ST309 Group Project Report

Analysing the extent to which market efficiency holds in both developed and developing countries following a natural disaster

Candidate Number	Individual Contribution
38871	1/3
43144	1/3
40311	1/3

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1. Introduction

1.1 Describing the Problem

The problem tackled in this report is to evaluate the extent to which market efficiency holds in both developed and developing countries following natural disasters, and thus, the degree to which arbitrage opportunities present themselves. Market efficiency has been a critical field explored by academicians and practitioners in the world of Finance. Previous research conducted has shown that natural disasters in the past have led to enormous costs, for instance, $150 billion for Hurricane Katrina in 2005 in the USA, and $122 billion for the Tohoku Earthquake and Tsunami in 2011 in Japan. In both these cases, research suggests that the financial markets did not efficiently price in the information[1] [2]. Hence, our **goal** is understanding the extent to which natural disasters impact market efficiency in stock markets, in particular, contrasting results in both developed and developing countries, which has not been examined thoroughly in previous research that we have come across.

Stock market efficiency describes the degree to which the market prices reflect all relevant and available (past and present) information[3]. Under market efficiency, arbitrage opportunities are not available, and consequently, investors should not be able to make abnormal returns from trading securities. All information should be reflected instantly and accurately in the market, i.e. stocks are fairly valued at all times.

1.2 Importance of the Problem for the Subject Matter

The problem explained before is essential to explore, due to the increasing risks of natural disasters occurring, with both more frequency and more intensity, as a result of various factors such as climate change and more extreme and unpredictable weather patterns[4].

This report focuses on contrasting stock market performance and market efficiency in two countries, Japan (developed country) and India (developing country), following similar scale floods (the natural disaster) in 2018. Floods throughout south-west Japan between late June and mid-July resulted in damage costs of approximately $3-4 billion[5], whilst in south India (in the state of Kerala), heavy rainfall began in July,

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[1] B. Fakhry et al., "THE IMPACT OF A RECENT NATURAL DISASTER ON THE JAPANESE FINANCIAL MARKETS: EMPIRICAL EVIDENCE," *Journal of Competitiveness* 10, no. 2 (2018), doi:10.7441/joc.2018.02.04.

[2] "Effect of Catastrophic Disaster in Financial Market Contagion," Taylor & Francis, last modified February 13, 2017, https://www.tandfonline.com/doi/full/10.1080/23322039.2017.128

[3] "Market Efficiency Defintion," Investopedia, last modified January 4, 2004, https://www.investopedia.com/terms/m/marketefficiency.asp.

[4] "Natural Disasters Increasingly Linked to Climate Change, New Report Warns," The Independent, last modified December 11, 2017, https://www.independent.co.uk/environment/climate-change-natural-disasters-link-increase-global-warming-report-warning-a8103556.html.

[5] "AIR Worldwide Estimates Insured Losses from Japan Floods Could Reach US$4B," Insurance Journal, last modified August 21, 2018, https://www.insurancejournal.com/news/international/2018/08/21/498685.htm.

leading to floods in August, which resulted in costs of approximately $3.5 billion[6]. We chose to examine floods because of the increasing threats they pose globally, as they have risen by 50% in the last decade[7].

We expect market efficiency to hold in Japan, in a semi-strong form, due to the fact it is a developed nation and the Tokyo Stock Exchange is the 3rd largest exchange in the world, with a market capitalisation of $5.61 trillion. In contrast, the Bombay Stock Exchange in India is the 10th largest and has a smaller market capitalisation of $2.05 trillion[8]. Hence we expect more arbitrage opportunities to be present in India after the floods, where abnormal returns can be made, as a result of portfolio and asset mis-pricing.

While natural disasters like floods negatively impact some industries like insurance, as property damage claims spike immediately after a flood, some other industries like construction are positively impacted since infrastructural and repair work increases[9]. Thus, by following a methodology which incorporates stocks from multiple industries, allows us to find a cumulative average statistic which comments on broad-based market efficiency. The findings of this research could then be applied to other stock markets in various nations to evaluate whether abnormal returns can or cannot be made following a natural calamity.

1.3 Problem as a Data Analytic Problem

With an abundance of stock market data and datasets available around the time periods of both the Japan and India floods in 2018, data analytics – primarily through the use of machine learning – will help us analyse and evaluate any trends, and ultimately, infer whether abnormal returns can be made in both markets. Our dataset is multi-dimensional, and thus allows us to use data analytics to analyse market efficiency and predict any abnormal returns in the absence of the flood (i.e. predicting a counterfactual if the disaster did not take place).

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[6] World Bank, "How Much Do Floods Cost India?," Medium, last modified November 15, 2018, https://medium.com/world-of-opportunity/how-much-do-floods-cost-india-4a9446117f71.

[7] Arthur Neslen, "Flooding and Heavy Rains Rise 50% Worldwide in a Decade, Figures Show," The Guardian, last modified March 22, 2018, https://www.theguardian.com/environment/2018/mar/21/flooding-and-heavy-rains-rise-50-worldwide-in-a-decade-figures-show.

[8] "Top 10 Largest Stock Exchanges In The World By Market Capitalization," ValueWalk, last modified February 4, 2020, https://www.valuewalk.com/2019/02/top-10-largest-stock-exchanges/.

[9] S. Surminski and J. Eldridge, "Flood insurance in England - an assessment of the current and newly proposed insurance scheme in the context of rising flood risk," *Journal of Flood Risk Management* 10, no. 4 (2015), doi:10.1111/jfr3.12127.

2. Description of Data

2.1 Source of Data

Our project scope seeks to be extensive, requiring data for 2 countries in particular time-frames, and for several stocks in each respective stock market; as such, a complete dataset was not readily available.

Thus, we created our own dataset by using the R package, *Quantmod*. This package sources stock data from Yahoo Finance and allows us to select a time frame specific to the period under study. The data is sourced by using the unique ticker code for each stock in the Tokyo Stock Exchange and the Bombay Stock Exchange. The time frame under consideration for our analysis is one month before and one month after the occurrence of the disaster. This length is sufficient and comprehensive for us to study the extent of market efficiency in Japan and India.

Severe floods in Japan started on the 28th June - hence, the stock market data we extracted from *Quantmod* covers the period of 28th May to 28th July. Similarly, in south India, severe floods took place on the 16th of August, and thus the data extracted here covers a period of 16th July to 16th September. Our event window covers a period of 5 days (e.g. for Japan, the event window begins on the 22nd June and ends on 4th July).

2.2 Appropriateness for the Goal of the Study

The data has been sourced appropriately to achieve our goal of analyzing market efficiency across Japan and India after a natural disaster. For our analysis, we decided to randomly select 5 stocks from each country's well known market indices to get a holistic view of how the floods affect the market. The random nature for the selection of stocks is critical - this allows us:

(i) to ensure that our findings and conclusions are unbiased

(ii) to establish a causal relationship

(iii) eliminate most idiosyncratic risk by not limiting our analysis to particular industries - by randomly selecting stocks from each market index, we managed to select companies from multiple industries and consequently make inferences on broad-based market efficiency.

The 5 stocks and their respective industries, selected from each country (and index), are listed in the table below.

Japan (Nikkei 225)		India (SENSEX)	
Stock	***Industry***	***Stock***	***Industry***
Amada Holdings Co.	Manufacturing	Tata Steel Limited	Steel
Hokuetsu Corporation.	Paper Mill	Tech Mahindra Limited	Information Technology
Mitsubishi Motors	Automotive	Bajaj Auto Limited	Automotive
Secom	Security	ICICI Bank Limited	Financial Services
Tokyu Fudosan Holdings Corporation	Real Estate	Larsen & Toubro Limited	Conglomerate

Table 1: Stocks & Industries

2.3 Data Cleansing Conducted

After sourcing the data from *Quantmod*, for each date (i.e. row) for all stocks, there is data for 6 default column variables - opening price, high price, low price, closing price, adjusted closing price, and volume. All the columns for each stock were renamed for consistency and ease, from the default 'ticker.variable' format, to 'stockname.variable format' - for instance, Amada's ticker is 6113.T, and thus variables were named from the default of 6113.T.Close to Amada.Close, etc.

Otherwise, the downloaded data was extremely clean and had no missing values and the formatting of data was also correct. An exception however is weekends and public holidays when markets in both countries are closed and not operating; these periods have been excluded from our analysis.

Lastly, for the event study, we calculated the returns separately for the 5 stocks in each country and merged them together into a single "zoo" file (for our subsequent code).

3. Data Analysis

3.1 Event Study

3.1.1 Description of the Methodology for the Event Study

In order to analyse the event study we install the *eventstudies* package. The first thing we need is a summary of the events that actually happened, which would include the name of the stocks under study and the date at which the floods occurred, which is 28th June for Japan and 16th August for India. The data frame, ‘eventDateJP’ and ‘eventDateIN’ were created for Japan and India respectively. The second file we need for the event study is daily stock returns. Daily stock returns in percentages were calculated for each stock individually across the time period and then merged together creating ‘StockPriceReturnsJP’ and ‘StockPriceReturnsIN’. These objects were in the “zoo” format so that we could execute the event study formula. The column names of ‘StockPriceReturnsJP’ and ‘StockPriceReturnsIN’ must match the stock name (i.e. the name of the unit of observation) in ‘eventDateJP’ and ‘eventDateIN’.

We use an event window of 5 days as per common convention. In this event study, we are doing no adjustment and this is done by setting type to “None”. Once we have daily returns, we are concerned with the cumulative abnormal returns as part of the event study. In order to achieve this, ‘to.remap’ is set to TRUE and we ask that this remapping be done using “cumsum”. Finally, the event study is instructed to ask for bootstrap inference. The object returned is of class ‘es’; and the vector ‘outcomes’ displays the disposition of each event in the events table, in which “success” denotes a successful use of the event. The graph also displays the 95% confidence interval which has been derived based on the standard deviation of returns and the cut-off values, leaving out 2.5% on either side of the normal distribution.

While it is true that averaging across events or stocks isolates the event-related fluctuations, there is a loss of statistical efficiency, because of a smaller sample size and a larger standard error that comes from stock price fluctuations, which is unrelated to firm level reactions. As mentioned earlier, since our stocks have been picked randomly and the floods affect the market on a non-idiosyncratic scale, the cumulative abnormal returns do indeed link to market efficiency rather than being a result of omitted variable bias in the mathematical model prepared.

3.1.2 Reasons for our Approach

We focus on the *eventstudies* package in R, which allows us to more succinctly express the cumulative abnormal returns, and also depict the confidence interval on the graph. Initially, we had approached the analysis by trying to calculate abnormal returns manually; we later realised that with the multitude of variables like *type* and *remap*, the *eventstudy* function allowed us to study different possible outcomes by just changing one input variable, rather than having to replicate the analysis and calculate regression intercepts and slopes across multiple stocks in both countries.

3.1.3 Evaluation and Analysis of Results

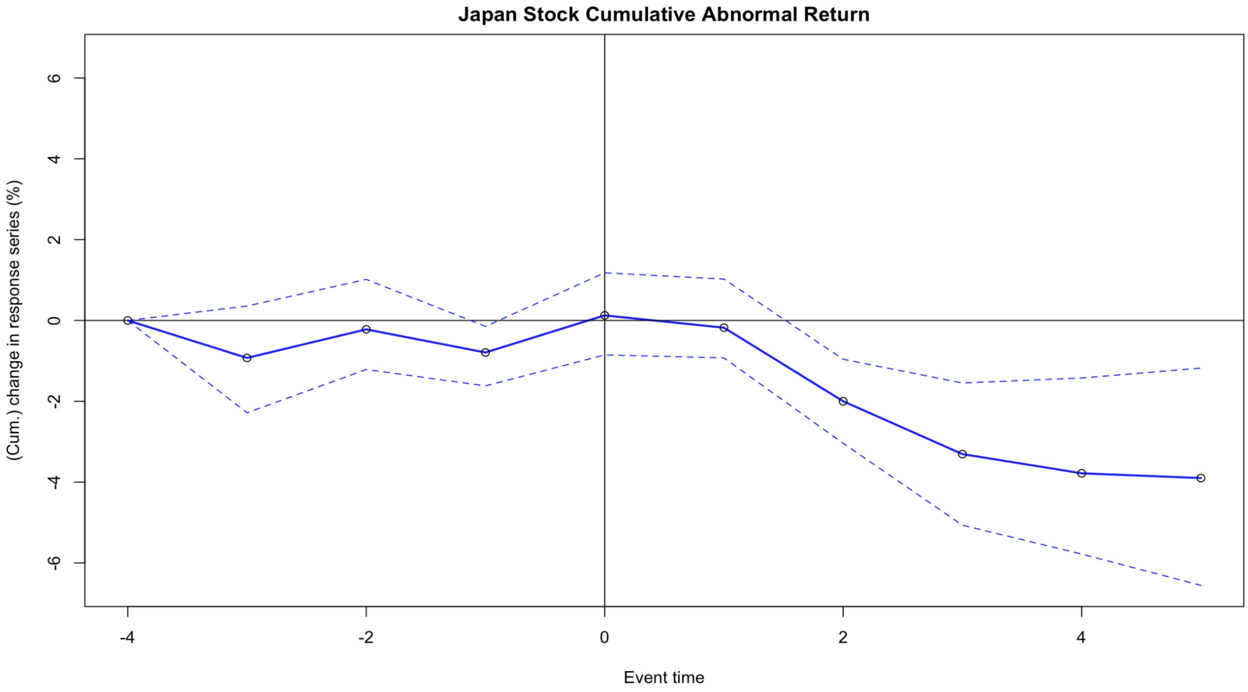
We have the cumulative abnormal returns (CAR) as observed in Japan and India over the event window of +4 and -4 days from the event. As per our hypothesis, we expect stock markets in Japan to price in the effect of the event more rapidly with a reduced error rate, as compared to India.

<u>Japan</u>

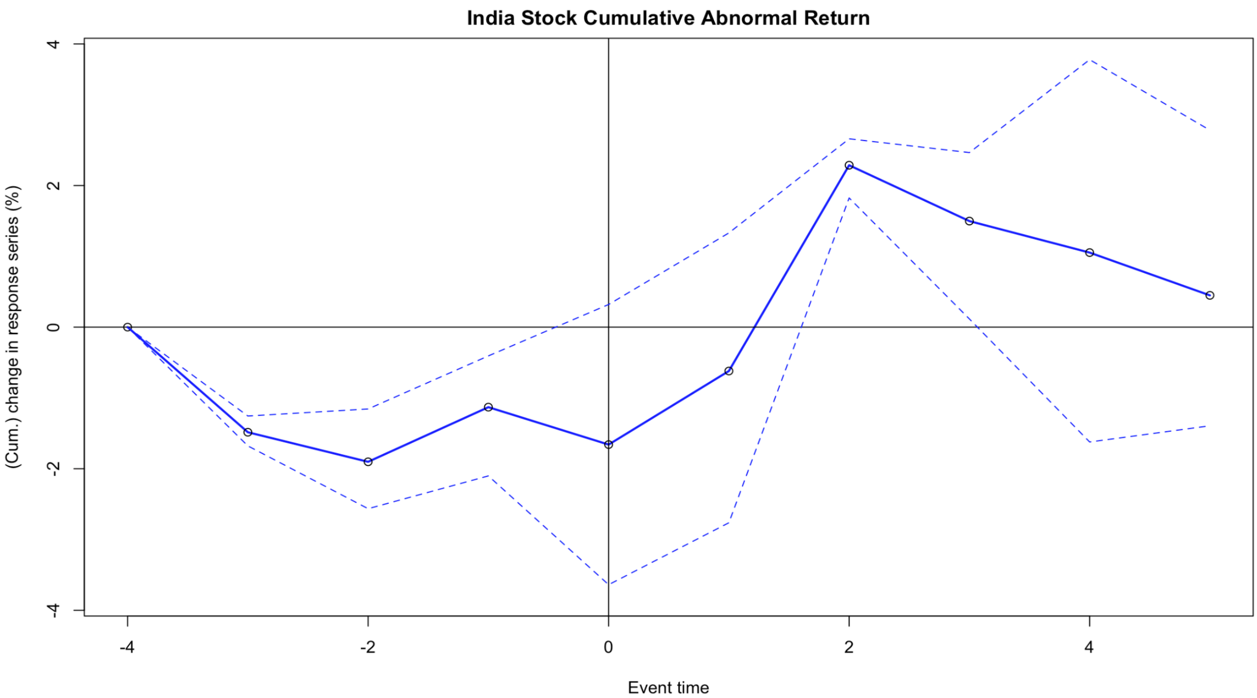
Before the event, we see that the CAR is close to zero, which means that there isn't evidence of information leakage, which could have led to excess risk adjusted returns. Moreover, we see 4 out of 5 successes. After the event, we observe the stocks showing signs of momentum, so there is an initial under-reaction and the returns follow a trend to slowly adjust to the 'correct' level. The under-reaction is also expected given that companies would not immediately see the effects of the floods, which might come in the form of increased insurance claims or reduced automotive output for instance. While there is evidence of semi-strong form market efficiency being violated, as an arbitrator can simply short the stock after the natural disaster and benefit from the opportunity, the 95% confidence interval is within 5-7 units, which means that the standard error of the data is relatively low.

<u>India</u>

In India, even 2-3 days before the event has happened, we see information leakage is not being priced in. The fall in the returns before the event might be explained by an over-reaction caused by the prediction of the floods, which then reverses until the point the Flood actually takes place on 16th August. After the event, we see a much larger jump of 2 unit points (an overreaction), which is followed by a sharp reversal as more information becomes available to market participants and they price it in their trades relatively slowly. Even the confidence intervals are larger, which signals a larger estimated standard error in the dataset for cumulative abnormal returns. We expect asymmetric information distribution and thus drastic cumulative abnormal returns results in a developing country. Similar to the case in Japan, 4 out of 5 successes are obtained.



Graph 1: Japan Stock Cumulative Abnormal Return during the Event Window



Graph 2: India Stock Cumulative Abnormal Return during the Event Window

3.2 Price Forecasting

Forecasting is used to predict future values from past and present values, to infer about future happenings or about different datasets. We prepare a time series, where we try to predict the price of the 10 stocks under study, and use them as a counterfactual (i.e. find results if the Flood did not take place) to compare with actual prices as observed both in the event window and in the period after the event windows.

3.2.1 Description of the Methodology for the Forecast

Our goal here is to predict the prices as we would observe in the event window of the two countries, aiming to get a sense of the absolute impact of the floods on the financial markets. For this, we would split and train the dataset to predict prices for the following period. The difference visually observed between this predicted price and the actual price in the event window would give us a measure of the effect on the average stock prices. The predicted price allows us to obtain a counterfactual and by comparing with the actual, find the effect of the calamity that has had a direct effect on company valuations and market participants.

We begin by computing a weighted average price for each country, where the prices are weighted by the stock value in relation to the total stock value at any given day.

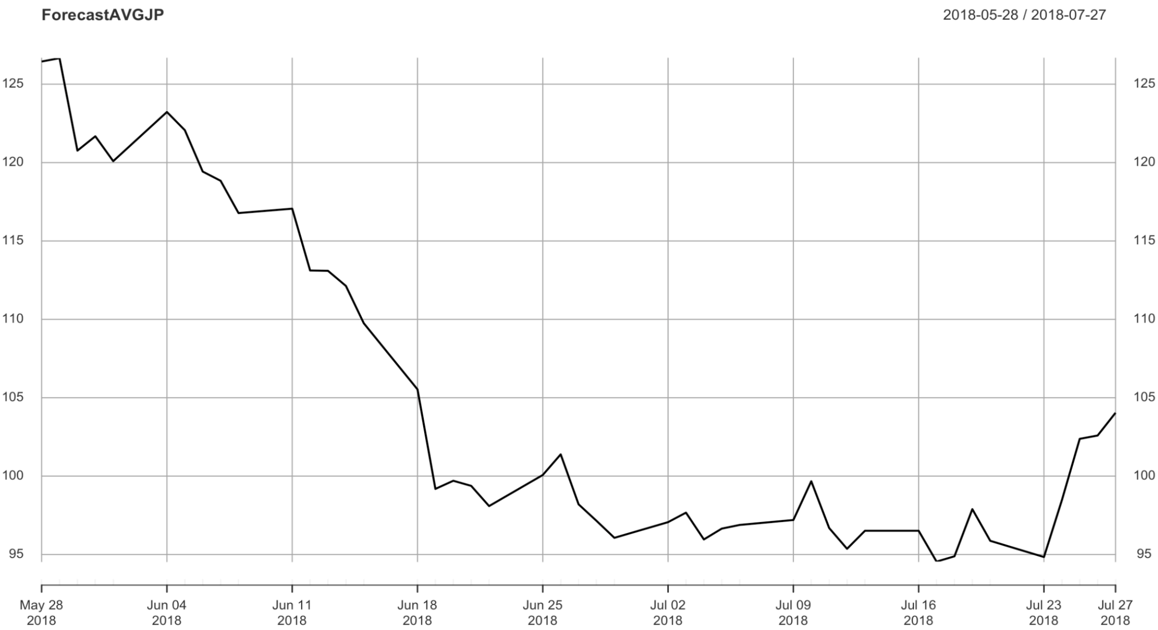
$$\text{Weighted Average Price} = \sum_{i=1}^{n} xw$$

We begin our analysis with ARIMA models - they are generally used with non-stationary time series dataset series, i.e. when their means, variance, and auto-covariance change over time. In short, once we have adjusted and selected the best model, we can make a forecast based on probabilistic future values. As we can see in the output however, the predictive intervals observed for the data under ARIMA time series modelling are highly variant - encompassing more than 10 unit points of the data in both directions; moreover, the prediction gives a linear function, which by observation does not appear to be indicative of the trend previously observed in the data. Consequently, we move our analysis to feedforward neural network, which will allow us to get a better fit for the data.

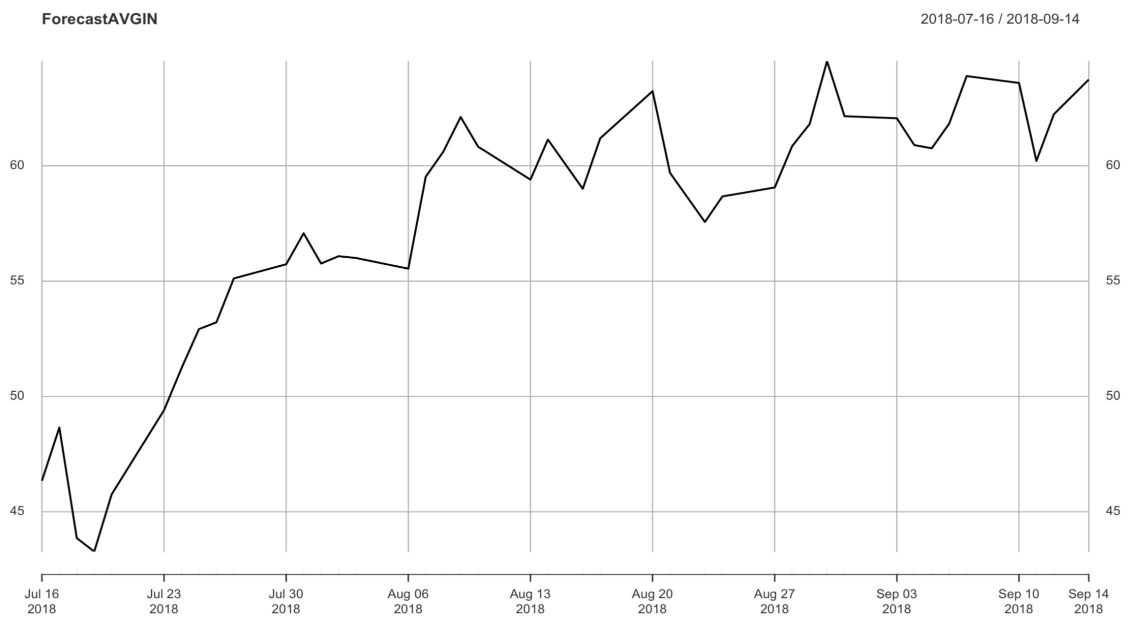
To predict from the prices, we use a feedforward neural network, which allows for a better, non-linear fit for the data, and smaller predictive intervals than ARIMA testing. By conducting research into some new machine learning models in accordance with our project scope, we reached a new neural network function in the forecast package called *nnetar*. It has an input layer, a hidden layer, and an output layer and each one is connected to each of the other ones. Giving an interconnected network of nodes - the objective of the neural network is to differentiate the error function and minimise it with respect to the parameter of study. The feedforward neural network is one of the simplest artificial neural networks, as in this network, the information flows in one direction (forward), from the input notes to the output notes.

3.2.2 Evaluation and Analysis of Results

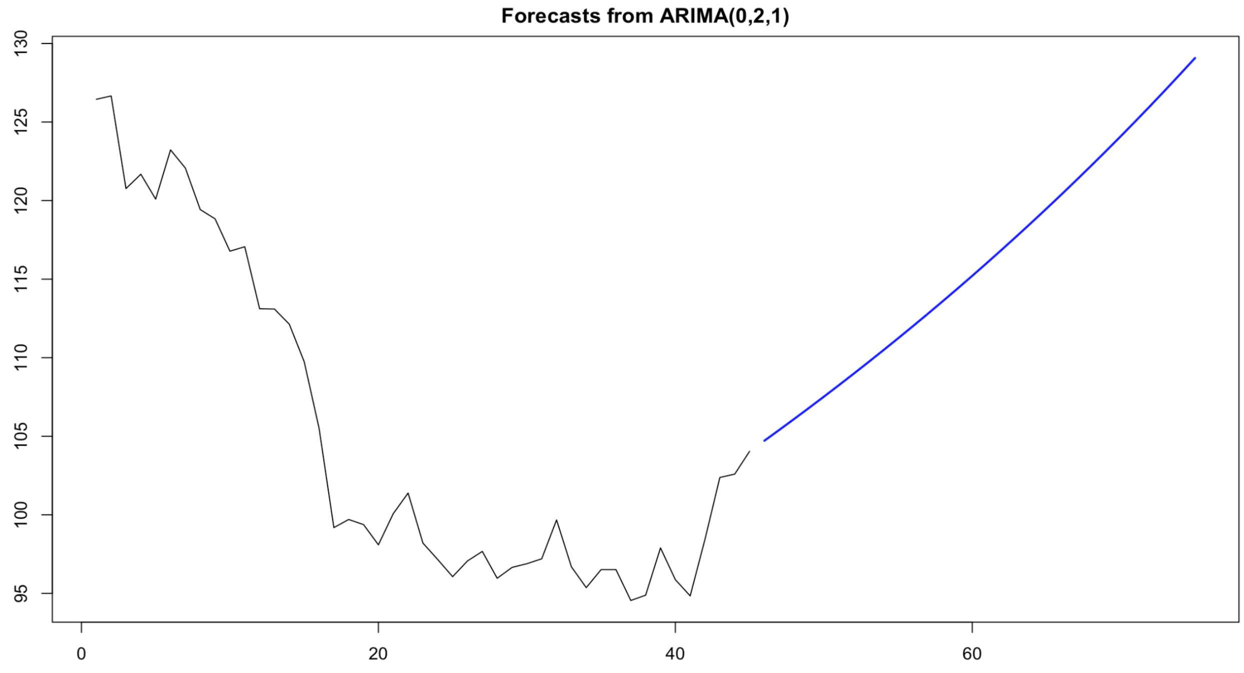
The predicted prices in Japan have a horizontal asymptote at close to 97, which is coherent with the actual price average; this adds to our previous finding by indicating that stock price wasn't significantly impacted after the natural event, and a significant deviation did not occur. For India however, while the data predicts a similar relation to the one observed in Japan, the actual returns spike quite significantly, as evidenced by earlier findings which signal an over-reaction and subsequent reversal 2-4 days after the event.



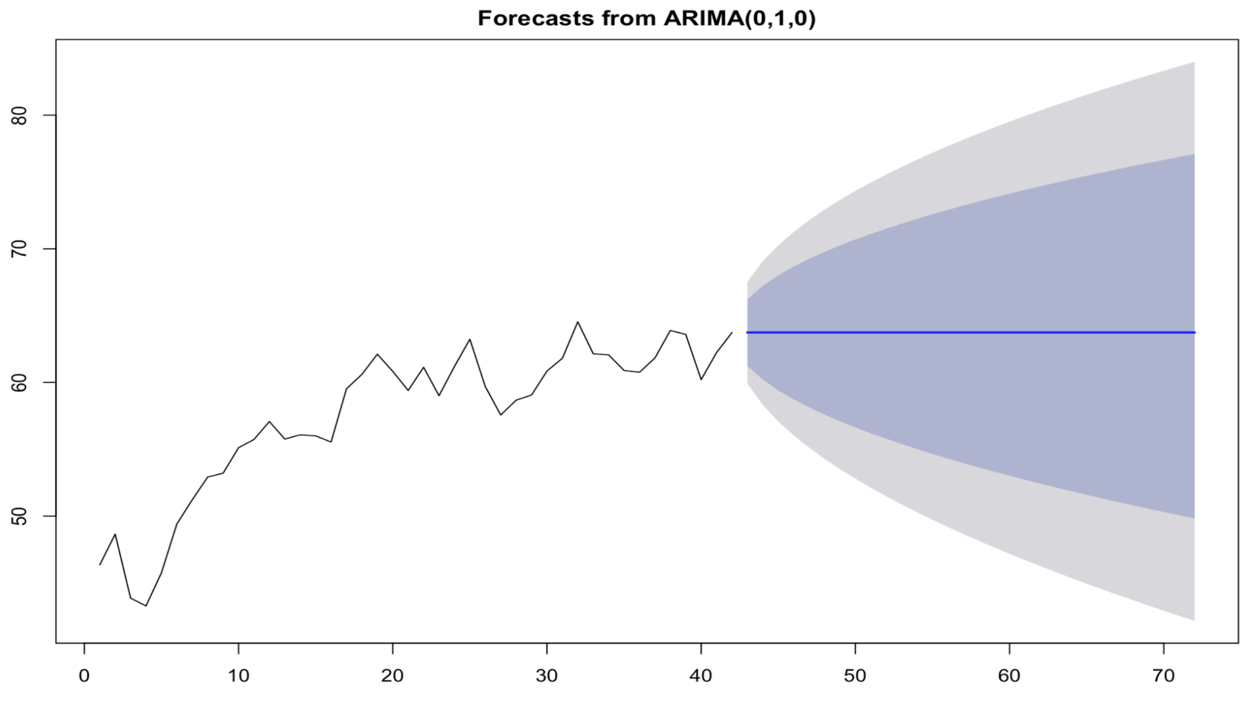
Graph 3: Japan Stock Weighted Average True Price



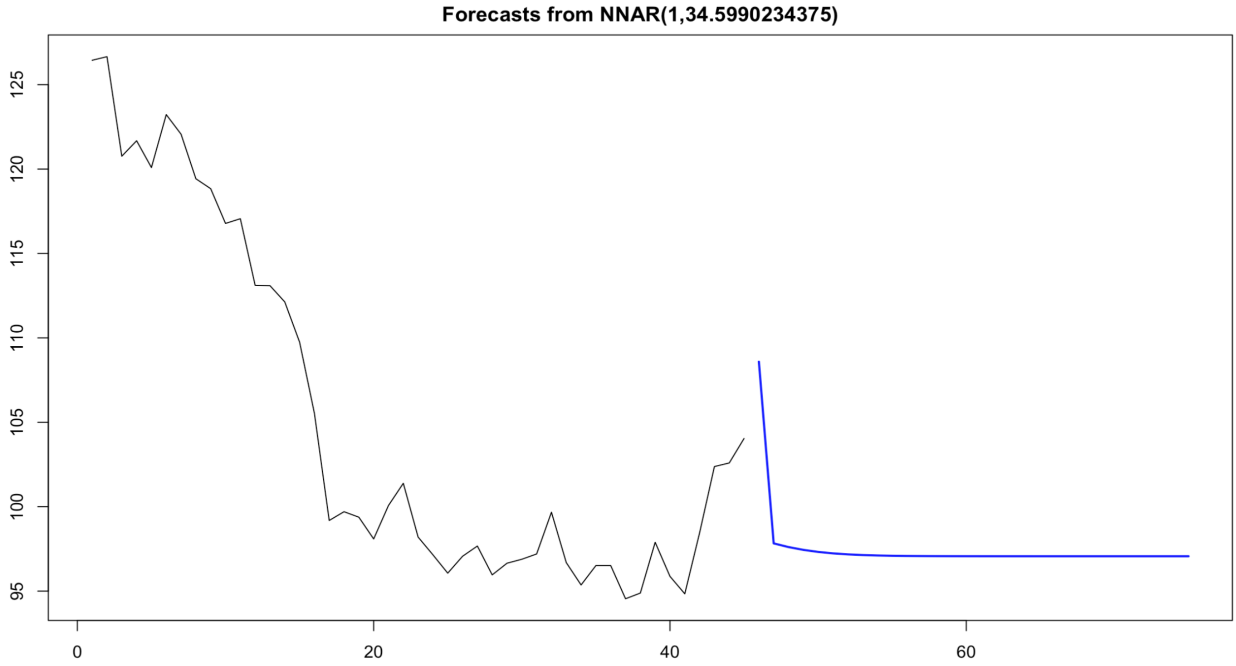
Graph 4: India Stock Weighted Average True Price



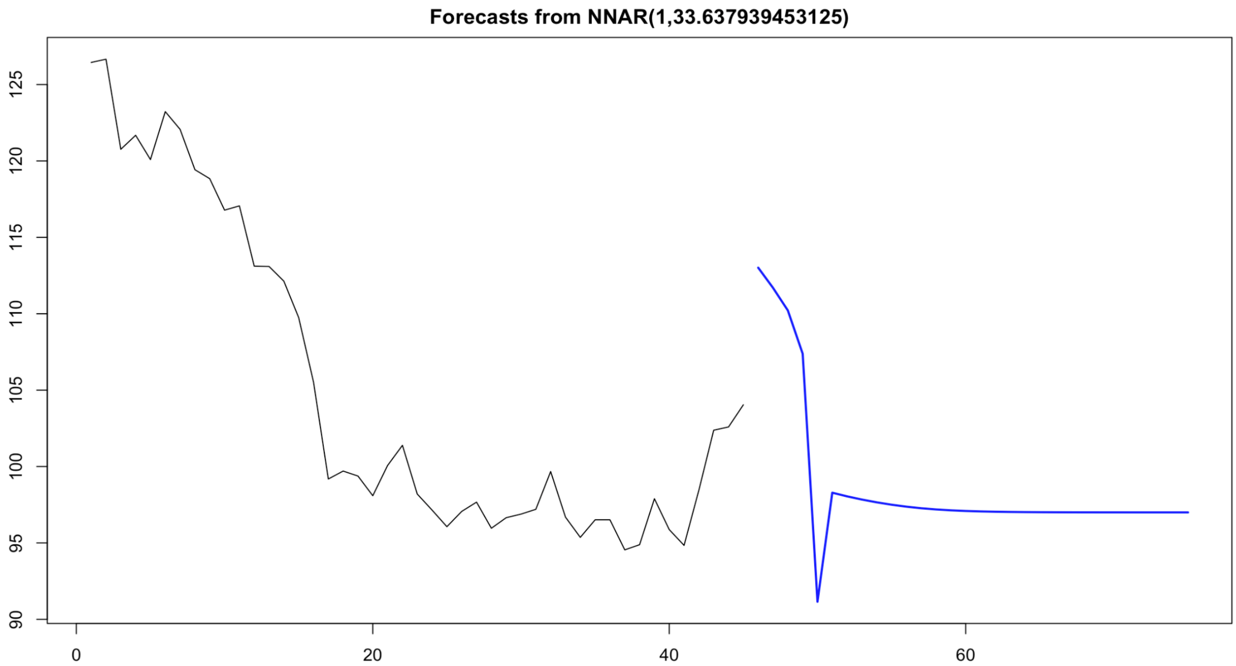
Graph 5: ARIMA Price Predictions for Japanese Stocks



Graph 6: ARIMA Price Predictions for Indian Stocks with Predictive Interval



Graph 7: Feedforward Neural Network Price Predictions for Japanese Stocks



Graph 8: Feedforward Neural Network Price Predictions for Indian Stocks

4. Conclusion

4.1 Important Learnings from our Data Analysis on the Subject Matter

Differences in market efficiency observed in developed and developing countries have serious implications for financial systems and market participants worldwide. In our analysis, we observed that stock markets react much more quickly and adjust accordingly to systemic shocks (Floods) in developed countries like Japan - without the prevalence or large scale trends - and thus, arbitrage opportunities are scarce, with the absolute impact on stock prices relatively small as well. On the other hand, in India, our analysis showed that stock markets have much larger trends around such systemic events and take much longer to adjust, indeed as our original hypothesis assumed. Furthermore, in India, the implications on the absolute value of stock prices are more severe with a much larger standard deviation, which means that other nominal metrics such as CPI and GDP, which also factor into multi-factor asset pricing models, could also be affected. Hence, our findings can have a large impact on financial and investment strategies in these economics' stock markets following a natural calamity.

With the advent of AI and machine learning especially in this day and age, quant traders are constantly working hard to find stock alphas and make abnormal returns. Given that these investors are abundant in developed economies, and the fact that we observe large differentials in the market efficiency across developed and developing economies - the medium for which is natural non-idiosyncratic events - we can conclude and suggest that current investment strategies in developing economies should indeed be refined such that the potential valuable opportunities are appropriately priced in.

4.2 Limitations of the Current Analysis and Potential Improvements

While our analysis and research have a lot to offer, there are some limitations that exist nonetheless. Firstly, although the stocks were chosen randomly, through appropriate means, the analysis could be made more robust by controlling for more variables or introducing time-fixed parameters in the analysis, to account for any omitted variable bias that may affect outcomes. This would also improve the accuracy of both the event study results and the predictions.

In addition, due to the nature of an event study having a limited number of days in the event window, our analysis might have suffered from using a smaller than normal sample size (of days) and hence impacted the standard errors and the confidence intervals whilst carrying out the predictions. Perhaps extrapolating our study, by collecting data from a larger number of stocks in a wider range of countries, based on a larger number of natural and non-idiosyncratic events, could have been considered in order to make the results even more comprehensive and applicable to multiple different settings. Lastly, to improve the efficiency of our event study model, we can compare the individual stock returns against the market returns to get a better idea of how the calamity relatively impacted the stock market.

Although we have identified potential shortcomings and subsequent room for improvements, it is key to remember that given the scope of this report, we have still obtained concrete results contrasting stock market performance in both Japan and India following floods. Hence, we have contributed to existing studies, not just of academic interest, but one which also has strong implications for financial market stakeholders, and identified ways to take this topic forward in this field. Further analysis can be done in the future to uncover greater insights beyond the report's scope.