisis in the past. An in-depth investigation is therefore required to assess how the progress of integration varies in normal vis-à-vis crisis periods. This calls for a sound measurement of the degree of financial integration and analysis of trend across the various states of the economy.

The prime motivation for our analysis stems from acknowledging that the multiple dimensions of financial integration and the accompanying complexity prohibit drawing conclusions based on a single indicator of integration. This lack of clarity paralyses the policy making process as the focus varies across dimensions. This is essentially a measurement issue. The definition of financial integration and thus, the corresponding indicator to measure it depends upon the dimension which one is focussing on. We consider multiple dimensions of integration at the same time as it helps in building a broader and general perspective about the progress of integration, rather than a narrow one which concentrates only on one of the sub-fields.

The study simultaneously examines the generally held view that high income economies are more likely to integrate with the external world owing to higher cross-border capital flows as they typically have more stable macroeconomic policies, better financial and institutional architecture, along with deeper markets. For the purpose of this analysis, the sample EMU economies are classified into three groups (A, B and C) based on their economic size measured as GDP. The time period investigated under the study starts from the introduction of Euro as the Currency-in-Circulation. To check for financial integration over time, we divide the total period into three non-overlapping sub-periods covering pre-crisis Normal Period, Global Financial Crisis (GFC), along with the ensuing European Debt Crisis (EDC) that had a significant effect on the global stock markets (Ahmad *et al.* 2013).

The paper is organised as follows. The second section discusses the extant literature in brief. The data are described in Section 3. Section 4 puts forth the array of indicators of financial integration along with the econometric methodologies for the measurement of these indicators. The empirical results are presented and analysed in Section 5. The final section offers concluding remarks and policy observations.

2. Literature Review

The EMU has garnered the attention of academicians as well as policy makers around the world. The integration of the region's economies has been under active discussion over the past two decades due to multiple reasons such as the deliberate attempts to integrate the economies based on Maastricht criteria (see for example, Afxentiou 2000), development of a common currency region (e.g., Bartram *et al.* 2007), expansion of the currency union (e.g., Boubakri 2012; Kelemen *et al.* 2011) and the recent European Debt Crisis (e.g, Andrade and Chhaochharia 2012; Majone 2012).

Over time, various studies have attempted to measure the degree of financial integration in Europe using wide range of empirical methodologies. Fratzscher (2002) employed GARCH model with time-varying coefficients to analyse the impact of EMU on integration process of European equity markets and finds that European equity markets have become highly integrated only since 1996 by the drive towards EMU. Miloudi (2003) applied cointegration methods to analyse the impact of euro on integration between sixteen European stock indexes. The author observed that the number of long-term relationships between the national stock indexes of EMU members was augmented when Austria, Finland and Greece were withdrawn from the analysis. Baele *et al.* (2004) observed an increasing degree of financial inetgartion based on the analysis of using three categories of integration measures, namely price-based, news-based and quantity-based measures. Kim, *et al.* (2005) estimated the time-varying correlation using DCC-EGARCH model to examine the influence of EMU on stock market integration and find an increase in European stock market integration. Bley (2009) examines the factor that determines the dynamics and contemporaneous interactions of Euro stock markets at the country and economic sector level and reveals the time-varying nature of the financial market integration process. Mylonidis and

Kollias (2010) used dynamic cointegration technique and concluded that the introduction of the euro epitomizes European economic integration in the major European stock markets in the first euro-decade, with German and French markets showing highest degree of convergence.

Using an asset-pricing model, Hardouvelis et al. (2006) find full integration among the euro-area stock markets by the end of the 1990s. However, Bartram *et al.* (2007), Fratzscher (2002), Kim *et al.* (2005) report that the integration in the region is evolving over time and far from being complete. Bekaert, *et al.* (2013) concluded that the adoption of the Euro was not associated with increased integration. Recently, Samitas & Tsakalos (2013) employed the asymmetric DCC model and copula functions to measure financial contagion in European stock markets. They concluded that contagion effect existed during GFC period but not during the Greek debt crisis.

While active research has been undertaken to study the integration amongst the stock markets in Eurozone, this study fills important gaps in the existing literature: i) there is a lack of research on how the progress of integration varies in normal vis-à-vis crisis periods. In this paper, we have split the sample period into three sub-periods, that is, normal time period as well as for the GFC and EDC periods to capture the dynamics of integration; ii) the existing studies cover only a subset of EMU economies. This paper studies the progress of integration for the entire set of 17 EMU economies, classified into three income groups; iii.) the existing studies on Eurozone integration are limited in scope, as they do not focus on multiple dimensions of integration. We employ seven different indicators to measure different dimensions of stock market integration in the region.

3. Data and their Time Series Properties

The sample set consists of 17 countries that are the member states of EMU. It is generally maintained. In order to check this premise that economies with high income typically exhibit higher financial integration, we classify the sample EMU economies in three groups based on the size of economy (measured as GDP). We group Belgium, France, Germany, Italy, Netherlands and Spain under Group A. Austria, Finland, Greece, Ireland, and Portugal are classified under Group B and; Cyprus, Estonia, Malta, Slovakia, Luxembourg and Slovenia constitute Group C. It is noteworthy that in Group C, all the members except Luxembourg are very new entrants, having joined EMU only after January 2007. Table 1 provides the information regarding the size of economies, size and depth of their stock markets and the date of EMU membership for the sample countries. The US is included as a proxy for global factor as in prior research (Baele *et al.* 2004; Bartram *et al.* 2007). In addition, a pan-EMU index is used to account for stock price information for the entire Eurozone area. The data comprises of daily stock index values on sample countries. These share market indices are sourced from Bloomberg. The national stock market returns are computed as the log of changes in closing index prices from one trading day to the next for each stock index.

[Insert Table 1 about here]

The sample period for this study stretches from the date of introduction of Euro cash, that is, January 01, 2002 up to June 30, 2013. However, due to unavailability of data for Cyprus, Finland, Slovakia and Slovenia, the sample periods for these economies starts from September 06, 2004, January 02, 2003, January 07, 2002 and April 01, 2003 respectively. The non-trading days vary across the countries on account of different holidays, hence to avoid complications, the value of corresponding index on such days is assumed to remain constant and equal to its closing value on the last trading day before the holiday. In order to study the dynamics of integration in normal vis-à-vis crisis period, we break the entire sample period into three sub-periods. The first sub-sample covers the period from January 01, 2002 to Aug 08, 2007, which is the pre-crisis period. The crisis period starts from August 09, 2007 (see e.g., Angelini *et al.* 2011; Trichet 2010).[1] The crisis period is split into two sub-periods, that is, the Global Financial Crisis (GFC) period from August 09, 2007 to October 18, 2009, and the Eurozone Debt Crisis (EDC) period which is October 19, 2009 onwards (see Ahmad *et al.* 2013). Dividing the crisis period into two sub-periods enables the separate analysis of the EDC as this study concentrates on EMU.

The descriptives reveal substantial differences in the financial states of the economies during the sub-periods.[2] While the GFC yielded severe setbacks as the average return on national stock indices turned negative for all the economies; the EDC period had milder impacts and a few economies, led by Germany showed some signs of recovery from the GFC. The distributions of these stock market returns for the sample countries are statistically non-normal as they exhibit positive skewness, leptokurtosis and statistically significant Jarque-Bera multiplier in all periods. The Ljung Box statistics provides evidence of serial correlation for most of the return series in the level and of autoregressive conditional heteroskedasticity for the squared level of equity returns series.

As a pre-cursor to the time-series analysis, we conducted the ADF test for stationarity. In addition, as the European markets have undergone multiple structural changes over

[1] Although subprime mortgage lenders started to report losses in February 2007 (Cecchetti 2009), August 09, 2007 is considered as the advent of financial market crisis when BNP Paribas ceased activity in three hedge funds which was followed by sharp rise in cost of credit. This date is in agreement with The Guardian's timeline of financial crisis (see http://www.theguardian.com/business/2012/aug/07/credit-crunch-boom-bust-timeline), the BBC Timeline (see, http://news.bbc.co.uk/2/hi/business/7521250.stm) as well as Bank of International Settlements (BIS, 79th Annual Report, retrieved from http://www.bis.org/publ/arpdf/ar2009e2.pdf).

[2] The results on descriptive statistics, normality and Ljung-Box tests are available upon request from the authors.

the period, we also performed the Perron (1997) test to detect structural break under structural break. The Perron (1997) test provides for structural breaks both in the null as well as alternative hypothesis. The test statistics for both ADF and Perron (1997) indicate that all series are I (1).[3]

4. Methodology

In this section, we describe the methodologies of constructing different indicators employed to measure multiple dimensions of equity market integration in the EMU. As the tests established breaks in the time series, all the measures of integration in this study incorporate rolling estimation to capture the time varying dynamics of equity market integration.

4.1. Beta Convergence

Barro & Sala-I-Martin (1992) pioneered the concept of beta convergence to measure the convergence of levels of growth across economies. While the absolute value of Beta indicates the speed at which the stock returns of the country's national index converges towards the returns on the regional index, the negative sign of beta coefficient indicates mean reversion of returns and hence the presence of convergence. Beta convergence is quantified by estimating the following regression:

$$\Delta ER_t = \alpha + \beta_t ER_{t-1} + \sum_{l=1}^{L} \gamma_l \, \Delta ER_{t-1} + \varepsilon_t \qquad (1)$$

Where ER_t represents the return differential between country *i's* index and the benchmark index at time *t*. β_t is the convergence coefficient and provides the estimate of speed of convergence. The lag length *l* has been determined using the Schwarz Information Criteria (SIC). The beta coefficient is made time varying using rolling

[3] For the brevity of space, the unit-root test results are not provided here. The results are available upon request.

regression technique with a fixed window of 65 trading days, which approximates to one quarter. Under the null hypothesis of no convergence, β is equal to zero. A negative coefficient means that convergence takes place and the absolute magnitude of beta measures average speed of convergence. The larger is the beta in absolute value, the faster is the convergence

4.2. Sigma Convergence

Along with Beta Convergence, Sigma Convergence forms the twin pillars of Convergence Growth literature. Sigma convergence appraises the extent to which markets are already integrated. In essence, sigma convergence gauges the cross-sectional dispersion of returns relative to the benchmark. This measure, in principal, tests whether the law of one price holds good. The law states that if the economies are to be integrated, returns on assets with identical structures should be equalised across these economies. The value of sigma is estimated as:

$$\sigma_t = \sqrt{N^{-1} \sum_{i=1}^{N} [R_{i,t} - R_{b,t}]^2} \qquad (2)$$

Where, $R_{i,t}$ *and* $R_{b,t}$ are the returns on stock indices of country i and the benchmark index respectively. N is the number of economies in the analysis. To gauge the progress of cross-sectional convergence over time, we undertake estimation over the rolling samples of 65 days each for each country. The value of sigma is always positive. A high value of sigma indicates very low level of integration; whereas sigma equals to zero is the sign of full integration.

4.3. Variance Ratio

The variance ratio is based on second moments and it examines the significance of a common regional/global risk in explaining the national returns/yields variation. As, variance ratio analyses the cross-market transmission of information (news), it is called the news-base measure of integration (Baele *et al.* 2004). If the economies in the region are integrated, the regional shocks will play a larger role than local shocks in explaining the country *i's* returns.

Under the estimation process, first, the returns on the national index of country *i* are specified as an AR (p) process and lag length is selected using SIC criterion

$$r_{i,t} = \alpha_{i,t} + r_{i,t-1} + \varepsilon_{i,t} \tag{3}$$

Where $r_{i,t}$ are country *i's* returns at time *t*. The error terms $\varepsilon_{i,t}$ is the unexpected component of return and it captures financial shocks. It can be decomposed into a local shock ($e_{i,t}$), reaction to regional news (proxied by the unexpected component of regional market return,$\varepsilon_{EMU,t}$) and reaction to global innovations (proxied by the unexpected component of world market return,$\varepsilon_{US,t}$).

$$\varepsilon_{i,t} = \gamma_{1,i,t}\varepsilon_{EMU,t} + \gamma_{2,i,t}\varepsilon_{US,t} + e_{i,t} \tag{4}$$

To capture the time-varying impact of cross-market innovations, we used rolling regression technique with a fix window of 65 days. The conditional variances in the EMU, US and country *i's* stock markets are assumed to follow EGARCH (1, 1) process. From (4), the total variance of country *i* can be given by

$$\sigma_{i,t}^2 = (\gamma_{1,i,t})^2 {\sigma_{EMU,t}}^2 + (\gamma_{2,i,t})^2 {\sigma_{US,t}}^2 + h_{i,t} \tag{5}$$

The model assumes that the respective shocks of country *i,* EMU and US are uncorrelated with each other.

Regional Variance Ratio explains the proportion of total domestic volatility contributed by regional innovations. The conditional variances estimated above are used to obtain the ratio as

Euro Variance Ratio $(VR_{i,t}^{EMU}) = \frac{(\gamma_{1,i,t})^2 \sigma_{EMU,t}{}^2}{\sigma_{i,t}^2}$ (6)

Under full integration, only regional news should drive local returns, and the variance proportion should be close to one.

4.4. Asymmetric Dynamic Conditional Correlation Model

Higher correlation implies that markets are integrated through the co-movement of returns, offering similar assets with limited diversification benefits. However, static measure of correlation is inadequate to measure integration across different regimes. This paper utilizes the Asymmetric DCC-EGARCH (ADCC-EGARCH) model introduced by Cappiello et al. (2006) which accounts for heteroskedasticity and continuously adjusts for the time varying volatility. While, ADCC accounts for the asymmetry in correlations that are observed to increase more after a joint negative shock[4] than a positive shock (Baumohl 2013), the exponential GARCH (EGARCH) model accommodates the asymmetries in conditional variances of returns as the bad news have greater impact than the good news (Nelson 1991).

The mean equation is specified as an AR (1) process (based on SIC criteria):

$$r_t = \alpha_t + \beta r_{t-1} + \gamma r_{US,t-1} + \varepsilon_t \quad (7)$$

Where $r_t = \left(r_{i,t}, r_{EMU,t}\right)$ and $\varepsilon_t = (\varepsilon_{i,t}, \varepsilon_{EMU,t})$, $\varepsilon_t | \beth_{t-1} \sim N(0, H_t)$. The lagged US returns proxy for global effects.

The conditional variance of the residuals thus generated is modelled to follow EGARCH (1, 1) process:

[4] Joint bad news refers to both returns being negative (Cappiello *et al.* 2006).

$$\log(h_t) = \omega + \sum_{j=1}^{p} \psi_j \log(h_{i-j}) + \sum_{k=1}^{q} \varphi_i \left| \frac{\varepsilon_{t-k}}{\sqrt{h_{t-k}}} \right| + \sum_{k=1}^{q} \delta_k \frac{\varepsilon_{t-k}}{\sqrt{h_{t-k}}} \quad (8)$$

Whereω, ψs, φs and δs are the parameters to be estimated. The residuals obtained from mean equation are normalised as $\vartheta_{i,t} = \varepsilon_{i,t}/\sqrt{h_{i,t}}$ which are then utilised to generate negative residuals series to capture the asymmetries, η_t =I [ε_t < 0]o ε_t. This represents the element by element Hadamard product of the residuals if sector shocks are negative, and otherwise $\eta_t = 0$.

The evolution of correlation equation in ADCC model (Cappiello *et al.* 2006a) is given by

$$Q_t = (1 - \theta_1 - \theta_2)\bar{Q} - g\bar{N} + \theta_1(\varepsilon_{t-1}\varepsilon'_{t-1}) + \theta_2 Q_{t-1} + g(\eta_{t-1}\eta_{t-1}{}') \quad (9)$$

Where Q_t = ($q_{ij,t}$) is the (n×n) symmetric positive definite matrix of ε_t, $\bar{Q} = E(\varepsilon_t\varepsilon'_t)$ is the (n×n) unconditional correlation matrix of the standardized residuals ε_t, $\overline{N} = E(\eta_t\eta_t{}')$ and the asymmetric term *g* captures the periods where both markets jointly experience negative shock. The scalar parameters θ_1 and θ_2 are non-negative and satisfy $\theta_1 + \theta_2 < 1$. Thus, the evolution process, Q_t, of the conditional correlation consists of impact, persistence and asymmetric effect parameters θ_1, θ_2 and *g* respectively.

Finally, the dynamic correlation matrix between the two series is given by

$$P_t = Q_t^{*-1} Q_t Q_t^{*-1} \quad (10)$$

where $Q_t^* = \left[\sqrt{q_{iit}}\right]$ is a diagonal matrix with the square root of the *i*th diagonal elements of Q_t as its entries.

4.5. Dynamic Cointegration

The long run relationship amongst the stock markets affects the potential long run gains from diversification (Taylor & Tonks 1989). This calls for an analysis of long run dynamics of stock market integration. The cointegration analysis of long-run co-movements tests for the presence of common trends amongst stock markets. The static measure of cointegration suffers from the drawback of a measure of realized convergence rather than convergence as a dynamic process. Thus, rolling cointegration analysis with a fixed-length window is more econometrically suited since it accommodates the time varying character of long-run relationships.

Using a bivariate approach of Johansen (1991) cointegration, the long run relationship is assessed between country i's equity index and the pan-EMU equity index. Johansen developed two statistics to test for the null hypothesis of no cointegration, i.e., maximum eigen-value (λ_{max}) and trace statistics (λ_{tr}). As per the previous studies, between these, λ_{tr} is more preferable than λ_{max} (Serletis and King 1997). The rolling cointegration test statistics are calculated setting the fixed window size as 750 trading days (approximately 3 years) as a wider window is ideal for cointegration analysis (Fung, Tam, & Yu 2008). The window is rolled by adding one observation to the end and removing the first observation for each sample[5]. The trace statistics obtained from the rolling cointegration tests are scaled by the adjusted critical values at the 5% significance level (i.e. 54.079). If the scaled trace statistic value exceeds one, it implies rejection of null hypothesis of no cointegration, thus implying presence of long run relationship.

While the trace test statistic uncovers the presence of long run relationship, the error correction term (ECT) augments this information by describing the responses of variables to the deviations from this long-run equilibrium. The absolute value of coefficient of error correction term (ECT), α, thus, measures the speed of adjustment of short run

[5] The authors would like to thank Dr. Nikolaos Mylonidis for providing us with his Eviews code for rolling cointegration test.

deviations to the long run equilibrium. An increasing speed of adjustment implies a progressively higher degree of stock market convergence. The time varying α provides an alternative, and probably more appealing, measure of convergence (Mylonidis and Kollias 2010). The rolling speed of adjustment coefficients are estimated based on one cointegrating vector. The comparison of coefficients of ECTs for individual countries and Pan-EMU index shall help in understanding the lead-lag relationship between two systems.

4.6. Market Synchronisation

If the financial market cycles are synchronised, that is, if at a given point of time, both the stock indices experience the same regimes of financial market cycle, then it indicates that the markets are integrated. The degree of integration is measured by estimating correlation between the probabilities of two market indices of being in regime *k*. We define the two regimes of stock market cycle as "bull" phase with high average return and "bear" phase that exhibits lower average return (Maheu, et al 2010). In order to identify these phases, we employ Markov Regime Switching Auto Regressive (MR-AR) model introduced by Hamilton (1989) that does not require an explicit identification of a common crisis start date across the examined countries. MR-AR model offers an endogenous determination of the transition date between regimes whilst, at the same time, accounting for non-linearities in the shock transmission process. The model assumes that the errors are serially correlated and allows for time varying conditional heteroskedasticity as market migrates from one regime to another. For the purpose of this indicator, we use monthly returns instead of daily returns, as high frequency data may lead to unreliable classification of different regimes. Since MRS model is essentially a non-linear model, before estimating the model, we run the BDS independence test (Brock *et al.* 1996) to test for non-linearity. We conducted the test for the embedding dimensions from 2 to 6 and for increasing values of ε, that is, 0.5, 1.0, 1.5 and 2.0 standard deviations, to increase the power of test (Brock et al. 1992).

For the MRS estimation, the mean equation depends on lag states with mean and variance both are allowed to switch in states

$$r_t = \mu(s_t) + \sum_{i=1}^{j} \phi_i \left(r_{t-i} - \mu(s_{t-i})\right) + \sigma^2(s_t)\upsilon_{t,} \quad (11)$$

Where r_t is an AR (p) process, the unobserved state is governed by the state variables s_t and s_{t-i} that take the value of 1 or 2 that corresponds to the regime labelled as bull or bear market. j is the number of lags which is estimated using the SIC, ϕ_i is the model parameter and $\upsilon_t \sim i.i.d\ (0,1)$. $\mu(s_t)$ and $\sigma^2(s_t)$ are mean and variance conditional on the regime at time *t*. The unknown parameters of the model can be estimated using the nonlinear filter proposed by Hamilton (1989), which is based on the log-likelihood. The transition between the states is governed by the first-order Markov assumption that requires that the probability of a market being in a regime depends on the previous state, so that

$$P(s_t = j | s_{t-1} = i) = p_{ij}(t) \quad (12)$$

Where *i, j* =1, 2,…, m; and $\sum_{j=1}^{m} p_{ij} = 1$ for all *i, j* ϵ S_t. Therefore, $p_{ij}(t)$ represents the probability of transitioning from regime *i* in period *t-1* to regime *j* in period *t.*

In the next step, the probabilities generated by MS-AR model are transformed using logit transformation to remove the 0-1 range restrictions from the probability values (Ahmad *et al.* 2014). Let $\widehat{\rho_{\iota t}}$ be the probability of market *i* being in bear regime at period *t.* Then,

$$\text{Logit}\ (\widehat{\rho_{\iota t}}) = \log\left(\frac{\widehat{\rho_{\iota t}}}{1-\widehat{\rho_{\iota t}}}\right) \quad (13)$$

Financial market integration is measured using Market Synchronisation Correlation which is quantified as the unconditional correlation between the logits of the regime probabilities of two markets i.e. country i and EMU index.

4.7. Common Factors Model

When the markets are fully integrated, investors price only common risks. Thus, instead of the concept of the price convergence, the common factors model measures integration by assessing whether the markets are affected by common risk factors. The European augmented Fama-French factors constitute the common fundamental risk factors. Based on the Carhart (1997) augmented Fama- French factor model, for each economy *i,* the stock market returns has following dynamic factor structure:

$$y_{i,t} = \mu_i + \beta_i EBR_{i,t} + \gamma_i SMB_{i,t} + \delta_i HML_{i,t} + \varphi_i WML_{i,t} + \varepsilon_{i,t} \qquad (14)$$

Where, $y_{i,t}$ is the excess equity return of country *i*, that is, the stock returns on national indices in excess of less than one month EURIBOR, the four components factors are the European Fama French factors- the market risk premium- excess benchmark return (EBR), the size factor - small minus big (SMB), the value factor-high minus low (HML) and the momentum factor- winners minus losers (WML) obtained from Kenneth French's website.[6] For the purpose of this analysis, we used monthly returns and divided the full sample into two parts i.e. Normal Period (January 2002 up to July 2007) and Crisis Period (i.e. August 2007 up to June 2013) to ensure sufficient number of observations in both sub-periods for estimation purposes. The dynamics of integration over time are captured by using a 3-year rolling window OLS.[7] The adjusted R-square of the regression measures the degree of equity market integration as it represents the

[6] Kenneth R. French-Data Library http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

[7] Only for Cyprus in period 1, the window length has been fixed at 2-years due to unavailability of sufficient data.

contribution of common regional components in explaining total variance of excess equity return in the country i at a given point of time t.

5. Empirical Results

The results reveal heterogeneity of regional integration process in the EMU. We perform empirical analysis for the three EMU groups over the normal as well as the two crisis periods.

[Insert Table 2 about here]

5.1. Beta Convergence

The Beta coefficient measures the speed of convergence of country *i*'s returns with the EMU returns. Figure 1 plots the beta coefficient for the three groups of countries over the sample period. For all EMU members, beta coefficient is always negative implying that the convergence process has been in place in EMU throughout the sample period.

[Insert Figure 1 about here]

The second observation that emerges out of the beta coefficient analysis is regarding the average speed of convergence as depicted by the absolute values of betas. Panel A of Table 2 reports the average values of beta coefficients across the three sub periods for EMU members. The average speed of convergence for the Group A and Group B economies declines as we move from normal to crisis period. However, Austria and Greece (Group B) showed steep surge during the GFC period. Thus, the crisis adversely affected the convergence process of the established members of the EMU. On the other hand, the convergence speed increases for the Group C countries as one moves from normal to crisis period, with an exception of Cyprus which registered a steep decline during the GFC period before recovering in EDC period. An improvement in convergence speed of Group C countries during crisis can be explained by the coincidence of their joining of EMU during the crisis period.

5.2. Sigma Convergence

Figure 2 displays the sigma convergence for the three subsets of EMU economies over time, and Panel B of Table 2 displays the average sigma values. The cross sectional dispersion of country *i*'s returns from EMU's returns, as measured by the sigma values declined substantially for all the countries up to 2005. Hence, up to 2005, integration strengthened for all the sample countries before Group B and Group C economies experienced a setback because of first Greek shock[8]. However, towards the end of normal period, these economies registered a recovery in the integration process. The Group A economies remained stable and highly integrated during Normal period. Following the onset of GFC, all the EMU member countries showed a steep rise in dispersion during 2008. However, these economies reported a decline in dispersion from GFC to euro-zone crisis. The economies of Spain, Greece and Cyprus which were among the most troubled economies during the latter crisis are exceptions in this regard as they continued to show further disintegration during the EDC.

[Insert Figure 2 about here]

Throughout the sample period, the Group A economies remained most resilient and highly integrated with very low sigma values, ranging between 30 and 100 basis points. Amongst Group A economies, France and Belgium remained the most and least integrated economies respectively during all sub-periods, while Germany displayed a stable degree of integration throughout the sample period. The Group B economies

[8] The fiscal audit in 2005 revealed that the true public debt and deficit positions were considerably worse than previously thought (OECD 2005).

reported higher cross-sectional dispersion from EMU as the sigma values generally ranged between 100 and 180 bps. Greece displayed higher sigma values than other Group B countries and reported exceptionally high dispersion during the EDC period with an average sigma value of 220 bps. On the other hand, Finland's value remained below the group's average implying its Group A type integration characteristics. The sigma values for Group C economies range between 110 bps and 220 bps, with Cyprus exhibiting much higher values than the group average during all periods. It is noteworthy, that during the crisis, Cyprus acted in exactly the same fashion as Greece. The sigma coefficient values for Cyprus and Greece, the two most troubled and inter-locked economies of Eurozone, remained substantially high during the EDC. Thus, this indicator re-confirms the results of beta convergence, that as we move from Group A to Group C economies, we notice lower integration and higher volatility for the equity markets.

5.3. Variance Ratio

Figure 3 plots the variance ratio of the countries over time while Panel C of Table 2 reports average variance ratio per country for each sub-period. The variance ratio gives the proportion of variance in country *i*'s returns explained by the innovations in EMU's returns.

[Insert Figure 3 about here]

The results indicate that the Group A economies exhibit strong integration with very high variance ratio of 0.75 and above during all the phases. The only exception is Belgium, which remained between 0.60-0.70 during the first two periods, making it least integrated among the Group A economies. The Group B economies registered variance ratio in the range of 0.15 and 0.65. Amongst these economies, Finland showed strongest integration throughout fast catching up with the integration levels of Group A economies. The troubled economy of Greece reported a steep increase in variance ratio from normal to GFC; however, it plunges to below normal period values during EDC. The Group C economies registered the variance ratio of very low magnitude (below 0.10) indicating the important role of local factors and hence lower financial integration with the EMU. The two noteworthy exceptions are Luxembourg, which showed exceptionally high variance ratio during the crisis periods, and Cyprus whose variance ratio surged during the GFC before experiencing a steep decline in EDC period. Cyprus, hence behaves like Greece, with which it is highly inter-related. This re-confirms the results of above discussed indicators. It is further observed that the variance ratio increases over the sub-periods for all the countries. For Group A, the rate of increase is higher from first crisis to the second, while for Groups B and C economies, the increase in variance ratio is higher from Normal to GFC period. This indicates that the Group A economies, being more integrated, suffered from high contagion effects during crisis as compared to Group B and C economies.

In general, the results of variance ratio show that Group A economies exhibit higher integration along with Finland from Group B. Group B exhibits moderate level of financial integration, which is even lower for Group C members.

5.4. Asymmetric Dynamic Conditional Correlation

The dynamic correlation is estimated for the conditional variances to measure the co-movements between the markets using ADCC-EGARCH model. The EGARCH (1, 1) estimation[9] show that long run volatility persistence as measured by ψ_j Eq. (8) is statistically significant and very high ranging over 0.85 throughout the sample period for

[9] The results are available upon request.

all the markets. The asymmetric effects of news on volatility were found to be significant for all sample markets during the GFC, thus justifying the use of EGARCH (1, 1) model to generate conditional variances of the returns. An analysis of ADCC[10] reveals highly significant values of $\theta_1 and\ \theta_2$ for Equation (9) throughout the sample period. This indicates towards presence of substantial time varying co-movements of the markets with the EMU during normal as well as crisis periods. The persistence of conditional correlation as measured by $(\theta_1 + \theta_2)$ is mixed and ranges between 0.46 and 0.85. Slovakia showed the least persistence during the first two periods. The asymmetric influence of joint bad news (Cappiello et al. 2006) on correlation coefficient between country *i* and EMU, as measured by, *g* in Equation (9) is reported to be insignificant for most of the markets. This implies that there are forces other than the joint downturns of markets that are driving the co-movements of countries' returns with the EMU.

[Insert Figure 4 about here]

Stronger co-movements between markets show integration and thus, an increase in correlation (as a measure of co-movements) among financial markets may signal increased convergence (Kuper and Lestano 2007). The ADCC-EGARCH model generates time-dependent correlation coefficients. Figure 4 plots the dynamic correlations and Panel D of Table 2 shows the average correlation coefficient for the three periods. The Group A countries, led by France, show the highest correlation with the EMU during normal as well as crisis periods. The correlation coefficients for these economies remained over 0.84 during all the sub-periods. France exhibited least variability and highest average correlation during the sample period. For the Group B economies, the correlation values range between 0.32 and 0.84, thus showing moderate

[10] The results are not provided for the sake of brevity. These are however, available upon request.

levels of integration. The Group C economies displayed very low levels of integration with correlation coefficient ranging between 0.01 and 0.66. Luxembourg remained the highest correlated economy of Group C throughout and registered significant rise from normal to crisis period. On the other hand, Malta showed a negative correlation during EDC and Slovakia during both the crisis. The Group B and Group C countries exhibit the highest variability in correlations throughout all sub-periods. Except for Netherland, the correlations for member EMU countries were most fluctuating during the Normal period.

The general increase in ADCC values from normal to crisis period may not be actually showing integration, but may be depicting contagion effects among the EMU economies. The average correlation of Greece and Cyprus with the EMU increased by 130% and 66% respectively during GFC period before falling down to their Normal Period values during EDC. This huge increase in correlation may signal towards contagion (Collins and Biekpe 2003) in these two markets.

5.5. Dynamic Cointegration

The sequence of trace statistic generated from the rolling Johansen cointegration estimation has been scaled by their 5% critical values. Figure 5 plots the scaled trace statistics for each group of countries for the null hypothesis of r = 0. The null hypothesis of no cointegration stands rejected when the scaled statistics is greater than one, thus indicating the presence of long run relationship between country *i*'s index and the EMU index. Panel E (a) of Table 2 provides results for average trace statistics for the countries for each period.

[Insert Figure 5 about here]

In Group A, the trace statistic ranges between 0.57 and 1.81. For most of the Normal period, the trace statistics for Group A economies remained greater than one, thus signalling their convergence with the EMU stock markets. During the normal period, all economies showed significant and strong cointegration with an exception of France and Italy which exhibited significant but weak level of cointegration. All Group A economies, except Italy, registered a decline in trace statistic during the GFC. This was followed by a slight improvement in trace statistics during the EDC with an exception of Spain, which displayed a consistently insignificant trace (value less than one) during the crisis period. The Group B countries exhibited stronger convergence than the Group A countries. For these economies, the decline from Normal to Crisis period was not as high as for Group A economies. With an exception of Ireland, all the Group B economies exhibited an increasing trend towards the end of sample period, indicating towards resurgence of integration. The Group C countries seem to be highly converging than Group A and Group B economies. These economies consistently reported very high trace statistic values (greater than one) across all the sub-periods, thus implying high degree of long-run relationship with the EMU. This may be because of the continuous policy initiatives undertaken by the Group C economies in order to satisfy the EMU membership criteria as they prepared to join the EMU, which happened between the years 2008 and 2011. On the other hand, the Group A and B economies joined the EMU before the crucial policy step of introduction of euro was undertaken. However, the information regarding the introduction of euro had already been absorbed by the stock markets during the run up to euro and later on, with no other equally substantial structural policy changes towards convergence along with the outset of crisis, the markets further moved away from the long run equilibrium with the EMU.

All the economies registered a decline from Normal to crisis periods with the exception of Portugal in Group B and Slovenia and Cyprus in Group C, which surged very high during the GFC before falling down during the EDC. Overall, we observe that as we move from Group A to Group C, the level of cointegration improves. Furthermore, as we move from normal to crisis periods, trace statistic values decline, implying that financial turmoil affected the long-run equilibrium of each market with EMU.

[Insert Figure 6 about here]

The next observation that emerges out of Dynamic Cointegration analysis pertains to the speed of adjustment as measured by the coefficient of ECT, α. Intuitively, a higher value of α (in absolute terms) indicates a greater response to deviations from the long-run equilibrium, implying higher integration and efficient markets. Figure 6 plots the rolling α values and Panel E (b) of Table 2 displays the average α values for every country in each period. For Group A economies, the absolute value of α ranges between 0.005 and 0.064 on an average. It was observed that France and Italy showed a steep rise in speed of adjustment during EDC. While, the adjustment speed declined continuously for Germany and Netherlands, Spain and Belgium which remained constant. For Group B, the absolute values of α lie in the range of 0.006 and 0.033 on an average. All the Group B economies showed an increase in speed from normal to crisis period. However, Greece displayed substantial fall in the speed of adjustment during EDC, while Ireland showed continuous increase in speed over the sub-periods. The α value for the Group C economies range between 0.02 and 0.21. Amongst, these economies, Cyprus exhibits highest speed during the Normal as well as GFC period, but like Greece, falls steeply during the EDC period. With an exception of Cyprus, all other economies of Group C show an increase in the speed from Normal to crisis period.

Overall, Group A countries exhibit highest speed, followed by Group B and Group C countries. Thus, Group A economies seem to be more integrated and having more efficient markets, than the other two, in the sense that they return faster back to equilibrium after a shock. Moreover, it is observed that all the EMU member countries with an exception of Germany, Netherlands and Cyprus experienced an increase in speed of adjustment from Normal to Crisis Periods.

5.6. Market Synchronisation

This indicator analyses the degree of correlation between probabilities of country *i* and EMU being in the same regime *k.* Higher correlation imply an overlap of the regime cycles, and thus integration of both indices. The MS-AR's endogenous regime selection mechanism divided the sample period into two regimes-bull phase and bear phase. The correlation between the logit transformed regime probabilities generated by MS-AR process measure integration of the indices in terms of their market cycle synchronisation. We first check the necessary condition of non-linearity using BDS test. The test results report that the null of IID is strongly rejected[11]. As linear structures have been removed using AR process, the rejection of null implies the presence of non-linear dependencies in the returns series (Panagiotidis 2002).

We now analyse the estimated MS-AR results. As the MS-AR regime probability of country *i* being in bear phase is the complement probability of being in bull phase, the correlations calculated for both the phases are similar in magnitude and trend. Here, we provide results from the perspective of bull regime. Panel F of Table 2 displays the correlation results for Bull regime for every country in each sub-period. The entire Group

[11] To conserve space the results are not reported but are available on request.

A economies registered highest correlation during the Normal period with an exception of Italy which showed highest correlation with the EMU during GFC which can be attributed to contagion. For other Group A economies, the correlation declined continuously during the subsequent crisis periods. France exhibited very high and stable correlation with the EMU during the entire sample period. In Group B, Austria and Finland registered exceptional increase in correlation during the crisis periods, which may be due to contagion, while Greece displayed steep decline during EDC period. Other Group B economies also show relatively lesser correlation with EMU during EDC. In Group C, Cyprus and Estonia experienced substantial increase in correlation during GFC, while others shows continuous decline in correlation from Normal to Crises Periods. Malta, Slovakia and Slovenia showed negligible and mostly negative correlation with EMU, indicates towards the absence of integration. However, amongst these economies, Luxembourg is observed to be behaving like Group B economies throughout the sample period as its correlations well exceeded the group's average and mostly stayed in the Group B's range expect during Normal Period when it is highly correlated with the EMU due to its highly active and deep financial markets. The GIPSI economies[12] showed the lowest correlation with the EMU during the EDC as compared to Normal Period and GFC. They registered significant increase in correlation during GFC and then show a very sharp decline during EDC.

5.7. Common Factors Model

The adjusted R-square ($\bar{R}^2$) values for Normal and Crisis periods obtained from 3-year rolling estimation of Equation (14) represent the variance of country i's returns explained by these common factors. Larger $\bar{R}^2$ implies higher contribution of these common risk

[12] GIPSI is used to represent the five troubled European economies i.e., Greece, Ireland, Portugal, Spain and Italy. (see e.g., Castro 2013).

factors in explaining country *i*'s returns, thus indicating towards higher convergence with the region. Figure 7 plots the rolling $\bar{R}^2$ for the three groups over the period and Panel G of Table 2 shows the average $\bar{R}^2$ values for each country for normal as well crisis periods.

[Insert Figure 7 about here]

For the Group A countries, the $\bar{R}^2$ values range between 0.5 and 0.87, thus showing the high contribution of common components in explaining these countries' returns. The Group B economies display the $\bar{R}^2$ values between 0.35 and 0.76 implying the moderate explanatory power of common components in explaining the returns of Group B members. For the Group C economies, the $\bar{R}^2$ values remain below 0.60 during both the periods. Luxembourg showed integration pattern similar to Group B with the $\bar{R}^2$ values far exceeding the Group C average. Cyprus and Estonia registered steep surge in $\bar{R}^2$ from Normal to Crisis periods. Hence, the results again confirm that Group A economies exhibit high level of integration followed by Group B and Group C economies. Further, we observe from the results that all the countries, with an exception of Malta and Germany registered an increase in average $\bar{R}^2$ from normal to crisis period. For Malta, although negligible in both periods, the average $\bar{R}^2$ value doubled during the crisis period. For Germany, this value remained stable. For the other economies of Group A, this increase in the explanatory power of common components may indicate towards the presence of spill over and contagion effects during the crisis. In Group C countries of Cyprus, Slovenia and Estonia reported significant rise in $\bar{R}^2$ volatility during the crisis period. Apart from these Group C economies, the GIPSI countries along with Austria displayed high jumps in $\bar{R}^2$ values from normal to crisis period. It is noteworthy that Slovenia which reported a negative $\bar{R}^2$ value throughout the normal period showed positive value with an increasing trend during the crisis period, which may be on account of beginning of its EMU membership during this period.

Overall, the results suggest that the multi factor model provide better explanation of returns for Group A and B economies than for Group C.

6. Conclusions and Policy Observations

The paper employed an array of integration indicators to study the various dimensions of financial integration during normal and crisis periods. We categorised the EMU members into three groups based on the size of the economy as Group A comprising of old members with large economies, Group B comprising of medium sized economies with old membership and Group C which contains small sized economies. We examined the multiple dimensions of time-varying stock market integration through seven indicators, that are, Beta Convergence, Sigma Convergence, Variance Ratio, ADCC-EGARCH, Dynamic Cointegration, Market Synchronisation Measure and Common Factors Model.

[Insert Table 3 about here]

Table 3 provides the summary on the status of integration in the EMU across the sub-groups for Normal and crisis periods, as indicated by the different indicators of integration. The results revealed the heterogeneous and incomplete nature of integration in the European Monetary Union. The Group A economies displayed stable and high degree of integration; Group B economies show moderate financial integration while the Group C economies are still very far away from desired level of financial integration. From the perspective of global portfolio management, this implies that immense diversification opportunities are still available within the EMU, which is otherwise considered as homogeneous regional block. It is noteworthy, that the highly developed, stable and integrated Group A economies behave like large-cap stocks, the Group B economies that are behaving like mid-cap stocks can offer diversification benefits as Group C economies are unstable and volatile.

We identified four borderline economies, that is, Belgium, Finland, Greece and Luxembourg. Among the Group A economies, Belgium exhibited least level of integration and needs to undertake continuous policy measures to strengthen financial infrastructure to bid away the risk of downgrading to Group B. The Group B economies of Finland and Greece display polar opposite characteristics, in that while Finland displayed integration levels above the group's average; the level of integration for Greece has significantly deteriorated during the EDC period. The analysis suggests that Finland has the potential to achieve Group A level of integration if moderate regulatory and institutional policy initiatives are undertaken in the direction of regulatory and institutional architecture. Greece on the other hand is showing symptoms of strong disintegration from EMU and hence requires structural reforms as in case of Group C economies, so that they can be better integrated with rest of EMU. The results for Luxembourg are interesting and should be interpreted with caution. Luxembourg being a small economy (classified in Group C because of GDP) has disproportionately large market compared to its economic size, which may partly explain its Group B like behaviour. Furthermore, it is interesting to observe that Greece and Cyprus exhibit similar integration patterns, which can be explained by the high interdependency between the two economies.

The analysis of these groups across the sub-periods also offers interesting insights. As we move from GFC to EDC, the Group A countries shows better degree of integration than the other two groups. This *prima facie* indicates towards an improvement in degree of integration over time, however, here a caveat is necessary. Forbes and Rigobon (2002) defined the increase in cross-market linkages following an economic shock in one country, as ‘shift-contagion’. It should be noted that these countries are already very highly integrated, thus, an improvement in the integration may actually imply the presence of contagion effects during the crisis period. Contagion effects are also apparent for Group B and Group C economies; however, they are not as strong as for Group A economies.

Two important obstacles on the path of full financial integration of EMU are the lack of political and fiscal union, and inconsistency between powers and accountability. There is a need to modify domestic legislations in line with EMU agreements to ensure democratic legitimacy to these regional agreements. Furthermore, as independent national regulations tend to lead to cross-border regulatory arbitrage, the regional financial regulatory and supervision systems along with macroeconomic surveillance should be coordinated to supervise and stabilise common financial market, guide and coordinate fiscal as well as economic policies, ensure competitiveness and encourage sustainable growth. In addition, structural changes need to be introduced to induce harmonisation of standards across stock markets and enhanced transparency in form of access to comprehensive and standardised information to all market participants. It will in turn contribute to the competitiveness and efficiency of EMU’s financial system and consequently help strengthen integration through the improved comparability of financial instruments across borders.

The study has important implications for the policymakers in EMU and worldwide as well as the global portfolio managers. The lack of full integration, on one hand, offers opportunities of portfolio diversification within EMU, while on the other, it calls for the immediate attention of EMU policy makers to initiate necessary steps as discussed above. The study also has important implications for the global policy makers especially in the light of enhanced inter-dependence amongst economies, increasingly global nature of financial risks as well as growing number of regional co-operation initiatives worldwide. Further research on Eurozone integration should essentially focus on assessing multiple dimensions of integration from the perspective of bond market, banking sector, money market, alternative investment markets and the corresponding derivative markets.

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Table 1 Sample Set Details

This table provides an overview of the economic size of the sample countries as well as their year of joining the EMU. These countries have been categorised in Groups A, B and C based on their economic size. This table also provides an overview of the size and depth of stock markets of the sample countries as well as their year of joining the EMU. The fourth column indicates the symbol used in this study to represent these economies.

Group	Country	GDP 2012 (millions of euro)[a]	Year of joining EMU	Symbol Used	Market Capitalization as a % of GDP (2012)[a]	Stock Value Traded as a % of GDP (2012)[a]
Group A	Germany	26,43,900	1999	Ger	43.4	35.75
	France	20,29,877	1999	Frc	69.8	43.12
	Italy	15,65,916	1999	Ita	23.8	37.71
	Spain	10,49,525	1999	Spn	75.2	81.41
	Netherlands	6,00,638	1999	Net	84.5	57.27
	Belgium	3,76,840	1999	Bel	62.1	21.37
Group B	Austria	3,09,900	1999	Aus	26.9	11.96
	Greece	1,93,749	2001	Grc	17.9	5.96
	Finland	1,94,469	1999	Fin	64.1	50.90
	Portugal	1,65,409	1999	Por	30.9	12.54
	Ireland	1,63,595	1999	Ire	51.7	5.75
Group C	Slovakia	71,463	2009	Sla	5.1	0.18
	Luxembourg	44,425	1999	Lux	127.5	0.21
	Slovenia	35,466	2007	Sle	14.3	0.88
	Cyprus	17,886	2008	Cyp	8.8	1.28
	Estonia	16,998	2011	Est	10.4	0.80
	Malta	6,755	2008	Mal	41.6	0.49

[a] International Monetary Fund, World Economic Outlook Database, April 2013 edition

Table 2 Measures of Financial Integration

The table reports the results of the seven indicators of integration used in this study to measure stock market integration in EMU. (i) Beta convergence measures the speed of convergence, (ii) Sigma Convergence is used to gauge the dispersion in returns relative to a benchmark, (iii) Variance Ratio examines the significance of a common regional factor in explaining the national returns variation, (iv) Dynamic correlations are estimated using ADCC-EGARCH model to measure time varying integration based on correlations of the conditional volatility of returns, (v) Dynamic Cointegration analysis involves long-run common stochastic trend analysis which is dynamic in nature. This is augmented by estimating time-varying parameter of error correction term (ECT) to measure speed of adjustment to equilibrium (vi) Market Synchronisation Correlation is quantified as the unconditional correlation between the logits of the regime (bull/bear) probabilities of two markets i.e. country *i* and EMU index. (vii) Common Components Approach provides an alternative to the price convergence measures as it defines integration as the state of markets being significantly affected by the common global factors.

Panel A: Beta Convergence

	Group A						Group B					Group C					
	Bel	**Frc**	**Ger**	**Ita**	**Net**	**Spn**	**Aus**	**Fin**	**Grc**	**Ire**	**Por**	**Cyp**	**Est**	**Lux**	**Mal**	**Sla**	**Sle**
Normal Period	-1.19	-1.12	-1.09	-1.08	-1.11	-1.09	-1.06	-1.24	-1.10	-1.19	-1.17	-1.13	-1.08	-1.57	-1.06	-1.08	-1.11
GFC Period	-1.03	-1.08	-1.09	-0.99	-0.99	-1.03	-1.14	-1.07	-1.22	-1.11	-1.11	-1.01	-1.13	-1.61	-1.17	-1.14	-1.39
EDC Period	-1.11	-1.06	-0.94	-1.10	-1.06	-1.02	-1.15	-1.10	-1.17	-1.27	-1.00	-1.06	-1.13	-1.70	-1.11	-1.28	-1.14

Panel B: Sigma Convergence

	Group A						Group B					Group C					
	Bel	**Frc**	**Ger**	**Ita**	**Net**	**Spn**	**Aus**	**Fin**	**Grc**	**Ire**	**Por**	**Cyp**	**Est**	**Lux**	**Mal**	**Sla**	**Sle**
Normal Period	69.79	28.76	59.43	55.07	45.04	59.54	130.44	75.78	129.76	111.57	114.17	148.31	151.00	138.62	157.12	173.67	115.47
GFC Period	103.82	38.39	58.25	71.46	70.36	69.13	156.02	100.76	161.53	181.59	124.83	238.26	214.17	159.56	214.45	241.98	217.11
EDC Period	55.55	26.03	47.42	64.22	53.53	70.80	86.95	77.49	215.32	94.62	94.41	321.32	157.60	106.12	162.19	189.00	168.10

Panel C: Variance Ratio

	Group A						Group B					Group C					
	Bel	**Frc**	**Ger**	**Ita**	**Net**	**Spn**	**Aus**	**Fin**	**Grc**	**Ire**	**Por**	**Cyp**	**Est**	**Lux**	**Mal**	**Sla**	**Sle**
Normal Period	0.60	0.85	0.81	0.76	0.78	0.71	0.20	0.37	0.17	0.27	0.24	0.05	0.05	0.10	0.02	0.02	0.02
GFC Period	0.66	0.85	0.87	0.78	0.79	0.77	0.54	0.65	0.38	0.44	0.49	0.29	0.05	0.36	0.02	0.02	0.05
EDC Period	0.79	0.94	0.85	0.82	0.81	0.79	0.63	0.64	0.15	0.50	0.52	0.11	0.10	0.40	0.03	0.02	0.03

Panel D: Asymmetric Dynamic Conditional Correlations (ADCC)

	Group A						Group B					Group C					
	Bel	**Frc**	**Ger**	**Ita**	**Net**	**Spn**	**Aus**	**Fin**	**Grc**	**Ire**	**Por**	**Cyp**	**Est**	**Lux**	**Mal**	**Sla**	**Sle**
Normal Period	0.79	0.97	0.94	0.89	0.93	0.88	0.47	0.71	0.40	0.55	0.48	0.19	0.14	0.33	0.01	0.04	0.04

GFC Period	0.84	0.98	0.96	0.92	0.92	0.92	0.76	0.84	0.66	0.69	0.68	0.55	0.23	0.66	0.01	-0.06	0.19
EDC Period	0.90	0.98	0.93	0.91	0.91	0.90	0.80	0.81	0.38	0.72	0.74	0.28	0.28	0.66	-0.02	-0.04	0.10

Panel E (a): Dynamic Cointegration-Trace Statistic

	Group A						**Group B**					**Group C**					
	Bel	**Fra**	**Ger**	**Ita**	**Net**	**Spain**	**Aus**	**Fin**	**Gre**	**Ire**	**Por**	**Cyp**	**Est**	**Lux**	**Mal**	**Sla**	**Sle**
Normal Period	1.18	0.89	1.10	0.81	0.91	1.14	1.77	1.23	1.90	1.03	1.15	1.37	1.58	1.69	1.41	1.35	1.31
GFC Period	0.85	0.57	1.10	0.70	0.82	0.69	0.84	0.96	1.55	0.78	1.31	1.66	1.00	0.91	1.07	1.14	1.73
EDC Period	0.90	0.88	0.83	0.84	0.76	0.64	1.05	0.76	0.96	0.82	0.99	0.98	0.97	0.85	1.33	0.78	1.16

Panel E (b): Dynamic Cointegration- ECT coefficient

	Group A						**Group B**					**Group C**					
	Bel	**Frc**	**Ger**	**Ita**	**Net**	**Spn**	**Aus**	**Fin**	**Grc**	**Ire**	**Por**	**Cyp**	**Est**	**Lux**	**Mal**	**Sla**	**Sle**
Normal Period	0.008	0.038	0.026	0.016	0.025	0.009	0.007	0.009	0.021	0.006	0.008	0.021	0.002	0.009	0.003	0.002	0.003
GFC Period	0.023	0.027	0.006	0.011	0.023	0.015	0.016	0.015	0.033	0.010	0.014	0.018	0.007	0.010	0.006	0.011	0.007
EDC Period	0.015	0.064	0.005	0.027	0.015	0.008	0.012	0.009	0.005	0.015	0.010	0.006	0.005	0.009	0.015	0.006	0.008

Panel F: Market Synchronisation (Bull Phase)

	Group A						**Group B**					**Group C**					
	Bel	**Frc**	**Ger**	**Ita**	**Net**	**Spn**	**Aus**	**Fin**	**Grc**	**Ire**	**Por**	**Cyp**	**Est**	**Lux**	**Mal**	**Sla**	**Sle**
Normal Period	0.95	0.99	0.98	0.82	0.99	0.95	0.17	0.22	0.88	0.87	0.90	0.22	-0.23	0.90	0.38	0.00	0.00
GFC Period	0.79	0.98	0.95	0.88	0.75	0.95	0.75	0.73	0.91	0.58	0.62	0.84	0.62	0.66	-0.43	-0.59	-0.28
EDC Period	0.75	0.97	0.74	0.55	0.75	0.63	0.70	0.55	0.59	0.56	0.63	0.34	0.42	0.63	-0.34	-0.40	0.10

Panel G: Common Factors Approach (Adjusted R-squares)

	Group A						**Group B**					**Group C**					
	Bel	**Frc**	**Ger**	**Ita**	**Net**	**Spn**	**Aus**	**Fin**	**Grc**	**Ire**	**Por**	**Cyp**	**Est**	**Lux**	**Mal**	**Sla**	**Sle**
Normal Period	0.62	0.60	0.67	0.49	0.54	0.49	0.37	0.45	0.47	0.35	0.36	0.16	0.06	0.48	0.08	0.02	-0.01
Crisis Period	0.77	0.85	0.66	0.87	0.67	0.84	0.76	0.67	0.66	0.49	0.62	0.48	0.42	0.59	0.05	0.09	0.37

Table 3 Summary of Stock Market Integration in EMU

The table provides a summary on the status of integration in the EMU as indicated by the different indicators of integration that are used for the purpose of this study.

Measure	Description of the Measure	Results
1. Beta Convergence	A negative Beta coefficient (β) implies convergence. The estimated value of Beta indicates the speed of convergence.	β is negative for all EMU members throughout all sub periods. Speed of convergence of Group A and B economies declined during crisis. However, the Group C economies exhibit an increase in convergence during the crisis which may be because of their joining of EMU during this period.
2. Sigma Convergence	Lower cross-sectional dispersion from benchmark (EMU), as measured by sigma value, implies higher return convergence.	Group A economies show highest integration and Group C showed least integration. All the EMU economies showed disintegration during the GFC, followed by a decline in dispersion during the EDC, except Spain, Greece and Cyprus which showed further disintegration during the EDC.
3. Variance Ratio	Higher EMU variance ratio implies more important role of regional factors than local factors in explaining country *i*'s returns	Group A economies exhibit highest level of integration followed by Group B and C. For Group A, rate of increase in VR is higher from GFC to EDC, while for Groups B and C, the increase is higher from Normal to GFC period. Thus, Group A economies suffered from high contagion effects during crisis as compared to Group B and C.
4. Asymmetric Dynamic Conditional Correlation Model	A higher time-varying dynamic correlation indicates greater co-movement of returns. Significant coefficient of asymmetric impact implies the presence of impact of joint bad news on correlations.	The Group A countries show the highest correlation with the EMU during normal as well as crisis periods, Group B showed moderate levels while Group C displayed lowest integration. The general increase in ADCC values from normal to crisis period may be depicting contagion effects among the EMU economies.
5. Dynamic Cointegration	- Scaled trace statistic consistently greater than one is an indicator of long run relationships between the indices. - Higher the absolute value of rolling coefficient of Error Correction Term, higher is the speed of adjustment to long run equilibrium, and hence greater convergence.	- During the normal period, all economies showed significant trace statistics. The Group C countries exhibit higher cointegration than Group A and Group B economies which may be because of the effect of their policy initiatives as they prepared to join the EMU. - Group A countries exhibit highest speed, followed by Group B and Group C countries. Thus, Group A economies seem to be more integrated and having more efficient markets.
6. Market Synchronisation	Higher the correlation between the Markov Switching Model's regime *k* probabilities of two indices, higher the integration between them.	Group A and Group B economies show relatively lesser correlation with EMU during crisis periods. Group C showed negligible and negative correlation with EMU, indicating towards the absence of integration. The correlation of GIPSI economies with the EMU declined to the lowest during the EDC.
7. Common Factors Model	Increase in time-varying adjusted R-squared values implies greater contribution of common risk factors in explaining country *i's* returns, implying higher regional integration.	Group A economies exhibit high level of integration followed by Group B and Group C economies. Average $\bar{R}$^2 increased from normal to crisis period which indicates towards the presence of spillover and contagion effects during the crisis.

Figure 1
Beta Convergence

The figure displays the using the rolling Beta values that measure levels of Beta Convergence for Normal Period, Global Financial Crisis (GFC) and European Debt Crisis (EDC) for the Group A, Group B and Group C.

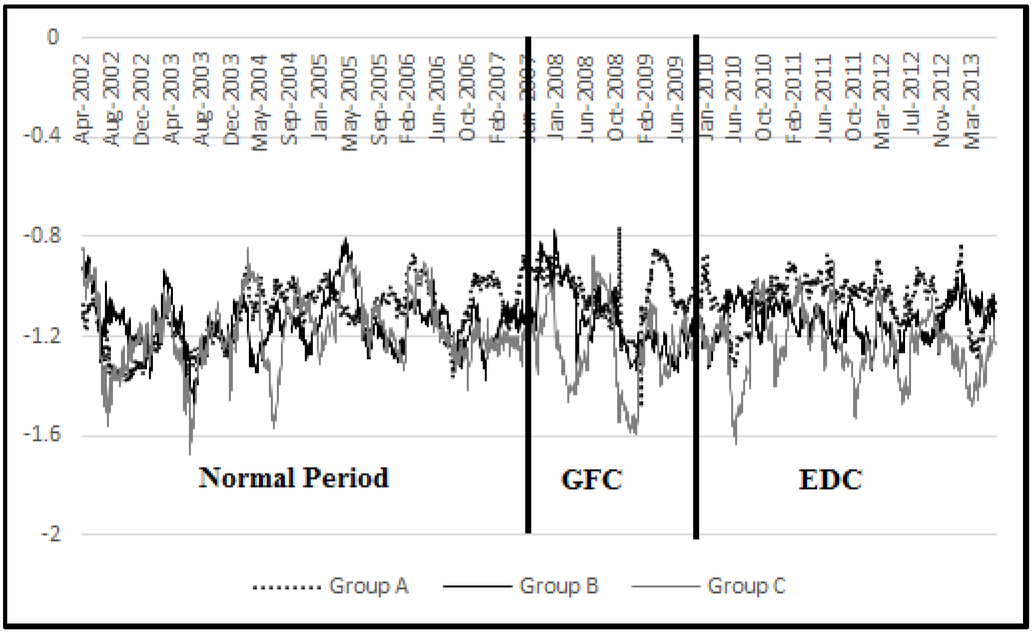

Figure 2

Sigma Convergence

The figure displays the values of cross-sectional dispersion that represent levels of dynamic Sigma Convergence for Normal Period, Global Financial Crisis (GFC) and European Debt Crisis (EDC) displayed separately for Group A, B and C countries.

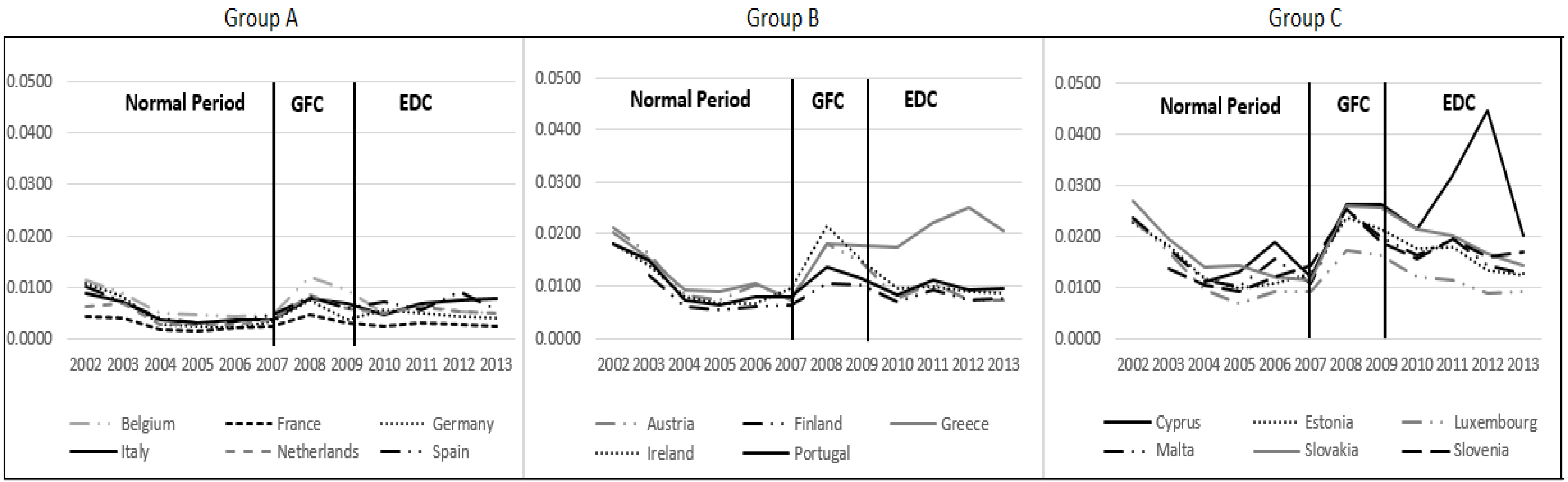

Figure 3
Variance Ratio

The figure displays the values of variance ratio that represent levels of Variance Ratio for Normal Period, Global Financial Crisis (GFC) and European Debt Crisis (EDC) for Group A, Group B and Group C.

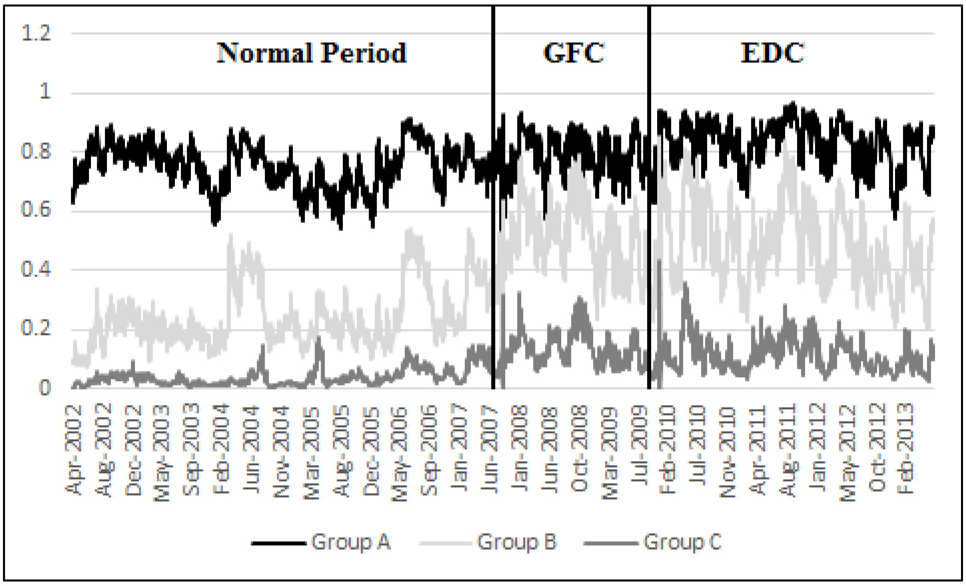

Figure 4

Asymmetric DCC

The figure shows the average dynamic correlation of the EMU stock returns with the stock returns of Group A, B and C respectively.

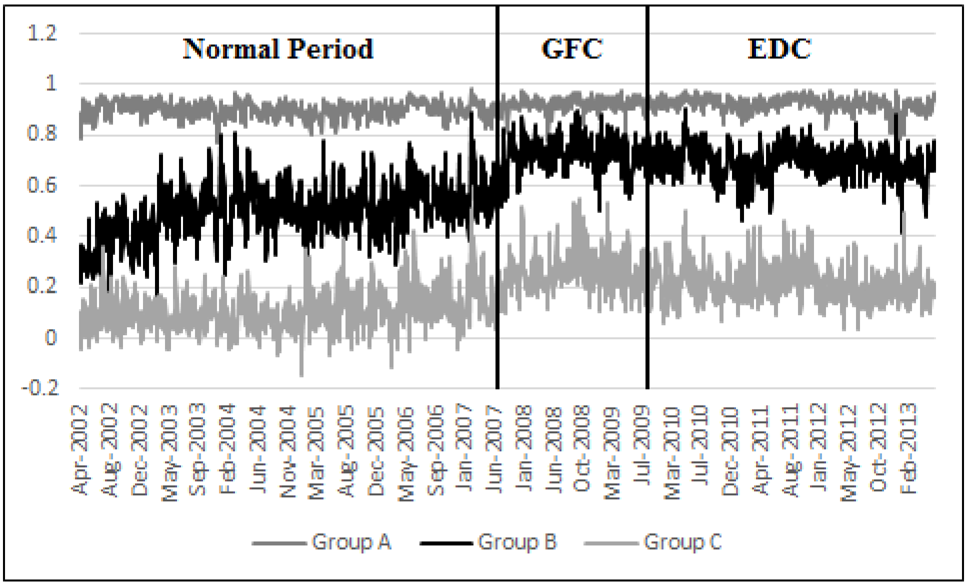

Figure 5

Rolling Trace Statistics

The figure displays the rolling unweighted average trace statistics (scaled by its critical value) for each group across the three sub-periods, viz. Normal Period, Global Financial Crisis (GFC) and European Debt Crisis (EDC).

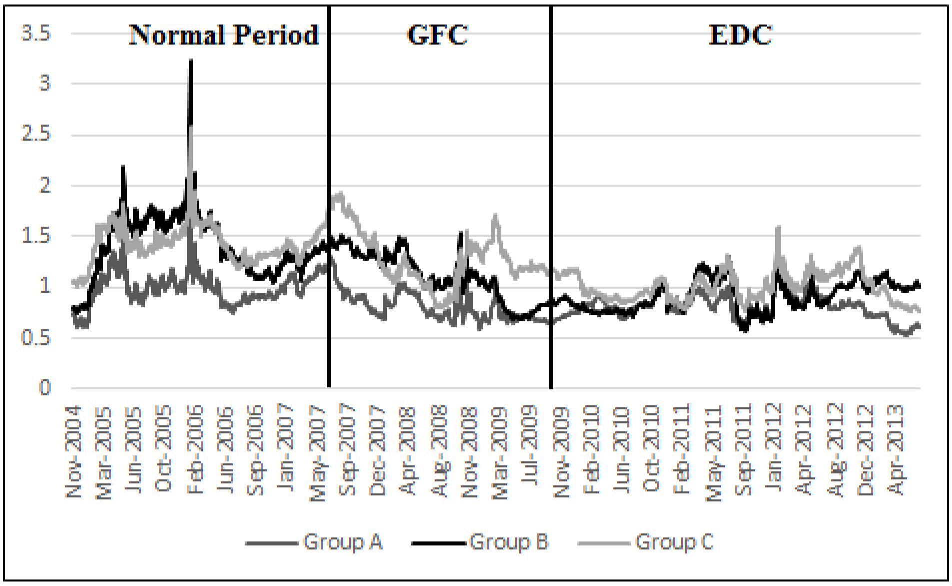

Figure 6

Dynamic Cointegration- Coefficient of Error Correction Term

The figure displays the unweighted average of the absolute values of rolling coefficient of error correction term (ECT) generated from the Dynamic Cointegration analysis, for three sub-periods viz. the Normal Period, the Global Financial Crisis (GFC) and the European Debt Crisis (EDC).

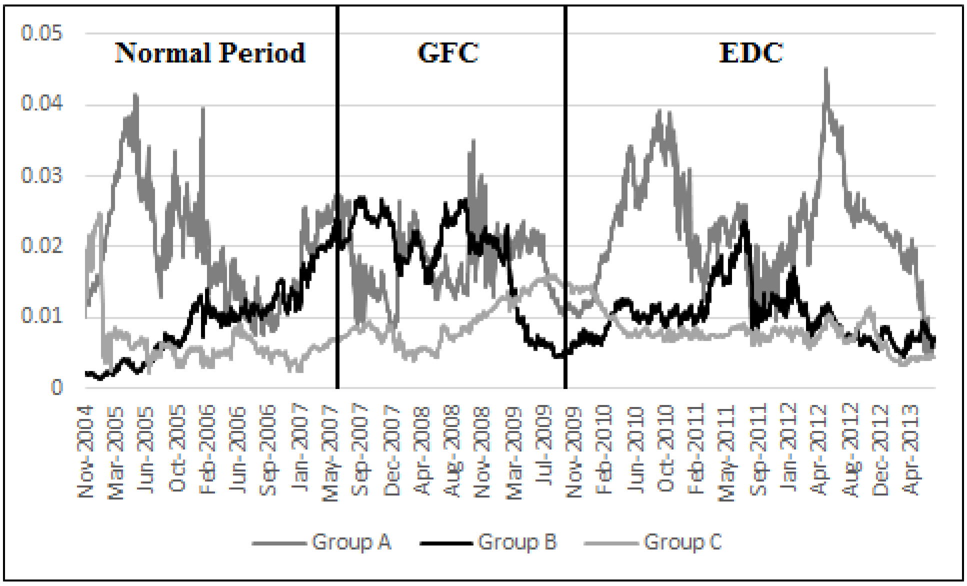

Figure 7

Rolling Adjusted R-square of Common Components Approach

The figure displays, separately for the countries of Group A, B and C, the rolling adjusted R-squares obtained from regressing country *i's* returns on European Common Components.