Economics Bulletin

Volume 35, Issue 2

The Great East Japan Earthquake and Stock Prices

Jacques Jaussaud
University of Pau et Pays de l''Adour

Sophie Nivoix
University of poitiers, France

Serge Rey
CATT-UNIV PAU & PAYS ADOUR

Abstract

The Great East Japan Earthquake of March 11, 2011, which led to a massive tsunami and the nuclear accident at Fukushima, moved Japanese authorities to close most of the country's nuclear reactors for inspection (only 2 of 54 total currently are working), as well as to reassess its national energy policy. This article investigates the volatility of stock prices before and after the disaster. The evolution of stock prices of electric utility companies differs greatly, compared with those of firms in other industries.

We thank the two referees for their useful comments and help to improve this paper. We also thank Denis Pelletier for providing his Matlab source codes.
Citation: Jacques Jaussaud and Sophie Nivoix and Serge Rey, (2015) "The Great East Japan Earthquake and Stock Prices", *Economics Bulletin*, Volume 35, Issue 2, pages 1237-1261
Contact: Jacques Jaussaud - jacques.jaussaud@univ-pau.fr, Sophie Nivoix - sophie.nivoix@univ-poitiers.fr, Serge Rey - serge.rey@univ-pau.fr.
Submitted: December 21, 2013. **Published:** June 01, 2015.

1. Introduction

As Gordon et al. (2004) note, the economic consequences of natural disasters, especially earthquakes, have received insufficient attention from both economists and managers. The immediate effect of an earthquake is physical, including the destruction of buildings and infrastructure, and the magnitude of its casualties depends on the quality of the structures damaged by the shock. Economic consequences follow. Households, direct victims of an earthquake, and companies that suffer destruction of property are affected initially. Subsequent to these effects, we can begin considering the consequences at regional, national, or global levels, as well as the temporary or permanent responses exhibited by economic systems.

Companies experience severe disruptions to their activity, due to the destruction of buildings, roads, rail networks, power lines, and so forth. In studying the effects of the January 17, 1995, Kobe earthquake, Chang (2000) demonstrates that the destruction of port facilities had a significant impact on container traffic for example.[1]

The Great East Japan Earthquake on March 11, 2011, differed from other natural disasters, in that the earthquake started a huge tsunami, which then led to an unprecedented nuclear catastrophe in Fukushima. Unlike past events, a dual disaster was in effect, caused by both natural and human factors. The human factors included the initial choice to build nuclear plants without accounting sufficiently for the risk of tsunamis (though it is very difficult to establish the probabilities of such events; Stein and Stein, 2012, 2014). The natural factors clearly were in play. because Japan sits in a very active seismic zone.

Nevertheless, in the long run Japanese authorities will continue to reassess their energy policies and spatial planning; firms may have to reconsider the locations of their factories in areas now regarded as risky. A destructive event on this scale severely affects firms: Not only are their production units destroyed or halted by supply problems, but they may be unable to export goods, even if they can produce them. If the firms suffer important activity losses and cannot earn profits, their financial situation becomes dire. Therefore, we expect a negative effect on stock returns, such that the stock prices of impacted firms likely drop dramatically, due to the high level of uncertainty surrounding the natural disaster event.

More than two years after the disaster, this research seeks to study the evolution of the stock prices of firms directly affected by the earthquake. We check whether the shock had short-term effects or long-lasting consequences for stock prices. A long-term negative effect on stock prices could reduce firms' capacity to finance future investments and instigate a negative wealth effect for Japanese households, even as the country continues to struggle with the cumulative effects of a global economic crisis and an aging population. Moreover, a long-term increase in uncertainty, due to the dynamic conditions in several key economic sectors, would keep risk perceptions high, such that investors likely expect (difficult-to-attain) higher returns.

However, it is difficult to pursue a further analysis of the consequences of this disaster without strong knowledge of the responses by financial markets, as manifested in the evolution of stock prices of companies in both the electricity sector and other sectors that could be affected indirectly. We propose to study, in detail, the statistical properties of the stock returns of firms and Japan's main economic sectors. The remainder of this article is organized as follows: In Section 2, we present a brief review of prior literature. Section 3 contains descriptive statistics about stock returns. We analyze the interdependence among stock returns in Section 4, then explicate volatilities in Section 5, focusing on one particular case. Section 6 offers our conclusions.

---

[1] The ports of Pusan (South Korea) and Kaohsing (Taiwan) took advantage of this situation to increase their shares.

2. Literature review

Some researchers, such as Davis and Weinstein (2002), conclude that temporary shocks, even very severe ones (e.g., nuclear explosions during World War II), have had little impact on the long-term spatial structure of the Japanese economy. These authors also empirically test for the existence of multiple equilibriums to explain the geographical distribution of activities in Japan but reject this hypothesis in favor of a unique equilibrium, with some notable implications: "In the aftermath of a shock, there is a strong tendency for city populations, aggregate manufacturing and even the particular industries that existed prior to the shock to return to their former importance" (Davis and Weinstein 2008, p. 63).

2.1 Japan and lessons of the past

We summarize the main earthquakes that hit Japan during the twentieth century in Table 1. The consequences of these disasters, in human, economic, and social development terms, may help predict the possible effects of the March 11, 2011, disaster.

Table 1: Large twentieth century earthquakes in Japan

Date	Place	Deaths	Magnitude	Tsunami or Fire
09/01/1923	Kantō	142 800	7.9	Yes
03/07/1927	Tango	3 020	7.6	Yes
03/02/1933	Sanriku	3 000	8.4	Yes
09/10/1943	Tottori	1 190	7.4	No
12/07/1944	Tōnankai	998	8.1	Yes
01/12/1945	Mikawa	1 961	7.1	No
12/20/1946	Nankaido	1 362	8.1	Yes
06/28/1948	Fukui	3 769	7.3	Yes
01/16/1995	Kōbe	5 502	6.9	Yes

Sources: J. Hammer, "The Great Japan Earthquake of 1923," *Smithsonian Magazine*, May 2011; "Major Japanese Earthquakes of the 20th Century" and "The Great Tohoku, Japan Earthquake & Tsunami: Facts, Engineering, News & Maps," MCEER publications, University of Buffalo, http://mceer.buffalo.edu/infoservice/disasters/Honshu-Japan-Earthquake-Tsunami-2011.asp

Unfortunately earthquakes are not uncommon in Japan, and sometimes they lead to a significant number of deaths. They also wreak destruction on the infrastructure, which penalizes economic activity. For most earthquakes, the data needed to estimate economic damages are unavailable, though some evaluations have been conducted. For example, the Bank of Japan estimated damages of 4.6 billion yen (29% of gross domestic product [GDP]) for the Kanto earthquake in 1923 and 9900 billion yen (2% of GDP) for Kobe in 1995 (Shirakawa 2011).

2.2 Japan in 2011

The 2011 earthquake was obviously not the first to hit Japan. However, it had some particular characteristics, compared with previous events. It did not directly affect a large city, as did the January, 17, 1995, earthquake in Kobe, for which damages were estimated at about 10,000 billion yen and more than 5500 people died. Yet its 9.0 magnitude on Richter scale made it the largest earthquake in Japan ever, leading to the deaths of more than 15,000 people and the destruction of more than 900,000 buildings, whether partly or totally, which left about 22 million tons of waste to remove from the area. Its epicenter, located 24 km below sea level and 130 km offshore of Sendai (300 km northeast of Tokyo), also created a huge tsunami with 15-meter waves that seriously impaired the Fukushima nuclear plant run by TEPCO (Tokyo Electric Power Company). More than 300,000 people were forced to leave the seismic area, and 50,000 temporary homes were built during the emergency. This earthquake obviously had a major impact on the Japanese energy sector, especially nuclear energy. The nuclear disaster reached level 7, the highest level on the International Nuclear Event Scale, similar to Chernobyl in 1986. About 2 million irradiated people may ask TEPCO for compensation. The whole country will face long-term financial consequences, because the reconstruction costs could reach 20,000 billion yen, and the government approved supplementary budgets four times during the year after the catastrophe.

A year later, only 2 of the 54 Japanese nuclear reactors were producing electricity; prior to the earthquake, nuclear power covered 28% of electricity demand. This shift demanded increased imports of expensive coal, oil, and gas resources, as well as conservation efforts at the national level. As of 2013, the same 2 nuclear reactors remained the only ones generating electricity.

On March 30, 2011, the Japanese government asked electric utility sector firms to take measures to protect themselves against another such tsunami. They have responded in various ways. For example, Hokuriku Electric built a 700-meter long, reinforced concrete anti-tsunami wall, 4 meters higher than its previous one (which was already 11 meters high), around its Shika nuclear plant. In addition, the firm installed a discharge gate to protect against flooding, beyond the protection of a dam, and a reserve pump capable of drawing in sea water to cool the reactor. At 45 nuclear plants, anti-tsunami dams are under construction, and the sealing capacity of the equipment is being upgraded.

In its Shimane plant, Chugoku Electric decided to raise its dam from 11 to 15 meters above sea level. Chubu Electric will build an 18-meter high anti-tsunami dam for its Hamaoka plant (in the Shizuoka region), because it is more exposed to seismic risk. The construction of these dams should be completed by 2015. In contrast, for nuclear plants located in southern Japan, no new works are planned, because their protection walls are considered high enough.

2.3. Event studies and market reactions

An economic, environmental, or political shock generally creates an immediate, often temporary reaction in financial asset prices. Determining the best method to measure this reaction raises several questions: What exactly do we want to measure? Compared with which norm or benchmark? How can we choose and establish such a benchmark? Over which time span?

The theoretical and methodological answers to these questions are varied and depend on both the topic and the context. For example, Ziobrowski et al. (2004) seek to measure abnormal returns in the stock market after government decisions, so they perform standard calculations of the cumulative abnormal returns of asset portfolios during a specific time period. The returns then can be compared against a benchmark, such as the capital asset pricing model or the three-factor model suggested by Fama and French (1993), in terms of their beta coefficients, a size parameter (small minus big capitalizations), and a market capitalization parameter (high minus low book-to-market ratios). This method is useful for portfolios, but it may be less relevant for stock price changes. Considering the amplitude of return changes after the 2011 earthquake, we regard such a comparison with so-called normal returns somewhat irrelevant, so we focus instead on volatilities.

To study strong variations of stock prices, we might investigate, for a specific period, all price increases and decreases greater than a specific value. For example, in Asian stock markets, Wong (1997) analyzes cumulative price increases and declines over the prior 50 days whose returns average more or less than 2 standard deviations. He detected no mean reversion effect or trend change after a large price variation but identified that emerging markets (Hong Kong, Singapore, Taiwan, Thailand, and the Philippines) exhibited a momentum effect after a large price drop, whereas Japan and South Korea did not. With this methodology, it is possible to understand market overreactions to important news (De Bondt and Thaler, 1985, 1987). Then the investigation must continue, to determine if overreactions are sufficient to challenge a weak form of market efficiency, in that the absence of liquidity may increase momentum or the mean reverting effects. Despite its relevance, we avoid this method, because our goal is to assess the impact of the 2011 earthquake on stock prices, not to measure the impacts of all large price changes on the Japanese market. Therefore, we did not want to mix the price changes after the earthquake with all price variations over the rest of the year.

Similar to event studies, we need to specify the time span for our observations carefully. For a unique event, the window usually spans from several days before to several days after the event (e.g., mergers and acquisitions; Ma et al., 2009). For the 2011 earthquake though, its consequences could not be immediately and fully evaluated, because of the duration of successive damages in the Fukushima nuclear plant. To account more fully for the long-term consequences, including repair costs, a frozen economic area, the need for new energy sources, and the potential compensation that TEPCO likely will have to pay, we chose a long-term data observation, namely, from one year before to one year after the date of the catastrophe.

3. Statistical analysis of stock returns

3.1. Data and descriptive statistics

The stock prices of the firms and the indexes we used came from the international Factset database, gathered from March 11, 2010, to March 11, 2012. Because it was the main sector affected by the earthquake, we began by considering electric utility firms listed on the Tokyo Stock Exchange. We then built a sample of representative firms to investigate the effects of the earthquake on several potentially impaired industries, such as electronic equipment, electronic appliances, automobiles, steel, wholesale retailing, and pharmaceuticals (see Appendix 1). All these firms are listed in the first section of the Tokyo Stock Exchange, indicating their large size, so they should be representative of market reactions.

To address the financial impact of the earthquake, beyond the damaged area and TEPCO itself, we observe the evolution of the market capitalization of firms included in three of our selected industries (Table 2). The data are unquestionable for TEPCO: Between March 2010 and March 2011, its market capitalization fell by slightly more than 10%, similar to many stocks in the bearish market. However, TEPCO's capitalization decreased by nearly 90% from the day before the earthquake to one year later; the market confirmed fears about the firm's future, its industry, and more generally its related sectors. We also find sharp drops in the market capitalization of other firms in this industry after the disaster (40–50%, depending on the firm), as well as of firms in the steel industry, which requires huge quantities of electricity. Yet wholesale retailing firms (Table 2) retained nearly the same capitalization during this period (e.g., Marubeni) or even enjoyed growth (e.g., Itochu). The economic shock accordingly was very deep, such that an assessment of the financial consequences could not be considered complete even a year later, whereas in the case of a stock market crash, a large price increase often follows several months after the major drop.

Table 2: Market capitalization of firms (in billion yens)

Electric utility	03/11/2010	03/10/2011	03/10/2012
Tokyo Electric Power	3895	3451	372
Chubu Electric Power	1778	1637	1184
Kansai Electric Power	1893	1919	1257
Tohoku Electric Power	969	948	496
Kyushu Electric Power	949	891	593
Steel			
Sumitomo Metal Industries	1242	923	779
Kobe Steel Ltd.	534	621	399
JFE Holdings Inc.	1840	1329	896
Nippon Steel Corp.	2139	1793	1466
Wholesale retailing			
Itochu Corp.	1233	1320	1450
Marubeni Corp.	973	1047	1034
Mitsui & Co. Ltd.	2820	2675	2551
Sumitomo Corp.	1263	1495	1533
Mitsubishi Corp.	3858	3633	3211

Source: Factset database.

To specify the price changes over the year, we investigate the electric utility sector in particular. Figure 1 shows the stock price evolutions of the five main Japanese electricity producers over a two-year period, all of which were involved in nuclear generation. Unsurprisingly, TEPCO experienced the largest price drop immediately after March 11, 2011, but all firms exhibited declining market capitalization throughout the subsequent quarter. Beyond this quarter, stock price changes were smaller and showed a fairly stationary trend over the medium term.

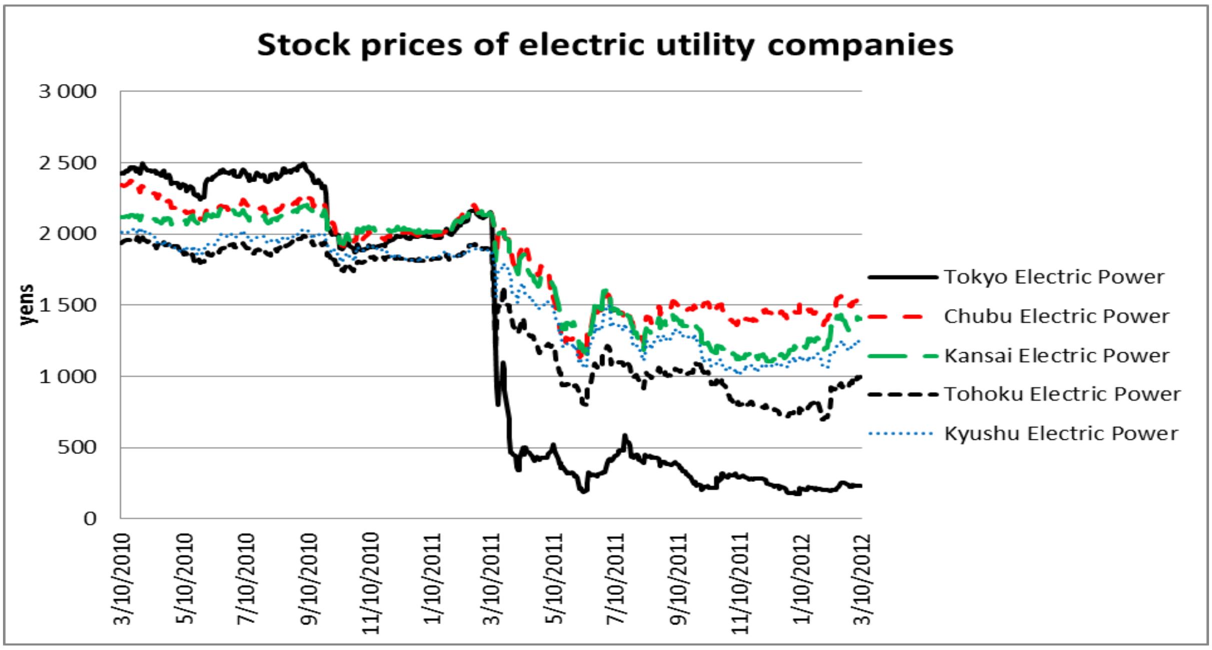

Figure 1: Stock prices of the main electric utility companies

Finally, we complement this analysis with descriptive statistics about daily stock returns. At the industry level, the daily returns R_t are defined by $R_t = 100.\ln(P_t / P_{t-1})$, where P represents a stock price or market index. The descriptive statistics in Table 3 offer more details about the return characteristics of the seven sectors that we studied.

Table 3: Daily returns of industry indexes, 11/03/2010–10/03/2012

	TOPIX_100	TOPIX_500	Electric utility	Electronic appliances	Electronic equipment	Steel	Wholesale retailing	Pharma-ceuticals	Automobile
Average	-0.01513	-0.00906	-0.00161	-0.00077	-0.00030	-0.00072	0.00012	-0.00005	0.00016
Median	0.00000	-0.00015	0.00000	0.00000	0.00000	-0.00037	0.00000	0.00006	0.00000
Maximum	5.64719	5.10687	0.17068	0.06772	0.04862	0.08208	0.08808	0.02638	0.06591
Minimum	-7.43794	-10.2385	-0.17657	-0.09369	-0.09494	-0.12875	-0.07134	-0.06394	-0.07580
Std. Dev.	1.05651	1.25652	0.02756	0.01732	0.01577	0.01946	0.01692	0.00875	0.01532
Skewness	-0.8121	-1.1568	0.270	-0.430	-0.619	0.030	0.014	-1.033	-0.052
Kurtosis	11.07	12.7	16.10	5.79	7.03	7.95	5.84	8.63	4.52
J-B test	1477.0	2175.6	3742.5	186.5	387.0	533.6	176.1	783.7	50.7
H_0	rejected	rejected	rejected	rejected	rejected	rejected	rejected	rejected	rejected
p-value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Obs.	522	522	522	522	522	522	522	522	522

[φ] Rejected at a 10% significance level but not at a 5% significance level.

Over the two-year period, the average daily returns were negative in most industries except automotive and wholesale retailing, as the two TOPIX indexes indicate, because the market was bearish. The largest daily variations appeared in the electric utility industry, with a maximum daily increase of 17.06% and minimum value of –17.65%. Only the steel industry also experienced a daily price change greater than 10%: It dropped by 12.87%. The standard deviation of electric utility returns thus was approximately twice that of the other industries, which indicated clearly higher volatility.

In the return distribution, we found generally low skewness coefficients, with predominant negative returns (lack of symmetry in the distribution of returns). A slight predominance of negative returns also appeared in the pharmaceutical industry, though not in the electric utility sector. That is, despite the violence of the catastrophic shock, the number of negative daily returns did not dominate over the course of two years, which suggested that though the shock was significant, it did not dramatically change the structure of the returns. The kurtosis values were distinctly higher in the electric utility (16.10) than in other sectors (cf. next highest value 8.63), indicating the presence of several extreme returns after the earthquake. In all sectors, the return distributions consistently exhibited fatter tails than the Gaussian case.

With a standard Jarque-Bera (JB) test, we rejected the null hypothesis of normality of daily returns in all industries, particularly for the electric utility. Such a result is not surprising in itself, because non-Gaussian and heavy tail distributions are well-documented phenomena in international markets (Cont, 2001). Such distributions sometimes persist even after corrections of the returns for volatility clustering with a GARCH-type model (see Section 5).

When we distinguish two sub-periods,[2] to represent the eras before and after the earthquake, the normality tests again rejected the null hypothesis in all cases after the earthquake, whereas for the first sub-period, the null hypothesis could not be rejected for the automobile or electronic equipment industries.

We also studied the stock price changes for firms affected by the earthquake, to uncover any patterns after March 11, particularly in terms of volatility. The descriptive statistics for the electric utility companies demonstrated the importance of the change, especially in terms of decreases in the average and median returns across all firms. With an even larger measure than that for sectors, we found that electric companies' values exhibited more important outliers (unusually large maximum and minimum values after the catastrophe) more frequently (standard deviations three to four times higher than usual values—even eight times higher for TEPCO). Again, we thus detected long-lasting stock market characteristics, as confirmed by the kurtosis increases (cf. TEPCO, which already revealed a high value) and a skewness drop. Similar to many stock markets around the world, no firm exhibited a Gaussian distribution of returns, before or after the earthquake. Because the return series did not follow Gaussian distributions, we checked for autocorrelations to detect possible momentum effects.

3.2. Autocorrelation in stock returns

The first-order autocorrelation is defined as:

$$\rho = \frac{E\left[\left(R_t - E\left[R_t\right]\right)\left(R_{t-1} - E\left[R_{t-1}\right]\right)\right]}{\sigma_{R_t} \times \sigma_{R_{t-1}}} \tag{1}$$

where t indicates one trading day in the stock market. It is usually analyzed with the Ljung-Box (1978) test.

Table 4 shows that before and after the earthquake, the electric utility sector was the only one in which we must reject the null hypothesis of no autocorrelation at the 5% error level. This finding contrasts with most conventional situations, for which returns are not correlated and follow no trend. The only other industry that rejected the null hypothesis was wholesale retailing before the earthquake at the 10% error level. Therefore, even without the catastrophe, the electric utility industry index exhibited serial autocorrelation in its returns.

A closer look at the firm returns of the electric utility sector indicated that the autocorrelation of returns surprisingly was higher before the catastrophe for four companies, whereas it increased after the disaster for one of them (Tohoku Electric Power). Tokyo Electric Power also exhibited long-lasting, significant return autocorrelations, such that the returns appeared to have strong momentum, which is "a quantitative signature of the well-known phenomenon of *volatility clustering*: large price variations are more likely to be followed by large price variations" (Cont, 2001, p. 230).

[2] Out of space considerations, we do not present the detailed statistics for the sub-periods here; they are available on request.

Table 4: Ljung-Box tests

	Before Earthquake		After Earthquake	
Index by Industry	Q-statistic	*p*	Q-statistic	*p*
Electric utility	38.830	0.038**	41.988	0.018**
Electronic appliances	25.330	0.444	25.306	0.445
Electronic equipment	27.939	0.311	18.670	0.813
Automobile	14.001	0.962	19.956	0.768
Steel	30.291	0.214	23.667	0.539
Wholesale retailing	36.358	0.066*	13.563	0.969
Pharmaceutical industry	22.651	0.598	14.386	0.955
TOPIX 100 index	29.643	0.238	18.620	0.815
TOPIX 500 index	23.378	0.556	19.415	0.777
Electric Utility Firms				
Chubu Electric Power	33.003	0.104*	29.046	0.218
Kansai Electric Power	34.727	0.093*	26.420	0.385
Kyushu Electric Power	39.861	0.030**	31.827	0.163
Tohoku Electric Power	22.820	0.588	35.551	0.079*
Tokyo Electric Power	50.116	0.002**	37.810	0.048**

* Null hypothesis rejected at the 10% significance level.
** Null hypothesis rejected at the 5% significance level.

4. Interdependence between stock returns indices

Interdependence can be analyzed through an investigation of causal relationships. To analyze the causal dependence between stock returns, we performed pairwise Granger-causality tests, before and after the earthquake. Consider two daily stock returns R_i and R_j that are stationary processes. Granger causality implies that in an observation, the cause occurs prior to its effects. Formally, R_i Granger-causes R_j if taking its past value into account provides a better prediction of the future value of R_j than would have been possible solely with the history of R_j. In practice, we consider a stationary,[3] bivariate, autoregressive system and suppose that each variable depends on its past values and the past values of the other variables in the system. In the first equation, we test the null hypothesis that R_j does not Granger-cause R_i (i.e., all coefficients of past values of R_j in the R_i equation are null). Next, we test the null hypothesis that R_i does not Granger-cause R_j.

We present two diagrams, for 2010–2011 and for the post-earthquake period. The direction of the arrows indicates causality between stock returns. That is, $R_i \rightarrow R_j$ indicates that R_i Granger-causes R_j, so we can reject the null hypothesis.

Before the earthquake, Figure 2 reveals that the stock returns of the electric utilities industry were endogenous, depending on the returns in four other sectors. The performance of the electricity sector thus was closely linked to the performance of other sectors that were upstream of it and that needed electricity for their activity. Only the pharmaceutical industry and steel sector did not directly influence the electric industry. However, the stock returns for the steel industry indirectly influenced the returns of electric utilities through two other sectors: electronic equipment and automobiles. In contrast, two stock return indices appeared

[3] A detailed analysis of the stationarity is provided in Appendix 2. It confirms that all stock returns were stationary.

strictly exogenous, namely, electronic appliances and the pharmaceutical industry. After the earthquake (Figure 3), the interactions between return indices changed substantially. The stock returns of the electric utilities industry no longer depended on other sectors, except for automobiles. We also observed Granger causality with feedback in seven cases, confirming the increased interdependence between returns after the earthquake.

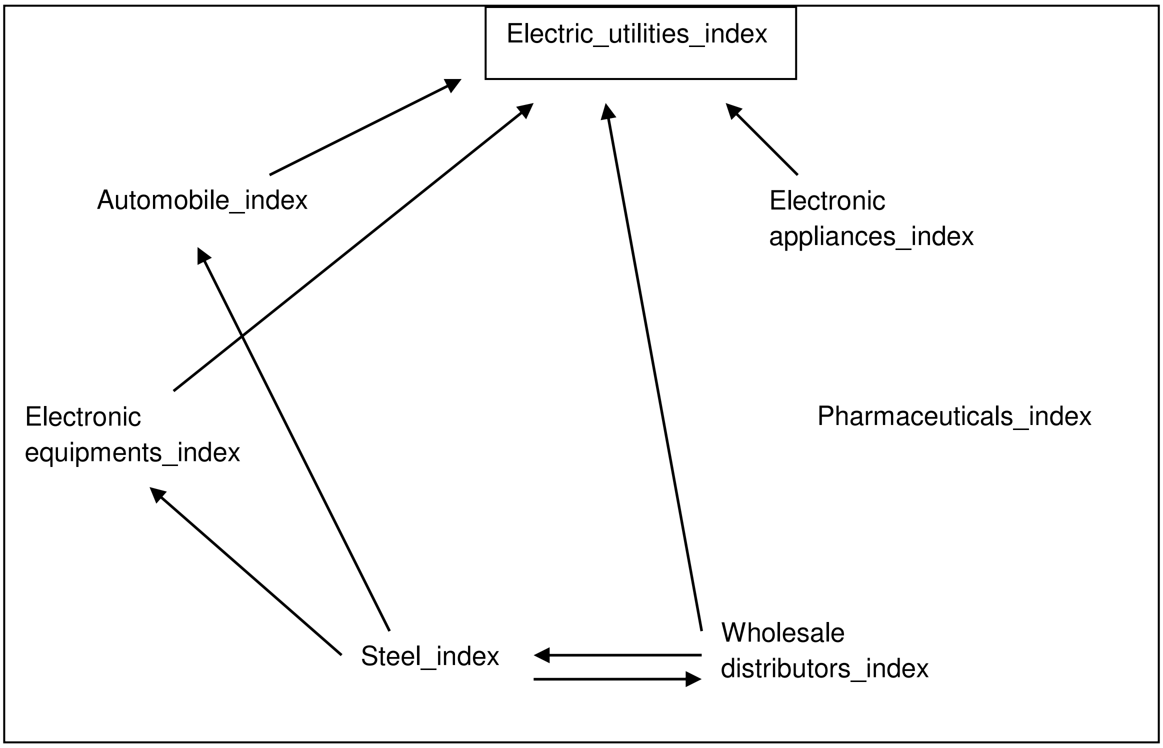

Figure 2: Causality relationships between stock return indices, before earthquake

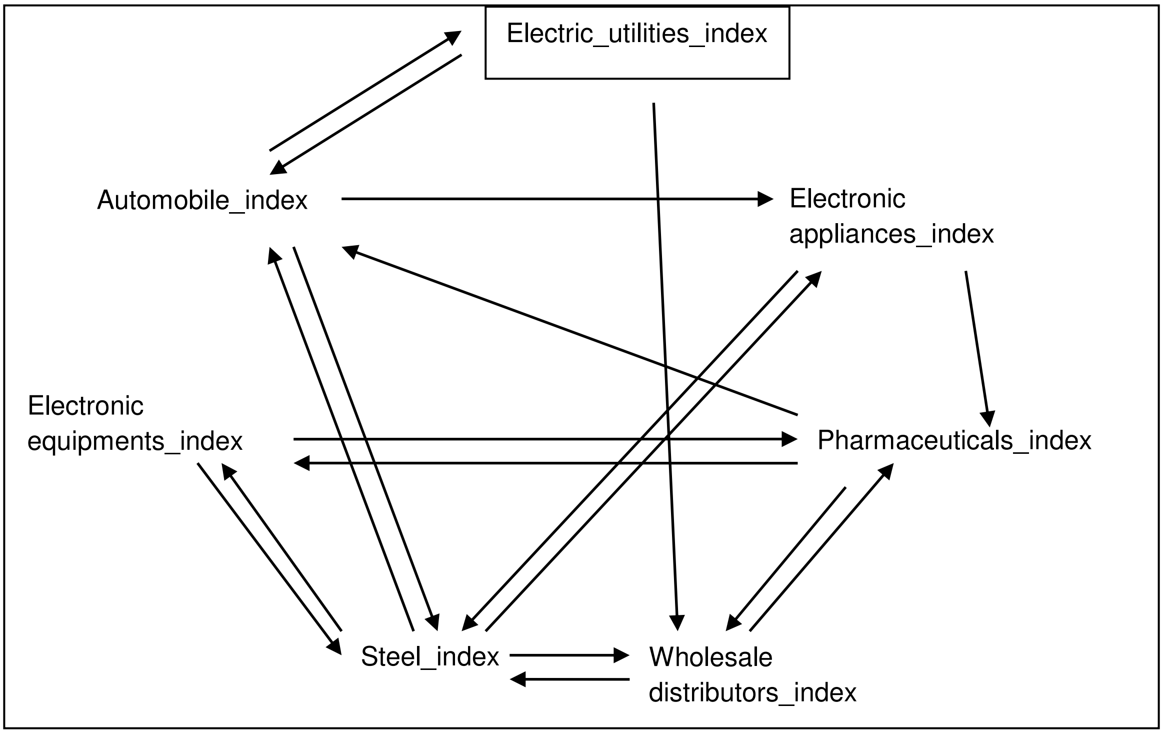

Figure 3: Causality relationships between stock return indices, after earthquake

These results confirm that the crisis mainly affected the electricity sector, and then the decline in equities spread to the entire market.

5. Volatility and dynamic in the correlations of stock returns

In a first step, we present univariate GARCH models to analyze the variance of the stock returns of different sectors and of different firms belonging to the electric sector. In a second step, we focus on the dynamic conditional correlation between TEPCO and other stock returns.

5.1. GARCH models

We tested an adjustment of return series with a generalized autoregressive conditional heteroskedasticity (GARCH) model (Bollerslev, 1986; Engle, 1982). Such models express the present volatility of assets as depending linearly on an α coefficient that represents dependence on the residuals of an underlying stationary process of return and a β coefficient that represents dependence on past volatility. To account for shocks during the period, we estimated three GARCH *(1,1)* specifications: a standard GARCH, the Engle (1982) EGARCH, and an asymmetric GARCH, also known as GJR-GARCH (Glosten, Jaganathan, and Runkle, 1993). The results in Appendix 3 reveal that in most estimations, the coefficients were highly significant, so the GARCH models performed well. In a comparison of log-likelihood values, we obtained higher values from the EGARCH for sectoral indices, except for electricity utilities, and from the GJR-GARCH for firms in the electric sector, except for Tohoku. From the EGARCH model, we gathered negative values for the parameter of asymmetry (ξ), confirming a negative relationship between volatility and return. In addition, we obtained positive and significant values for ξ from the GJR-GARCH models, suggesting an asymmetric impact in which negative shocks had a greater impact on conditional variance than positive shocks.

5.2. Dynamic volatilities

The results in the previous section revealed the characteristics of our GARCH models; we now turn to the evolution of daily volatility around the event. First, Figure 4 presents the patterns of the TOPIX 100 index (the results are similar for the TOPIX 500 and NIKKEI 225 indexes, so we do not display them here). The volatility jump was very large (more than three times its usual value) and occurred during a short time span; volatility returned to its pre-earthquake values after barely a month. The index's diversification explains this smoothing effect, in that some firms' activity does not depend heavily on electricity production.

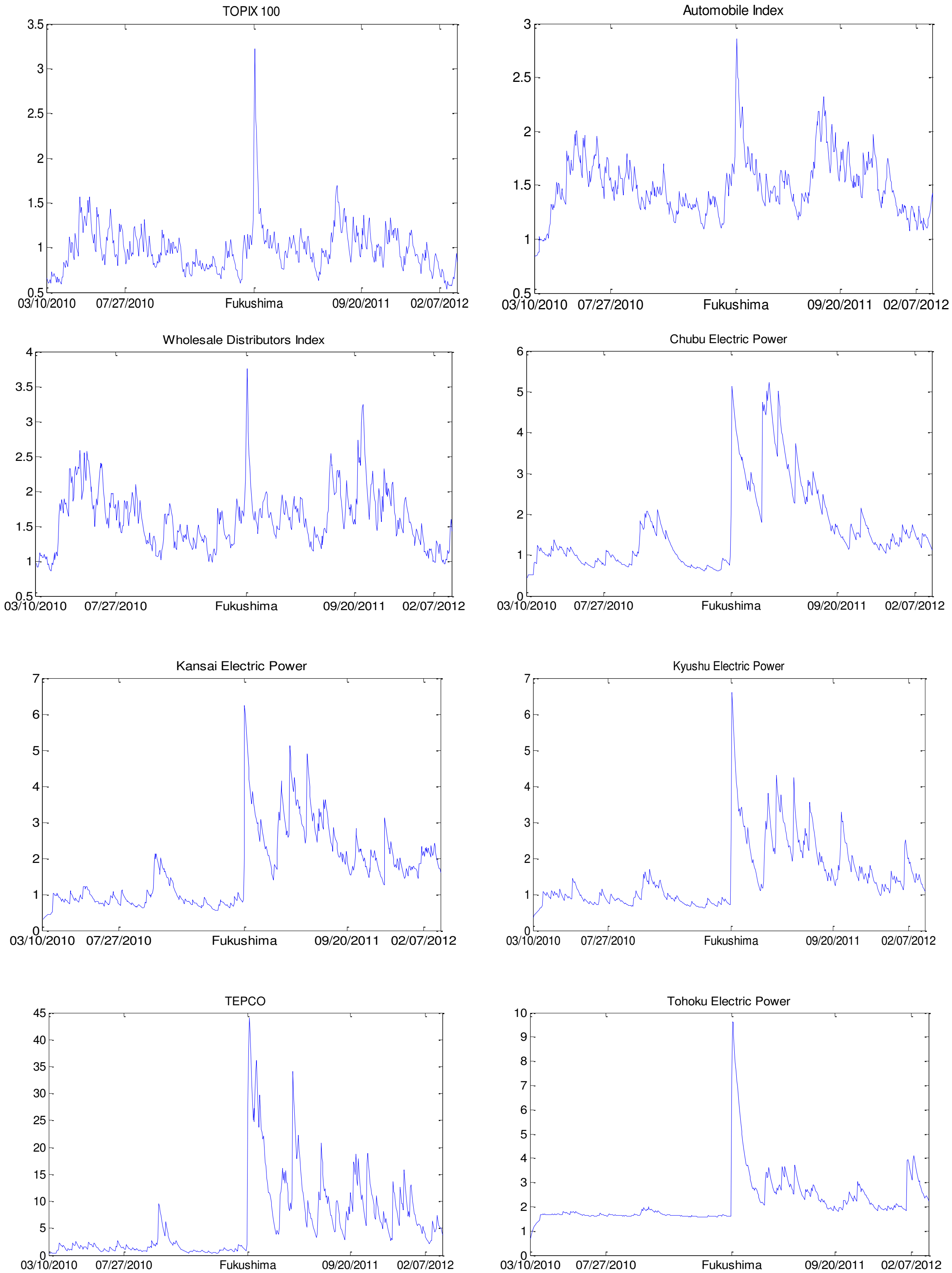

Figure 4: Plots of conditional standard deviations, EGARCH, and GJR-GARCH

Second, some sectors, such as automobiles and wholesale distributors, were not directly affected by the earthquake, so their volatility took more time (a little more than a month) to return to its usual level. Because an industry obviously is less diversified than a market index, the average volatility of any specific sector was higher (by about 1.5 times) than the index volatility. This trend appeared for both the automobile and wholesale retailing industries.

Third, some firms were directly stricken by the disaster, either through an immediate impairment of their production capacities (e.g., TEPCO) or because their future activity would require new security and cost considerations (e.g., other electric utility firms). The immediate increase of return volatility was clearer for these firms than it would be in other stock prices; the volatility values were five to six times higher than usual. One year after the disaster, the volatilities of TEPCO—and to a lesser extent, the volatilities of other firms of electric sector—had not recovered to their pre-earthquake values. Because TEPCO was the primary firm affected by this shock, we conducted a more detailed analysis of its return, to account for the possibility of regime switching.

5.3 The case of TEPCO

If the stock returns of TEPCO revealed regime switching after the earthquake, it would indicate volatility of both the stock and the correlations of other stocks on the Japanese market. We start by seeking regime switching in volatilities, with an assumption of Markov switching in GARCH (MS-GARCH) parameters. In a regime-switching model, some parameters may switch across different regimes or states of the world, according to a Markov process (Rey et al. 2014). Accordingly, we rely on the model proposed by Dueker (1997) and Klaassen (2002).

The MS-GARCH for the return R_t can be written as:

$$R_t|\psi_{t-1} \sim \begin{cases} f(\theta_t^{(1)}) \; with \;\; probability \; p_{1,t} \\ f(\theta_t^{(2)}) \; with \;\; probability \; (1-p_{1,t}) \end{cases} \tag{2}$$

where *f(.)* represents conditional distributions that can be Normal (*N*), Student's *t*, or a generalized error distribution (GED); and $\theta_t^{(i)}$ is the vector of parameters in the *i*-th regime, $\theta_t^{(i)} = (\mu_t^{(i)}, h_t^{(i)}, v_t^{(i)})$, for which μ is the conditional mean, h is the conditional variance, and v is the shape parameter of the conditional distribution.

In Table 5,[4] we demonstrate a clear distinction between the low and high volatility regimes for the two states. Figure 5 confirms these results; we observe regime switching after the earthquake, from a low volatility regime to a high volatility regime that persists for at least one year after the catastrophe.

[4] We realized these estimates using the MATLAB code developed by Marcucci (2005).

Table 5: Maximum likelihood estimates of MS-GARCH models with different conditional distributions

	MS-GARCH-N	MS-GARCH-t2	MS-GARCH-t	MS-GARCH-GED
δ_1	-0.9699**	0.0245	-0.4415*	2.32E-12
	(-2.124)	(0.473)	(-1.681)	(0.088)
δ_2	0.0159	-0.4421**	0.0256	-3.41E-14
	(0.375)	(-5.117)	(0.633)	(-0.039)
α_0^1	9.5537**	0.5997*	0.6103	1.2253**
	(9.863)	(1.653)	(0.107)	(35.32)
α_0^2	0.3464**	3.7620**	0.8829*	0.7534**
	(9.844)	(15.76)	(1.681)	(6.298)
α_1^1	0.0829**	0.1261	0.3910**	0.1820**
	(3.958)	(0.498)	(3.044)	(4.277)
α_1^2	0.00001	0.3782**	0.1761	0.2025**
	(1.11E-06)	(3.938)	(1.188)	(6.088)
β^1	0.7888**	0.2845**	0.6081**	0.8172**
	(25.54)	(6.204)	(4.940)	(19.22)
β^2	0.3263**	0.6209**	0.3077	0.2372**
	(9.135)	(6.777)	(0.886)	(2.087)
P_{11}	0.9647**	0.9980**	0.9980**	0.9980**
	(106.45)	(399.71)	(344.82)	(325.39)
P_{22}	0.9743**	0.9980**	0.9980**	0.9980**
	(128.03)	(392.86)	(433.57)	(337.52)
v_1		2.9390**	2.4780**	0.5944**
		(6.602)	(15.65)	(13.82)
v_2		2.4520**		
		(15.22)		
Log(L)	-1202.9969	-1132.4467	-1132.8110	-1127.8220

Notes: The t-statistics in parentheses were calculated with asymptotic standard errors. N = Normal, t and t2 = Student errors, and GED = generalized error distribution. *Log(L)* is the log-likelihood value.

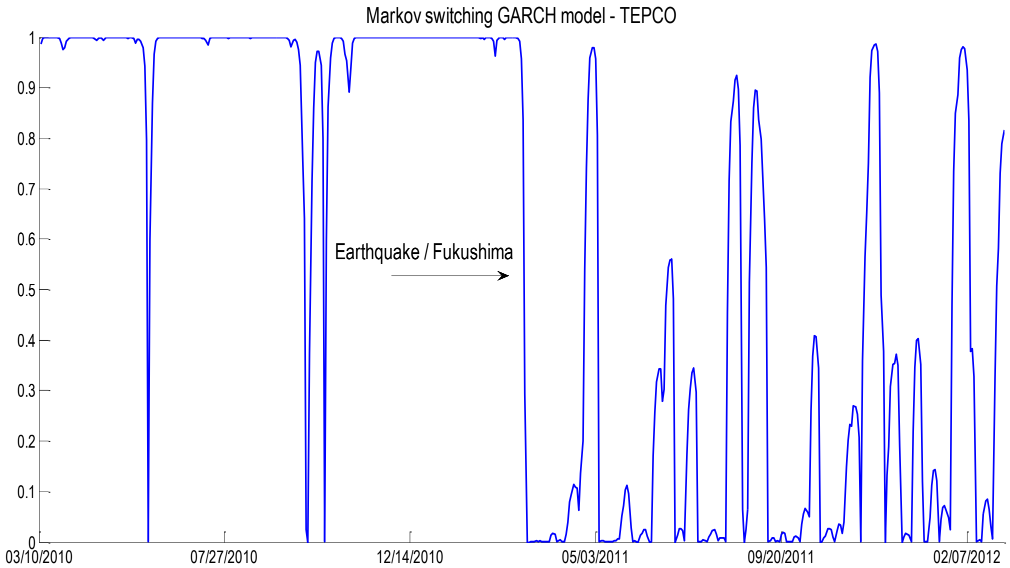

Figure 5: Smoothed probabilities of the low volatility regime for a two-state model

Next, we addressed the potential conditional correlation of TEPCO stock with Kyushu Electric Power and with Tohoku Electric Power, using the regime-switching dynamic correlation model of Pelletier (2006)[5]. 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 consider two states marked by low and high conditional correlations. According to Figure 6, the state probability between TEPCO and Kyushu Electric Power was relatively stable for the period, at around 50%, except on the date of the earthquake. This model can be reduced to a single-state model. Similar observations arose for the correlations between TEPCO and other firms in the electric sector,[6] with the exception of Tohoku Electric Power.

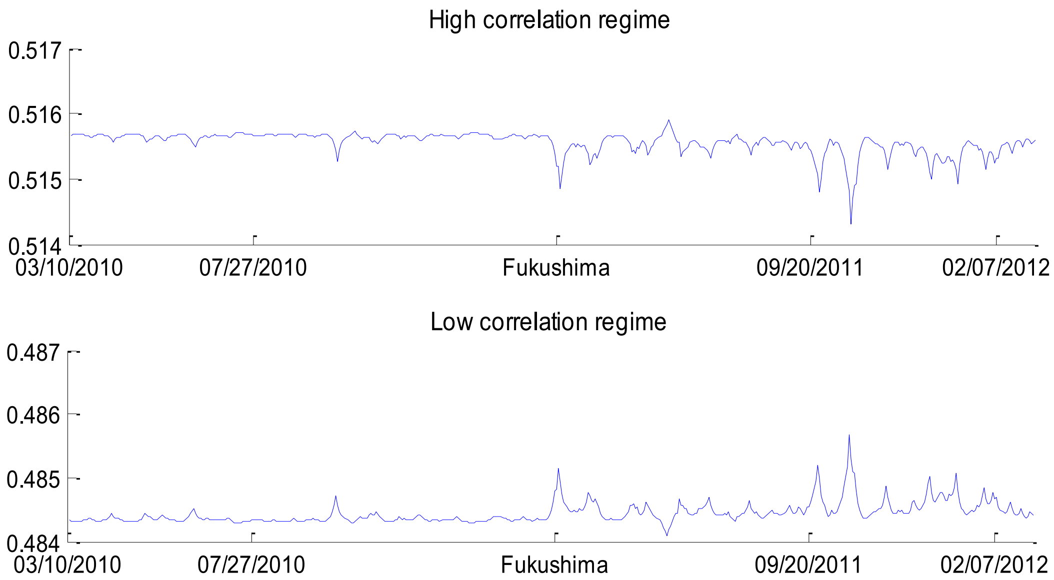

Figure 6: Smoothed probabilities of the two-regime regime-switching dynamic correlation model for TEPCO and Kyushu Electric Power

For Tohoku, we instead observed a regime switch after the earthquake (Figure 7), indicating a disconnection in the stock returns. This surprising result may be explained by reconsidering the firms' strategies for protecting against risks. That is, most firms, and particularly TEPCO, believed that their existing protections against tsunamis were sufficient. In contrast, Tohoku Electric Power adopted a distinct strategy:

> When the first unit was built in the 1970s, the site elevation of the station was set as 14.8 meters above sea level. A literature review and interview surveys revealed that the maximum tsunami height at the Onagawa site was estimated to be about 3 meters, but the 14.8 meter site elevation was considered appropriate (Ishiwatari and Sagara, 2012, p. 12).

Therefore, the markets appropriately differentiated between Tohoku Electric Power, with its much higher elevation, and other firms in the sector.

---

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

[6] The graphs for the other firms are available on request.

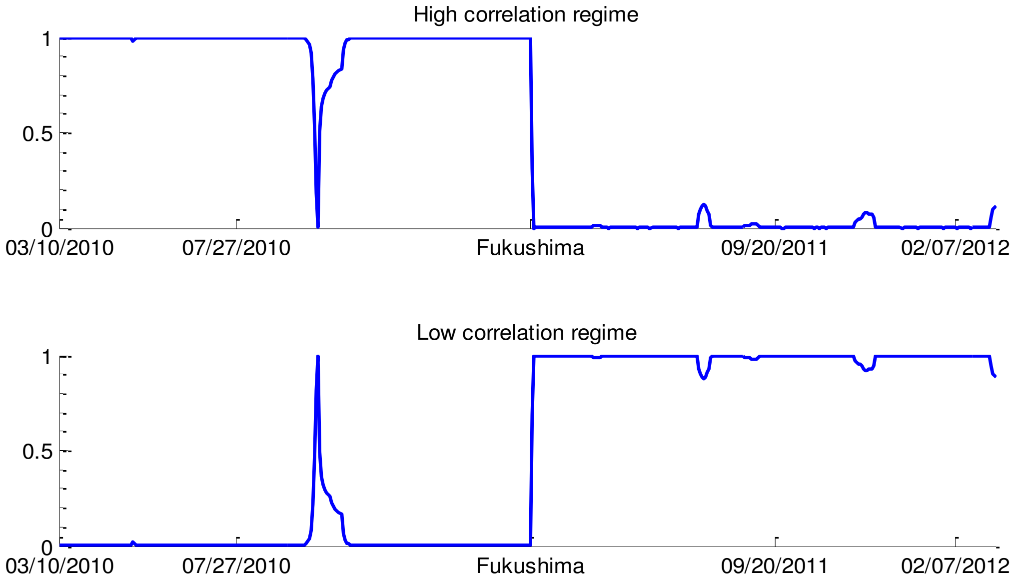

Figure 7: Smoothed probabilities of the two-regime regime-switching dynamic correlation model for TEPCO and Tohoku Electric Power

6. Conclusion

The massive earthquake that hit Japan in 2011 was unprecedented in scale, mainly because it was accompanied by a tsunami and a nuclear disaster. A collapse in the stock prices of the companies directly affected by this phenomenon may hinder sustainable economic activity, because the traditional financing channels for investments were blocked. Through its effects on the Japanese financial market, we study the economic impacts of the earthquake.

In particular, we studied the stock return behaviors of major industries and major companies in each industry, with a particular focus on the electricity sector. We chose to study the behavior of stock prices and compare them for the year prior to the disaster and then the year following the disaster. These analyses provide three notable results:

1. During 2010–2011, the power sector was under the influence of other sectors, whereas after 2011, it became dominant and even Granger-caused other sectors.
2. Higher volatility marked the Japanese stock market index a few weeks after the earthquake, especially among firms in the electric sector.
3. According to an empirical analysis of TEPCO's stock returns, regime switching occurred, such that TEPCO moved from a low volatility state before the earthquake to a high volatility state after. Although we did not observe regime switching in the conditional correlation between TEPCO and the TOPIX 100 index, we clearly established regime switching between TEPCO and Tohoku Electric Power, likely due to the tsunami mitigation plan adopted and implemented by Tohoku.

A related point involves the general impossibility of predicting natural disasters. The historical locations of massive earthquakes reveal the inaccuracy of predictions by authorities. For three decades, major earthquakes have occurred in areas that had been denoted "less risky" (Stein et al. 2011). As Stein et al. (2012, p. 24) note: "The hazard maps predict than a

0.1% probability of shaking with intensity '6-lower' (on the Japan Meteorological Agency intensity scale) in the next 30 years. In other words, such shaking was expected on average only once in the next 30/0.001 or 30,000 years. However, within two years, such shaking occurred." Accordingly, it seems essential to obtain "a better quantification of the uncertainties in estimating the occurrence and effects of such extreme events and the resulting losses, from both a societal and an economic perspective" (Stein and Stein, 2014, p. 24).

References

Bollerslev, G. (1986) "Generalized autoregressive conditional heteroskedacticity" *Journal of Econometrics* **31**, 307-327.

Bai, J and P. Perron (1998) "Estimating and testing linear models with multiple structural changes" *Econometrica* **66**, 47-78.

Bai, J and P. Perron (2003) "Computation and analysis of multiple structural change models" *Journal of Applied Econometrics* **18**, 1-22.

Billio, M and M. Caporin (2005) "Multivariate Markov switching dynamic conditional correlation GARCH representations for contagion analysis" *Statistical Methods and Applications* **14**, 145-161.

Chang, S.E. (2000) "Disasters and transport systems: loss, recovery and competition at the Port of Kobe after the 1995 earthquake" *Journal of Transport Geography* **8**, 53-65.

Cont, R. (2001) "Empirical properties of asset returns: stylized facts and statistical issues" *Quantitative Finance* **1**, 223-236.

Davis, D.R. and D.E. Weinstein (2002) "Bones, bombs, and break points: The geography of economic activity" *American Economic Review* **92**, 1269-1289.

Davis, D.R. and D.E. Weinstein (2008) "A search for multiple equilibria in urban industrial structure" *Journal of Regional Science* **48**, 29–65.

De Bondt, W.F.M. and R.H. Thaler (1985) "Does the stock market overreact?" *Journal of Finance* **40**, 793-805.

De Bondt, W.F.M. and R.H. Thaler (1987) "Further evidence on investors overreaction and stock market seasonality" *Journal of Finance* **42**,557-581.

Dueker, M.J. (1997) "Markov switching in GARCH processes and mean-reverting stock-market volatility" *Journal of Business & Economic Statistics* **15**, 26-34.

Elliott, G., Rothenberg, T. J. and J.H. Stock (1996) "Efficient Tests for an Autoregressive Unit Root", *Econometrica,* **64**, 813-836.

Engle, R.F. (1982) "Autoregressive conditional heteroskedasticity with estimates of the variance of United Kingdom inflation" *Econometrica* **50**, 987-1007.

Fama, E.F. and K.R. French (1993) "Common risk factors in returns on stocks and bonds" *Journal of Financial Economics* **33**, 3-56.

Glosten, L.R., Jaganathan, R. and D.E. Runkle (1993) "On the relation between the expected value and the volatility of the nominal excess return on stocks" *Journal of Finance* **48**, 1779-1801.

Gordon, P., Moore, J., Richardson, H., Shinozuka, M., An, D. and S. Cho (2004) "Earthquake disaster mitigation for urban transportation systems: An integrated methodology that builds on the Kobe and Northridge experiences" in *Spatial and Economic Impacts of Natural Disasters* by Y. Okuyama and S. E. Chang, Eds., Springer: Berlin, 205-232.

Ishiwatari, M. and J. Sagara (2012) "Structural measures against tsunamis" Knowledge note 1-1, Cluster 1: Structural Measures, The World Bank.

Klaassen, F. (2002) "Improving GARCH volatility forecasts with regime-switching GARCH" *Empirical Economics* **27**, 363-394.

Ljung, G.M. and G.E.P. Box (1978) "On a measure of lack of fit in time series models" *Biometrika* **66**, 67–72.

Lumsdaine, R.L. and D.H. Papell (1997) "Multiple trend breaks and the unit root hypothesis" *Review of Economics and Statistics* **79**, 212-218.

Ma, J., Pagan, J.A. and Y. Chu (2009) "Abnormal returns to mergers and acquisitions in ten Asian stock markets" *International Journal of Business* **14**, 235-250.

Marcucci, J. (2005) "Forecasting stock market volatility with regime-switching GARCH models" *Studies in Nonlinear Dynamics & Econometrics* **9**, 1-55.

Pelletier, D. (2006) "Regime switching for dynamic correlations" *Journal of Econometrics* **131**, 445-473.

Rey, C., Rey, S. and J.-R. Viala (2014) "Detection of high and low states in stock market returns with MCMC method in a Markov switching model," *Economic Modelling* **41**(C), 145-155.

Shirakawa, M. (2011) "Great East Japan Earthquake: Resilience of society and determination to rebuild" Bank of Japan, April.

Stein, S., Geller, R. and M. Liu (2011) "Bad assumptions or bad luck: Why earthquake hazard maps need objective testing" *Seismological Research Letters* **82**, 623-626.

Stein, S., Geller, R. J. and M. Liu (2012) "Why earthquake hazard maps often fail and what to do about it" *Tectonophysics* **562-563**, 1–25.

Stein, J.L and S. Stein (2012) "Formulating natural hazard policies under uncertainty" *SIAM News* **45**, 24-25.

Stein, J.L. and S. Stein (2014) *Playing against Nature: Integrating Science and Economics for Cost-Effective Natural Hazard Mitigation*, Wiley-Blackwell Publications.

Wong, M.C.S. (1997) "Abnormal stock returns following large one-day advances and declines: Evidence from Asia-Pacific markets" *Financial Engineering and the Japanese Markets* **4**, 171–177.

Ziobrowski, A.J., Cheng, P., Boyd, J.W. and B.J. Ziobrowski (2004) "Abnormal returns from the common stock investments of the US Senate" *Journal of Financial and Quantitative Analysis* **32**, 661-676.

Appendix 1: Firms in the industry indexes

Electronic appliances: Fujifilm Holdings, Nikon Corp., Sharp Corp., Sony Corp.
Automobiles: Denso, Honda, Nissan, Suzuki, Toyota
Electronic equipment: Canon Inc., Hitachi Ltd., Keyence Corp., Kyocera Corp., Mitsubishi Electric Corp., NEC Corp., Panasonic Corp., Ricoh CO Ltd., Toshiba Corp.

Wholesale retailing: Itochu Corp., Marubeni Corp., Mitsubishi Corp., Mitsui & Co Ltd., Sumitomo Corp.
Pharmaceutical: Astellas, Daiichi Sankyo, Eisai Co., Takeda
Electric utility: Chubu, Kansai, Kyushu, TEPCO, Tohoku
Steel: JFE Holdings, Kobe Steel Ltd., Nippon Steel Corp., Sumitomo Metal Industries

Appendix 2: Granger causality tests

We retained a stationary bivariate variance autoregressive (VAR) model, with *l* lags, written as:

$$R_{it} = \sum_{k=1}^{m} \alpha_k R_{it-k} + \sum_{k=1}^{m} \beta_k R_{jt-k} + u_{it}, \text{ and} \tag{A1}$$

$$R_{jt} = \sum_{k=1}^{m} \gamma_k R_{it-k} + \sum_{k=1}^{m} \delta_k R_{jt-k} + u_{jt},$$

where $l = 1, \dots, m,$ and u_i and u_j are independently and identically distributed. For each equation in the VAR, we retain the Wald-statistics for the joint significance of each of the other lagged endogenous variables in that equation. The null hypothesis is that R_j does not Granger-cause R_i in the first equation ($\beta_1 = \ldots = \beta_m = 0$) and that R_i does not Granger-cause R_j in the second equation ($\gamma_1 = \ldots = \gamma_m = 0$).

To verify the stationarity of the stock returns we proceed to unit root tests. But, to the extent that significant events occurred during this period, it is possible that breaks appeared in these returns. So in a first step, we test the presence of breaks. Following Bai and Perron (1998, 2003), we consider a multiple linear regression with *m* breaks:

$$R_t = x_t^{'}.\beta + z_t^{'}.\delta_r + u_t, \qquad t = T_{r-1}+1,\dots,T_r \tag{A2}$$

for $r = 1, \dots, m+1$. The breaks ($T1,\dots, Tm$) are treated as unknown. x_t (p x 1) and z_t (q x 1) are vectors covariates. In addition, since $T = 522$ we use a trimming $\varepsilon = 0.05$. We consider $p = 0$ and we present the estimation of the model in two cases; first, with only a constant as regressor (i.e. $z_t = \{1\}$); second for an *AR(1)* structure of the model (i.e. $z_t = \{1, R_{t-1}\}$). We use the sup*F* type test of no structural break $m = 0$ versus $m = r$ breaks and the SupF_T ($\ell + 1 \mid \ell$) test of ℓ versus $1 + \ell$ breaks. So, the estimation of the number of breaks is realized using the sequential (noted seq.) method suggested by Bai and Perron, supplemented by the use of the Bayesian Information Criterion (BIC) and a modified Schwarz criterion (LWZ). The results are presented in Table A2.1. If one considers the two estimates of the model A2, it is only for the stock return of the Electric Utilities index, and in the case of the autoregressive model, that the three tests and criteria used conclude to the presence of one break. In all other cases the BIC and LWZ criteria and the sequential test don't give convergent results.

So in a second step, considering the uncertainty on the presence of breaks, we choose to use two unit root tests, a test with break developed by Lumsdaine and Papell (LP, 1997) and a test without break proposed by Elliott, Rothenberg and Stock (ERS, 1996).

First, we test the presence of unit roots in a model with a break, using LP test that adopts a modified version of the augmented Dickey-Fuller test with two endogenous breaks. The model of stock returns (*R*) then can be written as:

$$\Delta R_t = \mu + \beta.t + \theta.DU_{1t} + \gamma.DT_{1t} + \omega.DU_{2t} + \psi.DT_{2t} + \alpha.R_{t-1} + \sum_{i=1}^{k} c_i.\Delta R_{t-i} + \varepsilon_t ,$$

where DU_1 and DU_2 are dummy variables that capture structural changes in the intercept, and DT_1 and DT_2 are two other dummy variables that capture shifts in the trend variable, at times TB_1 and TB_2, respectively. The optimal lag length (k) is determined on the basis of a general-to-specific approach (t-test, $k_{max} = 8$). We consider the unit-root hypothesis that $\alpha = 0$. For all indices, the null hypothesis is rejected at the 1% level, confirming the stationarity of *R*.

Second, ERS propose an efficient test, modifying the Dickey-Fuller test statistic using generalized least squares (GLS). Results presented in Table A2.3 confirm that in all cases the unit root hypothesis is rejected.

Regard these findings we test for causality in a bivariate VAR with the model A1.The optimal lag is determined using both the Akaike and standard information criteria. In all cases, they conclude at 0 or 1 lag, depending on the criterion. We chose to estimate all bivariate VAR models with 1 lag; the detailed results (i.e., F-statistics) are available on request.

Table A 2.1: Bai and Perron estimate results for the number of breaks

Specifications							
	q=1; p=0		$z_t = \{1\}$	$\varepsilon = 0.05$		*m=4*	
Index by industry	Automobile	Wholesale distrib.	Steel	Pharma-ceuticals	Electronic appliances	Electric utilities	Electronic equipments
SupF_T (1)	7.35	4.62	4.20	9.66[b]	4.57	3.34	7.03
SupF_T (2)	4.93	4.69	4.41	8.22	4.72	1.31	5.04
SupF_T (3)	5.01	4.07	1.51	5.85	4.22	2.73	5.50
SupF_T (4)	3.13	5.70	2.26	4.81	4.23	2.01	2.71
SupF_T (2 | 1)	2.09	5.31	4.72	6.82	1.75	4.31	7.59
SupF_T (3 | 2)	4.66	2.89	2.77	2.55	3.18	5.01	6.63
SupF_T (4 | 3)	2.12	10.02	5.54	3.11	2.36	4.97	3.43
UDmax	7.35	5.70	4.41	9.66[b]	4.72	3.34	7.03
WDmax	7.35	7.61	4.83	9.66[b]	5.17	3.34	7.03
Number of breaks							
Seq.	0	0	0	0	0	0	0
LWZ	0	0	0	0	0	0	0
BIC	0	0	0	0	0	3	0

Specifications							
	q=2; p=0		$z_t = \{1, R_{t-1}\}$	$\varepsilon = 0.05$		*m=4*	
Index by industry	Automobile	Wholesale distrib.	Steel	Pharma-ceuticals	Electronic appliances	Electric utilities	Electronic equipments
SupF_T (1)	2.92	2.90	3.66	4.05	3.43	18.60[a]	3.57
SupF_T (2)	10.79	6.09	9.98	10.93	8.02	12.90[a]	4.58
SupF_T (3)	9.22	5.68	8.64	8.66	7.26	13.09[a]	4.95
SupF_T (4)	7.88	1.25	7.55	7.80	6.43	11.02[a]	4.71
SupF_T (2 | 1)	18.46[a]	9.20	16.09[a]	17.54[a]	12.45	6.78	5.53
SupF_T (3 | 2)	5.68	4.66	5.61	3.87	5.47	12.33	5.51
SupF_T (4 | 3)	3.60	4.41	3.95	4.83	3.72	4.31	3.82
UDmax	10.79	6.09	9.98	10.93	8.02	18.60[a]	4.95
WDmax	11.98	7.20	11.08	12.14	9.21	18.60[a]	6.28
Number of breaks							
Seq.	0	0	0	0	0	1	0
LWZ	0	0	0	0	0	1	0
BIC	2	0	2	2	2	3	0

Note: See the unpublished appendix of Bai and Perron (2003) for the critical values of different tests. http://people.bu.edu/perron/papers/tab-cv.pdf.

[a, b] Statistic significant at the 5% and 10 % levels, respectively.

Table A 2.2: Lumsdaine and Papell unit root tests of the stock returns

Sectors	Electric Utilities	Electronic Appliances	Electronic Equipments	Pharma-ceuticals	Automobile	Steel	Wholesale Distrib.
TB1	*03/11/11*	*07/08/11*	*07/01/10*	*02/21/11*	*02/17/11*	*02/17/11*	*07/02/10*
TB2	*07/21/11*	*10/28/11*	*07/26/11*	*10/19/11*	*07/08/11*	*08/01/11*	*10/05/11*
μ	-0.075	-0.132	0.642	-0.124	-0.254	-0.298	0.305
	(-0.229)	(-0.714)	(1.778)	(-1.112)	(-1.294)	(-1.154)	(0.741)
β	0.0004	0.0003	-0.019	0.001	0.003	0.002	-0.014
	(0.181)	(0.365)	(-2.553)	(1.306)	(1.873)	(1.106)	(-1.668)
θ	-2.918	-1.167	1.063	-0.299	-1.077	-0.862	1.258
	(-4.404)	(-2.662)	(2.713)	(-1.719)	(-2.942)	(-1.939)	(2.992)
γ	0.049	0.023	0.018	0.0003	0.009	0.007	0.011
	(4.718)	(2.740)	(2.410)	(0.192)	(1.714)	(1.182)	(1.347)
ω	-2.546	-1.352	-0.454	-0.409	-1.235	-1.221	0.816
	(-3.718)	(-2.594)	(-1.459)	(-1.858)	(-3.260)	(-2.559)	(2.188)
ψ	-0.043	-0.009	0.007	0.006	-0.003	0.001	0.002
	(-3.899)	(-0.915)	(2.389)	(1.993)	(-0.593)	(0.202)	(0.427)
α	-0.856 [a]	-0.979 [a]	-0.974 [a]	-1.017 [a]	-1.075 [a]	-1.125 [a]	-1.083 [a]
	(-19.71)	(-22.26)	(-22.11)	(-23.12)	(-17.48)	(-11.37)	(-12.78)
k	0	0	0	0	1	4	3

Model with breaks in intercept only

Sectors	Electric Utilities	Electronic Appliances	Electronic Equipments	Pharma-ceuticals	Automobile	Steel	Wholesale Distrib.
TB1	*02/22/11*	*07/02/10*	*08/25/10*	*07/20/10*	*02/17/11*	*08/01/11*	*07/05/10*
TB2	*06/10/11*	*09/26/11*	*10/06/11*	*11/22/11*	*07/08/11*	*11/21/11*	*10/06/11*
μ	0.106	-0.2466	0.0235	-0.0738	-0.4877	-0.1738	-0.1805
	(0.360)	(-1.255)	(0.149)	(-0.793)	(-2.795)	(-0.838)	(-0.933)
β	-0.0010	-0.0022	-0.0023	-0.0007	0.0044	0.0005	-0.0027
	(-0.504)	(-2.203)	(-2.200)	(-1.614)	(3.793)	(0.504)	(-2.798)
θ	-1.0922	0.6922	0.5229	0.2455	-0.9188	-0.6221	0.8300
	(-2.319)	(2.339)	(1.911)	(1.712)	(-3.382)	(-1.9237)	(2.850)
γ							
ω	1.5267	0.7283	0.6659	0.3808	-0.5256	0.9889	0.9474
	(3.462)	(2.514)	(2.432)	(2.592)	(-2.116)	(3.059)	(3.335)
ψ							
α	-0.8373 [a]	-0.9733 [a]	-0.9617 [a]	0.3808	-1.0545 [a]	-1.1110 [a]	-1.0737 [a]
	-19.28)	(-22.11)	(-21.88)	(2.592)	(-17.20)	(-11.32)	(-12.71)
k	0	0	0	0	1	4	3

Notes: The critical values are respectively for the two models: -7.19 (1%). -6.75 (5%). and -6.48 (10%); -6.74 (1%). -6.16 (5%) and -5.89 (10%). *t-statistics* in parentheses. [a] Significant at the 1% level.

Table A 2.3: Elliott-Rothenberg-Stock DF-GLS unit root tests of the stock returns

Sectors	Electric Utilities	Electronic Appliances	Electronic Equip.	Pharma-ceuticals	Automobile	Steel	Wholesale Distrib.
Lag (a)	0	6	6	6	0	3	5
t-stat.	-18.40***	-3.32***	-3.81***	-2.33**	-18.68***	-7.78***	-4.34***

Notes: (a) Optimal lag determined by *SIC* criterion. Critical values are respectively -2.56 (1%), -1.94(5%) and -1.61(10%).
***, ** Significant at the 1% level and the 5% level.

Appendix 3: GARCH models

To compute volatility, we used 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, we tested for the presence of ARCH effects in the residuals of the stock return model, $R_t = \mu + \varepsilon_t$. With the 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.

Volatility V was computed with the standard deviation of daily returns in a GARCH model, defined by $V = \sqrt{h}$, where h is the conditional variance derived from a GARCH(p, q) model, such as:

$$h_t = \delta + \sum_{i=1}^{q} \alpha_i . \varepsilon_{t-1}^2 + \sum_{j=1}^{p} \beta_j . h_{t-1} \tag{3}$$

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

The EGARCH method (Engle, 1982) can be advantageous for modeling exchange rate uncertainty for two reasons. First, it allows for asymmetry in the responsiveness of exchange uncertainty to the sign of shocks (innovation). Second, unlike the GARCH specification, the EGARCH model, as specified in logarithms, does not impose negativity constraints on parameters. We retain the following specification:

$$Logh_t = \delta + \sum_{i=1}^{q} \alpha_i \left| (\varepsilon_{t-i}) / (\sqrt{h_{t-i}}) \right| + \sum_{k=1}^{r} \xi_k \left[(\varepsilon_{t-k}) / (\sqrt{h_{t-k}}) \right] + \sum_{j=1}^{p} \beta_j Logh_{t-1} \tag{4}$$

The GJR-GARCH model includes leverage terms for modeling asymmetric volatility clustering. Large negative changes are more likely to be clustered than positive changes:

$$h_t = \delta + \sum_{i=1}^{q} \alpha_i . \varepsilon_{t-1}^2 + \sum_{i=1}^{q} \xi_i . I_{t-i}^{-} . \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j . h_{t-1} \tag{5}$$

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

Table A3.1: ARCH effects tests

Stock Return	Sectoral Indices					
	Lags	$LM = T.R^2$	p-value	Lags	$LM = T.R^2$	p-value
Electric utility	1	40.798	0.000	6	60.568	0.000
Electronic appliances	1	1047.304	0.000	6	107.522	0.000
Electronic equipment	1	92.279	0.000	6	95.368	0.000
Automobiles	1	42.586	0.000	6	77.632	0.000
Wholesale retailing	1	39.979	0.000	6	61.763	0.000
Pharmaceuticals	1	6.674	0.010	6	8.797	0.117
TOPIX 100	1	195.053	0.000	6	219.812	0.000
TOPIX 500	1	111.554	0.000	6	128.152	0.000
Electric Sector Firms						
TEPCO	1	45.685	0.000	6	56.298	0.000
Kansai Electric	1	20.216	0.000	6	36.060	0.000
Chubu Electric	1	3.908	0.048	6	34.932	0.000
Tohoku Electric	1	176.267	0.000	6	189.778	0.000
Kyushu Electric	1	29.264	0.000	6	38.977	0.000

Table A3.2: GARCH models for electric utility sector firms

Variable	GARCH		EGARCH		GJR-GARCH	
	Coef.	*p*	Coef.	*p*	Coef.	*p*
TEPCO						
δ	0.061	0.00	-0.056	0.00	0.001	0.87
α	0.075	0.00	0.265	0.00	0.209	0.00
β	0.932	0.00	0.968	0.00	0.746	0.00
ξ			-0.110	0.00	1.203	0.00
Log(L)	*-1402.9*		*-1371.0*		*-1354.7*	
Kansai Electric						
δ	0.027	0.01	-0.226	0.00	0.029	0.00
α	0.207	0.00	0.362	0.00	0.047	0.04
β	0.828	0.00	0.964	0.00	0.863	0.00
ξ			-0.131	0.00	0.205	0.00
Log(L)	*-932.4*		*-924.2*		*-921.6*	
Chubu Electric						
δ	0.025	0.00	-0.133	0.00	0.025	0.00
α	0.131	0.00	0.208	0.00	0.005	0.65
β	0.884	0.00	0.982	0.00	0.906	0.00
ξ			-0.144	0.00	0.179	0.00
Log(L)	*-932.2*		*-924.5*		*-915.0*	
Tohoku Electric						
δ	0.361	0.00	0.051	0.00	0.321	0.00
α	0.086	0.00	-0.048	0.00	0.038	0.01
β	0.853	0.00	0.987	0.00	0.868	0.01
ξ			-0.062	0.00	0.074	0.00
Log(L)	*-1126.6*		*-1098.6*		*-1123.2*	
Kyushu Electric						
δ	0.068	0.00	-0.199	0.00	0.056	0.00
α	0.187	0.00	0.326	0.00	0.042	0.03
β	0.808	0.00	0.938	0.00	0.839	0.00
ξ			-0.161	0.00	0.205	0.00
Log(L)	*-890.9*		*-878.2*		*-879.1*	

Notes: *Log(L)* is the log-likelihood value. We consider only the case of normal errors.

Table A3.3: GARCH models for the sectoral index

Variable	GARCH		EGARCH		GJR-GARCH	
	Coef.	*p*	Coef.	*p*	Coef.	*p*
Electric utility						
δ	0.079	0.00	-0.113	0.00	0.046	0.00
α	0.099	0.00	0.291	0.00	0.038	0.01
β	0.908	0.00	0.955	0.00	0.814	0.00
ξ			-0.187	0.00	0.581	0.00
Log(L)	*-1116.6*		*-1090.3*		*-1080.8*	
Electronic appliances						
δ	0.161	0.02	-0.068	0.03	0.135	0.02
α	0.098	0.00	0.148	0.00	0.035	0.17
β	0.851	0.00	0.950	0.00	0.867	0.01
ξ			-0.104	0.00	0.101	0.00
Log(L)	*-1002.3*		*-996.1*		*-999.1*	
Electronic equipment						
δ	0.279	0.01	-0.041	0.12	0.157	0.01
α	0.113	0.00	0.128	0.01	0.019	0.36
β	0.773	0.00	0.926	0.00	0.879	0.00
ξ			-0.129	0.00	0.139	0.00
Log(L)	*-953.1*		*-945.4*		*-947.8*	
Automobiles						
δ	0.135	0.12	0.018	0.64	0.161	0.04
α	0.066	0.00	0.065	0.07	0.002	0.92
β	0.877	0.00	0.915	0.00	0.880	0.01
ξ			-0.112	0.00	0.098	0.00
Log(L)	*-948.4*		*-940.7*		*-943.2*	
Steel						
δ	0.401	0.00	-0.090	0.01	0.231	0.01
α	0.174	0.00	0.235	0.00	0.048	0.06
β	0.729	0.00	0.928	0.00	0.825	0.00
ξ			-0.092	0.00	0.141	0.00
Log(L)	*-1054.4*		*-1051.9*		*-1052.1*	
Wholesale retailing						
δ	0.212	0.01	0.012	0.63	0.131	0.00
α	0.098	0.00	0.076	0.02	0.029	0.07
β	0.826	0.00	0.924	0.00	0.905	0.00
ξ			-0.172	0.00	0.156	0.00
Log(L)	*-986.7*		*-973.4*		*-975.8*	
Pharmaceuticals						
δ	0.205	0.00	-0.192	0.00	0.159	0.00
α	0.192	0.00	0.164	0.01	0.003	0.93
β	0.545	0.00	0.807	0.00	0.671	0.00
ξ			-0.165	0.00	0.222	0.00
Log(L)	*-652.4*		*-647.7*		*-648.1*	
TOPIX 100						
δ	0.164	0.05	-0.074	0.04	0.129	0.00
α	0.144	0.00	0.082	0.08	0.049	0.17
β	0.697	0.00	0.880	0.00	0.805	0.00
ξ			-0.193	0.00	0.215	0.00
Log(L)	*-727.7*		*-717.3*		*-719.6*	

TOPIX 500						
δ	0.376	0.01	-0.044	0.25	0.347	0.01
α	0.151	0.00	0.116	0.01	0.074	0.04
β	0.585	0.00	0.834	0.00	0.667	0.00
ξ			-0.219	0.00	0.299	0.00
Log(L)	*-817.7*		*-807.3*		*-807.4*	

Note: *Log(L)* is the log-likelihood value. We consider only the case of normal errors.