

On the Co-movements between Exchange Rate and Stock Price from Japan: A Multivariate FIGARCH-DCC Approach

Abstract

This paper aims to investigate the inter-dependence of exchange rate and stock index from Japan. For this purpose, we use a dynamic conditional correlation (DCC) model into a multivariate Fractionally Integrated Exponential GARCH (FIGARCH). Framework takes account long memory and time varying correlations. Our findings reveal time-varying Co-movements evidence, a high persistence of conditional correlation and dynamic correlations revolve around a constant level. The findings support the idea of cross-market hedging and sharing of common information by investors.

1. Introduction

The past decades have been characterized by financial crises which were caused such as the Asian financial crisis 1997, the Russian crisis 1998 and the Brazilian crisis 1999, the global financial crises 2007-2009 initiated from the largest and most influential economy, the US market, and were spreading over the other financial markets countries worldwide. Global financial crisis resulted in sharp declines in asset prices, stock and foreign exchange markets, and skyrocketing of risk premiums on interbank loans. It also disrupted country's financial system and threatened real economy with huge contractions, the recent crisis of sovereign debt in 2011, which led to high volatility in stock markets and foreign exchange markets. So an investor seeking to develop its heritage, regularly and without excessive risk (or with a lower risk) is then exposed to the risk of a very sharp rise or a very sharp drop in the value of his fortune. Therefore, it is interesting for him and for any long or short term financial decision maker to study this growing instability of markets, to predict later and based on this study the future volatility for a clear and encrypted idea on its degree of exposure to different risks, that can help them in making good decisions and strategies. In the field of modeling the volatility, the long memory has already been introduced, in particular in the process integrated fractionally ARFIMA and FIGARCH of Baillie Bollerslev and Mikkelsen (1996).

Numbers of studies that attempt to examine the exchange rates effect on stock prices, however, the findings are not uniform (Ibrahim (2000)). Some studies give evidence of negative exchange rates effects on stock markets (Soenen and Henningar (1988)), while others found positive effects (Aggarwal (1981)). Other studies contribute to these results and find that the exchange rate changes have no significant impact on the stock market (Solnik (1984)). Thus, the existing literature provides mixed results when analyzing the relationship between stock prices and exchange rate. For example, Yang and Doong (2004) find that stock market movements have a significant effect on future exchange rate changes for the G7 countries over the period 1979-1999. Pan et al. (2007) use a VAR approach to analyze the interaction between stock markets and exchange markets for seven East Asian countries, and provide evidence of a significant bidirectional relationship between these markets before the Asian financial crisis. Akgün and Sayyan (2005) have examined the asymmetric response of the yields of course fellows to Istanbul in using the models of the conditional Heteroscedasticity asymmetric (EGARCH, GJR, APARCH, FIEGARCH, FIAPARCH) for the period from 04 January 2000 until 25 May 2005. Their results show that the models APARCH and FIAPARCH provide the most accurate forecasts of volatility. Chkili et al. (2011) use a Markov-Switching EGARCH model to analyze the dynamic relationships between exchange rates and stock returns in four emerging countries (Singapore, Hong Kong, Mexico and Malaysia) during both normal and turbulent periods. They provide evidence of regime dependent links and asymmetric responses of stock market

volatility to shocks affecting foreign exchange market. Li and Giles (2015) have examined the volatility of the exchange rate for the developed countries (United States and Japan) and 6 Asian countries (China, India, Malaysia, Indonesia, Philippines and Thailand) by means of the model BEKK-MGARCH. More recently, Owidi and Mugo-Waweru (2016) have examined the behavior of the volatility performance of Kenya stock market by the FIEGARCH. These authors found that the model FIEGARCH has the ability to capture the asymmetry effect in taking into account the characteristics of the long memory of the volatility.

Following the March 2011 earthquake, the yen experienced an upward trend and even reached a new peak (Bloomberg News, June 21, 2011). Since its exporting character knows the Japanese economy, therefore Japanese companies and Japanese decision-makers closely supervise the yen's evolution, as the exchange rate has a great importance in boosting exports (Hashi and Ito (2009)).

The present study provides a robust analysis of dynamic linkages among exchange rate and stock index from Japan that goes beyond a simple analysis of correlation breakdowns. The time-varying DCC are captured from a multivariate FIGARCH-DCC model which takes into account long memory behavior, market information speed. The rest of the paper is organized as follows. First part presents the data and the econometric methodology. Second part displays and discusses the empirical findings and their interpretation, while final part provides our conclusion.

2. Data and Econometric methodology

2.1. Data

The data involves daily exchange rate and stock index from Japan. The data are taken from (<http://www.Federalreserves.gov>) and (<https://finance.yahoo.com>). The sample covers a period from 01/01/2000 until 31/12/2015, leading to a sample size of 10950 observations. For each exchange rate and stock index in first difference.

2.2. Univariate FIGARCH Model

We assume that stationary process can be described by an AR(1) model as follows;

$$r_{i,t} = \mu + \psi_{i,t-1} + \varepsilon_{i,t}, t \in N, \text{ with } \varepsilon_{i,t} = z_t \sqrt{h_{i,t}}, z_t \sim N(0,1) \quad (1)$$

Where $|\mu| \in [0, \infty)$, $|\psi| < 1$, and the innovation, $\{z_t\}$ are an independently and identically distributed (i.i.d) process. The conditional variance $h_{i,t}$ is positive with probability one and is measurable function of the variance-covariance matrix.

$$h_{i,t} = \omega + \alpha(L)\varepsilon_{i,t}^2 + \beta(L)h_{i,t} \quad (2)$$

Where $\omega > 0$, L denotes the lag or backshift operator, $\alpha(L) = \alpha L + \alpha_2 L^2 + \dots + \alpha_q L^q$

In case of GARCH(1,1) model, $\alpha \geq 0, \beta \geq 0$ and the persistence of conditional variances is measured by the sum $(\alpha + \beta)$. A common empirical finding is that the sum $(\alpha + \beta)$ is quite close to one, implying that shocks are infinitely persistent, which corresponds to an integrated GARCH (IGARCH) process of Engle and Bollerslev (1986).

Baillie et al. (1996) developed the fractional IGARCH (FIGARCH) model, which nests the GARCH and IGARCH models. The FIGARCH model allows for fractional orders of integration between zero and one, and thus captures the presence of long-memory behavior in the conditional variance. The FIGARCH (p,d,q) model can be represented as follows;

$$\phi(L)(1-L)^d \varepsilon_{i,t}^2 = \omega + [1 - \beta(L)](\varepsilon_{i,t}^2 - h_{i,t}) \quad (3)$$

Where the long-memory parameter, d , satisfies the condition $0 \leq d \leq 1$, $\phi(L)$ and $\beta(L)$ are finite order lag polynomials with roots assumed to lie outside the unit circle, and the fractional differencing operator $(1-L)^d$ is defined as (Hosking, 1981);

$$(1-L)^d = 1 - dL - \frac{1}{2}d(1-d)L^2 - \frac{1}{3!}d(1-d)(2-d)L^3 - \frac{1}{n!}d(1-d)((n-1)-d)L^n \quad (4)$$

The conditional variance process or the ARCH (∞) representation of the FIGARCH model is given by;

$$h_{it} = \omega + \beta(L)h_{i,t} + [1 - \beta(L)]\varepsilon_{it}^2 - \phi(L)(1-L)^d \varepsilon_{i,t}^2 = \omega[1 - \beta(L)]^{-1} + \lambda(L)\varepsilon_{i,t}^2, \quad (5)$$

The FIGARCH model provides greater flexibility for modelling the conditional variance, because it accommodates the covariance stationary GARCH model when $d = 0$, and the IGARCH model when $d = 1$, as special cases. For the FIGARCH model, the persistence of shocks to the conditional variance, or the degree of long-memory, is measured by the fractional differencing parameter d . Thus, the attraction of the FIGARCH model is that, for $0 < d < 1$, it is sufficiently flexible to allow for an intermediate range of persistence (Baillie et al., 1996).

2.3. Bivariate model FIGARCH with dynamic conditional correlations

To evaluate volatility spillovers, we applied a bivariate FIGARCH model to JPY/USD and NIKKEI225 index in first difference. We decided to model the structure of conditional correlations using the DCC approach of Engle (2002). This allows us to not only investigate the time-varying correlations between two indexes, but also to ensure the positive definiteness of the variance-covariance matrix (H_t) under simple conditions imposed on specific parameters. The parameterization of a FIGARCH-DCC model allows for directly inferring the time-varying correlations between JPY/USD and NIKKEI225 index in first difference as well as for dealing with a relatively large number of variables in the system without having a numerical convergence problem at the estimation stage. In the multivariate case which we use, the variance-covariance matrix of residuals is defined as follows;

$$H_t = D_t R_t D_t \quad (6)$$

where D_t is a (2×2) diagonal matrix of the time-varying conditional standard deviation of the residuals, obtained by taking the square root of the conditional variance, modelled by univariate AR(1)-GARCH(1,1) and AR(1)-FI GARCH(1,1) models, respectively. R_t is a matrix of time-varying conditional correlations, which is given by;

$$R_t = (\text{diag}(Q_t))^{-1/2} Q_t (\text{diag}(Q_t))^{-1/2} \quad (7)$$

$$\text{That is, } R_t = \begin{bmatrix} 1/\sqrt{q_{11}} & 0 \\ 0 & 1/\sqrt{q_{22}} \end{bmatrix} \begin{bmatrix} q_{11} & q_{12} \\ q_{21} & q_{22} \end{bmatrix} \begin{bmatrix} 1/\sqrt{q_{11}} & 0 \\ 0 & 1/\sqrt{q_{22}} \end{bmatrix}$$

The covariance matrix $Q_t = [q_{ij,t}]$ of the standardized residual vector

$$u_t = (u_{1,t}, u_{2,t}, \dots, u_{n,t})', \quad u_t = \varepsilon_{i,t} / \sqrt{h_{ii,t}}$$

$$Q_t = (1 - \alpha_{dcc} - \beta_{dcc})\bar{Q} + \alpha_{dcc}(u_{t-1}u'_{t-1}) + \beta_{dcc}Q_{t-1}, \quad (8)$$

With $\alpha_{dcc} > 0$, $\beta_{dcc} > 0$ and $\alpha_{dcc} + \beta_{dcc} < 1$. $\bar{Q}_t = \{\bar{q}_{ij,t}\}$ denotes the unconditional covariance matrix of ε_t . The coefficients α_{dcc} and β_{dcc} are the estimated parameters depicting the conditional correlation process. The dynamic correlation coefficient in a bivariate case can be expressed as;

$$\rho_{ij,t} = \frac{(1-\alpha_{dcc}-\beta_{dcc})\bar{q}_{ij} + \alpha_{dcc}u_{i,t-1}u_{j,t-1} + \beta_{dcc}q_{ij,t-1}}{\sqrt{[(1-\alpha_{dcc}-\beta_{dcc})\bar{q}_{ii} + \alpha_{dcc}u_{i,t-1}^2 + \beta_{dcc}q_{ii,t-1}][(1-\alpha_{dcc}-\beta_{dcc})\bar{q}_{jj} + \alpha_{dcc}u_{j,t-1}^2 + \beta_{dcc}q_{jj,t-1}]}} \quad (9)$$

The significance of α_{dcc} and β_{dcc} implies that the estimators obtained from the DCC-FIGARCH models were dynamic and varied with time. α_{dcc} indicates short-run volatility impact, implying the persistency of the standardized residuals from the previous period. β_{dcc} measures the lingering effect of shock impact on conditional correlations, indicating the persistency of the conditional correlation process. $\rho_{ij,t}$ indicates the direction and strength of correlation. If the estimated $\rho_{ij,t}$ is positive, then the correlation between stationary series is moving in the same direction and vice versa¹.

We estimate the DCC model using the quasi-maximum likelihood estimation method proposed by Bollerslev and Wooldridge (1992) in which the log-likelihood can be expressed as;

$$L = -\frac{1}{2} \sum_{t=1}^T [k \log(2\pi) + 2 \log|D_t| + \log|R_t| + \varepsilon'_t R_t^{-1} \varepsilon_t] \quad (10)$$

The DCC model's design allows for the two-stage estimation procedures of the conditional covariance matrix H_t , in the first stage, we fit the univariate GARCH-type models for each JPY/USD and NIKKEI225 index in first difference; then, estimates of h_{iit} , are obtained. In the second stage, we transform the first difference series using their estimated standard deviation, which is a result of the first stage. Then this information is used to estimate the parameters of the conditional correlation.

3. Empirical Results

3.1. Preliminary analyses and testes

In this section, I report the results of descriptive statistics in table 1, unit root tests in table 2, Serial correlation and LM-ARCH test in table 3, Long Memory tests in table 4 and the evolution of exchange rate and stock index in figure 1.

Table I : Descriptive statistics							
	Mean	Maximum	Minimum	Std.Deviation	Skewness	Kurtosis	Jarque-Bera
Log(JPY/USD)	4.650721	4.903570	4.327042	0.144385	-0.669031	2.397668	524.3077
Log(NIKKEI225)	9.416817	9.945974	8.861489	0.262888	0.187731	1.860414	350.5495

Summary statistics of stock price and exchange rate are displayed in Table 1. From this table, NIKKEI225 is the most volatile, as measured by the standard deviation of 26.2888%, while JPY/USD is the most volatile with a standard deviation of 14.4385%. Besides, we observe that NIKKEI225 has the highest level of kurtosis, indicating that extreme changes tend to occur more frequently for the stock price. In addition, the stock price and exchange rate exhibit high values of excess kurtosis. To accommodate the existence of “fat tails”, we assume t-student

¹ See Engle (2002) for further details on the estimation of time-varying conditional correlations.

distributed innovations. Furthermore, the Jarque-Bera statistic rejects normality at the 1% level for all stock prices and exchange rate. The Ljung-Box test for correlating series reject the null hypothesis of autocorrelation. This equates that conditional volatility of the returns series contains long memory.

In Table II, we verify the stationary of the Log(JPY/USD) and Log(NIKKEI225) index by the tests of **Dickey-Fuller (1979-1981)** in level and in first difference. For this, we use the sequential procedure to determine the optimal number of lags of this index on daily frequencies. Results reported in table 2 indicate that both series have a unit root since t-statistics are higher in level than the tabulated value of Mackinnon (1996). La présence d'une racine unitaire en niveau pour l'indice JPY/USD est détectée à partir d'un modèle sans constant et sans tendance linéaire. Par contre, l'indice NIKKEI225 contient une racine unitaire en niveau à partir d'une spécification avec constante et sans tendance linéaire. This unit root disappeared after a single differencing. Hence, the JPY/USD and NIKKEI225 index are integrated of order 1. The unit root for the JPY/USD and NIKKEI225 index are detected by the Dickey-Fuller test (1979) while the Dickey-Fuller-Augmented test (1981) is used to identify the existence of a unit root of the Log(JPY/USD) and Log(NIKKEI225) index.

	Lags	Models	Level		First difference		Integration order
			T-Statistic	Critical values	T-Statistic	Critical values	
Log(JPY/USD)	2	M1	0.053	-0.193	-38.37	-1,9409	I(1)
Log(NIKKEI225)	2	M2	0.066	-0.182	-37.612	-1,9409	I(1)

Furthermore, in Table 3 the Jarque-Bera statistic rejects normality at the 1% first difference for all exchange rates. Finally, we find that there is a problem of heteroscedasticity in the JPY/USD variance and NIKKEI225 index variance. Since the variance of residuals is heteroscedastic. In order to detect long-memory process in the data, we use the log-periodogram regression (GPH) test of Geweke and Porter-Hudak (1983) on two proxies of volatility, namely squared returns and absolute returns.

	Serial Correlation		LM-ARCH
	LB(20)	LB ² (20)	ARCH(10)
$\Delta \text{Log (JPY/USD)}$	33.5368 [0.029434]**	337.717 [0.0000]***	13.661 [0.0000]***
$\Delta \text{Log (NIKKEI225)}$	41.4636 [0.00324]***	3729.67 [0.0000]**	159.20 [0.0000]***

Notes: The superscripts ***, ** and * denote the statistical significance at 1%, 5% and 10% levels, respectively

In table 3 the Ljung-Box statistic was used to check for the presence of serial correlation in the standardized and squared standardized residuals up to the 20th order. ***denotes the rejections of the null hypothesis of no serial correlation at the 1% significance level. Thus, the series in first difference seemed to follow ARCH-type dependencies. The LM-ARCH test for conditional heteroscedasticity represents statistical significance at the 1% level. This further encourages the use of ARCH-type models in order to describe this feature of the data.

Table 4 : Long Memory tests				
Hurst-Mandelbrot R/S test	Squared		Absolute	
$\Delta \text{Log (JPY/USD)}$	6.551***		12.108***	
$\Delta \text{Log (NIKKEI225)}$	6.756***		12.985***	
Lo's modified R/S test	Squared		Absolute	
	$q = 1$	$q = 5$	$q = 1$	$q = 5$
$\Delta \text{Log (JPY/USD)}$	5.427***	3.954***	10.662***	7.725***
$\Delta \text{Log (NIKKEI225)}$	5.443***	4.457***	10.751***	8.021***
GSP test	Squared		Absolute	
	$m = T/4$	$m = T/16$	$m = T/4$	$m = T/16$
$\Delta \text{Log (JPY/USD)}$	0.222***	0.417***	0.326***	0.445***
$\Delta \text{Log (NIKKEI225)}$	0.258***	0.444***	0.395***	0.478***

Notes: The superscripts ***, ** and * denote the statistical significance at 1%, 5% and 10% levels, respectively.

The analysis in **table 4** was done via the Hurst-Mandelbrot R/S, Lo's modified R/S and GSP tests conducted on absolute and squared of the JPY/USD and NIKKEI225 index in first difference, as a proxy of variance. The results suggest that, at very high probability levels, the null hypothesis of no long-range memory should be rejected for all asset series. This is an indication of the persistence of volatility shocks for periods of time longer than the usual exponential decay for which standard GARCH models are appropriate. That suggests that FIGARCH approach should successfully measure the long memory presence in the volatility of the observed asset series.

Below, figure 1 illustrates the evolution of exchange rate and stock index during the period from January 1, 2000 until December 31, 2015. The figure shows significant variations in the levels during the turmoil, especially at the time of Lehman Brothers failure (September 15, 2008). Specifically, when the global financial crisis triggered, there was a decline for all prices. Moreover, Fig. 1 plots the evolution of exchange rate behavior and stock price behavior over time.

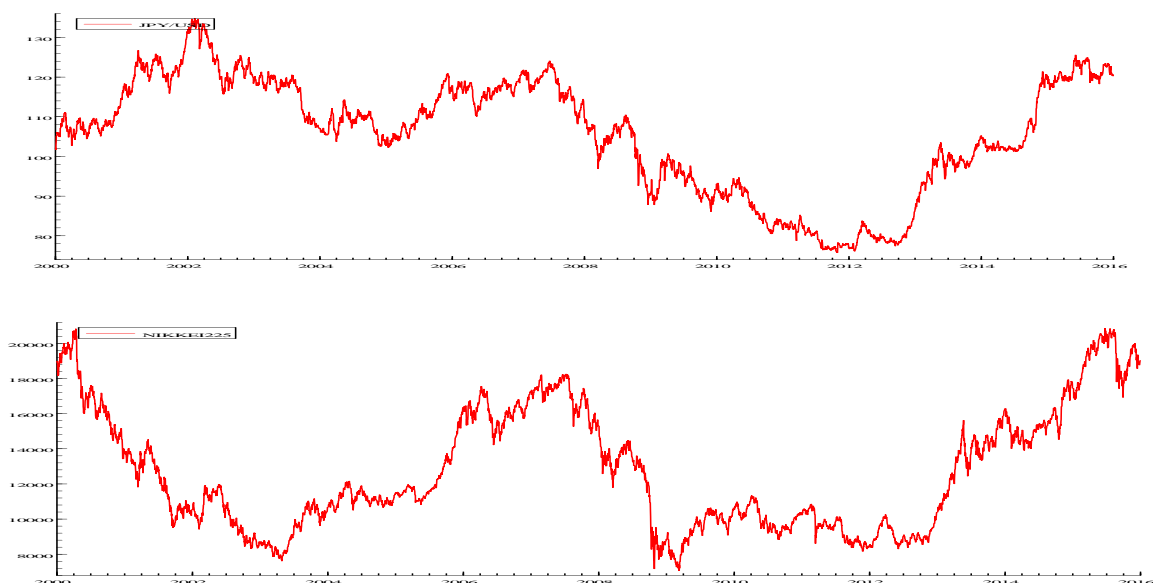


Figure. 1.1. Exchange rate and stock index behavior over time.

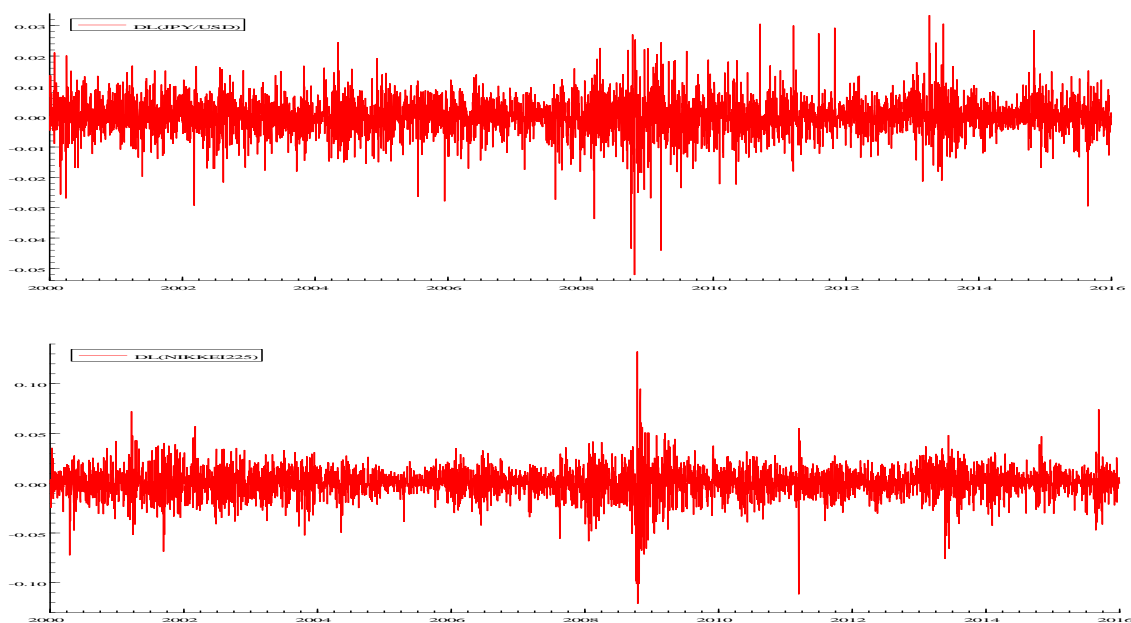


Figure.1.2. Exchange rate and stock index in first difference behavior over time.

The figure shows that all stock indexes and exchange rate trembled since 2008 with different intensity during the global financial and European sovereign debt crises. Moreover, the plot shows a clustering of larger return volatility around and after 2008. This means that stock price is characterized by volatility clustering, i.e., large (small) volatility tends to be followed by large (small) volatility, revealing the presence of heteroscedasticity. This market phenomenon has been widely recognized and successfully captured by ARCH/GARCH family models to adequately describe stock market returns dynamics. This is important because the econometric model will be based on the interdependence of the stock markets in the form of second moments by modeling the time varying variance-covariance matrix for the sample.

3.2. The univariate FIGARCH estimates

Table 5 reports the Maximum Likelihood Estimates (MLE) for the student-t-FIGARCH (1,d,1) model. $LB^2(20)$ indicate the Ljung-Box tests for serial correlation in the squared standardized residuals. Student-df denotes the t-student degrees of freedom parameter***,**and * denote statistical significance at 1%, 5% and 10% levels, respectively. ARCH (10) means the test of autoregressive conditional heteroskedasticity up to lag 10. The null hypothesis of ARCH test is no ARCH effects up to lag k. Diagnostic tests $LB^2(20)$ and ARCH (10) showed that the FIGARCH model with Student's t-distribution was well specified because standardized residuals are not subject to either serial correlation or ARCH effects. This result confirms our preliminary analysis and, subsequently, by the choice of the t-student as an appropriate distribution. The estimation results for the student-t- FIGARCH model suggest that the FIGARCH model captures the long-memory property in the volatility processes of the JPY/USD and NIKKEI225 index in first difference. In fact, the long-memory parameters (d-Figarch) are significant at the 1% level, suggesting that all index in first difference volatility processes were persistent over time. Overall, the FIGARCH model most accurately represents the long-memory property in the conditional variance of the JPY/USD and NIKKEI225 index in first difference. The presence of long-memory in volatility implies dependencies between distant observations over time, which can be used to predict future volatility values. The ARCH

and GARCH parameters are statistically significant and not negative at the 1% which justifying the appropriateness of the FIGARCH model and implying that the volatility is highly persistent in all JPY/USD and NIKKEI225 index in first difference².

Estimates	$\Delta \text{Log (NIKKEI225)}$		$\Delta \text{Log (JPY/USD)}$	
	Coefficients	t-prob	Coefficients	t-prob
CST(<i>m</i>)	0.0002	0.0050	0.0001	0.0015
AR(1)	-0.0295	0.0006	-0.0216	0.0155
CST(<i>v</i>)	0.1105	0.0004	1.4669	0.0021
d-Figarch	0.6619	0.0000	0.6821	0.0000
ARCH	0.2871	0.0000	0.3689	0.0000
GARCH	0.8694	0.0000	0.9286	0.0000
Student-df	2.3811	0.0000	2.3346	0.0000
Log-likelihood	18540.624		23370.182	
Diagnostic tests				
ARCH (10)	0.3012	0.9820	1.5084	0.1305
LB ² (20)	286.634	0.3407	128.700	0.11007

3.3. The bivariate FIGARCH (1, d, 1)-DCC estimates

This subsection considers volatility spillover effects between the JPY/USD and NIKKEI225 index in first difference using the bivariate FIGARCH (1,d,1)-DCC models with Student's t-distribution. Table 5 presents the estimation results of the bivariate FIGARCH-DCC model between the JPY/USD and NIKKEI225 index in first difference.

Estimates	$\Delta \text{Log (NIKKEI225)}$		$\Delta \text{Log (JPY/USD)}$	
	Coefficients	t-prob	Coefficients	t-prob
CST(<i>m</i>)	0.0003	0.0151	0.0005	0.0386
AR(1)	-0.0249	0.0377	-0.0117	0.0451
CST(<i>v</i>)	0.0260	0.0411	0.9418	0.0006
d-Figarch	0.5742	0.0000	0.5450	0.0000
ARCH	0.2616	0.0000	0.5374	0.0000
GARCH	0.7744	0.0000	0.7895	0.0000
Student-df	2.3964	0.0000	2.3745	0.0000

² The traditional efficient market hypothesis of Fama (1970) suggested that stock returns showed a random walk, making it impossible to make predictions from past patterns. Strictly speaking, it is to some extent inappropriate that the definition of the efficient market hypothesis is applied to stock price volatility. However, the long-memory property in stock returns or volatility has improved the definition of market efficiency, where predictable components occur in asset pricing.

Log-likelihood	17924.318	22554.245
Dynamic conditional correlation		
	Coefficients	t-prob
<i>Average COR_{ij}</i>	0.5211	0.0397
α_{dcc}	0.0055	0.0307
β_{dcc}	0.9920	0.0000
Student-df	2.6008	0.0000
2 Log-likelihood	42196.035	
Diagnostic tests		
	Coefficients	t-prob
<i>Hosking(20)</i>	164.055	0.0000
<i>Hosking²(20)</i>	26.5222	1.0000
<i>Li - McLeod(20)</i>	167.302	0.0000
<i>Li - McLeod²(20)</i>	26.5994	1.0000

The ARCH and GARCH term is positive and significant, implying volatility persistence or volatility clustering in the JPY/USD and NIKKEI225 index in first difference. The fractional integrated coefficient (d) is highly significant, indicating a high level of persistence in conditional variances. The JPY/USD and NIKKEI225 index addressed the higher persistence regardless of time intervals. The ARCH effect α_{dcc} is positive and significant, underlying the importance of shocks between the JPY/USD and NIKKEI225 index. For the GARCH effects β_{dcc} , the parameters are significant and very close to one for all JPY/USD and NIKKEI225 index in first difference, confirming the higher persistence of volatility between the JPY/USD and NIKKEI225 index. The sum of these parameters ($\alpha_{dcc} + \beta_{dcc}$) in each model is less than unity and this shows that conditional pair-wise correlations are mean-reverting. In sum, the significance of the parameters, especially (d), α_{dcc} and β_{dcc} indicates the existence of the dynamic and time-varying long-memory features. Similarly, the average conditional correlation *Average COR_{ij}* were all positive and significant at the 5% level, indicating bi-directional causality between JPY/USD and NIKKEI225 index. According to the diagnostic tests, Kroner and Ng (1998) have confirmed the fact that only few diagnostic tests are kept to the multivariate GARCH-class models compared to the diverse diagnostic tests devoted to univariate counterparts. Furthermore, Bauwens et al. (2006) have noted that the existing literature on multivariate diagnostics is sparse compared to the univariate case. In our study, we refer to the most broadly used diagnostic tests, namely the Hosking's and Li and McLeod's Multivariate Portmanteau statistics on both standardized and squared standardized residuals. According to Hosking (1980), Li and McLeod (1981) and McLeod and Li (1983) autocorrelation test results reported in Table 5 the multivariate diagnostic tests allow accepting the null hypothesis of no serial correlation on squared standardized residuals and thus there is no evidence of statistical misspecification.

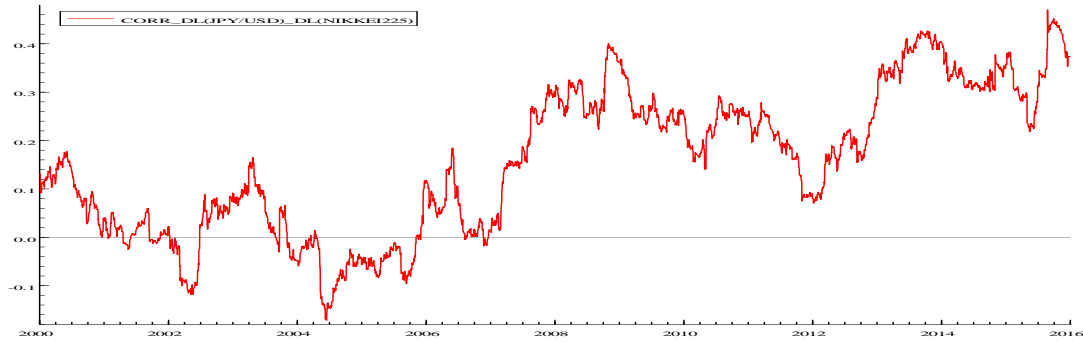


Figure.2. The DCC behavior over time.

Figure. 2 illustrates the evolution of the estimated dynamic conditional correlations dynamics among exchange rate and stock index in first difference. Compared to the pre-crisis period, the estimated DCC show a decline during the post-crisis period. Such evidence is in contrast with the findings of previous research on exchange rate and stock price, which show increases in correlations during periods of financial turmoil (Kenourgios & al. (2011), Dimitriou & al.(2013), Dimitriou and Kenourgios (2013)). Nevertheless, the different path of the estimated DCC displays fluctuations for all pairs of exchange rate and stock price during the phases of the global financial and European sovereign debt crises, suggesting that the assumption of constant correlation is not appropriate. The above findings motivate a more extensive analysis of DCC, in order to capture contagion dynamics during different phases of the two crises.

4. Conclusion

In this study, we tried to analyse the presence of long memory in volatility of the JPY/USD and NIKKEI225 index in first difference. We employ a univariate AR-FIGARCH and a multivariate FIGARCH-DCC model, during the period from 01/01/ 2000 to 31/12/ 2015, for the purpose of the analysis. In the first part, we tested for long memory in the absolute first difference series, and the squared first difference series, the latter two serving as a measure of conditional volatility. Next, we analysed the presence of long memory in conditional volatility by employing a univariate AR-FIGARCH and a multivariate AR-DCC-FIGARCH model with Student's t-distribution. Our results document strong evidence of time-varying comovement, a high persistence of the conditional correlation (the volatility displays a highly persistent manner) and the dynamic correlations revolve around a constant level and the dynamic process appears to be mean reverting. In addition, we was found that the JPY/USD and NIKKEI225 index in first difference has an underlying fractal structure, as the presence of long memory was confirmed by the analysis. The presence of long memory can have multiple implications. From a theoretical point of view the presence of self-similar patterns refutes the notion of the efficient market hypothesis in its weak form. Further, the presence of long memory in volatility series indicates that it would be better to develop and employ long-memory models as opposed to the traditional GARCH models to forecast market returns and volatility. **Kumar, D. (2013)** examines asymmetry and long memory properties in the volatility of Portugal, Italy, Greece, Ireland, and Spain, over the period 2003 to 2011 using the AR-GARCH, IGARCH, FIGARCH, FIGARCH, EGARCH and FIEGARCH for comparative purpose. The results show that the AR-FIGARCH model specification is better able to capture the long memory property of conditional volatility than the conventional GARCH and IGARCH models. From an investors' perspective, the presence of patterns in the market in volatility structure implies that it will be possible to predict trends in volatility. Hence the possibility of gaining extra-normal profit and diversifying risk exists.

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