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 for the whole period, but only for London and Frankfurt for the period after the introduction of EURO. 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.

Keywords: Stock Price; Multivariate EGARCH Model; Asymmetric Volatility Spillovers; Constant Conditional Correlation; Dynamic Conditional Correlation.

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.

Karolyi (1995) examines the short run dynamics of returns and volatilities for Toronto (TSE) and New York (NYSE) stock markets, under a multivariate GARCH model. He concludes that the transmissions from one market to another depend on "how the cross-market dynamics in the conditional volatilities of the respective markets are modeled". Generally he finds that the NYSE market influences TSE. This result (that NYSE market is the most influential market) is also supported by Peiro, Quesada, and Uriel (1998) who examine the relationships between New York, Tokyo and Frankfurt stock markets.

Further studies have been conducted for the interrelationships of other markets. For example Booth, Martikainen, and Tse (1997) use the multivariate EGARCH model and verify the results of Koutmos *et al.* (1995) for the Scandinavian stock markets. That is volatility transmission is asymmetric and spillovers are more pronounced for bad than good news. Ostermark, and Hoglund (1997) also adopt the multivariate EGARCH model to study the impact of Japanese stock prices on the Finnish market. They find that negative innovations of the Japanese stock market have a greater impact on volatility of the Finnish futures market (asymmetric effect).

Finally, Isakov, and Perignon (1999) examine the dynamic interdependence of returns and volatility of the Swiss market with the major stock markets of the world. They find that the Swiss market is influenced by events in foreign markets, and the greatest effect comes from the US market.

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 he 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.

Although there are some studies of stock market interdependence, relating to the European markets it is surprising that little research has been published to date on the correlation of European stock markets after the introduction of EURO. An important exception is the paper of Capiello *et. al.* (2003). Specifically they examine 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.

Although in previous studies 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?

- What is the role of US stock market during the period before the introduction of EURO and how this role altered after 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:

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

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 $|-1+\gamma_j| / (1+\gamma_j)$. 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:

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

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:

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

for the case of the CCC model and

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

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:

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

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:

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

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

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

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:

$$A = \begin{bmatrix} \alpha_1 & 0 & \ldots & 0 \\ 0 & \alpha_2 & & 0 \\ . & & . & . \\ . & & . & . \\ 0 & 0 & \ldots & \alpha_4 \end{bmatrix}, \; \mathrm{B} = \begin{bmatrix} \beta & 0 & \ldots & 0 \\ 0 & \beta & & 0 \\ . & & . & . \\ . & & . & . \\ 0 & 0 & \ldots & \beta \end{bmatrix}, \; \mathrm{C} = \begin{bmatrix} c_1 & 0 & \ldots & 0 \\ 0 & c_2 & & 0 \\ . & & . & . \\ . & & . & . \\ 0 & 0 & \ldots & c_4 \end{bmatrix} \qquad (10)$$

We leave the persistence term, *β,* constant over markets because the autoregression parameters, *β,* have similar magnitudes across the markets (Hafner and Franses, 2003). Furthermore, by imposing this restriction we avoid convergence problems in estimation[1]. 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:

$$R_t = Q_t^{*-1} Q_t Q_t^{*-1}, \tag{11}$$

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

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:

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

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, since our model consists of only four markets, we

[1] This model was firstly estimated without this restriction, but unfortunately we had convergence problems in estimation.

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*. but with restricting all β to be the same. 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 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

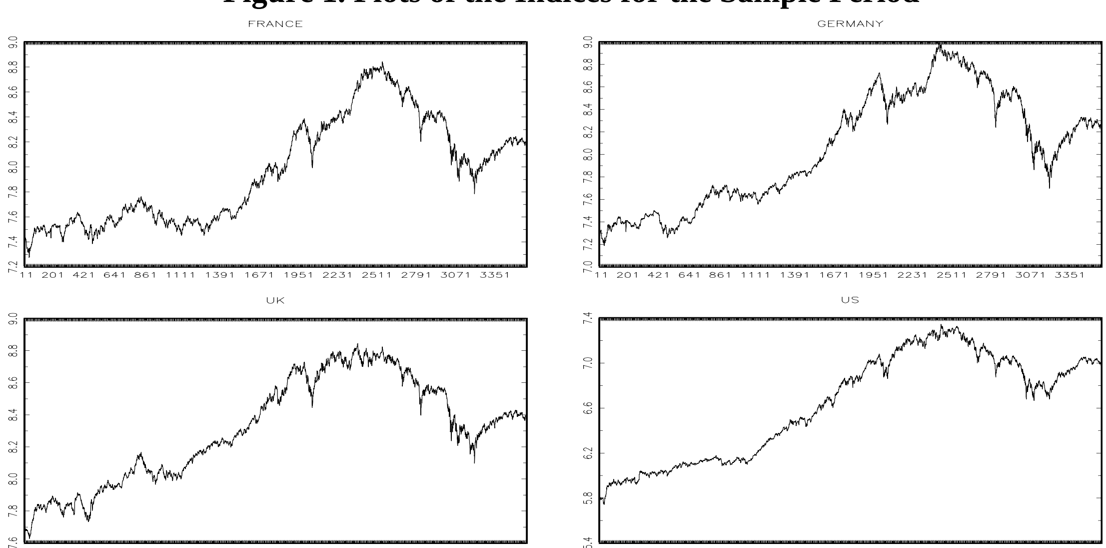


Table 1. Preliminary Statistics. Daily closing stock returns
Period: 3/12/1990 to 6/8/2004

Statistics	New York	London	Frankfurt	Paris
Sample mean	0.034	0.020	0.026	0.021
Variance	1.034	1.105	2.100	1.854
Kurtosis	6.263**	6.145**	6.609**	5.797**
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Skewness	-0.022**	-0.106**	-0.185**	-0.089*
	(0.0095)	0.00504	(0.0000)	(0.0150)
Min	-5.533	-5.885	-9.871	-7.678
Max	5.771	5.904	7.553	7.002
D	0.0735*	0.0488*	0.0485*	0.0469*
JB	5830.89**	5619.62**	6512.64**	4999.84**
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
LB(12) for R_t	22.5398*	51.3001**	27.3842**	27.5169**
	(0.0319)	(0.0000)	(0.0068)	(0.0065)
LB(12) for R_t^2	1067.37**	5554.34**	4962.9**	4704.65**
	(0.0000)	(0.0000)	(0.0000)	(0.0000)

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 (0.7484) followed by the correlation between London and Paris (0.7329).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. 6372	0.6067	0.6635
London		1.0000	0.6347	0.7329
Frankfurt			1.0000	0.7484
Paris				1.0000

II.Benchmark model

We first estimate the model given by equations (1)-(3) and (5) by restricting all cross-market coefficients to zero, thus not allowing for price and volatility spillovers. However, contemporaneous correlations between markets are not restricted and this allows cross-market effects to influence the error term (Bollerslev, 1990). This restricted model will be used as a benchmark. The estimates are presented in Table 3. The autoregressive coefficients $\beta_{i,i}$ are statistically significant for all markets. However, the negative sign of the AR coefficients for all markets is surprising.

The conditional variance for each market is a function of past innovations and past conditional variances, with coefficients $\alpha_{i,i}$ and δ_i respectively. Coefficient γ_i measures the leverage effect (or asymmetric impact) of past innovations on current volatility. As we can see from Table 3 all coefficients which measure asymmetry are highly significant. This fact gives support to our assertion that volatility spillovers may also be asymmetric. The degree of asymmetry, on the basis of the estimated γ_i coefficients, is highest for the New York market (negative innovations increase volatility approximately 6.37 times more than positive innovations), followed by the Paris market (approximately 5.41 times), the London market (approximately 4.88 times) and Frankfurt market (approximately 2.95 times).

Volatility persistence, measured by δ_i, is highest for New York, followed by London, Paris and Frankfurt. Furthermore, the hypothesis that the return series are homoskedastic (i.e. $a_{ii} = \gamma_i = \delta_i = 0$) is rejected at any sensible level of significance, on the basis of the likelihood ratio test.

The estimated conditional pairwise correlations are substantially lower than the unconditional estimates reported in Table 2. For example the correlation between the returns of New York and Frankfurt is reduced from 0.6067 to 0.6041. As it will be seen later, the estimated conditional correlations from the unrestricted model are even lower for some markets. Overall, these results suggest 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.

Diagnostic tests based on the standardized residuals show that the estimated means and variances are zero and one respectively as expected. However, the LB statistic for twelve lags show that some dependence still persists in the standardized residuals of all European markets. This may be due to the restriction imposed (zero mean and variance interactions).

Table 3. Results from benchmark model.
Full sample period: 3/12/1990 to 06/08/2004 (3570 obs.)

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

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=1,2,3,4

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	
$\beta_{1,0}$	0.0291* (0.0289)	$\beta_{2,0}$	0.0139 (0.3215)	$\beta_{3,0}$	0.0262 (0.1663)	$\beta_{4,0}$	0.0105 (0.5887)
$\beta_{1,1}$	-0.0715** (0.0000)	$\beta_{2,2}$	-0.0509** (0.0001)	$\beta_{3,3}$	-0.0543** (0.0001)	$\beta_{4,4}$	-0.0286* (0.0181)
$a_{1,0}$	-0.0010 (0.4866)	$a_{2,0}$	-0.0009 (0.5150)	$a_{3,0}$	0.0157** (0.0000)	$a_{4,0}$	0.0136** (0.0000)
$a_{1,1}$	0.0720** (0.0000)	$a_{2,2}$	0.0718** (0.0000)	$a_{3,3}$	0.0858** (0.0000)	$a_{4,4}$	0.0634** (0.0000)
γ_1	-0.7286** (0.0000)	γ_2	-0.6596** (0.0000)	γ_3	-0.4934* (0.0000)	γ_4	-0.6918** (0.0000)
δ_1	0.9894** (0.0000)	δ_2	0.9816** (0.0000)	δ_3	0.9734** (0.0000)	δ_4	0.9742** (0.0000)

Correlation Coefficients

	New York	London	Frankfurt	Paris
New York	1.0000	0.6041** (0.0000)	0.5708** (0.0000)	0.6296** (0.0000)
London		1.0000	0.5742** (0.0000)	0.6771** (0.0000)
Frankfurt			1.0000	0.7083** (0.0000)
Paris				1.0000

Model Diagnostics

	New York	London	Frankfurt	Paris
$E(z_{i,t})$	0.00263	0.00476	0.00379	0.00650
$E(z^2_{i,t})$	1.00112	0.99796	1.00235	1.00014
D	0.0393*	0.0278*	0.0387	0.0343
JB	3422.83** (0.0000)	2459.92** (0.0000)	10319.65** (0.0000)	3689.77** (0.0000)
$LB(12); z_{i,t}$	19.1419 (0.0852)	40.4948** (0.0001)	28.2715** (0.0050)	27.9278** (0.0057)
$LB(12); z^2_{i,t}$	9.0787 (0.6962)	53.5480** (0.0000)	12.2036 (0.4295)	34.6689** (0.0005)

LR test for $H_0: \alpha_{ii} = \gamma_i = \delta_i = 0$: 3312.4** (0.0000)

Log-likelihood = -17545.8687

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.

III. Price and Volatility Spillovers

In order to find price and volatility spillovers under the CCC framework, we estimate the system of equation (1) – (3) and (5). The maximum likelihood estimates are reported in Table 4. In terms of first moment interdependencies, there are significant price spillovers from London and Frankfurt to New York as well as from New York to Frankfurt. In addition, Frankfurt is also affected from London and Paris without any feedback effects. Paris is only affected by the London market. Finally, a remarkable result is that the London stock market is not significantly affected by any other market. This result contradicts the previous findings of Theodosiou and Lee (1993), Koutmos and Booth (1996), Antoniou *et. al.* (2003) among others. As far as the magnitude of coefficients is concerned, we observe that $\beta_{i,2}$ posses the highest positive value among the price spillover coefficients. That is, London has a great impact on US and European stock markets for this period, suggesting that London market plays a predominant role as an information producer.

An important question that an investor might have is whether or not these relationships are economically significant (do they give any information to investors in order to earn abnormal profits)? To answer this question we need to have an accurate knowledge of transaction costs between markets, exchange rates, regulations of the markets etc. However, uncentered R^2 estimates can provide an approximate measure of the extent to which past information in one market can be used to predict other markets' returns. These statistics can be calculated as $R^2 = 1 - [VAR(\varepsilon_i)/VAR(R_i)]$ and are reported in Table 4. They range from 0.051%, for New York, to 1.72% for London. Thus, the percentage of variation in returns that can be explained on the basis of past information is small for all markets. Hence, if we include a typical transaction cost for the investors, it is unlike to have any arbitrage opportunities in those markets. In other words these markets appear to be at least weak-form efficient.

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 FTSE stock index. In addition there are significant volatility spillovers from New York to London and Paris but not Frankfurt. The fact that London and New York markets have feedback effects (in second moment equations) agrees with the results of Koutmos and Booth (1995), who found that those markets have volatility spillover effects for the period from September 3 1986 to December 1 1993.This result is also supported by Veiga and McAleer (2003) for the period from October 12 1992 to July 7 2003. Another result is that the Paris market affects all the other European markets and it is only affected by New York. Finally, 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 our assertion (as far the restricted baseline model) 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) 2.41, (ii) 8.12, (iii) 2.24, (iv) 3.96 times respectively more than a positive innovation. These figures also measure the differential impact of own past innovations on the current conditional variance. Comparing those values with the restricted model we can see an increase in the size of asymmetries in the London market and a decrease in the New York market. This finding suggests that asymmetries have been transmitted from markets abroad and they might have been caused by feedback noise traders (Antoniou *et al* 2003).

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 statistics for twelve lags find no significant dependence in the standardized residuals, with exception the LB statistic for the squared residuals of the UK and Paris markets. This is very significant, indicating that the volatility for London is not fully modeled. As far as the degree of volatility persistence, δ_i is concerned we observe that it is higher in the benchmark model (except for the case of Frankfurt). This is because the model does not take into account volatility interactions across markets and it is in agreement with Lastrapes (1989), who supports that the high degree of volatility persistence may be due to omitted variables. To test the joint significance of first and second markets' interactions we use the likelihood ratio statistic[2]. The estimated value of he likelihood ratio statistic is 281.95 thus rejecting the benchmark model at any level of significance. The presence of first and second moment interdependencies implies that the specific markets are integrated in the sense that news from one country affects asset pricing in other countries.

[2] The likelihood ratio test is given by $\lambda = L(\beta_R)/L(\beta_{UR})$. The denominator is based on the unrestricted model; as a result, it must be at least as greater as the numerator. Therefore, λ must lie between 0 and 1. If the null hypothesis is true, we expect λ to be close to 1; if it is not true, we expect λ to be close to 0. Intuitively, therefore, we expect to reject the null hypothesis when λ is sufficiently small. The likelihood ratio test that can be applied to evaluate the null hypothesis builds on the fact that for large sample sizes, $-2[L(\beta_R) - L(\beta_{UR})] \sim \chi^2_m$ where *m* is the number of restrictions. To do test we simply compare the calculated value of χ^2_m above with the critical value. If χ^2_m is greater than the critical value, we can reject the null hypothesis that the restrictions do not apply. For our case, $LR = -2(LL_R - LL_{UR}) \sim \chi^2_{24}$. Where LL_R and LL_{UR} restricted and unrestricted log-likelihood respectively.

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

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

New York		London		Frankfurt		Paris	
$\beta_{1,0}$	0.0355** (0.0090)	$\beta_{2,0}$	0.0230 (0.1007)	$\beta_{3,0}$	0.0418* (0.0253)	$\beta_{4,0}$	0.0261 (0.1787)
$\beta_{1,1}$	-0.1270** (0.0000)	$\beta_{2,1}$	-0.0173 (0.4192)	$\beta_{3,1}$	-0.0669* (0.0200)	$\beta_{4,1}$	-0.0515 (0.0701)
$\beta_{1,2}$	0.1121** (0.0000)	$\beta_{2,2}$	0.0186 (0.4237)	$\beta_{3,2}$	0.1751* (0.0000)	$\beta_{4,2}$	0.1207** (0.0001)
$\beta_{1,3}$	0.0482** (0.0027)	$\beta_{2,3}$	0.0152 (0.3686)	$\beta_{3,3}$	-0.1428** (0.0000)	$\beta_{4,3}$	0.0157 (0.4949)
$\beta_{1,4}$	-0.0219 (0.2185)	$\beta_{2,4}$	0.0018 (0.9258)	$\beta_{3,4}$	0.1372** (0.0000)	$\beta_{4,4}$	-0.0337 (0.2112)
$a_{1,0}$	-0.0029 (0.0739)	$a_{2,0}$	-0.0020 (0.1804)	$a_{3,0}$	0.0127** (0.0000)	$a_{4,0}$	0.0140** (0.0000)
$a_{1,1}$	0.0593** (0.0000)	$a_{2,1}$	-0.0238** (0.0064)	$a_{3,1}$	-0.0095 (0.3041)	$a_{4,1}$	-0.0342** (0.0004)
$a_{1,2}$	0.0425** (0.0000)	$a_{2,2}$	0.0569** (0.0000)	$a_{3,2}$	0.0118 (0.2026)	$a_{4,2}$	0.0092 (0.2884)
$a_{1,3}$	-0.0018 (0.8553)	$a_{2,3}$	0.0210* (0.0297)	$a_{3,3}$	0.0619** (0.0000)	$a_{4,3}$	0.0126 (0.2499)
$a_{1,4}$	0.0071 (0.5403)	$a_{2,4}$	0.0248* (0.0227)	$a_{3,4}$	0.0283* (0.0226)	$a_{4,4}$	0.0741** (0.0000)
γ_1	-0.4150** (0.0003)	γ_2	-0.7807** (0.0000)	γ_3	-0.3836** (0.0030)	γ_4	-0.5966** (0.0000)
δ_1	0.9763** (0.0000)	δ_2	0.9793** (0.0000)	δ_3	0.9760** (0.0000)	δ_4	0.9707** (0.0000)
R^2	0.0172		0.00051		0.0125		0.00338

Correlation Coefficients

	New York	London	Frankfurt	Paris
New York	1.0000	0. 6024** (0.0000)	0. 5734** (0.0000)	0.6290** (0.0000)
London		1.0000	0. 5697** (0.0000)	0. 6731** (0.0000)
Frankfurt			1.0000	0. 7130** (0.0000)
Paris				1.0000

Model Diagnostics

	New York	London	Frankfurt	Paris
$E(z_{i,t})$	-0.00629	-0.00895	-0.01032	-0.00753
$E(z^2_{i,t})$	1.00121	0.99635	1.00270	1.00050
D	0.0333**	0.0207	0.0320**	0.0262*
JB	3024.62 (0.0000)	2409.48** (0.0000)	13657.18** (0.0000)	3933.26** (0.0000)
$LB(12); z_{i,t}$	14.8435 (0.2501)	17.2257 (0.1413)	14.8035 (0.2524)	19.6046 (0.0749)
$LB(12); z^2_{i,t}$	8.3841 (0.7544)	32.9684** (0.0010)	7.6464 (0.8121)	23.5299* (0.0235)

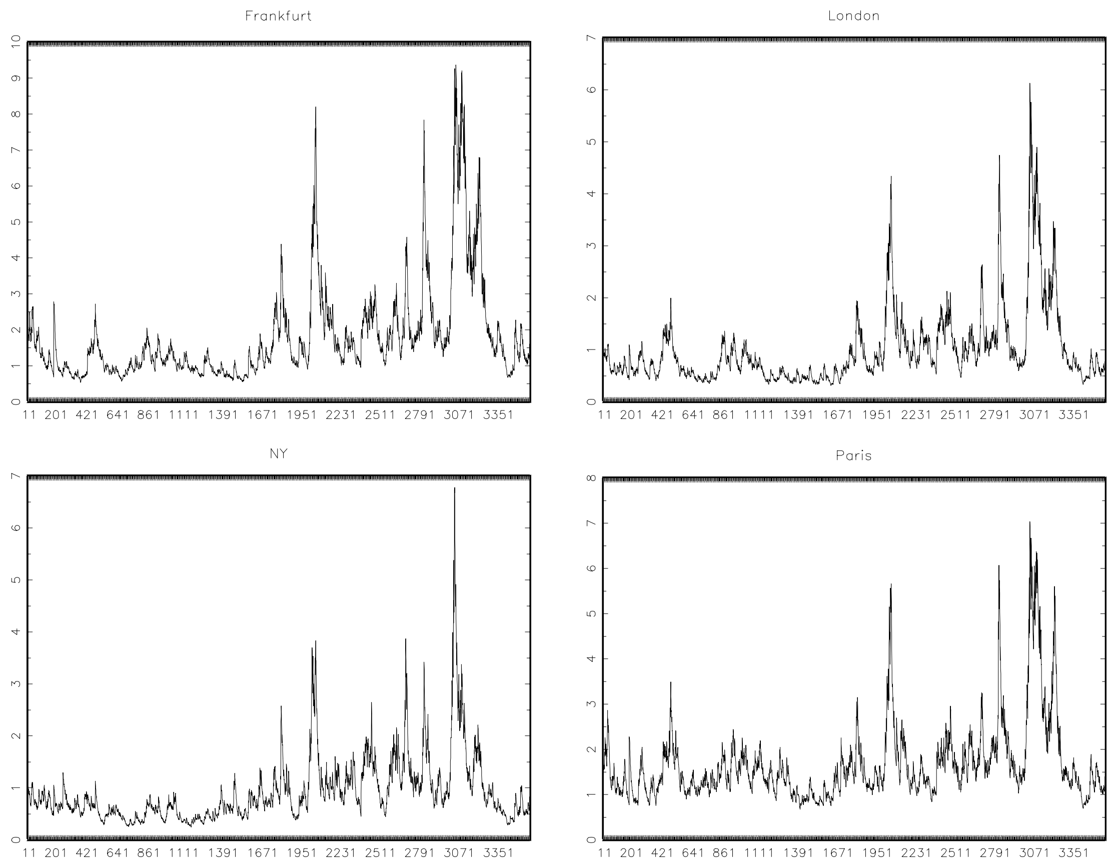
LR test for $H_0 : \alpha_{ij} = \beta_{ij} = 0$: 281.95** (0.0000)

Log-likelihood = -17404.8935

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 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 1. 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 5 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 5. Impact of Innovation on Volatility				
Innovation	%Δ New York	%Δ London	%Δ Frankfurt	%Δ Paris
+5%in N.Y	-	0.070	-0.028	-0.100
-5% in N.Y	-	0.168	0.067	0.242
+5% in Lon.	0.047	-	0.013	0.010
-5%i n Lon.	0.378	-	0.105	0.082
+5% in Frank.	-0.006	0.065	-	0.039
-5% in Frank.	0.012	0.145	-	0.087
+5% in Paris	0.014	0.050	0.057	-
-5% in Paris	0.057	0.198	0.226	-

IV. Post and Pre EURO Period

It is very interesting to examine how the introduction of EURO affected major stock markets and especially European stock markets. To investigate the possible impact, including the behavior of price and volatility spillovers, we estimate the CCC model for the period before and after the EURO.

The results for the CCC model for the pre-EURO period are reported in Table 6. There is evidence of price spillovers only from Paris and London to Frankfurt. The rest of the markets are only affected by their own market's lag returns. Turning to volatility spillovers it can be inferred that there are spillovers from New York to London and Paris, with London having feedback effects to New York. It is also affected by the Paris market.

These spillovers are again asymmetric for European markets since the coefficients measuring asymmetry are significant. Spillovers from New York are not asymmetric (positive and negative shocks have approximately the same impact on the volatility of own and other markets). The results for European markets are in line with the results of Antoniou et al. (2003) and Koutmos (1996), who found feedback effects in both mean and variance within and between those countries. However, the multidirectional nature of the above relationships suggests that no market plays a predominant role as an information producer.

Table 6. Multivariate EGARCH model. Price and volatility spillovers.
Pre EURO period: 3/12/1990 to 31/12/1998 (2109 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: $\sigma^2_{i,t} = \exp\{a_{i,0} + a_{i,i} f_i(z_{i,t-1}) + \delta_i \ln(\sigma^2_{i,t-1})\}$ for *i,j*=1,2,3,4 and *i≠j*

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

New York		London		Frankfurt		Paris	
$\beta_{1,0}$	0.0594** (0.0001)	$\beta_{2,0}$	0.0474** (0.0038)	$\beta_{3,0}$	0.0550** (0.0099)	$\beta_{4,0}$	0.0422 (0.0766)
$\beta_{1,1}$	-0.0699* (0.0106)	$\beta_{2,1}$	-0.0403 (0.1312)	$\beta_{3,1}$	-0.0605 (0.0853)	$\beta_{4,1}$	-0.0562 (0.1360)
$\beta_{1,2}$	0.0303 (0.2701)	$\beta_{2,2}$	0.0820** (0.0054)	$\beta_{3,2}$	0.1017** (0.0059)	$\beta_{4,2}$	0.0109 (0.7922)
$\beta_{1,3}$	-0.0019 (0.9200)	$\beta_{2,3}$	-0.0157 (0.4327)	$\beta_{3,3}$	-0.1321** (0.0000)	$\beta_{4,3}$	-0.0290 (0.3222)
$\beta_{1,4}$	0.0200 (0.3008)	$\beta_{2,4}$	0.0194 (0.3604)	$\beta_{3,4}$	0.2231** (0.0000)	$\beta_{4,4}$	0.0743* (0.0180)
$a_{1,0}$	-0.0065* (0.0117)	$a_{2,0}$	-0.0044* (0.0180)	$a_{3,0}$	0.0053** (0.0094)	$a_{4,0}$	0.0083** (0.0043)
$a_{1,1}$	0.0571** (0.0000)	$a_{2,1}$	0.0220* (0.0188)	$a_{3,1}$	0.0016 (0.9097)	$a_{4,1}$	-0.0331* (0.0111)
$a_{1,2}$	0.0389** (0.0016)	$a_{2,2}$	0.0359** (0.0027)	$a_{3,2}$	0.0011 (0.9269)	$a_{4,2}$	-0.0101 (0.3553)
$a_{1,3}$	-0.0094 (0.4065)	$a_{2,3}$	0.0079 (0.4394)	$a_{3,3}$	0.0735** (0.0000)	$a_{4,3}$	0.0243 (0.0686)
$a_{1,4}$	0.0176 (0.2244)	$a_{2,4}$	0.0353** (0.0096)	$a_{3,4}$	0.0014 (0.9248)	$a_{4,4}$	0.0661** (0.0000)
γ_1	-0.1885 (0.1996)	γ_2	-0.7759** (0.0044)	γ_3	-0.4947** (0.0003)	γ_4	-0.6597* (0.0005)
δ_1	0.9819** (0.0000)	δ_2	0.9870** (0.0000)	δ_3	0.9764** (0.0000)	δ_4	0.9738** (0.0000)

Correlation Coefficients

	New York	London	Frankfurt	Paris
New York	1.0000	0.5990** (0.0000)	0.4989** (0.0000)	0.5634** (0.0000)
London		1.0000	0.5306** (0.0000)	0.6541** (0.0000)
Frankfurt			1.0000	0. 6147** (0.0000)
Paris				1.0000

Model Diagnostics

	New York	London	Frankfurt	Paris
$E(z_{i,t})$	-0.00209	-0.00816	-0.00191	-0.00592
$E(z^2_{i,t})$	1.00372	0.99533	1.00728	1.00222
D	0.0395**	0.0188	0.0417**	0.0331*
JB	6519.11** (0.0000)	2957.94** (0.0000)	7573.20** (0.0000)	3176.73** (0.0000)
$LB(12); z_{i,t}$	9.6088 (0.6502)	11.2984 (0.5035)	13.3914 (0.3412)	17.1150 (0.1453)
$LB(12); z^2_{i,t}$	3.4199 (0.9918)	16.2133 (0.1817)	3.0862 (0.9949)	11.3143 (0.5022)

Log-likelihood = -9410.7352

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 order to gain a complete picture of the effects of the introduction of EURO, we present in Table 7 the estimates for the period after the EURO. The interactions now are different from those documented for the pre-EURO period. For New York and Paris the leverage effect is insignificant. For this period there are significant price spillovers from Paris to all markets, from London to the rest of the markets except Frankfurt and from Frankfurt to the rest of the markets except London. New York does not seem to have any price spillover effects to any other market. In terms of second moment interactions there are no longer effects from New York to any of the European markets. In contrast, there are volatility spillovers from the Frankfurt stock market to London and Paris and from London to Frankfurt and Paris. These spillovers, as mentioned before, are asymmetric. Finally it can be said that the New York market does not influence any of the European markets, and also it responds symmetrically to own past innovations but asymmetrically to the past innovations of the London market.

Table 7. Multivariate EGARCH model. Price and volatility spillovers.
Post EURO period: 1/1/1999 to 6/8/2004 (1461 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	
$\beta_{1,0}$	-0.0327 (0.2142)	$\beta_{2,0}$	-0.0551* (0.0371)	$\beta_{3,0}$	-0.0429 (0.2572)	$\beta_{4,0}$	-0.0380 (0.2503)
$\beta_{1,1}$	-0.2019** (0.0000)	$\beta_{2,1}$	0.0209 (0.0000)	$\beta_{3,1}$	-0.0315 (0.5381)	$\beta_{4,1}$	-0.0103 (0.8262)
$\beta_{1,2}$	0.2227** (0.0000)	$\beta_{2,2}$	-0.0588 (0.1116)	$\beta_{3,2}$	0.2721** (0.0000)	$\beta_{4,2}$	0.2669** (0.0000)
$\beta_{1,3}$	0.1671** (0.0000)	$\beta_{2,3}$	0.1013** (0.0011)	$\beta_{3,3}$	-0.0558 (0.2022)	$\beta_{4,3}$	0.1514** (0.0001)
$\beta_{1,4}$	-0.1656** (0.0000)	$\beta_{2,4}$	-0.1097** (0.0064)	$\beta_{3,4}$	-0.1370* (0.0178)	$\beta_{4,4}$	-0.3204** (0.0000)
$a_{1,0}$	0.0075* (0.0271)	$a_{2,0}$	0.0087* (0.0246)	$a_{3,0}$	0.0262** (0.0000)	$a_{4,0}$	0.0209** (0.0000)
$a_{1,1}$	0.0595** (0.0024)	$a_{2,1}$	-0.0012 (0.9429)	$a_{3,1}$	-0.0170 (0.3756)	$a_{4,1}$	0.0045 (0.7317)
$a_{1,2}$	0.0845** (0.0001)	$a_{2,2}$	0.0908** (0.0000)	$a_{3,2}$	0.0555** (0.0064)	$a_{4,2}$	0.0662** (0.0016)
$a_{1,3}$	-0.0054 (0.8028)	$a_{2,3}$	0.0872** (0.0004)	$a_{3,3}$	0.0669** (0.0029)	$a_{4,3}$	0.0562** (0.0018)
$a_{1,4}$	-0.0227 (0.4841)	$a_{2,4}$	-0.0322 (0.2671)	$a_{3,4}$	0.0478 (0.0945)	$a_{4,4}$	0.0184 (0.4543)
γ_1	-0.8093 (0.0661)	γ_2	-0.5661** (0.0084)	γ_3	-0.4397* (0.0155)	γ_4	-0.2905 (0.1961)
δ_1	0.9704** (0.0000)	δ_2	0.9663** (0.0000)	δ_3	0.9709** (0.0000)	δ_4	0.9688** (0.0000)

Correlation Coefficients				
	New York	London	Frankfurt	Paris
New York	1.0000	0.6159 **	0.6608**	0.7072**
		(0.0000)	(0.0000)	(0.0000)
London		1.0000	0.6109**	0.6987**
			(0.0000)	(0.0000)
Frankfurt			1.0000	0.8268**
				(0.0000)
Paris				1.0000

Model Diagnostics				
	New York	London	Frankfurt	Paris
$E\left(z_{i,t}\right)$	0.01634	0.01859	0.01846	0.01985
$E\left(z_{i,t}^2\right)$	1.00540	1.01174	1.00997	1.01713
D	0.0365*	0.0346	0.0290	0.0260
JB	1227.24**	1521.51**	1403.87**	1579.68**
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$LB(12); z_{i,t}$	13.9230	24.3009*	16.1658	16.3481
	(0.3057)	(0.0185)	(0.1838)	(0.1758)
$LB(12); z_{i,t}^2$	6.0318	19.6092	44.2323**	22.4812*
	(0.9145)	(0.0748)	(0.0000)	(0.0325)
Log-likelihood =-7714.8815				

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.

A comparison of the results from the pre –and post EURO periods reveals that the major market which produces information that affects asset prices in other markets is Paris. During the pre-EURO period, we do not have a specific market with a predominant role, (as far as the price spillovers, in Table 6, are concerned). For the post EURO period all markets have become more sensitive to news originating from Paris. Finally, the findings indicate that for the case of volatility spillovers for the post-EURO period, Frankfurt and London obtain a predominant role within Europe. All European markets seem to be affected from DAX's and FTSE's behavior. The reason that the German stock market has increased its influence may be because of its important role in European monetary policy. Most striking is the finding that the volatility transmission mechanism is asymmetric as for the whole period in the sense that bad news in one market has a greater impact on the volatility of the others. This finding is confirmed only for European markets for pre EURO period and only for London and Frankfurt markets for post EURO.

Another remarkable result is the following: By observing the period after EURO and according to the correlation of the standardized residuals, we can infer that the markets are more integrated than they were before EURO. For example, the conditional correlation between German and French stock market is 0.827 for the period after EURO, while their corresponding conditional correlation for the period before EURO was 0.615. In addition, the conditional correlation between New York and German stock market has been increased from 0.498 to 0.661.

V. DCC Estimation

Since there is evidence that the stock returns across different national markets exhibit time-varying correlations (TSE 2000), there is a need to extend the CCC model to incorporate time-varying correlations. Thus, we now estimate the DCC model by maximizing again the log likelihood function over the parameters of the model. In Table 8 we present the results of this estimation along with the diagnostic tests.

Table 8. 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	
$\beta_{1,0}$	0.0383** (0.0019)	$\beta_{2,0}$	0.0315** (0.0096)	$\beta_{3,0}$	0.0397* (0.0140)	$\beta_{4,0}$	0.0383* (0.0161)
$\beta_{1,1}$	-0.1295** (0.0000)	$\beta_{2,1}$	-0.0359* (0.0456)	$\beta_{3,1}$	-0.0476* (0.0410)	$\beta_{4,1}$	-0.0471* (0.0361)
$\beta_{1,2}$	0.1007** (0.0000)	$\beta_{2,2}$	0.0589** (0.0051)	$\beta_{3,2}$	0.1466* (0.0000)	$\beta_{4,2}$	0.1387** (0.0000)
$\beta_{1,3}$	0.0441** (0.0029)	$\beta_{2,3}$	0.0001 (0.4970)	$\beta_{3,3}$	-0.1686** (0.0000)	$\beta_{4,3}$	-0.0049 (0.4150)
$\beta_{1,4}$	-0.0065 (0.3606)	$\beta_{2,4}$	0.0081 (0.3287)	$\beta_{3,4}$	0.1591** (0.0000)	$\beta_{4,4}$	-0.0163 (0.2490)
$a_{1,0}$	-0.0005 (0.3606)	$a_{2,0}$	-0.0009 (0.2591)	$a_{3,0}$	0.0096** (0.0000)	$a_{4,0}$	0.0094** (0.0000)
$a_{1,1}$	0.0676** (0.0000)	$a_{2,1}$	-0.0145 (0.0514)	$a_{3,1}$	-0.0039 (0.3363)	$a_{4,1}$	-0.0202* (0.0121)
$a_{1,2}$	0.0492** (0.0000)	$a_{2,2}$	0.0746** (0.0000)	$a_{3,2}$	0.0274** (0.0025)	$a_{4,2}$	0.0333** (0.0002)
$a_{1,3}$	-0.0052 (0.2954)	$a_{2,3}$	0.0222** (0.0091)	$a_{3,3}$	0.0686** (0.0000)	$a_{4,3}$	0.0304** (0.0008)
$a_{1,4}$	0.0063 (0.2816)	$a_{2,4}$	0.0225* (0.0185)	$a_{3,4}$	0.0116 (0.1542)	$a_{4,4}$	0.0547** (0.0000)
γ_1	-0.3966** (0.0003)	γ_2	-0.6301** (0.0000)	γ_3	-0.4102** (0.0030)	γ_4	-0.5193** (0.0001)
δ_1	0.9831** (0.0000)	δ_2	0.9847** (0.0000)	δ_3	0.9855** (0.0000)	δ_4	0.9815** (0.0000)

Model Diagnostics

	New York	London	Frankfurt	Paris
$E(z_{i,t})$	-0.00994	-0.01922	-0.00767	-0.01985
$E(z^2_{i,t})$	0.98599	0.99218	0.97987	1.00707
D	0.0336**	0.0191	0.0330**	0.0228*
JB	3119.47** (0.0000)	2434.02** (0.0000)	17276.32** (0.0000)	4881.45** (0.0000)
$LB(12); z_{i,t}$	14.36 (0.2501)	14.85 (0.297)	16.13 (0.1855)	19.02 (0.0881)
$LB(12); z^2_{i,t}$	5.33 (0.9459)	14.51 (0.2694)	3.70 (0.9882)	7.84 (0.7974)
Log-likelihood = -17096.59				

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.

As far as the mean equations are concerned New York is affected by the previous day's returns of New York, London and Frankfurt. London stock market is affected by New York and by its own returns, while Frankfurt is affected by all markets (including its own previous day's returns). Finally, Paris is affected only by New York and London. Generally, the results are similar to those of CCC model for New York and Frankfurt stock markets. However, there are some differences in lead-lag relationships for London and Paris stock markets.

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 from at least one of the other three markets. Specifically, the New York market is not only affected by its own market innovations but also by FTSE stock index. Moreover, London is affected only by European markets while Frankfurt only by London and its own innovations. Finally, Paris is the market, which is affected by all other markets' innovations. All γ_i estimates are negative and significant, which means that negative shocks have greater impact than that of positive innovations.

Those results are similar to the results of CCC model but again with some differences. More specifically, London is no longer affected by New York while Frankfurt is no longer affected by Paris. Finally, the volatility equation of Paris stock market is also affected by London and Frankfurt.

The coefficients of the diagonal asymmetric DCC model (equations 8, 9 and 10) are reported in Table 9. We find evidence of highly persistent correlations but without evidence of asymmetric effects (except for the Frankfurt stock market). The strong persistence is evident from the highly significant β coefficient of the lag term Q_{t-1}. This coefficient is equal to 0.9786. 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 low relatively to the a_i coefficient estimates, and insignificant (except the coefficient for Frankfurt, which is significant for 1 percent level). The above result indicates that negative returns do not induce stronger co-movements than positive returns, across markets.

This finding contradicts previous results that correlation among equity returns increases in bear markets and decreases in bull markets. At this point it is worth mentioning that for our study we use daily observations to carry out the estimations. Hence we are able to capture daily correlation dynamics something which might have different results than the results we get by using weekly or monthly data. In addition, the fact that we include a term in volatility equation of each market, which captures the asymmetry, might remove the asymmetric effect in correlations.

Table 9. Diagonal Asymmetric DCC Model Estimates						
	α	p-value	β	p-value	C	p-value
USA	0.1394**	[0.0000]	0.9786**	[0.0000]	-0.0404	[0.1208]
UK	0.1501**	[0.0000]	0.9786**	[0.0000]	-0.0408	[0.1551]
Germany	0.1512**	[0.0000]	0.9786**	[0.0000]	-0.0755**	[0.0031]
France	0.1834**	[0.0000]	0.9786**	[0.0000]	-0.0054	[0.4353]

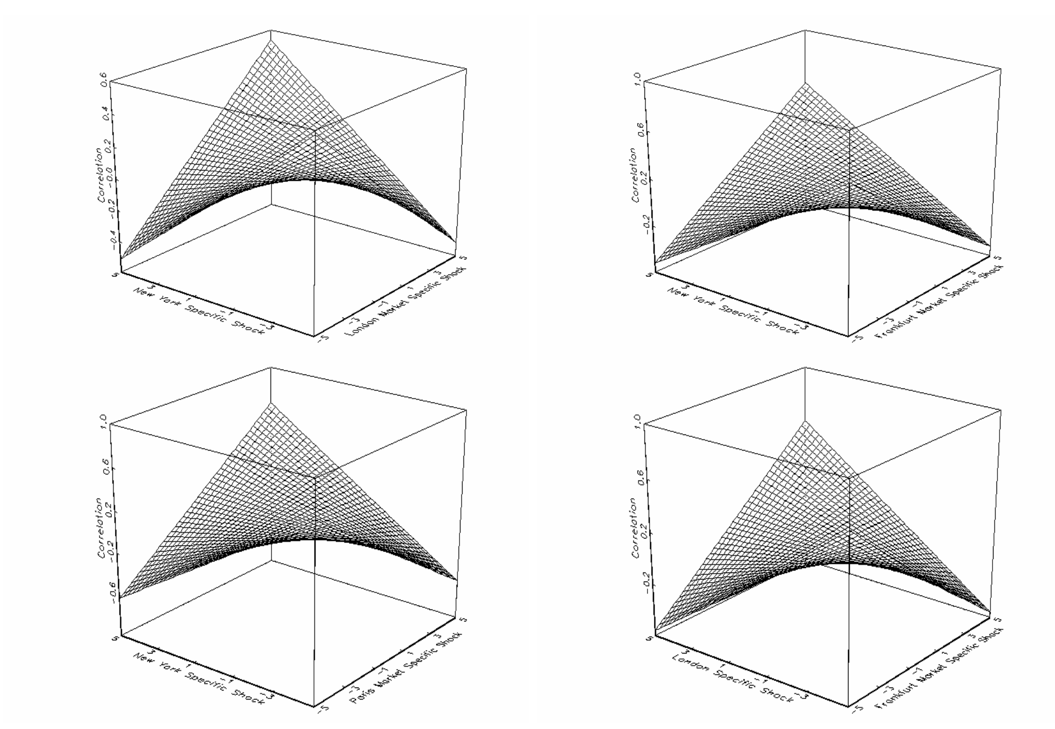
* denotes significance at the 5% level.
** denote significance at the 1% level.

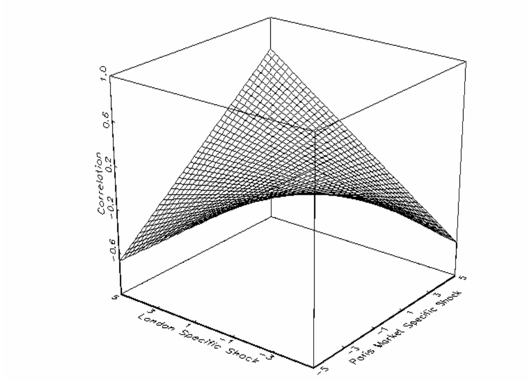
To illustrate the symmetric response of correlations to joint positive or negative shocks we use the news impact surfaces. The news impact surface for the correlation is given by

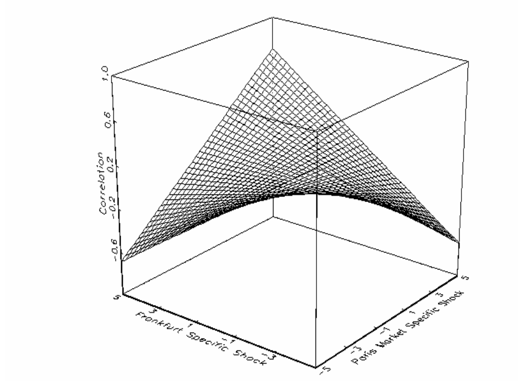
$$\begin{aligned} f(z_i, z_j) &\approx \tilde{q}_{ij} + (a_i a_j + c_i c_j) z_i z_j, \qquad && \text{for } z_i, z_j < 0 \\ f(z_i, z_j) &\approx \tilde{q}_{ij} + a_i a_j z_i z_j, && \textit{otherwise} \end{aligned} \tag{13}$$

where z_i, are the standardized residuals. Figure 3, presents the graphs of news impact surfaces. It is obvious that in all cases, the correlation news impact surface is symmetric, showing almost equal response to joint good or bad news.

Figure 3. News Impact Surfaces

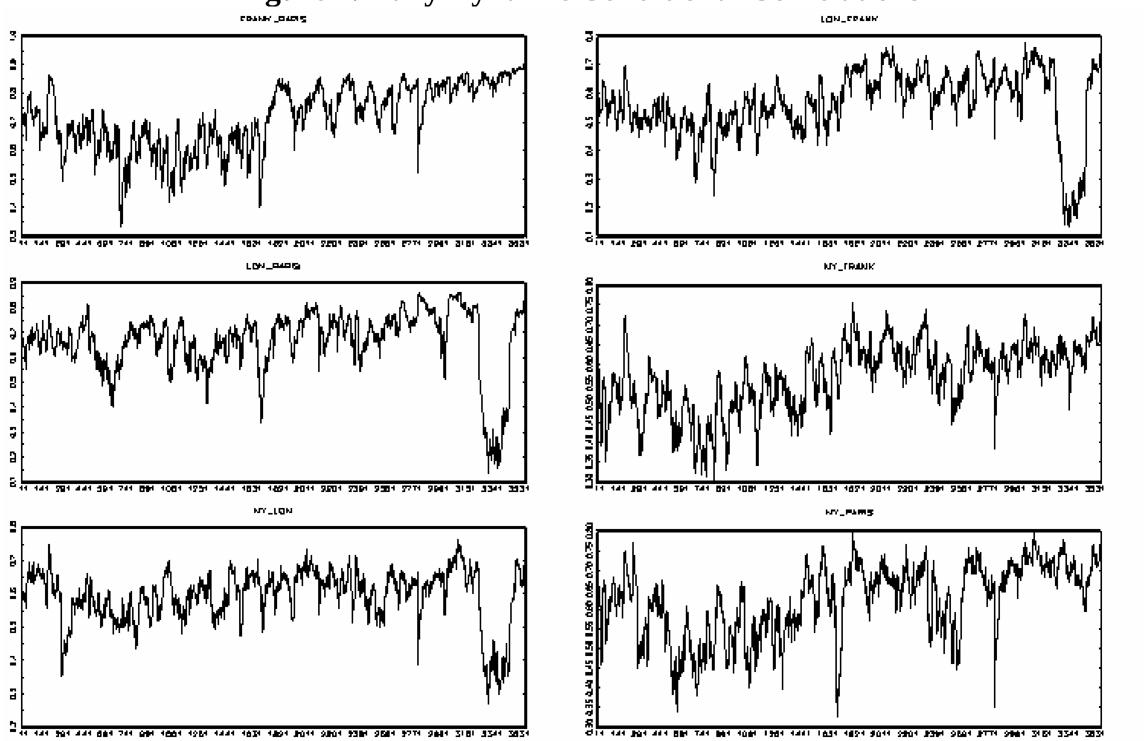






The next step of this section is to use the model estimates to plot the conditional correlations for the four markets under investigation. Figure 4 plots the daily conditional correlations for the four markets and reveals that the correlation between Germany and France has trended upwards. Furthermore, a similar pattern is established for the correlations between US and Germany and US and France. A similar pattern, but in a smaller degree, is observed for the correlation between the UK with Germany and France respectively.

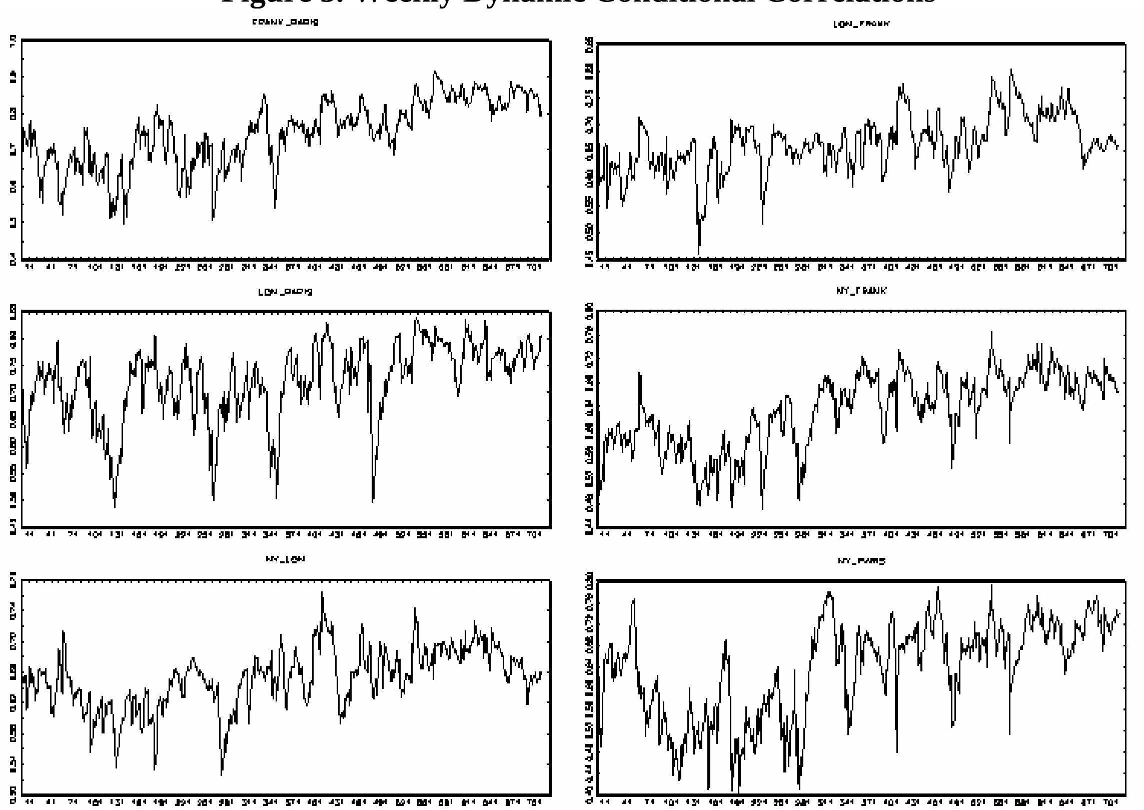
Figure 4. Daily Dynamic Conditional Correlations



During that period (around the December 14th, 1997) the “Dublin Declaration took place, in which the legal mechanisms for the phase 3 of European Monetary Union was outlined. Reasoning behind the upward trend after this specific event may be the following: After the outline of the mechanism for the adoption of the EURO, investors realized that we were moving to a new socio-economic situation which affects the whole world and especially stock markets. Hence, they adjusted their expectations by taking into consideration the benefits from the adoption of EURO. This had as an effect the increase in correlations in the aforementioned markets.

However, the correlation between US and UK seems to remain stable for the whole period except for the period between April 2003 and February 2004, where we observe a huge decrease in correlation. This pattern also appears in correlation between UK and France and UK and Germany. Thus, we can conclude that this is an effect coming from London. By comparing the plots of daily dynamic correlation with the plots of weekly correlation (Figure 5) we infer that "London effect" is not obvious. Nevertheless, we can not find any reasonable explanation for this tremendous decrease in correlation for such a long period.

Figure 5. Weekly Dynamic Conditional Correlations



Another remarkable result arising from the plots is that the correlations between France with UK and Germany with UK have similar pattern with their respective correlations with US. However, the volatility of the correlation with the UK seems to be higher than that of the correlations of Germany with US and France with US, respectively. This fact indicates that news coming from European markets is absorbed quicker by other European markets than the news coming from US markets. Of course this result has to be investigated further by calculating the amount of volatility for each pair of correlations something which is beyond the scope of this study.

Returning to the daily 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 10. Average Correlations

	New York	London	Frankfurt	Paris
Before EURO				
New York	1	0.5947	0.5306	0.5792
London		1	0.5421	0.6534
Frankfurt				0.6447
Paris				1
After EURO				
New York	1	0.5953	0.6256	0.6771
London		1	0.5886	0.6715
Frankfurt			1	0.8073
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 (0.6447 – 0.8073) followed by New York – Paris (0.5792 – 0.6771) and New York Frankfurt (0.5306 – 0.6256). A smaller increase in average correlation is observed for London – Frankfurt (0.6481-0.6696) and even smaller for New York – London (0.5947 – 0.5953). In addition, if we compare those results with the results of CCC for Pre and Post EURO period, 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 a Multivariate EGARCH model 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 model is used to investigate the first and second moment interdependencies among the various markets for the period from December 3 1990 to August 6 2004. To avoid the problem of non-synchronous data, we use pseudo closing prices.

In addition, the same model is used to examine these relationships for the period before the introduction of EURO (from December 3 1990 to December 31 1998) and for the period after EURO (from January 1 1999 to August 6 2004). The results from applying the model to the aforementioned markets provide evidence that the domestic stock prices and volatilities are influenced by the behaviour of foreign markets. The New York stock market has a predominant role for the whole period for both price and volatility spillovers.

For the pre-EURO period, New York market remains the most influencing market as far as the volatility spillovers are concerned. For the period after the introduction of EURO, the estimates showed some alterations on the results. More specifically, European markets have price spillover effects on the other markets while France is the only market, which has price spillover effects on the other three markets displacing New York stock market.

A remarkable result, for the whole period, 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. However, this result holds only for London and Frankfurt after the introduction of EURO. Finally, according to the constant correlation coefficients, we can infer that the markets are more integrated for the period after the introduction of EURO. This result is also confirmed by the DCC model. Figure 4 shows clearly an increase in correlation for the most of the markets. Hence, we can infer that the CCC model captures the changes in conditional correlation only if use sub-periods 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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