An empirical examination of stock market integration in EMU

Matei, Florin

December 2014

An empirical examination of stock market integration in EMU

Florin Matei

Abstract

This thesis provides clear empirical evidence that the establishment of the EMU has influenced the stock market integration process within the Euro-area. This is mostly evident across the large four EMU-stock markets: France, Germany, Italy and Netherlands, which appear to be near to perfect integrated after 2001. A considerable influence, but at a lower extent is also found for medium sized markets of Belgium, Finland, Portugal and Spain. Smaller markets such as Greece and Ireland appear to be modestly influenced by the establishment of the EMU, while Austria is the least integrated market within the single currency area. These findings indicate that the stock market integration process remains relatively incomplete for the medium-sized and smaller markets. Thus, the EMU-area cannot yet be considered as a single financial block implying that potential benefits of international portfolio diversification still exist across the EMU countries.

JEL Classification: G15, F15, C32, O52

Keywords: EMU, stock markets, cointegration, DCC

1. Introduction

On January 1, 1999 eleven European Union member states, Austria, Belgium, Finland, France, Germany, Ireland, Italy, Luxembourg, Netherlands, Portugal, and Spain (EU-11 henceforth), completed the final stage of European Monetary Union by adopting a single currency. The introduction of the Euro was the ultimate part of an economic, monetary and financial convergence process that has spanned over two decades from the creation of the European Monetary System. The new common currency eliminated the exchange rate risk among the EMU countries and marked the beginning of a single monetary policy for the EMU countries.

It is widely believed that the European Monetary Union had undoubtedly a strong impact on the level of financial market integration in Europe. According to the academic literature, the process towards the EMU resulted in a gradual convergence among economic and monetary constituents of European economies which had also a strong influence on stock markets. In particular, three factors can be considered as the most influential:

1. The economic and monetary convergence process diminished the differences in macroeconomic factors across countries.
2. The uniform structural and regulatory framework for financial institutions eliminated numerous barriers and restrictions for capital movements and stimulated the harmonization of financial instruments.
3. The introduction of the Euro currency eliminated the exchange rate risk and marked the beginning of an entirely integrated money market.

Apart from the role of EMU as an important driver for change, stock market developments in Europe are considered as part of a global phenomenon. Recent developments in information technology, financial innovation, cross–border capital mobility and the increasing economic integration due to international trade relations, are only some of the reasons that spurred financial integration among European countries. Over the last two decades, the role of stock markets has become crucial for "smooth functioning" industrialized economies. At the same time, bond and stock markets integrated closer together and tend to exhibit similar behavior across countries nowadays. Consequently, national economies appear to be more sensitive in disturbances from foreign stock markets and these disturbances tend to have deeper and more far-reaching effects.

The growing degree of integration among European stock markets, both within and outside the single currency area is important for several reasons. For investors, the formation of a well-diversified portfolio depends on the degree of correlation of equity returns among different countries. If the degree of integration between European stock markets is high, the potential benefit from international diversification across these stock markets will be minimal (Bessler and Yang, 2003). A recent report of Morgan Stanley Dean Witter states that "...while country influences will continue to be important, the Intra-EMU-Europe activity will likely over time shift away from country level decisions, and more toward more active stock and sector strategies" (Rouwenhorst, 1998). For the regulatory authorities in each member country, the level of international financial integration is crucial because it is fundamentally linked to economic growth (Arestis, Demetriades and Lunitel, 2001).

Although the academic literature on comovements among international stock markets is large, only a few academic papers focus on European stock market comovements with the objective to evaluate the effects of EMU on stock markets. Recent studies by Hardouvelis et al. (1999), Fratzscher (2002), Worthington et al. (2003), Yang et al. (2003) and Kim et al. (2004) provide evidence that the EMU has strengthened stock market integration among member countries. However, these studies are limited to stock market data and changes up to 2003. Moreover, most of them analyze selected EMU countries only.

This study attempts to analyze the evolving process of stock market integration among EMU countries by employing modern time series analysis used in the academic literature. The analysis is conducted from three different perspectives: the short-run, the long-run and the dynamic perspective of market integration.

The empirical findings of this thesis indicate that the establishment of the EMU and the introduction of the common currency had a strong impact on the integration process among the Euro-11 stock markets. Although cointegration analysis provides no evidence of an increase in long-term interdependencies, the analysis of short-term interrelationships indicate that the short-term linkages among the EMU markets have significantly strengthened after the EMU. These findings are also confirmed by the results of the Dynamic Conditional Correlation model which show a significant increase in correlations among EMU markets in the post-EMU period. In particular, the empirical results indicate that large EMU markets (France, Germany, Italy and Netherlands) have become highly integrated in the post-EMU period. The strength of co-movements across these markets appears to be striking especially after 2001. An increased level of integration, but at a lower extend is also found for the medium-sized markets (Belgium, Finland, Portugal and Spain). Smaller markets of Greece and Ireland appear to be modestly influenced by the EMU while Austria is the only market that is found to be relatively isolated in the Euro-area. The above findings clearly show that the process of stock market integration in the Euro-area remains relatively incomplete. Thus, the EMU cannot yet be considered as a single financial block. The findings of this thesis have significant implications for both international portfolio diversification and policy authorities which are thoroughly analyzed in the last section.

1.1. Economic and Monetary Union and Stock Market Integration

The European Union represents probably the highest degree of regional, economic, political and financial integration worldwide. Its history starts in 1950s with the Treaty of Rome and the establishment of the European Community. The Treaty of Rome provided the free movement of goods, services and capital within the Community without focusing on unification of capital markets. In the 1970s, the economic recession that followed the oil crisis and the Bretton Woods collapse, set back the momentum towards the economic integration. At the beginning of 1980s the growth rates in Europe had shrunk considerably comparing to the United States of America and Japan. It was clear that the momentum to recovery from the recession was through the single market envisaged in the Treaty of Rome.

The general scheme of the Treaty of Rome (1957) to achieve an "ever closer union" was effectuated by the White paper in 1985 which provided the necessary background for stock market integration in Europe. According to the section 107 of the White Paper: …."Work currently in hand to create a European stock market system, based on Community stock exchanges, is also relevant to the creation of an internal market. This work is designed to break down barriers between stock exchanges and to create a Community-wide trading system for securities of international interest. The aim is to link stock exchanges electronically, so that their members can execute orders on the stock exchange market offering the best conditions to their clients. Such an interlinking would substantially increase the depth and liquidity of Community stock exchange markets, and would permit them to compete more effectively not only with stock exchanges outside the community but also with unofficial and unsupervised markets within it."

In 1987, the Single European Act was proclaimed. The Act provided the regulatory basis for the free movement of goods, services, people and capital in the European Economic Community. The Act however did not include the monetary union among its priorities.

The Maastricht Treaty in 1992 finally set the regulatory framework for the European member states to form a Monetary Union. According to the Maastricht Treaty, the member states were obliged to meet certain macroeconomic criteria in order to attain economic convergence. Among them, controlling inflation and budget deficit limits, low interest rates and less volatile exchange rates were the most important criteria to achieve economic integration. Moreover, the creation of the European Central Bank in 1998 and its responsibility to carry out a uniform monetary policy among member countries diminished the differences in macroeconomic factors across countries.

The introduction of the Euro currency in 1999 marked the third and final stage of the EMU. Money market integration was an immediate consequence of the Euro introduction. The common currency eliminated intra-European exchange rate volatility and the cost of hedging that risk and positively influenced the cross-European stock holdings (Hardouvelis et. al, 1999). Table 1 in the appendix summarizes the main economic and political events towards the process of EMU in more details.

The mentioned milestones towards an economic, monetary and regulatory convergence as well as the currency unification are believed to have a substantial influence on the degree of stock market integration across the EMU. However, one should be very careful in defining the determinants of stock market integration in Euro-area. Focusing only on the exchange rates ignores other factors that may significantly affect the process of stock market integration (Fratzscher, 2002). Thus, understanding the fundamental factors behind the European stock market integration requires a broad approach that takes into account the effect of these different sources.

1.2. Research Objectives

Acknowledging that the process of stock market integration in Europe is influenced by a variety of economic, monetary and regulatory factors, this study attempts to provide an examination of the level of integration among EMU-countries and the possible impact of the EMU on stock market linkages[1]. The analysis employed in this thesis is a return-based approach, based on price-weighted country indexes for all EMU-stock markets. The impact of the EMU on stock market linkages is examined by using a variety of econometric methods proposed in the empirical literature. Applying these methods, this thesis attempts to evaluate the effects of the EMU on stock markets from three different perspectives: the long-run, the short-run and the dynamic perspective.

The sequential steps of the employed econometric methodology can be described as follows: In the first step, the well-known Augmented Dickey-Fuller and the Phillips-Perron tests are applied to examine the stationary properties of the stock-market data. Given the rejection of the hypothesis of stationarity, this study investigates the long term common stochastic trends between the stock indexes using the well-known Johansen - Juselius (1990) multivariate cointegration technique. To examine the effects of the EMU on the short run dynamic causal linkages across the stock markets, the recently developed tests of Generalized Impulse Response Functions (GIRFs) and Generalized Forecast Error Variance Decompositions (GFEVDs) developed by Koop, Pesaran and Potter (1996) and Pesaran and Shin (1998) are employed. Finally, to examine the dynamic structure of the degree of comovements among the EU-stock markets for the pre- and the post EMU period, the Dynamic Conditional Correlation (DCC) model of Engle (2002) is employed, as this technique is well-suited to explain and time varying conditional correlations among

[1] This thesis does not seek to examine the relative importance of the different determinants of the stock market integration in Euro-area.

EMU stock returns. To the knowledge of the author, this is the first study that applies all these tests simultaneously.

This thesis contributes to the existing literature by:

1. Incorporating the latest assessment of Greece in the EMU which took place on 02/01/2001. Only Worthington et al. (2003) examined European equity market integration within the entire EMU. However, Worthington's study employs only cointegration methodologies and it is not suitable for examining the short-run and the dynamic process of stock market integration across EMU countries.
2. Incorporating a variety of recently developed econometric techniques in order to examine the issue European stock market integration from three different perspectives: short-run, long-run and dynamic perspective.
3. Employing Engle's (2002) DCC-GARCH model to estimate the dynamic structure of the time-varying conditional correlations among EMU-stock market returns. This model has been proved to be superior for modeling financial data, thus providing a consistent estimate of the degree of correlation among EMU-stock markets.
4. Using higher frequency (daily) data to examine the comovements among the European stock markets, the pre- and the post-EMU period are investigated and compared.
5. Employing an extended and equally balanced dataset of the last 15 years, from 09/05/1991 to 09/05/2006; this study minimizes the probability of a possible sample bias.

This thesis is organized as follows. Section 2 presents an overview of measurements of stock market integration as well as a review of the previous academic literature. Section 3 briefly presents the data used in the econometric modeling. Section 4 describes the methodology used in this study. Section 5 presents and analyzes the empirical results of this thesis. Finally, Section 6 discusses the implications of the results on asset allocation strategies and policy actions and concludes.

2. Overview of European Stock Market Integration

2.1. Issues in Measuring Stock Market Integration

A formal definition of market integration does not seem to exist in the financial literature. According to Cappiello et. al (2006), market and economic integration can be considered as the strengthening of the financial and real linkages between economies. Most of the academic literature that focuses on this issue, investigates the changes in the comovements across countries using financial asset returns. In the same spirit, this study investigates the process of stock market integration among EMU-markets by using price-weighted MSCI indexes for all EMU-stock markets.

The question of integration is not only important from an international perspective but similarly can be applied to the national perspective in order to test integration across different sectors. In fact, a high level of integration across national markets may motivate investors to diversify their portfolio across sectors rather than countries.

In the financial literature we find several approaches to measure the level of integration among international stock markets. Several studies (e.g. Dumas and Solnik 1995, Hardouvelis et al 1999) use a theoretical International Capital Asset Pricing Model to test for integration. According to this international CAPM:

$$E_{t-1}(r_{i,t}) = \lambda_w \beta_{iw} + \lambda_d \beta_{id}$$

where $r_{i,t}$ is the excess return of the country portfolio i, λ is the market risk premium, β_{iw} is the risk of the portfolio i relative to the world portfolio and β_{id} is the risk for the domestic market portfolio d. If $\lambda_d = 0$, then the local portfolio is priced according to the world portfolio. Thus, in a fully integrated market, the expected local returns in this market depend only on international factors and vice versa (Fratzscher, 2002).

There is also an increase in literature where modern time series analysis is used to investigate the stock market linkages across countries. This analysis consists of cointegration tests (Engle –Granger (1987), Johansen-Juselius (1990)) and innovation accounting methods such as Forecast Error Variance Decompositions and Impulse

Response functions. In general, cointegration analysis examines the long-run comovements among non-stationary variables. If two variables are cointegrated, then they share common stochastic trends such that they will tend to drift together in the long run. Given the existence of cointegration relationships, innovation accounting techniques can be applied to estimate the speed of the price information transmission among the European markets. Both cointegration and innovation accounting techniques are valuable in analyzing linkages among international stock markets and examine whether there are any common forces that drive the short-run or long-run movement of the series under investigation. These methods, used also in this study, are thoroughly analyzed in the next section.

Correlation analysis has been also fundamental in the academic literature to examine the interrelationships across international markets. While earlier studies were mostly based on the limiting simple correlation coefficients; over the last decade, an increase in literature of the dynamics of correlation of assets has been developed, based on GARCH modeling. Since it is well-known that correlations are not stable through time, there exists a greater need to capture the dynamic properties of the time-varying market correlations. In this concept, the Dynamic Conditional Correlation (DCC) model introduced by Engle (2002) is used in this paper. The DCC model has computational advantages over the multivariate GARCH models and provides a very good approximation for various time varying correlation processes (Engle, 2002).

2.2. Literature Review

The issue of stock market integration globally has received considerable attention both in theoretical and empirical literature, not least because of its implications to asset allocation strategies. Nevertheless, there are only a few articles in the literature exclusively focusing on stock market integration in the Euro-area, in an attempt to evaluate the impact of the EMU on stock markets.

Kasa (1992) using Johansen cointegration tests, provides evidence of common stochastic trends in the equity markets of the U.S., Japan, England, Germany, Canada over the period 1974-1990. Similarly, utilizing the analysis of Kasa (1992), Engsted and Lund (1997) applied a Johansen cointegration test with restrictions in cointegrating vectors and conclude that dividends in Denmark, Germany, Sweden and UK share common trends, during the period 1950 to 1988.

Chan, Cup and Pan (1997) examine the integration of international stock markets by including 18 nations over a 32-year period. Their analysis, based on Johansen cointegration tests, shows that only a small number of stock markets are cointegrated with others. In particular, their findings show that before the October 1987 stock market crash, the cointegrating vectors among the four European Big Markets (UK, Germany, France, and Italy) increased. However after the crash, they found no evidence of cointegration relationships across these markets.

Contrary to the finding of Chan, Cup and Pan (1997), Dickinson (2000) argues that there exists one cointegration equation between the major European stock markets after the 1987 crash. His study based on Johansen cointegration tests and error correction models contended that there are key macroeconomic variables (e.g. inflation, interest rates, and output) that partly explain the stock market movements across these countries. Furthermore, Gerrits and Yuce (1999) examined the interdependence between stock prices in Germany, UK, Netherlands and the U.S. from the period of 1990 to 1994. Their results show that the three European stock markets significantly influence each other in the short and long run, Therefore, diversification among these markets will not greatly reduce the portfolio risk without sacrificing expected return.

Yang, Min and Li (2003) examine the possible effects of the EMU on stock market integration in the Euro-area using daily stock indexes of ten EMU countries from January 1996 to June 2001. By using Johansen cointegration tests, generalized forecast error variance decompositions and generalized impulse response functions, they investigate market integration through three different perspectives: contemporaneous, short-run and long run. Their findings indicate that European stock markets as a whole are more integrated in the short run after the EMU period. Additionally, they find evidence that large markets exhibit stronger inter-relationships while the smallest markets become more isolated at the post-EMU period. Moreover, Worthington, Katsuura and Higgs (2003), applying similar methodology for the EMU equity markets draw similar conclusions. In the same spirit, Aggarwal, Lucey and Muckley (2003), examined the integration of EMU equity markets over the 1985-2002 period using traditional Johansen cointegration and dynamic cointegration analysis that allow the measurement of time-varying comovements in equity prices.

Their findings indicate a large increase in the level of integration especially for the 1997-1998 period. After that period, they detect a decrease in measured integration which can be attributable to the stock market bubble in the year 2000.

Recent studies have used univariate and multivariate GARCH models to capture the dynamic process of stock market integration. These models aim to capture the strong variations in stock markets over time. Fratzscher (2001), building a multivariate GARCH model, estimates that the degree of integration among EMU countries has increased due to the common monetary policy and the elimination of the exchange rate risk. His findings suggest that European equity markets are highly integrated especially after the 1996.

Another study of Hardouvelis et al. (1999) uses an asset pricing model which allows for a time varying degree of integration to analyze the pre-EMU period. The results indicate that a country's level of integration is expected to be higher, the higher the probability that this country will join the EMU. Kim et al. (2005) building a bivariate GARCH contends that there is a clear regime shift in European stock market comovements and integration after the introduction of Euro. Furthermore, they examine the direction of causality between currency unification and stock market integration and conclude that the EMU has been an important causal factor to the process of integration since evidence of unidirectional causality is found. At the other hand, another study by Berben and Jansen (2005) employs a GARCH model with a smoothly time-varying correlation to estimate the conditional cross-country correlation in nine EMU-bond and stock markets over the period 1980-2003. While EMU-bond markets appear to be perfectly correlated after the EMU, they contend that there is hardly any evidence of EMU influence over the pace of stock market integration within Europe. According to their findings the integration trend across EMU-stock markets in late 1990s appears to reflect global factors and not Euro-area factors.

Cappiello, Engle and Sheppard (2003) apply a Dynamic Conditional Correlation (DCC) GARCH model to explore the dynamic changes in correlation among European, U.S. and Australasian bond and stock markets. According to this paper, the conditional equity correlations have significantly increased especially for the major European markets since the introduction of Euro. Additionally, they find evidence of near to perfect correlation among bond returns within the EMU.

Summarizing the literature to date, the impact of the EMU on European stock markets has received considerable academic scrutiny. A large part of the empirical research, mentioned above, argues that the influence of the EMU on EU-stock markets is crucial. This appears to be more intense especially for the major EU-markets which seem to be closely integrated after the introduction of the Euro.

3. Data and its statistical properties

3.1. Data

The dataset employed in this paper consists of price-weighted indexes for all EMU-stock markets, i.e. Austria, Belgium, Finland, France, Germany, Greece, Ireland, Italy, Netherlands, Portugal and Spain. The data include all EMU-participating countries except Luxembourg[2]. This analysis does not include the U.S. or U.K. or other markets outside the EMU because its main focus is to measure the developing process of integration and the inter-dependence across the EMU stock markets. All data is derived from Morgan Stanley Capital International (MSCI)[3] and include 15 years of daily observations, spanning from 09/05/1991 to 09/05/2006, providing 3914 observations in total. All indexes are denominated in Euro. The main reason for using MSCI-country indexes is the uniformity in the analysis. The MSCI indexes share the same construction, methodology, are consistent among countries and allow for comparative analysis between different markets.

Unlike Cappiello, Engle and Sheppard (2003) that used weekly stock and bond market data to calculate the conditional correlations across a sample of the European, the U.S. and the Australasian markets, this study uses daily returns. According to Kim et al. (2005), the choice of using daily data frequency is more suitable given that the comovements in stock returns may often change rapidly as investors shift their asset allocation. Elyasiani et al. (1998) contends that, in general, daily return data is preferred to the lower frequency data such as weekly and monthly returns because longer horizon returns can obscure transient responses to innovations which may last for a few days only.

As with Kim et al. (2005), the daily returns are calculated as the natural logarithms of the closing index level from one trading day to the proceeding, i.e. $R_{it} = \ln\left(P_t / P_{t-1}\right)$ for market i on day t.
$\times 100$

[2] The MSCI Luxembourg indexes were removed from the MSCI EU Index series on February 28, 2002.

[3] MSCI indexes are sourced from Thompson DataStream.

In order to evaluate the impact of the EMU on stock markets and measure the extent that monetary unification has raised the degree of stock market integration across member countries, the analysis is divided into two sub periods: the pre-EMU period containing data from 09/05/1991 to 31/12/1998, and the post-EMU period containing data from 01/01/1999 to 09/05/2006.

3.2. Descriptive Statistics

Before proceeding with the econometric modeling, it is interesting to examine the statistical properties of the daily stock market returns of the eleven EMU countries. The emphasis lays on the distribution properties of the stock market returns characterized by the skewness, kurtosis, Jarque-Bera test statistic, the mean and the standard deviation of the corresponding distributions.

The statistical properties of the stock market indexes from the sample are presented in Tables 1a and 1b. The analysis is divided in two periods: the pre-EMU period (09/05/1991 – 31/12/1998) and post-EMU period (01/01/1999 - 09/05/2006).

Table 1a: Descriptive Statistics for the Pre-EMU period (09/05/1991 – 31/12/1998)

	Mean	Std. Dev.	Skewness	Kurtosis	Jarque-Bera
AUSTRIA	-0.008	1.024	-0.686	13.320	9009.974*
BELGIUM	0.055	0.779	-0.439	8.144	2263.780*
FINLAND	0.101	1.654	-0.141	8.354	2388.973*
FRANCE	0.045	1.086	-0.258	6.224	885.906*
GERMANY	0.047	1.090	-1.007	11.994	7061.716*
GREECE	0.053	1.581	-0.137	7.263	1517.201*
IRELAND	0.055	1.051	-0.161	11.484	5991.611*
ITALY	0.055	1.417	-0.156	5.381	479.474*
NETHERLANDS	0.061	1.001	-0.279	8.464	2507.829*
PORTUGAL	0.052	0.951	-0.717	15.851	13897.910*
SPAIN	0.063	1.213	-0.495	7.811	2005.853*

One and two asterixes denote rejection of the null hypothesis at the 5% and 1% level of significance

Table 1b: Descriptive Statistics for the Post-EMU period (01/01/1999 – 09/05/2006)

	Mean	Std. Dev.	Skewness	Kurtosis	Jarque-Bera
AUSTRIA	0.057	0.929	-0.398	4.967	359.681*
BELGIUM	0.002	1.252	0.339	9.175	3083.868*
FINLAND	0.020	2.651	-0.440	8.960	2900.569*
FRANCE	0.018	1.398	-0.103	5.734	600.571*
GERMANY	0.005	1.585	-0.079	5.628	553.874*
GREECE	0.014	1.552	-0.041	7.040	1304.964*
IRELAND	0.002	1.161	-0.664	8.059	2186.239*
ITALY	0.007	1.219	-0.169	5.935	697.429*
NETHERLANDS	-0.002	1.429	-0.151	6.979	1272.294*
PORTUGAL	-0.003	0.992	-0.220	5.089	364.238*
SPAIN	0.016	1.359	0.033	5.663	567.152*

One and two asterixes denote rejection of the null hypothesis at the 5% and 1% level of significance

The results from Tables 1a and 1b indicate that stock market returns in all EMU markets exhibit a slightly negative skewness and excess kurtosis. That means that the distribution of returns in these eleven markets is characterized by sharper peakness and fat tails relative to a normal distribution. The Jarque-Bera statistic also rejects the hypothesis of a normal distribution in the stock market returns.

As discussed analytically later, the econometric modeling used in this thesis accounts for non-stationarity and non-normality in the data.

4. Econometric Methodology

4.1. Stationarity Tests – Market Efficiency

Researchers in finance have long been interested in the long-run time-series properties of asset returns, with particular attention to whether asset returns can be characterized as random walks (having unit roots) or mean reverting (trend stationary) processes.

A random walk process implies that any shock to asset prices is permanent and there is no tendency for the asset price to return to a trend path over time. In a broad sense, a stationary process is a process that its probability distribution remains unchanged through time. A stationary series is defined as a series with a mean and variance that will not vary within the sampling period. In such series the effect of a shock will die away over time and the asset price will tend to return to the mean (mean reversion). In contrast, a non-stationary series exhibits a time varying mean and variance. In such series the error term of a model will not decline after a 'shock' is occurred (mean aversion). Since the variance of a non-stationary series is not constant through time, conventional asymptotic theory cannot be applied for those series.

In the empirical financial literature, there is substantial evidence of unit root (non-stationarity) characteristics in stock market indexes. The existence of unit roots is important to examine the weak form of market efficiency across the EMU markets. According to the weak form of market efficiency, no investor can earn excess return by developing investment strategies based on historical prices or other financial data. As shown in Chan, Cup and Pan (1997), if the hypothesis of unit roots in stock prices cannot be rejected, then the stock prices follow a random walk. Thus, the stock market can be characterized as weak-form efficient.

Additionally, non-stationarity is a requisite condition in order to proceed to cointegration analysis. To determine the stationary properties of the stock market series, we conduct two different Unit Root tests: the Augmented Dickey Fuller and the Phillips-Perron test.

4.1.1. Augmented Dickey Fuller Test

Unit Root tests of the null hypothesis of non-stationarity are conducted, using the well known Augmented Dickey-Fuller (ADF) test. This unit root test, developed by Dickey and Fuller (1979) is conducted in the form of the following regression equation:

$$\Delta Y_{it} = \alpha_0 + \alpha_1 t + \rho_0 Y_{it-1} + \sum_{i=1}^{p} \rho_i \Delta Y_{it-i} + \varepsilon_{it} \tag{1}$$

where Y_{it} denotes the stock market index for the i-th country at time t, p is the number of lag terms, t is the trend variable, α_1 is the estimated coefficient for the time trend, α_0 is the constant, ρ are coefficients to be estimated, and ε_t (white noise) is standard normal distributed. This test differs from the standard Dickey-Fuller test in that it also incorporates lags of first-differences of the variables to correct for the possible serial correlation. The number of lags cannot be arbitrarily chosen as too few lags will leave autocorrelation in the errors and too many lags will reduce the power of the test. Here, the number of lags is selected by using the Bayesian Information Criterion (BIC or SIC). The null hypothesis for the ADF test is that the series in question contains a unit root versus the alternative hypothesis that the variable is stationary. The critical values of the ADF test are provided by MacKinnon (1996).

The ADF test is performed on both the levels and the first differences of the stock market indexes. At the beginning the more general ADF test is performed including a trend and a drift. In the case of no-rejection of the null hypothesis, an ADF test only with a drift is performed and finally the most restrictive ADF test without a trend and a drift. When the series are non-stationary in levels and stationary in first differences, it can be concluded that the series are individually integrated of order one, I (1). According to Engle and Granger (1987), if two or more series are I (1), but a linear combination of them is I (0) (stationary), then the series are said to be cointegrated.

This characteristic of the I (1) variables is very important and allows us to proceed to the next step of the analysis, i.e. apply cointegration techniques to search for common stochastic trends in European stock markets.

4.1.2. Phillips - Perron Test

Phillips and Perron (1988) suggested an alternative to the Augmented Dickey – Fuller test. This approach is nonparametric[4] with respect to nuisance parameters, allowing for a wide class of time series models in which there is a unit root (Phillips and Perron, 1988). Since the Augmented Dickey – Fuller assumes that the errors are standard normal distributed with constant variance; this can lead to erroneous conclusions in the presence of structural breaks (such as a market crash) in the time series data. This problem is circumvented by adopting the nonparametric adjustment introduced by Phillips and Perron. This test is a generalization of the Augmented Dickey – Fuller test in the form of the following regression equation:

$$y_t = a_0 + a_1 y_{t-1} + a_2 \ (t - T/2) + \mu_t \qquad (2)$$

where T is the number of observations and E $(\mu_t) = 0$, but the disturbance term may not be homogeneous or serially uncorrelated.

As in the ADF test, the null hypothesis is of a unit root against the alternative of stationarity in the stock market indexes. Similarly to the ADF test, the PP test is performed on both the levels and the first differences of the stock market indexes. Again, a more general PP test is performed including a trend and a drift. In the case of no-rejection of the null hypothesis, a PP test only with a drift is performed and finally the most restrictive PP-test without a trend and a drift. The critical values of the PP test are provided by MacKinnon (1996).

4.2. Johansen VECM approach

Given the non-stationary properties of the European stock market indexes, cointegration analysis is fundamental in order to examine the existence of common stochastic trends and long–run comovements among the European stock markets. Two

[4] In technical terms, nonparametric methods do not rely on the estimation of parameters (such as the mean or the standard deviation) describing the distribution of the variable of interest in the population. Therefore, these methods are also sometimes called parameter-free methods or distribution-free methods.

fundamental approaches exist to address the issue of cointegration among the European stock market indexes: the bivariate Engle – Granger (1987) method and its multivariate extension, the Johansen – Juselius (1990) approach. In this paper, only the latter is employed as it appears to be more reliable and compatible with this study, since more than two I(1) time series are involved in the analysis.

The idea of cointegration was initially introduced by Granger in 1981. Granger and Newbold (1974) pointed out that the standard OLS between non-stationary series can lead to incorrect conclusions, i.e. to get very high values of R^2 (sometimes even higher than 0.95) while the variables used in the analysis have no interrelationships. In their influential paper, Engle and Granger (1987) proved that cointegration can tackle this problem and provide unbiased results. According to Engle and Granger (1987), if a linear combination of non-stationary time series exhibit stationarity, then the series are said to be cointegrated. Nevertheless, the Engle-Granger methodology is bivariate, i.e. it tests for cointegration between pairs of variables and it is not applicable in this study.

In this paper, we apply only the Johansen and Juselius (JJ) multivariate cointegration framework to examine the existence of multiple cointegrating vectors among the eleven time series employed in this analysis. This methodology has many advantages over the bivariate Engle-Granger test: 1) it is not based on the limiting assumption of a single cointegrating vector, but it examines the presence of multiple cointegration relations, 2) it is invariant to the choice of the dependent variable in the cointegration equation, assuming that all variables in the system are endogenous, 3) it applies the maximum likelihood method in order to estimate the number of cointegrating vectors in the pre- versus the post-EMU period, 4) the long-run model estimates does not suffer from small sample bias.

In particular, the Johansen-Juselius (1990) approach is based on a Vector Autoregressive model of order p:

$$y_t = A_1 y_{t-1} + A_2 y_{t-2} + \dots + A_p y_{t-p} + Bx_t + \varepsilon_t \qquad (3)$$

where y_t is a k-dimensional vector of I(1) endogenous variables, x_t is a d-vector of deterministic variables and ε_t is a vector of innovations. The VAR (p) model can be rewritten in the form of a vector error correction model with p-1 lags (which is equivalent to a level VAR with p lags):

$$\Delta y_t = \Pi y_{t-1} + \sum_{i=1}^{p-1} \Gamma_i \Delta y_{t-i} + ... + Bx_t + \varepsilon_t, \tag{4}$$

where

$$\Pi = \sum_{i=1}^{p} A_i - I \qquad (5), \qquad\qquad \Gamma_i = - \sum_{j=i+1}^{p} Aj \qquad (6)$$

Granger's representation theorem asserts that if the coefficient matrix Π has reduced rank r<k, then there exist $k \times r$ matrices α and β, each with rank r, such that $\Pi = \alpha\beta'$ and $\beta' y_t$ is I (0). In this case, r is the number of cointegrating relations (the cointegrating rank) and each column of β is the cointegrating vector. Johansen's method is to estimate the Π matrix from an unrestricted VAR and to test whether we can reject the restrictions implied by the reduced rank of Π. The rank of the Π matrix determines the number of the distinct cointegrating vectors in the system. Johansen and Juselius (1990) derive two likelihood ratio test statistics for the rank of the Π matrix: the trace and the maximum eigenvalue statistics. The trace statistic tests the null hypothesis of r cointegrating relations against the alternative of k cointegrating relations, where k is the number of exogenous variables, for r = 0,1,…,k-1. The alternative of k cointegrating relations corresponds to the case where none of the series has a unit root, i.e. a stationary VAR may be specified in terms of the levels of all the series. The trace statistic of the null hypothesis or r cointegrating relations is
computed as:

$$LR_{tr}(r \mid k) = -T \sum_{i=r+1}^{k} \log(1 - \lambda_i) \tag{7}$$

where λ_i is the i-th largest eigenvalue of the Π matrix (equation (5)).

The second test statistic is the maximum eigenvalue statistic of the null hypothesis or r cointegrating relations against the alternative of r + 1 cointegrating relations. This test is computed as:

$$LR_{max}(r|r+1) = - T\log(1-\lambda_{r+1}) = LR_{tr}(r|k) - LR_{tr}(r+1|k) \tag{8}$$

To determine the number of cointegrating relations r, the Johansen cointegration test proceeds sequentially from r = 0 to r = k – 1 until it fails to reject.

To carry out the Johansen cointegration test, assumptions regarding the trend in the data need to be made. Similar to the analysis of Worthington et. al (2003) and Yang, Min, Li (2003), the assumption of no deterministic trend in the data and no intercept or trend in the cointegration equation has been used[5]. The Johansen cointegration test is implemented in this paper using the Eviews 5.1. software. The analysis is divided in two sets of perions: the pre-EMU and the post-EMU period. The choice of the number of lags in the VAR equation is based on the the Akaike and the Swartz (Bayesian) information criteria. The critical values for the trace and the maximum eigenvalue statistics are derived from Osterwald and Lenum (1992).

The Johansen VECM framework described in this section, focuses on the long-run cointegration relationships across the European stock markets. However, as critically noted in Pesaran and Shin (1996 p.118), focusing on the long run by testing for cointegration, has the danger of making the research irrelevant or at best of rather limited use for policy analysis. Therefore, it is important to examine the short-run dynamic linkages across the EMU stock markets. For this purpose, this paper employs two recent econometric techniques developed by Koop, Pesaran and Potter (1996) and Pesaran and Shin (1998); the Generalized Forecast Error Variance Decompositions and the Generalized Impulse Response Functions analyzed in the next section.

4.3. Generalized Forecast Error Variance Decompositions

According to Pesaran and Shin (1996), "it is important that the analysis of cointegration is accompanied by some estimates of the speed with which the markets under consideration return to their equilibrium states, once they are shocked. Such an analysis would be particularly valuable in cases where there are two or more cointegrating relations characterizing equilibrium, where we will be able to estimate the relative adjustment speeds of different markets towards the equilibrium". This is very important to this study, because even if the effect of the EMU on stock market integration is not represented by an increase in the number of cointegrating vectors (for the post EMU-period), a faster adjustment speed towards the equilibrium indicates that the EMU positively affects the level of stock market integration in the long run (Yang, Min, Li, 2003).

---

[5] The variables are tested for unit roots and the hypothesis of (trend-) stationarity is rejected in favor of unit roots. Thus, no linear trend in the cointegration equation is needed in the model.

In this spirit, the GFEVDs estimate the speed of price information transmission mechanism among the European markets. Additionally, they show the proportion of which the variation in one market can be explained (decomposed) by innovations in the other markets.

In the context of the VECM described earlier, the short-run dynamics of stock market integration can be identified through the parameters Γ_i and α in equations (5) and (6) described in section 4.2. The parameter Γ_i represents the short-run adjustment to changes in the variables, while the parameter α represents the error correction adjustment through which the system is pulled back to its long run equilibrium. However, as shown in Sims (1980) and Lutkepohl and Reimers (1992), the individual coefficients of an ECM are difficult to interpret. Thus, innovation accounting methods, such impulse response functions and variance decompositions may give the best description of the short-run dynamic structure.

However, an important limitation of conventional VAR-type analysis is its reliance on a Choleski factorization[6]. Traditional orthogonalized impulse response functions and variance decomposition tests, based on the Choleski factorization, were very sensitive to the ordering of variables in the VAR model (Koop et. al, 1996; Pesaran and Shin, 1998). By contrast, the Generalized Impulse Response Functions and the Generalized Forecast Error Variance Decompositions for linear multivariate models applied in this paper, overcome this problem, thus being invariant to the ordering of variables in the VAR.

The Generalized Forecast Error Variance Decomposition test developed by Pesaran and Shin (1998) considers the proportion of the variance of the n-step forecast errors of y_t that are explained by conditioning on the non-orthogonalized shocks, u_t, u_{t+1}, …,u_{t+n}, but explicitly allowing for the contemporaneous correlations between these shocks and the shocks to the other equations in the system.

Beginning with the VECM described in equation (4), Δy_t can be rewritten as an infinite moving average process:

$$\Delta y_t = \sum_{i=0}^{\infty} A_i \varepsilon_{t-i}, \quad t = 1,3,,\ldots T. \tag{9}$$

[6] For further details about Choleski factorization, see Hamilton D. J., “Time Series Analysis”, pp.91-92, 147.

where A_i is the coefficient matrices in the moving average representation.

As shown in Pesaran and Shin (1998), the forecast error of predicting Δy_t conditional on the information at time t-1 is given by:

$$\xi_{t,n} = \sum_{l=0}^{n} A_l \varepsilon_{t+n-l} \qquad (10)$$

and the total forecast error variance-covariance matrix is:

$$\mathrm{Cov}\,(\xi_{t,n}) = \sum_{l=o}^{n} A_l \Sigma A'_l \qquad (11)$$

Consider now the proportion of the variance of the n-step forecast errors of y_t that are explained by conditioning on the non-orthogonalized shocks, ε_{it}, $\varepsilon_{i,t+1}$,...., $\varepsilon_{i,t+n}$, but explicitly allowing for the contemporaneous correlations between these shocks and the shocks to the other equations in the system. Assuming that ε_{it} ~N (0, Σ), conditioning on the information means that:

$$E(\varepsilon_{t+n-l} \mid \varepsilon_{i,t+n-l}) = (\sigma_{ii}^{-1} \sum e_i)\varepsilon_{i,t+n-l},\ l=0,1,2,\ldots,n,\ i=1,2,\ldots,p \qquad (12)$$

Correspondingly, the forecast error vector (equation 10) of predicting Δy_t conditional on the information at time t-1 becomes:

$$\xi_{t,n}^{(i)} = \sum_{l=0}^{n} A_l(\varepsilon_{t+n-l} - \sigma_{ii}^{-1} \sum e_i \varepsilon_{i,t+n-l}) \qquad (13)$$

Taking unconditional expectations yields to:

$$\mathrm{Cov}\,(\xi_{t,n}^{(i)}) = \sum_{l=o}^{n} A_l \Sigma A'_l - \sigma_{ii}^{-1} \left[\sum_{l=0}^{n} (A_l \sum e_i e_i' \sum A'_l) \right] \qquad (14)$$

Using equations (11) and (14) it follows that a decline in the n-step forecast error variance of z_t obtained as a result of conditioning on the future shocks to the i-th equation is given by

$$\Delta_{in} = \mathrm{Cov}\,(\xi_{t,n}) - \mathrm{Cov}\,(\xi_{t,n}) = \sigma_{ii}$$

Scaling the j-th diagonal element of Δ_{in} by the n-step ahead forecast error variance of the i-th variable in Δy_t, it gives the following generalized forecast error variance decomposition:

$$\theta_{ij}^{g}(n) = \frac{\sigma_{ii}^{-1}\sum_{l=0}^{n}\left(e_i' A_l \Sigma e_j\right)^2}{\sum_{l=0}^{n} e_i' A_l \Sigma A_l' e_i}, \quad i,j = 1,\ldots\ldots,p. \tag{16}$$

where $\theta_{ij}^{g}(n)$ is the proportion of the n-step ahead forecast error variance of the i-th variable which is accounted by innovations in j-th variable in the VAR, σ_{ii} is the i-th diagonal element of the covariance matrix Σ, A_l is the coefficient matrices in the moving average representation.

The Generalized Forecast Error Variance Decompositions provide information about the proportion of the variation in a stock market series "due to its own shocks" versus the shocks in the other markets in the system. Thus, they are considered as measures of the relative importance of other markets in driving market returns in a particular market (Yang, Min, Li, 2003). The GFEVD analysis is conducted by using Microfit 4.1. econometric software (Pesaran and Pesaran, 1997).

4.4. Generalized Impulse Response Functions

An Impulse Response Function describes the time profile of the effect of a shock on the variables in a dynamical system. According to the traditional IRF method introduced by Sims (1980), a shock to the i-th variable not only affects i-th variable but is also transmitted to all of the other endogenous variables through the dynamic (lag) structure of the VAR. Thus, an IRF traces the effect of a one-time shock to one of the innovations on current and future values of the endogenous variables in the system.

The major limitation of the traditional IRFs is its reliance on a Choleski factorization (discussed in section 4.3.). Nevertheless, the Generalized IRFs approach manages to circumvent this problem, thus being invariant to the ordering of the variable in the VAR (Pesaran and Shin, 1998). This approach was introduced by Koop et al. (1996) for non-linear multivariate model and extended by Pesaran and Shin (1998) for linear multivariate models.

As shown in Pesaran and Shin (1998), in the context of the VAR model described in equation (4), the generalized impulse response function for a system wide shock, u_t^0, is given by:

$$GI_x(n,\delta,\Omega_{t-1}) = E(x_{t+n} | \varepsilon_t = \delta, \Omega_{t-1}) - E(x_{t+n} | \Omega_{t-1}) \qquad (17)$$

where E(•|•) is the conditional expectations taken with respect to the VAR model, Ω_{t-1} is a particular historical realization of the process at time t-1 and δ is a m x 1 vector of shocks hitting the system at time t.

According to the Sims' (1980) Choleski decomposition, the m x 1 vector of the orthogonalized IRF of a unit shock to the jth equation on x_{t+n} is defined as:

$$\psi_j^o = A_n P e_j, \qquad n = 0,1,2,\ldots, \qquad (18)$$

where e_j is a m x 1 selection vector with its j-th element equal to unity and zeros elsewhere.

Pesaran and Shin (1998) suggested that instead of shocking all the elements of ε_t in the VAR model, we can choose to shock only one element, (i.e. the j-th element), and integrate out the effects of other shocks using an assumed or the historically observed distribution of the errors. In this case, the GIRFs can be rewritten as:

$$GI_x(n,\delta_j,\Omega_{t-1}) = E(x_{t+n} | \varepsilon_{jt} = \delta_j, \Omega_{t-1}) - E(x_{t+n} | \Omega_{t-1}) \qquad (19)$$

Hence, the m x 1 vector of the generalized impulse response of a shock in the j-th equation on x_{t+n} at time t is given by:

By setting $\delta_j = \sqrt{\sigma_{jj}}$, (i.e. by measuring the shock by one standard deviation) the scaled generalized impulse response function is defined as:

$$\psi_j^g(n) = \sigma_{jj}^{-\frac{1}{2}} A_n \sum e_j, \qquad n = 0,1,2,\ldots \qquad (22)$$

which measures the effect of one standard error shock to the j-th equation at time t on expected values of x at time t+n. As analytically shown in Koop et. al (1996), the

GIRFs take into account the correlation between the different shocks and reduce the traditional impulse responses provided by the Choleski factorization. Unlike the orthogonalized IRFs, the generalized IRFs are unique and are not affected by the re-ordering of the variables in the VAR.

The Generalized Impulse Response Function methodology implemented in this paper provides a measure of how responsive the EMU stock markets are due to a shock in a particular market. They are considered as measures of how fast the information transmits from one market to the others. Contrary to GFEVDs, they also provide information about the direction (positive or negative) of the impact of one market on the others. The Generalized Impulse Response Function analysis is carried out using Microfit 4.1. econometric software (Pesaran and Pesaran, 1997).

4.5. Dynamic Conditional Correlations

Correlation analysis is a very important tool in order to examine the role of EMU on Emu-stock market integration. Earlier studies on stock market comovements across countries used simple correlation analysis (Pearson's correlation coefficients) and rolling correlations estimators (moving windows). However, as shown by Boyer, Gibson and Loretan (1999), changes in correlation over time cannot be detected by splitting the sample of the data according to ex post realizations. In particular, these methods proved to be inadequate when dealing with financial data because they lack of dynamism and are inefficient in modeling financial data that exhibit time varying volatility. Additionally, these measures equally weight all the observations in the past – giving rise to biasedness - since they are expected to give more weight to the observations in the recent past and less (but nonzero) to long past.

This study moves a step ahead by utilizing the recently developed approach introduced by Engle (2002), a Dynamic Conditional Correlation multivariate GARCH model (DCC-GARCH). Under this approach, the estimated conditional correlation between the variables under investigation depends on both the past realizations of their correlation and the volatility that each series has exhibited in the past.

According to Engle (2002), the Dynamic Conditional Correlation models have the flexibility of univariate GARCH models but not the complexity of conventional multivariate GARCH. These models estimate the conditional correlation between two series in two steps: In the first step, univariate volatility estimates for each series are calculated using GARCH models. In the second step, the standardized residuals are used to estimate the correlation dynamics. As analytically shown by Engle's (2002), the DCC model provides a very good approximation to a variety of time-varying correlation processes. The comparison between the Dynamic Conditional Correlation model and simple multivariate GARCH models in Engle (2002), showed that the DCC model is often the most accurate estimator of the correlation dynamics among financial data.

Following Engle (2002), the model assumes that returns from k series are normally distributed with zero mean and conditional covariance matrix H_t:

$$r_t | F_{t-1} \sim N(0, H_t) \tag{23}$$

$$H_t = D_t R_t D_t . \tag{24}$$

where r_t is a kx1 vector of stock market returns conditional on the information at time t-1, R_t is a correlation matrix that varies over time, D_t is a diagonal matrix of time varying standard deviations obtained from the univariate GARCH models. The DCC model differs from the Bollerslev's (1990) constant conditional correlation (CCC) estimator (which uses $H_t = D_t R D_t$) only in allowing R to be time varying (i.e. R_t).

As shown in Engle (2002), the simplest specification of the correlation matrix is the exponential smoother which is defined as:

$$\rho_{i,j,t} = \frac{\sum_{s=1}^{t-1} \lambda^s \varepsilon_{i,t-s} \varepsilon_{j,t-s}}{\sqrt{(\sum_{s=1}^{t-1} \lambda^s \varepsilon_{i,t-s}^2)(\sum_{s=1}^{t-1} \lambda^s \varepsilon_{j,t-s}^2)}} = [R_t]_{i,j} , \tag{25}$$

where ε are the standardized residuals and λ [-1, 1] is a parameter that emphasizes current data but has no fixed termination point in the past where data becomes informative. In accordance with RiskMetrics, the value of lambda used is this analysis is 0.94.

The Dynamic Conditional Correlations (DCC-GARCH) among the European stock markets are carried out using Eviews 5.1. econometric software.

5. Empirical Results

5.1. Unit Root test Results

The results from the Augmented Dickey - Fuller and the Phillips – Perron unit root tests are presented in Tables 2.1. – 2.2. in the Appendix. The tests are applied both to the levels and the first differences of the stock market indexes. The analysis is divided in two sub-periods: the pre-EMU period (09/05/1991 – 31/12/1998) and the post-EMU period (01/01/1999 - 09/05/2006). The null hypothesis for each of the two tests is that the series in question contain a unit root versus the alternative that the series are stationary.

Without a single exception, the ADF and the PP tests fail to reject the null hypothesis of a unit root in levels at the 1% level of significance, i.e. all the series are non-stationary. At the other hand, the two tests reject the null hypothesis in the first differences of the series, indicating that in the series display a mean reverting behavior only when viewed in their first differenced form. Consequently, all the stock market indexes are integrated in order one, I(1). This allows us to move to the next step in the analysis, i.e. to apply cointegration techniques to test for common stochastic trends between the eleven European stock markets.

5.2. Johansen Multivariate Cointegration results

The effect of the EMU on the EU-11 stock market comovements in the long-run can be analyzed by comparing the Johansen-Juselius cointegration equations in the pre- and post-EMU period. In general, the establishment of the EMU and the currency unification in 1999 is a priori expected to influence the degree of integration among the EMU markets. If this is the case, it can be depicted by an increase in the number of the long-run cointegrating relations in the post-EMU period.

The results from the JJ - VECM approach are presented in Tables 1.a. and Table 1.b. As discussed earlier, the JJ cointegration test covers all the EMU-participating markets, rather than bivariate combinations. Two types of statistics are reported: the trace and maximum eigenvalue statistics. In a multivariate system of eleven variables, the maximum number of cointegrating vectors is ten. The null hypothesis is that the cointegration rank is $r=r_0$, versus the alternative that the cointegration rank is equal to $r=r_0+1$. The critical values for the test statistics are derived from Osterwald – Lenum (1992).

The JJ cointegration results for the pre-EMU period (09/05/1991 – 31/12/1998) are presented in Table 1.a. Both the trace and the maximum eigenvalue statistics indicate the existence of two cointegrating vectors at the 5% level of significance. In particular, for both r = 0 and r ≤ 1, the trace statistics are greater than the Osterwald-Lenum critical values, thus rejecting the null hypothesis for both cases. When r ≤ 2 the null hypothesis is not rejected in favor of the alternative, r >2, indicating the existence of two cointegrating vectors for the pre-EMU period.

Table 1a. Johansen Cointegration test. Period 1 (09/05/1991–31/12/1998)

				Critical values	
		Test statistics		Trace	λ_{max}
H_0	H_1	Trace	λ_{max}	5%	5%
r = 0	r >0	306.5064**	70.6619**	255.27	65.30
r ≤ 1	r >1	235.8445**	66.1870**	212.67	59.06
r ≤ 2	r >2	169.6575	48.0694	175.77	53.69
r ≤3	r >3	121.5880	37.3106	141.20	47.99
r ≤ 4	r >4	84.2773	28.4851	109.99	41.51
r ≤5	r >5	55.7921	20.6911	82.49	36.36
r ≤6	r >6	35.1010	14.8279	59.46	30.04
r ≤7	r >7	20.2730	10.1167	39.89	23.80
r ≤8	r >8	10.1563	5.8383	24.31	17.89
r ≤9	r >9	4.3179	4.2690	12.53	11.44
r≤10	r>10	0.0488	0.0488	3.84	3.84

r, number of cointegrating vectors. k, number of lags in underlying VAR model. Two asterixes denote significance at the 5% level. The critical values are provided by Osterwald - Lenum (1992). The optimal lag length in the VAR model is selected using the Bayesian Information criterion (BIC or SIC).

The JJ cointegration results draw a similar conclusion when considering the post-EMU period. As seen in Table 1.b., both the trace and the maximum eigenvalue statistics indicate the existence of two cointegrating vectors at the 5% level of significance. Thus there is no evidence of an increase in the level of integration for the post-EMU period.

Table 1b. Johansen Cointegration test. Period 2 (01/01/1999 – 09/05/2006)

		Test statistics		Critical values	
				Trace	λ_{max}
H_0	H_1	Trace	λ_{max}	5%	5%
r = 0	r >0	291.0417**	73.6148**	255.27	65.30
r ≤ 1	r >1	217.4269**	61.1047**	212.67	59.06
r ≤ 2	r >2	171.3222	35.2407	175.77	53.69
r ≤3	r >3	136.0815	29.5880	141.20	47.99
r ≤ 4	r >4	106.4935	27.1902	109.99	41.51
r ≤5	r >5	79.3033	25.5190	82.49	36.36
r ≤6	r >6	53.7843	22.0591	59.46	30.04
r ≤7	r >7	31.7251	14.9046	39.89	23.80
r ≤8	r >8	16.8205	7.9260	24.31	17.89
r ≤9	r >9	8.8945	5.8938	12.53	11.44
r≤10	r>10	3.0007	3.0007	3.84	3.84

r, number of cointegrating vectors. k, number of lags in underlying VAR model. Two asterixes denote significance at the 5% level. The critical values are provided by Osterwald - Lenum (1992). The optimal lag length in the VAR model is selected using the Bayesian Information criterion (BIC or SIC).

The primary finding from the Johansen-Juselius cointegration analysis is that the long run relationships among the EU-stock markets are found to be stable through time. The cointegrating vectors appear to be unchanged after the introduction of the Euro, thus providing evidence that the eleven EU-markets drift to a stable long-run equilibrium. These results are in accordance with Yang, Min & Li (2003) and Worthington et. al (2003) which also find two common stochastic trends among the EU-stock markets for both the pre- and post-EMU period.

Nevertheless, the interpretation of this finding is multidimensional. In general, the presence of common stochastic trends in the long run is expected to reduce significantly the diversification benefits especially for investors with long holding periods (Kasa, 1992). As discussed in Garrett and Spyrou (1999), even if the EU-stock markets exhibit common stochastic trends, some countries may have no influence on the common trends and no impact on the long run equilibrium defined by the common trends. Thus, it cannot be argued that since all the eleven EU-markets move together in the long run the benefits from international diversification will disappear. In other words, the finding of two common stochastic trends for the post-EMU period may not significantly reduce the diversification benefits in the long run, because all the stock markets are not expected to react identically to these trends.

The results from the Johansen-Juselius cointegration approach indicate that the level of stock market integration is not changed after the EMU. However, the presence of two cointegrating vectors in both periods shows a considerable degree of long-term interdependency among the EMU stock markets. Thus, further analysis is required in order to examine the short-term linkages among the EMU markets. According to Pesaran and Shin (1996), the analysis of cointegration must be accompanied by estimates of the speed with which the EU-11 markets return to their equilibrium states, once they are shocked. This analysis is particularly valuable in the case that two or more cointegrating relations characterize the equilibrium. Thus, although the effect of the EMU on stock market integration is not represented by an increase in the number of cointegrating vectors (period 2), a faster adjustment speed towards the equilibrium may provide evidence that the EMU positively influenced the level of stock market integration in the long run (Yang, Min, Li, 2003).

5.3. Generalized Forecast Error Variance Decomposition Analysis results

Given the existence of two stable cointegrating vectors among the eleven European stock market indexes, this section presents the results of the Generalized Forecast Error Variance Decompositions of the VAR system. The GFEVDs examine the level of integration of a specific market, by testing the degree of exogeneity (unresponsiveness) to the other EU-markets. Thus, if the error variance of a stock market is mainly explained by its own innovations, the market is considered to be unresponsive. At the other hand, if the error variance of a stock market is largely explained by innovations in the other markets, the markets are considered to be integrated.

Table 3 presents the results of the GFEVD analysis for period 1 and period 2. To save space, the table only presents the variance decompositions for a 20-days time horizon[7]. Each row shows the percentage of the forecast error variance of a particular market explained by innovations in the markets listed on the top. The reported results in Table 3 show significant differences in the EU stock market linkages between the two periods.

At both periods, the error variance of the small markets, i.e. Austria, Finland, Greece and Portugal, is mostly explained by their own innovations (larger than 30%) implying that the small markets are modestly influenced from the introduction of the Euro currency. Austria and Greece are found to be more isolated in period 2, having an even larger amount of return variation explained by their own innovations (32.73% and 43.28% in period 1, versus 43.03% and 46.00% in period 2). Conversely, for France, Italy, Netherlands and Spain, the results show a significant decrease in the return variation attributable to their own innovations in period 2 (almost 50% decrease). This diminution appears to be substituted by an increase in the percentage of return variation explained by the four dominant EMU-markets, i.e. France, Germany, Italy and Netherlands. Interestingly, with the only exception of Austria, the results indicate that the all the EMU-stock markets tend to be more influenced and integrated with the four large markets (France, Germany, Italy and Netherlands) in period 2. In particular, the percentage of variations of the EMU stock markets explained by innovations in the four large stock markets is larger in period 2 in almost every case.

Similarly with the analysis of Yang, Min, Li (2003), Table 4 is constructed to show precisely the aforementioned changes in the stock market linkages across the EMU countries. This table makes a comparison between the explanatory power of the large versus the small EMU countries in explaining the return variation of the EMU stock markets. Each entry is computed as the total percentage of the return variation of a particular country explained by the large and small EMU countries (excluding its own percentage).

.Table 3. Generalized Forecast Error Variance Decompositions. (Day 20, percentage)

Period	AUS	BEL	FIN	FRA	GER	GRE	IRE	ITA	NET	POR	SPA
					Austria (AUS)						
1	32.73	6.031	3.703	11.69	8.359	1.611	4.327	8.382	9.708	2.7	10.76
2	43.03	8.269	3.25	7.621	7.638	0.805	3.349	6.273	6.309	4.197	9.26
					Belgium (BEL)						
1	4.06	27.45	4.42	14.15	8.16	0.95	4.60	7.01	13.22	3.73	12.25
2	3.56	23.98	3.20	12.55	10.54	2.16	5.52	9.34	13.51	5.72	9.91
					Finland (FIN)						
1	3.67	7.97	41.40	8.67	5.94	0.51	3.48	7.12	10.23	3.22	7.79
2	0.66	5.17	30.36	12.91	10.25	3.36	2.65	8.97	9.06	6.87	9.74
					France (FRA)						
1	4.74	9.78	3.75	28.64	6.85	1.03	4.21	7.69	14.93	4.72	13.66
2	1.92	9.78	8.62	17.37	13.00	2.20	3.73	12.23	12.95	6.48	11.72
					Germany (GER)						
1	7.28	9.71	5.24	13.50	18.36	1.26	4.06	7.48	14.94	4.78	13.39
2	1.95	9.43	7.97	14.15	18.13	2.37	4.13	11.27	12.22	6.59	11.79
					Greece (GRE)						
1	4.01	7.17	4.42	7.15	6.62	43.28	4.58	2.58	6.69	4.20	9.31
2	1.47	6.61	4.99	6.24	7.88	46.00	3.45	5.41	5.89	5.25	6.82
					Ireland (IRE)						
1	5.95	9.29	6.65	9.25	7.92	0.93	28.22	6.23	12.16	3.02	10.39
2	2.13	9.51	4.05	10.75	10.42	2.12	25.66	8.87	10.44	5.72	10.34
					Italy (ITA)						
1	4.69	8.35	5.96	10.16	5.41	0.26	2.64	38.34	9.22	4.27	10.71
2	1.86	9.83	7.63	14.60	11.53	1.93	3.73	18.20	12.11	6.45	12.13
					Netherlands (NET)						
1	5.04	10.21	5.67	14.08	8.58	0.61	5.33	6.20	28.31	3.93	12.04
2	2.22	11.42	6.79	14.68	12.60	2.25	4.96	11.63	17.41	5.25	10.79
					Portugal (POR)						
1	4.69	7.14	3.69	8.70	5.54	0.63	2.42	5.57	10.04	34.00	17.57
2	0.92	7.11	8.28	10.32	10.20	1.68	3.07	9.11	7.85	30.62	10.83
					Spain (SPA)						
1	4.18	7.46	3.95	13.39	6.75	0.57	3.18	7.66	11.53	5.56	35.77
2	2.11	8.96	7.53	13.67	11.08	2.23	4.03	12.42	11.28	7.82	18.86

Each entry shows the percentage forecast error variance of each specified market explained by the markets in the first row.
The forecast error variance decompositions have been standardized for each of the explained market so that the sum is 100%.

The results in Table 4 clearly show that the large EMU stock markets (France, Germany, Italy and Netherlands) have become more integrated with each other after the EMU. For example, Italy exhibit almost 38% return variation explained by the large markets in period 2, which is almost 14% higher than the pre-EMU period. Additionally, these large markets appear to have almost the same degree of interdependency with the small EMU countries in both periods. For example, Netherlands exhibit about 44% return variation explained by small countries in period 2 contrary to almost 43% in period 1 (only exception is Italy which has 7% higher return variation explained by small EMU countries in period 2).

The conclusions are ambiguous considering the small EMU stock markets. Spain, Portugal and Finland appear to be more integrated with the large EMU markets after the EMU. However, Greece, Belgium and Ireland only show only a minimal increase in integration with the large markets in period 2. Finally, Austria shows a high degree of unresponsiveness and appears to be relatively isolated in period 2. Almost 43% of its return variation is explained by its own innovations while its integration with the large EMU markets appears to be significantly decreased.

Table 4. Generalized Forecast Error Variance Decompositions. Large against Small Stock Markets

Market Explained	By Innovations in: Large EMU Countries		Small EMU Countries		Self Explained Variation	
	Period 1	Period 2	Period 1	Period 2	Period 1	Period 2
AUSTRIA	38,14	27,84	29,13	29,13	32,73	43,03
BELGIUM	42,54	45,94	30,01	30,07	27,45	23,98
FINLAND	31,95	41,19	26,65	28,44	41,40	30,36
FRANCE	29,47	38,18	41,88	44,45	28,64	17,37
GERMANY	35,92	37,65	45,73	44,23	18,36	18,13
GREECE	23,03	25,41	33,68	28,59	43,28	46,00
IRELAND	35,56	40,48	36,22	33,86	28,22	25,66
ITALY	24,78	38,24	36,88	43,56	38,34	18,20
NETHERLANDS	28,86	38,91	42,83	43,68	28,31	17,41
PORTUGAL	29,85	37,49	36,15	31,89	34,00	30,62
SPAIN	39,33	48,45	24,90	32,68	35,77	18,86

Each entry shows the percentage forecast error variance of the markets in the left column explained by large markets, small markets and by its own innovations.
The forecast error variance decompositions have been standardized for each of the explained marketsothatthesumis100%

The results from the Generalized Forecast Error Variance Decomposition analysis indicate that the short-run dynamic linkages among the EU countries have strengthened after the EMU. In particular, the above analysis suggests that there exists a high degree of integration among the large EMU markets in period 2. Smaller markets appear also to be more integrated with the large markets in period 2. At the same time, only Austria appears to be relatively isolated in the post-EMU period.

5.4. Generalized Impulse Response Functions results

According to the Generalized Impulse Response Function Analysis, a shock in one market not only directly affects itself, but is also transmitted to all of the endogenous markets in the system. An impulse response function allows us to measure the relative importance of each market in generating unexpected variations of returns to a particular market and thus to establish causal ordering among the European stock markets (Eun and Shim, 1989). Similar to the GFEVDs, the GIRF analysis is crucial in analyzing the short-run interdependence among European stock markets, providing evidence about the speed of information transmission across the EU-markets.

The GIRFs analysis results are presented in Table 5. To save space, the table only presents the impulse response functions for a 20-days time horizon in period one and period two.[1] Each entry shows the average impulse responses of a particular market due to shocks in the markets listed on the top. The findings from the GIRFs are consistent with the GFEVDs, showing significant differences in the EU stock market linkages between the pre- and the post-EMU period.

The results in Table 5 provide further evidence that the four large EMU-stock markets have become more integrated with each other in period 2. In particular, each of the four large markets appears to be highly responsive to its own innovations and to innovations taking place in the other large four markets (their responses are almost doubled in period 2 comparing with period 1). For example, France exhibits a response of 0.0116, 0.0094 and 0.0113 to innovations in Germany, Italy and

[1] The results are similar for a 40-days time horizon and are available upon request by the author

Netherlands in period 2. At the same time, Netherlands exhibits a response of 0.0103, 0.0106 and 0.0083 to innovations in France, Germany and Italy.

Moreover, Belgium, Finland, Portugal and Spain appear to respond more to innovations in the other EMU markets in period 2 compared to period 1. In particular, the results show that they tend to be more responsive to innovations in the large markets, thus strengthening the findings of the GFEVDs that these markets appear to be more integrated with the large four markets in period 2. For example, Finland exhibit a response of 0.0093, 0.0096, 0082 to innovations in France, Germany and Netherlands while the responses attributable to smaller markets range from 0.0031 (Austria) to 0.0072 (Spain).

At the other hand, smaller markets of Greece and Ireland, although they exhibit higher responses to innovations in the four larger markets in period 2, their responses remain relatively small in absolute values. For example, Greece exhibits a response of 0.0050, 0.0055, 0.0038, and 0.0050 to innovations in France, Germany, Italy and Netherlands respectively. These results are in accordance with the GFEVD analysis, which indicate only a minimal increase in the degree on integration of Greece and Ireland with the large European markets in period 2.

Finally, Austria in the only county that appears to less integrated with most of the EMU-countries after the EMU. In period 2, it is the only market that exhibits smaller responses to innovations in the most of the EMU-markets. Interestingly, many of the other EU-markets also appear to be less responsive to innovations in the Austrian market in period 2. This finding further supports the results from the GFEVD analysis indicating that Austria is the only market that remains relatively isolated in period 2.

Consistent with the GFEVD analysis, the results from the GIRF analysis provide further indication that the four large markets have become highly integrated after the EMU. Medium-sized markets of Belgium, Finland, Portugal and Spain also exhibit a higher level of integration with the large markets in period 2 than in period 1. Smaller markets of Greece and Ireland are found to be less influenced by the EMU while their degree of integration with the large markets appears to be slightly increased in period 2. Finally, Austria is the only market that remains relatively isolated after the introduction of the EMU.

Table 5. Generalized Impulse Response Functions. (Day 20, percentage)

Period	AUS	BEL	FIN	FRA	GER	GRE	IRE	ITA	NET	POR	SPA
					Austria (AUS)						
1	0.0093	0.0026	0.0037	0.0036	0.0047	0.0046	0.0044	0.0044	0.0038	0.0034	0.0037
2	0.0092	0.0045	0.0022	0.0040	0.0041	0.0029	0.0029	0.0033	0.0042	0.0017	0.0036
					Belgium (BEL)						
1	0.0038	0.0076	0.0072	0.0058	0.0059	0.0063	0.0059	0.0064	0.0059	0.0043	0.0057
2	0.0045	0.0105	0.0093	0.0089	0.0095	0.0066	0.0067	0.0078	0.0098	0.0055	0.0073
					Finland (FIN)						
1	0.0026	0.0028	0.0152	0.0025	0.0037	0.0048	0.0045	0.0049	0.0040	0.0029	0.0036
2	0.0031	0.0042	0.0221	0.0093	0.0096	0.0059	0.0043	0.0076	0.0082	0.0060	0.0072
					France (FRA)						
1	0.0062	0.0060	0.0069	0.0083	0.0066	0.0062	0.0052	0.0060	0.0067	0.0048	0.0070
2	0.0042	0.0080	0.0145	0.0121	0.0116	0.0059	0.0070	0.0094	0.0113	0.0061	0.0090
					Germany (GER)						
1	0.0040	0.0037	0.0041	0.0032	0.0064	0.0057	0.0045	0.0032	0.0044	0.0029	0.0040
2	0.0041	0.0070	0.0119	0.0100	0.0126	0.0067	0.0067	0.0078	0.0100	0.0060	0.0075
					Greece (GRE)						
1	0.0024	0.0013	0.0006	0.0014	0.0020	0.0103	0.0010	0.0002	0.0009	0.0001	0.0008
2	0.0010	0.0039	0.0096	0.0050	0.0055	0.0153	0.0032	0.0038	0.0050	0.0026	0.0042
					Ireland (IRE)						
1	0.0038	0.0035	0.0045	0.0037	0.0039	0.0046	0.0091	0.0035	0.0046	0.0025	0.0040
2	0.0027	0.0060	0.0065	0.0058	0.0065	0.0047	0.0097	0.0049	0.0070	0.0035	0.0050
					Italy (ITA)						
1	0.0055	0.0041	0.0069	0.0046	0.0050	0.0037	0.0049	0.0113	0.0041	0.0038	0.0052
2	0.0037	0.0067	0.0116	0.0099	0.0100	0.0055	0.0065	0.0100	0.0098	0.0056	0.0084
					Netherlands (NET)						
1	0.0056	0.0055	0.0077	0.0064	0.0072	0.0057	0.0065	0.0059	0.0095	0.0053	0.0067
2	0.0036	0.0082	0.0116	0.0103	0.0106	0.0058	0.0069	0.0083	0.0120	0.0052	0.0078
					Portugal (POR)						
1	0.0024	0.0027	0.0046	0.0036	0.0038	0.0042	0.0027	0.0044	0.0033	0.0084	0.0047
2	0.0033	0.0061	0.0107	0.0081	0.0087	0.0062	0.0057	0.0070	0.0072	0.0098	0.0075
					Spain (SPA)						
1	0.0060	0.0056	0.0068	0.0062	0.0071	0.0078	0.0063	0.0063	0.0064	0.0077	0.0118
2	0.0049	0.0071	0.0121	0.0099	0.0107	0.0067	0.0074	0.0084	0.0095	0.0063	0.0100

Each entry denotes the impulse response of each specified market explained by the markets in the first row.

5.5. Dynamic Conditional Correlation Results

The analysis of correlation across the EMU-stock market returns is fundamental in order to examine the level of integration and the short-term interdependencies among the EMU markets. Considering that correlation is a dynamic process that varies over time, the author only examines the dynamic nature of the time-varying conditional correlations as estimated by the Dynamic Conditional Correlation – GARCH model of Engle (2002).

Table 6 and Table 7 report the average conditional correlations among the EMU markets for period 1 and 2. Additionally Figures 1 - 11 at the Appendix depict the dynamic structure of the conditional correlations among EMU-daily stock market returns and their evolution over the sampling period.

The empirical findings of this study indicate that there exist significant increases in the correlation levels in the post-Euro period, implying that the EMU has positively influenced the degree of integration among the European stock markets. These findings are in accordance with the GFEVDs and GIRFs results analyzed in the previous sections.

Analytically, the comparison between the average conditional correlation coefficients in period 1 and 2 and the DCC graphs for the eleven EMU stock markets at the Appendix draw the following conclusions:

Table 6. Average Conditional Correlations of daily stock market returns. Period 1 (09/05/1991– 31/12/1998)

	AUS	BEL	FIN	FRA	GER	GRE	IRE	ITA	NET	POR	SPA
AUS	1.000	0.428	0.273	0.371	0.550	0.144	0.334	0.325	0.395	0.198	0.362
BEL		1.000	0.327	0.404	0.543	0.152	0.393	0.314	0.450	0.297	0.378
FIN			1.000	0.303	0.379	0.086	0.301	0.296	0.344	0.222	0.298
FRA				1.000	0.488	0.137	0.352	0.411	0.628	0.253	0.586
GER					1.000	0.158	0.397	0.368	0.529	0.303	0.445
GRE						1.000	0.136	0.057	0.113	0.154	0.103
IRE							1.000	0.259	0.440	0.206	0.299
ITA								1.000	0.403	0.191	0.424
NET									1.000	0.256	0.519
POR										1.000	0.284
SPA											1.000

Table 7. Average Conditional Correlations of daily stock market returns. Period 2 (01/01/1999– 09/05/2006)

	AUS	BEL	FIN	FRA	GER	GRE	IRE	ITA	NET	POR	SPA
AUS	1.000	0.356	0.269	0.387	0.365	0.189	0.302	0.335	0.395	0.275	0.368
BEL		1.000	0.429	0.663	0.625	0.297	0.407	0.602	0.670	0.424	0.609
FIN			1.000	0.650	0.590	0.265	0.359	0.558	0.619	0.431	0.575
FRA				1.000	0.840	0.308	0.458	0.817	0.839	0.549	0.802
GER					1.000	0.296	0.410	0.766	0.784	0.508	0.746
GRE						1.000	0.262	0.272	0.323	0.258	0.296
IRE							1.000	0.400	0.481	0.317	0.408
ITA								1.000	0.756	0.489	0.768
NET									1.000	0.488	0.745
POR										1.000	0.540
SPA											1.000

The average conditional correlations coefficients among the large four EMU countries are significantly increased in period 2 indicating that the Euro introduction has sharply influenced the integration process within these markets. As shown at the reported DCC graphs, these markets are found to exhibit an increasing degree of comovement after 1999. Especially after 2001, these markets appear to be near to perfect integrated having correlation coefficients that exceed 0.8. Taking a closer look at the average conditional correlations at Tables 6 and 7, in period 2, France exhibits a correlation of 0.840, 0.817 and 0.839 with Germany, Italy and Netherlands respectively, contrary to 0.488, 0.411 and 0.628 in period 1. Additionally, the reported DCC-graphs indicate that the correlations among the large four markets are following a stable increasing path since 1999. These findings are akin to Cappiello, Engle and Shepard (2003) who contend that the correlation increase across the large markets is so striking that not only is a mean change obvious, but correlations appear to be less volatile after the introduction of the Euro.

The average conditional correlations of Belgium, Finland, Portugal and Spain with all the EMU stock markets (except Austria) appear also to be increased in period 2. However, these markets appear to be more integrated with the four large EMU markets where the correlation coefficients are significantly larger in absolute values. For example, the results show an increase from an average of 0,404 to 0,663 for Belgium–France, but only an increase from 0.327 to 0.429 for Belgium-Finland when comparing period 1 and 2. This finding further supports the results of the GFEVDs and GIRFs, indicating that Belgium, Finland, Portugal and Spain exhibit a higher level of integration with the four large EMU markets in the Euro period. Among these countries, Spain reports the highest correlation coefficients with the four large markets in period 2, i.e. 0,802 with France, 0,746 with Germany, 0,768 with Italy and finally 0,745 with the Netherlands, indicating that the Spanish stock market is converging to the large four EMU markets in the post-EMU period. The reported DCC graphs for this group of countries show significant variations in the correlation structure with the other EMU-markets. The dashed lines for these countries indicate that correlations are increasing on average after 1999. However, these correlations are found to exhibit less variation only after 2002 onwards.

Greece and Ireland are found to be less influenced by the EMU. These markets appear to have slightly higher correlation coefficients with the rest EMU-markets in period 2; however, these coefficients are very small in absolute values. For example Greece exhibits an average correlation of around 0.3 with the large four stock markets in period 2, while the average coefficients with the rest EMU markets are even lower. At the other hand, Ireland exhibits an average correlation of around 0.4-0.45 with the large four markets and even lower correlations with the rest EMU. The reported DCC graphs at the appendix confirm the above findings. The two markets are found to exhibit large variations in the correlation level even after the introduction of the Euro. Among them, the variations with the large four markets and Spain appear to be relatively smaller. These findings further support the empirical evidence from GFEVDs and IRFs, indicating that the EMU has modestly affected the stock market integration process for Greece and Ireland.

Finally, Austria is the only country that appears to be uninfluenced from the EMU. It is the only country that reports lower correlation coefficients with many EMU markets in period 2 compared with period 1. For example, the results show a decrease from an average of 0,550 to 0,365 for Austria–Germany and from 0,428 to 0,356 for Austria-Belgium. Additionally, the reported DCC graphs for Austria appear to be highly volatile across time, providing no evidence of a shift in comovement with the other EMU markets. These findings further support the results from the GFEVDs and IRFs indicating that Austria is the only market that remains relatively isolated in period 2.

The results of the Dynamic Conditional Correlation analysis provide clear evidence that the introduction of the Euro has strongly influenced the integration process within the EMU-stock markets. Nevertheless, we cannot still consider the

EMU-stock markets as a single financial block. The empirical findings show that the EMU has significantly influenced the integration process across the large four stock markets (France, Germany, Italy and Netherlands). The strength of comovement across these markets appears to be striking especially after 2001. However, the process of integration remains incomplete for the smaller member countries. A considerable influence but at a lower extend is found for Belgium, Finland, Portugal and Spain. Smaller markets such Greece and Ireland appeared to be modestly influenced from the EMU. Finally, Austria appears to be the least integrated stock market in the euro area.

6. Conclusions, Implications and Further Research

6.1. Diversification Benefits and Policy Implications

The empirical findings of this study indicate that the establishment of the EMU in 1999 and the currency unification had a strong impact on the degree of integration among the European stock markets within the single currency area. Specifically, the cointegration analysis showed that the EMU stock markets share common stochastic trends at both periods indicating that the stock markets tend to move together in the long run. Moreover, the GFEVDs and IRFs provided additional evidence about the speed of information transmission and the short-run interdependence among the EMU markets. According to the empirical results, the large four markets have become highly integrated in period 2. An increasing degree of integration is also found for the medium-sized markets (Belgium, Finland, Portugal and Spain), however these markets cannot yet characterized as highly integrated. Smaller countries, Greece and Ireland appear to be modestly affected from the EMU while Austria is the only market that remains relatively isolated and unaffected in period 2. The above findings indicate that the integration process remains relatively incomplete, indicating that we cannot yet consider the EU-stock markets within the single currency area as a single financial block. These findings have significant implications for both the international portfolio diversification and policy makers.

According to the modern portfolio theory there exist two main strategies to achieve portfolio diversification: to invest in different asset classes that exhibit low or negative correlations or to diversify a portfolio internationally by investing in similar asset classes. Seminal studies in the area of international portfolio diversification (e.g. Grubel (1968), Levy and Sarnat (1970), Solnik (1974)) point out that an investor can gain substantial benefits in terms of risk and return by diversifying internationally. When negative or low positive correlations exist among international stock markets, an investor can diversify his portfolio across different countries in order to reduce the idiosyncratic risk while holding expected returns constant. In the same spirit, numerous studies (e.g. Taylor and Tonks (1989), Kasa (1992), Bessler and Yang, (2003)) examine the level of integration among countries and their implications on international portfolio diversification. According to these studies, the potential benefits from international portfolio diversification are minimal if the level of integration among markets is high.

Consequently, the documented higher level of integration across the EU-markets in the post-EMU period is expected to highly influence the asset allocation decisions of the international investor. As a result, the benefits from international portfolio diversification across the EMU-stock markets are considered to be significantly decreased after 1999. This is mostly evident across the highly integrated large four stock markets of France, Germany, Italy and Netherlands where diversification benefits are almost disappeared in the post-EMU period. The potential benefits for portfolio diversification are also significantly decreased among the medium-sized markets which exhibit an increased degree of integration after the 1999. However, diversification opportunities still remain especially across the smaller European stock markets such as Greece, Ireland and Austria. Although the empirical results showed that the EMU has modestly strengthened their interrelationships, the process of financial integration for these markets remains incomplete, indicating that international investors can achieve considerable gains by including them in their portfolio. Nevertheless, when diversifying a portfolio across to medium-sized and smaller markets, rational international investors should consider that the ongoing integration process will reduce the diversification benefits and significantly lower the expected returns (Bekaert and Harvey (2003)).

The issue of stock market integration among the European stock markets has also important implications for the supervisory authorities. As pointed out by Levine and Zervos (1998), Baele et. al (2004) and Beck and Levine (2004), the stock market developments and the increasing integration the stock markets is positively linked to economic growth. This appears to be evident through risk sharing benefits, higher liquidity, improvements in allocation efficiency and the reductions in macroeconomic volatility. Additionally, the increased integration of financial markets is also expected to have a positive influence on the European financial stability since it helps to improve the capacity of the economies to absorb risks (Weber , 2006). However, as Berben and Jansen (2005) contended, the higher interdependence among the EMU-stock markets in the post-EMU period may also have adverse effects. According to Berben and Jansen, the financial disturbances in one country are likely to be transmitted to the other countries, thus having adverse consequences for the stability of the European and the global financial system. Thus, it is important for policy makers to assess the dynamic structure of the stock market integration in the EMU-area in order to be able to deal with the challenges of increasing interdependences.

6.2. Summary and Conclusions

This thesis investigates whether the establishment of the European Monetary Union and the introduction of the common currency increased the level of integration among the European stock markets. The issue of stock market integration appears to be crucial for international investors since it influences their asset allocation decisions. Additionally, it is also important for the regulatory authorities since it is fundamentally linked to economic growth. Unlike previous studies, this thesis investigates the EMU stock market linkages from three different perspectives: the short-run, the long-run and the dynamic perspective.

The dataset employed in the research consists of eleven price-weighted country indexes derived from Morgan Stanley Capital International (MSCI) and includes 15 years of daily observations, spanning from 09/05/1991 to 09/05/2006. The analysis is divided into two sub-periods: the pre- EMU period (09/05/1991 – 31/12/1998) and the post-EMU period (01/01/1999 - 09/05/2006).

At the beginning the statistical properties of the dataset are analyzed with emphasis on the distribution properties on stock market returns. The results showed that all the stock market returns exhibit negative skewness and excess kurtosis, thus rejecting the hypothesis of normality in all cases. Moreover, the stationary properties of the eleven stock market indexes are analyzed. The analysis is conducted by using the Augmented Dickey-Fuller and the Phillips-Perron unit roots tests. The results indicated that all the stock market indexes appear to be integrated of order one, i.e. the stock market indexes follow a random walk, indicating that the stock markets can be characterized as weak-form efficient since no investor can earn excess returns based on historical prices.

Given the non-stationary properties of the eleven stock market indexes, the cointegration framework of Johansen and Juselius (1990) was applied in order to examine the long-run dynamic linkages of the EMU stock markets in both periods. Consistent with the previous studies of Yang, Min & Li (2003) and Worthington et. al (2003), the JJ test found two cointegration vectors for both the pre- and the post-EMU period. This finding can be characterized as multidimensional since the number of cointegrating vectors appears to be unchanged in the post-EMU period. However, the existence of two cointegrating vectors indicates that a considerable degree of long term interdependency exist in both periods.

To examine the short-run dynamic linkages across the eleven EMU markets, the innovation accounting techniques of Generalized Forecast Error Variance Decompositions and the Generalized Impulse Response Functions are employed. The results from these tests clearly showed that the four large EMU markets of France, Germany, Italy and Netherlands have become highly integrated with each other in the post EMU period. Additionally, the medium sized markets (Belgium, Finland, Portugal and Spain) appear to be more integrated with the large four markets in period 2. Smaller markets of Greece and Ireland appeared to be modestly influenced by the EMU since their degree of integration with the large markets was slightly increased in period 2. At the other hand, Austria was the only market that remained relatively isolated after the introduction of the EMU.

To further investigate the dynamic structure of the stock market interdependence within the EMU, the time-varying conditional correlations as estimated by the Dynamic Conditional Correlation model are examined. In accordance with the GFEVD and IRF analysis, the empirical findings provided further evidence that the introduction of the EMU has influenced the integration process among the EMU-stock markets in period 2. The empirical evidence appear to be striking when considering the large four markets which appear to be near to perfect correlated after 2001. A considerable influence but at a lower extend is found for medium sized markets of Belgium, Finland, Portugal and Spain. As in the GFEVDs and GIRFs, smaller markets such Greece and Ireland are found to be modestly influenced by the EMU while Austria is the least integrated market in the EMU area.

If we look to the main findings of this research we can conclude that the EMU and the currency unification had a significant influence on the level of stock market integration among the EMU stock markets. This appears to be to be mostly evident for the large four EMU markets. However, the integration process remains relatively incomplete for medium-sized and smaller markets. As a result we cannot yet consider the EMU stock markets as a single financial block.

The implication of this study for international investors is that the potential benefits of international portfolio diversification across the EMU countries are significantly decreased in the post-EMU period. This holds especially for the large four and the medium-sized stock markets. However, considerable diversification opportunities still remain across the smaller EMU markets. For supervisory authorities, the increasing integration among the EMU stock markets has important implications since it is expected to positively influence the European financial stability and to positively affect the level of economic growth. At the other hand, it may also have adverse consequences since disturbances in one country may affect the whole system thus destabilizing the European financial system.

The empirical findings of this study may be subjected to further research. A possible extension of this research would be the examination of EMU stock market interrelationships across industry sectors within the single currency area. Another extension would be the examination of the integration structure at the extreme observations, i.e. at the tails of the return distributions. It is well-known from the financial theory that in extremely volatile periods, the correlation structure among international markets may dramatically differ from the case under normal market conditions. As this research focuses on the EMU-stock market comovements at the complete distributions of the market returns, it would be interesting to examine whether the above results hold when the analysis is conditional at the tails of the return distributions. This would imply to use "extreme value theory" to examine the dependence structure of extreme observations of the EMU-stock market returns (Longin and Solnik (2001)). This analysis would be particularly valuable for risk and portfolio management which crucially depend on correct correlation estimates across international stock market returns.

References

Aggarwal, R., Lucey, B. & Muckley, C. 2004, 'Dynamics of equity market integration in Europe: Evidence of changes over time and with events', IIIS Discussion Paper, no. 19.

Arestis, P., Demetriades, P. & Lunitel, K. 2001, 'Financial Development and Economic Growth: The Role of Stock Markets', Journal of Money, Credit and Banking, vol. 33, no. 1, pp. 16-41.

Baele, L., Ferrando, A., Hordahl, P., Krylova, E. & Monnet, C. 2004, 'Measuring Financial Integration in the Euro Area', European Central Bank, Occasional Paper no.14.

Beck, T. & Levine, R. 2004, 'Stock markets, banks, and economic growth: Panel evidence', Journal of Banking and Finance, vol. 28, pp. 423–442.

Bekaert, G. & Harvey, C. R. 1995, 'Time-varying world market integration', Journal of Finance, vol. 50, pp. 403– 444.

Bekaert, G. & Harvey, C. R. 2003, 'Emerging markets finance', Journal of Empirical Finance, vol. 10, pp. 3-55.

Miguel A.G. Belmonte & Gary Koop & Dimitris Korobilis, 2014. 'Hierarchical Shrinkage in Time-Varying Parameter Models', Journal of Forecasting, vol. 33, pp. 80-94.

Bera, A. K., Carlos M. Jarque, C. M., 1980, 'Efficient tests for normality, homoscedasticity and serial independence of regression residuals', Economics Letters, vol. 6, no. 3, pp. 255–259.

Berben, R. P. & Jansen, W. J. 2005, 'Bond Market and Stock Market Integration in Europe', De Nederlandsche Bank, Working Paper, no. 060.

Bessler, D.A. & Yang, J. 2003, 'The structure of interdependence in international stock markets', Journal of International Money and Finance, vol. 22, pp. 261–287.

Bollerslev, T. 1990, 'Modelling the Coherence in Short-run Nominal Exchange Rates: A Multivariate Generalized ARCH Model', Review of Economics and Statistics, vol. 72, pp. 498-505.

Boyer, B. H., Gibson, M. S. & Loretan, M. 1999, 'Pitfalls in Tests for Changes in Correlations', Federal Reserve Board, IFS Discussion Paper, no. 597R.

Campbell, J. Y., Lo, A. W. & MacKinlay A. C. 1997, 'The Econometrics of Financial Markets', Princeton University Press.

Cappiello, L., Engle, R. F. & Sheppard, K. 2003, 'Asymmetric dynamics in the correlations of global equity and bond markets', European Central Bank, Working Paper, no. 204.

Cappiello, L., Gerard, B., Kadareja, A. & Manganelli, S. 2006, 'Financial Integration of new EU Member States', European Central Bank, Working Paper, no. 683.

Chan, K. C., Gup, B. E. & Pan, M. 1997, 'International Stock Market Efficiency and Integration: A Study of Eighteen Nations', Journal of Business Finance & Accounting, vol. 24, no. 6, pp. 803–813.

Dickey, D. A. & Fuller, W. A. 1979, 'Distribution of the Estimators for Autoregressive Time Series with a Unit Root', Journal of the American Statistical Association, vol. 74, pp. 427–431.

Dickinson, D. G. 2000, 'Stock market integration and macroeconomic fundamentals: an empirical analysis, 1980–95', Applied Financial Economics, vol. 10, pp. 261–276.

Dumas, B. & Solnik, B. 1995, 'The world price of foreign exchange risk', Journal of Finance, vol. 50, pp. 445-479.

Elyasiani, E., Perera, P. & Puri, T. N. 1998, 'Interdependence and dynamic linkages between stock markets of Sri Lanka and its trading partners', Journal of Multinational Financial Management, vol. 8, no. 1, pp. 89-101.

Engle, R. F., and Granger, C. W. J. 1987, 'Cointegration and Error Correction: Representation, Estimation and Testing', Econometrica, vol. 55, pp. 251-276.

Engle, R. F. 2002, 'Dynamic Conditional Correlation - A Simple Class of Multivariate GARCH Models', Journal of Business and Economic Statistics, vol. 20, pp. 339-350.

Engsted, T. & Lund, J. 1997, 'Common stochastic trends in international stock prices and dividends: an example of testing overidentifying restrictions on multiple cointegrating vectors', Applied Financial Economics, vol. 7, pp. 659-665.

Eun, C. & Shim, S. 1989, 'International transmission of stock market movements', Journal Financial and Quantitative Analysis, vol. 24, pp. 241-256.

Fratzscher, M. 2002, 'Financial market integration in Europe: On the effects of the EMU on stock markets', International Journal of Finance and Economics, vol. 7, pp. 165–193.

Garrett, I. & Spyrou, S. 1999, 'Common Stochastic Trends In Emerging Equity Markets', The Manchester School, vol. 67, no. 6.

Gerrits, R. J. & Yuce, A. 1999, 'Short- and long-term links among European and US stock markets', Applied Financial Economics, vol. 9, pp. 1–9.

Granger, C. W. J. 1981, 'Some properties of Time Series data and their use in Econometric Models Specification', Journal of Econometrics, vol. 16, pp. 121-130.

Granger, C. W. J. & Newbold, P. 1974, 'Spurious Regressions in Econometrics', Journal of Econometrics, vol. 2, pp. 111-120.

Greene, W. H. 2003, 'Econometric Analysis', Prentice Hall.

Grubel, H. G. 1968, 'Internationally Diversified Portfolios: Welfare Gains and Capital

Flows', American Economics Review, vol. 58, pp. 1299-1314. Hamilton, J. D. 1994, 'Time Series Analysis', Princeton University Press.

Hardouvelis, G. A., Malliaropulos, D. & Priestley, R. 1999, 'EMU and European Stock market integration', CEPR, Discussion Paper no. 2124.

Johansen, S. & Juselius, K. 1990, 'Maximum Likelihood Estimation and Inference on Cointegration – With Application to the Demand for Money', Oxford Bulletin of Economics and Statistics, vol. 52, pp. 169–210.

Johansen, S. 1991, 'Estimation and Hypothesis Testing of Cointegration Vectors in Gaussian Vector Autoregressive Models', Econometrica, vol. 59, pp. 1551–1580.

Kasa, K. 1992, 'Common Stochastic Trends in International Stock Markets', Journal of Monetary Economics, vol. 29, pp. 95-124.

Kim, S. J., Moshirian, F. & Wu, E. 2005, 'Dynamic stock market integration driven by the European Monetary Union: An empirical analysis', Journal of Banking & Finance, vol. 29, pp. 2475-2502.

Koop, G., Pesaran, M. H. & Potter, S.M. 1996, 'Impulse Response Analysis in Nonlinear Multivariate Models', Journal of Econometrics, vol. 74, pp. 119–147.

Koop, Gary & Korobilis, Dimitris, 2011. 'UK macroeconomic forecasting with many predictors: Which models forecast best and when do they do so?,' Economic Modelling, vol. 28, pp. 2307-2318.

Koop, G. & Korobilis, D., 2013. 'Large time-varying parameter VARs', Journal of Econometrics, vol. 177, pp. 185-198.

Korobilis, D. 2013. 'Assessing the Transmission of Monetary Policy Using Time-varying Parameter Dynamic Factor Models', Oxford Bulletin of Economics and Statistics, vol. 75(2), pp. 157-179.

Korobilis, D., 2013. 'Hierarchical shrinkage priors for dynamic regressions with many predictors', International Journal of Forecasting, vol. 29, pp 43-59.

Levine, R. & Zervos, S. 1998, 'Stock Markets, Banks and Economic Growth', American Economic Review, vol. 88, pp. 537-558.

Levy, H. & Sarnat, M. 1970, 'International Diversification of Investment Portfolios', American Economic Review, vol. 60, pp. 668-675.

Longin, F. and Solnik, B. 2001, 'Extreme Correlation of International Equity Markets', Journal of Finance, vol.56, pp. 649-676.

Lutkepohl, H. & Reimers, H. E. 1992, 'Impulse response analysis of cointegrated systems', Journal of Economic Dynamics and Control, vol. 16, pp. 53-78.

MacKinnon, J. G. 1996, 'Numerical Distribution Functions for Unit Root and Cointegration Tests', Journal of Applied Econometrics, vol. 11, pp. 601-618.

Osterwald-Lenum, M. 1992, 'A Note with Quantiles of the Asymptotic Distribution of the Maximum Likelihood Cointegration Rank Test Statistics', Oxford Bulletin of Economics and Statistics, vol. 54, pp. 461–472.

Pesaran, M. H. & Shin Y. 1996, 'Cointegration and Speed of Convergence to Equilibrium', Journal of Econometrics, vol. 71, pp. 117–143.

Pesaran, M. H. & Pesaran, B. 1997, 'Working with Microfit 4.0: Interactive Econometric Analysis, Oxford University Press, Oxford.

Pesaran, M. H. & Shin Y. 1998, 'Generalized Impulse Response Analysis in Linear Multivariate Models', Economics Letters, vol. 58, pp. 17–29.

Phillips, P. C. B. & Perron, P. 1988, 'Testing for a Unit Root in Time Series Regression', Biometrika, vol. 75, pp. 335–346.

Rouwenhorst, G. K. 1998, 'European Equity Markets and EMU: Are the Differences between Countries Slowly Disappearing?', Yale School of Management.

Sims, C. 1980, 'Macroeconomics and Reality', Econometrica, vol. 48, pp. 1-48.

Solnik, B. 1974, 'Why not diversify internationally rather than domestically?', Financial Analysts Journal, vol. 30, pp. 48-54

Taylor, M. P. & Tonks, I. 1989, 'The Internationalization of Stock Markets and the Abolition of U.K Exchange Control', Review of Economics and Statistics, vol. 71, pp. 332–336.

Yang, J., Min, I. & Li, Q. 2003, 'European stock market integration: Does EMU matter?', Journal of Business, Finance and Accounting, vol. 30, no. 9–10, pp. 1253–1276.

Weber, A. A. 2006, 'European financial integration and (its implications for) monetary policy', Annual General Meeting 2006 of the Foreign Bankers, Amsterdam, 23 May 2006.

Worthington, A. C., Katsuura, M. & Higgs, H. 2003, 'Financial integration in European equity markets: The final stage of Economic and Monetary Union (EMU) and its impact in capital markets', Economia, vol. 54, no. 1, pp. 79-99.

APPENDIX

1. Key Political and Economic Events of the EMU Process

Date	Event
20-9-88	Margaret Thatcher, Prime Minister of the UK, delivers a heavily skeptical speech on the future development of the union (Bruges Speech)
12-4-89	Delors Report lays out the future roadmap for EMU
27-4-89	Madrid Declaration adopts the Delors Report and commits the EEC (sic) to EMU
9-11-89	Fall of Berlin Wall
9-12-89	Strasbourg Declaration declares that the EEC will move towards EMU. Start of Phase I of EMU
29-5-90	European Bank for Reconstruction and Development (EBRD) established
19-6-90	Schengen I agreement signed, providing for a common travel area in Europe
3-10-90	German Re-unification
15-12-90	Rome Declaration launches intergovernmental conference on EMU
10-12-91	Treaty of Maastricht agreed, transforming the EEC into the European Union
21-12-91	Soviet Union collapses
2-6-92	Danish referendum rejects Maastricht treaty
18-6-92	Irish referendum accepts Maastricht treaty
20-6-92	French referendum accepts Maastricht treaty
12-12-92	Edinburgh Declaration amends Maastricht treaty to assuage Danish and endorses moves to EMU
1-1-93	Single European Market (part of Maastricht treaty) in force. This represents the culmination of the original aims of the European Economic Community – the Common Market.
18-5-93	Second Danish referendum accepts Maastricht treaty
2-8-93	ERM bands widened from 2.25% to 15% each direction
29-10-93	Brussels Declaration on the start of Phase II of EMU
1-11-93	European Union created with ratification of all elements of Maastricht treaty
1-1-94	European Monetary Institute (EMI) – forerunner of European Central Bank is established, launching Phase II of EMU
12-6-94	Austria votes to join EU, including EMU
16-10-94	Finland votes to join EU, including EMU
13-11-94	Sweden votes to join EU, including EMU
28-11-94	Norway votes to not join EU
26-3-95	Schengen II extends common travel area
31-5-95	Green Paper on practicalities of monetary union (note transfer etc)
16-12-95	Madrid Declaration II adopts Jan 1 1999 for launch of Euro and start of Phase III of EMU
14-12-96	Dublin Declaration outlines the legal mechanisms for Phase III of EMU
2-10-97	Treaty of Amsterdam ratifies into law the Dublin Declaration
25-3-98	Phase III membership notified: 11 members that may adopt the Euro and move to Phase III named
3-5-98	Determination Mechanism for irrevocable conversion rates outlined
26-5-98	European Central Bank (ECB) Board agreed
1-6-98	ECB established
1-1-99	Euro Launched
22-9-00	ECB intervention to support Euro
28-9-00	Danish Referendum rejects joining Euro
2-1-01	Greece becomes 12th Euro zone member
1-1-02	Euroreplacesnationalcurrencies.PhaseIIIends.EMUComplete

Source: Aggarwal, R., Lucey, B. & Muckley, C. 2004, ‘Dynamics of equity market integration in Europe: Evidence of changes over time and with events’.

LISTOFTABLES

2. Unit Root Tests

2.1. Augmented Dickey Fuller test

Table2.1.1.ADFtest- PriceLevelSeries. Period1(09/05/1991–31/12/1998)

Countries	Model 1 (Trend and Drift)	Model 2 (Drift)	Model 3 (No trend, no drift)
Austria	-2.5924	-2.2945	-0.3758
Belgium	-0.7728	-1.2250	0.0423
Finland	-2.1333	-1.5211	0.2323
France	-1.2320	-1.2550	0.5134
Germany	-0.9182	-1.1678	0.0882
Greece	-0.3734	-0.8094	0.2932
Ireland	-0.9081	-1.3748	0.0156
Italy	-1.0290	-1.2667	0.2210
Netherlands	-1.1459	-1.2543	-0.1143
Portugal	-0.4778	-1.2250	-0.1636
Spain	-1.1375	-1.2135	0.4767

Critical Values are from MacKinnon (1996). One, two and three asterixes indicate significance at the 10%, 5% and 1% levels, respectively. The optimal lag length is selected using the Bayesian Information Criterion

Table 2.1.2. ADF test - Price Differenced Series. Period 1 (09/05/1991 – 31/12/1998)

Countries	Model 1 (Trend and Drift)	Model 2 (Drift)	Model 3 (No trend, no drift)
Austria	-39.7234***	-39.7234***	-39.7309***
Belgium	-39.2912***	-39.1882***	-39.0235***
Finland	-31.8334***	-31.7828***	-31.6309***
France	-42.3748***	-42.3571***	-42.2998***
Germany	-33.7293***	-33.6966***	-33.6072***
Greece	-37.6337***	-37.5703***	-37.5446***
Ireland	-40.5643***	-40.5299***	-40.4382***
Italy	-40.7230***	-40.6982***	-40.6529***
Netherlands	-33.3862***	-33.3678***	-33.1894***
Portugal	-38.2198***	-38.1494***	-38.0623***
Spain	-40.0701***	-40.0011***	-39.9140***

Critical Values are from MacKinnon (1996). One, two and three asterixes indicate significance at the 10%, 5% and 1% levels, respectively. The optimal lag length is selected using the Bayesian Information Criterion

Table 2.1.3. ADF test - Price Level Series. Period 2 (01/01/1999 – 09/05/2006)

Countries	Model 1 (Trend and Drift)	Model 2 (Drift)	Model 3 (No trend, no drift)
Austria	-0.3499	1.9907	2.7821
Belgium	-0.7728	-1.2250	0.0423
Finland	-2.1333	-1.5211	0.2323
France	-1.2320	-1.2550	0.5134
Germany	-0.9182	-1.1678	0.0882
Greece	-0.3734	-0.8094	0.2932
Ireland	-0.9081	-1.3748	0.0156
Italy	-1.0290	-1.2667	0.2210
Netherlands	-1.1459	-1.2543	-0.1143
Portugal	-0.4778	-1.2250	-0.1636
Spain	-1.1375	-1.2135	0.4767

Critical Values are from MacKinnon (1996). One, two and three asterixes indicate significance at the 10%, 5% and 1% levels, respectively. The optimal lag length is selected using the Bayesian Information Criterion

Table 2.1.4. ADF test - Price Differenced Series. Period 2 (01/01/1999 – 09/05/2006)

Countries	Model 1 (Trend and Drift)	Model 2 (Drift)	Model 3 (No trend, no drift)
Austria	-41.7146***	-41.5605***	-41.4245***
Belgium	-26.9429***	-26.8576***	-26.8645***
Finland	-44.0505***	-44.0596***	-44.0686***
France	-43.9310***	-43.9404***	-43.9448***
Germany	-45.1200***	-45.1188***	-45.1301***
Greece	-38.7961***	-38.7790***	-38.7865***
Ireland	-41.0808***	-41.0508***	-41.0614***
Italy	-43.9829***	-43.9758***	-43.9858***
Netherlands	-44.6435***	-44.6464***	-44.6579***
Portugal	-40.0470***	-40.0013***	-40.0115***
Spain	-44.3607***	-44.3523***	-44.3578***

Critical Values are from MacKinnon (1996). One, two and three asterixes indicate significance at the 10%, 5% and 1% levels, respectively. The optimal lag length is selected using the Bayesian Information Criterion

2.2. Phillips – Perron test

Table 2.2.1. PP test - Price Level Series. Period 1 (09/05/1991 – 31/12/1998)

Countries	Model 1 (Trend and Drift)	Model 2 (Drift)	Model 3 (No trend, no drift)
Austria	-2.5281	-2.2452	-0.3673
Belgium	-1.0166	1.7378	2.9871
Finland	-2.3030	0.7682	2.5818
France	-1.6543	0.2168	1.8718
Germany	-1.9463	0.3757	2.0391
Greece	-2.3350	0.3908	1.3148
Ireland	-2.5349	0.4705	2.1335
Italy	-2.0182	0.2004	1.6473
Netherlands	-2.1915	0.3404	2.7231
Portugal	-1.9779	0.5506	1.9147
Spain	-1.7770	0.9339	2.2752

Critical Values are from MacKinnon (1996). One, two and three asterixes indicate significance at the 10%, 5% and 1% levels, respectively.

Table 2.2.2. PP test - Price Differenced Series. Period 1 (09/05/1991 – 31/12/1998)

Countries	Model 1 (Trend and Drift)	Model 2 (Drift)	Model 3 (No trend, no drift)
Austria	-39.7345***	-39.7234***	-39.7309***
Belgium	-39.2034***	-39.1534***	-38.9848***
Finland	-39.4966***	-39.4830***	-39.3573***
France	-42.3177***	-42.3007***	-42.2454***
Germany	-43.6735***	-43.6408***	-43.5749***
Greece	-37.4646***	-37.3684***	-37.3484***
Ireland	-40.6045***	-40.6246***	-40.5961***
Italy	-40.6392***	-40.6232***	-40.5835***
Netherlands	-42.7394***	-42.7294***	-42.6196***
Portugal	-38.7657***	-38.8248***	-38.8897***
Spain	-39.9611***	-40.0129***	-39.8637***

Critical Values are from MacKinnon (1996). One, two and three asterixes indicate significance at the 10%, 5% and 1% levels, respectively.

Table 2.2.3. PP test - Price Level Series. Period 2 (01/01/1999 – 09/05/2006)

Countries	Model 1 (Trend and Drift)	Model 2 (Drift)	Model 3 (No trend, no drift)
Austria	-0.4080	1.8699	2.6455
Belgium	-0.6222	-1.1510	0.0526
Finland	-2.0784	-1.4690	0.2513
France	-0.9820	-1.0395	0.6231
Germany	-0.8018	-1.0945	0.1007
Greece	-0.2873	-0.7643	0.3131
Ireland	-0.8356	-1.2807	0.0190
Italy	-1.0223	-1.2649	0.2237
Netherlands	-0.9008	-1.1198	-0.1186
Portugal	-0.4332	-1.2134	-0.1637
Spain	-0.9341	-1.0320	0.5378

Critical Values are from MacKinnon (1996). One, two and three asterixes indicate significance at the 10%, 5% and 1% levels, respectively.

Table 2.2.4. PP test - Price Differenced Series. Period 2 (01/01/1999 – 09/05/2006)

Countries	Model 1 (Trend and Drift)	Model 2 (Drift)	Model 3 (No trend, no drift)
Austria	-41.7053***	-41.5722***	-41.4702***
Belgium	-39.0697***	-38.8713***	-38.8833***
Finland	-44.0968***	-44.1059***	-44.1129***
France	-44.5731***	-44.5746***	-44.5588***
Germany	-45.2040***	-45.1953***	-45.2069***
Greece	-38.5695***	-38.5795***	-38.5881***
Ireland	-41.0640***	-41.0511***	-41.0617***
Italy	-43.9852***	-43.9771***	-43.9871***
Netherlands	-45.0355***	-45.0239***	-45.0366***
Portugal	-40.0122***	-40.0068***	-40.0169***
Spain	-44.6198***	-44.5869***	-44.5877***

Critical Values are from MacKinnon (1996). One, two and three asterixes indicate significance at the 10%, 5% and 1% levels, respective