Were Japanese firms affected differently by Fukushima based on their energy dependence?

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ABSTRACT (Portuguese)

O objetivo deste estudo é analisar o efeito dos japoneses de 2011 no preço das ações das empresas japonesas dependentes de energia. Como o terramoto foi seguido pelo acidente nuclear de Fukushima Daiichi, o sector energético japonês foi grandemente impactado, pelo que esperamos que o sentimento dos investidores em relação às empresas dependentes de energia também seja afectado. Descobrimos que o preço das ações das empresas que dependem da flutuação dos preços da energia diminuiu mais acentuadamente após a catástrofe do que o das empresas não dependentes. Contudo, o grau de dependência não parece importar. A segunda conclusão foi que as empresas cujos preços das ações acompanharam os preços da energia foram mais negativamente afetadas pela catástrofe. A nossa última conclusão foi que as empresas que operam em sectores habitualmente referidos como sectores de utilização intensiva de energia (Energia, Materiais, Industriais e Serviços Públicos) sofreram perdas no preço das acções no curto prazo, mas ganharam com o incidente a médio e longo prazo após o incidente.

ABSTRACT (English)

The purpose of this study is to analyse the effect of the 2011 Japanese on the stock price of Japanese energy-dependent firms. As the Earthquake was followed by the Fukushima Daiichi nuclear accident, the Japanese Energy sector was greatly impacted, hence, we expect investor sentiment regarding energy-dependent companies to be impacted as well. We found that the stock price of firms that are dependent on energy price fluctuation declined more sharply after the disaster than that of non-dependent firms. However, the degree of dependence does not seem to matter. The second, finding was that firms whose stock price moved along with energy prices were more negatively impacted by the catastrophe. Our last finding was that firms operating in sectors commonly referred to as energy-intensive sectors (Energy, Materials, Industrials and Utilities) suffered from stock price loss in the short run but gained from the incident in the medium and long term after the incident.

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1 Introduction

The purpose of this study is to extent previous studies on the Impact of the 2011 natural disaster of Fukushima on the Japanese stock market. It is indisputable that the event of the 11th of March 2011 has impacted the Japanese stock market with the Topix undergoing its largest since the 2008 crisis. While other papers such as Kawashima & Takeda (2012) or Lopatta K. & Kaspereit T.(2014) investigate how firms that own nuclear plants and firms that depend on nuclear energy have been impacted by the event, this paper will look at how the overall energy dependence of firms could have affected them following such event.

The effects of Natural disasters have long been recognized as significant events with the potential to deeply impact societies, economies, and financial markets worldwide. The growing frequency as well as the growing financial loss resulting from these calamities in recent decades have drawn increasing attention from researchers, policymakers, and investors alike. Among the various types of natural disasters, geophysical disasters stand out as particularly devastating events, capable of causing devastation to infrastructure, disrupting supply chains, and causing widespread economic turmoil.. A type of natural disaster that produces the most reaction to the financial market after Climatological and Biological calamities (Pagnottoni et All, 2022).

The seismic event that struck Japan on March 11, 2011, commonly referred to as the Great East Japan Earthquake or the Tohoku earthquake, shows the profound repercussions natural disasters can have on financial markets. With a magnitude of 9.0, this earthquake triggered a massive tsunami that inundated coastal areas, causing extensive damage to buildings, roads, and critical infrastructure. The human toll was devastating, with thousands of lives lost and many more displaced from their homes. However, for researchers, it presents a unique opportunity to analyse the effect of the biggest and, in terms of economic damage, the most expensive natural disaster to ever happen in the world.

Beyond its immediate humanitarian impact, the 2011 Japanese earthquake sent shockwaves through global financial markets, raising investor concerns and market volatility. As Japan's economy was the third largest economy at the time, disruptions in its economic activity reverberated across international markets, highlighting the intricate links between natural disasters and financial systems.

The aftermath of the 2011 earthquake serves as an intriguing case study for examining the relationship between natural disasters and stock market dynamics. In the wake of such catastrophic events, investors grapple with uncertainty regarding the short- and long-term implications for affected industries, companies, and the broader economy. Consequently, financial markets often experience heightened volatility as investors reassess risk exposures and adjust their investment strategies in response to evolving circumstances. Moreover, beyond its unprecedented magnitude, this earthquake was notably marked by the subsequent nuclear disaster, highlighting a previously neglected risk associated with nuclear-powered energy.

A particularly interesting area to look at when assessing the impact of natural disasters on financial markets is the vulnerability of specific industries and sectors to such events. In the case of the 2011 Japanese earthquake, the energy sector appears to be a central point of analysis due to its critical role in Japan's economy and its susceptibility to disruptions after such a disaster. Companies dependent on energy, such as utilities and manufacturers that rely heavily on electricity, faced operational challenges and supply chain disruptions, raising concerns about their financial performance and market valuations.

The study will be divided into two parts, the first part, will define what is considered energy dependence in the framework of this study and separate Japanese firms by category depending on their stock price reaction to energy prices. The second part of this report undertakes an event study to investigate the impact of the 2011 Japanese earthquake on the Japanese stock market, with a specific focus on energy dependence. The concept of event studies provides a robust framework for analysing the effects of natural disasters on financial markets. By examining market reactions surrounding significant events, researchers can assess the extent to which stock prices incorporate new information and reflect investors' expectations regarding future developments. Event studies offer valuable insights into the efficiency and resilience of financial markets in processing information and pricing assets in the face of unforeseen shocks.

By analysing abnormal returns before, during, and after the earthquake, this study aims to clarify the magnitude of the earthquake's effects on stock prices. Furthermore, by examining whether companies more dependent on energy were abnormally affected by the earthquake, this study seeks to contribute to our understanding of sectoral vulnerabilities to natural disasters and their implications for financial markets.

2 Literature review

The first part of the paper will try to define which of the companies in the sample are energy-dependent. Many previous papers try to find a relationship between stock price and energy price even if most of them focus on oil prices of renewable energy. For instance, Basher and Sadorsky(2006) used an international multi-factor model to analyse the impact of oil prices on emerging stock markets and found strong evidence that oil prices impact the stock price return in emerging markets. Joo & Park 2021, on the other hand, apply both quantile regression and quantile-on-quantile regression approaches to look at the impact of oil price volatility on the stock market of large oil-importing countries (including Japan), the majority of which are developed countries. They found that the effect of oil price volatility on the stock market depends on the condition of the market. When both the oil price volatility and the stock market return are low, increasing the volatility of the oil price has a negative effect. However, when the oil price volatility is also low but the stock return is high, increasing the volatility results in an increase in stock returns.

Overall, the large majority of the studies find a negative relation between oil price and stock return, when oil price increase, stock return tend to decrease (Sadorsky, 1999,Jones and Kaul, 1996,Basher and Sadorsky, 2006; Nandha and Faff, 2008; Masih et al., 2011; Cunado and de Gracia (2014); Ready (2018); Tchatoka et al., 2019,). Other studies found little or no impact (Apergis and Miller, 2009; Chen et al., 1986; Henriques and Sadorsky, 2008; Huang et al., 2017; Sukcharoen et al., 2014) showing that the significance of the impact depends on the affected market and the oil price shock in question.

Only a handful of studies found that the oil price and stock indices have a positive relationship for some periods, both studies found that this positive relation was stronger after the 2008 crisis, showing once again that these relations are influenced by the current market condition.

If many studies look at the relationship of oil price or natural gas on the stock market, very few look at the relationship between the price of other energies, namely electricity, coal or fuel with the stock market. Oberndorfer (2009) analysed stock returns of energy corporations from the Eurozone. And found that the gas market does not influence Eurozone energy stocks and that coal does but to a relatively low extent compared to oil price impacts. The papers conclude that oil price is the main indicator of energy price development in the European stock market.

The second part of the paper will conduct an event study based on the methodology described by A. Craig MacKinlay in his 1997 paper. Given the unprecedented nature of this event, numerous previous studies have already examined the impact of the 2011 Fukushima disaster on both micro and macro-economic levels, its financial implications nationally and internationally, as well as its short- and long-term effects. The study by Kawashima and Takeda (2012) is particularly relevant to this paper, as it analyzes stock market reactions for Japanese utilities and differentiates between the degree of affectedness, i.e., firms whose facilities were directly hit by the tsunami, and firms that operate or do not operate nuclear power plants. Another closely related study is the study by Lopatta & Kaspereit (2013) the study analyses how the Fukushima nuclear accident has affected the stock market returns, using the factor loadings from the Carhart (1997) 4-factor model and the idiosyncratic volatility of shares in energy firms. While the first one found that directly affected firms suffered both more stock market losses and an increase in both systematic and idiosyncratic risk. The second one extended the research by employing an international sample and exploring whether changes in the regulatory environment and the firm-specific commitment to nuclear and renewable energies are associated with the capital market's responses to the Fukushima Daiichi accident. They found that a firm’s degree of nuclear dependence affects how it is affected by the event, the more dependence, the more its share price was hit. Their other relevant finding was that investing in renewable energies does not eliminate decreases in share prices but does significantly alleviate the increase in market beta linked to this event.

Betzer et al. (2013) highlight the policy changes following the Fukushima disaster and examine their impact on shareholder wealth of energy firms and firms in the green economy. They find highly significant negative abnormal returns for German nuclear and conventional energy firms on the first trading day after the accident, while green economy firms experience highly significant positive abnormal returns. Analysis of foreign stocks reveals that French firms in the nuclear and conventional energy industry experienced a decline in stock prices on the day Germany announced its nuclear phase-out. Swiss nuclear and conventional energy firms experienced even higher negative returns, while non-nuclear, conventional Italian energy firms' stock prices remained virtually unchanged after the disaster. In the U.S. market, no significant stock movements were found in the aftermath of the Fukushima accident.

Mama and Bassen (2013) provide evidence of a contagion effect in the electric utility industry. They focus on intra-industry information transfers in Europe and Japan using the event parameter model. Conventional utilities in Japan and Europe incurred significant financial losses after the Fukushima disaster, and evidence of cross-boundary interdependencies in the electric utility industry is provided. Market value losses in Europe appear to have been short-lived, while in Japan, the shock seems to have been long-term. Furthermore, shifts in market model parameters are tested, revealing an increase in the systematic risk of conventional electric utilities and a decrease in the systematic risk of alternative electric utilities for the whole sample. For Europe, a decrease in the idiosyncratic risk of conventional utilities is documented, while for Japan, evidence suggests that idiosyncratic and systematic risks have risen since the accident.

Another study by Ferstl et al. (2012) examines the short- and medium-term impact on nuclear and alternative energy stock returns. Significant declines in stock prices for nuclear energy companies in France, Germany, and Japan are found on the first trading day after the accident. Results for their subsample of nuclear energy companies in the U.S. are not significant. For alternative energy companies, an inverse effect is observed. Increased volatility of Japanese nuclear stocks is noted, reflecting uncertainty about future regulatory intervention and policy concerning nuclear energy firms.

3 Methodology

3.1. Energy Dependence Definition

3.1.1. Sectorial Energy Dependence

This section will explain the methodology used to define energy dependence of Japanese firms in order to be used in the main part of the study, the event study of Fukushima. From previous literatures, it is apparent energy prices may affect the stock market differently depending on the sectoral affiliation of the respective corporation analysed, the overall state of the market or the corporation itself. To try and make up for it, we will take two approaches to define energy dependence. First, firms will classified as being energy dependent based on their sectorial affiliation, second, we will define companies' energy dependence based on their stock's reaction to energy price fluctuation using a quantile-based categorization of beta coefficients.

To classify energy dependence at the sectoral level, we used the Global Industry Classification Standard (GICS) framework developed by Morgan Stanley Capital International (MSCI) and Standard & Poor's. This framework classifies firms in 11 sectors, 25 industry groups, 74 industries and 163 sub-industries. The 11 sectors are separated between those with high energy dependency and those with lower energy dependency. What we call high-dependence sectors, are sectors that are characterized by their energy-intensive operation, where energy plays a crucial role in their production processes and service delivery.

For instance, we classify the Industrial, Materials, Utilities, and Energy sectors as highly energy-dependent. The industrial sector in 2011 accounted for 46% of total current end-use energy consumption in Japan (Takase & Suzuki, 2011), which is not surprising due to the nature of the sector. The materials sector involves industries such as Chemicals or Metals & Mining both industries that are recognized by the European Commission as being part of the Energy Intensive Industries ecosystem due to the need for high temperatures and extensive machinery. Utilities, which include electricity, gas, and water services, are fundamentally reliant on energy for power generation, transmission, and distribution. Lastly, the Energy sector, comprising oil, gas, and coal industries, with its intrinsic relation with energy is obviously listed as a high-dependency sector.

In comparison, the remaining GICS sectors (Consumer Discretionary, Consumer Staples, Health Care, Financials, Information Technology, Communication Services, and Real Estate), are not as energy intensive as the formers and will be classified as low energy dependence. Even though, for some of these sectors, the classification might be sensitive, they primarily involve service-oriented or less energy-intensive operations.

3.1.2. Quantile-based Categorization of Beta Coefficients

The second approach goes beyond the sectorial level and looks at energy dependency at the firm level and looks at how each firm is influenced by energy prices, regardless of its sectorial affiliation (see Appendix 1). To define de degree of energy dependence for each Japanese firm, we will use a simple Ordinary Least Square (OLS) regression on each stock price and divide the firms that are dependent on energy price fluctuation with a 5 percent significance level, into 3 categories and 3 sub-categories.

The equation for the OLS regression used is as follows:

$$R_{it} = \alpha + \beta_1 ECPI_{t-1} + \beta_2 JPEX_{t-1} + \beta_3 JCC_{t-1} + \beta_4 LNG_{t-1} + \beta_5 Coal_{t-1} + \varepsilon_{it} \qquad (1)$$

Where the dependent variable R_{it} represent the excess stock return of the in-sample company i at time t. The five independent variables are price returns at t-1 for the five proxies used as a benchmark for the Japanese's energy price (those 5 proxies will be explained in detail later in the Data section). Each monthly return was calculated from the previous month to the next as follows:

$$Rit = ln\left(\frac{Pit}{Pit} - 1\right) - Rf_t \qquad (2)$$

Where R_{it} is the monthly continuously compounded return for stock i on month t, P_{it} is the adjusted closing price for stocks on month t, P_{it-1} is the adjusted closing price for stock i on month t-1 and Rf_t is the monthly risk-free rate at time t.

To organize dependent firm into different degree of dependence, we use a Quantile-based Categorization of Beta Coefficients. It is a widely used way to sort groups based on dependence in finance or economic studies. Fama and French (1992) for instance, used it in their paper "The Cross-Section of Expected Stock Returns" to sort stocks into portfolios based on their beta coefficients to study the risk-return trade-off.

The firms are separated into low, moderate and high dependence based on the quantile of each beta as follows:

High Dependence: $\beta < 5p$ or $\beta > 95p$

Moderate Dependence: $\beta > 5p$ & $\beta < 25p$ or $\beta > 75p$ & $\beta < 95p$

Low Dependence: $\beta > 25p$ & $\beta < 75p$

To be classified into one of those groups, firms' stock prices need to be influenced by fluctuation in energy prices of one or more energy proxies.

This method allows for a nuanced understanding of how sensitive each company is to changes in energy prices. By dividing the companies into categories based on the 5th and 95th percentiles for high dependence, and intermediate percentiles for moderate and low dependence, we can clearly identify which companies are most and least affected by fluctuations in energy prices. This categorization helps in understanding the risk profiles and potential vulnerabilities of companies to energy market dynamics.

In addition to the 3 degrees of dependence, low, moderate and high, a sub-category was created for each group separating them into positive and negative values of the Beta. This was done to identify firms with a positive or negative relation to energy price fluctuation. This allows us to test if, in addition to a higher energy dependence, the direction of the dependence also plays a role. Depending on the firm and its main activity, some are found to have a positive correlation with one proxy for energy prices but a negative with another one, hence, being excluded from the negative/positive categorisation.

3.2. Event Study

3.2.1. Event study methodology

In this section, we will discuss the methodology of the main study of this paper. An event study assesses the effect of a particular event on a company's value (Mackinlay, 1997). Specifically, this method helps identify whether an unexpected event causes an abnormal stock price change – meaning the returns differ from what would be expected based on a certain model for normal returns. The foundational methodology, introduced by Ball and Brown (1968) and Fama et al. (1969), is still in use today. Since examining each event in isolation provides limited insight, the main focus is on analysing the average and cumulative average abnormal returns of the sample securities around the event's occurrence (Khotari and Warner, 2006).

Although there is no strict structure for conducting event studies, Mackinlay (1997) provides a general process that can be followed in seven parts. First, we need to define the event of interest and determine the period during which the stock prices of affected firms will be analysed, period called the event window. Then, establish the criteria used to decide which firms to include in the study and ensure that the sample is representative and relevant.

Next, define and compute the normal and abnormal returns (ARs) for the event. This can be done using different models such as the Market Model or the constant mean return model to calculate the normal returns. Afterwards, the estimation window has to be set, which is the period preceding the event window, to estimate the model parameters without the influence of the event.

Subsequently, calculate the abnormal returns and cumulative abnormal returns (CARs) during the event window. Once these calculations are complete, define the testing framework for ARs and CARs, including the null hypothesis and techniques for aggregating ARs. It is important to use tests to determine the statistical significance of ARs. Researchers need to be aware of the statistical assumptions and limitations of different tests, as the quality of test statistics heavily depends on the characteristics of the data.

Finally, present the empirical results, interpret the findings, and draw conclusions. This step involves analysing the data in the context of the hypothesis and the existing literature to provide insights and implications of the study.

3.2.2. Event and Estimation Window

In the case of a natural disaster like the Earthquake of Japan 2011, setting up the event date and event window for the study is pretty straightforward. Contrary to corporate announcements, a natural disaster cannot be predicted by, for instance, insider trading, making it almost irrelevant to set up and pre-event window as this one will most likely not be significant or impactful. It is true that some meteorologic incidents can to a certain extent be predicted and while Japan is a seismically active region and prone to earthquakes, the specific magnitude and timing of the Tōhoku earthquake were not predicted. There were no meteorological signs that could have indicated the impending disaster and the timeline of the event was as described here:

Figure 1Disaster Timeline

11 March

14:46 JST The earthquake occurred.

15:42 TEPCO made the first emergency report to the government.

19:03 The government announced nuclear emergency.

20:50 The Fukushima Prefecture Office ordered 2km radius evacuation.

21:23 The government ordered 3km evacuation and to keep staying inside buildings in the area of 3-10km radius.

12 March

05:44 The government ordered 10km radius evacuation.

18:25 The government ordered 20km evacuation.

15 March

11:01 The government ordered to keep staying inside buildings in the area of 20-30km from the plant.

25 March The government requested voluntary evacuation in the area of 20-30km.

https://world-nuclear.org/

As the earthquake happened at 14:46 Japanese Standard Time and the Japanese stock market was still open at that time, the event date is set to the 11th of March however, most of the impact of the catastrophe is expected to be felt in the stock market on the next opening day on March 14. The length of the event window is expressed as $L_1 = t_2 - t_1 + 1$. For the sake of the main study, two event windows of (0:2) and (0:10) will be defined from March 11 to March 15 and

March 11 to March 25. The post-event window is relatively small but incorporates all relevant incidents and as previous literature suggests, the shortest the event window, the less noise relative to confounding events.

As for the estimation window, it was set to $(t_3, t_4) = (-210, -10)$ where $t_3$is the initial date of the estimation window (21st of May 2010) and t_4 is the last day of the estimation window (25th of February 2011). Ergo, the length of the estimation window is 200 days prior the event and is denoted as $L_2 = t_4 - t_3 + 1$. The last day of the estimation window t_4 is set at – 10 and not -1 to leave room for pre-event analysis. However, as expected no abnormal returns were found for a pre-event window (result not reported).

3.2.3. Hypothesis

To evaluate the effect of the Tohoku earthquake on Japanese stock return, we need to create a set of different hypotheses to be tested. The first two hypotheses are relatively similar, the first one looking at the sectorial level and the second one at the firm level. They are based on the two definitions of energy dependence made earlier in section 3.1.

H1

The Fukushima earthquake and subsequent events negatively affected the stock prices of firms in high energy-dependent sectors, to a larger extent than firms in lower dependence sectors.

H2

The Fukushima earthquake and subsequent events negatively affected the stock prices of energy-dependent firms, to a larger extent than non-dependent firms.

We would expect the Japanese companies whose stock market prices is correlated to energy prices to suffer from a larger negative impact than the rest. The Fukushima earthquake and its aftermath were expected to have a pronounced negative impact on the stock prices of firms dependent on electric energy. This expectation stems from several factors. Firstly, such firms rely significantly on a stable and affordable energy supply for their operations. The disaster disrupted energy production and distribution, leading to immediate operational challenges and increased energy costs. Secondly, the market often anticipates higher regulatory and operational risks for these firms in the wake of such events, resulting in negative investor sentiment and sell-offs. Lastly, energy-dependent companies might face longer recovery periods and increased costs to secure alternative energy sources, compounding their financial challenges. Therefore, it is reasonable to expect that Japanese companies with stock prices closely correlated to energy prices would suffer more substantial negative impacts compared to less energy-dependent firms, which brings us to the next hypothesis.

H3

Stocks of firms that have a higher degree of energy dependency were more negatively affected by the disaster than firms with a lower degree of energy dependence.

We would expect firms to be more affected based on their degree of dependence.

The last hypothesis that will be tested, is there to look if, in addition to the degree of energy dependence, firms are also impacted by the nature of their relation with energy prices. Would a positive or negative relation with energy prices impact firms in different ways?

H4

Firms will be differently affected depending on the direction of their relation to energy prices.

3.2.4. Abnormal Return

To test the different hypotheses, the next step is to define Abnormal Return. To calculate the Abnormal Return, a similar approach to Kawashima & Takeda (2012) was used, analysing the AR of previously created equally-weighted portfolios. We need to first determine the daily continuously compounded portfolio returns based on closing prices. Each daily return should be computed from the last day with a non-missing price and trading volume to the current day, using the same formula as (2) but for daily return. Where R_{it} is the daily continuously compounded return for portfolio i on day t, P_{it} is the adjusted closing price for stocks on day t and P_{it-1} is the adjusted closing price for stock on day t-1.

Then, the Abnormal returns have to be estimated using this equation:

$$AR_{it} = R_{it} - ER_{it} \qquad (3)$$

AR_{it} is the abnormal return of portfolio i at time t due to the event. R_{it} is the actual return of portfolio i at time t and ER_{it} is the return that was expected to happen in case the event never occurred.

To estimate the the ER for each portfolio, different models can be used. Typically, two models are commonly used: the constant mean return and the market model. The constant mean model even though being the simplest one usually yields similar results to the market model (Brown and Warner 1980, 1985). However, as MacKinley (1997) stated, with the market model the variance of abnormal return is reduce as the proportion of the return related to variation in the market is removed. Hence, the market model is usually the most common and the one we will be using for this study. It is defined as follow:

$$R_{it} = \alpha + \beta R_{mt} + \varepsilon_{it} \qquad (4)$$

where R_{it} and R_{mt} are the period-t returns on security i and the market portfolio and ε_{it} is the zero mean disturbance term. For the purpose of the research, the Topix will be chosen as a benchmark for the Japanese market. Another good alternative could have been the 225 nikkei nevertheless, it contains only 225 stocks selected from domestic common stocks in the Prime Market of the Tokyo Stock Exchange, compared to over 2,000 stocks traded on the Tokyo Stock Exchange (TSE) for the Topix. Thus, the Topix was decided to be more representative of the overall market. To study the abnormal return over the entire time of the event window, the Cumulative Abnormal Return (CAR) needs to be computed. The CAR is simply the sum of the respective portfolio's AR during the event-window, denoted as:

$$CARp(t1, t2) = \sum_{t=t1}^{t2} ARp, t \qquad (5)$$

The CAR is the most important indicator for an event study as it tells us how the event studied has impacted the relevant stock or portfolio. It is the total decrease (increase) in return lost(gain) due to the event. To test whether the event has really impacted our sample, we need to check if the CAR is statistically different from 0. We can use the Standardized Cumulative Abnormal Return (SCAR):

$$SCAR_p(t_1, t_2) = \frac{CAR_p(t_1,t_2)}{\sigma_p(t_1,t_2)} \sim N(0,1) \qquad (6)$$

where $\sigma_p(t1,t2)$ is the standard deviation of the CAR, which is calculated asymptotically by the variance of abnormal returns σεp2 as follows:

$$\sigma_p(t_1, t_2) \approx \sqrt{(}t_2 - t_1 + 1)\sigma^2_{\varepsilon_p} \qquad (7)$$

This test was suggested by Patell (1976), residuals are initially estimated as in a typical t-test. Before aggregating them over time and across events, they are standardized to account for the greater standard deviation of event-period residuals compared to estimation-window residuals. This standardization involves dividing the event-period abnormal returns by the standard deviation of the estimation window, adjusted for forecast error. This method accommodates heteroskedasticity in event window residuals and prevents high-volatility securities from disproportionately influencing the results.

As all equally-weighted portfolios each contain multiple firms of very diverse characteristics, they might not be very representative. This is why we will also look at the Average Cumulative Abnormal Return of firms across the different categories. Using an intercept-only model or mean estimation on firms belonging to different categories previously defined, we can infer the ACAR of the firms by categories:

$$ACAR = \frac{1}{N}\sum_{i=1}^{N} CARi \qquad (8)$$

We then compare the mean of the different categories by using Welch's t-test invented by B. L. Welch in 1938 in his paper: The Significance of the Difference Between Two Means When the Population Variances Are Unequal. The test addresses the problem of comparing two sample means when the variances are not equal and the sample sizes may differ. Unlike the traditional t-test, Welch's t-test does not assume equal population variances. Instead, it adjusts the degrees of freedom using a specific formula that accounts for the unequal variances, providing a more accurate significance level for the difference between the means. This makes it particularly useful in practical applications where variance homogeneity cannot be assumed. The formula is as follows:

$$t = \frac{\overline{x_1} - \overline{x_2}}{\sqrt{\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}}} \qquad (9)$$

With degree of freedom:

$$df = \frac{\left(\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}\right)^2}{\frac{(\frac{s_1^2}{n_1})^2}{n_1 - 1} + \frac{(\frac{s_2^2}{n_2})^2}{n_2 - 1}} \qquad (10)$$

4. Data

4.1. Energy dependence test

To examine the impact of energy prices on the Japanese stock market, the sample included all monthly data for all Japanese firms available on Compustat for the period January 2005 to December 2022. This sample consists of 3202 Japanese firms. All companies of the sample were kept with no regard to the industry they operate in or the size of the companies. The only requirement was to have at least 12 firm-months with no missing data per company in the sample, firms with less than a year of monthly observation were dropped from the sample.

To that initial data set was added, the 10-years Japanese Government Bond Yields as a proxy for the risk-free rate. The 10-years Japanese Government Bond Yields was extracted from the Federal Reserve Economic Data(FRED). As well as the five energy prices used to define firms' energy dependence that were match in date and applied the same requirement, having at least 12 months of observations for each company.

The first proxy for energy dependence used was the Japanese Energy Consumer Price Index (Energy CPI). It was chosen for obvious reasons as the Energy CPI can provide a large amount of information and could impact companies in diverse means. The Energy CPI can influence companies' stock prices through its impact on costs, consumer spending, profit margins, and broader economic indicators. Companies with high energy dependencies are particularly sensitive to changes in the Energy CPI.

The second variable was a proxy for the electricity grid price, the Japan Electric Power Exchange (JEPX) spot prices. Electricity grid price was used as it reflects the dynamic interaction of supply and demand forces within the electricity market and plays a vital role in shaping energy market outcomes and electricity system operations. JEPX is the primary wholesale electricity market in Japan where electricity producers and retailers trade electricity. The spot prices determined in this market reflect the supply and demand dynamics of electricity in Japan at different points in time and locations within the country. More precisely, the JEPX extracted represents the Japan day-ahead spot power prices for delivery on high voltage grid network. The prices are for physically delivered trades and quoted in JPY/kWh. The monthly data for the JEPX was extracted from Bloomberg.

The third variable used is the Japanese Crude Cocktail (JCC) as one proxy for oil. JCC is the average price of crude oil imported into Japan, serving as a benchmark that reflects the cost of crude oil after it has passed through Japanese customs. This price is used as a reference in Japan for various purposes, including setting prices for liquefied natural gas (LNG) contracts and other energy products. JCC prices were extracted from DataStream. Another proxy for oil was the Liquified Natural Gas Asia import price available in Refinitiv (LNG ASIA). As Japan has for a long time been the largest LNG importer of Asia, until recently when China passed it, the total LNG import into Asia can be used as another reliable proxy.

The last variable is the Newcastle Thermal Coal Index as a proxy for coal prices. The Newcastle Thermal Coal Index is a crucial reference for Japan's thermal coal imports. Japan uses Australia as its primary supplier for thermal coal, and the NCTI plays a key role in determining the cost and economic viability of these imports. Many of Japan's long-term and spot market contracts for thermal coal are indexed to the Newcastle Thermal Coal Index. This index serves as a benchmark for pricing and is crucial for contract negotiations and price settlements.

The only data variables used to set up the sample for the first part of the study were:

R_{it} = the logarithm return of all Japanese firms available on Compustat at time t

En. CPI_{t-1} = The 1 month-lagged variable of the Energy CPI logarithm return

$JEPX_{t-1}$ = The 1 month-lagged variable of the JEPX logarithm return.

JCC_{t-1} = The 1 month-lagged variable of the Japanese Crude Cocktail logarithm return.

LNG_{t-1} = The 1 month-lagged variable of the LNG Asia import logarithm return.

$Coal_{t-1}$ = The 1 month-lagged variable of the Newcastle Thermal Coal Index logarithm return.

Table 1: Beta of energy-dependent firms

Beta of dependent firms							
	Obs	Mean	Median	5^{th}	25^{th}	75^{th}	95^{th}
β En. CPI	126	-1.20	-1.95	-11.67	-3.52	1.90	13.39
β JEPX	298	0.13	0.10	-0.26	0.07	0.15	0.40
β JCC	246	-0.27	-0.28	-0.80	-0.44	-0.16	-0.06
β LNG	312	0.20	0.18	-0.36	0.12	0.35	0.74
β Coal	182	-0.30	-0.35	-1.56	-0.75	0.30	0.78

This table present the summary statistics of the dependent firm's Beta to the 5 energy proxies. Dependent firms are defined as firms whose stock returns were affected by 1 or multiple energy proxies at a 5% confidence level.

4.2. Event study

The second and final data sample used in the event study was constructed using the result of the first part of the study. To analyse the impact of the Fukushima catastrophe on Japan's stock market, the daily data from the 3202 companies from our previous sample were extracted from Compustat. Observations with missing or incorrect data were dropped. As it seemed to have incoherence in the data in terms of the unit of choice. For a handful of stocks, the data was expressed in thousands of YEN, then randomly changing to units of Yen, those stocks were dropped. After cleaning the data we were left with a final sample size of 2358 firms.

The daily returns from TOPIX were extracted from Datastream and added to the sample. The log return of the stocks and the TOPIX was calculated the same way as in the previous sample using (2) but for daily return.

Using the beta from regression (1) (Table 1), the stocks were classified according to their degree of energy dependence, see Table 2)

Table 2: Distribution of firm dependence across the sample

N° of Firms			Positive	Negative
Sectorial-level Dependence	All Sample	2 358		
	No dependence	1 381		
	Dependent	977		
Firm-level Dependence	All Sample	2 358		
	No dependence	1 722		
	Dependent	636		
	Low dependence	367	199	140
	Moderate Dependence	224	154	58
	High Dependence	45	15	28
	Positive Dependence	368		
	Negative Dependence	226		

This table shows how the sample was classified by degree of energy dependence. On the firm level, dependent firms are defined as firms whose stock returns were affected by 1 or multiple energy proxies at a 5% confidence level. Note, that a certain number of firms have different positive and negative relations with more than 1 energy proxy and are accounted for in the degree of dependence test but not in the positive/negative test.

5. Results

5.1. Energy dependence results

After running regression (1) on every stock of the first sample separately and calculating their respective t-statistic. It was found that out of the 2358 companies in our sample 636 firms were impacted by the energy prices with a significance of 5% and 1722 yielded unsignificant results. The result of the beta for each energy proxy can be found in Table 1. In the companies that were significantly dependent on the energy prices, we found a negative correlation between oil price (JCC) and (Coal) price (Appendix 2), which is consistent with Oberndorfer (2009). We also found a very strong negative correlation between the Energy CPI and the Japanese stock return. Again this is not so surprising, since high energy prices increase the cost of production for many companies, especially those in manufacturing and heavy industries, it also means higher living expenses for consumers, which can reduce discretionary spending. What is more surprising is a positive correlation between the Japanese stock market and LNG Asian import prices & JEPX prices. A potential explanation could be that the positive correlation suggests that rising electricity and LNG prices reflect robust economic activity and higher energy demand, which generally support corporate profits and stock market growth. However, another explanation could be simply an error in the model. More precisely in setting up the lag of the energy prices return. To keep the model simple we assumed that the energy prices of the previous month would affect the stock price only 1 month apart. Although this is not always true, Kilian & Park (2009) showed that after an oil price shock, the effect would be felt in the stock market for up to 7 months and Oberndorfer (2009) determined the lag for his lagged oil price variable according to the Bayesian Schwarz Information Criterion (BIC) to be 3 months. This shows that lagging the variable by only 1 month might not have been optimal for all five energy prices.

5.2. Event study results

5.2.1. Portfolio analysis

To assess the Japanese natural disaster of 2011, we start by analysing the result of the CAR of each individual portfolio.

In Table 3, we can see the CAR for the two sectorial dependence portfolios. We see that both the high-dependence and low-dependence portfolios have statically significant abnormal returns for both event window. In the very short term, both portfolios suffered an immediate negative CAR. On the other hand, for the 10-days event window, firms operating in one of the 4 energy-intensive sector, exhibit a positive abnormal return. Two days post Fukushima, the high dependence sector manifests a – 9.52 % negative cumulative abnormal return while after 10 days, it shows a positive CAR of 3.47, showing that contrary to what was initially thought, the high energy intensity sector could have been positively impacted by Fukushima in the longer term.

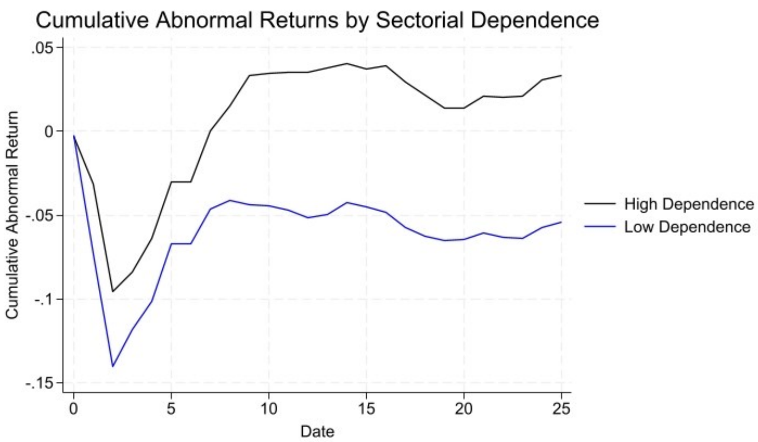
Table 3 Cumulative Abnormal Return for sectorial level dependence (in percent)

	(0,2)		(0,10)	
	CAR	SCAR	CAR	SCAR
Low-dependence	-14.05	-31.39***	-4.48	-5.22***
High-Dependence	-9.52	-20.76***	3.47	3.95***

This table represent the Cumulative Abnormal Return and their respective SCAR for the different portfolios and for 2 different event window. The estimation window is set at 210 days before the event. *** indicate statistical significance at the 1% levels.

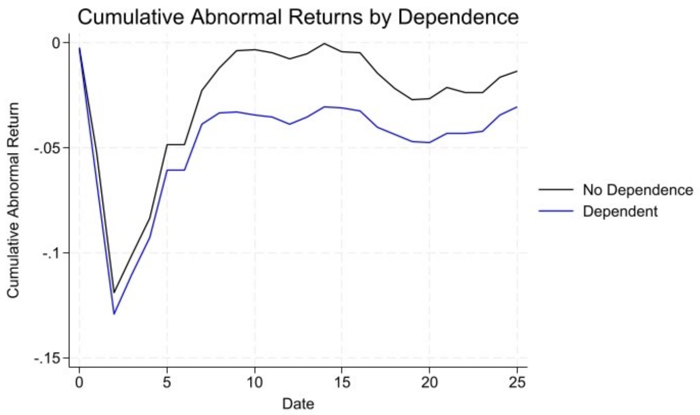
Those results are even clearer on Figure 1Figure 2, where we can see that from 7 days after the catastrophe, the portfolio of firms operating in the material, industrial, energy and utility sectors, showed positive abnormal returns. Not only that but for the whole duration of the event windows, the portfolio of low energy-dependent sector suffered a larger negative CAR then the high-dependence portfolio. A result that is in complete opposition to the first hypothesis (**H1**). From Appendix 2, we can see that the sector that was the most negatively impacted was the Communication services and the least impacted was surprisingly the energy sector.

Figure 2 Cumulative abnormal returns by dependence, sectorial level



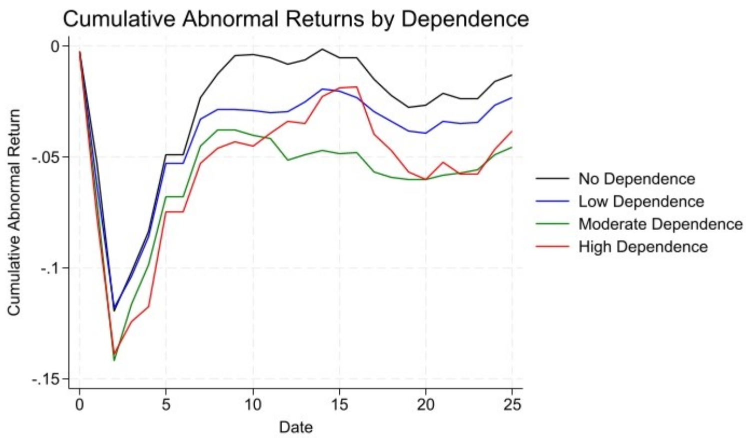
On the contrary, when looking at the second definition of energy dependence, on the firm level, we can see from Figure 3 that there is a clear pattern between the dependent and non-dependent portfolio's CAR and a clear gap that widens from day 7 post event to around 15 days after the event where it starts to slowly close again. This is in accordance with (**H2**), Japanese firms that are dependent on energy suffered a larger negative impact from the disaster.

Figure 3 Cumulative abnormal returns by dependence, firm level



In Table 4 we can see all the Cumulative Abnormal Return for the portfolio created based on the firm's energy dependence. Based on the third hypothesis (**H3**), the portfolio of firms with a high degree of energy dependence, is supposed to be more impacted by the event than less dependent firms. As we can see, the empirical results do not completely support this hypothesis. For the immediate event window, the high dependence portfolio shows a lower negative CAR than the moderate portfolio. The moderate dependence group exhibits the most significant negative CAR and SCAR in the immediate aftermath, indicating that these companies were more adversely affected by the disaster.

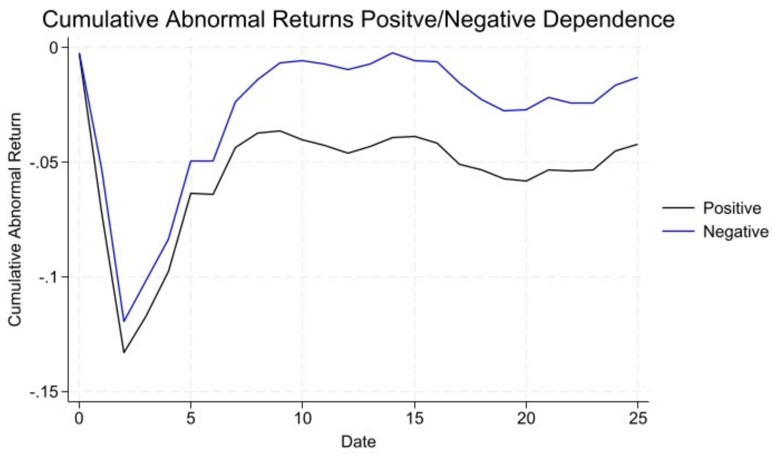
Figure 4 Cumulative abnormal returns for Japanese firms by degree of dependence



The results for the moderate-dependence group also show significant negative impacts that are stronger than the low dependence and no dependence portfolio. The low-dependence portfolio, has a negative impact larger than non-dependent firms for most of the post-event period except at day 2, reinforcing the notion that energy dependence exacerbates the negative effects of such events. Even though the Low dependence and No dependent groups experienced significant negative returns initially, the magnitude and persistence of these effects are less pronounced compared to the more energy-dependent groups.

What makes the third hypothesis (**H3**) somewhat ambiguous is that from Figure 4, we can see clearly that the high-dependence portfolio start behaving strangely 10 days after the event, to reach a lower negative CAR than even the low-dependence portfolio.

Figure 5 Cumulative abnormal returns for Japanese firms by positive and negative energy dependence



To test the fourth hypothesis, we can look at the last two rows of Table 4 and Figure 5. We see that for both event window, the CAR are negative and statistically significant. The distribution of the CAR follows the same line as in Figure 3, where the gap between the two portfolios widens from day 7 post-event.

We observe that the portfolio with positive energy dependence firms exhibits a larger negative CAR than its opposite portfolio. As it might seem surprising at first, it could be that Companies positively correlated with energy prices may be more directly involved in energy production or intensive energy use. The Fukushima disaster caused significant operational disruptions, impacting energy infrastructure and supply chains. The disaster likely created widespread uncertainty and negative sentiment in the market, disproportionately affecting sectors closely tied to energy due to anticipated regulatory changes, supply chain disruptions, and increased costs.

These findings are in relation to hypothesis 4 (**H4**), further than their degree of dependence, Japanese firms were differently impacted depending on the nature of their relation with energy prices.

Table 4 Cumulative Abnormal Return for firm level dependence (in percent)

	(0,2)		(0,10)	
	CAR	SCAR	CAR	SCAR
Non-dependent	-11.96	-27.29***	-0.38	-0.46
Dependent	-12.78	-27.17***	-3.41	-3.78***
Low dependent	-11.79	-24.14***	-2.90	-3.10***
Moderate dependent	-14.18	-28.85***	-4.02	-4.27***
High dependent	-13.90	-12.96***	-4.49	-2.16**
Positive dependence	-13.23	-26.11***	-3.97	-4.10***
Negative Dependence	-12.12	-24.76***	-2.62	-2.72**

This table represent the Cumulative Abnormal Return and their respective SCAR for the different portfolios and for 2 different event window. The estimation window is set at 210 days before the event. *** and ** indicate statistical significance at the 1% and 5% levels, respectively.

Overall, from our portfolio analysis, it seems that (H2) and (H4) hold, (H3) only to a certain extent and (H1) does not hold and the results were actually the exact opposite. The significance of the difference between the groups will be tested further in the next section.

5.2.2. Average Cumulative Abnormal Return

From previous result we have seen that our hypotheses (**H2**) & (**H4**) hold so far and (**H1**) as the opposite result of what was expected. However, the significant difference between portfolios needs to be assessed. To do so, we will look at the mean CAR or ACAR for the different companies in the portfolio and assess their statistical difference using Welch's t-test. In this section, another event window of (0:20) is added to analyse the significance longer-term result of the graphs in the previous section.

In Table 5, we report the Average Cumulative Abnormal Return of firms by sectorial dependence. The results confirm those of the Portfolio analysis. The Welch's t-test tells us that the ACAR of firms in higher and lower dependence sectors is statistically significant for any event window. While all initially suffered an immediate negative ACAR, companies operating in energy-intensive sector seem to have gained from the disaster in the medium to long term.

Table 5 ACAR Comparison, sectorial level

		(0,2)	(0,10)	(0,20)
High-Dependence	Mean CAR (a)	-9.54	3.48	1.38
Low-Dependence	Mean CAR (b)	-14.02	-4.45	-6.47
	Difference (a-b)	4.48	7.93	7.85
	t-Stat	6.39***	12.92***	11.77***

This table represent the Average Cumulative Abnormal Return as well as Welch's t-test for the different firms and for 3 different event windows. The estimation window is set at 210 days before the event. *** indicate statistical significance at the 1%..

In Table 6, we can see the ACAR of energy-dependent firm and non-dependent is not statistically different for the shortest event window (0:2). Nevertheless, the more we prolonged the event window (t + 10 and t + 20) the more the hypothesis seems to hold. We witness a difference between the two groups of -3.06% at (0,10) and of -2.14% at (0:20), a difference that is statistically significant at a 1% level for both windows. This confirms the second hypothesis.

To confirm (**H3**), we need to look at the difference in impact depending on the degree of energy dependence. In Table 6, the mean difference between Moderate and Low-dependence is reported. It is significant for all event windows, although it exhibits a low degree of significance for the event window (0:10). The difference between Low & High and Moderate & High were also tested using a similar method for a similar event window but none of the difference was showed a significant result (not reported). This again confirms that hypothesis 3 is a bit more ambiguous as on the one hand there is a significant difference between low and moderate energy dependence, on the other hand, other degrees do not seem to have any significant differences.

Table 6 ACAR Comparison, firm level

		(0,2)	(0,10)	(0,20)
Dependent	Mean CAR (a)	-12.86	-0.34	-2.64
Non-Dependent	Mean CAR (b)	-11.92	-3.40	-4.78
	Difference (a-b)	-0.89	-3.06	-2.14
	t-Stat	-1.27	-5.60***	-3.18***
Mod-dependence	Mean CAR (a)	-14.31	-4.06	-6.07
Low-dependence	Mean CAR (b)	-11.77	-.2.86	-3.84
	Difference (a-b)	-2.54	-1.20	-2.23
	t-Stat	-2.17**	-1.50*	-1.76*
Positive	Mean CAR (a)	-13.32	-4.03	-5.81
Negative	Mean CAR (b)	-12.07	-2.50	-3.39
	Difference (a-b)	-1.25	-1.53	-2.42
	t-Stat	-1.04	-1.76**	-2.21**

This table represent the Average Cumulative Abnormal Return as well as Welch's t-test for the different firms and for 3 different event windows. The estimation window is set at 210 days before the event. ***,** and ** indicate statistical significance at the 1%., 5% and 10% levels, respectively.

Finally, we can see from Table 6 that there is a statistically significant difference between companies that have a positive relation with energy prices and firms that have a negative relation but only for the two longer event windows. It seems that the longer the event window, the wider the difference. Firms that are positively related to energy price fluctuation have suffered more from the Tohoku Earthquake.

6. Summary & Discussion

In this paper, we investigated the effect of the Great East Japan Earthquake followed by the Fukushima Daiichi nuclear incident on the stock prices of Japanese companies. Those companies were separated into different categories based on their energy dependence. By analysing the effect of the 2011 earthquake on the different categories of firms, we reported that firms operating in sectors commonly referred to as energy-intensive sectors,(Industry, Materials, Utilities and Energy) suffered less from the earthquake than the rest of the Japanese firms, even showing positive Abnormal Return from 7 days after the event. The second finding is that firms whose stock prices are related to fluctuation in energy prices were more negatively affected by the event than firms that do not have a relationship with energy prices. This shows that shareholders, on the verge of such a dramatic event were uncertain about the future of those companies. Thirdly, we found that the degree of energy dependence among firms does not seem to significantly change the impact of Fukushima on Japanese firms. Finally, it seems that firms whose stock prices are positively related to energy price fluctuation showed a larger negative impact from the disaster than firms whose stock price moves oppositely to the energy prices.

Although some of the results might look strange at first, I refer to the result for the sectorial categorisation of energy-dependence, it might be explained by the activity of the firm classified as operating in high energy-intensity sectors. Koerniadi et All (2016) found that although most firms suffer from natural disasters, firms operating in the construction and material industry are generally positively affected by natural disaster due to the subsequent recovery and rebuilding phases that often create economic opportunities.

While this paper provides valuable insights into the impact of the Great East Japan Earthquake and subsequent Fukushima Daiichi nuclear incident on Japanese firms, several future research could be done to further elucidate the complexities of these effects. For instance, future research could benefit from a more comprehensive and robust definition of energy dependence that incorporates additional parameters. This could include factors such as the proportion of energy costs relative to total costs, energy consumption intensity, and exposure to energy price volatility. Enhancing the definition of energy dependence would improve the accuracy and reliability of the findings and provide deeper insights into the relationship between energy dependence and stock market performance in the aftermath of natural disasters.

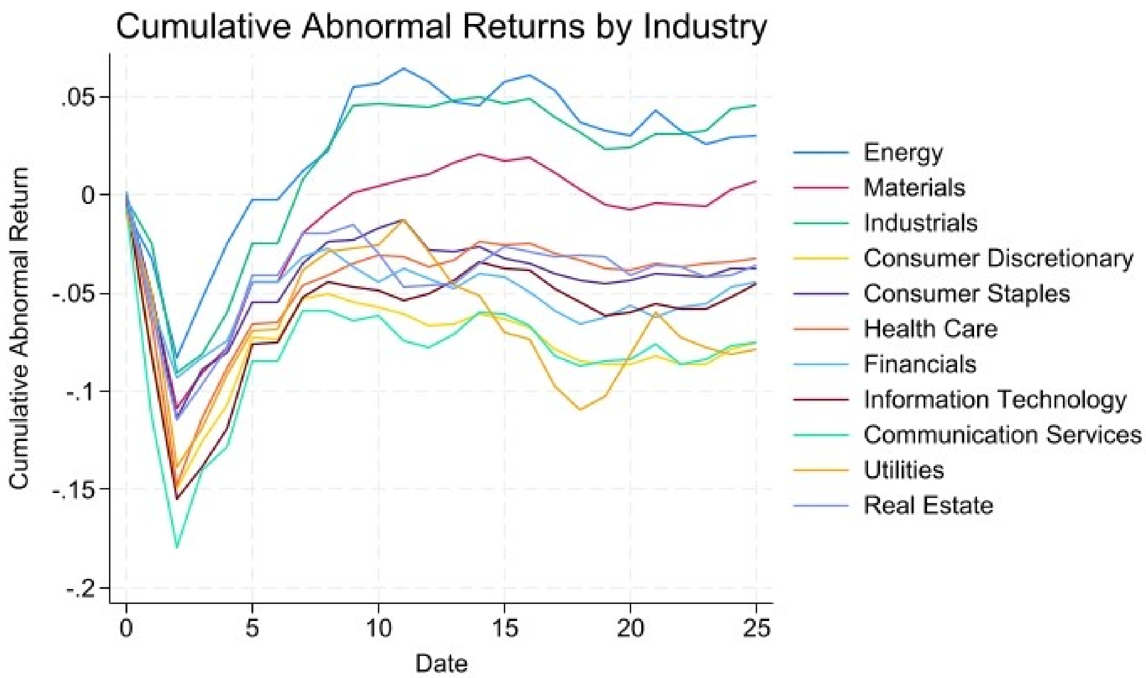
In our study, we only looked at Japanese firms, future studies could look at Cross-Country Comparisons. Locating a similar natural disaster in another country, that disrupted in a relatively similar way the energy sector.

Appendix

Appendix 1: Sample distribution by sector in percentage

GICS industry classification	No Dependence	Low Dependence	Moderate Dependence	High Dependence
N° of Firms	1 722	358	224	45
10 Energy	0.93	0.54	0.45	0
15 Materials	9.18	11.99	10.71	6.67
20 Industrials	31.59	26.16	22.77	31.11
25 Consumer Discretionary	19.57	19.62	25.45	28.89
30 Consumer Staples	9.70	6.54	12.05	4.44
35 Health Care	4.41	4.90	3.57	6.67
40 Financials	4.41	4.36	5.80	6.67
45 Information Technology	13.88	22.89	14.29	15.56
50 Communication Services	2.26	1.09	2.68	0
55 Utilities	1.34	0	0.45	0
60 Real Estate	2.73	1.91	1.79	0

Appendix 2 Cumulative Abnormal Returns by Industry



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