Volatility, Spillover Effects and Correlations in US and Major European Markets

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Abstract

This paper investigates the transmission mechanism of price and volatility spillovers across the New York, London, Frankfurt and Paris stock markets under the framework of the multivariate EGARCH model. Also, the correlation between those markets is investigated for the periods before and after the introduction of euro under the Constant and Dynamic Conditional Correlation frameworks. By using daily closing prices recorded at 16:00 London time (pseudo-closing prices) we find evidence that the domestic stock prices and volatilities are influenced by the behaviour of foreign markets. The volatility is found to respond asymmetrically to news/innovations in other markets. The findings also indicate that the correlations of returns have increased for all markets since the launch of euro, with that between Frankfurt and Paris experiencing the largest increase.

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1. Introduction

In the period of globalization, the transmission mechanism in international financial markets is an issue of great interest for investors and policy makers. It is well known and consistent with the efficient market hypothesis that stock traders incorporate into their decisions not only information generated domestically but also information produced by other stock markets (Koutmos, and Booth (1995)). For that reason many researchers have tried to find more successful hedging and trading strategies by investigating the extent of linkages among financial markets.

At the beginning, these studies mainly focused on the interaction and interdependence of stock markets in terms of the conditional first moments of the distribution returns. However, more recent studies investigate stock market interactions in terms of both first and second moments.

Grubel, (1968) examines the comovements and correlations between different markets and investigates the gains of international diversification from a US perspective. He concludes that portfolio efficiency could be improved through international diversification. Hamao, Masulis, and Ng (1990) use a univariate GARCH model to examine the volatility spillovers between New York, Tokyo and London stock markets. They find that an increase in volatility in one market induces an increase in volatility in another market. Koutmos *et al.*, (1995) investigate the transmission mechanism of price and volatility spillovers across the same stock markets, using a multivariate EGARCH model. Their results reveal strong evidence of asymmetric volatility spillovers, especially for the period after October 1987.

Antoniou, Pescetto and Violaris (2003) provide evidence that the domestic spot-future relationship is influenced by the behavior of foreign markets. Furthermore, they found that volatility responds asymmetrically, with bad news having greater impact on stock markets than the good news. These results are in line with those of Koutmos (1996), who finds that the major European stock markets are integrated with the volatility transmission mechanism being asymmetric. Although their studies concentrate on major European spot and future markets, they do not include any effects from the US market, which is the predominant and most influencing market in the world. Finally, Veiga and McAleer (2003) test for the existence of volatility spillovers between USA, UK and Japan using intra-daily data and they find volatility spillovers from UK to USA and Japan and from USA to UK.

Generally, the main results from the literature are that dynamic interactions exist between markets. Furthermore, stock markets have become more interdependent with fewer arbitrage opportunities, presumably because of the higher speed that the information travels. In addition, as Antoniou *et .al.* (2003) indicate, the international flow of funds reveal that the European stock markets are the most important destinations of international equity capital, dominating the leadership that the US and Japanese markets experienced in previous periods.

As far as the European markets are concerned, some scholars try to identify the effects from the introduction of euro. For instance Melle (2003) uses a VAR analysis procedure to identify whether the introduction of the euro affects the integration of the European stock markets. Her results show that the integration of European stock markets has been increased after the introduction of the euro. Furthermore, the German stock exchange has become the leader for the rest of the European markets. However, under the VAR framework she is not able to capture the volatility spillovers or the time-varying correlations.

Cheung and Westermann (2001), examine the relationship between German and US equity markets for the periods before and after the introduction of the euro. They find that the volatility persistence of the German stock index has fallen significantly, compare to the volatility of the US index. However, the causal relationships between the two equity markets have not changed between the two periods. The result of lower volatility after the introduction of euro for Germany is not in line with the results of Billio and Pelizzon (2002) who find that the volatility for German and France has increased after the introduction of euro. For their study they use multivariate switching regime models. By using a three regime-switching shock spillover models, Baele (forthcoming) investigates how US and aggregate European volatility spills over into various European stock markets. Christiansen (2003, 2005) finds significant volatility spillover effects from aggregate US and European bond and stock markets, into national European markets. Also, the introduction of euro is associated with a structural break. However, by using aggregate measures they cannot capture the individual spillovers from one market to another.

An important study is that of Capiello *et. al.* (2003) who examine the worldwide linkages in the dynamics of volatility and correlation under the Dynamic Conditional Correlation (DCC) framework. Their findings suggest that there is significant evidence of a structural break in the correlation after the introduction of the euro. Nevertheless, they use weekly data and they do not include any price or volatility spillovers effects in the returns and volatility equations respectively. Taylor *et. al.* (2005) under a time-varying copula model, confirmed the above results but only for the large equity European markets. Recently, Kim *et. al.* (forthcoming) find an increase in correlations of all EMU countries with a weighted EMU index. In addition, they find that the introduction of euro has strengthened the European volatility linkages. However, by comparing the correlations with a weighted index, they cannot capture the pattern in correlations between individual countries. Moreover, the linkages between markets might suffer from some noise due to the non-synchronized data (especially for the case of US stock market).

Although there are some studies of stock market interdependence, relating to the European markets and to their correlations after the introduction of euro, it is surprising that the majority of those studies neglect the effects from the returns in other markets as well as the volatility spillovers (especially the studies that use a time-varying correlation framework). Neglecting these effects might lead to bias results. Furthermore, although the constant-correlation assumption provides a convenient way to estimate the multivariate GARCH model, there are indications that the stock returns across different national markets exhibit time-varying correlations (for instance see Tse (2000)). For that reason DCC-type models seem to be preferred over CCC-type models. Of course the validity of each model should be assessed empirically.

In addition, the fact that most of the aforementioned studies have used weekly or closing price data may cause the following problems: "Low frequency data leads to small samples, which is inefficient for multivariate modelling. Moreover, monthly or weekly data cannot capture daily correlation dynamics, while closing prices tend to underestimate the conditional correlation. Finally, even if instead of using closing prices, we use open-to-close or close-to-open returns, we cannot distinguish a spillover from a contemporaneous correlation" (Marten and Poon (2001)). Hence, to overcome those difficulties, we use daily closing prices recorded at 16:00 London time (pseudo-closing prices).

The introduction of euro on January 1 1999 changed the structure and the functioning of international financial markets. The Euro changeover costs, in turn, significantly affected the total operating costs of the financial market participants (Rehman, (2002)). Furthermore, the introduction of the euro might be important for EU stock markets since the euro removes the potentially important uncertainty connected with exchange rate fluctuations, and hence should reduce uncertainties concerned with stock market investments across country borders within the euro area.

Since little work has been done in this area, this paper seeks to investigate the relationships between stock indices of the major European stock markets along with the US market. "The US market is the market that investors watch more closely than any other market. The American market is regarded as so important because the US is the biggest economy in the world and is home to many of the world's largest companies. So, what happens to the American stock market tends to influence the performance of every other market in the world" (The London Stock Exchange website). The UK market has a similar role in Europe (even if UK has not adopted the euro currency yet). Hence, we include both countries in our study. In detail, this paper will try to provide answers to the following research questions:

- Do volatility spillovers exist among US and European markets and which is the direction of influence within those markets before and after the introduction of euro?
- To what extent are the movements of one market affected by past movements in the other markets?
- Have the correlations between US and European markets changed after the introduction of euro?

The main contribution of this paper to the ongoing debate about stock market interaction is to fill in an important missing gap in the literature by providing evidence on price, volatility spillovers, and correlations across US and the major European markets for the periods before and after the introduction of euro, using daily closing prices recorded at 16:00 London time.

The rest of the paper is organized as follows: Section 2 discusses the methodological design of the study; Section 3 analyses the data and the empirical findings and Section 4 summarizes the study and concludes.

2. Methodology

This study uses a multivariate EGARCH model specification to investigate market interdependence and volatility transmission between stock markets in different countries. The correlations between markets are modeled by using both Constant Conditional Correlation model (Bollerslev, 1990) and Dynamic Conditional Correlation model (Engle, 2002). Our sample consists of daily observations on the markets of New York (S&P 500), London (FTSE 100), Frankfurt (DAX 30), and Paris (CAC 40).

To model the short-run dynamic relationships between stock markets, we use the following Vector Autoregressive (VAR) model:

$$\mathrm{Re}t_{i,t} = \beta_{i,0} + \sum_{j=1}^{n} \beta_{i,j} \, \mathrm{Re}t_{j,t-1} + \varepsilon_{i,t} \qquad (1)$$

The conditional mean in each market $(\mathrm{Re}t_{i,t})$ is a function of own past returns and cross-market past returns $(\mathrm{Re}t_{j,t})$. $\beta_{i,j}$, captures the lead-lag relationship between returns in different markets, for $i \neq j$. Market *j* leads market *i* when $\beta_{i,j}$ is significant.

Following Koutmos and Booth (1995), Antoniou *et. al.* (2003) among others, we model the conditional variances according to the multivariate EGARCH model:

$$\sigma_{i,t}^{2} = \exp[\alpha_{i,0} + \sum_{j=1}^{n} \alpha_{i,j} f_j(z_{j,t-1}) + \delta_i \ln(\sigma_{i,t-1}^{2})] \qquad (2)$$

$$f_j(z_{j,t-1}) = \left(| z_{j,t-1} | - E(| z_{j,t-1} |) + \gamma_j z_{j,t-1} \right) \qquad (3)$$

Equation (2) describes the conditional variance in each market as an exponential function of past standardized innovations, $(z_{j,t-1} = \varepsilon_{j,t-1} / \sigma_{j,t-1})$, coming from both its own market and other markets. The persistence in volatility is given by δ_i, with the unconditional variance being finite if $\delta_i < 1$ (Nelson, 1991). If $\delta_i = 1$, then the unconditional variance does not exist and the conditional variance follows an integrated process of order one. The asymmetric influence of innovations on the conditional variance is captured by the term $\sum_{j=1}^{n} \alpha_{i,j} f_j(z_{j,t-1})$. This term is defined in equation (3) and the partial derivatives (which determine the slope of $f(.)$) are:

$$\partial f_j(z_{j,t})/\partial z_{j,t} = 1+\gamma_j, \text{ if } \mathrm{z_j} > 0 \text{ and,}$$
$$\partial f_j(z_{j,t})/\partial z_{j,t} = -1+\gamma_j, \text{ if } \mathrm{z_j} < 0.$$

Thus equation (3) allows the standardized own and cross-market innovations to influence the conditional variance in each market asymmetrically. Asymmetry is judged to be present if γ_j is negative and statistically significant. A statistically significant positive $\alpha_{i,j}$ coupled with a negative (positive) γ_j implies that negative innovations in market *j* have a greater impact on the volatility of market *i* than positive (negative) innovations. The term $|z_{j,t}| - E(|z_{j,t}|)$ measures the size effect. Assuming $\alpha_{i,j}$ is positive, the impact of $z_{j,t}$ on $\sigma^2_{i,t}$ will be positive (negative) if the magnitude of $z_{j,t}$ is greater (smaller) than its expected value $E(|z_{j,t}|)$. The magnitude effect can be reinforced or offset by the sign effect depending on the sign of the coefficient and the sign of the innovation. The relative importance of the asymmetry (or leverage effect) can be measured by the ratio $|\text{-}1+\gamma_\mathrm{j}|/(1+\gamma_\mathrm{j})$. Moreover, the EGARCH model does not need parameter restrictions to ensure positive variances at all times.

Finally, the residuals of Equation (1) are assumed to be conditionally multivariate normal with mean zero and conditional covariance matrix H_t:

$$\varepsilon_t \,|\, \xi_{t-1} \sim N(0, H_t) \qquad (4)$$

where ξ_{t-1} is the information set containing all historic returns.

The conditional covariance $\sigma_{i,j,t}$ is specified by using firstly the CCC model and secondly the DCC model. Both models use the fact that H_t can be decomposed as follows:

$$H_t = D_t R D_t \text{ or } \sigma_{\mathrm{ij,t}} = \rho_{ij}\sigma_{i,t}\sigma_{j,t} \qquad (5)$$

for the case of the CCC model and

$$H_t = D_t R_t D_t \text{ or } \sigma_{\mathrm{ij,t}} = \rho_{ij,t}\sigma_{i,t}\sigma_{j,t} \qquad (6)$$

for the case of the DCC model.

D_t is a $n \times n$ diagonal matrix with time-varying standard deviations, i.e. $\sigma_{i,t}$, on the diagonal and R_t is the time-varying symmetric correlation matrix:

$$D_t = \begin{bmatrix} \sigma_{1,t} & 0 & \dots & 0 \\ 0 & \sigma_{2,t} & & 0 \\ . & & . & . \\ . & & . & . \\ 0 & 0 & \dots & \sigma_{n,t} \end{bmatrix}, \; R_t = \begin{bmatrix} r_{1,1,t} & r_{1,2,t} & \dots & r_{1,n,t} \\ r_{2,1,t} & r_{2,2,t} & & r_{2,n,t} \\ . & & . & . \\ . & & & . \\ r_{n,1,t} & r_{n,2,t} & \dots & r_{n,n,t} \end{bmatrix} \quad (7)$$

The CCC model specification reduces the number of parameters to be estimated compared with time-varying correlations and its validity, of course, must be assessed empirically. For the CCC, the matrix of residuals is used to estimate the correlation matrix R. As indicated by Koutmos and Booth (1995), modeling the returns of stock markets simultaneously improves efficiency of estimation and the power of tests for spillovers, compared with a univariate approach.

To estimate the DCC model we standardize the residuals as:

$$z_{i,t} = \frac{\varepsilon_{i,t}}{\sigma_{i,t}}, \text{ or } z_t = D_t^{-1}\varepsilon_t \quad (8)$$

where z_t indicates the standardized residuals. With these residuals we define the asymmetric diagonal DCC equation (hereafter AGDCC):

$$\begin{aligned} Q_t &= (\bar{Q} - A'\bar{Q}A - B'\bar{Q}B - C'\bar{N}C) + \\ &\quad A'z_{t-1}z_{t-1}'A + B'Q_{t-1}B + C'\eta_{t-1}\eta_{t-1}'C \end{aligned} \quad (9)$$

with $\bar{Q}$ and $\bar{N}$ being the unconditional correlation matrices of z_t and η_t, with $\eta_{i,t} = l_{[z_{i,t}<0]}z_{i,t}$, where $l_{[z_{i,t}<0]}$ is the indicator function which takes the value unity when $z_{i,t} < 0$. This model is a generalization of Engle's original DCC model to capture asymmetric correlations and was first used by Capiello *et al.* (2003). For our purposes A, B and C on the 4x4 matrices as follow:

$$A = \begin{bmatrix} \alpha_1 & 0 & 0 & 0 \\ 0 & \alpha_2 & 0 & 0 \\ 0 & 0 & \alpha_3 & 0 \\ 0 & 0 & 0 & \alpha_4 \end{bmatrix}, \; \mathrm{B} = \begin{bmatrix} b_1 & 0 & 0 & 0 \\ 0 & b_2 & 0 & 0 \\ 0 & 0 & b_3 & 0 \\ 0 & 0 & 0 & b_4 \end{bmatrix}, \; \mathrm{C} = \begin{bmatrix} c_1 & 0 & 0 & 0 \\ 0 & c_2 & 0 & 0 \\ 0 & 0 & c_3 & 0 \\ 0 & 0 & 0 & c_4 \end{bmatrix} \quad (10)$$

Q_t will be positive definite with probability one if $(\bar{Q} - A'\bar{Q}A - B'\bar{Q}B - C'\bar{N}C)$ is positive definite. Because, Q_t does not have ones on the diagonal, we scale it to get a proper correlation matrix R_t:

$$R_t = Q_t^{*-1} Q_t Q_t^{*-1},$$

$$Q_t^{*-1} = \begin{bmatrix} \sqrt{q_{1,1,t}} & 0 & 0 & 0 \\ 0 & \sqrt{q_{2,2,t}} & 0 & 0 \\ 0 & 0 & \sqrt{q_{3,3,t}} & 0 \\ 0 & 0 & 0 & \sqrt{q_{4,4,t}} \end{bmatrix} \tag{11}$$

Although an extensive literature exists for explaining asymmetric volatility, little explanation can be found for of asymmetric responses to joint bad news in correlations (both returns being negative). As Cappiello *et. al*. (2003) state "If, due to negative shocks, the variances of two securities increase, investors will require higher returns to compensate the larger risk they face. As a consequence, prices of both assets will decrease and asset correlation will go up. Correlation may therefore be higher after a negative innovation than after a positive innovation of the same magnitude, indicating its sensitivity to the sign of past shocks".

Model Estimation

Following Engle (2002), we estimate each model by maximizing the log-likelihood function. As $\varepsilon_t \mid \xi_{t-1}$ is normally distributed, the log likelihood can be expressed as:

$$\begin{aligned} L &= -\frac{1}{2}\sum_{t=1}^{T}(n\log(2\pi) + \log|H_t| + \varepsilon_t{}' H_t^{-1}\varepsilon_t) \\ &\quad -\frac{1}{2}\sum_{t=1}^{T}(n\log(2\pi) + \log|D_t R_t D_t| + \varepsilon_t{}' D_t R_t D_t^{-1}\varepsilon_t) \end{aligned}$$

which can be maximized over the parameters of the model. Nevertheless, as Engle (2002) suggests, one of the objectives of this formulation is to allow the model to be estimated more easily even when the covariance matrix is very large. Hence, we can estimate the model by using a two step approach which gives consistent but inefficient estimates of the parameters of the model. However, Wong and Vlaar (2003) show that the loss of efficiency from the two-step procedure is relatively large. Since our model consists of only four markets, we choose to estimate the model by maximizing the likelihood in one step. All computations were carried out using GAUSS.

At this point it is worth to mention how our model differs from that of Capiello *et. al*. Firstly, by including the lag returns from each market in the mean equation, we are able to capture the price spillover effects from one market to another. Similarly, by including the innovations coming from other markets into volatility equation, we are able to capture the volatility spillover effects. Furthermore, the EGARCH specification allows capturing the asymmetric effects in each market. The covariance equation is modeled in a similar way to Capiello *et. al*. so as to be able to capture the possible asymmetry in correlations.

Finally, we use one-step estimation procedure, which gives consistent and efficient estimations in contrast to the two-step approach, which gives consistent but inefficient estimations.

3. Empirical Findings

I. Data and preliminary statistics

The data consist of daily prices recorded at 16:00 London time (pseudo-closing prices) of S&P-500 (USA), FTSE-100 (UK), DAX-30 (Germany), and CAC-40 (France) indices. We use 16:00 London time closing prices in order to avoid the problems of non-synchronous data (see Martens and Poon, 2001). The period is from December 3, 1990 to August 6, 2004. At the time of collecting the data this was the longest series available. The advantages of daily data (and especially of pseudo-closing prices) can be summarized by the following:

(i) Market efficiency would suggest that news is quickly and efficiently incorporated into stock prices. Thus, information generated yesterday is obviously more important in explaining prices today than the information generated last week or before.

(ii) Various announcements such as profit forecasts, changes in interest rates, changes in oil prices, declaration of war etc. might have different impacts on investors' behaviour. Using daily stock data permits an analysis of how a market reacts to such news and how the market's "psychology" can be transmitted from one market to another, Veiga *et al.* (2003).

(iii) Since these international stock markets have different trading hours, the usage of closing prices leads to an underestimation of the true correlation between stock markets. By using pseudo-closing prices we avoid this problem.

The above indices are basically designed to reflect the largest firms. The DAX-30 is a price-weighted index of the 30 most heavily traded stocks in the German market, while the FTSE-100 is the principal index in the UK and consists of the largest 100 UK companies by full market value. CAC-40 is calculated on the basis of 40 best French titles, listed on the Paris Bourse. Finally S&P-500 is a value weighted index representing approximately 75 percent of total market capitalization.

We analyze the returns of the above markets as follows:

$$\mathrm{Re}\,t_t = \log\left(\frac{P_t}{P_{t-1}}\right) * 100 \qquad (12)$$

where P_t is the price level of an index at time *t*. The logarithmic stock returns are multiplied by 100 to approximate percentage changes and avoid convergence problems in estimation.

Since the data comes from different countries, it is unavoidable to have different holidays for each market. We side-step this problem by taking the holiday (pseudo) closing price as being the same as the previous day. Hence the sample for each country contains all days of the week except weekends.

In Figure 1, we plot the logs of the raw series and in Table 1 we report summary statistics for the daily returns of the four markets, as well as statistics testing for normality. Average daily returns are positive for all markets with New York possessing the highest value followed by Frankfurt. The measures for skewness and kurtosis show that all return series are negatively skewed (except from London market) and highly leptokurtic with respect to the normal distribution. Likewise the Kolmogorov-Smirnov (D) statistic and Jargue-Bera (JB) test reject normality for each of the return series at least at 5 percent level of significance. The Ljung-Box (LB) statistic for up to 12 lags, for returns and squared returns, indicate the presence of linear and non-linear dependencies, respectively in the returns of all four markets. Linear dependencies may be due to some form of market inefficiency while non-linear dependence may be due to autoregressive conditional heteroskedasticity. Furthermore, the LB statistic for the squared returns is, in all cases, several times greater than that calculated for returns, indicating that second moment (nonlinear) dependencies are far more significant than first moment dependencies (Koutmos, 1996).

Figure 1. Plots of the Indices for the Sample Period

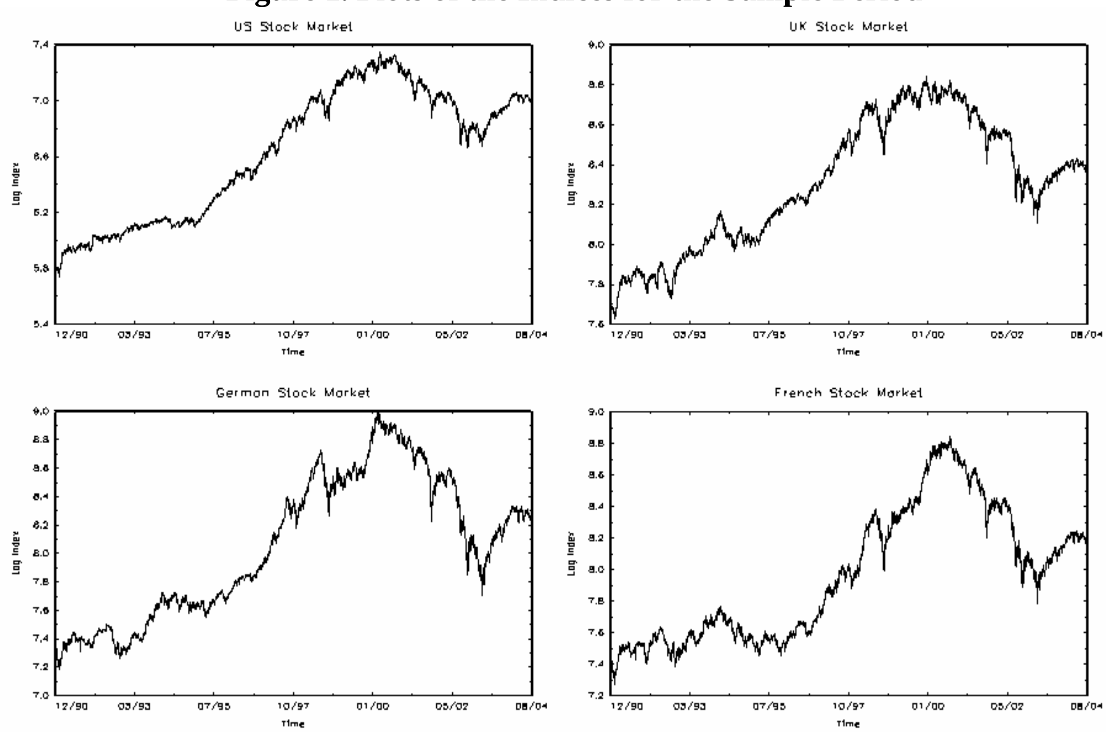

Table 1. Preliminary Statistics. Daily pseudo closing stock returns
Period: 3/12/1990 to 6/8/2004

Statistics	New York	London	Frankfurt	Paris
Sample mean	0.034	0.020	0.026	0.021
Variance	1.034	1.054	2.100	1.854
Kurtosis	6.263***	6.353***	7.118***	5.805***
Skewness	-0.022***	0.065***	-0.185***	-0.089**
Min	-5.533	-5.6347	-9.871	-7.678
Max	5.771	6.7195	7.0973	7.002
D	0.0735***	0.05***	0.0491***	0.0469***
JB	2591.26***	1674.71***	1584.85***	1176.32***
LB(12) for $\mathrm{Re}\,t_t$	21.40**	58.991***	25.546**	27.731***
LB(12) for $\mathrm{Re}\,t_t^2$	3620.26***	4814.50***	3763.10***	4673.82***

Notes:
Period Dec 3, 1990 to Aug 6, 2004 (3570 days). Kolmogorov-Smirnov test for normality (5% critical value is 1.36/√N, where N is the number of observations); LB(n) is the Ljung-Box statistic for up to n lags (distributed as χ^2 with n degrees of freedom); Jargue-Bera test for normality (distributed as χ^2 with 2 degrees of freedom)
** denotes significance at the 5% level.
*** denote significance at the 1% level.

In Table 2, we present the sample correlations for all markets. We find that the highest correlation is that between Frankfurt and Paris (0.7545) followed by the correlation between London and Paris (0.7458).However, these are unconditional values and the main question is whether these correlations change across the time. We use the CCC and DCC models to shed some light on this question.

Table 2. Unconditional Correlation Coefficients

	New York	London	Frankfurt	Paris
New York	1.0000	0. 6792	0.6407	0.6645
London		1.0000	0.6965	0.7458
Frankfurt			1.0000	0.7545
Paris				1.0000

II. Price and Volatility Spillovers under the CCC framework

In order to find price and volatility spillovers under the CCC framework, we estimate the system of equations (1) – (3) and (5). The maximum likelihood estimates are reported in Table 3. In terms of first moment interdependencies, there are significant price spillovers from Paris to New York but surprisingly not from New York to any other market. This result is in line with the findings of Martens and Poon (2001) who find significant spillovers from Europe to the US. In addition, London is affected from Frankfurt and Paris with feedback effects only to Frankfurt. Frankfurt is also affected by the Paris market while Paris is only affected by Frankfurt. The above results reveal different relationships from the previous findings of Theodosiou and Lee (1993), Koutmos and Booth (1996), Antoniou *et. al.* (2003) among others, suggesting that the relationships between stock markets change over time. As far as the magnitude of coefficients is concerned, we observe that $\beta_{i,4}$ posses the highest positive value among the price spillover coefficients. That is, Paris has a great impact on US and European stock markets for this period, suggesting that the Paris market plays a predominant role as an information producer.

Turning to volatility spillovers (second moment interdependencies), it is observed that in addition to own past innovations, the conditional variance in each market is also affected by innovations coming at least from one of the other three markets. Specifically, the New York market is not only affected by its own market innovations but also by the innovations coming from other markets. However, there are significant volatility spillovers from New York only to Paris. Previous studies document feedback effects in second moment equations for London and New York markets (for instance see the results of Koutmos and Booth (1995), Veiga and McAleer (2003)) suggesting that ignoring the time lag between US and Europe might lead to different inferences[1]. However, this result may be attributed to the well-known intraday volatility patterns. Various studies (such as Chan *et. al.* (1991), Engle *et. al.* (1994), Andersen (2000) among others) have shown that the volatility in US stock market is higher during the opening and colosing times (U-shape). 16:00 London time corresponds to 11:00 New York time, where the S&P500 volatility reaches its lowest level. Finally, another result is that the Paris market affects all the other European markets while the London market is also affected by Frankfurt.

More importantly, the volatility transmission mechanism is asymmetric in all markets. The coefficients measuring asymmetry, γ_j, are significant for all four markets. This result reinforces the assertion that bad news in one market may increase volatility more than good news. The size of these asymmetries can be assessed using the estimated coefficients. Thus, a negative innovation in (i) New York, (ii) London, (iii) Frankfurt, (iv) Paris increases volatility in the other three markets by (i) 2.85, (ii) 3.19, (iii) 1.53, (iv) 2.51 times respectively more than a positive innovation. These figures also measure the differential impact of own past innovations on the current conditional variance.

The coefficient δ_i which measures the volatility persistence is close to one and highly significant indicating that the conditional stock returns variances are highly persistence. Furthermore, the conditional correlations are lower than the unconditional estimates suggesting that hedging models that ignore market interdependence are likely to produce biased estimates of hedge ratios. Those results are in line with the findings of Koutmos (1996), Koutmos and Booth (1995), Antoniou *et. al.* (2003) among others.

Finally, the diagnostic tests based on the standardized residuals show no serious evidence against this model specification, with means and variances close to zero and one respectively. The LB and the Multivariate LB statistics for twelve lags find no significant dependence in the standardized residuals (except from some dependency in the squared standardized residuals of London stock market). To test the joint significance of first and second markets' interactions we use the likelihood ratio statistic. The estimated value of

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[1] The same procedures were applied to the same markets using closing prices and the results suggest different interdependencies.

Table 3. Multivariate EGARCH model. Price and volatility spillovers.
Full sample period: 3/12/1990 to 6/8/2004 (3570 obs.)

Mean: $R_{i,t} = \beta_{1,0} + \beta_{i,i} R_{i,t-1} + \varepsilon_{i,t}$ for i,j=1,2,3,4 and $i \neq j$

Variance: $\sigma^2_{i,t} = \exp\{a_{i,0} + a_{i,i} f_i(z_{i,t-1}) + \delta_i \ln(\sigma^2_{i,t-1})\}$ for i,j=1,2,3,4 and $i \neq j$

Covariance: $\sigma_{i,j,t} = \rho_{i,j}\sigma_{i,t}\sigma_{j,t}$ for i,j=1,2,3,4 and $i \neq j$

New York		London		Frankfurt		Paris	
$\beta_{1,0}$	0.03690 *** [0.014] (0.0069)	$\beta_{2,0}$	0.02290 [0.014] (0.1011)	$\beta_{3,0}$	0.04110 ** [0.019] (0.02790)	$\beta_{4,0}$	0.03010 [0.019] (0.1186)
$\beta_{1,1}$	-0.06110 *** [0.022] (0.0059)	$\beta_{2,1}$	0.01420 [0.022] (0.5136)	$\beta_{3,1}$	0.04160 [0.029] (0.1535)	$\beta_{4,1}$	0.04250 [0.029] (0.1407)
$\beta_{1,2}$	-0.00810 [0.023] (0.7290)	$\beta_{2,2}$	0.02480 [0.024] (0.3089)	$\beta_{3,2}$	0.06290 ** [0.032] (0.04990)	$\beta_{4,2}$	-0.02580 [0.033] (0.4280)
$\beta_{1,3}$	-0.01540 [0.016] (0.3380)	$\beta_{2,3}$	-0.06780 *** [0.017] (0.0001)	$\beta_{3,3}$	-0.2061 *** [0.023] (0.0000)	$\beta_{4,3}$	-0.08440 *** [0.023] (0.0002000)
$\beta_{1,4}$	0.03780 ** [0.018] (0.03200)	$\beta_{2,4}$	0.04810 ** [0.019] (0.01130)	$\beta_{3,4}$	0.2206 *** [0.025] (0.0000)	$\beta_{4,4}$	0.04230 [0.026] (0.1081)
$a_{1,0}$	-0.002300 [0.0017] (0.1719)	$a_{2,0}$	-0.003100 * [0.0019] (0.09000)	$a_{3,0}$	0.01620 *** [0.0028] (0.0000)	$a_{4,0}$	0.01460 *** [0.0029] (0.0000)
$a_{1,1}$	0.06960 *** [0.0090] (0.0000)	$a_{2,1}$	-0.01040 [0.010] (0.3142)	$a_{3,1}$	-0.0092 [0.0098] (0.3485)	$a_{4,1}$	-0.02300 ** [0.011] (0.03000)
$a_{1,2}$	0.02530 ** [0.012] (0.03650)	$a_{2,2}$	0.05080 *** [0.010] (0.0000)	$a_{3,2}$	0.01890 [0.014] (0.1836)	$a_{4,2}$	0.001000 [0.011] (0.9244)
$a_{1,3}$	-0.02960 ** [0.012] (0.01240)	$a_{2,3}$	-0.02980 ** [0.014] (0.03160)	$a_{3,3}$	0.05720 *** [0.014] (0.00010)	$a_{4,3}$	-0.008400 [0.014] (0.5534)
$a_{1,4}$	0.04000 *** [0.013] (0.002900)	$a_{2,4}$	0.09090 *** [0.016] (0.0000)	$a_{3,4}$	0.04110 *** [0.015] (0.0065)	$a_{4,4}$	0.1062 *** [0.014] (0.0000)
γ_1	-0.4802 *** [0.12] (0.0001)	γ_2	-0.5237 ** [0.23] (0.02060)	γ_3	-0.2085 * [0.1238] (0.09210)	γ_4	-0.4301 *** [0.078] (0.0000)
δ_1	0.9760 *** [0.0033] (0.0000)	δ_2	0.9715 *** [0.0042] (0.0000)	δ_3	0.9681 *** [0.0045] (0.0000)	δ_4	0.9709 *** [0.0046] (0.0000)

Correlation Coefficients

	New York	London	Frankfurt	Paris
New York	1.0000	0.6556 ***	0.5888 ***	0.6357 ***
		[0.0096]	[0.011]	[0.010]
		(0.0000)	(0.0000)	(0.0000)
London		1.0000	0.6270 ***	0.7098 ***
			[0.010]	[0.0084]
			(0.0000)	(0.0000)
Frankfurt			1.0000	0.7081 ***
				[0.0086]
				(0.0000)
Paris				1.0000

Model Diagnostics

	New York	London	Frankfurt	Paris
$E\left(z_{i,t}\right)$	-0.00709	-0.00734	-0.01158	-0.00916
$E\left(z^2_{i,t}\right)$	1.00190	0.99791	1.00327	1.00103
D	0.0368***	0.0246**	0.0392***	0.0288***
JB	3196.37***	2765.37***	13191.07***	4165.14***
$LB(12); z_{i,t}$	13.81	20.82	12.34	20.88
$LB(12); z^2_{i,t}$	7.51	23.26**	11.49	20.79
$MLB(12); z_{i,t}$	121.92			

LR test for $H_0 : \alpha_{ij} = \beta_{ij} = 0$: 267.62*** (0.0000)

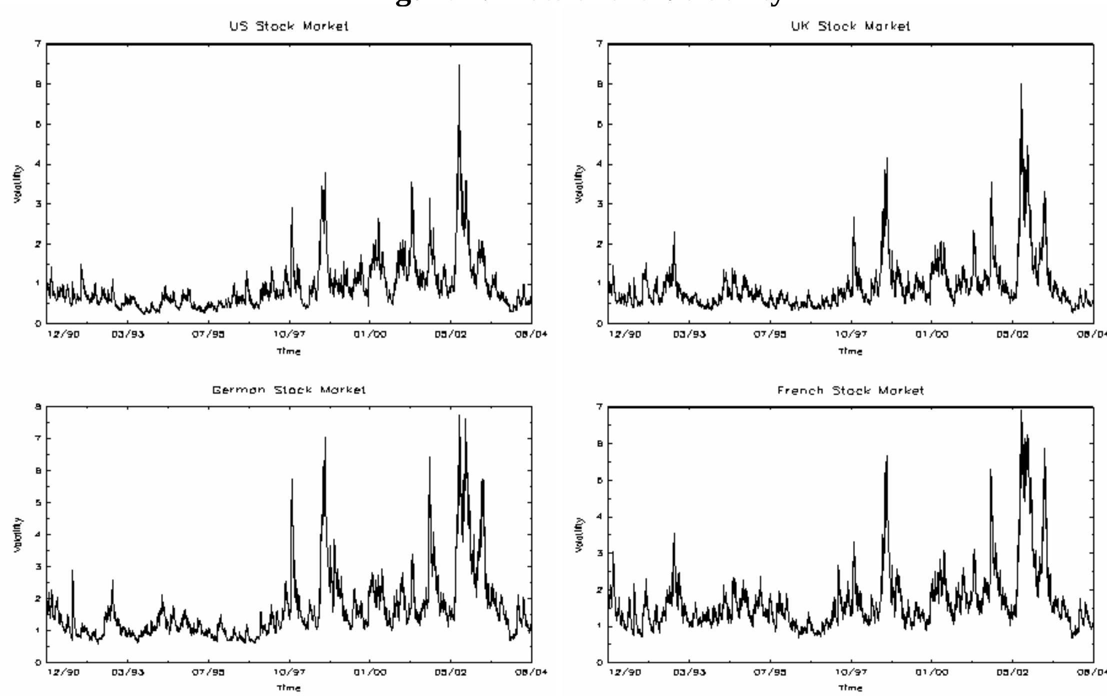
Log-likelihood = -17061.43

Notes: Period Dec 3, 1990 to Aug 6, 2004 (3570 days). Kolmogorov-Smirnov test for normality (5% critical value is 1.36/√N, where N is the number of observations); LB(n) is the Ljung-Box statistic for up to n lags (distributed as χ^2 with n degrees of freedom); Jargue-Bera test for normality (distributed as χ^2 with 2 degrees of freedom)
** denotes significance at the 5% level.
*** denote significance at the 1% level.

the likelihood ratio statistic is 267.62 thus rejecting the hypothesis of “no price or volatility spillovers” at any level of significance.

We illustrate our EGARCH estimates for all markets by plotting the conditional volatility for the entire sample period. Figure 2 plots the volatility of the four indices and the graphs illustrate the strong volatility persistence for all markets. It is apparent that volatility increases after the beginning of 1998 for all markets and reaches its highest point during the 11th of September incidents and during the wars in Afghanistan and Iraq. This result supports the assertion that volatility is higher in turbulent periods.

Figure 2. Plots of the Volatility



To further investigate the volatility transmission mechanism among the four aforementioned markets, the pairwise impacts of a ±5% innovation in one market at time *t*-1 on the conditional volatility of all other markets at time *t* are reported in Table 5. Following Koutmos and Booth (1995) and Koutmos (1996), the contributing factor of a negative innovation in market *i* on the volatility of market *j* is proportional to $|-a_{i,j} + a_{i,j}\gamma_j|$, whereas a positive innovation will affect market in proportion $(a_{i,j} + a_{i,j}\gamma_j)$.

The results in Table 4 confirm that the impact of a negative innovation is at least double the impact of positive news, showing that the informational asymmetries exist. Furthermore the magnitude of the impacts confirms that there is interdependence among markets for this period.

Table 4. Impact of Innovation on Volatility				
Innovation	%Δ New York	%Δ London	%Δ Frankfurt	%Δ Paris
+5%in N.Y -5% in N.Y	- -	-0.027 0.077	-0.024 0.068	-0.060 0.170
+5% in Lon. -5%i n Lon.	0.060 0.193	- -	0.045 0.144	0.002 0.008
+5% in Frank. -5% in Frank.	-0.117 0.179	-0.118 0.180	- -	-0.033 0.051
+5% in Paris -5% in Paris	0.114 0.286	0.259 0.650	0.117 0.294	- -

Although the above analysis reveals some interesting results about the price and volatility spillovers, under the CCC framework we are not able to investigate any possible alterations in the correlations after the introduction of euro. Hence, we propose the following modification in the conditional correlations.

In the conditional covariance specification of the CCC model we include two dummy variables. The first dummy, *dum1*, takes the values 1 for all observations before the introduction of euro and 0 afterwards, while *dum2* takes the values 0 for the pre-period and 1 for the period after the introduction of euro. By including these dummies the conditional covariance is given by the following specification:

$$H_t = D_t(dum_1 R_1 + dum_2 R_2)D_t \qquad (13)$$

where R_1 and R_2 capture the correlations before and after the introduction of euro respectively.

Table 5 reports the results for the new model. The estimations for the mean equations are very similar to those of Table 3. Nevertheless, the results for the second moment interdependencies reveal some changes. More specifically, after the inclusion of the structural break in the correlations the London stock market affects the volatility equations of all other markets, while the German market is no longer influencing any of the other markets (apart from the volatility of its own market).

However, the most important result is the change in correlation coefficients. We observe a tremendous increase in the correlations of all markets after the launch of euro. For instance, the conditional correlation between German and French stock market is 0.8443 for the post euro period, while their corresponding conditional correlation for the period before euro was 0.5812. In addition, the conditional correlation between London and German stock markets has increased from 0.5281 to 0.7287. The smallest increase is observed for New York and London markets which is sensible since none of these counties has direct effects from the introduction of the new currency.

Table 5. Multivariate EGARCH model. Price and volatility spillovers.
Full sample period: 3/12/1990 to 6/8/2004 (3570 obs.)

Mean: $R_{i,t} = \beta_{1,0} + \beta_{i,i} R_{i,t-1} + \varepsilon_{i,t}$ for i,j=1,2,3,4 and $i \neq j$

Variance: $\sigma_{i,t}^{2} = \exp\{a_{i,0} + a_{i,i} f_i(z_{i,t-1}) + \delta_i \ln(\sigma_{i,t-1}^{2})\}$ for i,j=1,2,3,4 and $i \neq j$

Covariance: $\sigma_{i,j,t} = (dum_1 \rho_{1,i,j} + dum_2 \rho_{2,i,j}) \sigma_{i,t} \sigma_{j,t}$ for i,j=1,2,3,4 and $i \neq j$

New York		London		Frankfurt		Paris	
$\beta_{1,0}$	0.03770 *** [0.013] (0.0045)	$\beta_{2,0}$	0.02190 [0.014] (0.1068)	$\beta_{3,0}$	0.03950 ** [0.018] (0.02780)	$\beta_{4,0}$	0.03270 * [0.018] (0.07350)
$\beta_{1,1}$	-0.08350 *** [0.022] (0.00020)	$\beta_{2,1}$	-0.00960 [0.022] (0.6562)	$\beta_{3,1}$	0.01360 [0.029] (0.6454)	$\beta_{4,1}$	0.01230 [0.029] (0.6711)
$\beta_{1,2}$	-0.0020 [0.023] (0.9303)	$\beta_{2,2}$	0.02840 [0.024] (0.2411)	$\beta_{3,2}$	0.05820 * [0.032] (0.06670)	$\beta_{4,2}$	-0.0080 [0.032] (0.8061)
$\beta_{1,3}$	-0.01530 [0.016] (0.3365)	$\beta_{2,3}$	-0.06820 *** [0.017] (0.0000)	$\beta_{3,3}$	-0.2007 *** [0.022] (0.0000)	$\beta_{4,3}$	-0.08090 *** [0.022] (0.00030)
$\beta_{1,4}$	0.04740 *** [0.017] (0.00560)	$\beta_{2,4}$	0.06050 *** [0.018] (0.00100)	$\beta_{3,4}$	0.2242 *** [0.024] (0.0000)	$\beta_{4,4}$	0.05230 ** [0.025] (0.03670)
$a_{1,0}$	-0.00160 [0.0016] (0.3114)	$a_{2,0}$	-0.00250 [0.0017] (0.1332)	$a_{3,0}$	0.009800 *** [0.0019] (0.0000)	$a_{4,0}$	0.01080 *** [0.0021] (0.0000)
$a_{1,1}$	0.06870 *** [0.0084] (0.0000)	$a_{2,1}$	0.00150 [0.0087] (0.8592)	$a_{3,1}$	-0.00320 [0.0084] (0.6988)	$a_{4,1}$	-0.00820 [0.0086] (0.3386)
$a_{1,2}$	0.02910 *** [0.0094] (0.00190)	$a_{2,2}$	0.05350 *** [0.0094] (0.0000)	$a_{3,2}$	0.02810 *** [0.010] (0.00550)	$a_{4,2}$	0.01620 * [0.0085] (0.05850)
$a_{1,3}$	-0.00860 [0.011] (0.4227)	$a_{2,3}$	-0.01130 [0.0110] (0.3181)	$a_{3,3}$	0.05840 *** [0.012] (0.0000)	$a_{4,3}$	0.01060 [0.012] (0.3546)
$a_{1,4}$	0.02170 * [0.012] (0.07300)	$a_{2,4}$	0.07200 *** [0.014] (0.0000)	$a_{3,4}$	0.02000 * [0.011] (0.07690)	$a_{4,4}$	0.07870 *** [0.012] (0.0000)
γ_1	-0.5066 *** [0.12] (0.0000)	γ_2	-0.6309 *** [0.19] (0.00070)	γ_3	-0.2344 ** [0.094] (0.01240)	γ_4	-0.3412 *** [0.085] (0.000100)
δ_1	0.9818 *** [0.0025] (0.0000)	δ_2	0.9781 *** [0.0029] (0.0000)	δ_3	0.9824 *** [0.0026] (0.0000)	δ_4	0.9786 *** [0.0030] (0.0000)

Correlation Coefficients Pre Euro				
	New York	London	Frankfurt	Paris
New York	1.0000	0.6178 **	0.4899 ***	0.5741 ***
		[0.013]	[0.017]	[0.014]
		(0.0000)	(0.0000)	(0.0000)
London		1.0000	0.5281 ***	0.6544 ***
			[0.016]	[0.012]
			(0.0000)	(0.0000)
Frankfurt			1.0000	0.5812 ***
				[0.014]
				(0.0000)
Paris				1.0000

Correlation Coefficients Post Euro				
	New York	London	Frankfurt	Paris
New York	1.0000	0.6887 ***	0.6882 ***	0.6913 ***
		[0.012]	[0.012]	[0.012]
		(0.0000)	(0.0000)	(0.0000)
London		1.0000	0.7287 ***	0.7636 ***
			[0.011]	[0.0097]
			(0.0000)	(0.0000)
Frankfurt			1.0000	0.8443 ***
				[0.0066]
				(0.0000)
Paris				1.0000

Model Diagnostics

	New York	London	Frankfurt	Paris
$E\left(z_{i,t}\right)$	-0.00719	-0.00267	-0.0080	-0.0129
$E\left(z_{i,t}^2\right)$	1.001	1.007	1.008	1.018
D	0.0342***	0.0257**	0.0345***	0.0268***
JB	3218.36***	3789.42***	21974.86***	4628.75***
$LB\left(12\right);z_{i,t}$	14.85	18.81	12.13	19.28
$LB\left(12\right);z_{i,t}^2$	3.71	12.26	6.83	9.44
$MLB\left(12\right);z_{i,t}^2$	115.27			
Log-likelihood = -16855.91				

Notes: Period Dec 3, 1990 to Aug 6, 2004 (3570 days). Kolmogorov-Smirnov test for normality (5% critical value is 1.36/√N, where N is the number of observations); LB(n) is the Ljung-Box statistic for up to n lags (distributed as χ^2 with n degrees of freedom); Jargue-Bera test for normality (distributed as χ^2 with 2 degrees of freedom)
** denotes significance at the 5% level.
*** denote significance at the 1% level.

Through the literature there are some indications that the date of the 15th of December 1996 (Van Dijk *et. al.*) might have been more important than that of the real introduction. On that date the formal decision to proceed with the euro was made (known and as the "Dublin Declaration"). Hence, similar analysis is performed by allowing for a structural break on that date. Although the log-likelihood is improved the improvement is not that large as in the case of the real introduction of euro. Thus, we concentrate only for the structural break on the 1st of January 1999.

To assess the significance of that change we perform a likelihood ratio test (Table 5). The estimated value of the likelihood ratio statistic is 411.04, thus rejecting the hypothesis of "no change in the correlations after the introduction of euro" at any level of significance.

Table 5. Log Likelihood values for the CCC models

Model	***Log-Likelihood***
CCC model	-17061.43
CCC model with a structural break on 15th December 1996	-16959.13
CCC model with a structural break on 1st of January 1999	-16855.91

Generally the results show that the correlation has increased between all four markets since the introduction of euro. Since there is evidence that the correlations are time-varying (TSE 2000), there is a need to extend the CCC model to incorporate time-varying correlations. Thus, we now estimate the AGDCC model by maximizing again the log likelihood function over the parameters of the model.

III.AGDCC Estimation

When the model firstly estimated, it became obvious that almost all the correlations have undergone a structural break around the period of the introduction of euro (confirming the results of the CCC model with structural break). The same result is supported by the analysis of Cappiello *et. al.* (2003). For that reason dummy variables were included in the mean equations and also in the correlation equation. However, the model with the dummies revealed that only the dummy in the correlation equation is significant. Hence, the model is estimated by using a dummy only in the correlation equation. It follows the new structure of Q_t.

Let *d* be 0 or 1 depending on whether $t > \tau$ or $t < \tau$. Then,

$$Q_t = (\bar{Q} - d\tilde{Q} - A'\bar{Q}A + dA'\tilde{Q}A - B'\bar{Q}B + dB'\tilde{Q}B - C'\bar{N}C + C'\tilde{N}C) \\ + A'u_{t-1}u_{t-1}'A + B'Q_{t-1}B + C'\eta_{t-1}\eta_{t-1}'C$$

where $\tilde{Q} = \bar{Q} - E[u_t u_t^{'}]$, for $t \geq \tau$.

Equivalently,

$$Q_t = (\bar{Q}_1 - A^{'}\bar{Q}_1 A - B^{'}\bar{Q}_1 B - C^{'}\bar{N}_1 C) + (\bar{Q}_2 - A^{'}\bar{Q}_2 A - B^{'}\bar{Q}_2 B - C^{'}\bar{N}_2 C)$$
$$+ A^{'}u_{t-1}u_{t-1}{'}A + B^{'}Q_{t-1}B + C^{'}\eta_{t-1}\eta_{t-1}{'}C$$

where $\bar{Q}_1 = E[u_t u_t^{'}]$, for $t \leq \tau$ and $\bar{Q}_2 = E[u_t u_t^{'}]$, for $t \geq \tau$, with $\bar{N}_1$ and $\bar{N}_2$ analogously defined.

To include the structural break into the correlation equation we substitute $\bar{Q}$ with $\bar{Q}_t$ which is defined as:

$$\bar{Q}_t = \bar{Q}_1 I[t \leq \tau] + \bar{Q}_2 I[t \geq \tau]$$

where $I[.]$ is the indicator function for the event A and τ denotes the break point (Van Dijk *et. al., 2005).*

As the above model nests the standard DCC specification and some of its extensions, we test if any of them performs better than the AGDCC model including the standard DCC model without any breaks. It is shown that the AGDCC specification outperforms all the other models. Table 6 reports the log-likelihood of each model.

Table 6. Log Likelihood values for the DCC models with structural break

Model	***Log-Likelihood***
Standard DCC model (no breaks)	-16739.91
Standard DCC model	-16681.33
Standard DCC model with asymmetry	-16679.01
GDCC model	-16673.52
AGDCC model	-16660.53

The results for the first and second moment interdependencies (Table 7) from the estimation of the AGDCC model are identical to those of the CCC with structural break. For that reason we turn our interest to the conditional correlations specification of this model. Table 8, reports the coefficients of the diagonal asymmetric DCC model (equations 8, 9 and 10).

Table 7. Multivariate EGARCH model. Price and volatility spillovers.
Full sample period: 3/12/1990 to 6/8/2004 (3570 obs.)

Mean: $R_{i,t} = \beta_{1,0} + \beta_{i,i} R_{i,t-1} + \varepsilon_{i,t}$ for *i,j*=1,2,3,4 and *i≠j*

Variance: $\sigma^2_{i,t} = \exp\{a_{i,0} + a_{i,i} \sum_{i=1} f_i(z_{i,t-1}) + \delta_i \ln(\sigma^2_{i,t-1})\}$ for *i,j*=1,2,3,4 and *i≠j*

New York		London		Frankfurt		Paris	
$\beta_{1,0}$	0.03370 *** [0.013] (0.0043)	$\beta_{2,0}$	0.01960 * [0.013] (0.0688)	$\beta_{3,0}$	0.03330 ** [0.017] (0.02647)	$\beta_{4,0}$	0.03030 ** [0.017] (0.03825)
$\beta_{1,1}$	-0.0702 *** [0.022] (0.0006)	$\beta_{2,1}$	0.00380 [0.021] (0.4279)	$\beta_{3,1}$	0.03340 [0.027] (0.1072)	$\beta_{4,1}$	0.04310 ** [0.025] (0.04240)
$\beta_{1,2}$	-0.00590 [0.022] (0.3929)	$\beta_{2,2}$	0.01660 [0.021] (0.2135)	$\beta_{3,2}$	0.05280 ** [0.028] (0.02925)	$\beta_{4,2}$	-0.00330 [0.028] (0.4529)
$\beta_{1,3}$	-0.01000 [0.018] (0.2871)	$\beta_{2,3}$	-0.0594 *** [0.018] (0.0006)	$\beta_{3,3}$	-0.1854 *** [0.024] (0.0000)	$\beta_{4,3}$	-0.0794 *** [0.024] (0.00055)
$\beta_{1,4}$	0.04980 *** [0.017] (0.0021)	$\beta_{2,4}$	0.06550 *** [0.018] (0.00014)	$\beta_{3,4}$	0.2145 *** [0.024] (0.0000)	$\beta_{4,4}$	0.04560 ** [0.024] (0.02824)
$a_{1,0}$	0.00001 [0.0013] (0.5000)	$a_{2,0}$	-0.0021 ** [0.0012] (0.0401)	$a_{3,0}$	0.00830 *** [0.0016] (0.0000)	$a_{4,0}$	0.0098 *** [0.0016] (0.0000)
$a_{1,1}$	0.07130 *** [0.0087] (0.0000)	$a_{2,1}$	0.00460 [0.0077] (0.2751)	$a_{3,1}$	-0.00080 [0.0079] (0.4597)	$a_{4,1}$	-0.0047 [0.0076] (0.2682)
$a_{1,2}$	0.03000 *** [0.0094] (0.0007)	$a_{2,2}$	0.05790 *** [0.0095] (0.0000)	$a_{3,2}$	0.02510 *** [0.0096] (0.00449)	$a_{4,2}$	0.02080 *** [0.0085] (0.00723)
$a_{1,3}$	-0.00070 [0.0096] (0.4709)	$a_{2,3}$	0.00200 [0.0099] (0.4200)	$a_{3,3}$	0.06900 *** [0.012] (0.0000)	$a_{4,3}$	0.02100 ** [0.010] (0.01790)
$a_{1,4}$	0.01550 * [0.010] (0.0625)	$a_{2,4}$	0.04420 *** [0.012] (0.0000)	$a_{3,4}$	0.00950 [0.011] (0.1851)	$a_{4,4}$	0.05880 *** [0.011] (0.0000)
γ_1	-0.5529 *** [0.1090] (0.0000)	γ_2	-0.5772 *** [0.15] (0.0000)	γ_3	-0.3281 *** [0.082] (0.0000)	γ_4	-0.5650 *** [0.12] (0.0000)
δ_1	0.9849 *** [0.0020] (0.0000)	δ_2	0.9844 *** [0.0020] (0.0000)	δ_3	0.9857 *** [0.0020] (0.0000)	δ_4	0.9847 *** [0.0021] (0.0000)

Model Diagnostics

	New York	London	Frankfurt	Paris
$E(z_{i,t})$	-0.0036	0.00025	-0.00048	-0.01199
$E(z^2_{i,t})$	0.992	1.058	1.011	0.967
D	0.0376***	0.0202	0.0341***	0.0268**
JB	3282.98***	4266.88***	34922.60***	4907.51***
$LB(12); z_{i,t}$	12.67	14.98	12.49	19.49
$LB(12); z^2_{i,t}$	3.65	9.73	5.03	7.84
$MLB(12); z^2_{i,t}$	112.34			
Log-likelihood = -16660.53				

Notes:
Period Dec 3, 1990 to Aug 6, 2004 (3570 days). Kolmogorov-Smirnov test for normality (5% critical value is 1.36/√N, where N is the number of observations); LB(n) is the Ljung-Box statistic for up to n lags (distributed as χ^2 with n degrees of freedom); Jargue-Bera test for normality (distributed as χ^2 with 2 degrees of freedom)
** denotes significance at the 5% level.
*** denote significance at the 1% level.

We find evidence of highly persistent correlations with evidence of asymmetric effects. The strong persistence is evident from the highly significant b_i coefficients of the lag term Q_{t-1}. These coefficients vary from 0.965 to 0.982. The most recent return co-movement captured by the term $z_{t-1}z_{t-1}'$ carries relatively large weight as the a_i coefficients estimates are high and significant for all markets. The coefficient estimates that represent the asymmetric effect appear to be relatively large and significant. The above result indicates that negative returns induce stronger co-movements than positive returns, across markets. This finding is in line with the results in the literature (for instance see Longin and Solnik (1998), Cappiello *et. al.* (2003), Martens and Poon (2001), etc).

Table 8. Diagonal Asymmetric DCC Model Estimates

	New York	London	Frankfurt	Paris
α	0.1162 *** [0.014] (0.0000)	0.1349 *** [0.019] (0.0000)	0.1462 *** [0.019] (0.0000)	0.1970 *** [0.015] (0.0000)
b	0.9818 *** [0.0058] (0.0000)	0.9649 *** [0.0077] (0.0000)	0.9719 *** [0.0068] (0.0000)	0.9691 *** [0.0048] (0.0000)
c	0.07480 *** [0.023] (0.00055)	0.1541 *** [0.034] (0.0000)	0.1171 *** [0.028] (0.0000)	0.05870 ** [0.029] (0.02297)

* denotes significance at the 10% level.
** denotes significance at the 5% level.
*** denote significance at the 1% level.

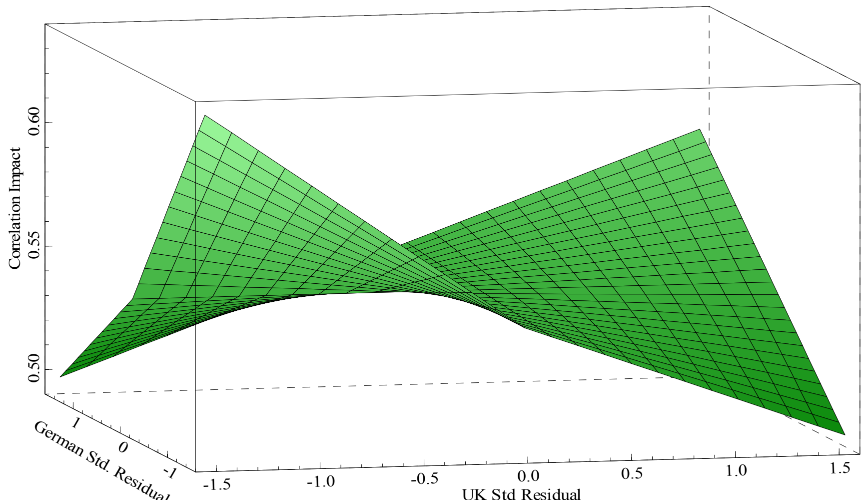
IV. News Impact Surfaces and Correlation Plots

To illustrate the asymmetric response of correlations to joint positive or negative shocks we use the news impact surfaces. The news impact surface for the correlation is given by

$$\begin{aligned} f(z_i, z_j) &\approx \tilde{q}_{ij} + (a_i a_j + c_i c_j) z_i z_j, && \text{for } z_i, z_j < 0 \\ f(z_i, z_j) &\approx \tilde{q}_{ij} + a_i a_j z_i z_j, && \textit{otherwise} \end{aligned} \qquad (14)$$

where z_i, are the standardized residuals. Figure 3, presents the graph of the impact of the standardized residuals of London and Frankfurt stock markets on their correlation. It is obvious that negative shocks in both markets have greater impact on correlation. This pattern is the most characteristic and applies for the rest of the combinations.

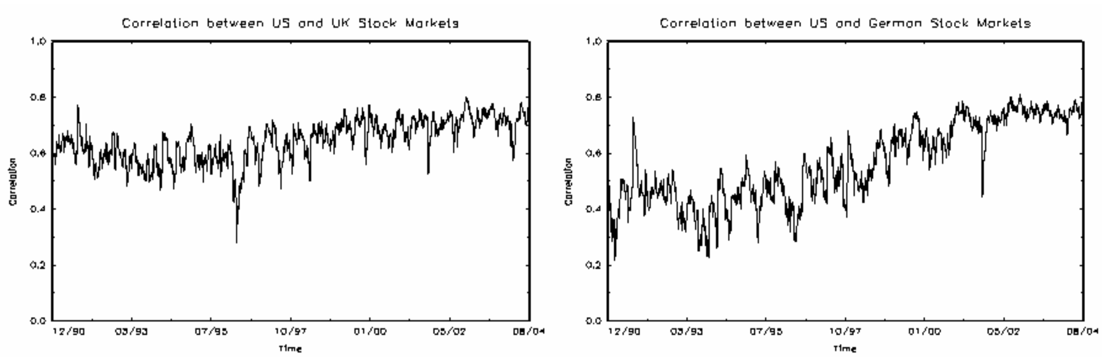
Figure 3. News Impact Surfaces



The next step of this section is to use the model estimates to plot the conditional correlations for the four markets under investigation. Figure 4 plots the daily conditional correlations for the four markets and reveals that the correlation between all markets has trended upwards. The increase is more pronounced for the German and French stock markets. However, the irrevocable fixing of the exchange rates for the EMU countries does not affect only Germany and France but also UK.

The correlation between London and Frankfurt or Paris has also increased. Moreover, an increase is observed between US and European markets. Nevertheless, that increase is most likely to be unrelated with the introduction of euro. It might be because of the general globalization trend or the internet (technology) boom. Finally, the correlation between US and UK is that with the lowest increase. Most probably this increase is due to the aforementioned reasons and not due the introduction of euro. Another result is that the correlations within European borders are less volatile since the introduction of euro.

Figure 4. Daily Dynamic Conditional Correlations



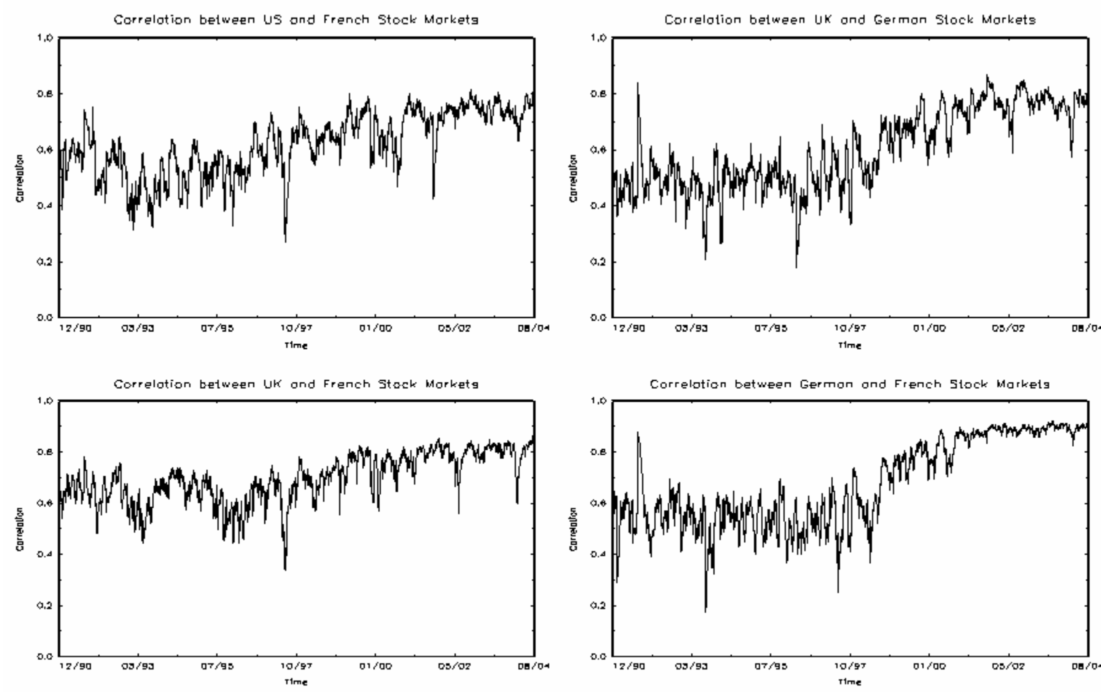
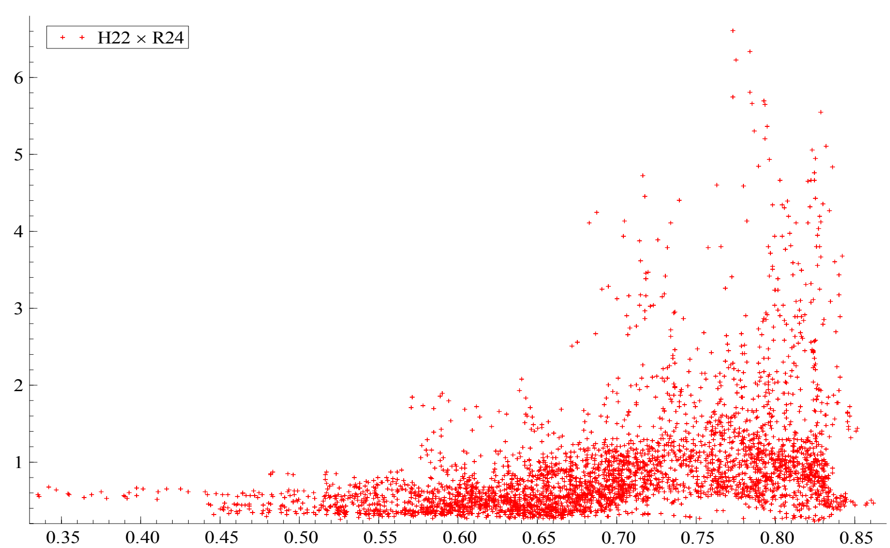


Figure 5 presents the scatter plot of the conditional correlation series against the volatility of the underlying markets (all the plots are very similar to the one below). The interesting feature we note is that for the correlations between those markets, extreme volatility values are associated with high correlation values. This result agrees with the findings of Kasch-Haroutounian (2005) giving an indirect verification to our assertion that negative shocks cause higher volatilities and consequently higher correlations

Figure 5. Scatter Plots between Volatility and Conditional Correlations



The above results support the proposition that the adoption of a common monetary policy have led higher correlations between returns not only for the markets within European Monetary Union (Frankfurt and Paris) but also for New York and London. In Table 10 we report the average correlations for the period before and after euro.

Table 9. Average Correlations

Before EURO				
	New York	London	Frankfurt	Paris
New York	1	0.6008	0.4622	0.5543
London		1	0.4991	0.6387
Frankfurt				0.5515
Paris				1
After EURO				
	New York	London	Frankfurt	Paris
New York	1	0.7053	0.7058	0.7115
London		1	0.7424	0.7787
Frankfurt			1	0.8532
Paris				1

While the correlation between New York and London remains stable, the rest of the correlations experience an increase during the period after EURO. These results are in line with the results of Capielo et al. (2003). More specifically, the highest average increase is observed for Frankfurt – Paris (0.5515 – 0.8532) followed by London – Frankfurt (0.4991 – 0.7424) and New York Frankfurt (0.4622 – 0.7058). The smallest increase in average correlation is observed for New York – London (0.6008 – 0.7053).

Finally, if we compare those results with the results of CCC for Pre and Post euro correlations, we observe that the correlations are very close for all cases. This result supports the notion that the CCC model behaves well for small periods but it fails to do the same for longer periods.

4. Main Findings and Conclusions

This paper formulates and estimates the CCC and the AGDCC Multivariate EGARCH models of the daily stock market returns for four major world markets, New York, London, Frankfurt and Paris reflecting the outlook of American and European investors. The models are used to investigate the first and second moment interdependencies among those markets for the period from December 3 1990 to August 6 2004 along with their correlations. To avoid the problem of non-synchronous data, we use pseudo closing prices.

The results from applying the models to the aforementioned markets provide evidence that the domestic stock prices and volatilities are influenced by the behaviour of foreign markets. The Paris stock market acts as an information producer for the period under investigation. It has price spillovers effects to all other markets while London market has volatility spillover effects to the rest of the markets. However, a remarkable result, under both frameworks, is that the volatility is found to respond asymmetrically to news/innovations in other markets, with a stronger response in the case of bad news than in the case of good news.

Since one of the major goals of this paper is to examine the effects on correlations after the introduction of euro, we re-estimate the CCC model including dummies that capture this change. The results suggest a significant increase since the introduction of the new currency. This result is also confirmed by the AGDCC model which in turn finds that the correlation responds asymmetrically to bad news (News Impact Surface, Figure 3). Figure 4 depicts this increase in correlations for all markets. Hence, we can infer that the CCC model captures the changes in conditional correlation only if use sub-periods (by including dummies) of the whole sample period.

All the above results motivate for further research. For instance, we can include more countries using euro in our sample and compare their correlations with other markets. In addition, we can examine those relationships by including in our sample futures or bond markets.

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