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Volatility Spillovers and Price Interdependencies; A Dynamic non Parametric Approach

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Abstract

This paper investigates the volatility spillovers of four major equity markets using a new approach namely, the Filtered Historical Simulation approach (FHS). The FHS captures very effectively the changes and interactions in the first and second moments. A dynamic system based on Filtered Historical Simulation (FHS) and nonparametric regression is used to obtain estimates of the variance-covariance of the set of standardised residuals. This system is then used to examine dependencies in covariance changes and to carry an impulse response analysis to investigate the dynamic responses to volatility shocks.

Keywords: FHS, Nonparametric regression, VAR, Impulse response functions

JEL Classification Codes: G10, G15.

1. Introduction

A very large body of empirical literature has been devoted to the investigation of financial market linkages and interactions. This growing body of literature seems to accompany the increasing globalization of the financial markets. For policy makers, investors and academic researchers it is extremely important to understand and quantify the manner in which markets interact and influence each other. For example, knowing how markets interact could be useful to policy makers in the sense that they can tailor regulation in a manner that promotes efficiency and inhibits the presence of systemic risks. Similarly, for investors, better understanding, can in principle lead to better portfolio allocation and risk management decisions.

Earlier studies have produced evidence on the linkages and lead-lag relationships of international financial markets and the fact that such relationships have grown in importance over time

(see for example [Koch and Koch 1991](#), [Becker et al. 1990](#) and [King and Wadhvani 1990](#)). More recently, researchers focused on both mean and variance interactions using recently developed econometric techniques in time series modelling. For example [Koutmos and Booth \(1995\)](#) investigate the transmission of price and volatility spillovers across the stock markets of the United Kingdom, the United States and Japan using a multivariate EGARCH model. They find strong evidence of both price and volatility spillovers that seem to have grown following the international stock market crash of October 1987. Several other studies have used similar methodologies and have documented similar results.

Recently, research interests have focused on methods that allow modelling the impact of innovations (shocks) across several variables over time along the lines of the vector autoregressive (VAR) framework of [Sims \(1980\)](#). More specifically, researchers have been interested in combining the class of models of Engle's (1982) autoregressive conditional heteroskedastic (ARCH) and Bollerslev's (1986) generalized ARCH (GARCH) with the VAR framework in order to calculate impulse response functions. Most of those efforts were focused in the analysis of shocks in volatility (see for example [Koop et al., 1996](#), and [Panagiotidis et al., 2003](#)). However, [Elder \(2003\)](#) argues that the computation and interpretation of impulse response functions presents severe challenges when using the VAR and GARCH frameworks. Especially, for financial time series, the main challenge in calculating impulse response functions is in the *a priori* assumption of imposing a realistic distributional structure in the conditionally heteroskedastic error terms (see [Hafner and Herwartz, 2006](#)). In addition, the absence of i.i.d. characteristics renders the historical financial time series inappropriate as a toll of analyzing the volatility spillovers and price interdependencies. Furthermore, there is evidence of time-varying skewness in equity returns, which if explored could better enable us to understand the market interactions (see for example [Harvey and Siddique, 2000](#), and [Chen et al., 2001](#)). Such challenges could be met by using a dynamic model based on Filtered Historical Simulation (FHS) combined with nonparametric regression.

The focus of this paper is the investigation of interdependencies of major equity markets by conducting an impulse response analysis using a nonparametric framework that enables us to capture the changes in the first and second moments by relaxing any assumptions on the distributional properties of the data series. Contrary to other similar studies that focus either on shocks in the mean or the variance, this paper conducts an impulse response analysis on both the conditional mean and conditional variance-covariance. In this regard, we are employing the Filtered Historical Simulation (FHS) of [Barone-Adesi et al. \(1999\)](#) to generate pathways for the conditional mean and variance-covariance of a set of time series. The standardized residuals are used as innovations in the FHS. First, they are adjusted with the Nadaraya-Watson regression, as in [Long and Ullah \(2005\)](#) and [Giannopoulos \(2008\)](#), so that they can capture the conditional dynamics of the full variance-covariance matrix in a total nonparametric manner as well as acquire any missing features of the series left by a GARCH VAR model used at an earlier stage. These two approaches are meant to prepare the ground for an impulse response analysis to investigate the dynamic responses of a shock across markets. In contrast to other studies, where the shocks are limited to one standard deviation, in this paper, we set the shocks equal to the extreme percentiles from the empirical distribution of the standardized residuals, which constitute a wide range of sizes of standard deviations.

This methodology offers two lines of innovation. The first is that the response in the mean function is generated jointly from the dynamic changes in the conditional first and second moments. The second is that no restrictions are imposed on the distributional characteristics of any of the series in the system. The remainder of this paper is organized as follows. Section 2 discusses the econometric methodology and Section 3 describes the data and presents the empirical findings. Section 4 concludes the paper.

2. Methodology

We model the four major national stock markets that are considered to be the most important centres of international capital intermediation, namely the US, the UK, Germany and Japan. For each of the four variables of interest, the model can be written as

$$\begin{aligned} R_{i,t} &= \mu_{i,1}R_{i,t-1} + \sum_{j \neq i} \mu_{i,j}R_{j,t-1} + \epsilon_{i,t}, \\ h_{i,t} &= \omega_i + \beta_i h_{i,t-1} + \alpha_i \epsilon_{i,t-1}^2, \end{aligned} \quad (1)$$

where $R_{i,t}$ is the return on stock index i where $i, j = 1, 2, 3, 4$ and $\epsilon_{i,t} \sim N(0, h_{i,t})$.

Our system ensures that any historical patterns are removed and puts in evidence the volatility persistence and transmission among different markets. The conditional mean in each market is a function of past returns as well as cross-market past returns. However, the functional forms of the conditional covariance matrix and conditional correlation matrix are linear, and this may lead to inconsistency and inefficiency of the estimates. Therefore, and to take into account the dynamic changes in the conditional covariances of the underlying variables and to capture what could not be explained by the GARCH specification, a nonparametric technique is used as in Long and Ullah (2005). From the system (1), we extract the standardized residuals and to account for correlation between innovations we adjust them by a nonparametric estimation of the conditional covariance matrix H_t . The latter is performed by using the Nadaraya-Watson (NW) estimator as follows:

$$H_t = \frac{\sum_{\tau=1}^T z_t z_\tau K_\lambda(s_\tau - s_t)}{\sum_{\tau=1}^T K_\lambda(s_\tau - s_t)}, \quad (2)$$

where T is the sample size, s_t is a conditioning variable, $K_\lambda(\cdot) = K(\cdot/\lambda)/\lambda$, $K(\cdot)$ is a kernel function, and λ is the bandwidth parameter. This particular nonparametric estimation ensures that H_t is positive semi definite. In addition, the choice of the kernel function is not as important as the choice of the optimal bandwidth. In this paper, we opt to work with the Gaussian kernel and to use a bandwidth $\lambda = b \times 1.06 \hat{S}_s T^{-1/(k+4)}$. The optimal bandwidth selection of the coefficient b is based on minimizing the $MSE(H_t)$, k is the number of parameters, and $\hat{S}_s$ represents the standard deviation of the conditioning variable.

The nonparametric correlations are estimated by decomposing the conditional covariance matrix H_t into conditional standard deviations and correlations as follows:

$$H_t = D_t R D_t, \quad (3)$$

$D_t = \text{diag}(h_{1,t}^{1/2}, \dots, h_{N,t}^{1/2})$, where N is the number of indices, and $R = [\rho_{ij}]$ is positive definite with $\rho_{i,i} = 1$ and $i = 1, \dots, N$. It follows that the off-diagonal elements of the conditional covariance matrix are defined as:

$$[H_t]_{ij} = h_{it}^{1/2} h_{jt}^{1/2} \rho_{ij}, \quad i \neq j, \quad (4)$$

where, $1 \leq i, j \leq N$.

The adjusted standardized residuals $z_{i,t}^*$, are then orthogonalized, using Choleski factorization, to accommodate the contemporaneous dependence of the innovations, and will serve as input in the following sequence of models:

$$\begin{aligned}
h_{i,T+1} &= \omega_i^* + \beta_i^* h_{i,T} + \alpha_i^* (\sqrt{h_{i,T}} z_{i,T}^*)^2, \\
R_{i,T+1}^* &= \mu_{i,1}^* R_{i,T} + \sum_{j \neq i} \mu_{i,j}^* R_{j,T} + \sqrt{h_{i,T+1}} z_{i,T+1}^*, \\
&\vdots \\
h_{i,T+n} &= \omega_i^* + \beta_i^* h_{i,T+n-1} + \alpha_i^* (\sqrt{h_{i,T+n-1}} z_{i,T+n-1}^*)^2, \\
R_{i,T+n}^* &= \mu_{i,1}^* R_{i,T+n-1} + \sum_{j \neq i} \mu_{i,j}^* R_{j,T+n-1} + \sqrt{h_{i,T+n}} z_{i,T+n}^*,
\end{aligned} \tag{5}$$

to form simulated pathways for the conditional mean and variance, and where T is the last day in the sample and n is the number of forecasting days ahead.

The simulation is conducted M number of times drawing from the orthogonalized standardized residuals on each future date, say for example 10,000 times. The result is a sequence of daily returns for day $T+1$ through day $T+n$ for each index i as $R_{i,T+1,T+n}^*$. The diagram goes as follows:

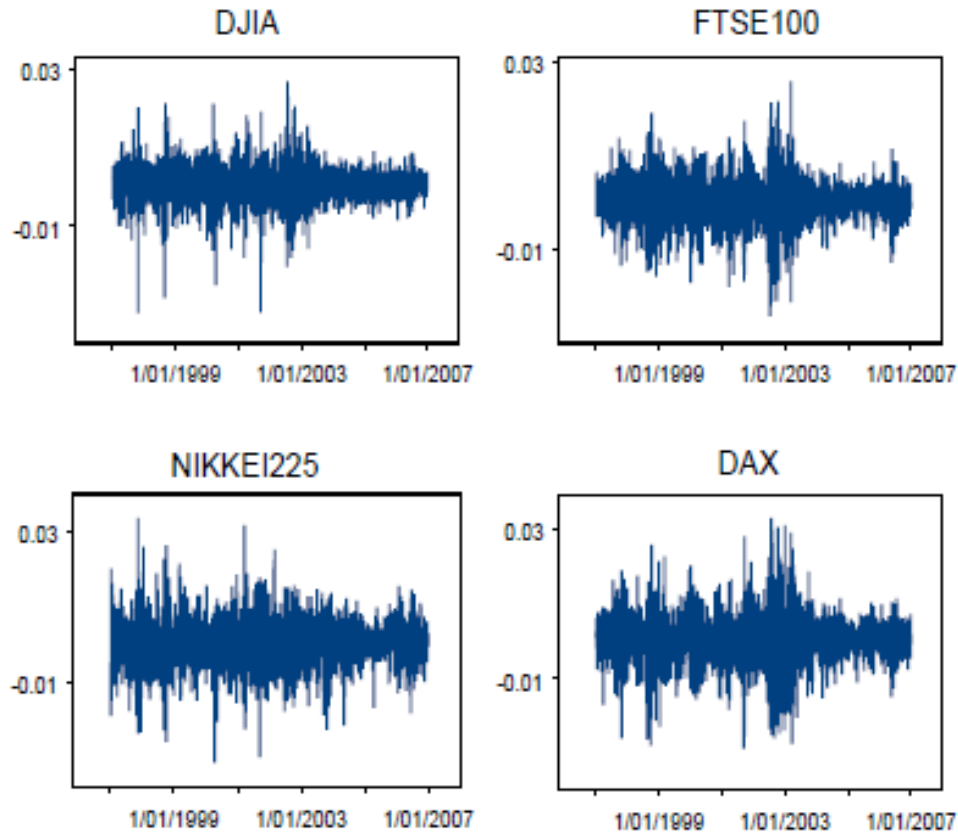
$$\begin{array}{ccccccc}
z_{1,T}^* \rightarrow R_{1,T+1}^* \rightarrow \sqrt{h_{1,T+2}^*} & \cdots & z_{1,T+n}^* \rightarrow R_{1,T+n}^* \\
z_{2,T}^* \rightarrow R_{2,T+1}^* \rightarrow \sqrt{h_{2,T+2}^*} & \cdots & z_{2,T+n}^* \rightarrow R_{2,T+n}^* \\
& \cdots & & \cdots & & \cdots \\
z_{M,T}^* \rightarrow R_{M,T+1}^* \rightarrow \sqrt{h_{M,T+2}^*} & \cdots & z_{M,T+n}^* \rightarrow R_{M,T+n}^*
\end{array}$$

Next, we inspect the dynamic responses across markets by considering two volatility shocks. Similar to [Koop *et al.* \(1996\)](#), we conceive a shock as being generated from the data generating process and hence “realistic” shocks. To proceed, we are taking from the past conditional volatility the 1% and 99% percentile as being the most severe outliers from the simulated data generating process. These shocks are taken as the first day input to simulate a set of pathways for the conditional mean and variance over a period of 10 days and hence to form volatility impulse responses (see the above diagram). This technique enables us to quantify both the size and the persistence of the two shocks in the conditional volatility.

3. Data and Results

To evaluate the models, we use four equity indices, the DJIA for the US, the FTSE100 for the UK, the NIKKEI-225 for Japan, and DAX for Germany. The data are obtained from Reuters and span the period January 1st, 1997 to January 1st, 2007. For all indices, we calculate daily log returns. Figure 1 shows the volatility clustering that is prevalent in almost all financial time series, especially in high frequencies.

Figure 1:



For all models and all equity indices, Equation 1, the results of the estimation of the parameters of the GARCH VAR volatility model are presented in Tables 1 - 4. The results presented in Table 1 displays the price spillovers from the UK, Japan, and Germany to the US, as well as the conditional volatility estimates. The estimated coefficients are significant at the 5% level. The price spillovers from the UK and Japan are negative whereas those from Germany are positive. Table 2 presents the spillovers into the UK market. Again the parameters are significant implying that past returns in the US, Japan and Germany can to some extent predict current returns in the UK. The findings are similar in regards to spillovers into the Japanese and the German markets in Tables 3 and 4 respectively. The volatility coefficients in all 4 markets depend on past innovations and past volatilities. The relevant parameters are significant with minor exceptions.

Table 1: US

$$R_{US,t} = \mu_{US}R_{US,t-1} + \mu_{UK}R_{UK,t-1} + \mu_{JP}R_{JP,t-1} + \mu_{BD}R_{BD,t-1} + \varepsilon_{US,t}$$

$$h_{US,t} = \omega_{US} + \beta h_{US,t-1} + \alpha_{US} \varepsilon_{US,t}^2$$

Coefficient	Value	Std Error
μ_{US}	-0.0315	0.0022*
μ_{UK}	-0.0067	0.0026*
μ_{JP}	-0.0293	0.0014*
μ_{BD}	0.0368	0.0020*
ω_{US}	0.8650	1.0000
β_{US}	0.9291	0.0162*
α_{US}	0.0640	1.4732

(*) denotes significance at the 5% level

Table 2: UK

$$R_{UK,t} = \mu_{UK}R_{US,t-1} + \mu_{US}R_{US,t-1} + \mu_{JP}R_{JP,t-1} + \mu_{BD}R_{BD,t-1} + \varepsilon_{UK,t}$$

$$h_{UK,t} = \omega_{UK} + \beta h_{UK,t-1} + \alpha_{UK} \varepsilon_{UK,t}^2$$

Coefficient	Value	Std Error
μ_{UK}	-0.1080	0.0027*
μ_{US}	0.3490	0.0023*
μ_{JP}	-0.0528	0.0014*
μ_{BD}	-0.0214	0.0020*
ω_{UK}	1.4260	0.3980*
β_{UK}	0.9036	0.0136*
α_{UK}	0.0830	0.0119*

(*) denotes significance at the 5% level.

Table 3: Japan

$$R_{JP,t} = \mu_{JP}R_{JP,t-1} + \mu_{US}R_{US,t-1} + \mu_{UK}R_{UK,t-1} + \mu_{BD}R_{BD,t-1} + \varepsilon_{JP,t}$$

$$h_{JP,t} = \omega_{JP} + \beta h_{JP,t-1} + \alpha_{JP} \varepsilon_{JP,t}^2$$

Coefficient	Value	Std Error
μ_{JP}	-0.1060	0.0015*
μ_{US}	0.3340	0.0022*
μ_{UK}	0.0990	0.0027*
μ_{BD}	0.0872	0.0020*
ω_{JP}	0.6800	0.3230*
β_{JP}	0.9262	0.0240*
α_{JP}	0.0688	0.0050*

(*) denotes significance at the 5% level.

Table 4: Germany

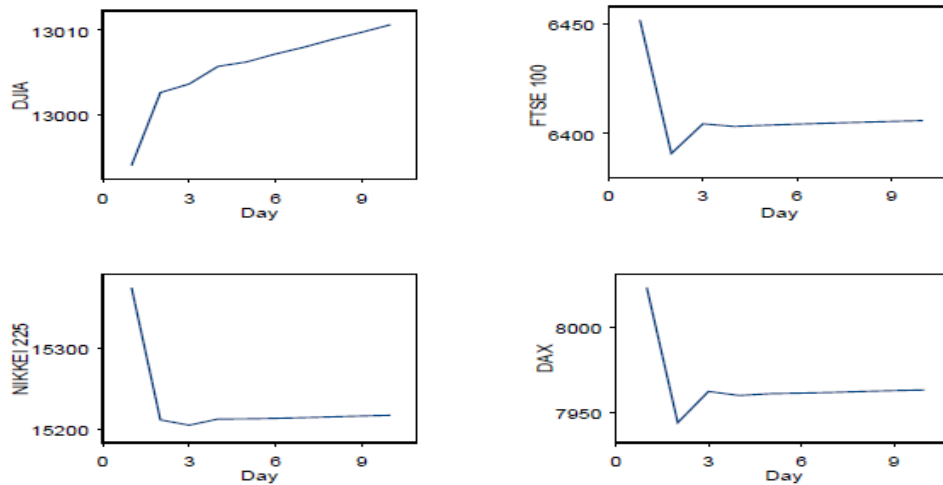
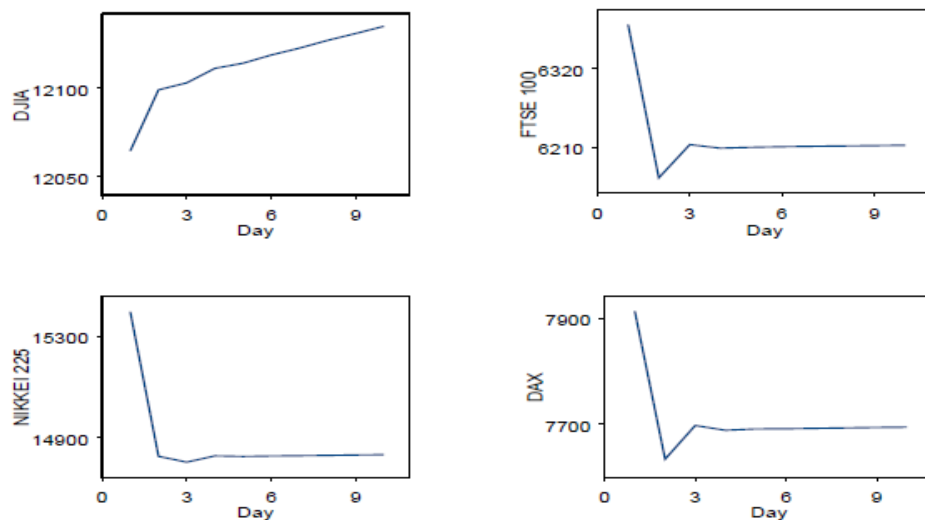
$$R_{BD,t} = \mu_{BD}R_{BD,t-1} + \mu_{US}R_{US,t-1} + \mu_{UK}R_{UK,t-1} + \mu_{JP}R_{JP,t-1} + \varepsilon_{BD,t}$$

$$h_{BD,t} = \omega_{BD} + \beta h_{BD,t-1} + \alpha_{BD} \varepsilon_{BD,t}^2$$

Coefficient	Value	Std Error
μ_{BD}	-0.0910	0.0021*
μ_{US}	0.3780	0.0022*
μ_{UK}	-0.0800	0.0028*
μ_{JP}	-0.0320	0.0015*
ω_{BD}	1.9860	0.5730*
β_{BD}	0.9167	0.0109*
α_{BD}	0.0720	0.0960*

(*) denotes significance at the 5% level.

Taking into consideration the methodology adopted in this paper, we proceed with investigating the impulse response analysis. The aim of this analysis is to enable us to quantify the size and the persistence of volatility shocks transmitted from the US market to the behavior of different structures of stock markets. In fact, there is a general consensus that the US market is the major volatility exporter to the other markets. The path of the impulse responses in the volatility of each country over a period of time of 10 days is displayed in Figure 2. With respect to a shock as 1% percentile of past conditional volatility in the US market (Panel a), it seems that it takes 3 days for the UK market as well as the German and Japanese market to absorb a volatility shock in the US market. There is a significant decrease in the price indices in a range between 1% to 5%. With respect to a shock as 99% percentile of past conditional volatility in the US market (Panel b), the volatility shock originating from the US market also die out within 3 days, whereas the decrease in the price indices in UK, German, and Japanese markets ranges between 5% and 10%.

Figure 2: Impulse responses of a shock in US market on Major Markets**a) Shock is 1% percentile of past conditional volatility****a) Shock is 99% percentile of past conditional volatility**

It follows from these results that there is evidence of volatility spillovers from the US to other markets such as the UK, the German, and The Japanese. In fact, there is a negative effect of the volatility shocks from the US market on these markets. Whether shocks at a daily level are not persistent enough to be explained by some reasons such as the existence of time-varying risk premia (see Poterba and Summers, 1986) is left to be further investigated.

4. Conclusion

This paper focuses on the market interdependencies of major equity markets by conducting an impulse response analysis using a nonparametric framework that enables us to capture the changes in the first and second moments by relaxing any assumptions on the distributional properties of the data series. The analysis was performed using daily closing stock index data from four major markets, US, UK, Germany, and Japan. The methodology is adopting an impulse response analysis on both the

conditional mean and conditional variance-covariance, employing the Filtered Historical Simulation (FHS), and capturing the conditional dynamics of the full variance-covariance matrix in a total nonparametric manner. A simulation is carried over to estimate the volatility impulse responses related to the four stock markets. These techniques enabled us to quantify the size and the persistence of two shocks in the conditional volatility.

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