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. By using daily closing returns 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 the Frankfurt and Paris experiencing the highest increase.

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, they 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 asymmetry 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 adopted the multivariate EGARCH model to study the impact of Japanese stock price 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 the same line with the results 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 were experiencing in previous periods.

Although, there are some studies on stock market interdependence, relating to the European markets (Theodosiou and Lee (1993); Koutmos, (1996); and Antoniou *et al.*, (2003)) it is surprising that little research has been published to date on the interdependence 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 structural break in the correlation after the introduction of EURO. Nevertheless, they use weekly data and they do not include any price or volatility spillovers effects in the returns and volatility equations respectively.

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 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). The UK market has 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.

Methodology

This study uses a multivariate EGARCH model specification to investigate market interdependence and volatility transmission between stock markets in different countries. 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). Although between New York and European markets there is only a two hour overlap, in order to simplify the analysis we assume that all markets open and close at the same time. Thus non-synchronous trading implies that the estimation of the mean and variance in New York market is conditional on own past information as well as information generated by the other three markets.

Specifically the multivariate EGARCH model as used by Koutmos (1996), Antoniou *et. al.* (2003) among others can be expressed as follows:

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

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

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

$$\sigma_{i,j,t} = \rho_{i,j}\sigma_{i,t}\sigma_{j,t} \qquad (4)$$

Equation (1) describes the returns from the *n* stock markets as a VAR, where the conditional mean in each market $(R_{i,t})$ is a function of own past returns and cross-market past returns $(R_{j,t})$. $\beta_{i,j}$, 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. 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 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 innovation 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 denote the slope of $f(.)$) are

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

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

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 $\alpha_{i,j}$ 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 $\sigma_{i,t}^2$ 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 $|\text{-}1+\gamma_\mathrm{j}| / (1+\gamma_\mathrm{j})$. Finally, the conditional covariance $\sigma_{i,j,t}$ is defined by equation (4) and captures the contemporaneous relationship between the returns on the n markets. In other words specification in (4) assumes constant correlation coefficients (Bollerslev, 1990). This specification reduces the number of parameters to be estimated compared with time-varying correlations and its validity, of course, must be assessed empirically.

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. Further, the multivariate EGARCH model allows us to test possible asymmetries in the transmission of volatility across markets. By testing the existence of asymmetries we test the possibility that bad news (or negative innovations) in one market increase the volatility in another market more than good news. Moreover, the EGARCH model does not need parameter restrictions to ensure positive variances at all times.

The estimation of the above specification is almost always done by maximum likelihood since the log-likelihood function is highly non-linear. Numerically, the maximasation of the likelihood function of the model is carried out employing the BFGS algorithm. Under the assumption of joint-normal distribution, the function could be written as:

$$L(\Theta) = -(1/2)(NT)\ln(2\pi) - (1/2)\sum_{t=1}^{T}(\ln|S_t| + \varepsilon_t^{'} S_t^{-1}\varepsilon_t) \quad (5)$$

where N is the number of equations, T is the number of observations, Θ is the 54 x 1 parameter vector to be estimated, $\varepsilon_t^{'} = [\varepsilon_{1,t} \;\; \varepsilon_{2,t} \;\; \varepsilon_{3,t} \;\; \varepsilon_{4,t}]$ is the 1 x 4 vector of innovations at time t, S_t is the 4 x 4 time varying conditional variance-covariance matrix with diagonal elements given by equation (2) for $i = 1,2,3,4$ and cross diagonal elements are given by equation (4) for $i, j = 1,2,3,4$ and $i \neq j$.

Empirical Findings

I. Data and preliminary statistics

The data consist of daily prices of S&P-500 (USA), FTSE-100 (UK), DAX-30 (Germany), and CAC-40 (France) indices. 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 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).

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:

$$R_t = \log\left(\frac{P_t}{P_{t-1}}\right) * 100 \qquad (6)$$

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.

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

Table 1 reports 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).

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

Statistics	New York	London	Frankfurt	Paris
Sample mean	0.033	0.020	0.026	0.021
Variance	1.050	1.105	2.100	1.854
Kurtosis	7.049**	6.145**	6.609**	5.797**
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Skewness	-0.096**	-0.106**	-0.185**	-0.089*
	(0.0095)	0.00504	(0.0000)	(0.0150)
Min	-7.114	-5.885	-9.871	-7.678
Max	5.573	5.904	7.553	7.002
D	0.0795*	0.0488*	0.0485*	0.0469*
JB	7390.47**	5619.62**	6512.64**	4999.84**
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
LB(12) for R_t	23.4501*	51.3001**	27.3842**	27.5169**
	(0.0241)	(0.0000)	(0.0068)	(0.0065)
LB(12) for R_t^2	3201.13**	5554.34**	4962.9**	4704.65**
	(0.0000)	(0.0000)	(0.0000)	(0.0000)

Correlation Matrix

	New York	London	Frankfurt	Paris
New York	1.0000	0.3931	0.46183	0.41145
London		1.0000	0.63472	0.73294
Frankfurt			1.0000	0.74835
Paris				1.0000

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.

II.Benchmark model

We first estimate the model given by equations (1)-(4) 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 model. The estimates are presented in Table 2. The autoregressive coefficients $\beta_{i,i}$ are statistically significant for New York, London and Frankfurt. For the Paris stock market this coefficient is insignificant. However, the negative sign of AR coefficients for all markets is surprising.

The conditional variance for each market is a function of past innovations and past conditional variances. Past innovations and past conditional variances are given by the 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 the results in Table 2 all coefficients which measure asymmetry are 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 French market (negative innovations increase volatility approximately 7.01 times more than positive innovations), followed by the New York market (approximately 6.54 times), the London market (approximately 4.02 times) and Frankfurt market (approximately 2.93 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 (except the correlation of New York with London) than the unconditional estimates reported in Table 1. For example the correlation between the returns of New York and Frankfurt is reduced from 0.46183 to 0.4199. As it will be seen later, the estimated conditional correlations from the unrestricted model are even lower. Overall, these results suggest that hedging models that ignore market interdependence are likely to produce biased estimates of hedge ratios. Those results are in the same line with the findings of Koutmos (1996), Koutmos and Booth (1995), Antoniou et al. (2003) among others.

Diagnostics 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 markets. This may be due to the restriction imposed (zero mean and variance interactions).

Table 2. 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	
$\beta_{1,0}$	0.0306* (0.0229)	$\beta_{2,0}$	0.0119 (0.3973)	$\beta_{3,0}$	0.0230 (0.2258)	$\beta_{4,0}$	0.0064 (0.7427)
$\beta_{1,1}$	-0.1443** (0.0000)	$\beta_{2,2}$	-0.0431** (0.0013)	$\beta_{3,3}$	-0.0424** (0.0032)	$\beta_{4,4}$	-0.0132 (0.2977)
$a_{1,0}$	0.0005 (0.7810)	$a_{2,0}$	-0.0012 (0.4568)	$a_{3,0}$	0.0180** (0.0000)	$a_{4,0}$	0.0155** (0.0000)
$a_{1,1}$	0.1013** (0.0000)	$a_{2,2}$	0.0838** (0.0000)	$a_{3,3}$	0.0920** (0.0000)	$a_{4,4}$	0.0664** (0.0000)
γ_1	-0.7349** (0.0000)	γ_2	-0.6019** (0.0000)	γ_3	-0.4911** (0.0000)	γ_4	-0.7504** (0.0000)
δ_1	0.9793** (0.0000)	δ_2	0.9777** (0.0000)	δ_3	0.9692** (0.0000)	δ_4	0.9704** (0.0000)

Correlation Coefficients

	New York	London	Frankfurt	Paris
New York	1.0000	0.4106** (0.0000)	0.4199** (0.0000)	0.4095** (0.0000)
London		1.0000	0.5733** (0.0000)	0.6759** (0.0000)
Frankfurt			1.0000	0.7094** (0.0000)
Paris				1.0000

Model Diagnostics

	New York	London	Frankfurt	Paris
$E(z_{i,t})$	0.00600	0.00628	0.00574	0.00928
$E(z^2_{i,t})$	0.99958	0.99864	1.00231	1.00085
D	0.0473	0.0282	0.0396	0.0335
JB	3422.83** (0.0000)	2459.92** (0.0000)	10319.65** (0.0000)	3689.77** (0.0000)
$LB(12); z_{i,t}$	99.2639** (0.0000)	35.7006** (0.0004)	24.2837* (0.0186)	23.7859* (0.0217)
$LB(12); z^2_{i,t}$	5.4225 (0.9424)	44.5035** (0.0000)	12.1208 (0.4360)	33.4672** (0.0008)
Log-likelihood = -18241.49				

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 we estimate the system of equation (1) – (4) in its unrestricted form. The maximum likelihood estimates are reported in Table 3. In terms of first moment interdependencies, there are significant price spillovers from New York to London, Frankfurt and Paris, from London to Frankfurt as well as from Frankfurt to London. In addition London and Frankfurt are also affected from Paris without any feedback effects. As far as the magnitude of coefficient is concerned, we observe that $\beta_{i,1}$ posses the highest positive value among the price spillover coefficients (the coefficients of Paris and Frankfurt are by far the most significant). That means, New York has a great impact on European stock markets for this period. However, at this point it is worth mentioning some limitations imposed by the usage of non-synchronous data. The $\beta_{i,1}$ could be capturing a timing effect, because news arriving after the closure of the European markets (but when New York is open) will be reflected in these coefficients. Outside the New York market, the multidirectional nature of these relationships among European countries suggests that no market plays a predominant role as an information producer.

Thus, a 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 3. They range from 0.05%, for New York, to 9.75% for London. Thus, the percentage of variation in returns that can be explained on the basis of past information is small only for New York. For the other markets this figure seems quite high leading to the notion that investors may have arbitrage opportunities in these markets. Of course this issue needs further investigation and those results are not very strong and we cannot base any conclusions on them.

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 the other three markets. Specifically, the New York market is not only affected by its own market innovations but also by FTSE stock index. In addition there are significant volatility spillovers from New York to London and 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. A remarkable result is that the Paris market is not affected (at 5% significance level) by any other market's volatility spillovers except from its own past innovations.

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	
$\beta_{1,0}$	0.0277* (0.0357)	$\beta_{2,0}$	0.0062 (0.6443)	$\beta_{3,0}$	0.0261 (0.1414)	$\beta_{4,0}$	0.0034 (0.8553)
$\beta_{1,1}$	0.0035 (0.8551)	$\beta_{2,1}$	0.3279** (0.0000)	$\beta_{3,1}$	0.4047** (0.0000)	$\beta_{4,1}$	0.4152** (0.0000)
$\beta_{1,2}$	0.0227 (0.2796)	$\beta_{2,2}$	-0.0530* (0.0156)	$\beta_{3,2}$	0.0689* (0.0182)	$\beta_{4,2}$	0.0186 (0.5336)
$\beta_{1,3}$	-0.0077 (0.6242)	$\beta_{2,3}$	-0.0274 (0.0922)	$\beta_{3,3}$	-0.1954** (0.0000)	$\beta_{4,3}$	-0.0438 (0.0511)
$\beta_{1,4}$	0.0197 (0.2432)	$\beta_{2,4}$	-0.0352* (0.0494)	$\beta_{3,4}$	0.0875** (0.0003)	$\beta_{4,4}$	-0.0856** (0.0009)
$a_{1,0}$	-0.0018 (0.4181)	$a_{2,0}$	-0.0038 (0.0359)	$a_{3,0}$	0.0132** (0.0000)	$a_{4,0}$	0.0144** (0.0000)
$a_{1,1}$	0.0939** (0.0000)	$a_{2,1}$	0.0221** (0.0028)	$a_{3,1}$	0.0268** (0.0003)	$a_{4,1}$	0.0043 (0.5523)
$a_{1,2}$	0.0422** (0.0003)	$a_{2,2}$	0.0670** (0.0000)	$a_{3,2}$	0.0155 (0.1838)	$a_{4,2}$	0.0139 (0.1909)
$a_{1,3}$	0.0107 (0.3541)	$a_{2,3}$	0.0125 (0.2265)	$a_{3,3}$	0.0583** (0.0000)	$a_{4,3}$	0.0039 (0.7241)
$a_{1,4}$	-0.0102 (0.4445)	$a_{2,4}$	0.0151 (0.2016)	$a_{3,4}$	0.0229 (0.0890)	$a_{4,4}$	0.0741** (0.0000)
γ_1	-0.8914** (0.0000)	γ_2	-0.6058** (0.0003)	γ_3	-0.3654** (0.0016)	γ_4	-0.5178** (0.0000)
δ_1	0.9732** (0.0000)	δ_2	0.9734** (0.0000)	δ_3	0.9721** (0.0000)	δ_4	0.9660** (0.0000)
R^2	0.0005		0.0975		0.0724		0.0872

Correlation Coefficients

	New York	London	Frankfurt	Paris
New York	1.0000	0. .3942** (0.0000)	0. 3933** (0.0000)	0. 3946** (0.0000)
London		1.0000	0. 5364** (0.0000)	0. 6494** (0.0000)
Frankfurt			1.0000	0. 6903** (0.0000)
Paris				1.0000

Model Diagnostics

	New York	London	Frankfurt	Paris
$E(z_{i,t})$	-0.00177	0.00098	-0.00594	0.00180
$E(z^2_{i,t})$	0.99915	0.99664	1.00212	1.00028
D	0.0390	0.0204	0.0278	0.0265
JB	3080.97** (0.0000)	2348.17** (0.0000)	14603.09** (0.0000)	3714.91** (0.0000)
$LB(12); z_{i,t}$	18.6356 (0.0977)	16.6844 (0.1619)	13.0375 (0.3663)	15.7681 (0.2021)
$LB(12); z^2_{i,t}$	4.3071 (0.9772)	36.9107** (0.0002)	5.3633 (0.9447)	17.6994 (0.1251)
Log-likelihood = -17901.05				

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.

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 (like the restricted model did) that bad news in one market may increase volatility in other markets 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 other three markets by (i) 17.416, (ii) 4.074, (iii) 2.152, (iv) 3.148 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 a tremendous increase of the size of asymmetries in New York market and tremendous decrease in Paris 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 the unrestricted model specification with means and variances close to zero and one respectively. The LB statistic for twelve lags show that no dependence exists in the standardized residuals, with exception the LB statistic for the squared residuals of UK market. 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[1]. The estimated value of the likelihood ratio statistic is 680.88 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.

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 4. 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 $(a_{i,j} + a_{i,j}\gamma_j)$.

[1] 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.

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 they confirm that there is substantial interdependence among market for this period.

Table 4. Impact of Innovation on Volatility				
Innovation	%Δ New York	%Δ London	%Δ Frankfurt	%Δ Paris
+5%in N.Y	-	0.012	0.0605	0.0023
-5% in N.Y	-	0.209	0.253	0.0407
+5% in Lon.	0.0832	-	0.0084	0.0274
-5%i n Lon.	0.3388	-	0.1244	0.1116
+5% in Frank.	0.034	0.0400	-	0.0124
-5% in Frank.	0.073	0.0853	-	0.0266
+5% in Paris	-0.0246	0.0364	0.0552	-
-5% in Paris	0.0774	0.1146	0.1738	-

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 unrestricted model for the period before and after EURO.

The results for the unrestricted model for the pre-EURO period are reported in Table 5. There is evidence of price spillovers from New York to London, Frankfurt and Paris. Also there are price spillovers from London to Paris and from Paris to New York. Frankfurt market does not seem to affect any other market. Turning to volatility spillovers it can be inferred that there are spillovers from New York to London and Frankfurt with London having feedback effects to New York. These spillovers are again asymmetric since the coefficients measuring asymmetry are significant.

The above results suggest that during the period before the EURO, New York market is the predominant stock market since it affects the three most important European markets (London, Frankfurt and Paris) according to the price spillovers estimates.

Table 5. 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: $\sigma_{i,t}^2 = \exp\{a_{i,0} + a_{i,i} f_i(z_{i,t-1}) + \delta_i \ln(\sigma_{i,t-1}^2)\}$ for *i,j*=1,2,3,4 and *i≠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	
$\beta_{1,0}$	0.0467** (0.0015)	$\beta_{2,0}$	0.0261 (0.0990)	$\beta_{3,0}$	0.0259 (0.1843)	$\beta_{4,0}$	0.0091 (0.6860)
$\beta_{1,1}$	0.0359 (0.1429)	$\beta_{2,1}$	0.3025** (0.0000)	$\beta_{3,1}$	0.4671** (0.0000)	$\beta_{4,1}$	0.4192** (0.0000)
$\beta_{1,2}$	-0.0068 (0.7926)	$\beta_{2,2}$	0.0134 (0.6324)	$\beta_{3,2}$	0.0000 (0.9996)	$\beta_{4,2}$	-0.0791* (0.0421)
$\beta_{1,3}$	-0.0088 (0.6240)	$\beta_{2,3}$	-0.0189 (0.3362)	$\beta_{3,3}$	-0.1421** (0.0000)	$\beta_{4,3}$	-0.0417 (0.1417)
$\beta_{1,4}$	0.0368* (0.0457)	$\beta_{2,4}$	-0.0292 (0.1539)	$\beta_{3,4}$	0.1508 (0.0000)	$\beta_{4,4}$	0.0057 (0.8521)
$a_{1,0}$	-0.0090* (0.0312)	$a_{2,0}$	-0.0057* (0.0220)	$a_{3,0}$	0.0048* (0.0425)	$a_{4,0}$	0.0083** (0.0021)
$a_{1,1}$	0.1199** (0.0000)	$a_{2,1}$	0.0222* (0.0158)	$a_{3,1}$	0.0489** (0.0015)	$a_{4,1}$	0.0184 (0.0670)
$a_{1,2}$	0.0497** (0.0041)	$a_{2,2}$	0.0486** (0.0009)	$a_{3,2}$	-0.0016 (0.9172)	$a_{4,2}$	-0.0142 (0.2296)
$a_{1,3}$	0.0052 (0.7267)	$a_{2,3}$	0.0042 (0.6986)	$a_{3,3}$	0.0842** (0.0000)	$a_{4,3}$	0.0172 (0.1701)
$a_{1,4}$	-0.0094 (0.5659)	$a_{2,4}$	0.0227 (0.0733)	$a_{3,4}$	-0.0124 (0.4442)	$a_{4,4}$	0.0603** (0.0000)
γ_1	-0.6243** (0.0000)	γ_2	-0.6309** (0.0053)	γ_3	-0.4900** (0.0001)	γ_4	-0.7375** (0.0003)
δ_1	0.9731** (0.0000)	δ_2	0.9828** (0.0000)	δ_3	0.9718** (0.0000)	δ_4	0.9723** (0.0000)
R^2	0.00052		0.0861		0.1352		0.0754

Correlation Coefficients

	New York	London	Frankfurt	Paris
New York	1.0000	0.3558** (0.0000)	0. 2468** (0.0000)	0.3140** (0.0000)
London		1.0000	0. 4856** (0.0000)	0.6296** (0.0000)
Frankfurt			1.0000	0. 5799** (0.0000)
Paris				1.0000

Model Diagnostics

	New York	London	Frankfurt	Paris
$E\left(z_{i,t}\right)$	0.00389	-0.00113	0.00258	0.00394
$E\left(z_{i,t}^2\right)$	0.99937	0.99455	1.00459	1.00054
D	0.0503	0.0196	0.0396	0.0342
JB	2315.90** (0.0000)	1487.57** (0.0000)	18989.35** (0.0000)	3265.34** (0.0000)
$LB(12); z_{i,t}$	11.4873 (0.4877)	13.6160 (0.3259)	15.6118 (0.2097)	15.8503 (0.1982)
$LB(12); z_{i,t}^2$	6.0803 (0.9120)	26.1981* (0.0101)	1.7433 (0.9997)	7.0215 (0.8562)

Log-likelihood = -9612.72

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 volatility spillovers are concerned New York market again affects London and Frankfurt stock markets. Within Europe borders, none of the markets seems to have a predominant role, since none of the European markets is affected by the volatility spillovers of the others. This result (for European markets) contradicts the results of Antoniou et al. (2003) and Koutmos (1996) who found feedback effects in both mean and variance within and between those countries.

In order to gain a complete picture of the effects of the introduction of EURO, we present in Table 6 the estimates of the period after EURO. The interactions now are different from those documented for the pre-EURO period. In all market except Paris the leverage effect is significant. For this period there are significant price spillovers from New York to all European markets and from London to the rest of the markets. Frankfurt and Paris do 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 Frankfurt stock market to London and Paris. These spillovers, as it was mentioned before, are asymmetric. Finally it can be said that although New York market does not influence any of the European markets, it responds asymmetrically to own past innovations and to the past innovation of London market.

Table 6. 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	
$\beta_{1,0}$	-0.0621** (0.0000)	$\beta_{2,0}$	-0.0697** (0.0067)	$\beta_{3,0}$	-0.0602 (0.0978)	$\beta_{4,0}$	-0.0506 (0.1105)
$\beta_{1,1}$	-0.0703* (0.0236)	$\beta_{2,1}$	0.3251** (0.0000)	$\beta_{3,1}$	0.3088** (0.0000)	$\beta_{4,1}$	0.3767** (0.0000)
$\beta_{1,2}$	0.0880* (0.0162)	$\beta_{2,2}$	-0.1189** (0.0008)	$\beta_{3,2}$	0.2032** (0.0001)	$\beta_{4,2}$	0.1770** (0.0001)
$\beta_{1,3}$	0.0286 (0.3834)	$\beta_{2,3}$	-0.0216 (0.4939)	$\beta_{3,3}$	-0.1887** (0.0000)	$\beta_{4,3}$	0.0029 (0.9413)
$\beta_{1,4}$	-0.0556 (0.1595)	$\beta_{2,4}$	-0.0654 (0.0783)	$\beta_{3,4}$	-0.1039 (0.0519)	$\beta_{4,4}$	-0.2700** (0.0000)
$a_{1,0}$	0.0124** (0.0053)	$a_{2,0}$	0.0087 (0.0519)	$a_{3,0}$	0.0302** (0.0000)	$a_{4,0}$	0.0236** (0.0000)
$a_{1,1}$	0.0457* (0.0320)	$a_{2,1}$	0.0142 (0.1452)	$a_{3,1}$	0.0105 (0.1919)	$a_{4,1}$	0.0102 (0.2332)
$a_{1,2}$	0.0544** (0.0078)	$a_{2,2}$	0.0971** (0.0001)	$a_{3,2}$	0.0400 (0.0546)	$a_{4,2}$	0.0567** (0.0069)
$a_{1,3}$	0.0203 (0.3336)	$a_{2,3}$	0.0883** (0.0017)	$a_{3,3}$	0.1060** (0.0000)	$a_{4,3}$	0.0935** (0.0000)
$a_{1,4}$	-0.0391 (0.058)	$a_{2,4}$	-0.0347 (0.1616)	$a_{3,4}$	-0.0068 (0.7109)	$a_{4,4}$	-0.0097 (0.5568)
γ_1	-2.5684* (0.0425)	γ_2	-0.7107* (0.0206)	γ_3	-0.3628** (0.0100)	γ_4	-0.9730 (0.1546)
δ_1	0.9716** (0.0000)	δ_2	0.9554** (0.0000)	δ_3	0.9673** (0.0000)	δ_4	0.9625** (0.0000)
R^2	0.0004		0.1094		0.0560		0.1093

Correlation Coefficients				
	New York	London	Frankfurt	Paris
New York	1.0000	0.4440 **	0.5587**	0.4932**
		(0.0000)	(0.0000)	(0.0000)
London		1.0000	0.6005**	0.6842**
			(0.0000)	(0.0000)
Frankfurt			1.0000	0.8160**
				(0.0000)
Paris				1.0000
Model Diagnostics				
	New York	London	Frankfurt	Paris
$E\left(z_{i,t}\right)$	0.03357	0.03517	0.02870	0.02992
$E\left(z_{i,t}^2\right)$	1.00225	1.00223	1.00057	1.00501
D	0.0388	0.0421	0.0305	0.0336
JB	815.94**	676.71**	656.01**	625.26**
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$LB(12); z_{i,t}$	11.7800	22.0627*	10.0189	9.7170
	(0.4635)	(0.0368)	(0.6143)	(0.6408)
$LB(12); z_{i,t}^2$	11.3735	20.0219	45.4135**	24.4577*
	(0.4972)	(0.0667)	(0.0000)	(0.0176)
Log-likelihood =-7980.48				

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 New York. While during the pre-EURO period, Paris was influencing other markets (as far as the price spillovers, Table5, and volatility spillovers, Table 4, are concerned), for the post EURO period this role was transferred to London. Finally, the findings indicate that for the case of volatility spillovers for the post-EURO period, Frankfurt obtains a predominant role within Europe. All European markets seem to be affected from DAX's behavior. The reason that the German stock market has increased its leadership may be because of its important role in European monetary policy. Most striking is the finding that the volatility transmission mechanism is asymmetric in the sense that bad news in one market has a greater impact on the volatility of the others. This finding is confirmed for both, pre and post EURO periods as well as for the whole period.

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 0.816 for the period after EURO, while their corresponding conditional correlation for the period before EURO was 0.58. The reason for that great increase might be the adoption of the same currency from those countries.

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 fires and second moment interdependencies among the various markets for the period from December 3 1990 to August 6 2004.

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 this period for both price and volatility spillovers.

Similar results where obtained for the period before EURO. For the period after the introduction of EURO, the estimates showed some alterations on the results. More specifically, New York and London have price spillover effects on the other markets while Frankfurt is the only market, which has spillover effects on the other two European markets displacing New York stock market.

A remarkable result, for all periods, 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. 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 motivates for further research. For instance, we can examine the relationships of those markets using a dynamic conditional correlation model. In addition, we can include more countries using EURO in our sample and compare their correlations with other markets.

Furthermore, we can relax the assumption that the markets open and close at the same time. Martens and Poon (2001) found that daily closing prices lead to an underestimation of the true correlations between stock markets. Hence, better results can be obtained by using daily stock market closing prices recorded at 16:00 London time (pseudo-closing prices). This work is under way.

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