E C O N O M I C S   B U L L E T I N

Abnormal Domestic Information Disseminate on Cross-listed Nikkei 225 Index Futures from Abroad?

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Abstract

This study extends the GARCH with autoregressive conditional jump intensity in Generalized Error Distribution (GARJI-GED) model to identify the fundamental characteristics of Nikkei 225 index and futures. Furthermore, this study applied the Granger causality test to investigate whether an abnormal information lead and lag relationship existed for the Nikkei 225, SIMEX-Nikkei 225 and OSE-Nikkei 225. Empirical results demonstrate that Nikkei 225 index and futures show jump phenomena, implying a jump process is necessary to match statistical features in spot and futures markets. Finally, the empirical results indicated that the abnormal information of the OSE-Nikkei 225 futures contract significantly leads the one of the SIMEX- Nikkei 225 and Nikkei 225 index.

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1. Introduction

The Japanese stock market is the biggest stock market in the world today. In 1986, Tokyo stock exchange, recorded trading volume exceeding 197 billion shares, or about 159 trillion￥. Following the establishment of the Chicago futures market, which introduced futures to the whole world, NIHON KEISAI SHIMHUN INC (NKS) agreed in 1985 to begin trading of Nikkei Average Futures. The Nikkei Average Futures have since grown to have the second largest trading volume on the Chicago Futures Market. SIMEX market also joined the goods in 1986. The stock on average of Nikkei is by 225 indexes is not merely only the index which represents Japan's stock market index, it is the index of the international finance of whole world even more. The index is calculated and managed by NIHON KEISAI SHIMHUN INC (NKS), and offer via various different media.

Recently studies on the development of econometric models[1] have combined diffusion with the jump process[2]. When governments and investors fail to comprehend the true features, they will make incorrect financial and economic decisions (Bakshi, Cao and Chen, 1997, and Das and Sundaram, 1999). Despite extensive research on the links between spot and futures markets, no previous study has attempted to investigate the feasibility of information quality being a crucial determinant of the degree of abnormal information. In considering the impact of jump characteristics generated by abnormal information, this study use a GARCH with autoregressive conditional jump intensity (GARJI) model developed by Chan and Maheu (2002), which gauges the jump intensity for obeying an ARMA process and incorporates a GARCH effect. The financial literature has long been aware that financial returns are non-normal and tend to have leptokurtic and fat-tailed distribution (Mandelbrot, 1963 and Fama, 1965); therefore, several distributions for returns innovation have been proposed to take into account the excess kurtosis. Nelson (1991), Taylor (1994), Lopez (2001), Lee et al. (2001) and Marcucci (2005) have proposed the use of the generalized error distribution. We will have to accommodate model to the situation which financial asset returns exhibit leptokurtic; furthermore, this study mixes the Generalized Error Distribution (GED)[3]. Therefore,

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[1] Such as the Poisson jump model (Ball and Torous, 1983), SV jump diffusion model (Craine, Lochstoer, and Syrtveit, 2000; Eraker, Johannes and Polson, 2003), GARCH-constant-jump model (Jorion, 1988; Vlaar and Palm, 1993; Nieuwland, Vershchoor, and Wolff, 1994; Kim and Mei, 2001; and Chang and Kim, 2001) and GARCH-time-varying jump model (Chan and Maheu, 2002; Chiu, Lee and Chen, 2005).

[2] The diffusion process captures continuous fluctuations in asset prices, due to liquidity or strategic trading as normal news disseminates, and the jump process represents occasional large changes in prices which can result from the impact of abnormal news, such as earning surprises (see Maheu & McCurdy (2004)).

[3] The GED(d) is described by Box and Tiao (1973), d is a scale parameter. For $d = 2$, the GED reduces to that of the normal distribution, for $d = 1$ it reduces to that of double exponential or

this study extends the GARJI with the GED model (GARJI-GED) to capture and comprehend the true features for Nikkei 225 index and futures, and thus avoids incorrect financial and economic decisions.

Previous studies have examined the lead-lag relationship between Nikkei 225 and Nikkei 225 futures market returns such as Lim (1992), Swinnerton et al. (1995), Iihara et al. (1996), Tse (1999) and Frino and West (2003). Vila and Bacha (1996) demonstrated total round trip transaction costs of 0.66% and 0.20% for the Nikkei 225 index and futures, respectively. Furthermore, Fleming et al. (1996) indicated that two or more markets trade similar products, informed traders will transact in the market with the lowest transaction costs to maximize profits generated from trading on their information. Consequently, new information is first traded on the lowest cost market followed by related markets in ascending order of costs. According to the transaction cost hypothesis, the transaction costs faced by stock traders are many times higher than those faced by futures traders, and the informed traders will transact in the market with the lowest transaction costs in order to maximize profits generated from trading on their information. This study conjectured the proposition that abnormal information in futures contracts should lead in their underlying indices. This study thus first test the hypothesis that abnormal information on Osaka Securities Exchange (OSE) and Singapore International Monetary Exchange (SIMEX) Nikkei 225 futures significantly lead abnormal information on the Nikkei 225 index. Frino and West (2003) indicated that SIMEX- and OSE-Nikkei 225 futures contract exhibit significantly different transaction costs[4] and that the lead-lag relationship between returns supports the transaction cost hypothesis. A few studies have examined the abnormal information issue related to the lead-lag relationship, owing to the historical difficulty of identifying abnormal information. This study thus employed the Granger causality test to examine abnormal information transmission including whether the lead-lag relationship supports the transaction cost hypothesis.

This paper is organized as follows. Section II describes the data and the GARJI-GED model. The empirical results are presented in Section III. The final section summarizes the results.

2. Data and methodology

2.1 Data

Laplace distribution, and for $d \to \infty$ it reduces to that of uniform or rectangular distribution. For values of $d < 2$, the GED density has fatter tails and higher peaks in the middle (leptokurtic) compared to the normal density.

[4] First, brokerage commissions are fixed in Japan and negotiated in Singapore; thus, the brokerage markets are regulated differently yielding significantly different brokerage charges. Second, margin levels also differ significantly between the exchanges.

Our analysis is based upon the daily closing prices index of Nikkei 225, and futures of SIMEX-Nikkei 225 and OSE-Nikkei 225 obtained from Bloomberg. The sample period for the study covers nine years, from September 19, 1989 to March 10, 2006. In this study, daily percentage returns in time period *t* R_t is calculated as logarithmic difference in daily closing prices as $R_t = (\ln P_t - \ln P_{t-1}) \times 100$, where P_t is the closing price in time period *t*, P_{t-1} is the closing price in time period *t-1*.

2.2 The Econometric Model

The purpose of this study investigates the relationship between abnormal information and trading costs. First, to capture the abnormal information (jump intensity) by GARJI-GED model, thus the model is described as follows:

$$R_t = \mu + \sum_{i=1}^{2} \phi_i R_{t-1} + \sqrt{h_t}\, z_t + \sum_{k=1}^{n_t} Y_{t,k}\ ,\ \ z_t \overset{iid}{\sim} \text{GED(d)} \tag{1}$$

$$h_t = \omega + \alpha \varepsilon_{t-1}^2 + \beta h_{t-1} \tag{2}$$

$$f(z_t) = \frac{d \cdot e^{-\frac{1}{2}\left|\frac{z_t}{\beta}\right|^d}}{B \cdot 2^{1+\frac{1}{d}}\, \Gamma(\frac{1}{d})}, \quad \text{where} \ \ B = \left(2^{-\frac{2}{d}} \frac{\Gamma(\frac{1}{d})}{\Gamma(\frac{3}{d})} \right)^{\frac{1}{2}}$$

where h_t represents the conditional heterogeneous variance, ε_{t-1}^2 is the coefficient of lagged residual square and h_{t-1} is the coefficient of the lagged conditional heterogeneous variance. z_t is a GED, $\Gamma(\cdot)$ is the gamma function and *d* is a scale parameter, controlling the shape of the GED[5]. $Y_{t,k}$ is presumed to be independent and normally distributed with mean θ_t and variance $\delta_t^{\ 2}$, that is

$$Y_{t,k} \mid \Omega_{t-1} \sim \text{N}(\theta_t\ , \delta_t^{\ 2}), \tag{3}$$

$$\theta_t = \eta_0 + \eta_1 R_{t-1} D(R_{t-1}) + \eta_2 R_{t-1} D(1 - R_{t-1})\ , \delta_t^{\ 2} = \zeta_0 + \zeta_1 R_{t-1}^2 + \zeta_2 h_t$$

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[5] For *d*=2, the density function of GED reduced to $f(z_t) = \frac{1}{\sqrt{2\pi}} \cdot e^{-\frac{z_t^2}{2}}$ which is the density for the normal distribution. For $d < 2$, Johnson and Kotz (1970) shows that the kurtosis, given by $E(z_t^4) = \frac{\Gamma(1/d)\Gamma(5/d)}{\left[\Gamma(3/d)\right]^2}$ is greater than 3, the tails is thicker than the Normal distribution. The GED is the Laplace distribution (for *d*=1) and the uniform distribution (for $d \to \infty$).

where $D(x)=1$ if $x>0$ and 0 otherwise. The jump stochastic process assumed to be Poisson distribution with a time-varying conditional intensity parameter, λ_t. The Poisson distribution with parameter λ_t conditional on the information set Ω_{t-1} is assumed to describe the arrival of discrete number of jumps, where $n_t \in \{0,1,2,\cdots,n\}$ over the interval $[t-1,t]$. The conditional density of n_t is expressed as follows:

$$P(n_t = j \mid \Omega_{t-1}) = \frac{e^{-\lambda_t}\lambda_t^{\,j}}{j!} \qquad \lambda_t > 0,\ j = 0,1,2,\cdots,n \tag{4}$$

The conditional jump intensity λ_t is the expected number of jumps conditional on the information set Ω_{t-1}, which is parameterized as:

$$\lambda_t = \lambda_0 + \rho\lambda_{t-1} + \gamma\xi_{t-1} \tag{5}$$

Where $\lambda_t > 0$, and $\lambda_0 > 0$ ， $\rho \geq \gamma$ ， $\gamma \geq 0$.

$$\zeta_{t-1} \equiv E[n_{t-1} \mid \Omega_{t-1}] - \lambda_{t-1} = \sum_{j=0}^{\infty} j\,P(n_{t-1} = j \mid \Omega_{t-1}) - \lambda_{t-1} \tag{6}$$

where $P(n_{t-1} = j \mid \Omega_{t-1})$, called the filter, is the ex post inference on n_{t-1} given the information set Ω_{t-1}, and $E[n_{t-1} \mid \Omega_{t-1}]$ is the ex post judgment of the expected number of jumps occurred from $t-2$ to $t-1$ and λ_{t-1} is the conditional expectation of $n-1$given the information set Ω_{t-2}. Therefore, ζ_{t-1} represents the change in the econometrician's conditional forecast of n_{t-1} as the information set is updated. Note from this definition that ζ_t is a martingale difference sequence with respect to information set Ω_{t-1}. Therefore $E[\zeta_t] = 0$ and $Cov(\zeta_t, \zeta_{t-i}) = 0$, i >0. Hence, the intensity residuals in a specified model shouldn't show any autocorrelation. Then the Log-Likelihood function for observations：

$$LL = \sum_{t=1}^{T} \ln\{P(R_t \mid \Phi_{t-1})\} \tag{7}$$

where

$$P(R_t \mid \Phi_{t-1}) = \sum_{j=0}^{\infty} f(R_t \mid n_t = j, \Phi_{t-1}) \cdot P(n_t = j \mid \Phi_{t-1}) \tag{8}$$

$$f(R_t \mid n_t = j, \Phi_{t-1}) = \frac{d}{B \cdot 2^{1+\frac{1}{d}}\Gamma(\frac{1}{d})\sqrt{(h_t + j\delta_t^2)}} \exp\left[-\frac{1}{2}\left|\frac{(R_t - \mu - \sum_{i=1}^{2}\phi_i R_{t-i} - j\theta)}{\beta \cdot \sqrt{(h_t + j\delta_t^2)}}\right|^d\right] \tag{9}$$

For the model specifications, parameters are estimated using the Quasi maximum likelihood estimation (MLE).The optimization algorithm used is the Broyden, Fletcher, Goldfarb and Shanno (BFGS) Quasi-Newton updating scheme.

3. Results

The descriptive statistics are shown in Table 1. The means and standard deviations of returns for spot, SIMEX-Nikkei 225 and OSE-Nikkei 225 futures are -0.0192±1.4790, -0.0196±1.5234 and -0.0196±1.4987, respectively. Spot return exhibit positive skew, while the spot, SIMEX-Nikkei 225 and OSE-Nikkei 225 returns exhibit kurtosis. As for the Ljung-Box Q^2 test for examining the serial correlation of square returns, both statistics with 5 and 10 lags are significant under the 1% level. This indicates that returns exhibit autocorrelation, linear dependence and strong ARCH effects.

Table 1. Descriptive Statistics

Statistics	Nikkei 225	SIMEX-Nikkei 225	OSE-Nikkei 225
Sample Mean	-0.0192	-0.0196	-0.0196
Standard Error	1.4790	1.5234	1.4987
Skewness	0.1692***	0.0552	0.0038
Kurtosis(Exc)	3.0943***	2.9778***	2.3298***
Jarque-Bera	1628.6820***	1492.5120***	912.4277***
Minimum	-7.2339	-9.9444	-10.1921
Maximum	12.2160***	9.3239	8.9010
Q^2 (5)	354.4253***	396.3431***	403.9932***
Q^2 (10)	514.4226***	603.8604***	642.4362***

Note: 1. Q^2 is the modified Ljung-Box portmanteau test, robust to heteroscedasticity, for serial correlation in the square standardized residuals with 5 and 10 lags for the respective models.

2. *** denote significance at the 1% level.

The estimates of GARJI with GED models[6] are listed in Table 2. The estimated parameters (*d*) of the Nikkei 225 SIMEX-Nikkei 225 and OSE-Nikkei 225 are 1.6762, 1.4603 and 1.4844 in the GARJI-GED model all of which are less than 2, that is, $d \neq 2$, so the density has a thicker tail than the Normal distribution. Consequently the return distributions are not normal distribution and the GARJI-GED model has better fit to the data.[7]

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[6] The estimates are analogous to those of Chan and Maheu (2002), AR(2) model for the condition mean of stock return for all models is necessary, for all models with GARCH(1,1) are appropriate. Misspecificed tests based on the modified LB statistic are reported for autocorrelation in the squared standardized residuals (Q^2) and the jump intensity residuals ($Q_{\xi t}$) for 5 and 10 lags at the bottom of table 2.

[7] This study notices the strong GARCH effect and the persistence of the conditional variance, with

Regarding the jump size distribution, the means[8](variances) of the jump size for the Nikkei 225, SIMEX-Nikkei 225 and OSE-Nikkei 225 are $\theta_t = \eta_0$ ($\delta_t^2 = \zeta_0 + \zeta_1 R_{t-1}^2$), because η_1 and η_2 (ζ_2) are not significant. As regards jump intensity, this study has established ARMA (1,1) which the parameters (λ_0, ρ and γ) for Nikkei 225, SIMEX-Nikkei 225 and OSE-Nikkei 225 are all statistically significant, demonstrating evidence of time-variation in the arrival of jump events. Notably the persistence parameters (ρ) for the arrival of jump events (jump clustering) are high. The parameter γ measures the effect of the most recent residual intensity, and ranges from 0.1821 to 0.5703. This statistical significance of both lagged intensity residual and jump clustering suggest that the arrival process can systematically deviate from its unconditional mean.

Figures 1–3 display the jump intensity for the Nikkei 225, SIMEX-Nikkei 225 and OSE-Nikkei 225. Notably, the time-varying jump component cannot be ignored in asset pricing. At first glance, the jump intensities of the Nikkei 225, SIMEX-Nikkei 225 OSE-Nikkei 225 are seemly discriminating; thus, this study is interested in the lead-lag relationship of abnormal information.

Table 2. Estimation of the Models ARJI with GED Model

Parameter	Nikkei 225		SIMEX-Nikkei 225		OSE-Nikkei 225	
	Coefficients	Std Error	Coefficients	Std Error	Coefficients	Std Error
μ	0.0809***	0.0263	0.1005***	0.0319	0.1903***	0.0455
ϕ_1	-0.0303	0.0189	-0.0834***	0.0199	-0.0975***	0.0202
ϕ_2	-0.0319**	0.0161	-0.0192	0.0160	-0.0065	0.0161
ω	0.0112***	0.0033	0.0118***	0.0033	0.0103***	0.0040
α	0.0422***	0.0100	0.0434***	0.0094	0.0671***	0.0093
β	0.9394***	0.0102	0.9402***	0.0098	0.9170***	0.0099
ζ_0	1.0654***	0.2427	1.0495***	0.2896	0.6937***	0.2032
ζ_1	-0.0161	0.0231	0.0442	0.0417	0.0645	0.0507
ζ_2	0.2175	0.1359	0.0381	0.1547	-0.2064	0.1836
η_0	-0.6897***	0.1921	-1.0200***	0.2103	-1.0326***	0.1719
η_1	0.1554*	0.0925	0.3591***	0.1056	0.3130***	0.1091
η_2	-0.1252	0.1121	-0.1025	0.1286	0.0221	0.1170

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parameters $\alpha + \beta =$ 0.9816 for spot, 0.9836 for SIMEX-Nikkei 225 futures and 0.9814 for OSE-Nikkei 225 futures. This indicated that SIMEX-Nikkei 225 has high levels of volatility clustering than the spot and OSE-Nikkei 225 futures.

[8] The fact that the impact of jumps on the conditional mean of returns tends to be centered around zero on average does imply that jumps do affect distribution of returns.

λ_0	0.0232**	0.0102	0.0153**	0.0067	0.0190*	0.0113
ρ	0.8944***	0.0389	0.9206***	0.0312	0.9271***	0.0401
γ	0.5703***	0.1911	0.3498**	0.1561	0.1821**	0.0882
d	1.6762***	0.1315	1.4603***	0.0792	1.4844***	0.0702
$Q_{\xi t}$ (5)	8.3089		4.4630		6.9427	
$Q_{\xi t}$ (10)	9.4870		6.2099		11.3413	
Q^2 (5)	2.4779		0.2905		0.5102	
Q^2 (10)	4.0162		1.6647		3.7537	
Log-likelihood	-6883.1343		-6974.9712		-6951.3118	

Note: 1. Q^2 is the Ljung-Box test in the square standardized residuals.

2. $Q_{\xi t}$ is the Ljung-Box test in the jump intensity residuals.

3. *, ** and *** denote significance at the 10%,5% and 1% levels, respectively.

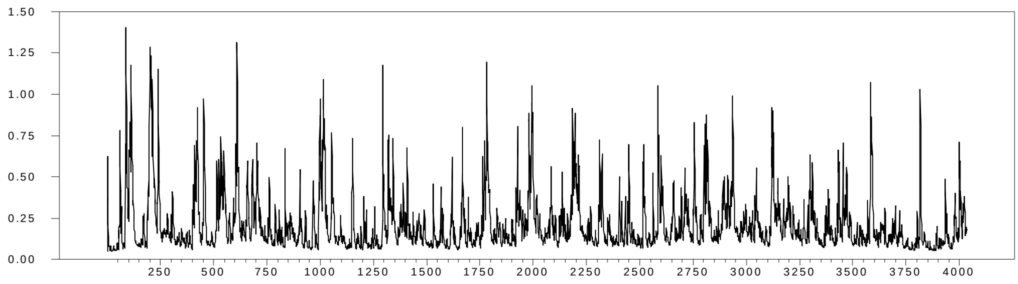

Figure 1. Jump intensity of Nikkei 225

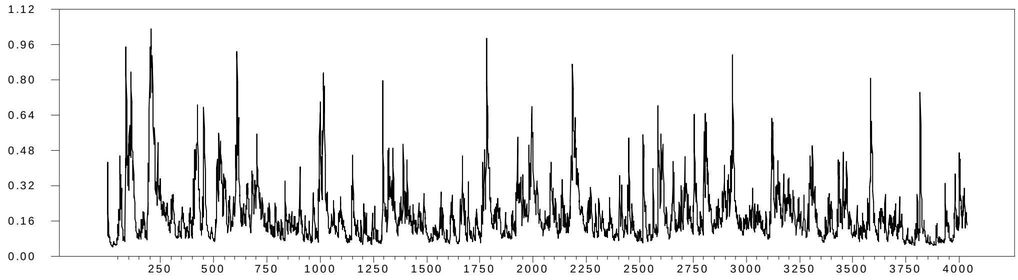

Figure 2. Jump intensity of SIMEX-Nikkei 225

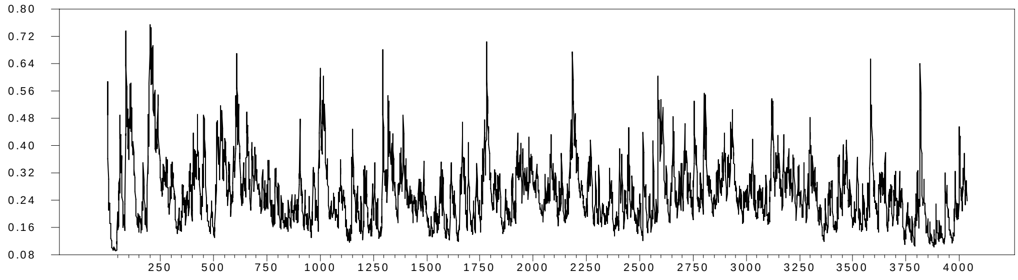

Figure 3. Jump intensity of OSE-Nikkei 225

Table 3 the optimal lagged period test for Granger Causality Tests

Lagged period	OSE- and SGX-Nikkei 225	Nikkei 225 and SGX-Nikkei 225	Nikkei 225 and OSE-Nikkei 225
1	-8.2448	-6.6381	-6.6381
2	-8.2528*	-6.6435*	-6.6435*
3	-8.2485	-6.6384	-6.6384
4	-8.2445	-6.6379	-6.6379
5	-8.2374	-6.6301	-6.6050

Note: * denote to employs SBC to select optimal lagged length.

Table 3 lists the results of using the SBC test to identify the best lagging period when using the proposed model. We find the optimal at lagged period two. The table 4 lists the results of the Granger causality test[9] for abnormal information of the Nikkei 225, SIMEX-Nikkei 225 and OSE-Nikkei 225. At the 0.01 levels, the OSE-Nikkei 225 futures contract significantly leads the SIMEX- Nikkei 225 and the Nikkei 225 index. According to Granger causality test there is feedback between the Nikkei 225 and the SIMEX-Nikkei 225. Empirical results for abnormal information indicate statistically significant unidirectional causality from the OSE-Nikkei 225 futures to the Nikkei 225 caused by futures having low overall transaction costs and high leverage in the futures market. Additionally, abnormal information movements in the OSE futures contract lead abnormal movements in the contract traded on the SIMEX futures. In conclusion, this study identified that the abnormal information of the OSE-Nikkei 225 futures contract significantly leads that of the SIMEX- Nikkei 225 and the Nikkei 225 index. The OSE-Nikkei 225 futures respond to new information faster than the SIMEX-Nikkei 225 futures.

Table 4. Granger Causality Tests for Abnormal information

Null Hypothesis:	F-Statistic
OSE-Nikkei 225 does not Granger Cause Nikkei 225	32.3682***
Nikkei 225 does not Granger Cause OSE-Nikkei 225	1.4401
SIMEX-Nikkei 225does not Granger Cause Nikkei 225	36.03***
Nikkei 225 does not Granger Cause SIMEX-Nikkei 225	5.04023***
SIMEX-Nikkei 225 does not Granger Cause OSE-Nikkei 225	0.5904
OSE-Nikkei 225 does not Granger Cause SIMEX-Nikkei 225	8.2615***

Note: *, ** and *** denote significance at the 10%, 5% and 1% levels, respectively.

4. Conclusion

This study extended the GARJI-GED model to identify the Nikkei 225 index and

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[9] Unit root test results are not reported here but are available upon request from the authors.

futures. Furthermore, this study applied the Granger causality test to investigate whether the abnormal information support the transaction cost hypothesis.

Empirical results demonstrate that Nikkei 225 index and futures exhibit jump phenomena, implying the jump process must match statistical characteristics of the Nikkei futures and spot markets. Furthermore, the GED is more appropriate to fit the data. This study demonstrated that while abnormal information of OSE-Nikkei 225 futures leads the underlying index, abnormal information on OSE -Nikkei futures leads abnormal information on SIMEX-Nikkei 225 futures. It may be when there are significant information issues on the market, and this information is reflected on the local futures price will be faster than elsewhere. This study thus identified that the OSE-Nikkei 225 futures respond to new information faster than the SIMEX-Nikkei 225.

Finally, the process governing the arrival of jumps may be heterogeneous with respect to all news. Restated, jump dynamics may differ according to news and financial instruments. This study suggests that it is important to consider the time series dynamics in the jump-diffusion process.

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