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Earthquakes and Stock Market Performance: Evidence from Japan

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EARTHQUAKES AND STOCK MARKET PERFORMANCE:
EVIDENCE FROM JAPAN

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Abstract

This paper examines the stochastic behaviour of the number of earthquakes (in total and also classified by magnitude) and stock market log prices and returns in the case of Japan over the period from January 2009 to February 2024 using fractional integration methods. Their linkages are then investigated by means of regression analysis. The results indicate that the former variable exhibits short-memory, I(0) behaviour. By contrast, stock market prices appear to be an I(d), fractional integration process, with d less than 1. Since the orders of integration of the two variables are different, we treat seismic events as exogenous in the context of a regression model with stock returns. The findings suggest that earthquakes have a statistically significant, though relatively small, negative impact on the Nikkei 225 index. More specifically, there exists a negative relationship between the magnitude and number of earthquakes and monthly stock returns. This suggests that seismic activity creates uncertainty in the market, which in turn affects its performance.

Keywords: Stock market prices; earthquakes; Japan; persistence; fractional integration

JEL Classification: C22; C58; G14; Q54

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1. Introduction

Climate change is arguably the greatest challenge faced by mankind in the 21st century. One of its main causes is the increase in greenhouse gas emissions which has led to an increase in global temperatures as well as in the frequency of natural disasters such as earthquakes. Such events have a devastating impact on the physical environment but also affect the economy, including its financial sector. This type of risk has been classified in the literature as physical risk to distinguish it from the transition risk resulting from the policies adopted by governments to achieve in the long run net-zero emissions, i.e. a balance between (lower) greenhouse gas emissions and the amount removed from the atmosphere, such that the net effect on climate change is neutral (see FSB, 2020, and OECD, 2021). Some recent evidence suggests that physical risk is becoming relatively more important (see, e.g., Le Tran et al., 2023), and that it has significant effects on financial stability (see, e.g., Liu et al., 2024, and Caporale et al., 2025).

The present study contributes to this area of the literature by focusing on Japan and providing new evidence on the stochastic behaviour of the number of earthquakes and stock market performance as measured by the Nikkei 225 index. The analysis is carried out using a fractional integration framework which is more general than the standard one based on the stationary I(0) versus non-stationary I(1) dichotomy. Specifically, it allows the differencing parameter d to take any real values, including fractional ones. Using this approach, it is possible to capture a wider range of stochastic behaviours and to shed light on the persistence and short/long memory properties of the series of interest.

The analysis indicates that, whilst logged stock prices can be characterised as an I(d), long-memory process, earthquakes exhibit I(0), short-memory patterns. Since the two series have different orders of integration, in order to examine their relationship we treat earthquakes as exogenous in the context of a regression model with stock returns. The evidence suggests that there is a significant, though small effect of earthquakes on the Japanese stock market, which increases with their magnitude.

The layout of the paper is the following: Section 2 briefly reviews the relevant literature; Section 3 outlines the econometric framework; Section 4 describes the data; Section 5 presents the empirical results; Section 6 offers some concluding remarks.

2. Literature Review

There exist several studies analysing the relationship between natural phenomena and financial markets and highlighting the importance of understanding and mitigating potential risks. Japan, as one of the most earthquake-prone countries globally, is a major focus of attention (Japan Meteorological Agency); even most recently, in 2021, it has experienced numerous significant earthquakes, which underscores its seismic vulnerability (Japan Times, 2024).

A substantial body of research has shown that natural disasters can lead to considerable stock market volatility and affect investor behaviour, with both short-term disruptions and long-term consequences (Worthington & Valadkhani, 2004; Noy, 2009). In particular, various studies have provided evidence that catastrophic events have negative effects on stock prices as a result of higher uncertainty and heightened risk aversion among investors (Pagnottoni, Spelta, & Pammolli, 2022). Such non-financial shocks can have long-lasting effects, including changes to the way businesses operate and make investment decisions. Therefore, it is crucial for financial investors to understand how earthquakes affect the stock market in order to assess risks and opportunities arising from them and make informed investment decisions.

A well-known feature of stock prices is their long memory or long-range dependence, with distant events in the past influencing current and future market behavior. This has been confirmed in the case of the Nikkei 255 index by numerous papers (Lien and Tse, 1999; Asai and McAleer, 2017; etc.). In such cases a fractional integration approach is ideally suited to capturing the behaviour of the series (Granger & Joyeux, 1980). In particular, the present study uses an ARFIMA (Autoregressive Fractionally Integrated Moving Average) model (Granger & Joyeux, 1980) to analyse the persistence and long-memory properties of the Nikkei 225 index and of the number of earthquakes in Japan. Their relationship is then investigated using a simple regression model treating earthquakes as an exogenous variable; this is because the two variables are found to exhibit different order of integration.

Note that the fractional integration framework has a number of advantages over standard models; in particular, by allowing the difference parameter d to be any real number, including fractional ones, it is better suited to capturing both short- and long-term dependencies (Huang, Chan, Chen, & Ing, 2022). It is also more efficient compared to classical methods (Roume, Ezzina, Blain, & Delignières, 2019; Bhardwaj, Gadre, & Chandrasekhar, 2020), and yields highly informative evidence on the long-memory properties of financial data, thereby enhancing and complementing the analysis typically performed using traditional algorithms (Delignières, et al., 2006; Torre, Delignières, & Lemoine, 2007). Its usefulness for modelling financial time series and their persistence has been shown by various studies (e.g., Lenti & Gil-Alana, 2021; Gil-Alana, 2005, 2006, 2017; Vyushin & Kushner, 2009; Zhu, Fraedrich, Liu & Blender, 2010; Rea, Reale & Brown, 2011; Yuan, fu & Liu, 2013).

3. Methodology

As already mentioned, in this study we model the long-memory features of Japanese stock prices and earthquakes by employing a fractional integration approach to capture their persistence (see, e.g., Gil-Alana & Robinson, 1997; Gil-Alana, 2018; Gil-Alana et al., 2023, for other applications of this method).

3.1 Long-Memory Modelling

To illustrate the concept of long memory, consider a second-order stationary process[1] x(t) that evolves over time, $x(t),\ t = 0, \pm 1, \ldots$, and has an average value $E(x(t)) = \mu$. The autocovariance function for this process is defined as $\gamma(u) = E[(x(t) - \mu)\ (E(x(t+u) - \mu)]$.

The process x(t) is said to have long memory if the sum of its autocovariances across all time lags does not converge to a finite value. More precisely, x(t) exhibits long memory if:

$$\sum_{u=-T}^{T} |\gamma(\mathrm{u})| = \infty\,. \tag{1}$$

It is also possible to define long memory in the frequency domain. In this case, the spectral density function is expressed as the Fourier transform of the autocovariances:

$$f(\lambda) = \frac{1}{2\pi} \sum_{u=-\infty}^{\infty} \gamma \cos \lambda\, u, \qquad -\pi < \lambda \leq \pi. \tag{2}$$

A process x(t) is then said to exhibit long memory if its spectral density function has singularities or poles at certain frequencies – in other words, the function becomes infinite or undefined at those specific frequencies:

[1] In the case of such a process the mean, variance, and autocovariance remain constant over time.

$$f(\lambda) \to \infty, \quad as\ \lambda \to \lambda^*, \quad for\ at\ least\ one \quad \lambda^* \in [0, \pi]. \tag{3}$$

Many processes exhibit the properties mentioned above. Examples include the fractional Brownian motion (fBm) and fractional Gaussian noise (fGn) models, introduced by Hurst (1951; 1957), Mandelbrot and van Ness (1968), and Mandelbrot and Wallis (1968; 1969a; 1969b). In time series analysis a process is defined as fractionally integrated, or integrated of order d, if it can be represented as:

$$(1 - L)^d\, x(t) = u(t), \qquad t = 0, \pm 1, \pm 2, \dots, \tag{4}$$

with u(t) = 0 for t ≤ 0, where d is a fractional parameter, L is the lag operator, defined such that $Lx(t) = x\,(t - 1)$, and $u(t)$is $I(0)$ or short memory. This property can be identified in two ways: in the time domain, u(t) has short memory if the sum of its autocovariances is finite, whilst in the frequency domain it is characterised by a spectral density function that is both positive and bounded at all frequencies, namely $0 < f(\lambda) < \infty$ for every frequency λ.

In our model, given by equation (4), the spectral density function for x(t) can be expressed as:

$$f(\lambda;\, \tau, d) = \frac{\sigma^2}{2\pi} \left| \frac{1}{1 - e^{i\lambda}} \right|^d . \tag{5}$$

where λ stands for the frequency, and σ^2 is the variance of the error term. This function becomes very large as $\lambda \to 0^+$. This approach was introduced by Granger (1980), Granger and Joyeux (1980) and Hosking (1981). These authors observed that many series had high values at the zero frequency, suggesting the need for differentiation. However, after first differencing the data, these high values usually dropped to near zero, possibly indicating over-differentiation. These models have since been widely adopted in various fields including climatology and environmental sciences in addition to economics and finance.

For our purposes, we use a similar model but including deterministic terms, such as an intercept and a linear time trend, namely:

$$y(t) = \alpha + \beta(t) + x(t), \qquad (1 - L)^d \, x(t) = u(t). \tag{6}$$

In this setup, α and β are estimated along with d. As for the disturbance term u(t), we assume in turn that it is a white noise without autocorrelation (and hence a constant mean and variance), or that it is characterised by weak autocorrelation as in Bloomfield's (1973) exponential model whose spectral density function is given by:

$$f(\lambda;\, \pi) = \left[\frac{\sigma^2}{2\pi}\right] \exp\left[2 \sum_{i=0}^{n} \tau_i \, \cos(\lambda\, i)\right]. \tag{7}$$

where σ^2 is the variance of the error term and n the number of short-term dynamic terms. Bloomfield (1973) showed that this model closely approximates the spectral density of a stationary ARMA (p, q) process, which is given by:

$$u(t) = \sum_{r=1}^{p} \varphi_r \, u(t - r) + \varepsilon_t + \sum_{s=1}^{q} \theta_s \, \varepsilon(t - s), \tag{8}$$

where $\varepsilon(t)$ is white noise. The spectral density for this ARMA model is the following:

$$f(\lambda;\, \tau) = \frac{\sigma^2}{2\pi} \left| \frac{1 + \sum_{s=1}^{q} \theta_s \, e^{i\lambda s}}{1 - \sum_{r=1}^{p} \varphi_r \, e^{i\lambda r}} \right|^2 . \tag{9}$$

Bloomfield (1973) found that when p and q are small, the log of the function in equation (7) approximates well the log of the ARMA model's function in equation (9). An advantage of this method is that it does not require estimating many parameters. Moreover, it is stationary and easily implementable in the context of the test developed by Robinson (1994) and implemented here.

Specifically, the null hypothesis is given by:

$$H_0\!: \;\; d = d_{0,} \tag{10}$$

in the model given by Equation (6) for any real value d_0. The test is based on the Lagrange Multiplier (LM) principle, and therefore the model can be reformulated as:

$$y^*(t) = \alpha 1^*(t) + \beta t^*(t) + u(t), \tag{11}$$

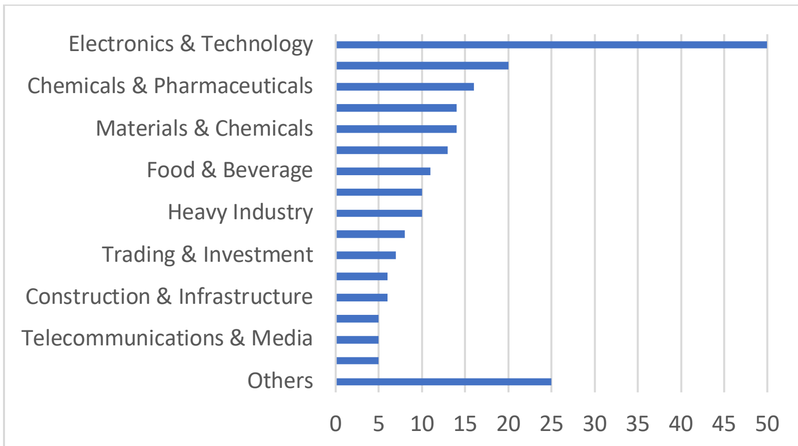
where $y^*(t) = (1-L)^{d0} y(t)$; $1^*(t) = (1-L)^{d0}\, 1$; and $t^*(t) = (1-L)^{d0}\, t$. This test allows to consider a group of values for which the null hypothesis cannot be rejected. If the model is well specified, the test statistic should decrease with d_0, creating a range of values for which the null hypothesis holds true. It is a flexible method, allowing to test any value of d_0 , including those outside the stationary range ($d_0 \geq 0.5$). Moreover, it follows a standard distribution and is efficient against local deviations from the null (for more details, see Gil-Alana and Robinson, 1997)

Having carried out the univariate analysis, next we analyse the relationship between stock returns and the frequency of earthquakes in Japan. In a multivariate context, the natural extension of the fractional integration approach is the concept of fractional cointegration initially introduced by Robinson and Hualde (2003) and Hualde and Robinson (2007), and later extended by Johansen and Nielsen (2010, 2012), who developed the fractional CVAR (FCVAR) model. However, a necessary condition for cointegration is that the series be of the same order of integration. Since the univariate analysis suggests that this is not the case, we estimate instead an OLS regression treating earthquakes as an exogenous variable rather than endogenous as in cointegration models.

4. Data Description

The Nikkei 225, also known as the Nikkei Stock Average, was established in 1950 and is the main Japanese stock market index. It includes 225 of the leading companies listed on the Tokyo Stock Exchange (TSE) (Ryszard, Paweł, & Robert, 2019), and it is a price-weighted index (Takahashi, 2023). It covers a wide range of sectors such as electronics and technology, chemicals and pharmaceuticals etc. (see Figure 1). Sony, Toyota, and Panasonic (Investing.com) are some of the best-known companies included. Unlike other market-capitalization-weighted indices, the Nikkei 225 is based purely on stock prices, and thus it focuses on price movement analysis (Bai & Guo, 2019).

Figure 1: Composition of the Nikkei 225 Index by Sector



To calculate this index a straightforward price-weighted average formula is used which takes into account the issuance of new stocks, dividends and stock splits (Shiomi, Takahashi, & Xu, 2021); because of this weighting, stocks with higher prices have a greater impact on the index (Takahashi, 2023). The Nikkei 225 is seen as a crucial benchmark for investors interested in the Japanese market and the Asia-Pacific region (Borhan, Halim & Amir, 2017), and it is frequently used as the basis for financial products such as futures, options, and exchange-traded funds (ETF´s), and for foreign investment in Japan (Ochiai & Nacher, 2014). It also features in various academic studies on option prices (Ryszard, Paweł, & Robert, 2019), speculative bubbles (Borhan, Halim & Amir, 2017), the relationship between market liquidity and the activity of informed traders (Ahn, Cai, & Chung, 2010), market volatility and skewness (Takahashi, Shyu, Chen, & Toda, 2022), and the impact of changes in its composition on the supply and demand of stocks and trading strategies (Okada, Isagawa, & Fujiwara, 2006). On the whole, the Nikkei 225 index is an essential component of global financial analysis (Shiomi, Takahashi, & Xu, 2021).

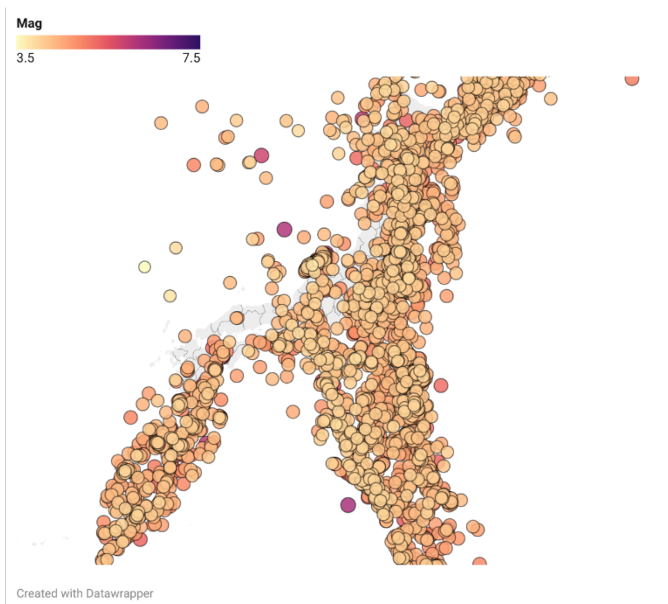
Japan is situated in one of the most seismically active regions in the world, which is known as the Pacific Ring of fire. This area is very active because several tectonic plates – such as the Pacific Plate, the Philippine Plate, the Eurasian Plate, and the North American Plate – meet and move against each other. These movements cause frequent earthquakes (see Figure 2) as well as volcanic eruptions in Japan (Smits, 2014).

Therefore earthquakes have had a big impact on both infrastructures and society throughout Japan's history. One example is the Great East Japan Earthquake of 2011, which was very powerful, reaching a magnitude of 9 points on the Richter scale, and leading to a huge tsunami and a nuclear crisis in Fukushima. It had a wide-ranging impact, causing extensive damage to buildings, bridges, and roads, and disrupting essential services such as water and electricity; moreover, it affected global supply chains and caused severe economic problems (Carvalho, Nirei, Saito, & Tahbaz-Salehi, 2021). Another major earthquake took place in the Kumamoto region in 2016; analysing it has helped scientist gain a better understanding of seismic activity in that geographical area (Takahashi, Shyu, Chen, & Toda, 2022). Earthquakes also have serious effects on public health. In particular, the stress and evacuation from the disaster areas increase the risk of hypertension among those who are evacuated (Ohira, et al., 2024).

To deal with these challenges, Japan has developed advanced strategies for preparation and mitigation. The Report of the Observer Panel for the US – Japan Earthquake Policy Symposium (1997) offered important recommendations to improve disaster readiness and responses. These include strict building standards for earthquakes, early warning systems, and regular emergency drills. Research in seismology engineering is crucial for improving resilience against earthquakes.

For instance, studies of long-term uplift patterns in the area hit by the 2016 Kumamoto earthquake have provided important insights into how seismic activity and geological changes occur over time. Such research is essential for developing new technologies and methods to better prepare for and reduce the impact of future earthquakes, further supporting Japan's efforts to enhance its earthquake resilience (Takahashi, Shyu, Chen, & Toda, 2022). With such efforts, Japan continues to strengthen its ability to handle earthquakes and protect its people.

Figure 2: Map of Seismic Events in Japan



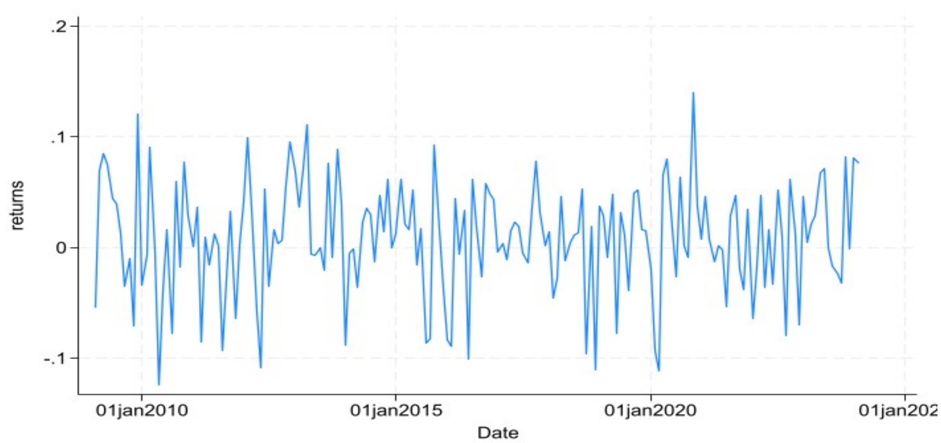
Prima facie evidence suggests that earthquakes also affect the Japanese stock market. For instance, the Nikkei 225 index dropped sharply in response to the 2011 Great East Japan earthquake (Carvalho, Nirei, Saito, & Tahbaz-Salehi, 2021). However, the Japanese stock market usually rebounds, showing resilience. The apparent linkages between earthquakes and stock market performance in Japan suggest the need to combine disaster readiness with financial planning to manage risks and ensure financial stability in the face of natural disasters, as argued in various policy reports (National Research Council; Division on Earth and Life Studies; Commission on Geosciences, Environment and Resources; U.S.-Japan Earthquake Policy Symposium Observer Panel, 1997).

In this study we analyse monthly data on (1) the closing prices of the Nikkei 225 index (in logs) and (2) the frequency of earthquakes in Japan, grouped by their magnitude. The sample period goes from January 2009 to February 2024. The data sources are respectively Yahoo Finance and the United States Geological Survey (USGS) Earthquake Database, accessible at USGS Earthquake Search. For the regression analysis we use the Nikkei 225 data to calculate returns, denoted as R(t), as follows:

$$R(t) = \log(P(t) - \log\big(P(t-1)\big). \tag{15}$$

where P(t) is the log price. This transformation helps stabilise the variance of the series. Moreover, log returns tend to follow a normal distribution. Figure 3 plots this series; visual inspection suggests that it is highly volatile but stationary.

Figure 3: Time Series Plot of Nikkei 225 Returns



The other series are the number of earthquakes per month, both in total and by their magnitude according to the Ritcher scale (see Table 1) [2]. The former is plotted in Figure 4. It can be seen that there is a spike in 2011, when the well-known Great East Japan Earthquake occurred.

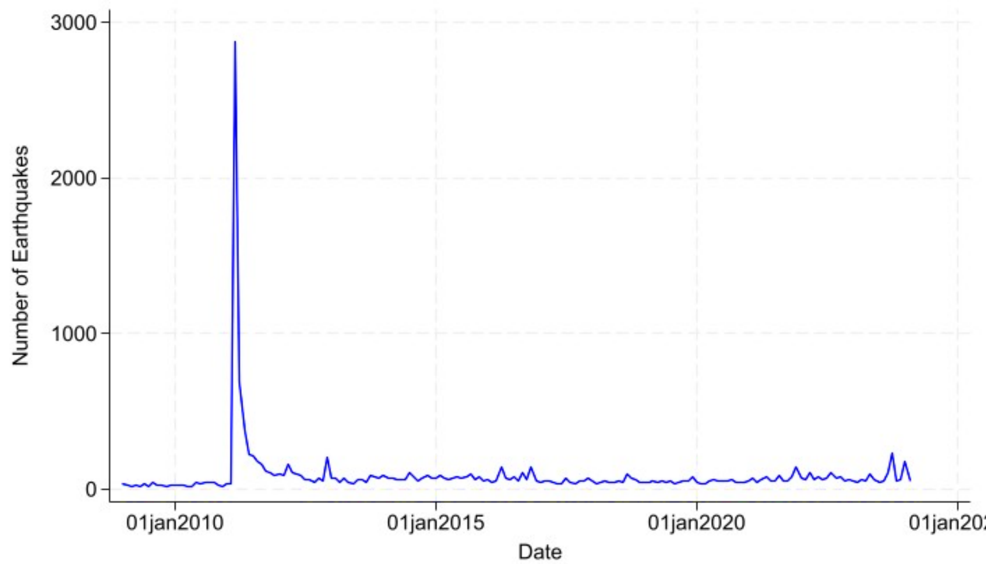
Table 1: Earthquake Magnitude and Effects according to the Richter Scale

Magnitude Category	Description
Higher than 3	**Description:** Earthquakes with magnitudes greater than 3.0 on the Richter scale. **Impact:** Generally considered minor. These earthquakes are often felt only by a limited number of people close to the epicenter and rarely cause significant damage. They usually cause minor vibrations.
Higher than 4	**Description:** Earthquakes with magnitudes greater than 4.0 on the Richter scale. **Impact:** Considered moderate. These can be felt over a larger area and may cause minor damage to structures, especially near the epicenter. They can cause concern among the population.
Higher than 5	**Description:** Earthquakes with magnitudes greater than 5.0 on the Richter scale. **Impact:** Classified as strong. These earthquakes can cause significant structural damage, especially near the epicenter, and are noticeable over a wide area. They often trigger emergency responses.
Higher than 6	**Description:** Earthquakes with magnitudes greater than 6.0 on the Richter scale. **Impact:** Considered very strong to severe. These earthquakes have a high potential to cause severe damage to structures and can affect extensive areas. The intensity is usually enough to cause substantial destruction and potentially lead to loss of life.
Number of earthquakes	**Description:** The total number of earthquakes recorded, regardless of magnitude. **Impact:** Represents the overall count of seismic events within the specified period, providing a comprehensive view of earthquake activity[3].

[2] The Richter scale is a logarithmic measurement that quantifies the magnitude of an earthquake, reflecting the energy released during the seismic event.

[3] Information on the impact of different earthquake magnitudes can be found on the Japan Meteorological Agency webpage.

Figure 4: Time series plot of the Number of Earthquakes.



5. Empirical Results

Table 2 reports the estimates of differencing parameter d in Equation (6) and the 95% confidence intervals for its non-rejection values; the series considered are logged stock prices, the total number of earthquakes, and their number by magnitude, under two alternative assumption about the errors (white noise and weak autocorrelation, respectively) and for the three following model specifications:

i. Without deterministic terms: in this case, the model does not include deterministic components, that is α and β are set equal to zero. The results for this specification are reported in column 2 of Table 2.

ii. With an intercept only: in this case the slope parameter β is set equal to zero. The corresponding results are shown in column 3.

iii. With an intercept and a linear time trend: in this case both deterministic terms are included in the model. These results are displayed in column 4.

The model selected in each case on the basis of the statistical significance of the regressors as indicated by their t-statistic is highlighted in bold.

It can be seen that, in the case of white noise errors, the estimated differencing parameter for the closing prices of the Nikkei 225 index is less than 1 (0.84), which suggests the presence of long memory; however, the confidence interval is wide (0.61, 1.13) and includes the unit root case (d = 1) (see column 4 in Table 2). Therefore, one cannot rule out the possibility of I(1) behaviour, which would require first-order differences to achieve stationarity.

As for the total number of earthquakes, the estimate of d is equal to 0.09 but the confidence interval includes the value 0, and thus this series might exhibit short-memory, I(0) behaviour. It also appears that, as the magnitude of earthquakes increases, the value of d decreases. For example, for earthquakes with magnitude greater than 3, the estimate of d is 0.09 with a confidence interval of -0.09 to 0.33, as shown in column 2 of Table 2. For magnitudes greater than 4, d is 0.04 with an interval of -0.12 to 0.25, and for magnitudes greater than 5 and 6, d decreases to -0.06 (with a confidence interval between -0.25 and 0.18) and -0.13 (with a confidence interval between -0.30 to 0.10), respectively. These results suggest that as the magnitude of earthquakes increases, long-term memory becomes less pronounced.

Table 3 reports in each case the full set of estimated coefficients, including α and β, for the preferred specification. The estimated value of d for the Nikkei 225 index is 0.84, with a confidence interval between 0.61 to 1.13, which implies long memory. Furthermore, the estimated intercept is 8.982 and the time trend is 0.0083, with t-statistics confirming their statistical significance. The estimate of d for the total number of earthquakes is instead 0.09, with a confidence interval between 0.07 and 0.32. The estimated intercept is 85.878, whilst the time trend is statistically insignificant, which supports the presence of short memory in this earthquake series. When classifying earthquakes by magnitude, it is found that the value of d decrease as the magnitude increases, which implies that long memory is a less important feature in the case of more severe earthquakes. It should also be mentioned that the possibility that the earthquakes series are characterised by I(0) behaviour cannot be ruled out, since the confidence intervals of d in many cases include the value 0, indicating the possible presence of short memory. Finally note that the results based on the assumption of autocorrelated errors as in Bloomfield's (1973) model (not reported to save space) are entirely consistent with those obtained in the white noise case in Tables 2 and 3, namely they confirm that stock market prices and the earthquake series exhibit different orders of integration.

Table 2: Estimates of the differencing parameter d

Series	No deterministic terms	An intercept	An intercept and a linear time trend
Nikkei (log prices)	0.98 (0.82, 1.20)	0.79 (0.62, 1.12)	**0.84 (0.61, 1.13)**
No. of earthquakes	0.09 (-0.10, 0.32)	**0.09 (-0.07, 0.32)**	0.03 (-0.15, 0.31)
Number of earthquakes by magnitude			
Higher than 3	0.09 (-0.09, 0.33)	**0.09 (-0.07, 0.32)**	0.04 (-0.15, 0.31)
Higher than 4	0.04 (-0.12, 0.25)	**0.04 (-0.10, 0.25)**	-0.03 (-0.21, 0.21)
Higher than 5	0.01 (-0.15, 0.23)	0.01 (-0.11, 0.20)	**-0.06 (-0.25, 0.18)**
Higher than 6	-0.09 (-0.29, 0.14)	-0.07 (-0.21, 0.11)	**-0.13 (-0.30, 0.10)**

Note: The values in parenthesis indicate the 95% confidence bands for the estimates of the differencing parameter d. In bold, the selected specification based on the statistical significance of the deterministic terms for each series.

Table 3: Estimated Coefficients for the Selected Models from Table 2

Series	d (95% band)	Intercept (t-stat)	Time trend (t-stat)
Nikkei (log prices)	0.84 (0.61, 1.13)	8.982 (181.70)	0.0083 (4.75)
No. of earthquakes	0.09 (-0.07, 0.32)	85.878 (3.57)	---
Number of earthquakes depending on magnitude			
Higher than 3	0.09 (-0.07, 0.32)	85.456 (3.72)	---
Higher than 4	0.04 (-0.10, 0.25)	10.177 (2.67)	---
Higher than 5	-0.06 (-0.25, 0.18)	1.8508 (3.37)	-0.0100 (-1.98)
Higher than 6	-0.13 (-0.30, 0.10)	0.1323 (4.01)	-0.0006 (-1.99)

Note: The values in column 2 are the estimates of d, with their 95% confidence intervals in brackets. The values in columns 3 and 4 are the estimates of the intercept and the time trend respectively, with their corresponding t-values in parenthesis.

Given the above evidence, which suggests that stock prices and the number of earthquakes have different integration orders, it is not possible to test for cointegration between those series. Therefore in order to examine their linkages we run OLS regressions with stock returns treating the number of earthquakes as exogenous or as a pre-determined variable. We include in the first instance both the total number of earthquakes and their number by magnitude (3, 4, 5, 6). Since none of the estimated parameters are found to be statistically significant, next we run regressions with only one of the series at a time. These results are now significant and produce interesting insights. More specifically, in the regression including the total number of earthquakes the estimated coefficient is -3.14e-05, which suggests that each additional earthquake is associated with a 0.00314% decrease in monthly returns, this effect being significant at the 1% level. The corresponding coefficient is the same for earthquakes with magnitude greater than 3, and also significant at the 1% level, while it is much higher for the other series, the size of the coefficient decreasing (increasing in absolute value) as the magnitude of the earthquakes increases, the estimates of d being equal to -0,000153, -0.00133 and -0.00709 for categories 4, 5, and 6 respectively, although the estimate for magnitude 6 is not statistically significant at the 5% level.

On the whole, our analysis yields evidence of a significant, though rather small, negative impact of earthquakes on Japanese stock returns. However, our results should be taken with caution, since stock returns are also driven by other factors not incorporated in our models. Future work should carry out a more thorough investigation including a set of appropriate control variables.

Table 4: Regression Coefficients and Significance Levels for the Impact of Earthquakes on Stock Returns

Variable	Regressor Coeff. (p-value)	Constant (p-value)
Number of earthquakes	-3.14e-05 *** (4.37e-06)	0.0115 *** (0.00391)
Higher than 3	-3.14e-05 *** (4.38e-06)	0.0115 *** (0.00391)
Higher than 4	-0.000153 *** (1.89e-05)	0.0103 *** (0.00384)
Higher than 5	-0.00133 *** (0.000252)	0.0100 *** (0.00383)
Higher than 6	-0.00709 (0.0098)	0.00933 ** (0.00389)
*** p < 0.01, ** p < 0.05, * p < 0.1		

6. Conclusions

This paper examines the stochastic behaviour of the number of earthquakes and the stock market in Japan using a fractional integration approach. Specifically, the series used for the analysis are the log closing prices from the Nikkei 225 index and earthquake numbers in total and by magnitude for the period from January 2009 to February 2024. The former series is found to exhibit short memory, whilst the latter appears to be highly persistent and to be characterised by long memory.

The linkages between stock returns and the number of earthquakes are then investigated by means of regression analysis treating the latter variable as exogenous (given the differences in the order of integration). The main finding is that seismic events have a significant, but relatively small, negative effect on the Japanese stock market, which increases as the magnitude of earthquakes increases. On the whole, seismic events appear to generate uncertainty that negatively affects market performance.

It should be pointed out that the present study has some limitations. In particular, future work should obtain more robust evidence on the impact of earthquakes on the Japanese stock market by estimating multivariate models including a set of suitable control variables, such as measures of monetary policy and economic growth, and proxies for uncertainty. Moreover, issues such as the possible presence of structural breaks and nonlinearities should be addressed using an appropriate econometric framework. For instance, tests for endogenous breaks could be carried out as in Bai and Perron (2003) or, in the specific case of fractional integration, as in Gil-Alana (2008) and Hassler and Meller (2014), whilst methods based on Chebyshev's polynomials (Cuestas and Gil-Alana, 2016) or on Fourier transform functions (Caporale et al., 2022) could be used to capture nonlinearities.

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