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Dynamic stock market integration driven by the European Monetary Union: An empirical analysis

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Abstract

This paper investigates the impacts of the introduction of the euro on the pattern of stock market linkages and the dynamic process of stock market integration over the period from 1989-2003. On a regional level, we examine integration among stock market indices of European Union (EU) countries with the European Monetary Union (EMU) while on a global level, integration of the EMU vis-à-vis Japan and the US are analyzed. We assess stock market integration within the context of a bivariate exponential generalized autoregressive conditional heteroscedasticity (EGARCH) framework with time varying conditional correlations. First, we discuss that European stock market integration has undergone a clear regime shift. Second, we find a striking number of significant return and volatility spillovers within the EMU and for the entire EMU region with the US and Japan and that these linkages have strengthened with currency unification. Third, we show that the introduction of the euro has indeed caused this stock market integration. Finally, our seemingly unrelated regression estimations (SURE) find that stock market integration is a persistent and seasonal process as its main determinants are the existing levels of integration and stock market development and there are signs of a positive January effect. While the introduction of the monetary union has in general been a significant driving force behind this regional and global phenomenon, the effectiveness of the different economic convergence criteria associated with the EMU in driving this process differs across member states. On a global level, the commitment to price stability has significantly strengthened stock market integration between the EMU and the US whilst convergence in industrial production has increased ties between the EMU and Japan.

JEL Classification: C32; E44; F3; G14; G15

Keywords: Euro, volatility, currency unions, stock market linkages, spillover effects, time-varying financial market integration.

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1. Introduction

There is no doubt that capital market integration was one motivation for the European Economic and Monetary Union (EMU). The euro was introduced as the single currency for the EMU on January 1st, 1999 following an economic convergence process that had spanned over two decades from the initial creation of the European Monetary System (EMS). The political creation of the euro as the single currency of the EMU presents a learning model for understanding the financial effects of currency unions given that the euro was introduced without a single euro area financial market. The concept of financial market integration is central to the international finance literature. It is well accepted in the theoretical literature that integration of financial markets is fundamentally linked to economic growth through risk sharing benefits and reductions in macroeconomic volatility (see Pagano, 1993, Obsfeld, 1998, Prasad et al., 2003). As there are significant potential benefits from financial market integration, the purpose of this paper is to investigate the nature and the determinants of stock market integration with a view to evaluating the effectiveness of the EMU in its promotion.

First, we discuss how European stock market linkages and integration dynamics have evolved over the past fifteen years on both a regional and global scale in response to the economic convergence process associated with the introduction of the euro. Second, we address the causality issue between currency unions and financial market integration to improve our understanding on the sequencing of financial market integration. Finally, we identify the factors that determine these integration patterns in a new empirical context and assess whether they are consistent for both regional and global stock market integration. The research questions addressed in this paper have obvious implications for policy-makers in an increasingly interdependent global financial architecture and for investors' asset allocation decisions[1]. There is a clear need to better understand how and why the euro has affected stock markets because of their important role in facilitating financing and investment decisions. Our analysis on the existing members of the European Union (EU) is also important for ensuring that the process of currency unification governed by the EMU is beneficial for both present and future members from a financial perspective.

In principle, it is reasonable for investors to view a single currency zone as a single area of financial opportunity. To a large extent, financial market integration is driven by market forces but constrained by regulatory barriers and the level of integration is not uniform across market segments nor across time. Hence, financial markets and investment returns should be driven to some time varying degree of convergence.[2] There has already been some empirical evidence on the effect of the euro in accelerating the process of financial integration in European financial markets. For example, Galati and Tsatsaronis (2001) and Reszat (2003) discuss the general impacts across Europe's financial markets; Frankel (1994) provide evidence of full convergence in bond and money markets; Hau et al. (2002) identify the specific impacts on foreign exchange markets; Kleimeier and Sander (2000) find convergence in the retail lending market and Harm (2001) reveals integration in private sector bonds and syndicate loans.

In relation to stock market integration, recent studies by Hardouvelis et al. (2001), Fratzscher (2002) and Morana and Beltratti (2002) determine the impacts of the introduction of the euro on European stock markets. In particular, Morana and Beltratti (2002) find that daily volatility of stock index returns decreased for Italy and Spain in the period from January 1988 to May 2000 using a three-regime Markov switching model and Fratzscher (2002), using a trivariate GARCH model over a similar sample period from January 1986 to March 2000 provides

[1] The covariance/correlation matrix of international stocks is a key determinant of asset allocation in investment portfolios. Modern portfolio theory asserts that international diversification of equity portfolios improves the risk-return tradeoff if there is a low correlation between national stock markets (Solnik, 1974).

empirical evidence of rapid integration in daily stock market index returns with the EMU in the two years prior to the formal introduction of the euro. However, these studies remain incomplete and have the following shortfalls: i) They are confined to stock market changes up to early 2000 *and* cover only a few selected countries. Thus longer term, post-euro impacts on international stock markets from the European currency unification are not well documented nor understood. Convergence towards the weighted average of the twelve members of the EMU has never been fully assessed. It is not even clear whether the introduction of the euro has fundamentally changed the integration process of European stock markets[3]. ii) These studies have merely associated the changes in European stock markets to various aspects of the currency union without addressing the fundamental causal relationship between the two. iii) European stock market integration has only ever been assessed on a country by country basis and rarely as a group or system of member states which are similar by nature of their common convergence towards the EMU. iv) Although both studies attempt to explain why European stock markets have changed with the introduction of the euro, their findings are conflicting especially with respect to the reduction in exchange rate risk. Fratzscher (2002) finds a key role for exchange rate stability together with real and monetary policy convergence in explaining time varying coefficients from his trivariate GARCH model whilst on the basis of a theoretical variance-covariance decomposition, Morana and Beltratti (2002) attributes changes in stock market volatility to the unification of interest rates and stabilization of macroeconomic fundamentals and *not* to the elimination of exchange rate risk and v) Specific stock market measures of development and liquidity have not been explicitly controlled for in previous studies and seasonal effects (especially January effects) have not been examined despite their presence in

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[2] The time varying nature of financial market integration is well established in the literature. See Bekaert and Harvey (1995), DeSantis and Gerard (1995), Longin and Solnik (1995), and Errunza et al. (1999).

[3] On a minor point, an assessment of Greece's late entry and integration into the EMU since 2001 has never received academic attention despite the important implications for the next stage of EU enlargement to begin in May 2004.

other stock market studies (eg. Longin and Solnik, 1995, Karolyi and Stulz, 1996 and Carrieri et al., 2001).

To address these gaps and disparities in the existing literature and to contribute an updated analysis on the extent to which stock market integration has been driven by the EMU, in this study we construct a bivariate daily exponential generalized autoregressive conditional heteroscedasticity (EGARCH) model for individual and value-weighted regional stock index returns. We focus primarily on documenting and explaining the time varying conditional correlations between these time series during the lead up to the establishment of the European currency union and beyond. Our contributions to the literature are in: i) Providing more comprehensive evidence from *all* EU15 members as well as Japan and the US on the evolution of stock market integration at the regional and global level over a longer post-euro period; ii) Illustrating a two step estimation methodology that is suitable for empirical research on European financial market integration; iii) Providing quantitative estimates on national and regional linkages between international equity markets during the different phases of European stock market integration; iv) Addressing the causal relationship between the EMU and stock market integration and v) Using additional information captured in linear systems estimations to find the determinants of stock market integration, including seasonal effects.

Our main findings with the benefit of a longer post-euro sample period are: i) a clear regime shift in stock market comovements within the EU; ii) deeper stock market linkages with the introduction of the euro; iii) the EMU has *caused* stock market integration between member states and vis-à-vis Japan and the US; iv) stock market integration is primarily a persistent and seasonal process where stock market development and existing levels of integration are vital; v) the January effect is significant but contrary to Karolyi and Stulz's (1996) study on the comovements between Japanese and US stock market returns, we find no day of the week effects in comovements with stock markets in the EMU and v) whilst the EMU has fostered stock market integration, we find that the reduction in exchange rate volatility has only been important for the smaller member states with historically different economic structures and that economic convergence within the region has had differing impacts on the integration of European stock markets.

The rest of the paper is organized in the following way. Section 2 provides a brief literature review. Section 3 offers discussions on the data and methodology as well as the findings on the nature of the time varying stock market integration. Section 4 examines the role of various determinants of the stock market integration process. Finally, concluding remarks are presented in Section 5.

2. Literature Review

Empirical studies into stock market integration have mainly utilized two related theoretical frameworks. In international finance, the literature has primarily focused on the international capital asset pricing model (ICAPM) based on the premise that regardless of trading location, assets of identical risk levels should provide the same expected return. 4 On the other hand, various interest rate parity conditions have been used in international macroeconomics research (eg. Kleimeir and Sander, 2000; Hardouvelis, 2001; Fratzscher, 2002). However, an apparent divergence exists in the theoretical and empirical research developments on stock market integration. The theoretical models are static models of long-run financial integration but the true process is dynamic and very difficult to measure.

A wide range of empirical methodologies have been used over time for analyzing financial integration and cross-market equity comovement. The most basic technique has been

[4] Karolyi and Stulz (2002) provides a detailed survey of international asset pricing studies.

the use of unconditional cross-country correlations on equity prices and returns. However, the debate on the relative importance of industry and country-specific effects in explaining cross-country correlations and volatility has not been resolved to date.[5] Later on, atheoretical vector autoregressions (VARs) were used by Eun and Shim (1989), King and Wadhwani (1990) and others. Gradually, ARCH variants were used due to the higher frequency data employed by researchers. For example, Hamao et al. (1990) examined linkages and spillovers using daily returns whilst Susmel and Engel (1994) used hourly data to analyze major stock markets in London, New York and Tokyo. However, it is now known that ARCH is less useful for the non-normal distributions exhibited by emerging market returns. Instead, semi-parametric ARCH (SPARCH) has been used by Bekeart and Harvey (1997) to capture the fat tails and skewness in emerging market returns.

On another front, both univariate and multivariate cointegration/error correction models have been used to model stock returns and prices for major and emerging markets.[6] However, we argue that the long-run stable equilibrium relationships conjectured by these techniques are not suitable for modeling the dynamic process of stock market integration as it is incomplete and continues to exhibit strong variations over time. Furthermore, only the existence of an equilibrating process and not the driving forces behind the long-run equilibrium are investigated in standard cointegration analyses.

In the past decade, multiple classes of univariate and multivariate generalized autoregressive conditional heteroscedasticity (GARCH and MGARCH) models have been the technique of choice for research into financial links across equity markets. This is due to the high degree of persistence in the conditional means and variances of asset prices at high frequency levels. It is also well accepted in the empirical finance literature that the volatility of rising and falling (especially during recessions and/or financial crises) financial markets differ and that

[5] See Forbes and Chinn (2003) for an exposition on the cross-country correlations in asset returns literature.

negative shocks (bad news) have a greater impact than positive shocks (good news).[7] Hence, variants of these models have been used to accommodate the possibilities of non-normalities and asymmetries in the variance of equity returns (Glosten, Jaganathan and Runkle, 1993, Bae and Karolyi, 1994, Bekaert and Harvey, 1997, Ng, 2000, and Fratzscher, 2002 among others). Closely related to these are the regime switching models with time varying transition probabilities for different states (regimes) used in Bekaert and Harvey (1995, 1997), Carrieri et al. (2001), Hardouvelis et al. (2001) and Morana and Beltratti (2002).

To address variations in stock market integration over time, researchers have performed regressions on different sub-periods to gain insight into long-term changes in stock market integration dynamics (see Longin and Solnik, 1995 and Bodart and Reding, 1999). More recently, rolling and recursive windows and time varying coefficients generated by instrumental variables have also been employed in Fratzscher (2002).

In this study, we employ a bivariate EGARCH model with a joint student *t* conditional density function for the residuals to explicitly account for positive and negative shocks and fat tails in the equity returns. We will show that this model is well suited for modeling the dynamics of stock market returns. While time varying coefficients on return spillovers have been estimated by Fratzscher (2002) to measure stock market integration, the orthogonality condition required for unbiased estimates may be difficult to ascertain. Instead we use time-variations in conditional correlations from the EGARCH model.[8] This provides a more direct indication of interdependence between individual stock markets and the EMU. It is also more meaningful than the arbitrary classification of volatility states required by regime switching models.

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[6] See Chen et al. (2000) for other empirical studies using the cointegration technique.

[7] See Nelson (1991) and Glosten, Jaganathan and Runkle (1993). The theoretical explanation for this is unclear. Financial and operating leverage have been argued to play a role but are unable to empirically explain the degree of the asymmetric response of return volatility to positive and negative shocks.

[8] The concerns of Forbes and Rigobon (2002) with using correlation coefficients to measure stock market comovements in the closely related financial contagion literature is not relevant to our study as reductions in European stock market volatility have already been shown by Morana and Beltratti (2002). Hence, we are confident that our conditional correlations are not a by-product of increasing volatility in stock returns.

3. Documenting Time-varying Stock market integration

In this section we show the extent to which international stock markets have been integrated with the EMU over the past one and a half decades. We first discuss the data used and their statistical properties before moving onto the empirical model. Following this, the results are presented and closely examined.

3.1 Stock market data

The current state of the EU provides a natural setting for analyzing the differential impacts on stock market performance from idiosyncratic developments between constituent members within a currency union. The empirical analysis is therefore conducted for a sample set of countries that fall into two distinct groups: 1) The twelve eurozone members that have adopted the euro as a common currency (Austria, Belgium, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, Netherlands, Portugal and Spain) [9] and 2) The non-eurozone countries which include the three remaining EU states that opted to stay out of the EMU (Denmark, Sweden, the UK) and Japan and US being the other two major stock markets in the world.

The national stock market (continuously compounding) returns examined in this study are measured as the log of changes in closing price levels from one trading day to the next such that, $R_{it} = \ln\left(P_t / P_{t-1}\right) \times 100$ for stock market *i* on day *t*. The national share price indices used are from Datastream International and are in local currency units with daily frequency from 2 January 1989 to 29 May 2003 (amounting to 3760 usable observations). Local currency returns are

[9] Greece had failed to meet the economic (convergence) criteria required under the Stability and Growth Pact of 1998. These convergence criteria were first set out in the 1993 Maastrict (EU) Treaty and aimed at forcing reductions in fiscal deficits and public debt in the EU member states. Greece adopted the euro on 1st January 2001.

needed in our study to explicitly investigate the impact of changes in exchange rate risk induced by the introduction of the euro. Also, daily frequency is important given that comovements in the equity return generating process may often change on a rapid basis. The stock market returns for the entire euro zone is calculated as the (market) value-weighted average return of those twelve EMU markets that have already adopted the euro. However, the value-weighted euro zone returns used for bivariate estimations with each individual EMU market *i,* is *exclusive* of that market itself in order to filter out idiosyncratic market shocks in the regional return index. The euro zone return index $R_{E,t}$ excluding each individual market *i* is calculated as

$$R_{E,t} = \frac{\sum_{k \neq i} w_{k,t} R_{k,t}}{\sum_{k \neq i} w_{k,t}} \qquad (1)$$

where w_k is the weight reflecting the market capitalization of each of the other *k* markets in the euro zone as a proportion of the total euro market comprising those *k* members.

The statistical properties of the stock returns are shown in Table 1. The descriptive statistics on the daily stock market index returns for each individual EMU country and for the euro zone excluding that country are shown in panel A of Table 1. In turn, those for each country in our sample outside of the euro zone and for the total euro zone are shown in panel B. As is evident from the summary statistics shown in this table, the distributions of all these national and regional daily stock returns are non-normal. Both the skewness and the excess kurtosis statistics for these return series are significantly higher than for comparable normal distributions at all meaningful significance levels. The higher excess kurtosis in national stock index returns relative to regional returns are to be expected given the law of averages but it appears that stock market returns for Portugal and Luxembourg are the most volatile and sensitive to external shocks. The univariate test results of the Ljung-Box Q tests for linear and non-linear serial correlation in each daily return series up to 20 lags are also shown in Table 1. All return series exhibit highly significant linear and nonlinear serial dependence and point to the presence of high persistence and time varying volatility (heteroskedasticity). Finally, the reported joint *iid* test statistics between each national and regional stock index return reported in Table 1 is for a bivariate version of the Ljung-Box portmanteau test (Hosking, 1980) of joint white noise properties for these returns, r_t defined as:

$$Q = T^2 \sum_{i=1}^{p} \frac{Tr\left(\hat{C}_i \hat{C}_0^{-1} \hat{C}_i \hat{C}_0^{-1}\right)}{(p-i)}, \quad \text{Where} \quad \hat{C}_i = \frac{1}{T} \sum_{t=i+1}^{T} \left(\hat{r}_t \hat{r}_{t-i}\right), \quad r_t = \begin{bmatrix} r_{1t} \\ r_{2t} \end{bmatrix}, \tag{2}$$

and T = number of observations, p = number of lags, Q ~ χ^2 with *df* = 4p. The test statistics for joint linear and nonlinear independence are all rejected at conventional significance levels, indicating that the first and second moments of the national and regional equity returns move closely together. Henceforth, modeling of these return series must address the bivariate and leptokurtic nature of these distributions in addition to the high degree of linear and nonlinear serial correlations.

An appropriately specified GARCH model with a non-normal conditional density for the residuals is suitable for modeling these daily compounding return series to capture the significant levels of excess kurtosis exhibited. Thus, we use bivariate *t* densities to model excess kurtosis in the standardized residuals from the model and adopt a bivariate version of Nelson's (1991) exponential GARCH (EGARCH) approach to address the asymmetric nature of volatility responses in the stock return series. There is a well-established need in the volatility literature to look at the effects of asymmetric shocks and previous studies have found that the logarithmic specification in EGARCH models with a suitable distributional assumption fits financial data very well.[10] We will show below how the EGARCH framework has been used to model the dynamics of stock market returns.

3.2 Econometric modeling

Our aim is to examine whether the establishment of a currency union has induced a dynamic change in stock market integration by making inferences from the behaviour of daily conditional volatility of stock index returns and their conditional correlations. There is much evidence to support the notion that financial market integration changes the conditional return generating process.[11] Markets are permanently in motion and comovements fluctuate on a daily basis, and so by allowing for asymmetric response characteristics in stock returns, the integration process of a member state with the currency union region as a whole is better captured. In recent times, multivariate GARCH models have been extended to incorporate time varying correlations and this feature is theoretically appealing for assessing dynamic financial market integration. Thus, we jointly model pairs of national and regional stock index returns in a parsimonious bivariate EGARCH(1,1)-*t* model.

In this paper, the conditional first moments (means) of the stock index returns are estimated as a parsimonious restricted bivariate ARMA(*p,q*)[12] process in order to capture the dynamics between mean stock market returns for each individual country and the euro zone[13]

$$\begin{aligned} R_{N,t} &= \alpha c_N + \sum_{i=1}^{p_E} \alpha r_{E,i} R_{E,t-p_E} + \sum_{j=1}^{q_N} m\alpha_{N,j} \varepsilon_{N,t-q_N} + \varepsilon_{N,t} \\ R_{E,t} &= \alpha c_E + \sum_{i=1}^{p_N} \alpha r_{N,i} R_{N,t-p_N} + \sum_{j=1}^{q_E} m\alpha_{E,j} \varepsilon_{E,t-q_E} + \varepsilon_{E,t} \end{aligned} \tag{3}$$

with

[10] By formulating the conditional variances in logarithmic terms, the EGARCH model overcomes the need for non-negativity constraints to ensure positive definite covariance matrices.
[11] See Bekaert and Harvey (2003).
[12] A bivariate exponential GARCH in mean (EGARCH-M) estimation was also conducted with no improvements in the qualitative results and has been omitted in this paper due to space constraints.
[13] With the exception that lagged US returns were used as 'contemporaneous returns' because the US market opens and closes *after* European stock markets and therefore affects the Euro zone only on the following day.

$$\varepsilon_t = \begin{bmatrix} \varepsilon_{N,t} \\ \varepsilon_{E,t} \end{bmatrix} \sim t(0, H_t, d),\ H_t = \begin{bmatrix} h_{N,t} & h_{NE,t} \\ h_{EN,t} & h_{E,t} \end{bmatrix}$$

In essence, $R_{N,t}$ is the national conditional mean return that is a function of past returns in the rest of the euro zone and past idosyncratic shocks, $\varepsilon_{N,t}$ and $R_{E,t}$ is the regional conditional mean return for the euro zone that is a function of past returns in country N and its own past shocks, $\varepsilon_{E,t}$. Specifically, the regional and country mean spillover effects can be quantified by the sign and magnitude of the estimated coefficients for the lagged euro zone and national returns respectively. Note that p_N and p_E are the number of autoregressive terms and q_N and q_E are the number of moving average terms needed to eliminate joint linear and nonlinear serial correlation in the standardized residuals, $\frac{\varepsilon_{N,t}}{\sqrt{h_{N,t}}}$ and $\frac{\varepsilon_{E,t}}{\sqrt{h_{E,t}}}$ which are jointly t distributed.

The conditional second moments (variances) of the estimated model also incorporate interdependencies in the innovations of national and regional stock market returns as shown below:[14]

$$\ln h_{N,t} = \beta c_N + \beta_{hN} \ln h_{N,t-1} + \left[\beta\varepsilon_{N1} \frac{\varepsilon_{N,t-1}}{\sqrt{h_{N,t-1}}} + \beta\varepsilon_{N2} \left(\frac{|\varepsilon_{N,t-1}|}{\sqrt{h_{N,t-1}}} - \sqrt{\frac{2}{\pi}} \right) \right] +$$
$$\left[\beta_{E1} \frac{\varepsilon_{E,t-1}}{\sqrt{h_{E,t-1}}} + \beta_{E2} \left(\frac{|\varepsilon_{E,t-1}|}{\sqrt{h_{E,t-1}}} - \sqrt{\frac{2}{\pi}} \right) \right], \tag{4}$$

[14] In the EGARCH-t model the conditional variance equation is defined in terms of $z_t \sim t(0,1,d)$:

$$\ln \sigma_t^2 = \omega + g(z_{t-1}) + \beta \ln \sigma_{t-1}^2$$

where g(.) is the asymmetric response function defined by

$$g(z_t) = \lambda z_t + \varphi\left(|z_t| - \sqrt{\frac{2}{\pi}} \right)$$

where z_t is the standardized unexpected return ε_t/σ_t. The second term in the asymmetric response function is the mean deviation of z_t since $E(|z_t|) = \sqrt{\frac{2}{\pi}}$. Hence, when φ>0, and λ<0 negative return shocks (z_{t-1}<0) will induce larger conditional variance responses than positive return shocks (These are known as the asymmetric and volume effects).

$$\ln h_{E,t} = \beta c_E + \beta_{hE} \ln h_{E,t-1} + \left[\beta\varepsilon_{E1} \frac{\varepsilon_{E,t-1}}{\sqrt{h_{E,t-1}}} + \beta\varepsilon_{E2} \left(\frac{|\varepsilon_{E,t-1}|}{\sqrt{h_{E,t-1}}} - \sqrt{\frac{2}{\pi}} \right) \right] +$$
$$\left[\beta_{N1} \frac{\varepsilon_{N,t-1}}{\sqrt{h_{N,t-1}}} + \beta_{N2} \left(\frac{|\varepsilon_{N,t-1}|}{\sqrt{h_{N,t-1}}} - \sqrt{\frac{2}{\pi}} \right) \right] \qquad (5)$$

which assumes that the conditional variance is determined by its own past variance, its own negative and positive past unanticipated shocks as well as those from the other stock index return. In this context, the regional and country volatility spillover effects can be measured by the magnitude of the estimated coefficients for the negative and positive lagged external innovations in the latter part of equations (4) and (5). Instead of assuming constant correlation between the national and regional stock index return series, as in Bollerslev (1990) and many others, we allow it to vary across time to capture the time varying nature of the stock market integration process. The conditional covariance equation is shown below: [15]

$$h_{NE,t} = \delta_0 + \delta_1 \sqrt{h_{N,t}.h_{E,t}} + \delta_2 h_{NE,t-1} \qquad (6)$$

where the dynamics of the conditional correlation coefficient have been modeled based on the cross-product of standard errors of the national and regional stock index returns and past conditional correlations. Hence, the time varying conditional correlations can be computed as the standardized covariance

$$\rho_t = \frac{h_{NE,t}}{\sqrt{h_{N,t}.h_{E,t}}} \qquad (7)$$

[15] An alternative covariance structure was estimated as $h_{NE,t} = \delta_0 + \delta_1 \sqrt{h_{N,t}.h_{E,t}}$ to ensure that the results obtained were robust to different functional forms for the conditional covariance equation. This alternative specification made no major differences to our parameter estimates for the bivariate EGARCH model. The cross-product of the unexpected returns (shocks) from the conditional mean equations has been omitted due to the complexity of these shock terms in the bivariate EGARCH framework.

and can be used to indicate the level of comovement between national and regional stock index returns. Specifically, this measures the contemporaneous conditional correlation between the two series and has been used in this paper to proxy the degree of integration between the stock market in a member state and stock markets in the rest of the euro zone[16]. Moreover, this has also been used to gauge the extent of integration between stock markets in Europe and Asia (represented by Japan) and also Europe and the USA. This second application of our empirical model provides invaluable insight into the globalization phenomenon of the past decades.

Finally, the bivariate ARMA-EGARCH-*t* model is implemented for the stock index returns data via maximum likelihood estimation of the following log likelihood function[17]

$$L_T\left(\theta_f\right)=\sum_{t=1}^{T} l_t\left(\theta_f\right)=\sum_{t=1}^{T}\left[\begin{array}{l}-\left(\frac{k}{2}\right)\log\left(2\pi\right)-\frac{1}{2}\log\left(\frac{d-2}{d}\right)-\frac{1}{2}\log\left|H_t\right|-\frac{k}{2}\log\left(\frac{d}{2}\right)\\+\log\Gamma\left(\frac{d+k}{2}\right)-\log\Gamma\left(\frac{d}{2}\right)-\left(\frac{d+k}{2}\right)\log\left(1+\frac{\varepsilon_t^{'}H_t^{-1}\varepsilon_t}{d-2}\right)\end{array}\right] \tag{8}$$

where k = 2 in the bivariate case, θ_f is the vector of parameters to be estimated, T is the number of observations. As discussed above, a conditional bivariate student's *t* distribution with variance-covariance matrix H_t and *d* degrees of freedom has been assumed for the joint distribution of the two error processes instead of the standard bivariate normal distribution in order to account for possible leptokurtosis in the joint conditional densities (see Bollerslev, 1987 and Hamilton, 1994). The advantage of employing this distribution is that the unconditional leptokurtosis observed in most high-frequency asset price data sets can appear as conditional

[16] Typically, time varying conditional correlations have been used more in the domain of risk management for calculating short-term hedge ratios to reflect current market conditions. However, time varying conditional correlations have been used in recent macroeconomic research papers in recognition that static correlations are too simplistic and are blurred by the transition process (see Babetski et al., 2002 and Sarkar and Zhang, 2002).

leptokurtosis and still converge asymptotically to the Normal distribution as *d* approaches infinity (usually in lower-frequency data). As shown below, this is well suited for the dynamics of those stock market returns employed.

3.3 Empirical Results

The bivariate estimation results for all individual market indexes with the euro zone market indexes are reported in Table 2. Estimates for parameters in the two conditional mean and volatility equations are shown followed by those in the covariance equation. The diagnostics of the estimations are shown in the bottom panel. In general, the EGARCH model is appropriate for all the index return pairs as significant negative asymmetric effects ($\beta\varepsilon_{N1}$, β_{E1}, $\beta\varepsilon_{E1}$ and β_{N1}) together with positive volume effects ($\beta\varepsilon_{N2}$, β_{E2}, $\beta\varepsilon_{E2}$ and β_{N2}) are present. The coefficients for the lagged conditional volatility (β_{hN} and β_{hE}) are fairly close to one for all countries suggesting a high persistence in shocks to the conditional volatility. The Ljung-Box Q statistics indicate that joint linear and non-linear serial correlations in the standardized residuals have been successfully eliminated in the bivariate ARMA-EGARCH-*t* models.

Figures 1 and 2 illustrate the path of time varying conditional correlations estimated from these bivariate EGARCH models for the twelve EMU members and the other five non-euro countries. Due to the differences in the industrial structure of the underlying stock market indices, the levels of comovement in stock returns will differ. By construction, countries such as Germany, France and Italy with larger stock market capitalizations will appear to be more integrated with the EMU regional core and this is reflected in the levels of conditional correlations in Figures 1 and 2. Nevertheless, it is clear that the pattern of stock market integration has varied strongly over time for all EU countries, having been more volatile prior to

[17] The Simplex algorithm was first used to determine appropriate starting values for parameter estimates then

the mid 1990s. In the aftermath of the severe and costly EMS crisis over 1992-93, stock markets in the region were to some extent heading towards further segmentation (reflecting the general state of uncertainty surrounding the single currency project) but this had stabilized in all EU countries by 1996. Since 1996-97 there has been a clear change in the dynamics of integration amongst stock markets inside the entire EU (ie. not just amongst those members that have adopted the euro) and the long-run trend towards regional integration is obvious. We note that from 1996 to late 1998, integration increased rapidly for most EU members. This period coincided with the final stages of the Treaty of Amsterdam in which political and institutional conditions were created to enable the EU to meet the challenges of the future with amendments to the Maastrict (EU) Treaty.[18] This was a major milestone in the path to integration as it eliminated a large amount of uncertainty leading up to the formal adoption of the euro and consequently kicked off the distinct upward trend in stock market integration for all EU countries. The phase of uncertainty preceding this phase of rapid integration is clearly more pronounced for Portugal, Ireland, the Netherlands and Greece. Interestingly, late entry has not been a major setback for integration of the stock market in Greece into the EMU. As previous European stock market studies have recognized, stock prices move in anticipation of future events and forward looking investors had already factored in the introduction of the euro into stock prices prior to its formal introduction (eg. Morana and Beltratti, 2002). A long lasting benefit since 1999, has been the effective stabilization of the integration process as indicated by dampened volatility in all estimated conditional correlation series. This is possibly due to the stabilization in macroeconomic fundamentals through the EMU convergence process as shown by Morana and Beltratti (2002). The view of these authors is that the introduction of the euro was "a macroeconomic news of varying importance for different countries which in no case has brought

numerical optimization was based on the Broyden, Fletcher, Goldfarb and Shanno (BFGS) algorithm.

[18] Maastrict Treaty (Treaty on EU) came into force on November 1, 1993 but the Treaty of Amsterdam was concluded on June 17, 1997.

about a revolution in the economic structure." Although to some extent, the changes in the integration patterns do vary amongst all the EU countries in line with this view, there is stark evidence that a regime shift has occurred under the currency union in most member states that have adopted the euro. This has been made clearer with our more recent sample period than that used in past studies. While Morana and Beltratti (2002) have focused on the changes in stock return volatility specifically before and after the introduction of the euro, our focus is on the overall changes in stock market comovements with the euro zone. It is clear that a new regime marked by increased stability and higher mean levels of integration has emerged for EMU countries in the post-euro era.

On the global front, ties between the euro region and the other two major markets were also strengthened during this period of monetary unification and is consistent with the general evolution towards more integrated financial markets documented by Ayuso and Blanco (2001) and Carrieri et al. (2001).[19] However, heterogeneity is evident between the euro zone and non-euro zone stock markets as there are important differences in their conditional correlation time series in our sample period. To the extent that investors did update their stock valuations leading up to the macroeconomic "news" regarding the formal introduction of the euro in the EU market, the anticipation was not as significant outside the EU, particularly in the Japanese stock market where there is much more noise in the conditional correlation series, as seen in Figure 2. Specifically, a regime shift in integration with the EMU is not obvious although the pattern is consistent with stock market integration inside the euro zone in that there was also an upward trend preceding the euro's formal introduction as the uncertainties were reduced and a plateau has also emerged in the post-euro period. Quantifying the linkages between stock market returns will aid our assessment on the differences in regional and global integration.

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[19] Although these authors argue that higher correlations of market-wide index returns are neither a necessary nor sufficient condition for greater market integration.

3.4 Conditional mean and volatility spillover effects

Spillovers in mean return and volatility occur when past information from the stock markets in the member country or the euro area (outside of that member) has persistent effects on the other. The coefficients of the mean spillover variables (lagged cross-market returns) and the spillovers in negative and positive unexpected cross-market shocks have been isolated in Tables 3 and 4 respectively. They have been estimated for the full sample period as well as three sub-samples justified on the basis of observed integration patterns. The first sub-sample period goes from the beginning of January 1989 to the end of 1995, indicating the period before major changes took effect in the integration process of these equity markets. The second sub-sample is the short intense pre-euro integration period between the start of 1996 and the end of 1998. Finally, the third sub-sample from the start of 1999 to the end of May 2003 is the extended post-euro period. In such an exercise, the econometric model that is suitable for the full sample may not necessarily be a good fit for individual sub-samples. However, a break down of the full sample period contributes to our understanding of the long-term dynamics of the stock market integration process.

First, to aid our analysis of the full sample period, the significant coefficients on cross-market returns from the previous day have been graphed in Figures 3 and 4. The first result that emanates from a comparison of these figures is that the sign of the significant coefficients from individual lagged country returns (country spillover effect) may be positive or negative but the coefficient from the euro zone (regional spillover effect) is always positive. This could simply be attributed to the law of averages in that the idiosyncratic differences in information transmission are more predictable for the value-weighted average of the whole euro zone. Based on the magnitudes of these significant regional spillover coefficients, for an equal percentage increase in stock returns for the rest of the euro zone, stock returns in the US stock market will move the most (0.426%) in the same direction on the next day, followed by the German (0.289%) then Japanese stock market (0.248%) and so on. The sensitivity of the US and Japanese stock markets to information flows from the euro zone is another indicator that globalization is a key feature of the 21st Century. It should also be noted that of all the countries in the sample, only Luxembourg required more than one lag in the regional mean return to fully eliminate serial correlation in its conditional mean equation. This suggests that this stock market is the most inefficient at incorporating information into stock prices and information from the rest of the euro zone takes almost a week to be fully priced. In Figure 4, it is revealed that changes in stock market returns for the euro zone are led by stock market returns in France, the UK, Spain and the Netherlands whilst stock market returns for the euro region react in an opposite direction to developments in Japan, the US and Denmark, Austria, Ireland, and Portugal.

As is evident in Tables 3 and 4, regional spillovers in mean returns and unexpected shocks tend to be larger than the country specific spillover effects. This is an intuitive result given the size difference of these sources. In regards to return spillovers reported in Table 3, the effects are not constant. The magnitude of these linkages has increased for most countries in line with the three distinct phases in stock market integration. As integration in stock markets proceeded, the interdependencies between national and euro zone stock markets have strengthened although not always in the same direction. Feedback effects in country and regional returns are apparently asymmetric in that information may spillover unidirectionally from a country into the euro region or vice versa. As expected, for most countries these feedback effects are bilateral. In regards to the volatility spillovers reported in Table 4, there is further evidence that European markets are largely integrated as the regional shocks appear to be relatively larger than the country specific shocks and are becoming increasingly more so. The asymmetric and volume effect from the past unexpected shock from each individual country and from the euro region are mostly significant and of the correct sign over the full sample period but not for all sub-sample periods.

In short, linkages between stock markets inside and outside of the Euro region are clearly present and have strengthened in the wake of currency unification. The significant spillover coefficients indicate the EMU members are crucial both to each other's prosperity and to the stability of the world economy as a whole. It can be inferred from these results that the benefits of portfolio diversification across international stock markets have decreased in recent times. This is not only consistent with the findings of increased correlations in cross-country stock returns documented by Longin and Solnik (1995) but more importantly the findings by Freimann (1998) on reduced diversification benefits in European stock markets with the introduction of the euro. Given so, what are the specific determinants of stock market integration? Are there particular factors related to the EMU that are driving stock markets to be more integrated? If so, a better understanding of these factors would not only assist portfolio managers and investors but also guide policy makers in the direction of more efficient financial markets.

3. The Determinants of Stock Market integration

In this section, we build on the work already presented and we utilize a two step estimation methodology to find the main determinants of stock market integration. First, we present the arguments for potential determinants selected. Following that, we test for causality between stock market integration and European currency unification to facilitate an appropriate modeling strategy. Finally, our empirical methodology and results will be discussed in detail.

4.1 Potential explanatory variables for stock market integration

To substantiate the link between stock market integration and the EMU we first test the significance of a euro dummy in explaining the previously estimated conditional correlation time series. We believe that a euro dummy (taking the value of one from 1 January 1999 and zero otherwise) is the broadest proxy for the introduction of the euro and can be used as a first assessment in regression analyses.

It has also been recognized in the literature that what drives time variations in financial market integration may not only be a country's own economic performance, but also the degree of real and financial convergence with other economies (eg. Ragunathan et al., 1999, Dickinson, 2000 and Fratzscher, 2002). The Optimal Currency Area (OCA) literature pioneered by Mundell (1961) and McKinnon (1963) offers several assessment criteria for the suitability of countries for a common currency area. There are three main channels identified in the literature through which a currency union can directly affect financial market integration and we will build on these and introduce other variables in a linear systems regression to determine the driving forces behind the regional and global integration of stock markets in the EMU.

Firstly, given that currency risk premia has been priced in most international asset pricing models since the seminal paper by Solnik (1974), it has been recognized that currency risk premia can be interpreted as a major impediment to financial integration and that the launch of a common currency directly eliminates most intra-union currency risk.[20] Although, elimination of intra-union exchange rates with the introduction of the euro has been shown by Morana and Beltratti (2002) in a theoretical variance decomposition of shocks to excess returns to cancel out components of exchange rate risks borne by a domestic investor holding foreign stock under a

[20] A single currency zone is equivalent to a system of irrevocably fixed exchange rates.

different currency, they argue that because the covariance between exchange rates and stock returns is empirically small, elimination of intra-union currency risk has not affected European stock markets. However, Fratzscher (2002) provides empirical evidence using rolling standard deviations of exchange rates against the Deutschmark and the US dollar that exchange rate stabilization does significantly explain stock market integration in Europe. We seek to resolve this disparity on exchange rate risk as we believe that this is a vital issue relating to stock market integration and currency unions. Theoretically, interdependent movements (estimated conditional correlations) between the individual national stock market returns should increase as foreign exchange volatility has reduced (inverse relationship).

Secondly, as EMU members knew in advance that they were required to meet various economic convergence criteria for EMU entry from the 1993 Maastrict (EU) Treaty, a significant degree of convergence has occurred in their real economies. It has long been found that business cycle conditions are intricately linked with asset returns (see Fama and French, 1989 and Rouwenhorst, 1995) and international equity correlations (see Erb, Harvey and Viskanta, 1994). If countries are in similar phases of the business cycle, the degree to which shocks are transmitted across financial markets will be increased. Thus, we expect *a priori,* increases in real convergence (via growth rates in industrial production) will stimulate higher stock market integration.

Finally, the EMU integration process has also been characterized by monetary policy convergence in that independent monetary policies have been replaced by a single one for all EMU members. For this reason, Morana and Beltratti (2002) also showed in their variance decomposition that the variance of interest rates have reduced through the convergence of monetary policies and attributed the decline in volatility of European stock markets mainly to the stabilization of fundamentals and expectations thereof.[21] Hence, we anticipate *a priori* that

[21] Fratzscher (2002) also provides a similar view.

monetary policy convergence (via short term interest rates and inflation rates) has also increased stock market integration.

In addition to these, we introduce control variables used in standard asset pricing studies to ascertain the true importance of these currency union variables. Our control variables include country specific aggregate stock market liquidity and development measures and other seasonal anomalies that might change stock market returns and hence, comovements. We test for the significance of domestic financial development as commonly measured by stock market capitalization as a proportion of Gross Domestic Product (GDP) and liquidity as proxied by the logarithm of turnover by volume. In addition, we test for a day of the week effect using a Friday dummy and the turn of the year effect using a January dummy.[22] Before these variables can be tested, we must establish the existence and nature of causality between the European currency union and observed stock market integration.

4.2 Direction of Causality: Stock Market integration and Currency Union

Although we have documented stock market integration in the period characterized by the introduction of the euro and beyond, it does not explicitly provide evidence of a causal relationship. To our knowledge, the causality issue between financial market integration and currency unification has never been addressed in the international finance literature. Indeed, questions remain about causality: do currency unions drive financial market integration in that a political decision to form a currency union could anchor exchange rate expectation and create incentives to establish integrated capital markets or does financial integration create more incentives for joining a currency union, or both? Although logic supports the former, economic theory purports that financial market integration promotes risk sharing benefits through asset

[22] A Monday dummy was also initially included but had no explanatory power for any country

markets and this may create economic incentives for countries to join a currency union and give up control of their monetary policy. Optimal currency area (OCA) theory clearly suggests that as integration proceeds, monetary unions will become more desirable as the costs for foregoing an independent monetary policy are higher for countries that are prone to asymmetric shocks. Given that each member state has unique challenges based upon its own degree of diversification in production (industry mix), economic, cultural, political and social institutions, causality from financial market integration to currency unification is also a reasonable assumption. Alternatively, there may not be causality either way but instead, independence. According to Krugman (1993), currency unions can exacerbate asymmetric shocks by inducing regional specialization of production based on comparative advantage considerations. In this way, a currency union may lead to greater segmentation rather than integration. It is clear that there is a need for deeper understanding of stock market integration in currency unions.

To address this issue, the Granger Causality test was conducted between the previously estimated time varying conditional correlations ($\hat{INT_t}$) and a euro dummy (EMU_t) which takes a value of one from January 1 1999. We used various lag structures (2,4, 6 and 8) for each of the individual countries, and found that there exists a uni-directional relationship running from the EMU to the stock market integration. The first null hypothesis ($\hat{INT_t}$ causing EMU_t) was rejected for all euro and non-euro countries at the 10% significance level but not France, Spain, Austria, nor Finland at the 5% level. However, the second null hypothesis (EMU_t causing $\hat{INT_t}$) could not be rejected for all meaningful significance levels indicating that financial market integration has not preceded the currency unification in Europe[23].

Our simple analysis provides a better understanding of the path to financial market integration on both a regional and global scale. There is consistent evidence across our sample of countries to show that the currency regime is a pre-requisite for financial market integration as the EMU was found to Granger cause stock market integration between all euro members. Furthermore, the EMU has also Granger caused financial integration of the EMU vis-à-vis Japan and the US. These results are not only illuminating but also helpful for finding a suitable model specification to determine the true extent to which the EMU is driving the time varying integration process in stock markets. We will account for this one-way direction of causality in the following section.

4.3 Methodology and Empirical evidence: explaining stock market integration

Given the upward trend in most integration (conditional correlation) series estimated from the bivariate EGARCH model, tests for non-stationarity were first conducted to determine the appropriate model for our dependent series. The results from unit root tests (Augmented Dickey Fuller (ADF) tests with a constant, trend and using 4 lags) are shown in panel A, Table 5. The null hypothesis of the presence of a unit root in each of the dependent series for the 12 EMU countries and for Japan and the US are rejected at the conventional 5% significance level. However, Durbin-Watson statistics revealed these dependent series to be highly autocorrelated, necessitating the inclusion of lags of these series in the econometric models in addition to Newey-West (1987) corrections for hetereoscedasticity and serial correlations.[24]

Ordinary least squares (OLS) and seemingly unrelated regression estimations (SURE) in the vein of Zellner (1962) have been sequentially applied to determine the drivers of the stock market integration process in the sample countries and the results are shown in Tables 6 and 7.

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[23] Details of the model construction of the tests and the results are not reported due to space constraints. Interested readers may obtain these from the corresponding author upon request.

[24] Serial correlations of residuals in a regression model with lagged dependent variables can potentially bias the estimators.

The assumption under SURE is that the error terms in a system of equations at any point in time are contemporaneously correlated because they are capturing similar effects. This is reasonable for our EMU and non-EMU countries given that these error terms contain the influence of omitted factors on their respective integration process eg. regulatory barriers, political, institutional, social and cultural factors. Since the members are similar in nature due to economic convergence required by the Maastrict (EU) Treaty, it is conceivable that the effects of the omitted variables on each country's integration will be similar. Hence, additional information normally excluded from separate least squares estimation of the equations is captured by this assumption. Contemporaneous correlations between error terms have been utilized to produce better estimates by jointly estimating these equations within a generalized least squares (GLS) framework[25].

Building on from the Granger causality tests, we begin our multivariate analysis with the simple assumption that stock market integration has been solely driven by the formal introduction of the euro (as proxied by the EMU dummy). To provide accurate estimates on the relative importance of this explanatory variable in explaining comovement in these stock markets, we control for stock market volume and financial development and other confounding seasonal anomalies that might change stock market returns. Thus, we also control for day of the week effects and turn of the year effects by introducing a Friday dummy and a January dummy respectively (See Appendix A). Furthermore, we account for persistence in the integration levels with lags of the dependent variable. Specifically, we estimate the following model both individually for each country using OLS and together for all EMU members and then for Japan and the US together using SURE:

[25] We performed correlation analyses between the residuals in each equation as reported in Tables 6 and 7. The results revealed fairly high correlations (average of aa for the Table 6 estimations and bb for the Table 7 estimations) providing justification for using the SURE.

$$\hat{INT}_{i,t} = \alpha_{1i} + \alpha_{2i} FIN\_DEPTH_{i,t-1} + \alpha_{3i} Log(VOL)_{i,t-1} + \alpha_{4i} FRI\_DUM_{i,t} + \alpha_{5i} JAN\_DUM_{i,t} + \alpha_{6i} EMU_{i,t} + \alpha_{7i} \hat{INT}_{i,t-1} + \alpha_{8i} \hat{INT}_{i,t-2} + u_{it} \quad (11)$$

where the dependent variable ($\hat{INT}_{it}$) is the estimated conditional correlation series for each country *i*, *FIN_DEPTH* = stock market capitalization divided by GDP, *LOG(VOL)*[26] = logarithm of the stock market's turnover by volume, *FRI_DUM* and *JAN_DUM* are the seasonal dummies, *EMU* is the euro dummy[27] which takes a value of one from 1st January 1999 and $\hat{INT}_{i,t-1}$ and $\hat{INT}_{i,t-2}$ are the first and second lags of the dependent variable.[28]

It can be seen in panel A, Table 5, that the benchmark OLS estimates are not very informative but in panel B, the SURE estimate for the EMU dummy variable is significant for most of the EMU member states and also for Japan but not the US. As expected, the SURE coefficients had lower standard errors than their OLS counterparts in most cases. However, p-values have been shown to facilitate our interpretation of statistical significance. As expected, the regressions indicate that introduction of the euro has had a significantly positive effect on the integration of their stock markets with the euro zone. The stock market control variables are nearly all significant suggesting that existing levels of stock market development are important for the integration process. The Friday dummy is significant only for Greece and the January effect is significant in Portugal, Greece and to a lesser extent in Japan implying that integration is subject to seasonality issues in these countries. This is the first study to have analyzed seasonality in European stock market integration and it is clearly present.

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[26] As a robustness check, the volume variable was also detrended by first estimating the regression $VOL_{it} = \alpha_i + \beta_i t + \xi_{it}$ where *t* is a time trend and then using $\hat{\xi}_{it-1}$ in equations (11)-(12) in place of $LOG(VOL)_{i,t-1}$. The significance of the two stock market variables did not differ greatly.

[27] As a robustness check, an alternative EMU dummy used for Greece took a value of one for dates after 1 January, 2001 (ie. Greece's formal entry into the EMU) but there were no qualitative differences in our results.

[28] We find that two lags sufficiently eliminate most of the serial correlation for all countries in our estimations.

Next, we attempt to replace the euro dummy with proxies for the three main channels through which the EMU has potentially affected stock market integration – namely, reduction in currency risk, convergence in the real economy and also in monetary policies.[29] The variables used in each category are those that are commonly employed in the OCA literature and are defined in Appendix A. In this study, we thoroughly weight all individual members to measure convergence in real and monetary terms with regional EMU levels. In the existing literature, convergence towards Germany has been commonly assessed as Germany is considered to be an anchor country to which other members in the union converge towards. However, given that economic performance between member states have been diverging in recent times, a weighted average of all members would be a better proxy for regional levels and provide a more accurate assessment of convergence due to the EMU. We recognize that in our attempt to explicitly model the different facets of currency unification, a degree of joint endogeneity may be introduced in that these changes coincided with the process of stock market integration in the transition period leading up to the EMU and also with each other. Thus, a degree of multicollinearity may also be introduced which potentially invalidates the inference of the estimators. Given the evidence on unidirectional causality from the monetary union to stock market integration, the independent variables that are not dummy variables have been lagged by one day in the regressions to separate the different contemporaneous sources of integration and to minimize bias in our estimated coefficients. Preliminary correlation analyses also suggest that multicollinearity is not of major concern in our models.[30] Specifically, we estimate the model below individually for each country using OLS and together for all EMU members and then for Japan and the US using SURE:

[29] Unlike Fratzscher (2002) who uses principal component analyses, we use individual proxies to facilitate more meaningful interpretation of estimated coefficients.
[30] Correlation matrices for all explanatory variables used in the regressions for each country have not been included due to space considerations but are available from the authors upon request.

$$\hat{INT}_{i,t} = \beta_{1i} + \beta_{2i}EX\_VOL_{i,t-1} + \beta_{3i}OUTPUT_{i,t-1} + \beta_{4i}IRATE_{i,t-1} + \beta_{5i}FIN\_DEPTH_{i,t-1} + \beta_{6i}Log(VOL \tag{12}$$

$$+\beta_{7i}FRI\_DUM_{i,t} + \beta_{8i}JAN\_DUM_{i,t} + \beta_{9i}\hat{INT}_{i,t-1} + \beta_{10i}\hat{INT}_{i,t-2} + u_{it}$$

where the dependent variable ($\hat{INT}_{it}$) is the estimated conditional correlation series for each country *i*, *EX_VOL* = conditional exchange rate volatility, *OUTPUT* = correlations in the growth of industrial production rates with euro area weighted averages, *IRATE* = correlations in nominal short term (30 day) interest rates with Euro area weighted averages, *FIN_DEPTH* = stock market capitalization/GDP, *LOG(VOL)* = logarithm of the stock market's turnover by volume, FRI_DUM and JAN_DUM are the seasonal dummies introduced before (See Appendix A) and $\hat{INT}_{i,t-1}$ and $\hat{INT}_{i,t-2}$ are the first and second lags of the dependent variable. It should be noted that we have used conditional exchange rate volatilities from a GARCH(1,1) to better capture the influence of past exchange rate variances.

The OLS and SURE results from this specification are shown in Table 6 and summarized in Table 9. From a statistical perspective, the model is adequate in explaining the variations in the integration series. While the adjusted R-squares are close to one in the presence of two autoregressive terms used to eliminate serial correlation, they fall to around 0.3-0.4 (with very low Durbin Watson Statistics) in their absence. Furthermore, significance of explanatory variables suggests that multicollinearity is not a problem in our model specification. From the economic perspective, most of the significant estimated coefficients have the expected signs. The intercept terms are significant and positive in most cases. Consistent with the initial specification, one of the two financial control variables (log of Volume and Financial depth) is positively significant for most countries in the EMU. This reinforces our belief that stock market integration is largely dependent on the existing size and level of financial development and is consistent with Carrieri et al.'s (2001) findings for the integration of emerging stock markets. The Friday dummy is insignificant for all countries whilst the January effect is significant for Japan and

Ireland, Portugal, Austria, Luxembourg and Greece. Contrary to Karolyi and Stulz's (1996) study on stock market comovements between Japanese and US markets, we find little evidence of day of the week effects. These are indeed new findings for integration in European stock markets.

Contributions made by the three different mechanisms of the monetary unification have varied for member states in the union and there are some differences in our results with existing studies due to our systems estimation approach. Reductions in conditional foreign exchange volatilities have only been important to stock market integration for the Netherlands and the two smaller countries, Luxembourg and Greece as indicated by the negative and significant coefficients. Our results appear to be a compromise between the theoretical arguments made by Morana and Beltratti (2002) and Fratzscher's (2002) empirical findings in that we find exchange rate stability conditioned on the past has only been important for the integration of some stock markets and not all. Our empirical results lend more support to the argument that changes in stock market comovements are not primarily due to changes in the currency risk premia, consistent with Bodart and Reding's (1999) finding that correlations in stock returns are not very sensitive to the exchange rate regime. This makes intuitive sense given that exchange rates have been required to fluctuate within narrow bands from a basket of European currencies (ECU) since 1979. This makes the euro a close substitute for the currencies of most major EMU countries anyway. Our results show that it is only in those smaller member states with fundamentally different economic structures, where the reduction in exchange rate risk has spurred integration in their stock markets. Our results for the other two EMU variables are not directly comparable with Fratzscher's (2002) findings as we have not used the principal component approach. Nevertheless, we are shedding light on the importance of the proxies which we have used. Real convergence via growth in industrial production appears to have provided impetus for the integration process in Italy, Portugal, Austria and to a lesser extent Japan. Finally, convergence towards a single interest rate has only been significant and beneficial for Italy.

These results are consistent with the existing evidence that reductions in the volatility of macroeconomic fundamentals associated with the Euro's introduction have been the key reason behind calmer stock market volatility in Italy (Morana and Beltratti, 2002). Although these authors also reach similar conclusions for stock market volatility in Spain, our analyses suggest that the EMU stabilization process has not played a key role in its path towards stock market integration.

An alternative specification estimated for Japan and the US is also shown in Table 6. Correlation in consumer price inflation is used to proxy monetary policy convergence instead of nominal short term interest rates. It is revealed that the commitment of monetary authorities to price stability has been an important factor behind higher levels of comovement between the EMU and the US whilst real convergence has been more important for increasing ties between the EMU and Japan. This suggests that implementation of a single currency area has enhanced supranational economic policy coordination by the European Central Bank (ECB) and has contributed to the phenomenal integration of stock market across regions. Although not tabulated, correlations in inflation rates were found not to have significant explanatory power for EMU members over correlations in short term interest rates in equation (12) perhaps due to the Balassa-Samuelson effect documented in the macroeconomic literature (eg. Eichengreen and Ghironi, 2001). In a currency union, the smaller and less developed economies tend to experience relatively higher levels of consumer price inflation due to increased competition resulting in major price imbalances.

All these results suggest that the increase in stock market integration has been a self-fuelling process driven by existing levels of stock market development in the economy. The EMU has played a significant role in stock market integration for those member states with fundamentally different macroeconomic structures or historically volatile stock markets and also on an inter-regional level through more coordinated policy stances.

4. Conclusions

The aim of this paper was to investigate the dynamic nature and determinants of regional and global stock market integration. We have documented that both intra-regional and inter-regional stock market integration was highly volatile prior to the second half of the 1990s and it had increased rapidly in the two years leading up to the official launch of the euro. Since 1999, the process has been much stronger and more stable than before and with the benefit of a longer post-euro sample period, a regime shift is revealed for all EMU stock markets. As a result, intra-regional and inter-regional return and volatility spillovers have been heightened in the period characterized by the introduction of the euro. We have also managed to shed light on the gaps and disparities in the link between currency unions and financial market integration. In particular, we have established unidirectional causality from the political creation of the European currency union to the integration between stock markets within EMU member states and also with Japan and the US. Moreover, our two step systems estimation approach for the group of EMU members reveals that increasing stock market comovements can be explained with the overall macroeconomic convergence process associated with the introduction of the euro rather than the specific effects of the elimination of the foreign exchange rate risk due to the currency conversion. However, financial market integration is largely a self-fueling process dependent on existing levels of financial sector development and is particularly strong during the month of January. In addition, we have found that the contribution of currency stability to stock market integration is only significant for the smaller EMU members with historically different economic structures. As a result of the European Monetary System introduced in 1979, the euro was already a very close substitute for most major European currencies. On a global level, the commitment to price stability has significantly strengthened stock market integration between the

EMU and the US whilst convergence in the industrial production has increased ties between the EMU and Japan. Although diversification benefits have reduced, the process of financial integration remains incomplete for the smaller member states and opportunities to invest in the euro zone remains. Complete integration of Europe's stock markets will ultimately depend on many factors and the removal of other impediments will take some time.

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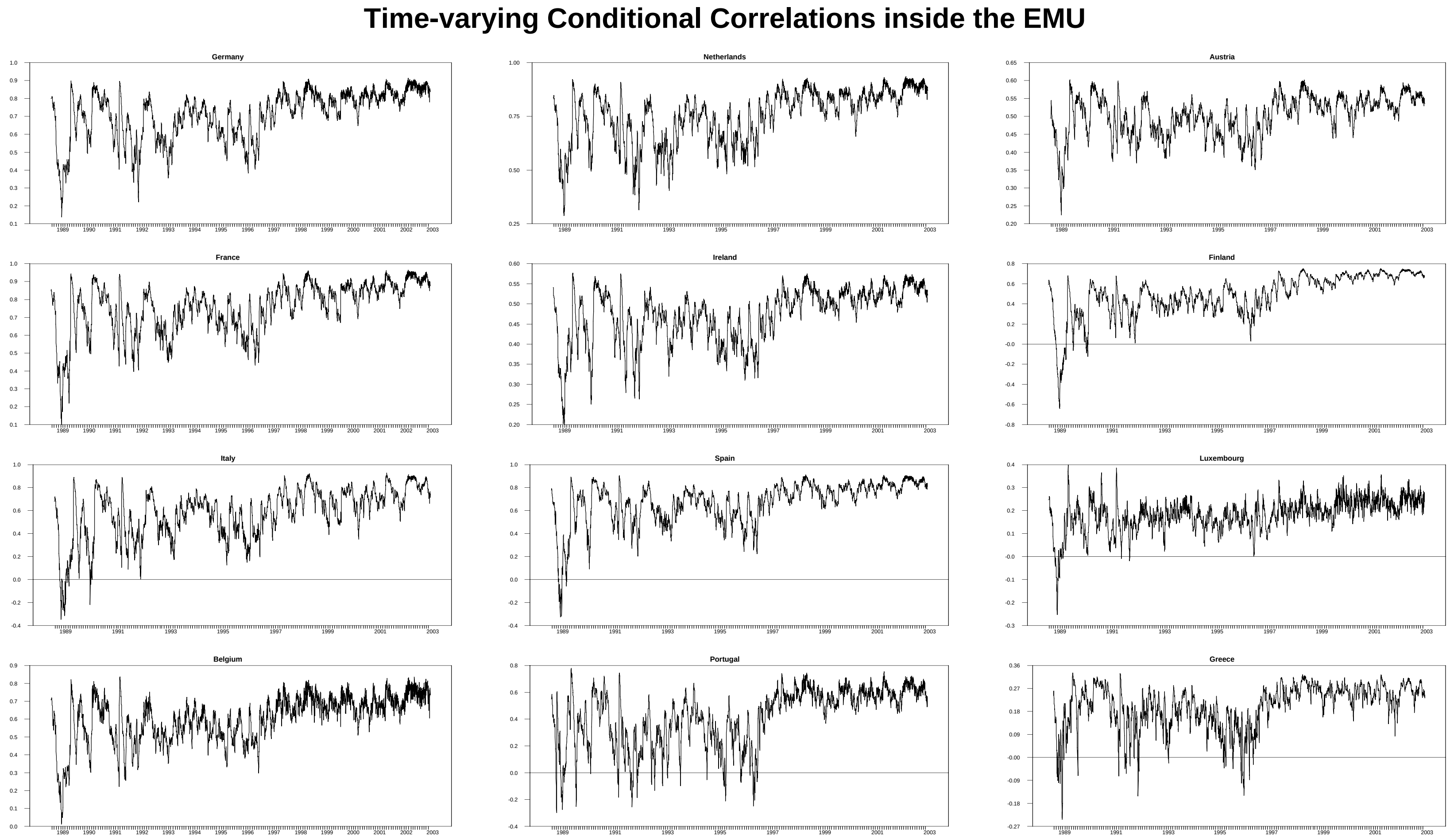

Figure 1. Time varying stock market integration, 1/1989-5/2003

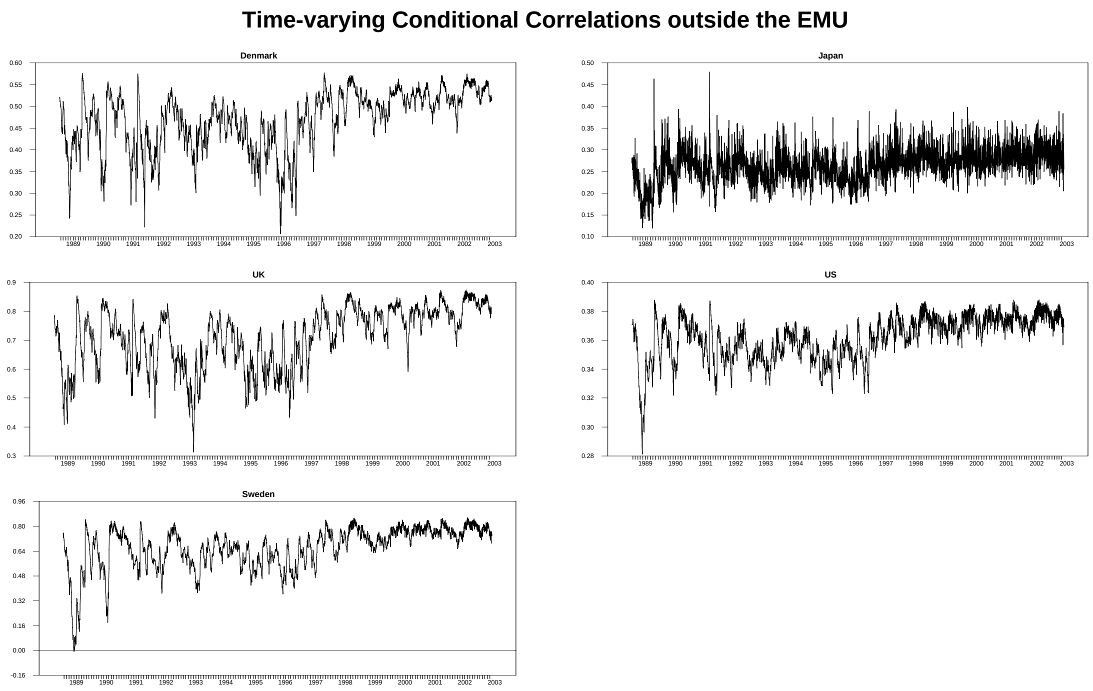

Figure 2. Time varying stock market integration, 1/1989-5/2003

Figure 3: Size of Regional Feedback Effect

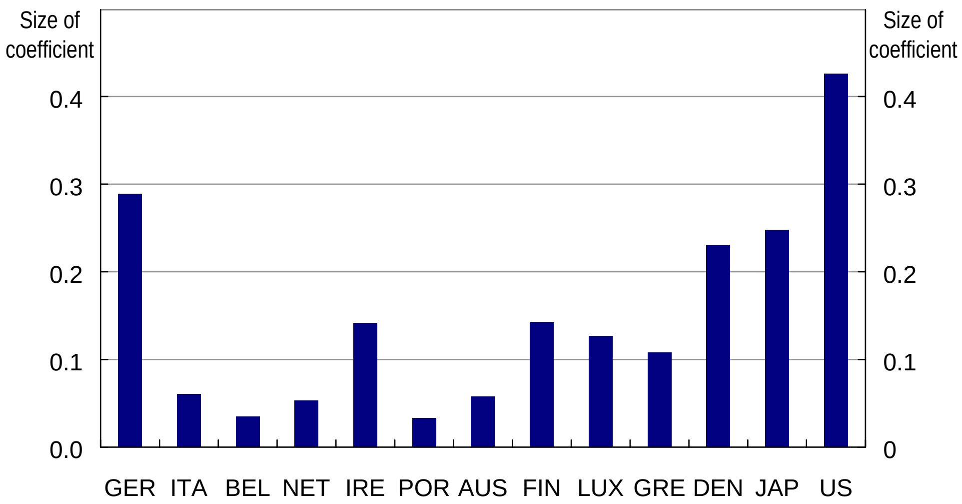

Figure 4: Size of Country Feedback Effect

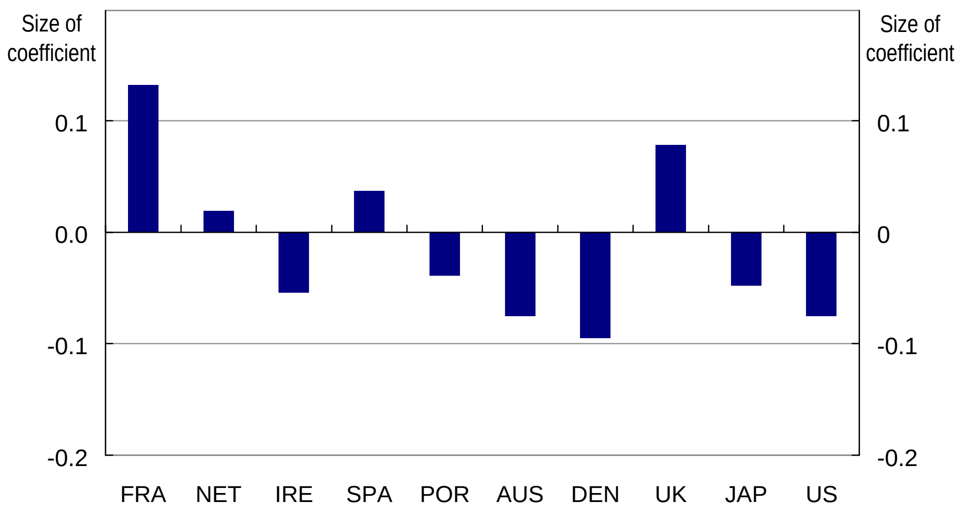

Table 1

Statistical properties of daily equity returns (%), 2/1/1989-29/5/2003

This table presents in panel A, the summary statistics on daily continuously compounding stock market index returns for the 12 countries belonging to the euro zone and the respective regional returns for the euro zone (*excluding* that country) weighted by stock market capitalization. In panel B, summary statistics for the three EU countries *not* belonging to the euro zone as well as Japan and the US are reported. The single regional return is for the total euro area weighted by stock market capitalization. Asymptotic p-values are shown in the brackets. *,**,*** denote statistical significance at the 10, 5 and 1% level respectively. Test results for H_0:Skewness=0 and H_0:Excess kurtosis=0 are indicated. Q(20) is the Ljung-Box test statistic for serial correlation up to the 20th order in the return series; $Q^2(20)$ is the Ljung-Box test statistic for serial correlation up to the 20th order in the squared returns. $Q_b(20)$ and $Q^2{}_b(20)$ are the bivariate Ljung-Box tests for joint white noise in the linear and squared national and regional stock returns up to the 20th order.

	National Stock Index Return				Test of univariate iid		Regional Stock Index Return				Test of univariate iid		Test of bivariate iid	
	Mean return	Variance	Skewness	Excess Kurtosis	Q(20): $\chi^2(20)$	$Q^2(20)$: $\chi^2(20)$	Mean return	Variance	Skewness	Excess Kurtosis	Q(20): $\chi^2(20)$	$Q^2(20)$: $\chi^2(20)$	$Q_b(20)$: $\chi^2(80)$	$Q^2{}_b(20)$: $\chi^2(80)$
Panel A: Euro zone														
GER	0.021	2.167	-0.429***	5.868***	38.482***	1512.131***	0.020	1.189	-0.287***	4.624***	87.712***	3471.027***	256.341***	3546.256***
					{0.008}	{0.000}					{0.000}	{0.000}	{0.000}	{0.000}
FRA	0.019	1.568	-0.207***	3.692***	69.661***	2916.583***	0.020	1.313	-0.428***	5.496***	66.605***	2127.954***	118.373***	3185.987***
					{0.000}	{0.000}					{0.000}	{0.000}	{0.003}	{0.000}
ITA	0.016	2.044	-0.151***	2.422***	65.952***	1208.035***	0.020	1.334	-0.385***	5.288***	73.595***	2700.775***	115.566***	3931.573***
					{0.000}	{0.000}					{0.000}	{0.000}	{0.006}	{0.000}
BEL	0.011	0.975	0.209***	7.141***	202.783***	2343.524***	0.020	1.339	-0.424***	5.327***	72.197***	2386.435***	249.010***	3384.443***
					{0.000}	{0.000}					{0.000}	{0.000}	{0.000}	{0.000}
NET	0.023	1.563	-0.214***	5.627***	87.180***	5568.123***	0.019	1.323	-0.437***	5.460***	71.713***	1872.402***	148.439***	5717.393***
					{0.000}	{0.000}					{0.000}	{0.000}	{0.000}	{0.000}
IRE	0.028	1.392	-0.413***	6.590***	66.336***	557.308***	0.019	1.314	-0.396***	5.304***	75.106***	2575.747***	172.565***	2832.559***
					{0.000}	{0.000}					{0.000}	{0.000}	{0.000}	{0.000}
SPA	0.023	1.742	-0.195***	3.669***	41.734***	2000.760***	0.019	1.315	-0.414***	5.404***	76.168***	2495.642***	99.108*	3026.535***
					{0.003}	{0.000}					{0.000}	{0.000}	{0.073}	{0.000}
POR	0.022	0.834	-0.770***	14.332***	222.748***	354.056***	0.019	1.314	-0.396***	5.303***	75.722***	2585.584***	288.342***	3335.936***
					{0.000}	{0.000}					{0.000}	{0.000}	{0.000}	{0.000}
AUS	0.020	1.153	-0.448***	7.383***	184.670***	1042.343***	0.020	1.308	-0.398***	5.335***	75.384***	2554.098***	204.305***	4004.139***
					{0.000}	{0.000}					{0.000}	{0.000}	{0.000}	{0.000}
FIN	0.045	4.734	-0.229***	6.892***	41.354***	1011.389***	0.019	1.262	-0.429***	5.601***	76.325***	2491.692***	105.219**	3251.184***
					{0.003}	{0.000}					{0.000}	{0.000}	{0.031}	{0.000}
LUX	0.022	0.949	-0.028	13.082***	94.641***	694.916***	0.019	1.305	-0.401***	5.338***	75.553***	2536.346***	192.518***	3228.246***
					{0.000}	{0.000}					{0.000}	{0.000}	{0.000}	{0.000}
GRE	0.049	3.203	0.120***	5.193***	127.703***	662.149***	0.019	1.317	-0.395***	5.336***	74.655***	2585.554***	163.823***	3344.325***
					{0.000}	{0.000}					{0.000}	{0.000}	{0.000}	{0.000}
Panel B: Non-Eurozone														
DEN	0.030	0.885	-0.451***	5.290***	89.261***	650.460***	0.019	1.027	-0.480***	5.304***	82.397***	1999.688***	195.123***	2274.888***
					{0.000}	{0.000}					{0.000}	{0.000}	{0.000}	{0.000}
UK	0.023	0.914	-0.160***	3.195***	81.346***	2947.509***							128.465***	3448.464***
					{0.000}	{0.000}							{0.000}	{0.000}
SWE	0.027	2.130	0.139***	4.404***	71.322***	1085.047***							130.191***	2426.712***
					{0.000}	{0.000}							{0.000}	{0.000}
JAP	-0.026	1.490	0.162***	4.152***	76.992***	580.898***							222.113***	2556.963***
					{0.000}	{0.000}							{0.000}	{0.000}
US	0.035	1.057	-0.179***	4.338***	46.424***	1295.261***							165.289***	3316.050***
					{0.001}	{0.000}							{0.000}	{0.000}

Table 2

Bivariate-ARMA-EGARCH-*t* Model Estimations

In this table, the results of the bivariate EGARCH estimations are reported. The bivariate EGARCH model for each country, as defined in equations (3)-(6), is

$$R_{N,t} = \alpha c_N + \sum_{i=1}^{p_E} \alpha r_{E,i} R_{E,t-p_E} + \sum_{j=1}^{q_N} m\alpha_{N,j}\varepsilon_{N,t-q_N} + \varepsilon_{N,t}$$
$$R_{E,t} = \alpha c_E + \sum_{i=1}^{p_N} \alpha r_{N,i} R_{N,t-p2} + \sum_{j=1}^{q_E} m\alpha_{E,j}\varepsilon_{E,t-q_E} + \varepsilon_{E,t} \quad (3a)$$

$$\ln h_{N,t} = \beta c_N + \beta_{hN} \ln h_{N,t-1} + \left[\beta\varepsilon_{N1}\frac{\varepsilon_{N,t-1}}{\sqrt{h_{N,t-1}}} + \beta\varepsilon_{N2}\left(\frac{|\varepsilon_{N,t-1}|}{\sqrt{h_{N,t-1}}} - \sqrt{\frac{2}{\pi}}\right)\right] + \left[\beta_{E1}\frac{\varepsilon_{E,t-1}}{\sqrt{h_{E,t-1}}} + \beta_{E2}\left(\frac{|\varepsilon_{E,t-1}|}{\sqrt{h_{E,t-1}}} - \sqrt{\frac{2}{\pi}}\right)\right], \quad (4a)$$

$$\ln h_{E,t} = \beta c_E + \beta_{hE} \ln h_{E,t-1} + \left[\beta\varepsilon_{E1}\frac{\varepsilon_{E,t-1}}{\sqrt{h_{E,t-1}}} + \beta\varepsilon_{E2}\left(\frac{|\varepsilon_{E,t-1}|}{\sqrt{h_{E,t-1}}} - \sqrt{\frac{2}{\pi}}\right)\right] + \left[\beta_{N1}\frac{\varepsilon_{N,t-1}}{\sqrt{h_{N,t-1}}} + \beta_{N2}\left(\frac{|\varepsilon_{N,t-1}|}{\sqrt{h_{N,t-1}}} - \sqrt{\frac{2}{\pi}}\right)\right] \quad (5a)$$

	Eurozone												Non-Eurozone				
	GER	FRA	ITA	BEL	NET	IRE	SPA	POR	AUS	FIN	LUX	GRE	DEN	UK	SWE	JAP	US
Mean: R_N																	
α_{cN}	0.041***	0.048***	0.033**	0.035***	0.043***	0.037***	0.058***	0.020**	0.038***	0.027	0.038***	0.012	0.038***	0.038***	0.080***	-0.036***	0.035***
	{0.003}	{0.000}	{0.029}	{0.001}	{0.000}	{0.008}	{0.000}	{0.047}	{0.006}	{0.156}	{0.000}	{0.598}	{0.002}	{0.001}	{0.000}	{0.002}	{0.000}
αr_{E1}	0.289***	0.013	0.061***	0.035***	0.053***	0.142***	-0.013	0.033***	0.058***	0.143***	0.127***	0.108***	0.230***	-0.006	0.029	0.248***	0.426***
	{0.000}	{0.580}	{0.006}	{0.000}	{0.000}	{0.000}	{0.193}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.793}	{0.222}	{0.000}	{0.000}
P_E	1	1	1	1	1	1	1	1	1	1	5	1	1	1	1	1	1
Q_N	7	1	5	3	5	3	3	4	8	5	9	3	0	1	2	1	7
Vol.:R_N																	
β_{cN}	1.485***	1.496***	1.482***	1.415***	1.452***	1.456***	1.464***	1.368***	1.439***	1.518***	1.197***	1.375***	1.422***	1.490***	1.473***	1.436***	1.465***
	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}
β_{hN}	0.987***	0.983***	0.972***	0.976***	0.983***	0.978***	0.980***	0.966***	0.966***	0.993***	0.921***	0.936***	0.968***	0.983***	0.984***	0.976***	0.979***
	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.00}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}
β_{uN1}	-0.019	-0.047***	-0.031**	-0.014	-0.049***	-0.003	-0.047***	0.017	-0.021	-0.013	0.012	-0.003	-0.012	-0.051***	-0.027**	-0.076***	-0.042***
	{0.187}	{0.000}	{0.014}	{0.278}	{0.000}	{0.790}	{0.000}	{0.233}	{0.105}	{0.419}	{0.316}	{0.737}	{0.412}	{0.001}	{0.044}	{0.000}	{0.001}
β_{uN2}	0.093***	0.078***	0.129***	0.109***	0.112***	0.096***	0.105***	0.205***	0.166***	0.102***	0.363***	0.329***	0.165***	0.091***	0.134***	0.157***	0.068***
	{0.001}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.002}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}
β_{E1}	-0.032***	-0.018	-0.010	-0.032**	-0.001	-0.026**	-0.006	-0.040**	-0.022*	-0.020*	-0.026**	-0.008	-0.028	-0.015	-0.025*	-0.019*	-0.030
	{0.003}	{0.258}	{0.487}	{0.012}	{0.893}	{0.017}	{0.672}	{0.046}	{0.094}	{0.086}	{0.027}	{0.294}	{0.107}	{0.371}	{0.057}	{0.078}	{0.108}
β_{E2}	0.055***	0.050***	0.036	0.104***	0.071***	0.085***	0.069***	0.054	0.029	0.009	0.101***	0.027***	0.041*	0.034***	0.029***	0.053***	0.087***
	{0.005}	{0.000}	{0.108}	{0.000}	{0.000}	{0.000}	{0.000}	{0.212}	{0.201}	{0.616}	{0.000}	{0.000}	{0.057}	{0.001}	{0.003}	{0.000}	{0.000}
Mean:R_E																	
α_{CE}	0.044***	0.045***	0.043***	0.049***	0.041***	0.044***	0.047***	0.041***	0.046***	0.032***	0.046***	0.042***	0.044***	0.040***	0.055***	0.044***	0.056***
	{0.000}	{0.000}	{0.000}	{0.000}	{0.001}	{0.000}	{0.000}	{0.001}	{0.000}	{0.004}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}
αr_{N1}	0.010	0.132***	0.016	0.016	0.019*	-0.054***	0.037***	-0.039***	-0.075***	0.003	-0.016	0.002	-0.095***	0.078***	0.016**	-0.048***	-0.075***
	{0.445}	{0.000}	{0.153}	{0.182}	{0.088}	{0.000}	{0.000}	{0.002}	{0.000}	{0.726}	{0.193}	{0.807}	{0.000}	{0.000}	{0.160}	{0.000}	{0.000}

P_N	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Q_E	6	1	3	0	5	7	1	2	5	2	4	3	4	1	1	4	2
Vol.: RE																	
β_{CE}	1.472***	1.471***	1.480***	1.468***	1.468***	1.469***	1.452***	1.478***	1.493***	1.482***	1.461***	1.464***	1.456***	1.452***	1.460***	1.439***	1.467***
	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}
β_{hE}	0.986***	0.984***	0.984***	0.981***	0.981***	0.982***	0.982***	0.983***	0.987***	0.980***	0.983***	0.983***	0.983***	0.980***	0.983***	0.979*	0.978***
	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}
β_{uE1}	-0.043***	-0.034	-0.037***	-0.053***	-0.033***	-0.056***	-0.017	-0.063***	-0.062***	-0.062***	-0.051***	-0.060***	-0.061***	-0.022**	-0.039***	-0.056**	-0.058***
	{0.000}	{0.117}	{0.000}	{0.000}	{0.000}	{0.000}	{0.234}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.236}	{0.002}	{0.000}	{0.000}
β_{uE2}	0.114***	0.121***	0.161***	0.130***	0.135***	0.150***	0.129***	0.131***	0.140***	0.141***	0.142***	0.148***	0.125***	0.131***	0.133***	0.159***	0.182***
	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}
β_{N1}	-0.009	-0.028	-0.025***	0.007	-0.035***	0.010	-0.046***	0.015	-0.018**	0.010	-0.003	-0.012**	0.016	-0.053***	-0.011	-0.033***	-0.008
	{0.533}	{0.108}	{0.001}	{0.504}	{0.000}	{0.380}	{0.005}	{0.206}	{0.039}	{0.289}	{0.653}	{0.025}	{0.217}	{0.009}	{0.426}	{0.000}	{0.385}
β_{N2}	0.039	0.033**	-0.016	0.029***	0.025*	0.008**	0.050***	0.013	-0.011	-0.001	0.026**	0.015***	0.045***	0.040***	0.030***	0.029***	0.030***
	{0.105}	{0.023}	{0.156}	{0.000}	{0.093}	{0.031}	{0.000}	{0.327}	{0.442}	{0.932}	{0.019}	{0.000}	{0.000}	{0.004}	{0.000}	{0.000}	{0.000}
Covariance																	
δ_0	-0.115***	-0.137***	-0.311***	-0.059***	-0.099***	-0.063***	-0.157***	-0.087***	-0.059***	-0.277***	-0.027***	-0.124***	-0.051**	-0.078***	-0.107***	-0.044**	-0.010
	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.015}	{0.000}	{0.000}	{0.010}	{0.662}
δ_1	0.712***	0.836***	0.814***	0.494***	0.806***	0.501***	0.791***	0.464***	0.524***	0.684***	0.140***	0.293***	0.523***	0.797***	0.657***	0.492***	0.347***
	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}
δ_2	0.210*	0.134**	0.145***	0.371***	0.130***	0.130***	0.134***	0.353***	0.131***	0.114***	0.514***	0.124**	0.095	0.091***	0.225***	-0.597***	0.099
	{0.056}	{0.047}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.002}	{0.000}	{0.010}	{0.610}	{0.005}	{0.000}	{0.000}	{0.366}
Diagnostics																	
d	48.410***	45.906***	52.603***	33.048***	47.207***	36.449***	42.039***	24.189***	40.404***	40.966***	25.505***	32.221***	35.929***	41.543***	40.126***	43.781***	48.034***
	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}
-Ln L	9316.048	8706.235	10326.733	8438.382	8461.270	9884.085	9415.108	8443.410	9423.102	11563.618	9185.353	11766.353	8633.881	7761.139	9488.770	9957.465	8791.552
$Q_b(10)$:	42.498	49.011	27.628	50.199	39.153	26.906	34.109	36.701	27.374	40.234	45.905	44.481	49.517	42.593	41.447	21.969	38.839
$\chi^2(40)$	{0.364}	{0.155}	{0.931}	{0.129}	{0.508}	{0.944}	{0.732}	{0.620}	{0.936}	{0.460}	{0.241}	{0.289}	{0.144}	{0.360}	{0.407}	{0.991}	{0.522}
$Q^2_b(10)$:	20.351	17.634	15.406	7.648	18.298	12.358	8.387	1.038	44.963	19.865	15.659	8.700	13.247	12.142	11.275	18.743	6.274
$\chi^2(40)$	{0.996}	{0.999}	{1.000}	{1.000}	{0.999}	{1.000}	{1.000}	{1.000}	{0.272}	{0.997}	{1.000}	{1.000}	{1.000}	{1.000}	{1.000}	{0.998}	{1.000}

*Notes: d is the degree of freedom in a student t distribution for the two joint error processes. -Ln L is the negative estimated value of log-likelihood. P-Values are shown in the brackets.***,*** denote significance at the 10%, 5% and 1% level respectively. $Q_b(10)$ and $Q^2_b(10)$ are the bivariate Ljung-Box tests for joint white noise in the linear and squared standardized residuals (z_t's and z^2_t's) up to the 10^{th} order.*

Table 3 Bivariate ARMA-EGARCH-*t* results for Stock Market (Mean) Return Spillovers

In this table, the estimated mean return spillovers from the national (αr_N) and regional (αr_E) stock markets are reported for the full sample period and three other sub-sample periods shown. Asymptotic p-values are shown in the brackets. *, **,*** denote statistical significance at the 10, 5 and 1% level respectively. The conditional mean equations, as defined in equation (3), is

$$R_{N,t} = \alpha c_N + \sum_{i=1}^{p_E} \alpha r_{E,i} R_{E,t-p_E} + \sum_{j=1}^{q_N} m\alpha_{N,j}\varepsilon_{N,t-q_N} + \varepsilon_{N,t};\ R_{E,t} = \alpha c_E + \sum_{i=1}^{p_N} \alpha r_{N,i} R_{N,t-p2} + \sum_{j=1}^{q_E} m\alpha_{E,j}\varepsilon_{E,t-q_E} + \varepsilon_{E,t} \qquad (3b)$$

	From Country i				From Eurozone			
Coefficient	αr_{N1}				αr_{E1}			
	Total	Sub sample periods			Total	Sub sample periods		
	1/89-5/03	1/89-12/95	1/96-12/98	1/99-5/03	1/89-5/03	1/89-12/95	1/96-12/98	1/99-5/03
Panel A: Eurozone								
GER	0.010	0.009	-0.065	0.179***	0.289***	0.298***	0.463***	-0.047
	{0.445}	{0.435}	{0.127}	{0.000}	{0.000}	{0.000}	{0.000}	{0.492}
FRA	0.132***	0.125***	0.161***	-0.096***	0.013	-0.016	-0.050	0.183***
	{0.000}	{0.000}	{0.000}	{0.008}	{0.580}	{0.596}	{0.267}	{0.000}
ITA	0.016	0.008	0.035**	0.063***	0.061***	0.199***	-0.051	0.064***
	{0.153}	{0.508}	{0.039}	{0.002}	{0.006}	{0.000}	{0.226}	{0.000}
BEL	0.016	-0.035	0.092	0.032	0.035***	0.107***	0.014	-0.037**
	{0.182}	{0.200}	{0.714}	{0.270}	{0.000}	{0.000}	{0.974}	{0.047}
NET	0.019*	0.049***	0.104	-0.085***	0.053***	0.017	0.008	0.199***
	{0.089}	{0.006}	{0.126}	{0.004}	{0.000}	{0.314}	{0.922}	{0.000}
IRE	-0.054***	-0.027	-0.111***	-0.092***	0.142***	0.159***	0.206***	0.102***
	{0.000}	{0.113}	{0.001}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}
SPA	0.037***	0.002	0.133**	-0.049	-0.013	0.026	-0.017	0.012
	{0.000}	{0.926}	{0.012}	{0.205}	{0.193}	{0.406}	{0.692}	{0.742}
POR	-0.039**	-0.042	-0.003	-0.029	0.033***	0.078***	-0.035	-0.006
	{0.002}	{0.123}	{0.931}	{0.329}	{0.000}	{0.000}	{0.127}	{0.639}
AUS	-0.075***	-0.048**	-0.114***	-0.143***	0.058***	0.188***	0.133***	0.278**
	{0.000}	{0.012}	{0.003}	{0.000}	{0.000}	{0.000}	{0.003}	{0.046}
FIN	0.003	0.015*	-0.075***	-0.005	0.143**	0.164***	0.218***	0.103**
	{0.726}	{0.088}	{0.000}	{0.328}	{0.000}	{0.000}	{0.002}	{0.048}
LUX	-0.016	-0.020	0.041	-0.029	0.127***	0.164***	0.106***	0.131***
	{0.192}	{0.200}	{0.101}	{0.345}	{0.000}	{0.000}	{0.000}	{0.000}
GRE	0.002	-0.001	0.014	-0.020	0.108***	0.074*	0.247***	0.092***
	{0.807]	{0.905}	{0.459}	{0.188}	{0.000}	{0.066}	{0.000}	{0.000}
Panel B: Non-Eurozone								
DEN	-0.095***	-0.072***	-0.180***	-0.065**	0.230***	0.278***	0.221***	0.214***
	{0.000}	{0.000}	{0.000}	{0.017}	{0.000}	{0.000}	{0.000}	{0.000}
UK	0.078***	0.088***	0.069**	-0.014	-0.006	-0.035	-0.019	0.038
	{0.000}	{0.000}	{0.042}	{0.810}	{0.793}	{0.180}	{0.893}	{0.156}
SWE	0.016	0.013	0.079	-0.018	0.029	0.009	0.005	0.151
	{0.160}	{0.471}	{0.977}	{0.348}	{0.222}	{0.780}	{0.999}	{0.000}
JAP	-0.048***	-0.032***	-0.083***	-0.052**	0.248***	0.153***	0.216***	0.342***
	{0.000}	{0.003}	{0.000}	{0.046}	{0.000}	{0.000}	{0.000}	{0.000}
US	-0.075***	-0.080***	-0.128***	0.004	0.426***	0.250***	0.480***	0.616***
	{0.000}	{0.000}	{0.001}	{0.883}	{0.000}	{0.000}	{0.000}	{0.000}

Table 4

Bivariate ARMA-EGARCH-*t* results for Stock Market Return Volatility Spillover

This table presents the estimated spillovers in negative and positive shocks from national (β_{N1}, β_{N2}) and regional (β_{E1}, β_{E2}) stock market returns. Asymptotic p-values are shown in the brackets. *, **, *** denote statistical significance at the 10, 5 and 1% level respectively. The conditional volatility equations, defined in equations (4)-(5), is

$$\ln h_{N,t} = \beta c_N + \beta_{hN} \ln h_{N,t-1} + \left[\beta\varepsilon_{N1} \frac{\varepsilon_{N,t-1}}{\sqrt{h_{N,t-1}}} + \beta\varepsilon_{N2}\left(\frac{|\varepsilon_{N,t-1}|}{\sqrt{h_{N,t-1}}} - \sqrt{\frac{2}{\pi}}\right)\right] + \left[\beta_{E1} \frac{\varepsilon_{E,t-1}}{\sqrt{h_{E,t-1}}} + \beta_{E2}\left(\frac{|\varepsilon_{E,t-1}|}{\sqrt{h_{E,t-1}}} - \sqrt{\frac{2}{\pi}}\right)\right], \qquad (4b)$$

$$\ln h_{E,t} = \beta c_E + \beta_{hE} \ln h_{E,t-1} + \left[\beta\varepsilon_{E1} \frac{\varepsilon_{E,t-1}}{\sqrt{h_{E,t-1}}} + \beta\varepsilon_{E2}\left(\frac{|\varepsilon_{E,t-1}|}{\sqrt{h_{E,t-1}}} - \sqrt{\frac{2}{\pi}}\right)\right] + \left[\beta_{N1} \frac{\varepsilon_{N,t-1}}{\sqrt{h_{N,t-1}}} + \beta_{N2}\left(\frac{|\varepsilon_{N,t-1}|}{\sqrt{h_{N,t-1}}} - \sqrt{\frac{2}{\pi}}\right)\right] \qquad (5b)$$

	From Country i								From Eurozone							
Coefficient	β_{N1}				β_{N2}				β_{E1}				β_{E2}			
	Total	Sub sample periods			Total	Sub sample periods			Total	Sub sample periods			Total	Sub sample periods		
	1/89-5/03	1/89-12/95	1/96-12/98	1/99-5/03	1/89-5/03	1/89-12/95	1/96-12/98	1/99-5/03	1/89-5/03	1/89-12/95	1/96-12/98	1/99-5/03	1/89-5/03	1/89-12/95	1/96-12/98	1/99-5/03
Panel A: Eurozone																
GER	-0.009	-0.022	-0.020	-0.090**	0.039	0.043	0.062	0.067	-0.032**	-0.024	-0.064	0.041	0.055***	-0.011	0.187***	0.111***
	{0.533}	{0.377}	{0.599}	{0.013}	{0.105}	{0.214}	{0.236}	{0.238}	{0.003}	{0.116}	{0.134}	{0.374}	{0.005}	{0.703}	{0.000}	{0.005}
FRA	-0.028	-0.051***	-0.163***	-0.021	0.033**	0.047***	0.024	-0.053*	-0.018	-0.017	0.139***	0.002	0.050***	0.023	0.181***	-0.010
	{0.108}	{0.002}	{0.000}	{0.404}	{0.023}	{0.002}	{0.586}	{0.096}	{0.258}	{0.197}	{0.001}	{0.891}	{0.000}	{0.120}	{0.000}	{0.534}
ITA	-0.025***	-0.019	-0.012	-0.019	-0.016	0.015	-0.023	0.104***	-0.010	-0.020	-0.041	-0.064***	0.036	0.008	0.062	-0.045
	{0.001}	{0.312}	{0.461}	{0.210}	{0.156}	{0.627}	{0.543}	{0.000}	{0.487}	{0.212}	{0.198}	{0.000}	{0.108}	{0.716}	{0.171}	{0.277}
BEL	0.007	0.027	-0.017	-0.030	0.029***	-0.005	-0.065	0.107***	-0.032**	-0.052**	-0.041	-0.057*	0.104***	0.134***	0.188	0.004
	{0.504}	{0.187}	{0.977}	{0.193}	{0.000}	{0.783}	{0.972}	{0.000}	{0.012}	{0.042}	{0.897}	{0.070}	{0.000}	{0.000}	{0.363}	{0.932}
NET	-0.035***	-0.039	-0.114***	-0.091***	0.025*	-0.024*	0.176***	0.032**	-0.001	-0.010	-0.006	0.054*	0.071***	0.059***	0.066	0.022**
	{0.000}	{0.265}	{0.001}	{0.000}	{0.093}	{0.095}	{0.000}	{0.042}	{0.893}	{0.695}	{0.908}	{0.052}	{0.000}	{0.005}	{0.342}	{0.036}
IRE	0.010	0.009	0.004	-0.005	0.008**	0.029**	0.021	-0.016	-0.026**	-0.026	0.047**	-0.048*	0.085***	0.074***	0.411***	0.071**
	{0.380}	{0.672}	{0.881}	{0.720}	{0.031}	{0.035}	{0.333}	{0.365}	{0.017}	{0.295}	{0.043}	{0.053}	{0.000}	{0.001}	{0.000}	{0.026}
SPA	-0.046***	-0.038***	-0.105	-0.051**	0.050***	0.064***	0.108	-0.006	-0.006	-0.009	0.027	-0.020	0.069***	0.014	0.199	0.085**
	{0.005}	{0.004}	{0.155}	{0.047}	{0.000}	{0.002}	{0.389}	{0.913}	{0.672}	{0.658}	{0.314}	{0.430}	{0.000}	{0.400}	{0.106}	{0.030}
POR	0.015	0.016	-0.090*	-0.008	0.013	-0.020*	0.099**	0.043**	-0.040**	-0.057**	-0.014	0.001	0.054	0.119**	0.184***	-0.022
	{0.206}	{0.211}	{0.067}	{0.622}	{0.327}	{0.090}	{0.020}	{0.003}	{0.046}	{0.020}	{0.746}	{0.959}	{0.212}	{0.018}	{0.000}	{0.294}
AUS	0.018**	0.023**	0.072**	-0.017	-0.011	0.049***	0.029	-0.033	-0.022*	-0.056***	-0.115***	0.017	0.029	-0.015	0.237***	0.030
	{0.039}	{0.031}	{0.010}	{0.361}	{0.442}	{0.000}	{0.406}	{0.122}	{0.094}	{0.002}	{0.009}	{0.505}	{0.201}	{0.465}	{0.001}	{0.220}
FIN	0.010	0.022	0.032	0.058***	-0.001	0.030***	0.059	-0.064***	-0.020*	-0.011	-0.101***	-0.085**	0.009	0.009**	0.138**	0.003
	{0.289}	{0.171}	{0.375}	{0.002}	{0.932}	{0.005}	{0.242}	{0.006}	{0.086}	{0.554}	{0.002}	{0.023}	{0.616}	{0.023}	{0.027}	{0.936}
LUX	-0.003	-0.001	-0.025	0.033	0.026**	0.025**	0.051***	0.035	-0.026**	0.015	-0.125***	-0.070**	0.101**	0.111***	0.172***	0.009
	{0.653}	{0.944}	{0.186}	{0.179}	{0.019}	{0.000}	{0.000}	{0.265}	{0.027}	{0.475}	{0.009}	{0.027}	{0.000}	{0.000]	{0.007}	{0.612}
GRE	0.012**	0.026***	-0.015	-0.028	0.015***	-0.004	0.034	0.047***	-0.008	-0.014	0.047	-0.033	0.027***	0.027***	0.198**	-0.017
	{0.025}	{0.003}	{0.588}	{0.122}	{0.000}	{0.161}	{0.339}	{0.000}	{0.294}	{0.331}	{0.215}	{0.269}	{0.000}	{0.000}	{0.019}	{0.258}
Panel B: Non-Eurozone																
DEN	0.016	0.012	0.051**	-0.027*	0.045***	-0.017***	0.133***	0.055***	-0.028	0.041	-0.100***	-0.087**	0.041*	0.092***	0.216***	0.060*
	{0.217}	{0.325}	{0.027}	{0.090}	{0.000}	{0.000}	{0.000}	{0.007}	{0.107}	{0.303}	{0.000}	{0.019}	{0.057}	{0.001}	{0.001}	{0.081}
UK	-0.053***	-0.047**	-0.094**	-0.142***	0.040**	0.083**	0.030	-0.020	-0.015	-0.024	-0.001	0.054***	0.034***	-0.015	0.132	0.029***

	{0.009}	{0.046}	{0.028}	{0.000}	{0.004}	{0.025}	{0.477}	{0.328}	{0.371}	{0.376}	{0.938}	{0.000}	{0.001}	{0.590}	{0.192}	{0.000}
SWE	-0.011	-0.018	-0.030	0.010	0.030***	0.040	0.120	0.038	-0.025*	-0.016	-0.062	-0.017	0.029***	0.029	0.149	0.022
	{0.426}	{0.426}	{0.978}	{0.392}	{0.000}	{0.127}	{0.833}	{0.152}	{0.057}	{0.382}	{0.179}	{0.533}	{0.003}	{0.331}	{0.974}	{0.370}
JAP	-0.033***	-0.030***	-0.065***	-0.016	0.029***	0.045***	0.067*	0.003	-0.019*	-0.020	0.001	-0.028	0.053***	0.006	0.102***	0.122***
	{0.000}	{0.009}	{0.003}	{0.331}	{0.000}	{0.000}	{0.099}	{0.616}	{0.078}	{0.270}	{0.955}	{0.287}	{0.000}	{0.620}	{0.014}	{0.000}
US	-0.008	-0.011	-0.040***	-0.016	-0.030***	-0.066***	0.068***	-0.036***	-0.030	-0.008	-0.038	-0.085**	0.087***	0.052	0.147**	0.092***
	{0.385}	{0.191}	{0.002}	{0.394}	{0.000}	{0.000}	{0.000}	{0.000}	{0.108}	{0.593}	{0.638}	{0.020}	{0.000}	{0.101}	{0.020}	{0.000}

Table 5

Regression results with Euro dummy alone

In panel A of this table, the OLS results and Augmented Dickey Fuller (ADF) Statistics are reported for each country. The OLS estimates are corrected for autocorrelation and heteroskedasticity in accordance with Newey West (1987). In panel B, the seemingly unrelated regression estimates are shown. The model estimated by both methods, as defined in equation (11) is

$$\hat{INT}_{i,t} = \alpha_{1i} + \alpha_{2i} FIN\_DEPTH_{i,t-1} + \alpha_{3i} Log(VOL)_{i,t-1} + \alpha_{4i} FRI\_DUM_{i,t} + \alpha_{5i} JAN\_DUM_{i,t} + \alpha_{6i} EMU_{i,t} + \alpha_{7i} \hat{INT}_{i,t-1} + \alpha_{8i} \hat{INT}_{i,t-2} + u_{it} \qquad (11a)$$

where the dependent variable ($\hat{INT}_{i,t}$) is the estimated conditional correlation series for each country *i*, *FIN_DEPTH* = stock market capitalization divided by GDP, *LOG(VOL)* = logarithm of the stock market's turnover by volume, *FRI_DUM* and *JAN_DUM* are the seasonal dummies, EMU is the euro dummy variable which takes a value of one from 1st January 1999 and $\hat{INT}_{i,t-1}$ and $\hat{INT}_{i,t-2}$ are the first and second lags of the dependent variable.

	Eurozone GER	FRA	ITA	BEL	NET	IRE	SPA	POR	AUS	FIN	LUX	GRE	Non-Eurozone JAP	US
Panel A: Single Equation Least Squares														
FIN_DEPTH_{t-1}	-0.0004	-0.0003	-0.0728	0.0051	-0.0010	-0.0026*	-0.0053**	0.0088**	-0.0211**	-0.0001	0.0024*	-	-0.0001**	-0.0002
	{0.9040}	{0.8617}	{0.4242}	{0.2686}	{0.4087}	{0.0956}	{0.0401}	{0.0126}	{0.0196}	{0.8209}	{0.0877}	0.0044*** {0.0009}	{0.0462}	{0.2746}
$Log(VOL)_{t-1}$	0.0005**	0.0007***	0.0014***	0.0007	0.0018**	0.0006	0.0033***	0.0004	0.0015***	0.0010***	0.0025***	0.0020***	0.0000	0.0003***
	{0.0470}	{0.0065}	{0.0000}	{0.3353}	{0.0282}	{0.3503}	{0.0000}	{0.2440}	{0.0000}	{0.0000}	{0.0001}	{0.0000}	{0.9023}	{0.0044}
FRI_DUM	-0.0009	-0.0012*	-0.0020*	-0.0005	-0.0010	0.0002	-0.0015*	0.0005	-0.0004	-0.0016**	0.0021	-	-0.0004**	-0.0002***
	{0.2597}	{0.0702}	{0.0514}	{0.6797}	{0.1545}	{0.7916}	{0.0593}	{0.6946}	{0.2139}	{0.0366}	{0.2058}	0.0019*** {0.0064}	{0.0212}	{0.0032}
JAN_DUM	0.0019*	0.0016	0.0031*	0.0031*	0.0020**	-0.0017*	0.0002	0.0062***	0.0009	0.0032***	0.0010	0.0036***	0.0007**	0.0002*
	{0.0722}	{0.1047}	{0.0899}	{0.0893}	{0.0537}	{0.0686}	{0.8180}	{0.0023}	{0.1151}	{0.0096}	{0.7063}	{0.0028}	{0.0466}	{0.0949}
EMU	0.0023*	0.0008	0.0009	0.0010	0.0003		-0.0009	0.0006	0.0005	-0.0004		0.0005	0.0010***	-0.0000
	{0.0780}	{0.4541}	{0.4698}	{0.6168}	{0.7344}		{0.4394}	{0.7060}	{0.2731}	{0.7005}		{0.5430}	{0.0000}	{ 0.9683}
$\hat{INT}_{t-1}$	1.0611***	1.2365***	1.2197***	0.8823***	1.1641***	0.6800***	1.2094***	1.1749***	1.2260***	1.1972***	0.7474***	1.1287***	0.9772***	0.9882***
	{0.0000}	{0.0000}	{0.0000}	{0.0000}	{0.0000}	{0.0000}	{0.0000}	{0.0000}	{0.0000}	{0.0000}	{0.0000}	{0.0000}	{0.0000}	{0.0000}
$\hat{INT}_{t-2}$	-0.0778**	-0.2556***	-0.2393***	0.0822***	-0.1878***	0.2461***	-0.2324***	-0.2083***	-0.2481***	-0.2131***	0.0898***	-	-0.0100	-0.0207
	{0.0372}	{0.0000}	{0.0000}	{0.0077}	{0.0000}	{0.0000}	{0.0000}	{0.0000}	{0.0000}	{0.0000}	{0.0031}	0.1808*** {0.0000}	{0.6320}	{0.3219}
INTERCEPT	0.0065*	0.0083**	0.0012	0.0148***	0.0002	0.0361***	-0.0144***	0.0084***	0.0040*	0.0017	0.0269***	-0.0011	0.0090***	0.0085***
	{0.0626}	{0.0163}	{0.8875}	{0.0006}	{0.9688}	{0.0016}	{0.0035}	{0.0035}	{0.0594}	{0.4328}	{0.0000}	{0.5756}	{0.0000}	{0.0003}
ADF Test Statistic	-6.4544	-6.9565	-6.9374	-7.9003	-7.1984	-6.6799	-6.8782	-7.5864	-7.3039	-7.1329	-10.8913	-8.4380	-6.4544	-6.9565
Adj. R^2	0.9796	0.9826	0.9821	0.9512	0.9783	0.8736	0.9781	0.9756	0.9778	0.9892	0.7165	0.9569	0.9527	0.9626
DW Statistic	2.0224	1.9781	1.9532	2.0437	2.0014	2.1099	1.9829	1.9950	1.9936	1.9957	1.9942	1.9267	1.9856	2.0025
Observations	3612	3600	3614	3578	3635	668	3345	3220	3516	3590	1086	3559	3362	3621

Panel B: SURE														
FIN_DEPTH	0.0056***	0.0029***	0.0429	0.0056	0.0009	-	0.0034	0.0102***	-0.0091*	0.0012***		-0.0021	-0.0001**	-0.0001
	{0.0094}	{0.0049}	{0.4009}	{0.1108}	{0.1201}	0.0048***	{0.1272}	{0.0004}	{0.0988}	{0.0030}	0.0003	{0.2100}	{0.0371}	{0.5091}
						{0.0000}					{0.8839}			
$Log(VOL)_{t-1}$	-0.0001	0.0005***	0.0019***	-0.0010**	0.0016***	0.0003*	0.0017***	0.0006***	0.0010***	0.0011***	0.0000	0.0022***	0.0005***	0.0002***
	{0.1980}	{0.0003}	{0.0000}	{0.0288}	{0.0000}	{0.0894}	{0.0000}	{0.0086}	{0.0000}	{0.0000}	{0.9727}	{0.0000}	{0.0000}	{0.0007}
FRI_DUM	-0.0006	-0.0002	-0.0011	-0.0014	-0.0008		-0.0008	0.0006	-0.0003	-0.0009		-	-0.0003	-0.0001
	{0.4890}	{0.7996}	{0.4018}	{0.3056}	{0.3244}	0.0002	{0.4475}	{0.6810}	{0.4338}	{0.2929}	0.0004	0.0022***	{0.1554}	{0.1663}
						{0.7987}					{0.8758}	{0.0043}		
JAN_DUM	0.0010	0.0013	0.0020	0.0004	0.0015	-	0.0014	0.0057***	0.0006	0.0020		0.0040***	0.0007*	0.0001
	{0.4675}	{0.2844}	{0.2601}	{0.8494}	{0.1981}	0.0027***	{0.3292}	{0.0081}	{0.2472}	{0.1200}	-0.0038	{0.0002}	{0.0519}	{0.6521}
						{0.0087}					{0.2070}			
EMU	0.0037***	0.0026***	0.0022*	0.0064***	0.0023***		0.0015	0.0037**	0.0015***	0.0011		0.0003	0.0009***	0.0001
	{0.0005}	{0.0099}	{0.0806}	{0.0004}	{0.0098}		{0.2132}	{0.0285}	{0.0002}	{0.3231}		{0.8236}	{0.0020}	{0.1677}
	1.0791***	1.0981***	1.1389***	1.0519***	1.0860***	0.7135***	1.1336***	1.1392***	1.1450***	1.1059***	0.6664***	1.0988***	0.9444***	0.9514***
$\hat{INT}_{t-1}$	{0.0000}	{0.0000}	{0.0000}	{0.0000}	{0.0000}	{0.0000}	{0.0000}	{0.0000}	{0.0000}	{0.0000}	{0.0000}	{0.0000}	{0.0000}	{0.0000}
	-	-	-0.1792***	-	-0.1391***		-0.1792***	-0.1914***	-0.1907***	-0.1427***		-	0.0184	0.0101
$\hat{INT}_{t-2}$	0.1244***	0.1431***	{0.0000}	0.1129***	{0.0000}	0.1351***	{0.0000}	{0.0000}	{0.0000}	{0.0000}	0.0777**	0.1617***	{0.2293}	{0.5171}
	{0.0000}	{0.0000}		{0.0000}		{0.0000}					{0.0230}	{0.0000}		
INTERCEPT	0.0316***	0.0276***	-0.0001	0.0405***	0.0230***	0.0818***	0.0137***	0.0134***	0.0171***	0.0107***	0.0629***	-0.0006	0.0046***	0.0112***
	{0.0000}	{0.0000}	{0.9795}	{0.0000}	{0.0000}	{0.0000}	{0.0003}	{0.0000}	{0.0000}	{0.0000}	{0.0000}	{0.7194}	{0.0069}	{0.0000}
Adj. R^2	0.9732	0.9760	0.9754	0.9242	0.9747	0.8665	0.9761	0.9747	0.9734	0.9837	0.5315	0.9576	0.9547	0.9642
DW Statistic	2.1182	1.8251	1.8405	2.3979	1.9350	2.1085	1.8571	1.9747	1.9245	1.8004	2.0641	1.8718	1.9607	1.9792
Observations	2783	2783	2783	2783	2783	617	2783	2783	2783	2783	617	2783	2747	2747

Notes: P-Values are shown in brackets.,**,*** denotes significance at the 10%, 5% and 1% respectively. Due to data limitations, the sample periods available for Ireland and Luxembourg are post-1999 meaning that there is no variation in the EMU dummy time series. For this reason, the OLS and SURE regressions for these two countries have omitted the EMU dummy as an explanatory variable .The SUR estimates shown for Ireland and Luxembourg are from a 12 equation SURE estimated using fewer observations and no EMU dummy whilst those for the other euro zone countries are estimated using 10 equations with an EMU dummy. A two equation SURE was estimated separately for Japan and US and the correlation between the two residuals was 0.7112. Critical Value for the Augmented Dickey Fuller (ADF) Test for a unit root at the 5% significance level is -3.4100. The appropriate ADF test included a constant, trend and 4 lags. As a robustness check, an alternative euro dummy used for Greece took a value of one for dates after 1 January, 2001 (ie. Greece's formal entry into the EMU) but there were no differences in our results.*

Table 6

Regression results with other currency union explanatory variables

In panel A of this table, the OLS results are reported for each country. The OLS estimates are corrected for autocorrelation and heteroskedasticity in accordance with Newey West (1987). In panel B, the seemingly unrelated regression (SUR) estimates are shown. The model estimated by both methods, as defined in equation (12) is

$$\hat{INT}_{i,t} = \beta_{1i} + \beta_{2i}EX\_VOL_{i,t-1} + \beta_{3i}OUTPUT_{i,t-1} + \beta_{4i}IRATE_{i,t-1} + \beta_{5i}FIN\_DEPTH_{i,t-1} + \beta_{6i}Log(VOL)_{i,t-1} + \beta_{7i}FRI\_DUM_{i,t} + \beta_{8i}JAN\_DUM_{i,t} + \beta_{9i}\hat{INT}_{i,t-1} + \beta_{10i}\hat{INT}_{i,t-2} + u_{it} \quad (12a)$$

where the dependent variable ($\hat{INT}_{i,t}$)is the estimated conditional correlation series for each country *i*, *EX_VOL* = exchange rate volatility, *OUTPUT* = correlations in the growth of industrial production rates with Euro area weighted averages, *IRATE* = correlations in nominal short term (30 day) interest rates with Euro area weighted averages, *FIN_DEPTH* = stock market capitalization/ GDP, *LOG(VOL)* = logarithm of the stock market's turnover by volume, *FRI_DUM* and *JAN_DUM* are the seasonal dummies introduced before and $\hat{INT}_{i,t-1}$ and $\hat{INT}_{i,t-2}$ are the first and second lags of the dependent variable. For Japan and the US, the results from an alternative specification with $INFLA_{t-1}$ in place of $IRATE_{t-1}$ is also reported.

	Eurozone												**Non-Eurozone**			
	GER	FRA	ITA	BEL	NET	IRE	SPA	POR	AUS	FIN	LUX	GRE	JAP	US	JAP	US
Panel A: Single Equation Least Squares																
EX_VOL_{t-1}	0.0022*	0.0015	-0.0516***	0.0254***	0.0002	0.0036***	0.0012	-0.0001**	0.0003	0.0009	0.0101***	0.0019**	0.0003**	-0.0002	0.0001	-0.0001
	{0.0677}	{0.1189}	{0.0000}	{0.0008}	{0.8440}	{0.0023}	{0.3245}	{0.0150}	{0.4819}	{0.3955}	{0.0001}	{0.0152}	{0.0414}	{0.2263}	{0.5194}	{0.5751}
$OUTPUT_{t-1}$	0.0017	0.0000	0.0006	0.0034**	-0.0006	0.0003	-0.0024	0.0039	0.0001	-0.0025	-0.0009	0.0000	0.0002	0.0000	0.0001	0.0000
	{0.3561}	{0.9904}	{0.6958}	{0.0272}	{0.5508}	{0.9270}	{0.2441}	{0.2559}	{0.8701}	{0.1358}	{0.6748}	{0.9917}	{0.3988}	{0.9827}	{0.7905}	{0.7383}
$IRATE_{t-1}$	-0.0004	-0.0022*	-0.0013	-0.0013	-0.0001	-0.0001	0.0004	-0.0010	0.0004	0.0004	-0.0008	-0.0001	-0.0003	0.0000		
	{0.7965}	{0.0634}	{0.5525}	{0.5845}	{0.8987}	{0.9661}	{0.7880}	{0.6019}	{0.4976}	{0.7205}	{0.8499}	{0.8969}	{0.1457}	{0.8702}		
$INFLA_{t-1}$															0.0000	0.0002**
															{0.9070}	{0.0488}
FIN_DEPTH_{t-1}	0.0057*	-0.0001	-0.0009	-0.0027	-0.0011	-0.0078***	-0.0036	0.0008	-0.0035	-0.0005	-0.0009	-0.0081***	0.0000	-0.0001	0.0000	-0.0001
	{0.0730}	{0.9738}	{0.5244}	{0.2836}	{0.3587}	{0.0009}	{0.2762}	{0.9017}	{0.7168}	{0.3444}	{0.6150}	{0.0000}	{0.7604}	{0.3988}	{0.9251}	{0.5363}
$Log(VOL)_{t-1}$	0.0001	0.0031***	-0.0097	0.0184***	0.0036***	0.0007	0.0045***	0.0042***	0.0015***	0.0025***	0.0027***	0.0060***	0.0006***	0.0005***	0.0007***	0.0003***
	{0.8623}	{0.0000}	{0.9331}	{0.0044}	{0.0000}	{0.2998}	{0.0000}	{0.0017}	{0.0001}	{0.0000}	{0.0006}	{0.0000}	{0.0019}	{0.0000}	{0.0000}	{0.0056}
FRI_DUM	-0.0006	-0.0002	0.0055***	0.0013	-0.0010	0.0004	-0.0009	0.0004	-0.0005	0.0000	0.0029*	-0.0009	0.0001	0.0000	-0.0004**	-0.0002**
	{0.5275}	{0.7960}	{0.0000}	{0.2535}	{0.2454}	{0.6214}	{0.3709}	{0.8228}	{0.2892}	{0.9628}	{0.0972}	{0.3126}	{0.5481}	{0.7640}	{0.0417}	{0.0274}
JAN_DUM	0.0017	0.0014	-0.0008	-0.0029*	0.0016	-0.0032***	0.0005	0.0053**	0.0008	0.0021	0.0003	0.0040***	0.0010**	0.0001	0.0007*	0.0000
	{0.2613}	{0.2942}	{0.4804}	{0.0859}	{0.2373}	{0.0082}	{0.7428}	{0.0279}	{0.2654}	{0.1035}	{0.9097}	{0.0063}	{0.0364}	{0.5242}	{0.0650}	{0.7160}
$\hat{INT}_{t-1}$	0.8499***	1.1636***	0.0012	0.0016	1.0443***	0.6692***	1.1788***	1.0858***	1.1169***	1.2003***	0.7474***	1.0378***	0.9793***	0.9815***	0.9730	0.9568***
	{0.0000}	{0.0000}	{0.5710}	{0.5714}	{0.0000}	{0.0000}	{0.0000}	{0.0000}	{0.0000}	{0.0000}	{0.0000}	{0.0000}	{0.0000}	{0.0000}	{0.0000}	{0.0000}
$\hat{INT}_{t-2}$	0.1307***	-0.1922***	1.2649***	0.7511***	-0.0753**	0.2350***	-0.2075***	-0.1257***	-0.1464***	-0.2287***	0.0731**	-0.1154***	-0.0066	-0.0316	-0.0043	-0.0064
	{0.0002}	{0.0000}	{0.0000}	{0.0000}	{0.0160}	{0.0000}	{0.0000}	{0.0001}	{0.0000}	{0.0000}	{0.0225}	{0.0024}	{0.8214}	{0.2917}	{0.8317}	{0.7526}
INTERCEPT	0.0092*	-0.0093*	-0.2905***	0.1786***	-0.0128	0.0475***	-0.0257***	-0.0163**	0.0052	-0.0048*	0.0231***	-0.0268***	-0.0003	0.0116***	-0.0005	0.0136***
	(0.0724}	{0.0998}	{0.0000}	{0.0000}	{0.1207}	{0.0002}	{0.0001}	{0.0360}	{0.1037}	{0.0932}	{0.0012}	{0.0000}	{0.8990}	{0.0001}	{0.8141}	{0.0000}

Adj. R^2	0.9688	0.9789	0.9814	0.9111	0.9732	0.8897	0.9806	0.9757	0.9748	0.9903	0.7363	0.9625	0.9601	0.9674	0.9526	0.9563
DW Statistic	2.0228	1.9950	1.9418	2.0735	2.0260	2.0933	1.9795	2.0210	2.0339	1.9682	1.9915	1.9627	1.9696	1.9832	1.9937	2.0057
Observations	1971	2022	2128	1966	2066	566	2027	2008	2128	1835	984	2028	2011	2017	2999	3005
Panel B: SURE																
EX_VOL_{t-1}	0.0010	0.0002	-0.0008	0.0013	-0.0011*	0.0008	0.0002	-0.0001	-0.0002	-0.0006	-0.0080**	-0.0017**	0.0001	-0.0002	0.0000	-0.0001
	{0.1458}	{0.7564}	{0.5375}	{0.3392}	{0.0519}	{0.2701}	{0.8129}	{0.8173}	{0.5905}	{0.3743}	(0.0140}	{0.0276}	{0.4790}	{0.1107}	{0.9503}	{0.2876}
$OUTPUT_{t-1}$	0.0002	0.0007	0.0033**	-0.0011	0.0005	-0.0011	-0.0004	0.0054**	0.0011*	-0.0004	0.0014	-0.0006	0.0005**	0.0000	0.0002*	0.0000
	{0.7374}	{0.3159}	{0.0121}	{0.4674}	{0.2814}	{0.3425}	{0.7678}	{0.0304}	{0.0714}	{0.7109}	(0.7088}	{0.6225}	{0.0500}	{0.8330}	{0.0811}	{0.6947}
$IRATE_{t-1}$	0.00042	0.0006	0.0022**	-0.0004	0.0002	-0.0005	0.0012	0.0014	-0.0002	-0.0003	0.0014	-0.0011	-0.0001	0.0000		
	{0.4598}	{0.3234}	{0.0484}	{0.7792}	{0.7866}	{0.4625}	{0.2211}	{0.3499}	{0.6371}	{0.6490}	(0.7877}	{0.2681}	{0.3264}	{0.7965}		
$INFLA_{t-1}$															0.0001	0.0002***
															{0.5005}	{0.0062}
FIN_DEPTH_{t-1}	0.0103***	0.0048***	0.0749	0.0153***	0.0024***	- 0.0062***	0.0053**	0.0074	0.0122*	0.0014***	-0.0023	- 0.0065***	0.0000	0.0000	0.0000	0.0000
	{0.0000}	{0.0000}	{0.3159}	{0.0014}	{0.0005}	{0.0000}	{0.0251}	{0.1118}	{0.0827}	{0.0006}	(0.4457}	{0.0002)	{0.7380}	{0.7855}	{0.8684}	{0.8666}
$Log(VOL)_{t-1}$	-0.0003**	0.0003	0.0039***	-0.0006	0.0013**	0.0002	0.0022***	0.0035***	0.0002	0.0015***	0.0006	0.0057***	0.0004***	0.0002***	0.0006***	0.0002***
	{0.0114}	{0.2883}	{0.0000}	{0.4061}	{0.0022}	{0.1970}	{0.0000}	{0.0001}	{0.4299}	{0.0000}	(0.4958}	{0.0000}	{0.0061}	{0.0003}	{0.0000}	{0.0050}
FRI_DUM	0.0002	0.0011	0.0010	-0.0019	0.0003	0.0003	0.0004	0.0005	0.0002	0.0005	0.0014	-0.0014	0.0001	0.0000	-0.0003	-0.0001
	{0.8928}	{0.2527}	{0.4620}	{0.3190}	{0.7885}	{0.6954}	{0.7359}	{0.7801}	{0.6104}	{0.5256}	(0.5721}	{0.1393}	{0.6991}	{0.6072}	{0.1656}	{0.1675}
JAN_DUM	0.0016	0.0020	0.0026	0.0006	0.0017	- 0.0033***	0.0022	0.0064**	0.0014**	0.0017	-0.0065*	0.0047***	0.0009**	0.0001	0.0008**	0.0001
	{0.3327}	{0.1456}	{0.1873}	{0.8347}	{0.2310}	{0.0075}	{0.1732}	{0.0155}	{0.0346}	{0.1477}	(0.0894}	{0.0005}	{0.0213}	{0.5851}	{0.0416}	{0.6792}
$\hat{INT}_{t-1}$	0.9663***	1.0418***	1.1658***	0.9568***	1.0128***	0.7211***	1.0690***	1.0874***	1.0485***	1.1295***	0.6487***	1.0293***	0.9678***	0.9734***	0.9477***	0.9510***
	{0.0000}	{0.0000}	{0.0000}	{0.0000}	{0.0000}	{0.0000}	{0.0000}	{0.0000}	{0.0000}	{0.0000}	(0.0000}	{0.0000}	{0.0000}	{0.0000}	{0.0000}	{0.0000}
$\hat{INT}_{t-2}$	-0.0165	- 0.0917***	- 0.2017***	-0.0298*	- 0.0685***	0.1214***	- 0.1212***	- 0.1526***	- 0.0964***	- 0.1637***	0.0753**	0.0205***	0.0001	-0.0100	0.0188	0.0092
	{0.1909}	{0.0000}	{0.0000}	{0.0573}	{0.0000}	{0.0000}	{0.0000}	{0.0000}	{0.0000}	{0.0000}	(0.0455}	{0.0000}	{0.9948}	{0.5843}	{0.2294}	{0.5644}
INTERCEPT	0.0360***	0.0331***	- 0.0316***	0.0428***	0.0276***	0.0867***	0.0112**	-0.0027	0.0220***	0.0061***	0.0577***	- 0.0247***	0.0039**	0.0101***	0.0020	0.0121***
	{0.0000}	{0.0000}	{0.0001}	{0.0000}	{0.0000}	{0.0000}	{0.0219}	{0.6149}	{0.0000}	{0.0013}	{0.0000}	{0.0000}	{0.0405}	{0.0000}	{0.1798}	{0.0000}
Adj. R^2	0.9669	0.9763	0.9813	0.9027	0.9717	0.8805	0.9790	0.9737	0.9747	0.9906	0.9026	0.9639	0.9592	0.9682	0.9540	0.9634
DW Statistic	2.2278	1.8793	1.8195	2.4020	2.0410	2.0753	1.8803	2.0650	1.9845	1.8140	1.9935	1.9060	1.9514	1.9397	1.9584	1.9774
Observations	1507	1507	1507	1507	1507	521	1507	1507	1507	1507	521	1507	1909	1909	2653	2653

Note: P-Values are shown in brackets., **,*** denotes significance at the 10%, 5% and 1% respectively. A two equation SURE was estimated separately for Japan and US and the correlation between the two residuals was 0.7243 and 0.7101 for including the $IRATE_{t-1}$ and $INFLA_{t-1}$ variable respectively. Again, the SUR estimates shown for Ireland and Luxembourg are from a 12 equation SURE estimated using fewer observations*

Table 9

Significance of variables in explaining stock market integration

In this table, a summary of significant variables for explaining each country's stock market integration with the EMU is presented. The estimated coefficients for EURO_DUM are shown in panel B of Table 6 and the other estimates are shown in panel B of Table 7.

	Economic Variables					**Financial Variables**		**Seasonal Effects**		**Persistence**	
	EURO_DUM	EX_VOL	OUTPUT	IRATE	INFLA	FIN_DEPTH	LOG(VOL)	FRI_DUM	JAN_DUM	$\hat{INT}_{t-1}$	$\hat{INT}_{t-2}$
Panel A:Euro zone:											
GER	X					X	X			X	
FRA	X					X				X	X
ITA	X		X	X			X			X	X
BEL	X					X				X	X
NET	X	X				X	X			X	X
IRE						X			X	X	X
SPA						X	X			X	X
POR	X		X				X		X	X	X
AUS	X		X			X			X	X	X
FIN						X	X			X	X
LUX		X							X	X	X
GRE		X				X	X		X	X	X
Panel B:Non-Euro zone:											
JAP	X		X				X		X	X	
US					X		X			X	

Appendix A

Variable Definitions and Data Sources

Category	Variable	Frequency	Source	Definition
Exchange Rate risk	EX_VOL	Daily	Datastream	Conditional variance from a GARCH(1,1) model for daily local currency to ECU/Euro exchange returns for each EMU member.
	EX_SD*	Daily	Datastream	Rolling standard deviations of daily changes in the foreign exchange rate over the past 3 months.
Real Convergence	OUTPUT	Monthly	IMF/Eurostat	Correlations in national and regional growth rates of seasonally adjusted industrial production (IP) – weighted by annual GDP for the Euro area over the past 12 months.
	DIVRATIO*	Daily	Datastream	Ratio of national dividend yield to that for the Euro area weighted by stock market capitalization.
	DIV_CHANGE_RATIO*	Daily	Datastream	Ratio of changes in national dividend yields to that for Euro area weighted by stock market capitalization.
	COR_DIV_CHANGE*	Daily	Datastream	Rolling correlations for changes in national and Euro area dividend yields (weighted by stock market capitalization) over the past month.
Monetary Policy Convergence	COR_SHORT_RATE	Daily	Datastream and IMF	Rolling correlations for national nominal short-term interest rates (1 month Eurocurrency rates) and the Euro area weighted by annual GDP over the past month.
	INFLA*	Monthly	Datastream and IMF	Correlations in seasonally-adjusted consumer price inflation with the Euro-area inflation index weighted by annual GDP over the past 12 months.
	SHORT_RATE_RATIO*	Daily	Datastream and IMF	Ratio of national nominal short-term interest rates (1 month Eurocurrency rates) to that for the Euro area weighted by annual GDP.
Control	VOLUME	Daily	Datastream	Logarithm of turnover by volume of trade for each national stock market.
	FIN_DEPTH	Daily	Datastream and IMF	Ratio of stock market capitalization to annual GDP in Euros.
	FRI_DUM	Daily		Indicator is equal to one if that trading day was a Friday, zero otherwise.
	MON_DUM*	Daily		Indicator is equal to one if that trading day was a Monday, zero otherwise.
	JAN_DUM	Daily		Indicator is equal to one if that trading day was in January, zero otherwise.
	EURO_DUM	Daily		Indicator takes a value of one if the Euro has already been introduced on the date ie. from 1st January 1999 onwards. (NOTE: An alternative dummy taking a value of one from 1st January 2001 was also tested for Greece due to its delayed entry into the EMU)

*Note: * These are NOT included in the final specification of the OLS and SURE regression models and have not been reported in this paper due to space considerations. Results from all other regressions are available upon request from the authors.*