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TEPCO's (Tokyo Electric Power Co Holdings) Stock Behaviour in the Long Run

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Abstract Noting the huge impact of the Fukushima accident on TEPCO's (Tokyo Electric Power Co Holdings) activity and stock price, this study investigates the long-run patterns of returns and volatility of its stock, relative to the main return and volatility features of the Nikkei 225 over the past 30 years. The best fitting volatility for both series comes from an asymmetric power GARCH model; the standard deviation of volatility does not depend primarily on large innovations. For the Nikkei, large negative changes are not more clustered than positive changes. A regime-switching correlation model with three states reveals that a high correlation regime is the most frequent for TEPCO, with low switching probability, whereas the regime associated with the Fukushima crisis is less persistent. A strong interaction arises between the less common regimes, but the stable, low volatility regime appears mostly independent. In two regimes, the Nikkei returns have significant and negative effects on TEPCO returns, but the reverse is not true. The Fukushima environmental and industrial crisis thus could spark a new energetic era in Japan, including a real transition toward more environmentally friendly electric power.

Keywords Stock market, Japan, Risk, Volatility, Earthquake, Electric utility companies, Regime-switching model, MS-VAR model

JEL Classification C1, C24, C32, G00, G01

1. Introduction

Analysing the volatility returns of a stock or stock index is particularly interesting when the specific economic, financial, environmental, or industrial context is sensitive to key events. For example, following several environmental and financial shocks, the Japanese utility company TEPCO entered a new period of growth and risk. Its unique situation, as the main electric and nuclear power utility for Japan, and powerful market reactions to events involving this company make it particularly interesting to study. In particular, the Fukushima catastrophe prompted substantial abnormal returns for TEPCO's stock. To leverage this pertinent and interesting case, we investigate the impact of several internal and external events on TEPCO's activity over a 30-year span. We compare these effects with trends in the broader Nikkei 225 index, to compare

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market reactions and the effects on stock return volatility. By assessing these long-run changes in market valuations, we help explain some transitions in the Japanese electric sector. With our comprehensive, econometric study of the market valuation of TEPCO, as a critical actor in the Japanese economy, we seek to identify main volatility breaks, analyse return correlations in the long run, and reveal any regime-switching dynamic correlations.

Furthermore, we seek to establish the best fitting model for volatility with generalized autoregressive conditional heteroskedasticity (GARCH) modelling. Günay (2015) asserts that the Markov regime-switching GARCH (MRS-GARCH) outperforms other GARCH models, so we include it in our tests. Marcucci (2005) further posits that the MRS-GARCH model performs better in the short run, but other GARCH models may be better adapted to long-run modelling. Boudt et al. (2012) also offer strong evidence of time variation within regime volatility. The consideration of GARCH models may have interesting implications, considering either the weak form of the efficiency market hypothesis or its semi-strong form. The weak form implies that all the available information is included in the present asset prices, which means that the use of past prices is useless for the investor who tries to forecast future prices. The semi-strong form implies that the market prices include all public information about the firms, i.e. all data about internal or external events. As a consequence, no abnormal return should be detected in the return series, and no abnormal profit should be reached by investors. The tests of various autoregressive conditional heteroskedasticity (ARCH) models reveal that the best fit for the volatility of both series is provided by the asymmetric power GARCH (APGARCH), which implies that the standard deviation of volatility does not depend on absolute large innovations or unexpected changes in asset market prices.

With regard to the regime-switching correlation, we test it with the Markov Switching 2 phases and 3 phases. According to Hamilton (1989), in this type of model, the state variable that controls the regime is exogenous. For TEPCO, exogenous factors include the general economic situation, factors that influence the electric utility industry, regulatory or environmental changes, and an earthquake. That is, TEPCO did not enter into an industrial transition voluntarily but instead was pushed into it by external events. For the Nikkei index in general, the exogenous factors include Japanese interest rates, exchange rates, and political or environmental issues. In a regime-switching correlation model with three states, we determine that the high correlation regime is the most frequent for TEPCO; a momentum effect also was more frequent than a mean-reverting effect. A high volatility Regime 3, which is characteristic of the Fukushima crisis, is less persistent. Regime 1, which indicates low volatility, has a very low probability of switching. In Regimes 1 and 3, we uncover a significant and negative effect of Nikkei returns on TEPCO returns, but no effects of TEPCO returns on Nikkei returns. These results suggest that TEPCO has a limited influence in the Japanese stock market, even during crises. Conversely, TEPCO's returns largely depend on market moves.

In the next section, we present our study data and methodology, followed by the main results of our volatility econometric analysis in Section 3. Then we detail the market reactions to key events that affect both TEPCO and the Nikkei 225 in Section 4, before we conclude in Section 5.

2. Data and methodology

We test various ARCH models for both the Nikkei and TEPCO returns. We also outline the data that inform this study.

2.1 ARCH models

To compute volatility, we use daily returns R_t. If $R_t = 100.\ln(P_t / P_{t-1})$, then $R_t = \mu + \varepsilon_t$, for which μ is the average of R_t, conditional on past information ψ_{t-1}. Before estimating the GARCH model (Bollerslev, 1986; Engle, 1982), we test for the presence of ARCH effects in the residuals ε_t of the stock return model. With a null hypothesis of no ARCH effects, the test statistic is $LM= T.R^2 \sim \chi^2(p)$, where T is the sample size, and R^2 is computed on the basis of an $AR(p)$ process for ε_t^2. Furthermore, volatility σ can be computed with the standard deviation of daily returns in a GARCH model, defined by $\sigma = \sqrt{h}$, where h is the conditional variance derived from GARCH(p, q), such as:

$$h_t = \delta + \sum_{i=1}^{q} \alpha_i.\varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j.h_{t-j} \tag{1}$$

where $\delta > 0$, $\alpha \geq 0$, and $\beta \geq 0$, because these conditions are sufficient to ensure a positive h_t. Then ε_t is the residual of an underlying process for a set of information ψ, such that $\varepsilon_t / \Psi_{t-1} \sim N(0,h_t)$, so it is weak white noise (implying a constant, finite variance). Unconditional expected variance exists when the process is covariance stationary, that is, $\sum \alpha_i + \sum \beta_i < 1$.
Accordingly, we estimate seven ARCH models for $p=q=1$.

2.1.1. GARCH(1,1)

Conditional variance is expressed as

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

By construction, this GARCH model is symmetric. But the curves of the causality measures for bad and good news should differ, so the most probable case is that the curves are asymmetric. The subsequent models take such asymmetry into account.

2.1.2. EGARCH(1,1)

Unlike the GARCH specification, the exponential GARCH model (Nelson, 1991), specified in logarithms, does not impose negativity constraints on parameters. We retain the following specification:

$$Logh_t = \delta + \alpha\left[\frac{|\varepsilon_{t-1}|}{\sqrt{h_{t-1}}} - \sqrt{2\pi}\right] + \gamma\left[(\varepsilon_{t-1}) / (\sqrt{h_{t-1}})\right] + \beta Logh_{t-1}$$

2.1.3. GJR-GARCH(1,1)

The Glosten-Jagannathan-Runkle-GARCH model (Glosten *et al.* 1993) includes leverage terms to model asymmetric volatility clustering. Large negative changes are more likely to be clustered than positive changes. Therefore,

$$h_t = \delta + \alpha.\varepsilon_{t-1}^2 + \gamma.I_{t-1}^{-}.\varepsilon_{t-1}^2 + \beta.h_{t-1},$$

where $I_{t-1}^{-} = 1 \ if \ \varepsilon_{t-1} < 0$, $\delta > 0$, $\alpha \geq 0$, $\beta \geq 0$, and $\alpha + \gamma \geq 0$. In this model, good news $\varepsilon_{t-i} > 0$, and bad news $\varepsilon_{t-i} < 0$ have differential effects on conditional variance.

2.1.4. TGARCH(1,1)

Threshold GARCH has been defined by Zakoian (1994) as

$$h_t = \delta + \alpha|\varepsilon_{t-1}| + \gamma|\varepsilon^{+}_{t-1}| + \beta\sqrt{h_{t-1}}$$

where "+" is a positive exponent, and γ denotes the coefficient of leverage effects. In this model, the standard deviation depends on both absolute innovations and the influence of large innovations relative to the traditional GARCH(p,q) model.

2.1.5. NGARCH(1,1)

In the nonlinear GARCH of Higgins and Bera (1992), the conditional standard deviation is a function of both the squared lagged conditional standard deviation and innovations raised to power 2:

$$h_t = \delta + \alpha\left(\varepsilon_{t-1} + \gamma\sqrt{h_{t-1}}\right)^2 + \beta h_{t-1}$$

2.1.6. PGARCH(1,1)

The power GARCH model can is an extension of the NGARCH model; it has the same structure, except that the conditional standard deviation and the innovation are raised to the power of *Φ*:

$$\left(\sqrt{h_t}\right)^{\phi} = \delta + \alpha\varepsilon^{\phi}_{t-1} + \beta\left(\sqrt{h_{t-1}}\right)^{\phi}$$

As Bollerslev (2008) acknowledges, the estimates for *Φ* are less than 2 in most financial rates of return.

2.1.7. APGARCH(1,1)

The asymmetric power GARCH model (Ding *et al.*, 1993) "nests the most popular univariate parameterizations" (Bollerslev, 2008, p. 6), as follows:

$$(\sqrt{ht})^{\phi} = \delta + \alpha\left(|\varepsilon t{-}1| + \gamma\varepsilon t_{-1}\right)^{\phi} + \beta\left(\sqrt{ht{-}1}\right)^{\phi} .$$

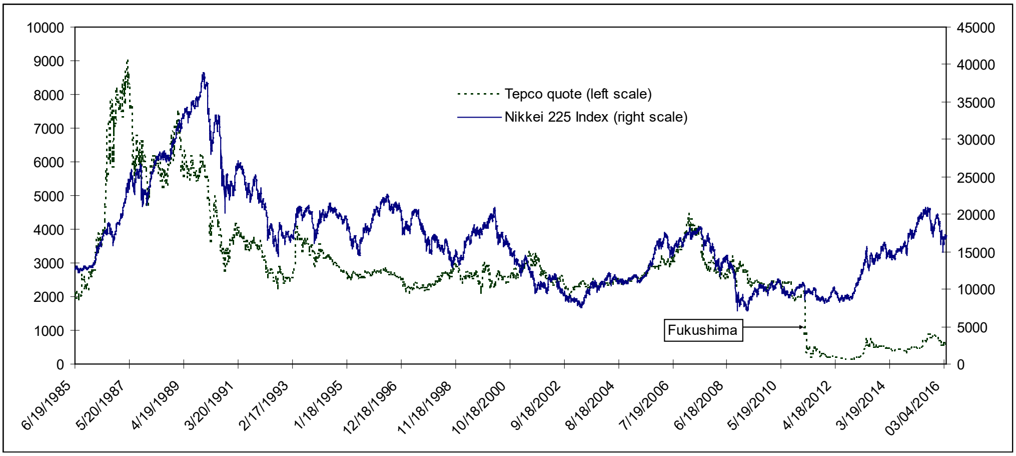
It can be reduced, for example, to GARCH(1,1) for *Φ=2* and *γ=0*, to GJR-GARCH for *Φ=2* and 0≤γ≤1, and to TGARCH for *Φ=1* and 0≤γ≤1.

2.2 Data

We studied stock returns and volatility for both TEPCO and the Nikkei 225 daily over a 30-year period (19 June 1985 to 29 March 2016), which produced 8017 stock or index prices. We start the analysis in 1985, because it was the year of the Plaza agreement, in which G5 countries decided to depreciate the U.S. dollar against the Japanese yen and Deutsche mark, to benefit U.S. exports through lower prices. The financial and stock market data come from the International Factset database.

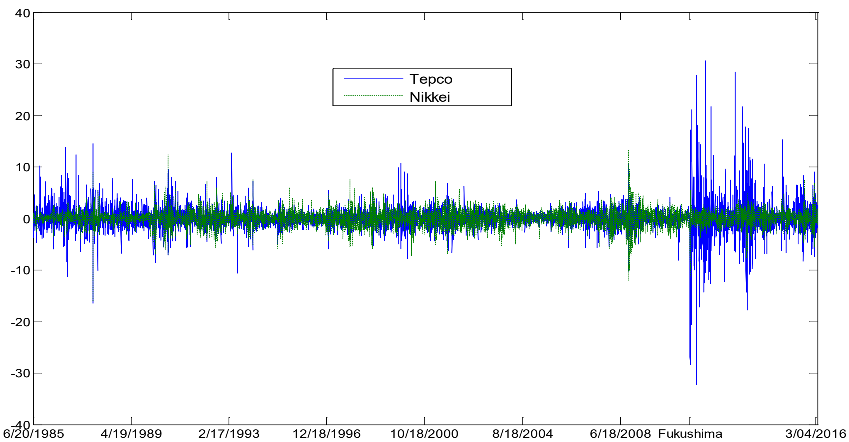
As Figure 1 reveals, the long-term Nikkei 225 index and TEPCO stock prices both exhibit huge variations between 1985 and 2016. Some economic or financial shocks are evident (e.g., 1987 market crash, Gulf War, real estate bubble burst in the early 1990s, Internet bubble burst in 2000s, subprime crisis of 2008, Fukushima earthquake of 2011). The Nikkei has not regained its 1990 high (more than twice its 2016 level); a similar pattern marks TEPCO's trends until the Fukushima disaster, after which TEPCO's stock price level fell to less than 5% of its highest value in 1987.

Figure 1 TEPCO and Nikkei 225 index: historical prices



Considering the main events that have affected both TEPCO and the Nikkei 225 in the past 30 years, the 2011 earthquake is critical, but different categories of events also have been influential, such as international political crises, international financial shocks, and events specific to the Japanese economy, including a stock market crash in 1987, real estate crisis in 1990, the bursting of the dot.com bubble in 2000, the international subprime crisis in 2008, and various political or financial scandals in Japan (e.g., Toshiba financial fraud in 2008–2014). Each of these shocks could constitute good or bad news, so we study the amplitude and persistence of the effects of positive or negative information on company returns and volatility. Just as the effects of minor or major events may differ, the impact of positive or negative information might not be symmetric or match in their duration. The descriptive statistics for the daily stock returns reveal that at the industry level, the daily returns Rt are defined by $R_t = 100.\ln(P_t / P_{t-1})$, where P is the stock price or market index. In Figure 2, the largest daily returns of the Nikkei 225 occur during the 2008 subprime crisis; index variations during the Gulf War in 1990 were the second largest. For TEPCO, the largest returns (mostly stock declines) happened in the weeks after the Fukushima earthquake and continued for a few years. The only other period with similarly notable price variations for this company was the aftermath of the 1987 crash.

Figure 2 Daily returns for TEPCO and the Nikkei 225



The descriptive statistics in Table 1 detail the return characteristics for TEPCO stock prices and the NIKKEI 225 index.

Table 1 Descriptive statistics of stock returns over 1985–2016

	TEPCO	Nikkei 225
Mean	-0.015454	0.003642
Median	0.000000	0.000000
Maximum	30.61160	13.23460
Minimum	-32.32730	-16.13540
Standard Deviation	2.387334	1.445844
Skewness	0.344394	-0.287542
Kurtosis	35.49625	11.07418
Jarque-Bera	352864.5	21884.74
Probability	0.000000	0.000000

These patterns thus differ somewhat. Whereas the median return is 0 for both, the mean value is -0.0154 for TEPCO and 0.0036 for the Nikkei. In the long run, the standard deviation in TEPCO stock is far greater than that exhibited by the Nikkei index. The difference is even more notable in the kurtosis, such that TEPCO (35.49) experienced many larger price variations than the index. Moreover, the return distributions are not symmetric, with slightly more positive returns for TEPCO but more negative ones for the Nikkei. Therefore, both return distributions include fat tails; as confirmed by the high values of the Jarque-Bera statistics, these patterns do not fit a Gaussian distribution (i.e., the normality hypothesis is rejected at a 0.001% error level). This result is fairly common in international market returns (Cont, 2001), but in the Japanese context, it also is interesting to consider volatility processes more closely. For example, autocorrelations might signal momentum effects, as suggested for TEPCO by Jaussaud et al. (2015).

3. Estimation of volatility models

Considering the ARCH effects, with a 10-day lag, both the TEPCO and Nikkei 225 returns exhibit significant values (Table 2). The TR^2 and F-statistics are significant at the 0.1% error level, indicating that the null hypothesis (i.e., no ARCH effect) can be rejected for both series. Engle (1984, p. 802) asserts that the Lagrange multiplier test can "be written in terms of the residuals from the estimate under the null. Thus, it provides a way of checking the residuals for non-randomness." For each alternative model we test, we will obtain a specific type of non-randomness.

Table 2 ARCH effects tests

Stock Return					
	Lags	$LM = T.R^2$	p-value	F-Statistic	p-value
TEPCO	10	1512.66	0.000	186.24	0.000
Nikkei 225	10	1129.86	0.000	131.37	0.000

Table 3 details the parameters of the various GARCH models for the Nikkei index. The best log-likelihood value results from an APGARCH model, though the other GARCH models offer similar log-likelihood values. In turn, we assert that the simple GARCH provides a good fit to volatility trends, but the other types offer slightly more precise modelling. With regard to TEPCO's historical volatility, the situation is fairly similar (see Table 4) The simple GARCH model again offers a good fit, but APGARCH is more precise. Whereas GJR-GARCH provides the smallest improvement over the basic GARCH model for the Nikkei, TGARCH exhibits a lower log-likelihood value than the basic GARCH for TEPCO. Accordingly, the threshold effect is not relevant for TEPCO, and the standard deviation of its volatility does not depend on absolute large innovations, despite the obvious influence of some major shocks. For the Nikkei, we conclude that large negative changes do not tend to be more clustered than positive changes.

Table 3 GARCH models for the Nikkei

Model	δ	α	β	γ	Power term		Log-likelihood
GARCH	0.0188 (0.00)	0.0927 (0.00)	0.9065 (0.00)				-12980.84
EGARCH	0.0209 (0.00)	-0.0969 (0.0)	0.9767 (0.00)	0.1607 (0.00)			-12896.82
TGARCH	0.0279 (0.00)	0.1425 (0.00)	0.9163 (0.00)	-0.1132 (0.00)			-12896.77
GJR-GARCH	0.0278 (0.00)	0.15851 (0.00)	0.8995 (0.00)	-0.1275 (0.00)			-12915.32
PGARCH	0.0174 (0.00)	0.0975 (0.00)	0.9147 (0.00)		1.4603 (0.00)		-12973.52
APGARCH	0.0279 (0.00)	0.0857 (0.00)	0.9132 (0.00)	**-0.6043 (0.00)**	1.2009 (0.00)		**-12894.3**
NGARCH	-0.0087 (0.18)	0.0946 (0.00)	0.8878 (0.00)	0.7463 (0.00)			-12907.9

Table 4 GARCH models for TEPCO

Model	δ	α	β	γ	Power term		Log-likelihood
GARCH	0.0561 (0.00)	0.1484 (0.00)	0.8631 (0.00)				-14745.18
EGARCH	0.0593 (0.00)	-0.0351 (0.00)	0.9772 (0.00)	0.2676 (0.00)			-14731.14
TGARCH	0.0345 (0.00)	0.1671 (0.00)	0.8870 (0.00)	-0.0467 (0.00)			-14750.02
GJR-GARCH	0.0549 (0.00)	0.1975 (0.00)	0.8620 (0.00)	-0.0873 (0.00)			-14731.82
PGARCH	0.0463 (0.00)	0.1522 (0.00)	0.8732 (0.00)		1.5836 (0.00)		-14739.5
APGARCH	0.0477 (0.00)	0.1543 (0.00)	0.8700 (0.00)	**-0.1466 (0.00)**	1.6594 (0.00)		**-14728.42**
NGARCH	0.0495 (0.00)	0.1505 (0.00)	0.8602 (0.00)	0.2729 (0.00)			-14737.35

According to the log-likelihood statistics, the APGARCH(1,1) model offers the best fit to the data. In this model, the large negative values of the γ coefficient indicate that the market responds with more volatility to bad news in returns (decreases) than it does to good news in returns (increases). The results we obtain align with standard findings in financial literature, in that the power term Φ is less than 2 (Bollerslev, 2008) but significantly greater than 1 for both PGARCH and APGARCH, for the Nikkei and TEPCO. Therefore, the power model is relevant, particularly for TEPCO, for which the impacts of unexpected price components were substantial in the years following the Fukushima accident. For both return series, we also note that the γ values are negative for TGARCH, GJR-GARCH, and APGARCH but positive for EGARCH and NGARCH, confirming the stronger impact of negative (relative to positive) unexpected variations on price volatility.

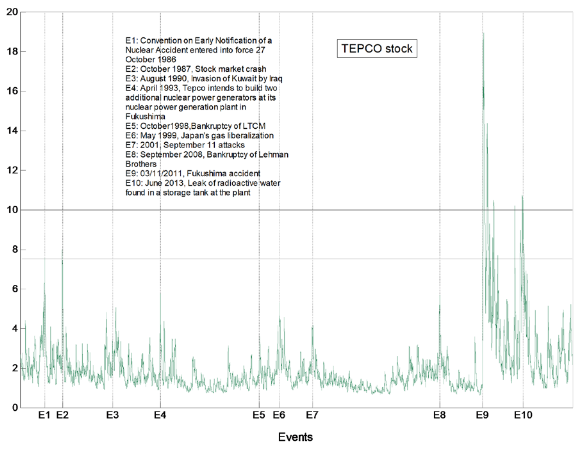
4. Volatility and main events that affect TEPCO or the Nikkei

In this section, we focus on the standard deviation of TEPCO and the Nikkei index, based on APGARCH model estimates. We analyse switches in volatility, according to key events at the international level and in Japan. Appendix 1 lists these events.

4.1. Major highs and lows in TEPCO stock returns over the past 30 years

We surveyed major events (Appendix 1) that could influence the volatility of TEPCO stock. We also note the main periods of high volatility for TEPCO over the past 30 years. The APGARCH(1,1) model (Figure 3) displays the situation clearly, similar to the other models (e.g., TEPCO PGARCH(1,1) in Appendix 3).

Figure 3 TEPCO APGARCH(1,1) standard deviation and main events

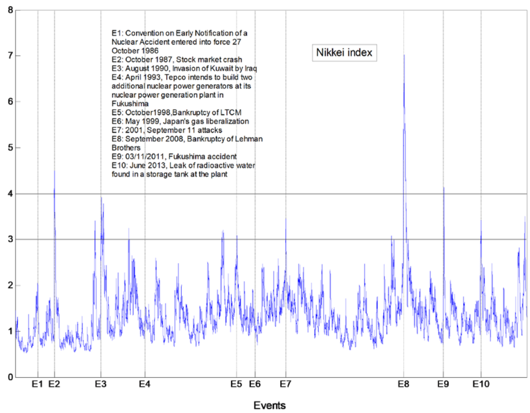


The period marked by the highest volatility for TEPCO was the post-Fukushima period, which lasted several months after 11 March 2011, spanning into 2012 and 2013. This environmental and industrial catastrophe boosted TEPCO's return volatility by more than 5 times, relative to its usual long-term value. No other event had similar effects on stock volatility over the past 30 years. However, another high volatility event involved the October 1987 stock market crash, which impaired nearly all companies worldwide. It increased the volatility level up to 3 times the usual long-term value. A third high volatility event, in summer 1986, increased TEPCO stock by about 20% between July and the end of October, following the Chernobyl accident in April 1986 and the adoption in September 1986 of the *Convention on Early Notification of a Nuclear Accident* to establish a rating system and requirements for data reporting (time, location, radiation). This convention entered into force on October 27, 1986. Other events exert smaller impacts on volatility. For example, the September 2001 attacks in New York prompted an increase in volatility, as did the Gulf War. Financial shocks following the bankruptcies of Long Term Capital Management (LTCM) in 1998 and Lehman Bothers in 2008 generated high volatility. At firm level, the construction of two nuclear generators by TEPCO in 1993, as well as reports in June 2013 of important leaks of radioactive water, created uncertainty and stronger volatility. With regard to nuclear, environmental, and safety issues since 1993 (see Appendix 5), the Fukushima catastrophe had the most severe impacts on TEPCO's return volatility. Even the 1993 Hokkaido earthquake and 1995 Kobe earthquake did not create significant or long-term volatility changes, for either TEPCO or the Nikkei index. Considering nuclear activity by TEPCO, security issues arose in May 2002 (inquiries about misconduct in inspections and repairs between 1986 and 2001), October 2002 (reports of leaks in the primary containment vessel at Fukushima Daiichi), and March 2004 (TEPCO admitted a series of misconducted inspections and reports about cracks in Fukushima Daiichi). A weak market reaction also followed the Niigata Chuetsu Oki earthquake (west of Fukushima) in July 2007, despite damages to TEPCO's Kashiwasaki-Kariwa nuclear power plant. After the Fukushima earthquake in March 2011, numerous press accounts of safety failures and noncompliance in nuclear plants caused the high volatility level of stock returns to persist for several years.

4.2. Major highs and lows in the Nikkei 225 returns

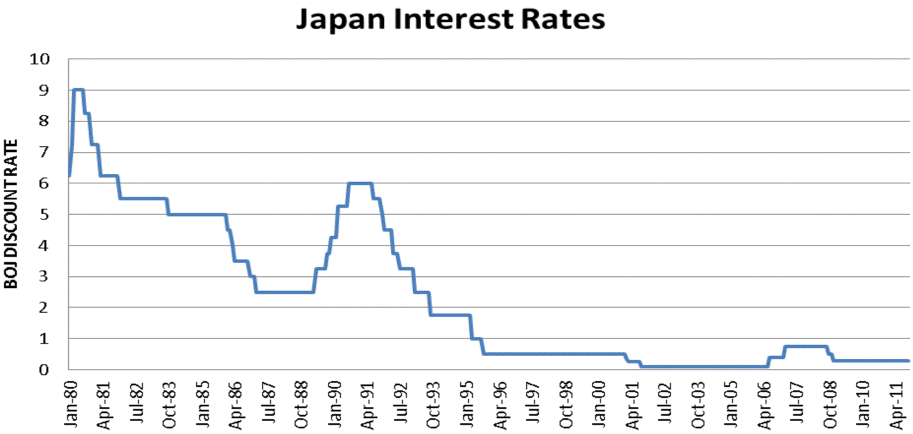
We studied the highs and lows of the Nikkei index's volatility, measured by the standard deviation derived from the APGARCH(1,1) (Figure 4). In considering the main political and economic events that affect its volatility, we also offer a comparison with the results for TEPCO. Specifically, for the Nikkei index, the main event is the subprime crisis following the Lehman Brothers bankruptcy on 15 September 2008. Volatility began to increase a few days before this announcement and reached a climax (about 3 times its usual long-term value) in mid-October 2008. It took about six months for volatility to return to its pre-crisis level. A second volatility peak was caused by "black Monday," October 19, 1987, when stock markets crashed worldwide, though its span lasted only about a month and a half. Only during the four highest volatility periods did the Nikkei index's volatility reach a level higher than twice its usual value.

Figure 4 Nikkei APGARCH(1,1) standard deviation and main events



A third high volatility period occurred during the second half of 1990, reflecting two pertinent events. On 2 August 1990, Iraq's invasion of Kuwait triggered the first Gulf War, which increased volatility across world markets. In addition, an internal crisis took place in Japan, leading to a real estate collapse: On 2 October 1990, the Bank of Japan tightened its monetary policy and increased the official discount rate from 4.25% to 6.00%. Thereafter, the rates decreased in the long run (Figure 5).

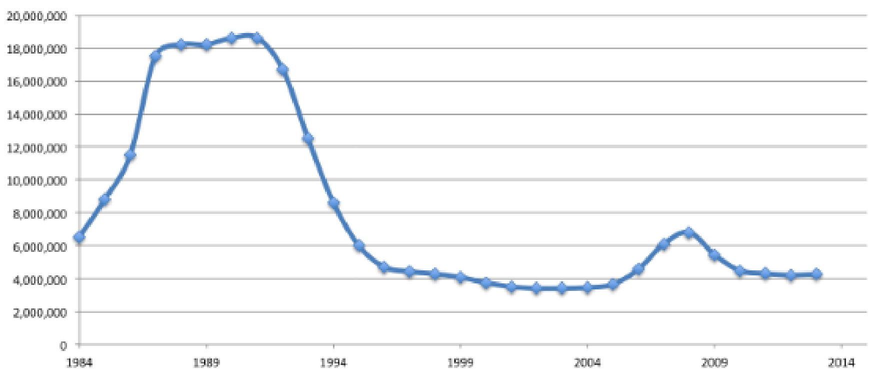
Figure 5 Japan's interest rates in percent



Source: https://housingjapan.com/2011/11/10/a-history-of-tokyo-real-estate-prices/

Meanwhile, the Japanese yen (JPY) dropped to 158 JPY per U.S. dollar (USD) in April 1990, then bounced back to 129 JPY/USD in November. As a consequence, the Nikkei 225 decreased from 37,189 at the beginning of January to 23,849 on 3 December 1990. This index has not surpassed 21,000 again in the subsequent 26 years. After the 1982–1990 bubble, real estate prices also began to collapse in 1992 (Figure 6).

Figure 6 Land prices for commercial property in the Ginza-Chome 7, per square meter



Source : https://housingjapan.com/2011/11/10/a-history-of-tokyo-real-estate-prices/

A fourth volatility shock came from the Fukushima earthquake. For the index, this catastrophe did not have a long-lasting impact on volatility, because fears of a national economic collapse quickly disappeared. The main consequences instead centred on the electric power industry, and TEPCO activity specifically. We find another shock by the bankruptcy of the Long-Term Credit Bank on 7 October 1998. Over three days, the Nikkei's volatility level reached 10% of its highest values. Finally, a comparison of the positive innovations in the volatility process of TEPCO and the Nikkei index returns does not indicate a high correlation (0.26). When we consider negative innovations, the correlation is slightly higher (0.32), due to the absence of symmetry in the amplitude changes. Therefore, bad news tends to affect TEPCO more frequently but the Nikkei in the same way as good news.

5. Regime switching and the relationship between TEPCO and the Nikkei index

Generally, a diversification strategy depends on the degree of correlation among stocks or between stocks and the market. Therefore, we consider correlations between the volatilities, as well as the relationship of the returns for TEPCO and the Nikkei index. Our observations of the volatilities reveals two key characteristics. First, for the overall study period and also after the earthquake, the market responses for TEPCO and the Nikkei differ. Second, we observe asymmetric responses to shocks (GARCH estimations) and alternations between high and low volatility periods (Figures 1 and 2). To account for these characteristics, we adopt a regime-switching/Markov-switching model that we use to estimate conditional correlation between TEPCO and the Nikkei, as well as to estimate the relationship between their returns.

The main characteristic of a Markov-switching model is that the transitions between the regimes or states $st \in \{= 1, K, M\}$ are governed by a Markov chain. The transition probability from a state j to a state i is

$$p_{ij} = \Pr(s_{t+1} = j \mid s_t = i), \, with \sum_{j=1}^{M} p_{ij} = 1 \; \forall i,j \in \{1, K, M\} \tag{2}$$

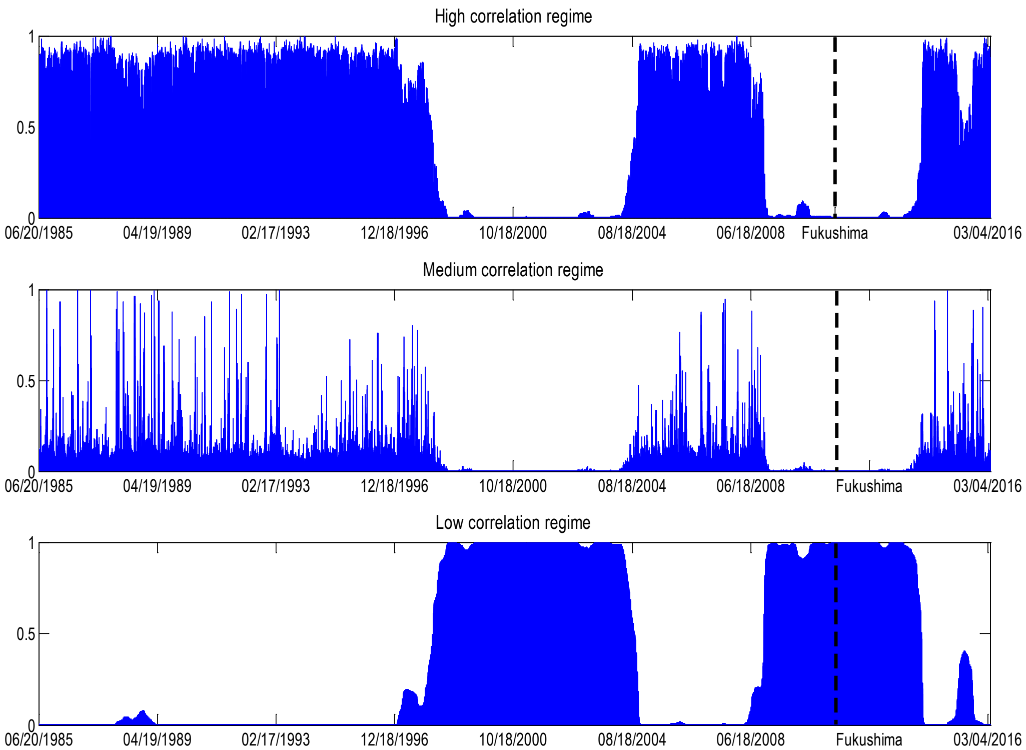
We do not analyse regime switching in TEPCO stock separately from that in the Nikkei index, but we consider regime switching in the conditional correlations and the relationships between both TEPCO returns and Nikkei returns.

5.1 Regime-switching dynamic correlation

To address the potential conditional correlation of TEPCO stock with the Nikkei, we use the regime-switching dynamic correlation model of Pelletier (2006).[1] Consider a K-variate process, $Y_t = H_t^{1/2} U_t$, where U_t is an i.i.d $(0, I_K)$ process; the time-varying covariance matrix H_t can be written as $H_t = S_t \Gamma_t S_t$, such that Γ_t contains the correlations, and S_t is a diagonal matrix of the standard deviations. We note three states, marked by low, intermediate, and high conditional correlations. In analysing the regime-switching correlation model with three states (Figure 7), we find that the high correlation regime is the most frequent for TEPCO over the past 30 years.

[1] See also the discussion of these models by Billio and Caporin (2005).

Figure 7 Smoothed probabilities of the three-regime model (TEPCO and Nikkei 225)



The momentum effect is more frequent than the mean-reverting effect among return patterns. The medium correlation regime is not very frequent; the low correlation regime is even less frequent. We identify two periods in which the low correlation regime dominated though: between 1997 and 2004 and between 2008 and 2014. The first includes the Long-Term Credit Bank failure and the Internet bubble burst effects; the second begins with the subprime crisis and includes the Fukushima catastrophe.

5.2 MS-VAR analysis

We also investigate the relationships between TEPCO's stock and the Japanese market index. Both TEPCO and Nikkei returns satisfy the stationary condition.[2] We start by analysing the relationships between endogenous variables using a vector autoregressive (VAR) approach (Sims, 1980), but "if the time series are subject to shifts in regime, the stable VAR model with its time invariant parameters might be inappropriate" (Krolzig, 1997, p. 11). In that case, a Markov switching VAR is preferable. The general idea behind this MS-VAR model is that the parameters of the underlying data-generating process of the observed time-series vector y_t depend on an unobservable regime/state variable *st.* For this study, the MS-VAR process (*MS(M)-VAR(p)*) contains *s* states and *p* lags, as given by

[2] To save space, we do not present the unit root tests here; they are available on request.

$$y_t = \delta(s_t) + A_1(s_t)\, y_{t-1} + \ldots + A_p(s_t)\, y_{t-p} + \varepsilon_t, \qquad \varepsilon_t / s_t \sim NID(0, \textstyle\sum(s_t)),. \tag{3}$$

For the empirical application, $y_t = \left(R_t^{tp}, R_t^{nk}\right)'$, using *tp* to indicate TEPCO and *nk* for Nikkei. For an *s* state and *p* = *k*, Equation (3) can be written as

$$\begin{aligned} R_t^{tp} &= \delta^{tp}(s_t) + \sum_{k=1}^{p} a_{k(S_t)} . R_{t-k}^{tp} + \sum_{k=1}^{p} a_{2k(S_t)} . R_{t-k}^{nk} + \sigma_{(S_t)} . \varepsilon_t^{tp} \\ R_t^{nk} &= \delta^{nk}(s_t) + \sum_{k=1}^{p} b_{1k(S_t)} . R_{t-k}^{tp} + \sum_{k=1}^{p} b_{2k(S_t)} . R_{t-k}^{nk} + \sigma_{(S_t)} . \varepsilon_t^{nk} \end{aligned} \tag{4}$$

where $\sigma_{(S_t)}$ is regime-specific volatility.
Considering three states $s_t = 1,2,3$ and two lags, the MS(3)-VAR(2) features switches in the coefficients of the variables and in the intercepts (δ). We present the results in Table 5. For the parameter estimation, we use the maximum likelihood method.

Table 5 MS(3)-VAR(2) estimation results

Model	**Regime 1**		**Regime 2**		**Regime 3**	
	Rtepco	Rnikkei	Rtepco	Rnikkei	Rtepco	Rnikkei
δ(s)	-0.01 (0.99)	-0.01 (0.99)	-0.001 (0.99)	0.001 (0.99)	-0.001 (0.99)	-0.001 (0.99)
$a_{11(s)}$	-0.01 (0.29)		-0.01 (0.99)		0.11** (0.00)	
$a_{12(s)}$	0.03 (0.99)		-0.04** (0.03)		0.08** (0.01)	
$a_{21(s)}$	-0.07** (0.00)		-0.02 (0.99)		-0.07** (0.02)	
$a_{22(s)}$	-0.01 (0.99)		0.01 (0.99)		-0.02 (0.99)	
$b_{11(s)}$		-0.02 (0.99)		-0.01** (0.04)		0.001 (0.99)
$b_{12(s)}$		0.001 (0.99)		0.01 (0.99)		-0.001 (0.99)
$b_{21(s)}$		-0.05** (0.00)		0.07** (0.00)		-0.07 (0.99)
$b_{22(s)}$		-0.04** (0.00)		0.06** (0.00)		-0.04 (0.02)
Duration	37.20		10.05		3.81	
V(S)	0.968**	1.526**	2.451**	0.547**	27.95**	6.928**
Transition Probability Matrix *P*						
Regime 1	0.97**		0.01**		0.08**	
Regime 2	0.00**		0.90**		0.19**	
Regime 3	0.03**		0.09**		0.74**	
** and * denote rejection of the null hypothesis at the 0.05 and 0.10 levels, respectively.						

Both TEPCO and Nikkei returns signal regime shifts in volatilities. Regime 1 is characterized by a low TEPCO volatility (0.968) and a limited Nikkei volatility (1.426). Regime 2 features a low Nikkei volatility and higher TEPCO volatility. Regime 3 contains high volatilities. Thus, they represent a low volatility regime (State 1), intermediate volatility regime (State 2), and high volatility regime (State 3). Regime 1 exhibits the longest average duration, of 37.2 days. Susmel (2000) offers a similar result for weekly exchange rates in Canada and the United States in the 1980s. Conversely, the duration of Regime 2 is just 10 days, and the high volatility state has the shortest duration, of 3.8 days.
These observations may be complemented by a consideration of the transition probabilities across different regimes.

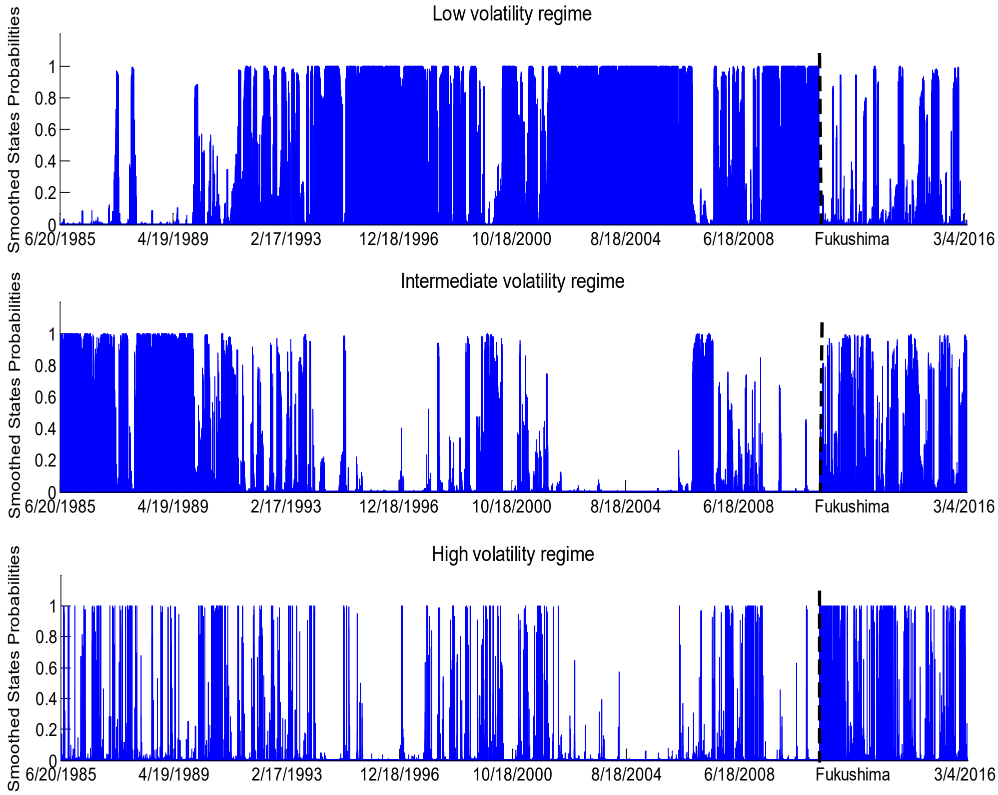
The transition probabilities matrix P can be defined as $P = \begin{bmatrix} & s1 & s2 & s3 \\ s1 & p_{1,1} & p_{1,2} & p_{1,3} \\ s2 & p_{2,1} & p_{2,2} & p_{2,3} \\ s3 & p_{3,1} & p_{3,2} & p_{3,3} \end{bmatrix}$, where

$p_{i,j}$ is the probability of switching from state j (column j) to state i (row i). Regime 3, which essentially reflects the Fukushima crisis, is less persistent than the two other regimes. Regime 1 shows a very low switching probability (Table 5). We also identify a strong interaction between Regimes 2 and 3, whereas Regime 1 is a low volatility, self-standing regime (Gallo and Otranto, 2013). Even if TEPCO's stock volatility remained higher than usual after the Fukushima disaster, the high volatility regime progressively switched to more moderate volatility over the subsequent few months.

In Regimes 1 and 3, we also find a significant, negative effect of the Nikkei returns on TEPCO's returns. However, TEPCO's returns do not influence the Nikkei returns. The causality relationship reverses in Regime 2, but the negative coefficient is lower in absolute value. In Appendix 4, we provide complementary estimations for a model with four regimes, and the conclusions are similar, such that in three regimes, the Nikkei returns "cause" TEPCO's returns, and at a 0.05 significance level, TEPCO's return "do not cause" the Nikkei return in any regimes. Therefore, the results confirm that TEPCO plays a limited role in determining the Japanese stock market, even during a massive crisis. In contrast, TEPCO's returns depend strongly on the wider market.

Figure 8 contains a chart of the smoothed probability of each state. During 1985–2016, we observe contrasting situations. Regime 1 dominates after 1990 until the Fukushima catastrophe. Except for the collapse of the dot.com bubble and the subprime crisis, this period remains "normal" and relatively stable. The intermediate regime mainly appears during the Japanese bubble in the 1980s and the two previous episodes of crisis. Regime 3 implies episodes of very high volatility, including the Japanese stock market crash but mostly after the earthquake that generated such substantial volatility in the TEPCO stock and that persisted up to five years later.

Figure 8 Smoothed probabilities in the MS(3)-VAR(2) model



6. Conclusion

This study highlights several interesting features pertaining to the long-run returns and volatility of TEPCO's stock and the Nikkei 225 index. For 1985–2016, we can reject the null hypothesis of no ARCH effect, which led us to examine which GARCH model provides the best fit to describe volatility for both TEPCO and the Nikkei. The simple GARCH model offers a good fit; the APGARCH is slightly more precise. However, the TGARCH model does not appear relevant for TEPCO, indicating that the standard deviation of its volatility does not depend on absolute large innovations, despite a clear impact of the major shocks. For the Nikkei, we also can conclude that large negative changes do not tend to be more clustered than positive changes.

In the APGARCH(1,1) model, large negative values of the γ coefficient indicate that the market responds with much more volatility to bad news in returns (decreases) than it does to good news in returns (increases). Thus we can conclude that the power model is relevant, particularly for TEPCO, because the impact of the unexpected price components remained fairly substantial in the years following the Fukushima accident.

When we analyse the regime-switching correlation model with three states, we determine that the high correlation regime is the most frequent for TEPCO; thus, the momentum effect has been more frequent than the mean-reverting one. A low correlation regime dominated during just two periods: 1997 to 2004 (i.e., failure of Long-Term Credit Bank and Internet bubble burst) and 2008 to 2014 (subprime crisis and Fukushima catastrophe).

Both TEPCO and Nikkei returns satisfy stationary conditions, and they exhibit regime shifts in their volatilities. Regime 1 involves low TEPCO volatility and limited Nikkei volatility, Regime 2 features low Nikkei volatility and higher TEPCO volatility, and Regime 3 indicates high volatilities, mainly related to the Fukushima crisis, such that it is less persistent than the other two regimes. Regime 1 instead tends to remain in place and self-contained, whereas we uncover some strong interactions between Regimes 2 and 3. Yet in Regimes 1 and 3, we note that the Nikkei exerts a significant, negative effect on TEPCO's returns, though the opposite is not true. Overall, our results show that TEPCO exerts limited influence on the Japanese stock market, even during crisis events, whereas the market largely defines TEPCO's returns.

These results pertaining to the returns, volatilities, and causal relationships between the Nikkei index and TEPCO's stock contribute to a better understanding of the long-run volatility process that appears in these series. Thus, the findings may help investors make better informed investment choices, related to assets or volatility, to generate more abnormal positive returns or adjust the risk–return balance in their portfolios. The economic and industrial crises that TEPCO has experienced over the past 30 years, among which Fukushima was the most notable, have led the company to enter a transition era. This transition will influence the market valuation and volatility of TEPCO's stock, but it also may affect the electric power industry as a whole, especially as renewable energies come to have a larger role in Japan's future energy policies.

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APPENDIX 1. Political and economic events, 1985–2016

E1: Following the Chernobyl nuclear plant accident (April 2016), the General Conference of the International Atomic Energy Agency in a session in Vienna on September 24–26, 1986, adopted the Convention on Early Notification of a Nuclear Accident. It established a notation system that requires states to report all data (time, location, radiation) necessary to assess crisis situations. It entered into effect on October 27, 1986.

E2: October 1987 stock market crash. On Black Monday, October 19, stock markets around the world crashed.

E3: August 1990, invasion of Kuwait by Iraq.

E4: April 1993, TEPCO announces plans to build two additional nuclear power generators at its nuclear power generation plant in Fukushima.

E5: October 1998, bankruptcy of LTCM.

E6: May 1999, Japan's gas sector liberalization.

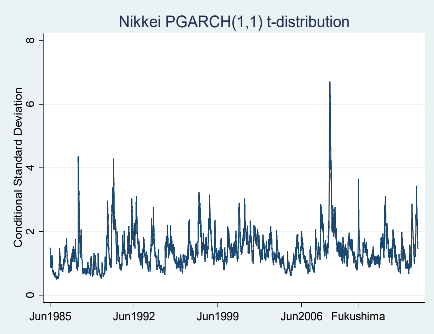
E7: 2001, September 11 attacks.

E8: September 2008, bankruptcy of Lehman Brothers.

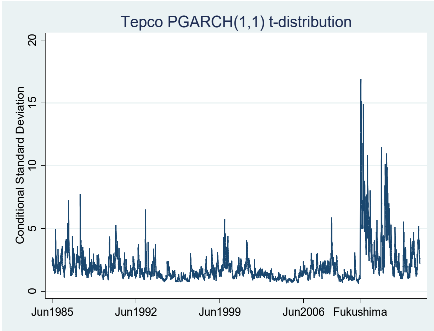
E9: 2011, Fukushima accident on March 11.

E10: June 2013, leak of radioactive water found in a storage tank at the plant. TEPCO announced a leak of 300 tons of highly radioactive water.

APPENDIX 2. Nikkei PGARCH(1,1)



APPENDIX 3. TEPCO PGARCH(1,1)



APPPENDIX 4. MS(4)-VAR(2) model

Model	Regime 1		Regime 2		Regime 3		Regime 4	
	Rtepco	Rnikkei	Rtepco	Rnikkei	Rtepco	Rnikkei	Rtepco	Rnikkei
δ(s)	0.001 (0.99)	0.01** (0.01)	-0.001 (0.99)	0.01 (0.99)	-0.06** (0.05)	0.01 (0.99)	0.03 (0.99)	-0.01 (0.99)
$a_{11(s)}$	-0.07 (0.99)		0.03 (0.99)		0.01 (0.99)		0.14** (0.00)	
$a_{12(s)}$	0.03** (0.00)		-0.05 (0.99)		-0.01 (0.99)		-0.11** (0.00)	
$a_{21(s)}$	-0.05 (0.99)		**0.04**** **(0.04)**		**-0.11**** **(0.00)**		**0.18**** **(0.00)**	
$a_{22(s)}$	-0.001 (0.99)		-0.001 (0.99)		-0.02 (0.99)		-0.001 (0.99)	
$b_{11(s)}$		0.03 (0.99)		0.02 (0.99)		0.01 (0.99)		0.001 (0.99)
$b_{12(s)}$		-0.001 (0.99)		0.001 (0.99		0.01 (0.99)		**0.001*** **(0.09)**
$b_{21(s)}$		-0.05 (0.99)		0.08** (0.00)		-0.10** (0.00)		0.06 (0.99)
$b_{22(s)}$		0.03 (0.99)		0.07** (0.00)		-0.08** (0.00)		-0.12** (0.00)
Duration	7.92		16.96		6.42		3.77	
V(S)	0.471**	0.842**	2.789**	0.412**	2.633**	2.743*	46.12**	7.856**
	Transition Probability Matrix *P*							
Regime 1	0.87**		0.00		0.12**		0.01**	
Regime 2	0.00		0.94**		0.00		0.11**	
Regime 3	0.13**		0.00		0.84**		0.15**	
Regime 4	0.00		0.06**		0.04**		0.73**	

** and * denote rejection of the null hypothesis at the 0.05 and 0.10 levels, respectively.