

The MacrotHEME Review

A multidisciplinary journal of global macro trends

The Impact of Sudden Changes on Volatility Spillover Effect in Japanese Financial Markets¹

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Abstract

This study considers the impact of sudden changes on volatility spillover effect in Japanese financial markets, the Japanese Yen (JPY) and Nikkei 225 index. Specifically, we examine the degree of volatility transmission allowing for sudden changes in variance. An iterated cumulative sums of squares algorithm is used to identify the time points at which sudden changes in volatility occurred, and the results are incorporated into the bivariate GARCH-BEKK framework with and without sudden change variables.

The degree of persistence of volatility was reduced by incorporating these sudden changes into the volatility model. In addition, our results indicate that ignoring sudden changes might overestimate the degree of information inflow and volatility transmission between Japanese financial markets. Consequently, accounting for sudden changes reduces volatility persistence and removes the volatility spillover effect in Japanese financial markets.

Keywords: Spillover effect, Sudden changes, Information transmission, Volatility persistence

1. Introduction

The price and volatility of stock markets is affected substantially by infrequent sudden changes or regime shifts, corresponding to domestic and global economic events. Examples include the 1997 Asian currency crisis, the IT dot com bubbles, and the recent global crisis in 2007-2010. Such a sudden change in the underlying economy and or fundamentals is an important component of managing market risk and uncertainty, and in the construction of investment portfolios and the pricing of derivative securities (Poon and Granger, 2003). In addition, these changes have brought about stock price and volatility linkages or information transmission channels across domestic and international markets (Malik and

¹ This work was supported by the National Research Foundation granted by the Korean Government (NRF-2013S1A5B6053791).

Ewing, 2009; Ewing and Malik, 2013). Consequently, it is important to take into account the possible existence of sudden changes in the time series behaviors of these prices or their volatilities.

Sudden changes result in increased volatility persistence, which is itself associated with volatility predictability (Lastrapes, 1989; Lamoureux and Lastrapes, 1990). Using the iterated cumulative sums of squares (ICSS) algorithms, the impact of sudden changes on volatility has been extensively documented and modeled by popular a generalized autoregressive conditional heteroscedasticity (GARCH) class models (Aggarwal Inclán and Leal, 1999; Malik and Hassan, 2004; Malik, Ewing and Payne, 2005; Hammoudeh and Li, 2008; Kang, Cho and Yoon, 2009; Wang and Moore, 2009; Kumar and Maheswaran, 2012). The results of these studies unanimously support the notion that the incorporation of sudden changes into GARCH-type of models results in a significant reduction in the persistence of volatility in international stock markets. As a result, ignoring changes in the variance will give rise to the false impression that the volatility of stock returns is highly predictable.

Another salient issue of sudden changes is the spurious inferences of information transmission across stock markets. It is well documented that volatility depends upon the information flow, suggesting that information from one market can be incorporated into the volatility process of another market (Hamao, Masulis and Ng, 1990; Karolyi, 1995; Koutmos and Booth, 1995). This flow of information may be influenced by changes which affect the intensity of the information flow, its direction, or even its origin. Understanding the origins, direction and transmission intensity of shocks is a crucial component of optimal asset allocation, construction of global hedging policies and the development of various regulatory requirements. In this context, some empirical studies suggested that sudden changes must be considered and incorporated into an advance multivariate model (Ewing and Malik, 2005, 2013; Aragó-Manzana and Fernández-Izquierdo, 2007; Cologni and Manera, 2009).

This study considers the impact of sudden changes on volatility persistence and volatility transmission, in Japanese financial markets, namely the Japanese Yen/US-\$ exchange rate (JPY) market and the Nikkei 225 market. Specifically, we examine the degree of volatility transmission allowing for sudden changes in variance. In doing it so, we re-examines the impacts of sudden changes on volatility persistence and information transmission using the univariate GARCH and bivariate GARCH models.

The principal objectives of this study are twofold: First, this study detects the sudden changes using the ICSS algorithm and evaluates the impact of sudden changes on volatility persistence using a univariate GARCH model. In particular, we examines whether the inclusion of sudden changes in the GARCH model reduces the coefficients of volatility persistence or not. Second, this study takes into account those sudden changes to analyze accurately the origin, intensity and direction of volatility transmission between Japanese financial markets. Only a few empirical studies have focused on the impact of sudden changes on volatility spillover mechanism between different financial markets. Our empirical finding indicated that ignoring the sudden changes might overestimate the degree of volatility transmission that actually exists between the conditional variance of Japanese markets.

The remainder of this paper is organized as follows. Section 2 briefly describes literature review. Section 3 explains the econometric methodologies of this paper. Section 4 provides the descriptive statistics of the sample data. Section 5 discusses the empirical results. The final section includes some concluding remarks.

2. Literature review

Empirical studies have found that such market shocks to volatility generate multiple breaks or sudden changes, which exhibit high persistence in time-varying conditional variance (Bollerslev, Chou, and Kroner, 1992; Bollerslev and Engle, 1993). However, Lastrapes (1989), and Lamoureux and Lastrapes (1990), argued that ignoring such sudden changes would induce persistence in the volatility of stock returns. Thus, the inclusion of sudden changes has been known to dramatically reduce estimates of persistence in GARCH class models.

Aggarwal, Inclan, and Leal (1999) detected time points of sudden shifts using the ICSS algorithm of Inclán and Tiao (1994) and concluded that ignoring sudden changes overestimates the volatility persistence. Subsequently, Malik and Hassan (2004) found that most breaks were associated with global economic and political events, rather than sector-specific events, and that these breaks increased volatility in most sector series. Malik, Ewing, and Payne (2005) suggested that controlling regime shifts dramatically reduces volatility persistence in the Canadian stock market. Hammoudeh and Li (2008) examined the significant reductions in volatility persistence for Gulf Cooperation Council (GCC) stock markets. Wang and Moore (2009) investigated the impact of sudden changes on volatility persistence in the transition economies of new European Union (EU) members. These studies unanimously agree that incorporating sudden changes into a GARCH model reduces volatility persistence in stock markets.

In addition, the issue of financial market integration is of interest in understanding the information transmission or volatility spillover from one market to another. These volatility spillovers are usually attributed to cross-market hedging and change in shared information, which may simultaneously alter expectations across markets (Arouri, Jouini and Nguyen, 2011, 2012; Vragó and Salvador, 2011). In addition, the existence of volatility spillover provides evidence of financial contagion, i.e. a shock increases the volatilities not only in its own asset or market but also in other assets or markets as well (Kodres and Pritsker, 2002).

Recent empirical studies applied a multivariate GARCH (MGARCH) model to estimate the volatility spillover effect across different markets. For example, Poshakwale and Aquino (2008) investigated volatility spillover between ADRs and their corresponding stocks using a MGARCH model with BEKK parameterization. Dean, Faff and Loudon (2010) employed the Dynamic Conditional Correlation (DCC) model of Engle (2002) to study the asymmetric correlation between stock and bond markets in Australia. Zhao (2010) used the BEKK parameterization of MGARCH to model the volatility transmission mechanism between the Renminbi (RMB) and Shanghai stock market index. Additionally, a few studies have focused on the impact of sudden changes on the volatility spillover

across different markets. Ewing and Malik (2005, 2013) re-examined the volatility transmission allowing for sudden change in variances. Their finding indicated that accounting for sudden changes reduces the transmission in volatility and removes the volatility spillover. Kang, Cheong and Yoon (2011) suggested that ignoring structural changes may distort the direction of information inflow and volatility transmission between crude oil markets.

3. Methodology

In accordance with the work of Inclán and Tiao (1994), this study identifies sudden changes in volatility with the ICSS algorithm, and then estimates the univariate and bivariate GARCH(1,1) models with and without change dummies.

3.1. Detecting points of sudden change in variance

The ICSS algorithm was utilized to identify discrete sub-periods of the changing volatility of stock returns. It assumes that the variance of a time series is stationary over an initial period of time, until a sudden change occurs as the result of a sequence of financial events; the variance then reverts to stationary until another market shock occurs. This process is repeated over time, generating a time series of observations with an unknown number of changes in the variance.

Let $\{\varepsilon_t\}$ denote an independent time series with a zero mean and an unconditional variance, σ_t^2 . The variance in each interval is given by σ_j^2 , $j = 0, 1, \dots, N_T$, where N_T is the total number of variance changes in T observations and $1 < K_1 < K_2 < \dots < K_{N_T} < T$ are the set of change points. The variance over the N_T intervals is defined as follows:

$$\sigma_t^2 = \begin{cases} \sigma_0^2, & 1 < t < K_1 \\ \sigma_1^2, & K_1 < t < K_2 \\ \vdots & \\ \sigma_{N_T}^2, & K_{N_T} < t < T \end{cases} \quad (1)$$

A cumulative sum of squares is utilized to determine the number of changes in variance and the time point at which each variance shift occurs. The cumulative sum of squares from the first observation to the k^{th} point in time is expressed as follows:

$$C_k = \sum_{t=1}^k \varepsilon_t^2, \quad \text{where } k = 1, \dots, T. \quad (2)$$

Define the statistic D_k as follows:

$$D_k = \left(\frac{C_k}{C_T} \right) - \frac{k}{T}, \quad \text{where } D_0 = D_T = 0, \quad (3)$$

in which C_T is the sum of the squared residuals from the whole sample period. Note that if no changes in variance occur, the D_k statistic will oscillate around zero (if D_k is plotted against k , it will resemble a horizontal line). However, if one or more changes in variance occur, then the statistic values drift up or down from zero. In this context, significant changes in variance are detected using the critical values obtained from the distribution of D_k under the null hypothesis of constant variance. If the maximum absolute value of D_k is greater than the critical value, the null hypothesis of homogeneity can be rejected. Define k^* as the value at which $\max_k |D_k|$ is reached, and if $\max_k \sqrt{(T/2)} |D_k|$ exceeds the critical value, then k^* will be used as the time point at which a variance change in the series occurs. The term $\sqrt{(T/2)}$ is required for the standardization of the distribution.

In accordance with the study of Inclán and Tiao (1994), the critical value of 1.358 is the 95th percentile of the asymptotic distribution of $\max_k \sqrt{(T/2)} |D_k|$. Therefore, the upper and lower boundaries can be established at ± 1.358 in the D_k plot. A change point in variance is identified if it exceeds these boundaries. However, if the series harbors multiple change points, the D_k function alone will not be sufficiently powerful to detect the change points at different intervals. In this regard, Inclán and Tiao (1994) modified an algorithm that employs the D_k function to search systematically for change points at different points in the series. The algorithm works by evaluating the D_k function over different time periods, and those different periods are determined by breakpoints, which are themselves identified by the D_k plot.

3.2. Univariate GARCH(1,1) model with sudden change dummies

The univariate GARCH(1,1) model of Bollerslev (1986) is as follows:

$$y_t = \mu + \varepsilon_t, \quad \varepsilon_t = z_t \sqrt{h_t}, \quad z_t \sim N(0,1), \quad (4)$$

$$h_t = \omega + \alpha \varepsilon_{t-1}^2 + \beta h_{t-1}, \quad (5)$$

where $\omega > 0$, $\alpha \geq 0$, $\beta \geq 0$, which ensures that the conditional variance (h_t) is positive, and $(\alpha + \beta) < 1$ are introduced for covariance stationarity. In the GARCH model, the sum of α and β quantifies the persistence of shocks to conditional variance.

Lastrapes (1989) and Lamoureux and Lastrapes (1990) have argued that the GARCH model tends to overestimate volatility persistence when sudden changes are prevalent and ignored in conditional variance. In an effort to calculate accurate estimates of the model parameters, changes should be incorporated into the GARCH model. From Equation (5), we have modified the GARCH(1,1) model with multiple break changes that were identified via the ICSS algorithms, as follows:

$$h_t = \omega + d_1 D_1 + \dots + \alpha \varepsilon_{t-1}^2 + \beta h_{t-1}, \tag{6}$$

in which D_1, \dots are dummy variables that take a value of one from each point of change of variance onwards, and take a value of zero elsewhere.

2.3. Bivariate GARCH(1,1) model

In this study, we further analyze the information flow and volatility transmission between Japanese financial markets, using a bivariate framework of the BEKK parameterization (Engle and Kroner, 1995) which does not impose the restriction of constant correlation among variables over time. From Equations (4) and (5), a BEKK model can be characterized by the following expressions:

$$H_t = C' C + A' \varepsilon_{t-1} \varepsilon_{t-1}' A + B' H_{t-1} B, \tag{7}$$

$$H_t = \begin{bmatrix} h_{11,t} & h_{12,t} \\ h_{21,t} & h_{22,t} \end{bmatrix} = \begin{bmatrix} c_{11} & \\ & c_{22} \end{bmatrix}' \begin{bmatrix} c_{11} & \\ & c_{22} \end{bmatrix} + \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}' \begin{bmatrix} \varepsilon_{1,t-1}^2 & \varepsilon_{1,t-1} \varepsilon_{2,t-1} \\ \varepsilon_{2,t-1} \varepsilon_{1,t-1} & \varepsilon_{2,t-1}^2 \end{bmatrix} \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} + \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix}' \begin{bmatrix} h_{11,t-1} & h_{12,t-1} \\ h_{21,t-1} & h_{22,t-1} \end{bmatrix} \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix}, \tag{8}$$

where H_t is a 2×2 matrix of conditional variance-covariance at time t , and C is a 2×2 lower triangular matrix with three parameters. A is a 2×2 square matrix of parameters and measures the extent to which conditional variances are correlated past squared errors. The diagonal elements in matrix A capture their own ARCH effect (a significant squared error term, a_{11} and a_{22} would indicate that conditional variances are affected by past squared errors, respectively), whereas the diagonal elements in matrix B measure their own GARCH effect (significant lagged variance, b_{11} and b_{22} would suggest that current conditional variance is affected by their own past conditional volatility, respectively). Additionally, the off-diagonal elements (a_{12} , a_{21} and b_{12} , b_{21}) in matrices A and B reveal the manner in which shock and volatility are transmitted over time and across the crude markets. For example, the cross-product of the error terms a_{12} and a_{21} would interpret the direction of shocks or news, whereas the covariance terms b_{12} and b_{21} would demonstrate the direction of volatility transmission.

The parameters of the bivariate GARCH model can be estimated via the maximum likelihood estimation method optimized with the Berndt, Hall, Hall, and Hausman (BHHH) algorithm. The conditional log likelihood function $L(\theta)$ is expressed as follows:

$$L(\theta) = -T \log 2\pi - 0.5 \sum_{t=1}^T \log |H_t(\theta)| - 0.5 \sum_{t=1}^T \varepsilon_t(\theta)' H_t^{-1} \varepsilon_t(\theta), \quad (9)$$

in which T is the number of observations and θ denotes the vector of all the unknown parameters.

4. Data and descriptive statistics

This study considers two weekly price data, Japanese Yen/US dollar (JPY) and Nikkei 225 market index over the period from 1 January 1990 through 24 December 2012, respectively.² The chosen study period permits to examine the sensitivity of Japanese financial markets including financial events, such as, Asian currency crisis in 2007-2008, IT dot.com bubble in 2001 and recent global financial crisis in 2007-2008. Weekly data seem to capture the dynamic interaction of exchange rate and stock prices better than daily and monthly data. The reason is that the use of daily data often induces potential biases arising from the bid-ask bounce, non-synchronous trading days, and the effects of illiquidity on asset prices, while monthly data may have some volatility transmission mechanisms due to time aggregation and compensation effects.

The price series are converted into the logarithmic percentage return series for all sample indices, i.e. $r_t = 100 \times \ln(P_t/P_{t-1})$ for $t=1, 2, \dots$, where r_t is the returns for each index at time t , P_t is the current price, and P_{t-1} is the price from the previous week. Table 1 provides the descriptive statistics and the results of the unit root test for both sample returns. As is shown in Panel A of Table 1, the means of both return series are quite negative and small, but the corresponding standard deviations of both returns are substantially higher. The standard deviation of Nikkei 225 is twice more than that of JPY, implies that the Nikkei 225 prices is more volatile in sample period over 1990-2012. The distribution of returns is not normally distributed, as is indicated by the skewness, kurtosis, and Jarque-Bera tests. The Ljung-Box Q, $Q^2(12)$, statistic indicates the squared return series evidences significant signs of serial correlation at a significance level of 1%. These results are in favor of a model that incorporates ARCH/GARCH features.

² We obtained the JPY data from the database of Federal Reserve Bank of St. Louis, and the Nikkei 225 market index from the database of Yahoo Finance.

Table 1 Descriptive statistics and unit root tests

	JPY	Nikkei 225
Panel A: Descriptive statistics		
Mean	-0.044	-0.107
Standard deviation	1.217	3.107
Maximum	4.698	11.45
Minimum	-9.727	-27.88
Skewness	-0.768	-0.695
Kurtosis	7.278	9.092
Jarque–Bera	1028.58 [0.000]	1942.96 [0.000]
$Q^2(12)$	106.64 [0.000]	93.73 [0.000]
Panel B: Unit root tests		
ADF	-26.99***	-22.75***
PP	-26.99***	-35.75***
KPSS	0.063	0.134

Notes: The Jarque–Bera corresponds to the test statistic for the null hypothesis of normality in sample returns distribution. The Ljung–Box statistics, $Q^2(n)$, check for the serial correlation of the squared returns up to the n^{th} order, respectively. Mackinnon's 1% critical value is -3.435 for the ADF and PP tests. The critical value for the KPSS test is 0.739 at the 1% significance level. *** indicates a rejection of the null hypothesis at the 1% significance level.

Additionally, Panel B of Table 1 provides the results of three types of unit root test for each of the sample returns: the augmented Dickey-Fuller (ADF), Phillips-Peron (PP) and Kwiatkowski, Phillips, Schmidt, and Shin (KPSS). The null hypothesis of the ADF and PP tests is that a time series contains a unit root, whereas the KPSS test has the null hypothesis of a stationary process. As is shown in Panel B, large negative values for the ADF and PP test statistics reject the null hypothesis of a unit root, whereas the KPSS test statistic does not reject the null hypothesis of stationarity at a significance level of 1%. Thus, both return series are a stationary process.

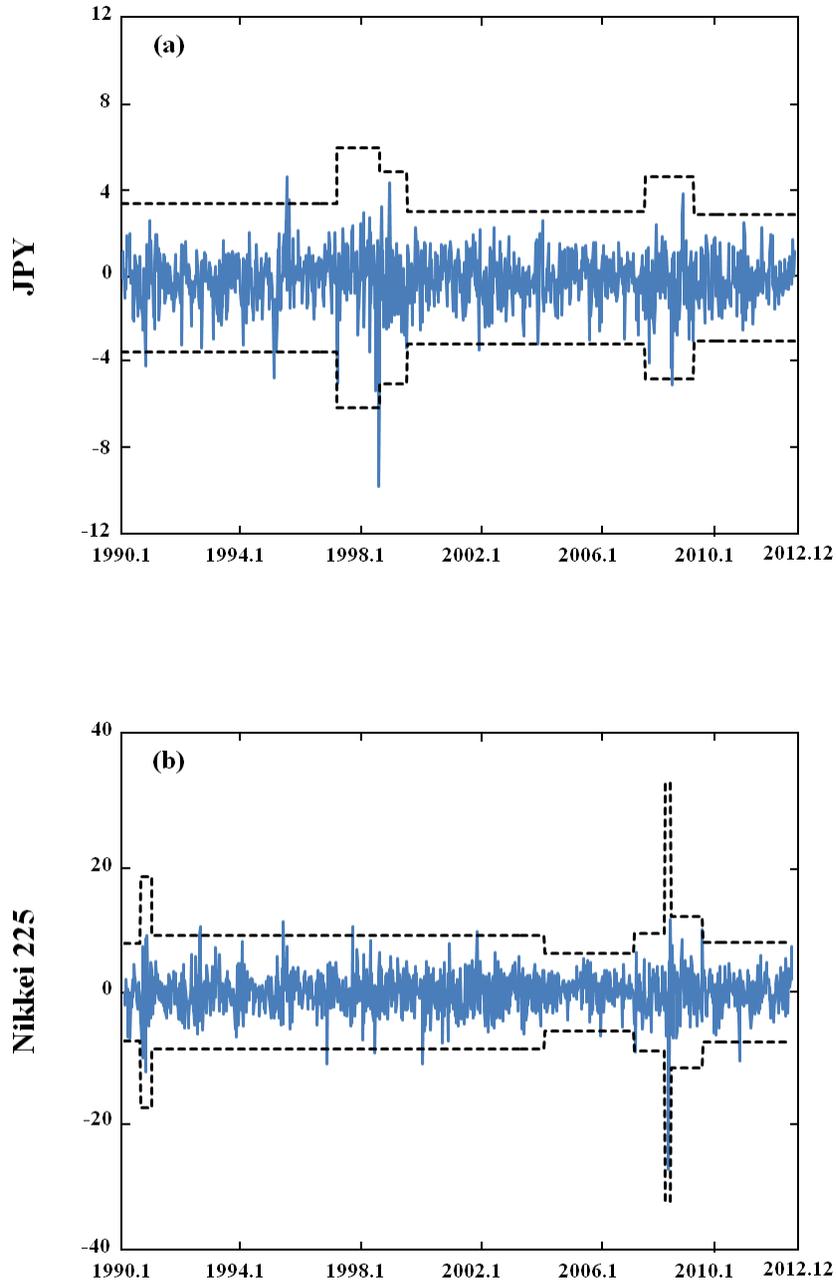
5. Empirical results

5.1. Sudden changes in variance

The ICSS algorithm calculates the standard deviations between the change points to determine the number of sudden changes. Figure 2 illustrates the returns of the JPY and Nikkei 225 series with the points of sudden change and ± 3 standard deviations. Table 2 indicates the time periods of sudden changes in volatility as identified by the ICSS algorithm. The JPY returns show five sudden change points, making for six distant volatility regimes whereas the Nikkei 225 returns evidence seven sudden change points, corresponding to eight distinct volatility regimes.

Looking at Figure 1 and Table 2, the time points of sudden change in volatility are correlated to a moderate degree with a global economic event. In the case of JPY returns, the largest volatility change in 1997-1998 corresponded to the Asian currency crisis. The second largest volatility change was identified the global financial crisis of 2008. In the case of Nikkei 225, the largest volatility shift occurred by the consequence of the bubble of Nikkei 225. Subsequent regimes were tranquil and stable due to the recession of Japanese economy. The Nikkei 225 experienced one of the worst bear markets in recent history from the early 1990s through 2004. The second large volatility change was affected by the global financial crisis of 2008 and JPY's appreciation. And then, both returns became stable in 2010-2012.

Figure 1 Weekly returns dynamics of stock returns; (a) JPY, (b) Nikkei 225



Note: Bands (dot lines) are at ± 3 standard deviations where sudden change points are estimated by the ICSS algorithm

Table 2 Sudden changes in conditional variances as detected by the ICSS algorithm

Series	Number of change points	Time period	Standard deviation
JPY	5	1 January 1990–5 May 1997	1.148
		19 May 1997–19 October 1998	2.015
		26 October 1998–20 September 1999	1.649
		27 September 1999–5 November 2007	1.025
		12 November 2007–13 July 2009	1.571
		20 July 2009–24 December 2012	0.983
Nikkei 225	7	1 January 1990–16 July 1990	2.563
		23 July 1990–10 December 1990	6.0625
		17 December 1990–21 June 2004	2.964
		28 December 2004–16 July 2007	2.053
		23 July 2007–18 August 2008	3.058
		25 August 2008–27 October 2008	10.94
		3 November 2008–30 November 2009	3.948
7 December 2009–24 December 2012	2.599		

Note: Time periods were detected by the ICSS algorithm.

5.2. Univariate GARCH model with and without sudden changes

After identifying the time points of sudden changes in the variance of the JPY and Nikkei 225 returns using the ICSS algorithm, the next step is to incorporate these sudden changes in the variance of univariate GARCH model. We apply the GARCH (1,1) model to evaluate the impact of sudden breaks on volatility persistence.

Tables 3 reports the estimation results from the univariate GARCH (1,1) model with and without sudden change dummy variables. The GARCH model without the dummy

variables evidences highly significant α and β , and the sums of the parameters (0.956 for the JPY and 0.827 for the Nikkei 225) are close to one, which is reflective of volatility persistence, i.e. shocks have a permanent impact on the variance of returns.

However, the inclusion of dummy variables reduces the sum of the parameters (0.714 for the JPY and 0.368 for the Nikkei 225) in the volatility of both markets. This evidence is consistent with the studies of Aggarwal Inclán and Leal (1999) and others, whom have argued that the standard GARCH model overestimates volatility persistence when ignoring sudden changes in conditional variance.

Finally, the insignificance of $LM(5)$ and Ljung-Box $Q^2(12)$ tests shows that no ARCH effect or serial correlation can be observed in the residual series, indicating that the GARCH model without sudden changes dummy variables is well-specified. Additionally, due to the lower values of the Schwarz-Bayesian information criterion (SBIC) and the Akaike information criterion (AIC), the univariate GARCH model with those dummy variables performs better than does their counterpart models without the dummy variables.

Table 3 Univariate GARCH(1,1) model with and without sudden change variables in conditional variance

Panel A: GARCH (1,1) model without dummy variables									
Series	α	β	$\alpha + \beta$		log-likelihood	$Q^2(12)$	$LM(5)$	AIC	SBIC
JPY	0.067 (0.013)***	0.889 (0.023)***	0.956		-1847.64	14.21 [0.220]	2.137 [0.058]	3.10585	3.12716
Nikkei 225	0.165 (0.016)***	0.662 (0.052)***	0.827		-2998.55	6.797 [0.815]	1.054 [0.384]	5.01838	5.03969
Panel B: GARCH (1,1) model with dummy variables									
Series	α	β	$\alpha + \beta$	Persistence decline	log-likelihood	$Q^2(12)$	$LM(5)$	AIC	SBIC
JPY	0.057 (0.024)**	0.657 (0.127)***	0.714	0.242	-1827.29	8.921 [0.629]	0.051 [0.821]	3.08180	3.12868
Nikkei 225	0.087 (0.030)***	0.281 (0.089)***	0.368	0.459	-2946.45	8.711 [0.649]	0.303 [0.911]	4.96136	5.01676

Notes: The Ljung-Box test statistics $Q^2(n)$ check for the serial correlation of squared residual series. The $LM(5)$ test statistic checks the remaining ARCH effects in estimated residuals. AIC is the Akaike information criterion and SBIC is the Schwarz Bayesian information criterion. P-values are in brackets and t-statistics are in parentheses.

5.3. Information flow and volatility transmission between Japanese financial markets

Increasing integration of the world economy has generated a great deal of interest in assessing the transmission of market shocks across markets. In particular, considerable interest has been focused of late in determining whether or not conditional volatility is indeed transmitted across markets.

We evaluate the influence of sudden changes in volatility and the direction of the transmission of information between the JPY and Nikkei 225 markets. Table 4 summarizes the results for the bivariate GARCH(1,1) model both with and without the consideration of sudden changes in variance.

In the bivariate GARCH model, the diagonal elements (a_{11} and a_{22}) capture the own past shock effect, while the diagonal elements (b_{11} and b_{22}) measure the own past volatility effect. From Table 4, the estimated diagonal parameters are all significant, indicating the presence of strong ARCH and GARCH effects, i.e., own past shocks and past volatility that affect the conditional variances of both series.

The off-diagonal elements (a_{12} and a_{21}) capture cross-market effects such that shocks occurring in one market influence the volatility of another market. When ignoring sudden change dummies, we find a uni-directional impact from the JPY market to the Nikkei 225 owing to the significance of the parameter (a_{21}). It can be clearly appreciated that news regarding shocks on the JPY market affects the volatility of the Nikkei 225 market, but reverse case is impossible. However, when incorporating sudden change dummies, both parameters (a_{12} and a_{21}) are no longer significant, thereby implying that there is no shocks transmission between two markets. This finding implies that accounting sudden changes reduces the degree of information transmission and, in essence, eliminates information linkage between Japanese financial markets.

The off-diagonal elements (b_{12} and b_{21}) measure volatility spillover across Japanese financial markets. As is shown in Table 4, the significance of parameters (b_{21}) shows a uni-directional causality relationship from the JPY to Nikkei 225 markets in the model without sudden dummies. Whereas, simply by taking into consideration the sudden changes, a no volatility linkages can be found, owing to the insignificance of both parameters (b_{12} and b_{21}). This evidence implies that accounting for sudden changes reduces the transmission of volatility and remove the volatility spillover between the JPY and Nikkei 225 markets. Thus we concluded that ignoring sudden changes results may cause misinterpretations of the degree of volatility transmission that actually exists between the conditional variances of Japanese financial markets.

Panel B of Table 4 presents the results of diagnostic tests: (1) the Ljung-Box Q-statistics, $Q_i^2(12)$ check for serial correlation for standardized squared residuals estimated from the GARCH-BEKK framework; (2) the likelihood ratio statistic (LR) tests the statistical validity of sudden change dummies. $LR = 2 \times [L(\Theta_1) - L(\Theta_0)]$, where $L(\Theta_1)$ and $L(\Theta_0)$ are the maximum log likelihood values estimated from the GARCH-BEKK framework with and without change dummies, respectively. The test results illustrate the importance of considering sudden changes in modeling stock market volatility. Namely, the bivariate GARCH model with dummies can be well-specified owing to the insignificance of the Ljung-Box Q-statistic, $Q_1^2(12)$. Additionally, the likelihood ratio statistic (LR) clearly rejects the null hypothesis of no changes in volatility at a significance level of 1%.

Table 4 Volatility transmission with sudden changes using the bivariate GARCH model.

JPY (1) – Nikkei 225 (2): Bivariate GARCH (1,1)–BEKK model		
	Without dummies	With dummies
Panel A: Estimates		
c_{11}	0.189 (0.057)***	0.163 (0.078)**
c_{21}	-1.534 (0.179)***	-0.281 (0.988)
c_{22}	-0.001(0.747)	2.259 (0.208)***
a_{11}	0.145 (0.037)***	0.186 (0.021)***
a_{12}	0.134 (0.128)	-0.011 (0.289)
a_{21}	-0.054 (0.016)***	-0.051 (0.054)
a_{22}	0.445 (0.039)***	0.474 (0.050)***
b_{11}	0.938 (0.019)***	0.962 (0.022)***
b_{12}	-0.004 (0.075)	0.202 (0.206)
b_{21}	0.072 (0.012)***	0.011 (0.077)
b_{22}	0.751 (0.051)***	0.476 (0.101)***
Panel B: Diagnostic tests		
$Q_1^2(12)$	20.77 [0.0053]	14.09 [0.294]
$Q_2^2(12)$	6.146 [0.908]	6.177 [0.906]
log-likelihood	-4820.38	-4829.63
LR		18.5 [0.000]***

Notes: The diagonal elements in matrix A capture internal and cross-market ARCH effects, whereas the diagonal elements in matrix B measure internal and cross-market GARCH effects. $Q_i^2(n)$ is the Ljung-Box test statistic applied to the squared standardized residuals of the JPY ($i = 1$) and Nikkei 225 ($i = 2$) equations, respectively. LR is the log-likelihood test statistic for the validity of sudden change dummies. **, *** indicates significance at the 5% and 1% levels, respectively. P-values are in brackets and standard errors are in parentheses.

With these results, we can assert that ignoring sudden changes can lead to spurious results regarding the degree of shock transmission and volatility spillover occurring across Japanese financial markets. This finding is similar to that of Ewing and Malik (2005, 2013) who study the ignoring the sudden changes generate the overestimation of the degree of volatility spillover in different markets.

6. Conclusions

This study assessed the impacts of sudden changes on volatility persistence, and then incorporated these impacts into the bivariate GARCH estimation in order to understand the information flow and volatility transmission between Japanese Yen exchange rate market and the Nikkei 225 stock market.

In an effort to assess the impact of sudden changes, we identified the time points at which sudden changes in volatility occurred using the ICSS algorithm, and then incorporated this information into the bivariate GARCH BEEKK framework with and without sudden change variables. According to the estimation results, we determined that the degree of persistence of volatility was reduced by incorporating these sudden changes into the volatility model. We also determined that ignoring sudden changes might overestimate the degree of information inflow and volatility transmission between Japanese financial markets.

Consequently, the accounting for sudden changes reduces volatility persistence and removes the volatility spillover effect in the Japanese financial markets. These findings provide important implications for building accurate asset price models, forecasting volatility of stock returns, managing market capitalization and further understanding information transmission mechanism.

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