

The Effect of Climate Risk on Stock Market Performance Evidence from Sri Lanka.

¹Priyadarshani, G.W.Y. and ²Perera, L.A.S.

^{1,2}Department of Finance, University of Kelaniya, Sri Lanka.

¹yanushikagunasekara@gmail.com, ²shanakala@kln.ac.lk

Abstract

This study aims to identify the effect of climate risk on stock market performance in Sri Lanka. As an island, the country is frequently affected by climate change variabilities. Due to the higher climate risk exposure of Sri Lanka, it is highly needed to identify the risk at a prior stage. As, this is the first study in Sri Lanka to identify the climate risk impact on stock market performance the primary objective of this study is to identify the climate risk effect on the All-Share Price Index, Standard and Poor's SL20 index and 20 industry groups according to the GICS classification. The considered climate risk variables are drought, flood, high wind, heavy rain, landslide, and lightning. The findings of the study revealed there is no significant impact from climate risk variables to the All-Share Price Index, and Standard and Poor's SL20 index. However, the analysis discovered significant impact of several climate risks to certain specific sectors of CSE such as drought significantly impacts automobiles and components, banking and transportation sectors. At the same time, the high wind is a key factor for food, beverage and tobacco. The drought and high wind influence are significant in sectors like capital goods, utilities, consumer durable and apparel, consumer services, healthcare, equipment and services, materials and household and personal products. As well as drought and lightning have a significant impact on the commercial and professional service sector and energy sector while the diversified financial sector is impacted by drought, high wind and heavy rain. Apart from that, sectors like food and staples, retailing, insurance, real estate and telecommunication are unaffected by any climate risk factor. At the same time, the pharmacy and biotech industries are impacted by all the climate risk variables except floods. Ultimately, the study's findings will provide direction to decision-makers including potential investors to consider the climate risk in their decisions making processes.

Keywords: Climate risk, Stock market performance, GICS classification, All Share Price Index, Standard and Poor's SL 20 Index

Introduction

Climate Risk is a formal analysis of the likelihood and responses due to climate change. By today, the topic had received much attention from different parties, insisting on identifying the effect of climate risk in advance. The Climate change effect is anticipated to increase despite the mitigation actions taken. The ongoing changes occurring in the climate with uncertainty are complicated when assessing the associated risk. The critical component of climate risk is natural disasters. According to the Intergovernmental Panel on Climate Change (UN Environmental Program) IPCC, natural disasters can be defined as the impact of climate-related extremes, such as heat waves, droughts, floods, cyclones, and wildfires, reveal the significant exposure of some ecosystems and human systems to current climate vulnerability. According to the country's climate risk profile, Sri Lanka is an island state with a tropical climate and a physically diverse geography. Due to its geographical nature, the country is highly vulnerable to climatic changes.

The annual climate risk report issued by the World Bank Group depicts that the country possesses a hot and humid climate with significant differences across variations in the topography, such as four distinct rainfall seasons that can be identified and these seasonal variations occur differently with the topography in the country. El-Nino and La-Nina conditions and the inter-convergence zone also impact the precipitation patterns. These rains are the main robust factor for forests' biodiversity, covering 30% of the island. However, deforestation is a critical threat to forest coverage in Sri Lanka. Currently, for that reason, only one-third of the natural coverage exists in the country, and ultimately, this has been influenced by frequent landslides and land erosion. The temperature seems to fluctuate a slight amount on an annual basis. The average temperature in coastal areas is between 26 °C and 28 °C, while at higher altitudes, it is between 15 °C and 19 °C. Moreover, the country frequently experiences moderate cyclones, mainly in the northern region, with significant threats from cyclone-related storms and coastal erosion. Some of the key features identified in the country's historical climate trends include a rise in mean annual temperature of 0.2°C per decade. In contrast, the mean daytime and nighttime minimum temperatures were 1°C and 0.7 °C, respectively, between 1961 and 2001. There was a significant decline in island-wide mean annual precipitation of 144 mm between 1961 and 1990 and a continuous rise in the frequency and intensity of droughts, floods, etc. According to the USAID (2021) report, forecasted climate change included some projected changes like a rise in average annual temperature between 0.8 °C and 2 °C by 2060, a rise in frequency and intensity of Cyclones, the severity of floods, drought incidence, landslides, etc. For those projections, it is better to identify the effect of climate change vulnerabilities on the economy in advance.

As the first study in Sri Lanka to identify the impact of climate change on stock market performance, this study aims to determine the effect on three aspects of the ASPI, the S&P SL 20 index, and industry groups according to the Global Industry Classification Standards. The research follows a quantitative approach and test results are identified using the empirical research method.

Problem Identification

The climate risk is not only an environmental issue but also an investment issue. As an example, coastal erosion can impact real estate, create supply chain issues and create manufacturing issues in the bottom lines of companies, etc. Therefore, the large economic and ecological damages from climatic disasters currently threaten many economies.

In accordance with past research, the importance of identifying the impact of climate risk on stock market performance indicates that it is a fast-growing concept among developing countries with higher climatic risk. (Naiqian Wu, et al., 2022), reported that there is a negative relationship between corporate climate risk and stock market prices in China. (Dietz, et al., 2016) Revealed that global financial assets will be severely affected due to the considerable value of loss arising from the climate change variabilities, based on estimation from the Value at Risk (VaR) to the climate changes. As well as (Bansal, et al., 2016), analyze the fluctuations in temperature will affect aggregate stock market valuation. However, many sources emphasize the importance of identifying the effect of climatic change on a country's stock market. Yet, this kind of research has not been conducted in Sri Lanka. Therefore, if this study can identify any significant impact of climate risk on stock market performance at a prior stage, decision-making parties can take the necessary actions to minimize the risk.

According to the identified research problem, the main research objective is to identify the effect of climate risk on stock market indices, (In the Sri Lankan context, the study examined the performance of two main indices as All Share Price Index, Standard and Poor's SL20 index) along with the main objective, this study also served secondary objective of examine the climate risk effect on stock performance of industry groups according to the GICS classification.

Significance of the Study

Climate risk is not a single risk; it is the root cause of many risks, as follows: Physical risk occurs when climatic changes negatively impact human lives and properties. For instance, storms and floods have dangerous effects on infrastructure; droughts will lead to crop failures, severely affecting sectors like agriculture, health care, real estate, and the tourism sector.

Regulation risks arise when the government endeavors to reduce the climate risk, which will influence the economy. However, this cost should be considered when evaluating investment decisions. For instance, newly implemented laws will raise commodity prices, which will have a negative impact on customer demand.

Competitive risk is a competitive disadvantage that occurs when companies lose their attention to climate risk. This will result in higher production costs and, ultimately, lower profits. Production risk is the most frequent risk to emerge due to climate risks in Sri Lanka. Natural disasters disrupt the continuous supply of production and lead to price increments. Reputational risk involves all the risks mentioned above. Due to the negative impact of climatic change, companies may lose their reputation. Therefore, Sri Lanka needs to pay much attention to this topic for several reasons. According to the Global Climate Risk Index which depicts the country's risk exposure, Sri Lanka is placed in 30th place among 180 countries, and as a developing country, it is highly needed to secure the economy from the severe hazards of natural disasters. Therefore, identifying the impact of climate change is a significant and crucial factor for Sri Lanka.

However, this study only focuses on one category of climate risk, natural disasters, due to the resource's availability and climate change pattern relevant to the country. In the Sri Lankan context, as the country is not very industrialized, some crucial climate change factors, like carbon emissions, are not considered for this study. Further, the unavailability of daily disaster data in summary reports issued by the National Disaster Relief Services Center before 2017 was a major limitation of the study.

Literature Review

Introduction

The main aim of this section is to provide some prominent theories regarding climate change and studies that have influenced this scope of climate change influence in past and recent research studies done in different countries. Theories related to climate change and the empirical findings by other researchers have been studied further to identify the factors, relationships, methodologies, and other facts necessary to carry out this research effectively.

Theories Related to Climate Risk

Global climate change is the most controversial issue of the twenty-first century. According to the (Stern, 2007) studies regarding the climate, it has received much attention among the community due to the evolutionary impact on economic activities, including financial markets. Climate change is a speeding-up concept. Ambitious and effective global action to deal with the effects and potential consequences of the climate crisis is now more critical than ever. The recent uptick in support for governments' climate commitments is more significant. However, the major challenge remains translating increased political aspirations on climate emergencies into results that ensure a net zero transformation by 2050. Although climate finance is rising, developed countries remained USD 20.4 billion short of achieving the objective of mobilizing USD 100 billion per year to support developing countries' green transitions at the end of 2019. Tremendous growth in corporations, financial institutions, and institutional investors is attempting to evaluate physical and transition risks and publicly release climate transition plans that aim for net zero emissions. As a result, financial markets are beginning to incorporate climate transition risks and opportunities into making investment decisions.

Climate Risks in Financial Markets

According to the past literature on climate finance, climate risk comprises two components: physical risk and transition risk. (Giglio, et al., 2021) Physical risk refers to risks that directly impair firm performance and profitability. According to the Prudential Regulation Authority PRA, (2015), physical risk is identified as the risk that originates from weather-related events, and directly impacts property damage, disruptions in supply chains and resource scarcity. For example, there will be adverse effects on firms, in their business operations, assets value and sustainability due to the threat of damages from extreme climate events. (Ginglinger & Moreau, 2021). Transition risk is the financial risk associated with the subsequent societal response to climate change. Implementing a carbon tax for high-carbon emission firms will reduce profitability. (Li, et al., 2021). However, another category of climate risk called Liability risk, which emerges as a climate change effect causes actors to recover losses from responsible parties, who transfer costs to insurance firms under third-party liability contracts. (Naiqian Wu, et al., 2022), reported a negative relationship exists between corporate climate risk stock market prices in China.

In this study, firm-specific risk represents the independent variable, while stock prices represent the dependent variable. The methodology started with variable measurement and sample selection. Corporate climate risk is measured using the corporate climate risk index, and the dependent variable is the stock market reaction, measured through the cumulative abnormal return over a two-day event window. The data was collected from different sources: textual transcripts retrieved from the WinGo Textual Analytics database, briefing characteristic data obtained from Chinese Research Data Services, and a sample period

selected according to the performance briefing transcripts—the final sample comprised 618 firm-year observations. After running the regression model, several analyses were performed. The Univariate test conducted to identify the correlation between the climate risk of an individual firm and its stock price reaction and the result of the univariate relationship between CCR (Corporate Climate Risk) and CAR (Cumulative Abnormal Return) proved that firms associated with higher climate risk have a higher probability of immediate stock price declines during the period of initial reaction window. A robustness test has been done to ensure the creditability of the results. This test included a series of sensitivity tests with an alternative measure of corporate climate risk. The ultimate result confirmed the negative impact of Corporate Climate Risk on Stock Prices by expressing essential moderators that shape the association between corporate climate risk and the adverse market reaction, such as Industry Carbon emissions, Local abnormal temperature, State Ownership, Institutional shareholdings, Dividend payout, etc., and this study suggests that disclosure of climate-related information can help the stock market to price climate risk more efficiently.

(Dietz, et al., 2016), explore that climate changes pose substantial challenges to financial market participants since the real economy highly backs some financial assets. For instance, on July 20, 2021, there was record-breaking heavy rainfall in the provincial capital of China's Henan province. As a result of that severe flood, the stock market performance of some publicly listed companies was affected. According to (Giglio, et al., 2021), climate change exposes firms to new risks and has significant financial implications for the underlying stocks.

According to the literature, there is a significant debate on financial market efficiency concerning climate risk and consensus has yet to emerge; however, they argue that, as climate changes considerably influence the operations and profitability of the firms, it is essential to reflect the exposure of the cash flow to climate risk through assets prices.

Therefore, in recent research, it was highlighted that the community had much focus on the above argument. (Bansal, et al., 2016), analyze how fluctuations in temperature will affect aggregate stock market valuation. Further, this reveals that there is a negative impact on equity valuation, though there is an effect of an increase in global temperature expected to be realized in the distant future. Moreover, (Dietz, et al., 2016) reveal that global financial assets will be severely affected due to the considerable value of loss arising from the climate change variabilities, based on estimation from the Value at Risk (VaR) to the climate changes. During periods of substantial negative news about long-run climate risk, firms subject to higher regulatory climate risk will have a lower stock return (Engle, et al., 2020). While (Choi, et al., 2020) demonstrate that, carbon-intensive firms underperform with low emission in situations where local temperatures are abnormally high and during which investor's expectations and attention to global warming also increases. Accordingly, (Bolton & Kacperczyk, 2021) show the effect of a firm's carbon emissions on the cross-sectional pattern of stock returns, and they correctly price firms in the stock market with high carbon emissions at a discount.

At the same time, little research has depicted the importance of potential inefficiencies in the financial markets. (Hong, et al., 2019), revealed the impact of long-term drought influences on cross-country food stock returns. While they claim that the stock market cannot fully understand information about climate risk, they will finally delay stock price adjustments. After finding evidence that proves that the market failed to detect the threat of rising sea levels and limited price effect (Murfin & Spiegel, 2020) examined the impact of climate risk on sea levels, which leads to a rise in house prices. (Greenwood & Warren, 2022), provide that the investment process in the United Kingdom asset management context and present climate risk management strategies hold the potential to address the traditional way of climate risk investor behavior. According to the findings, using ESG investment strategies (Environmental, Social,

and Governance) is a 'Grey Area' in mitigating climate risk according to the undefined management practices under the sustainability of the board and responsible investment agendas. The independent variable is the climate risk disclosure organ, which provides an approach to climate risk management. The methodology of this study has been done as an inductive approach, using the mono-method method to analyze reports and financial disclosure.

The research done by (Faccini, et al., 2022) assesses different climate risk sources reflected in stock prices. They use textual analysis with a two-step validation approach, constructing novel proxies for market-wide physical and transition risks. The results found that only risks arising from US climate policy appear to be priced, and pricing is a recent phenomenon. The findings revealed that stock prices are a risk generated by government intervention rather than a direct risk from climate change.

(Barnett, 2019) using the standard mean-variance framework, discover that institutional investors are less conscious of climate change risk and that the market is not appropriately pricing the risk. Therefore, investors can reduce ex-post risks by divesting from some fossil fuel stocks, and the cost of de-risking their Bayesian portfolio is relatively low. Failure to correctly price climate change risk raises questions about market efficiency. According to the Efficient Market Hypothesis (EMH), under a semi-strong form of market efficiency, stock prices should reflect all publicly available information (Fama & Macbeth, 1973). Opponents of EMH attempt to disprove it by taking advantage of arbitrage opportunities in public climate data or translated data such as climate trends and creating a green investment strategy by purchasing companies that disclose more greenhouse gas emissions and selling companies that disclose less. The strategy generates significantly positive returns, which may be evidence of market inefficiency regarding climate change risk. Accordingly, the green investment strategy (Hong, et al., 2019) proposes a long-short approach that adjusts to systematic climate risk in the stock market while rejecting the EMH. Most studies concentrate on just one or two aspects of climate risks. Meanwhile, there is a lack of measures that reflect the firms' overall climate risk. To address this empirical challenge, (Sautner, et al., 2020) developed a measure of firm-level climate risk by employing a machine learning technique to identify climate-related information from earnings conference call conversations among analysts and the management team.

Several researchers have also investigated the effects of firms' environmental disclosure on share price discovery. The worthiness of management's environmental disclosure and discovered voluntary and mandatory disclosures provide beneficial information about the companies in stock price changes. According to (Palmer, 1965), the reliability of voluntary environmental disclosure has a positive relationship with the company's future stock price. (Griffin, et al., 2010) Discovered that voluntary disclosure of emissions of greenhouse gases under the Carbon Disclosure Project results in equity value penalties, resulting in an instantaneous stock price response when investors acquire new emission-related information.

Besides that, several analyses revealed the impact of climate risk on the stock market returns and the market efficiency. The effect of climate risk on market efficiency (Hong, et al., 2019) depicts regulatory worries about markets underrating climate risks. It suggests further exploration of the value of corporate disclosure about exposure risk. The analysis explained the importance of PDSI as a helpful drought metric to form portfolios and manage risk by using international drought measures to calculate food industry profitability and a cross-country portfolio strategy based on PDSI. The Palmer Drought Severity Index (PDSI) is an independent variable. In contrast, food companies' stock prices are considered dependent variables and explored climate change and stock market returns using the daily price of ETF's

and climate-related events. At the same time (Warren, 2019) depicts the climate risk disclosure and the climate risk management in UK asset managers. The results revealed that climate risk management strategies hold the the potential to address traditionally climate risk-averse investor behavior and investment process in the United Kingdom and the use of investment strategies to mitigate climate risk.

Contingency Theory and Climate Risk

Climate has become a significant source of challenges for organizations due to the higher probability of disruptions in the operations of supply chains. The continuous rise in uncertainty caused by climate change required a knowledgeable business community to restructure their business (Gordorn & Narayanan, 1984). Thus, the Contingency theory is more relevant as it focuses on organizational management due to external events (Lawrence & Lorsch, 1967) as it is based on an organization's decision-making process, which addresses the contingent on circumstances.

There are few studies about the climate change-related contingencies in economies of emerging countries and consequent responses from businesses. According to (Drazin & Van De Ven, n.d.) the core of this theory provides the structure and organizational processes that must be fitted to the objective to survive or be effective. Though there is no unique way to apply the contingency theory (Horisch, 2013) and (Lee, 2012) assert that the theory can be applied as a strategy for climate risk, which affects supply chains. Some research (Drazin & Van De Ven, n.d.) (Gordorn & Narayanan, 1984) (Sousa & Voss, 2008) (Volberda, et al., 2012) states that main contingency factors such as internal organization structure for low carbon management, adoption of low carbon operation practices and effects on performance.

The first variable, internal organization structure for low carbon management, reveals the organization's capabilities of taking action against emergent contingencies. (Gordorn & Narayanan, 1984) (Volberda, et al., 2012) Later, the researchers found crucial factors that the company should manage. Such as the commitment and leadership establishment to low carbon management, written policies regarding training programs for employees, making performance reporting procedures for emission, etc. (Renukappa, et al., 2013)

The second variable is adopting low-carbon operation practices, which concerns actions organizations can respond to prevailing and future contingencies. (Bouttcher & Muller, 2015)

The outside events the organizations cannot directly control can be identified as Contingency. The article (Sousa & Voss, 2008)introduced four possible contingencies that affect supply chain management, such as lack of resources and difficulties in accessing the raw materials, highly advanced technology, regulations, and extra costs to bear. Moreover, companies benefit from low carbon management practices (Hoffman, 2005)such as improvement in risk management strategies, acceptability of new sources of capital, anticipation and impact of climate-related regulations, operational developments, improvement of human resource management and company reputation, identifications of new markets, etc. However, the research done by (Faccini, et al., 2022) states that these improve organizational performances significantly and discover that controlling and monitoring climate contingencies are essential and should be done permanently and systematically.

Methodology

Introduction

This section provides a deep analysis of the research design, including the research philosophy, logic, approach, conceptual framework, hypotheses, and operationalization of the study. Moreover, the methodology used for the study, its strengths and weaknesses, and the type and method of data collected for the analysis are elaborated, respectively.

Research Design

According to past literature on climate change's impact on the stock market performance, climate change influence is more vital to economic activities. Thus, this study focuses on identifying the effect of climate change on stock market performance evidence from Sri Lanka.

- This research follows a **positivistic philosophy** approach, which determines cause and effect or result of the study with more focus on calculations using secondary data.
- For this study, research logic is in the **deductive approach**, which is determined by using empirical studies, applying, and testing the influence of climate change on the volatility of stock prices. Logic begins with developing hypotheses and forming strategies to test them convex to verify or reject the claims.
- As well as this study relies on numerical data and test results are measured using numerical data therefore, this study uses a **quantitative research method**.

Conceptual Framework and Operationalization

Conceptual Framework

The visual representation of the considerable variables of the study is given below. Accordingly, independent variables include six significant climate change events for representing climate change, while the stock market indices and sector indices represent the stock market and sector performance, which is the dependent variable of the study.

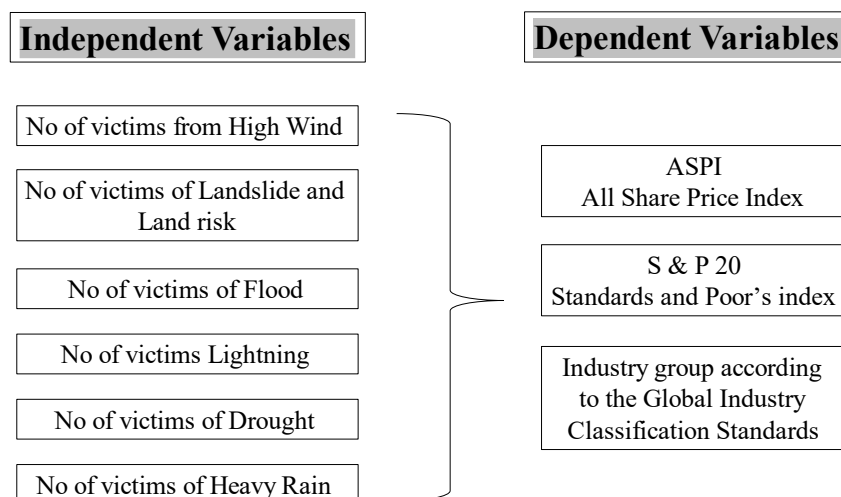


Figure I: Conceptual Framework of the Study

Population and Sample Selection

The considered population for the study is the number of people affected by the six significant variables of climate risk daily from 01-01-2018 to 15-11-2022 with 1130 observations for the Share Price indices analysis. For the industry group analysis, data is collected from 20-01-2020 to 17-10-2022 with 620 observations due to information availability. The Sample of a study is a specific group identified according to the gathered data; however, as a special case, the selected sample for this study is the *entire country*.

Data Collection Method

The data used for this study is extracted from secondary data sources. For independent variables, stock indices data was collected through the Colombo Stock Exchange website. Climate change data was gathered from situation summary reports of the National Disaster Relief Services Center and other reports on the country's risk profile issued by the Ministry of Disaster Management and the World Bank.

Techniques of Data Analysis

This section provides a detailed examination of the research topic by categorizing the ultimate results into smaller, logical topics to build reasonable conclusions with proof of supporting evidence. In the first part of the analysis, gathered data was identified as the *Time-Series Data* which were recorded over a consistent time interval and followed several steps with the help of E-views software to identify the impact of climate change on stock market performance reflected indices. After testing the basic assumptions, the ARIMA model was used to capture the trends and patterns of data using a combination of past values, errors and differences. However, the remaining part of the analysis is about the impact of climate risk on industry groups according to the GICS classification. Here, the effects of extreme climate events are identified separately for twenty sectors. The regression is processed through the E-views software and the test results are interpreted accordingly.

Hypotheses Development

The related hypotheses to this study can be identified as the frequent and specific predictions found after analyzing existing evidence.

H₀ - There is no significant impact from the number of victims of high wind on the ASPI/S&P 20/Industry group according to the GICS classification.

H₁ - There is a significant impact from the number of victims of high wind on the ASPI/S&P 20/Industry group according to the GICS classification.

H₀ - There is no significant impact from the number of victims of landslides on the ASPI/S&P 20/Industry group according to the GICS classification.

H₂ - There is a significant impact from the number of victims of landslides on the ASPI/S&P 20/Industry group according to the GICS classification.

H₀ - There is no significant impact from the number of victims of floods on the ASPI/S&P 20/Industry group according to the GICS classification.

H₃ - There is a significant impact from the number of victims of floods on the ASPI/S&P 20/Industry group according to the GICS classification.

H₀ - There is no significant impact from the number of victims of lightning on the ASPI/S&P 20/Industry group according to the GICS classification.

H₄ - There is a significant impact from the number of victims of lightning on the ASPI/S&P 20/Industry group according to the GICS classification.

H₀ - There is no significant impact from the number of victims of drought on the ASPI/S&P 20/Industry group according to the GICS classification.

H₅ - There is a significant impact from the number of victims of drought on the ASPI/S&P 20/Industry group according to the GICS classification.

H₀ - There is no significant impact from the number of victims of heavy rain on the ASPI/S&P 20/Industry group according to the GICS classification.

H₆ - There is a significant impact from the number of victims of heavy rain on the ASPI/S&P 20/Industry group according to the GICS classification.

Findings and Discussion

Introduction

The data considered for the analysis belongs to a time series and six significant climate risk variables are identified as independent variables. At the same time, the stock indices are reflected as dependent variables. Further, all the data has been extracted from different resources daily. Thus, it is recognized under the category of Secondary data. For the ultimate objective of identifying the climate risk effect on Stock performance, analysis was done using several models.

Findings - Analysis for All share index and Standard and Poor's Index

Descriptive Analysis

Dependent variables comprise the All-Share Price Index (ASPI), Standard and Poor's 20 Index (S&P 20), and Industry sector indices. The independent variables are the number of people affected by *Flood, Drought, Lightning, Heavy Rain, High Wind and Landslide risk* data extracted from daily situational reports issued by the National Disaster Management Centre in Sri Lanka. According to the descriptive analysis, Central Tendency, Dispersion, and Normality measures are used to identify the sample conveyed by the descriptive statistics. However, the test results show that both dependent and independent variables have a long right tail positive skewness and leptokurtic because the kurtosis values are greater than three. Further, the Jarque-Bera test represents the test statistic of measuring the difference between the skewness and kurtosis of the series from the normal distribution. The results show that the probability value for each variable is 0.0000, which is highly statistically significant ($0 < 0.5$). Therefore, the model rejects the null hypothesis of normally distributed data and indicates the *availability of outliers in flood* because it differs from every other observation with a drastically peaked curve of 11280.49%.

The Correlation test results indicated no close correlation between the variables.

In order to run the regression on this time series data, it is essential to ensure that variables are in stationary form with constant mean and constant variance over the period. The decision Criteria for stationarity test are as follows:

1) Autocorrelation Function

The pattern of the ACF chart decides that data is available in stationary form. If there is a clear pattern among the data, it provides a clue to confirming the availability of non-stationary. However, it can be identified as a subjective conclusion.

Table I: Autocorrelation Function

Independent Variable	P- Value at level form
Drought	P Stat (0.000) <0.05
Flood	P Stat (0.000) <0.05
Heavy rain	P Stat (0.000) <0.05
High Wind	P Stat (0.000) <0.05
Landslide Risk	P Stat (0.000) <0.05
Lightning	P Stat (0.000) <0.05

2) Unit Root Test

As the widely used method for testing stationarity, the probability of Augmented Dicky-Fuller test statistics depicts that data is free from non-stationary if the probability is lesser than the significance level.

Table II: Unit Root Test

Dependent Variable	P- Value at level form	P- Value at 1 st difference
A S P I	P Stat (0.5605) >0.05	P Stat (0.000) <0.05
S & P20 index	P Stat (0.1285) >0.05	P Stat (0.000) < 0.05

For ASPI and S&P 20 indices, the probability value is greater than the significance level, and the null hypothesis fails to reject the level form of data. However, at the first difference, both stock indices are stationary while rejecting the null hypothesis.

All the probability values of six independent variables are less than the significance level. This leads to rejecting the null hypotheses and concluding that all the climate risk variables are stationary at level form.

The Multicollinearity test indicates that dependent variables are not perfectly collinear when one regressor cannot be a linear function of another. The VIF (Variance Inflation Factors) test done for checking the multicollinearity of each variable proved that there is no multicollinearity among the variables included, as VIF values are less than five.

After checking the assumptions of the model, regression analysis has been performed.

Regression Analysis

ARIMA Model

As this time series data, the Autoregressive Integrated Moving Average Model has been used for forecasting the data, and it easily captures the trends and patterns of data using a combination of past values, errors, and differences. As ARIMA consists of sub-models which are AR, MR, ARMA, ARIMA and ARIMAX to identify the best matching model, the following process has been followed. Identification of AR and MA Lag terms by using the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) of the correlogram chart can identify the appropriate lag length for MA (q) and AR (p) terms can be identified. If the length of the bar exceeds the indicated significant level, then lag can be determined to be included in the model.

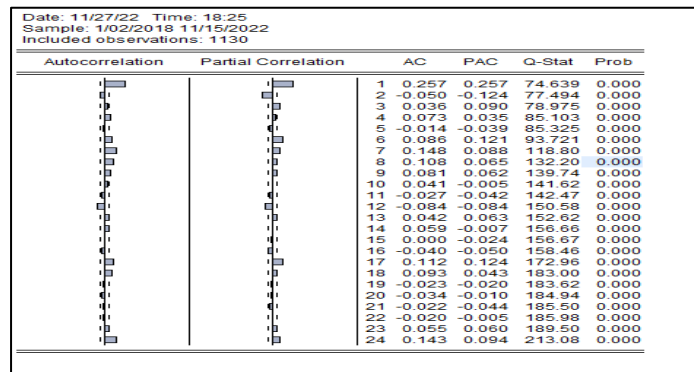


Figure II: AC and PAC for ASPI

For ASPI, by analyzing the ACF function, only the first lag is significant, and therefore, the MA (q) seems to be included 1. As well as, in the PACF function, there is a possible one lag for AR terms (p). Thus, the dependent variable ASPI is stationary at first difference.

For the S&P 20 index, by analyzing the ACF function, only the first lag is significant; therefore, the MA (q) seems to include 1. As well as, in the PACF function, there is a possible 1 lag for AR terms (p). Thus, the dependent variable S&P 20 is stationary at first difference.

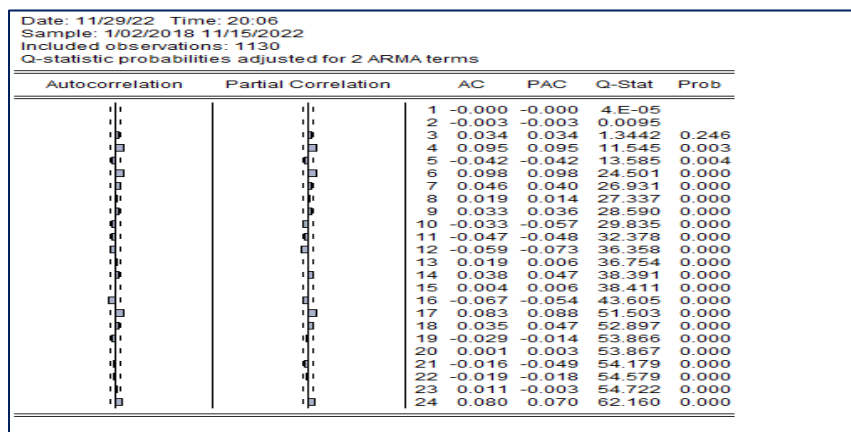


Figure III: AC and PAC for S&P SL 20

ARIMA Model- ASPI

As this is multiple regression using more than one dependent variable; the adjusted R squared value of 6.4% depicts the weight of independent variables collectively interpreting the dependent variable AS. As this is multiple regression using more than one dependent variable, the adjusted R squared value of 7.99% depicts the weight of independent variables collectively interpreting the dependent variable S&P 20. According to both ARIMA models and the independent variables, the ARIMA models' explanatory power is very low. Therefore, it is better to run another model like ARIMAX. The suitability of the selected AR and Lag terms can be confirmed through the roots of AR and MA terms. Since the AR roots and MA roots are within the confidence boundary, these selected lag terms are suitable for further analysis of the model.

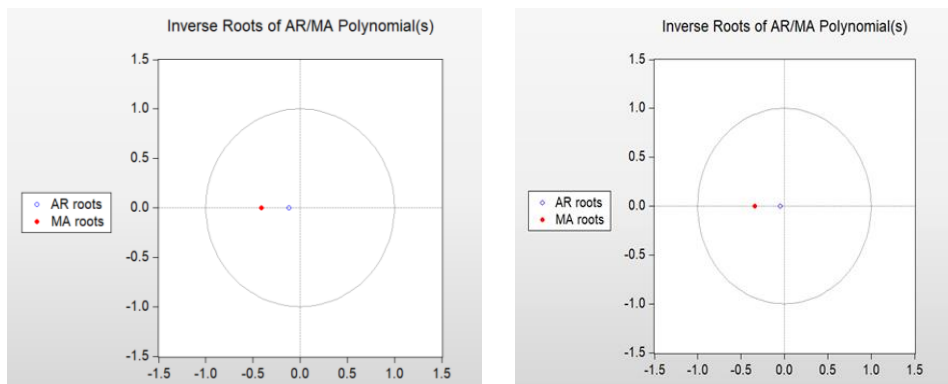


Figure IV: Inverse roots test of AR/MA for ASPI and S&P SL 20

ARIMAX Model

The above ARIMA model has been extended by including other explanatory variables which are drought, heavy rain, high wind, flood, landslide, and lightning.

Interpretation of Regression Results

Estimation Command:

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LS(OPTMETHOD=OPG) D(ASPI) C AR(1) MA(1) DROUGHT FLOOD HEAVY_RAIN HIGH_WIND
LANDSLIDE_RISK LIGHTNING
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Estimation Equation:

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D(ASPI) = C(1) + C(2)*DROUGHT + C(3)*FLOOD + C(4)*HEAVY_RAIN + C(5)*HIGH_WIND +
C(6)*LANDSLIDE_RISK + C(7)*LIGHTNING +
[AR(1)=C(8),MA(1)=C(9),UNCOND,ESTSMPL="1/03/2018 11/15/2022"]
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Substituted Coefficients:

```
=====
D(ASPI) = 1.76078755956 - 0.000452571462362*DROUGHT - 2.38699239424e-07*FLOOD +
0.00110139387192*HEAVY_RAIN + 0.00206577424922*HIGH_WIND -
0.00073818150747*LANDSLIDE_RISK + 0.000331109538847*LIGHTNING + [AR(1)=-
0.119222083865,MA(1)=0.417328432529,UNCOND,ESTSMPL="1/03/2018 11/15/2022"]
```

Variable	Coefficient	t-Statistic	Prob.
C	1.760788	0.418447	0.6757
Drought	-0.000453	-0.853429	0.3936
Flood	-2.39E-07	-1.55560E-02	0.9876
Heavy Rain	0.001101	1.228999	0.2193
High Wind	0.002066	0.217549	0.8278
Landslide Risk	-0.000738	-3.32E-01	0.9735
Lightning	-3.31E-04	0.001499	0.9988
AR(1)	-0.119222	-2.45622	0.0142
MA(1)	0.417328	8.908702	0.0000
SIGMASQ	10642.8	53.58737	0.0000
R-Squared	0.086466	Durbin- Watson Stat	2.004499
Adjusted R- Squared	0.079125		
F-statistic	11.77866		
Prob(F-Statistic)	0.0000		

Figure V: ARIMAX model test results for ASPI

Drought -The ASPI share prices may change by 0.000453 due to the change in the number of people affected by drought change in 1 person to the opposite direction.

Flood - The ASPI share prices may change by 2.39E-07 due to the change in the number of people affected by flood change in 1 person to the opposite direction.

Heavy Rain - The ASPI share prices may change by 0.001101 due to the change in the number of people affected by heavy rain change in 1 person to the same direction.

High Wind - The ASPI share prices may change by 0.002066 due to the change in the number of people affected by high wind change in 1 person to the same direction.

Landslide risk - The ASPI share prices may change by 0.000738 due to the change in number of people affected by landslide change in 1 person to the opposite direction.

Lightning - The ASPI share prices may change by 0.000331 due to the change in the number of people affected by lightning change in 1 person to the same direction.

AR (1) - The ASPI share prices may change by 0.119222 due to a change in ASPI share prices of 1 year ago by Rs.1 in the opposite direction.

MA (1) - The ASPI share prices may change by 0.119222 due to a change in the error term of the previous year by Rs.1 in the same direction.

Intercept- When all other explanatory variables are equal to 0, the change in ASPI would be Rs.1.760788.

Estimation of ARIMAX Model for S&P 20

Estimation Command:

```
LS(OPTMETHOD=OPG) D(ASPI) C AR(1) MA(1) DROUGHT FLOOD HEAVY_RAIN HIGH_WIND
LANDSLIDE_RISK LIGHTNING
```

Estimation Equation:

```
D(ASPI) = C(1) + C(2)*DROUGHT + C(3)*FLOOD + C(4)*HEAVY_RAIN + C(5)*HIGH_WIND +
C(6)*LANDSLIDE_RISK + C(7)*LIGHTNING +
[AR(1)=C(8),MA(1)=C(9),UNCOND,ESTSMPL="1/03/2018 11/15/2022"]
```

Substituted Coefficients:

```
D(ASPI) = 1.76078755956 - 0.000452571462362*DROUGHT - 2.38699239424e-07*FLOOD +
0.00110139387192*HEAVY_RAIN + 0.00206577424922*HIGH_WIND -
0.00073818150747*LANDSLIDE_RISK + 0.000331109538847*LIGHTNING + [AR(1)=
0.119222083865,MA(1)=0.417328432529,UNCOND,ESTSMPL="1/03/2018 11/15/2022"]
```

Variable	Coefficient	t-Statistic	Prob
C	-0.838126	-0.453341	0.6504
Drought	0.005679	0.170784	0.8644
Flood	-2.11E-04	-5.0727	0.9596
Heavy Rain	0.000317	0.11258	0.9104
High Wind	0.00038	0.480943	0.6307
Landslide Risk	6.87E-09	2.49E-03	0.998
Lightning	-0.000235	-1.332808	0.1829
AR(1)	-0.056689	-1.055196	0.2916
MA(1)	0.348791	6.542346	0.0000
SIGMASQ	1978.39	52.82402	0.0000
R-Squared	0.083763	Durbin- Watson Stat	1.99998
Adjusted R- Squared	0.0764		
F-statistic	11.37675		
Prob(F-Statistic)	0.0000		

Figure VI: ARIMAX model test for S&P SL 20

Interpretation of Regression Results

Drought - The S&P 20 share prices may change by 0.000235 due to the change in the number of people affected by drought change in 1 person to the opposite direction.

Flood - The S&P 20 share prices may change by 6.87E-09 due to the change in number of people affected by flood change in 1 person to the same direction.

Heavy Rain - The S&P 20 share prices may change by 0.000380 due to the change in the number of people affected by heavy rain change in 1 person to the same direction.

High Wind - The S&P 20 share prices may change by 0.000317 due to the change in the number of people affected by high wind change in 1 person to the same direction.

Landslide risk - The S&P 20 share prices may change by 0.000211 due to the change in the number of people affected by landslide change in 1 person to the opposite direction.

Lightning - The S&P 20 share prices may change by 0.005679 due to the change in the number of people affected by lightning change in 1 person to the same direction.

AR (1) - The S&P 20 share prices may change by 0.056689 due to the change in ASPI share prices of 1 year ago by Rs.1 opposite direction.

MA (1) - The S&P 20 share prices may change by 0.348791 due to a change in the error term of the previous year by Rs.1 in the same direction.

Intercept - When all other explanatory variables are equal to 0, the change in ASPI would be Rs.0.8381126.

Analysis, Testing of Assumptions and Findings

For ASPI and Climate Risk Factors

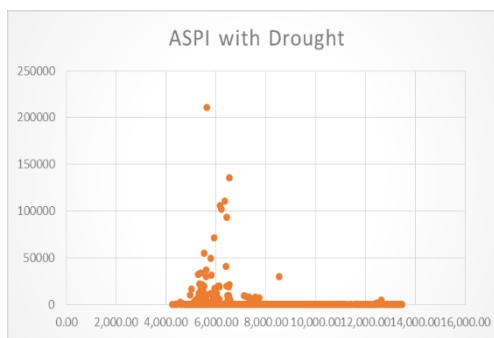


Figure VII: ASPI and Drought

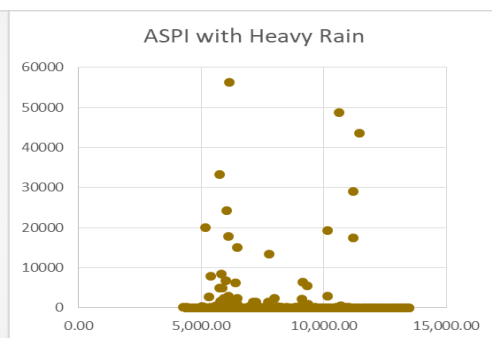


Figure VIII: ASPI and Heavy Rain

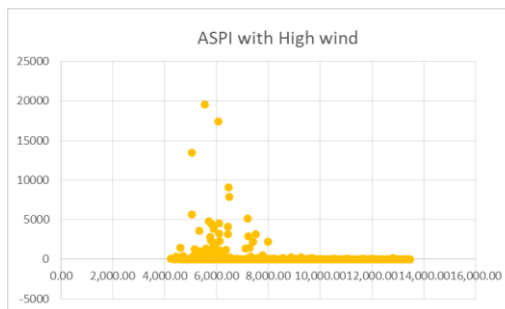


Figure IX: ASPI and High Wind

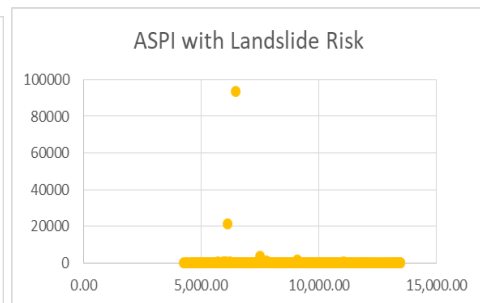


Figure X: ASPI and Landslide Risk

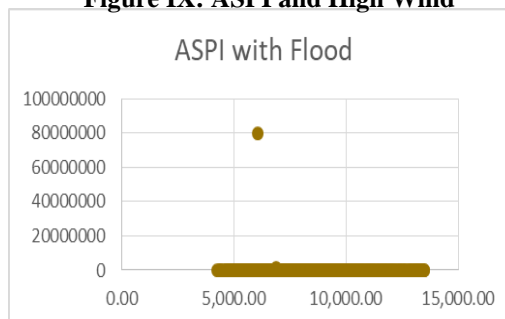


Figure XI: ASPI and Flood

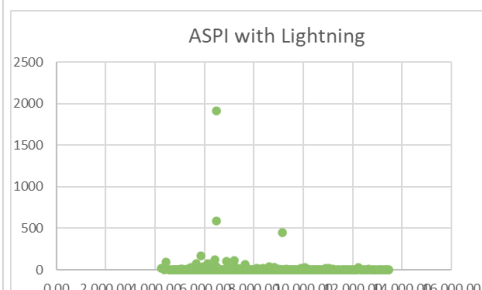


Figure XII: ASPI and Lightning

For S&P 20 Index and Climate Risk Factors

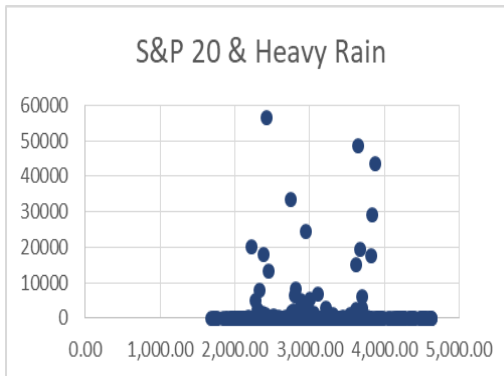


Figure XIII: S&P 20 and Heavy Rain

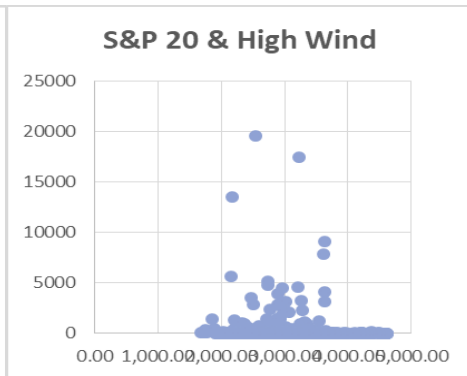


Figure XIV: S&P 20 & High Wind

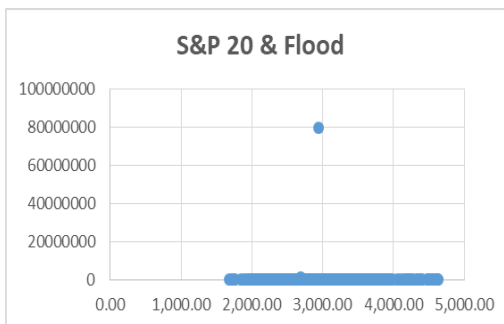


Figure XV: S&P 20 and Flood

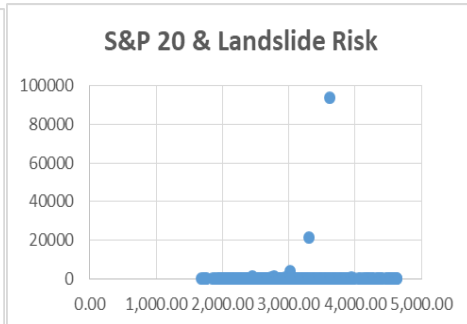


Figure XVI: S&P 20 and Landslide Risk

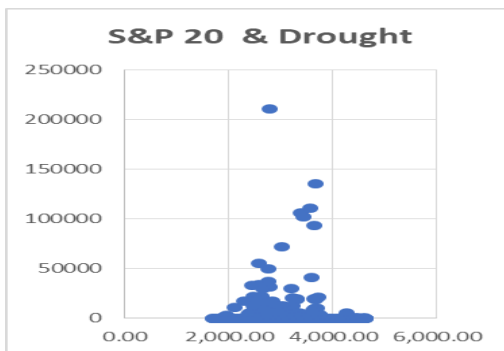


Figure XVII: S&P 20 and Drought

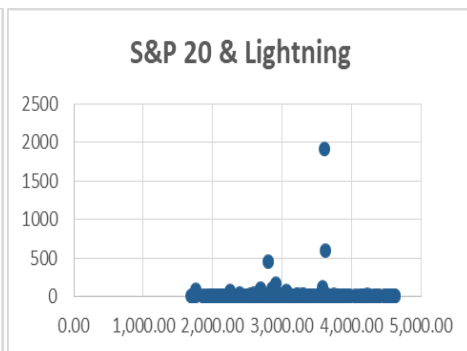


Figure XVIII: S&P 20 and Lightning

Normality Assumption

This is to check whether the error term has been normally distributed and whether the behavior of residuals is normal. The relevant hypothesis and the decision rule to the normality assumptions are given below.

H_0 : Residuals are normally distributed.

H_1 : Residuals are not normally distributed.

The decision rule rejects H_0 if the Jarque-Bera probability is less than a significant level. Since, in both cases, the Jarque-Bera probability (0.000) is lesser than the significance level (0.05), it fails to reject the null hypothesis at a 5% significance level.

Homoscedasticity

Homoscedasticity refers to the variance in the residuals that has to be constant or cannot be varied for lower or higher values of independent variables and the hypothesis and the decision rule regarding the homoscedasticity assumption are as follows:

H_0 : Residuals are Homoscedasticity.

H_1 : Residuals are Heteroskedastic.

The decision rule rejects H_0 if the Breusch - Pagan Godfrey probability is less than the significance level. Since it is 95% confidence, it depicts that residuals are homoscedasticity.

Autocorrelation

Autocorrelation refers to the lack of a systematic relationship between two error terms of the model. This is tested using the Durbin-Watson statistic. This is usually between 0 and 4. If the value is 2, no autocorrelation is detected in the sample. Values from 0 to less than 2 indicate that there is positive autocorrelation and values from 2 to 4 indicate that there is negative autocorrelation.

For ASPI, Since the Durbin-Watson statistic is 0.031464 which is less than 2, there is enough evidence to conclude that the model has positive autocorrelation.

For S&P 20 Index, Since the Durbin-Watson statistic is 0.017642 which is less than 2, there is enough evidence to conclude that the model has positive autocorrelation.

Testing the significance of the overall model

Hypothesis:

H_0 : $\beta_0 = 0, \beta_1 = 0, \beta_2 = 0, \beta_3 = 0, \beta_4 = 0, \beta_5 = 0, \beta_6 = 0, \beta_7 = 0, \beta_8 = 0$

H_1 : At least one $\beta \neq 0$

Determining the level of significance: 5%

Decision rule:

Reject H_0 if P Value of F < significance level.

Since Probability (F-statistic) $0.0000 < 0.05$, we can reject the H_0 .

Conclusion:

There is enough evidence to conclude at 5% level of significance, that at least one variable in the model has a statistically significant impact on the dependent variable which is the first lag value of the ASPI.

Testing the significance of individual variables using the two-tail P-values test.

Drought

H0: $\beta_1 = 0$

H1: $\beta_1 \neq 0$

Reject H0 if P value < significance level.

$0.3936 > 0.05$

Therefore, do not reject H0 at 5% level of significance.

The conclusion is that there is no statistically significant relationship between the drought and the first lag of the ASPI.

Flood

H0: $\beta_2 = 0$

H1: $\beta_2 \neq 0$

Reject H0 if P value < significance level.

$0.9876 > 0.05$

Therefore, do not reject H0, at 5% level of significance.

The conclusion is that there is no statistically significant relationship between the flood and the first lag value of the ASPI.

Heavy Rain

H0: $\beta_3 = 0$

H1: $\beta_3 \neq 0$

Reject H0 if P value < significance level.

$0.2193 > 0.05$

Therefore, do not reject H0, at 5% level of significance.

The conclusion is that there is no statistically significant relationship between the heavy rain and the first lag value of the ASPI.

High wind

H0: $\beta_4 = 0$

H1: $\beta_4 \neq 0$

Reject H_0 if P value < significance level.

$$0.8278 > 0.05$$

Therefore, do not reject H_0 , at 5% level of significance.

The conclusion is that there is no statistically significant relationship between the high wind and the first lag value of the ASPI.

Landslide risk

$$H_0: \beta_5 = 0$$

$$H_1: \beta_5 \neq 0$$

Reject H_0 if P value < significance level.

$$0.9735 > 0.05$$

Therefore, do not reject the H_0 at 5% level of significance.

The conclusion is that there is no statistically significant relationship between the landslide risk and the first lag of the ASPI.

Lightning

$$H_0: \beta_4 = 0$$

$$H_1: \beta_4 \neq 0$$

Reject H_0 if P value < significance level.

$$0.9988 > 0.05$$

Therefore, do not reject H_0 , at 5% level of significance.

The conclusion is that there is no statistically significant relationship between the lightning and the first lag value of the ASPI.

AR (1)

$$H_0: \beta_6 = 0$$

$$H_1: \beta_6 \neq 0$$

Reject H_0 if P value < significance level.

$$0.0142 < 0.05$$

Therefore, reject H_0 , at 5% level of significance.

The conclusion is that there is a statistically significant relationship between the ASPI of the previous year and the first lag value of the ASPI.

MA (1)

$$H_0: \beta_7 = 0$$

$$H_1: \beta_7 \neq 0$$

Reject H_0 if $P \text{ value} < \text{significance level}$.

$$0.0000 < 0.05$$

Therefore, reject H_0 , at 5% level of significance.

The conclusion is that there is a statistically significant relationship between the error term of the previous year ASPI and the first lag value of the ASPI.

Coefficient of Determination

This shows the amount of variance of the 1st lag value of the ASPI that explained by all the used independent variables in the model. As this is a multiple regression analysis, Adjusted R-squared is used for the testing.

Accordingly, the model explains 0.079125 or 7.9125 % of the variance in 1st lag value of the ASPI.

Testing the significance of the overall model – S&P 20

Hypothesis:

$$H_0: \beta_0 = 0, \beta_1 = 0, \beta_2 = 0, \beta_3 = 0, \beta_4 = 0, \beta_5 = 0, \beta_6 = 0, \beta_7 = 0, \beta_8 = 0$$

$$H_1: \text{At least one } \beta \neq 0$$

Determining the level of significance: 5%

Decision rule:

Reject H_0 if $P \text{ Value of } F < \text{significance level}$.

Since $\text{Prob (F-statistic)} 0.0000 < 0.05$, we can reject the H_0 .

Conclusion:

There is enough evidence to conclude at 5% level of significance, that at least one variable in the model has a statistically significant impact on the dependent variable which is the first lag value of the S&P SL 20.

The significance of individual variables using the two-tail P-values test.

Drought

$$H_0: \beta_1 = 0$$

$$H_1: \beta_1 \neq 0$$

Reject H_0 if $P \text{ value} < \text{significance level}$.

$$0.1829 > 0.05$$

Therefore, do not reject H_0 at 5% level of significance.

The conclusion is that there is no statistically significant relationship between the drought and the first lag value of the S&P SL 20.

Flood

$$H_0: \beta_2 = 0$$

$$H_1: \beta_2 \neq 0$$

Reject H_0 if P value < significance level.

$$0.9980 > 0.05$$

Therefore, do not reject H_0 , at 5% level of significance.

The conclusion is that there is no statistically significant relationship between the flood and the first lag value of the S&P SL 20.

Heavy Rain

$$H_0: \beta_3 = 0$$

$$H_1: \beta_3 \neq 0$$

Reject H_0 if P value < significance level.

$$0.6307 > 0.05$$

Therefore, do not reject H_0 , at 5% level of significance.

The conclusion is that there is no statistically significant relationship between the heavy rain and the first lag value of the S&P SL 20.

High wind

$$H_0: \beta_4 = 0$$

$$H_1: \beta_4 \neq 0$$

Reject H_0 if P value < significance level.

$$0.9104 > 0.05$$

Therefore, do not reject H_0 , at 5% level of significance.

The conclusion is that there is no statistically significant relationship between the high wind and the first lag value of the S&P SL 20.

Landslide risk

$$H_0: \beta_5 = 0$$

$$H_1: \beta_5 \neq 0$$

Reject H_0 if P value < significance level.

$$0.9596 > 0.05$$

Therefore, do not reject the H_0 at 5% level of significance.

The conclusion is that there is no statistically significant relationship between the landslide risk and the first lag value of the S&P 20.

Lightning

H0: $\beta_4 = 0$

H1: $\beta_4 \neq 0$

Reject H0 if P value < significance level.

$0.8644 > 0.05$

Therefore, do not reject H0, at 5% level of significance.

The conclusion is that there is no statistically significant relationship between the lightning and the first lag value of the S&P SL 20.

AR (1)

H0: $\beta_6 = 0$

H1: $\beta_6 \neq 0$

Reject H0 if P value < significance level.

$0.0000 < 0.05$

Therefore, reject H0, at 5% level of significance.

The conclusion is that there is a statistically significant relationship between the ASPI of the previous year and the first lag value of the S&P SL 20.

MA (1)

H0: $\beta_7 = 0$

H1: $\beta_7 \neq 0$

Reject H0 if P value < significance level.

$0.0000 < 0.05$

Therefore, reject H0, at 5% level of significance.

The conclusion is that there is a statistically significant relationship between the error term of the previous year S&P 20 and the first lag value of the S&P SL 20.

Coefficient of Determination for S&P 20

This shows the amount of variance of the 1st lag value of the S&P SL 20 that explained by all the used independent variables in the model. As this is a multiple regression analysis, Adjusted R-squared is used for the testing.

Accordingly, the model explains 0.076400 or 7.664 % of the variance in 1st lag value of the S&P SL 20.

Climate risk effect on industry group according to the GICS classification, Sri Lanka

Introduction

The data set represents time series data about some of the climate risk variables in Sri Lanka (Quantitative Variables) from 2020 to 2022 (20th January 2020 to 17th October 2022) on a daily provided Situational Report by the National Disaster Centre Sri Lanka since that is recognized under the category of Secondary data. The objective of the time series data analysis is to identify the effect of climate risk on the Stock performance of other industry groups according to the GICS classification.

Sectors in Colombo Stock Exchange (CSE)

According to the CSE data, there are 294 companies categorized under the 20 GICS industry groups as at 30th of September 2022 and current market capitalization is valued as Rs. 4,341.13 Bn.

- Energy sector
- Material
- Capital Goods
- Commercial and professional services
- Transportation
- Automobiles and Components
- Consumer Durable Apparel
- Consumer Services
- Retailing
- Food and Staples Retailing
- Food, Beverage and Tobacco
- Healthcare Equipment and Services
- Banks
- Diversified Financials
- Insurance
- Pharmacy and biotech
- Telecommunication Services
- Utilities
- Real Estate

According to the test results of time series regressions done for individual sectors, the climate risk impact on industry groups is as follows: The drought has a significant impact on the ASPI sector index of the Automobile and components sector under the 5% level of significance with an adjusted R squared of sector 2.2%. The banking sector shows an adjusted R squared of 0.4%, representing the drought's significant impact on the ASPI sector index. For the Capital Goods sector, the adjusted R squared value is 1.4%, and drought and high winds significantly impact the sector ASPI. Accordingly, drought and Lightning significantly affect the Commercial and professional services sector, while the adjusted R squared for the sector depicts 1.4%. In the Consumer durable and apparel sectors, the adjusted R squared is 1.8%, and drought and High winds significantly impact that sector. For the Consumer service sector, the adjusted R squared is 1.8%, and drought and High wind significantly impact the ASPI sector index. The Diversified financial sector depicts 1.8% of adjusted R squared, and drought, Heavy rain and High wind have the most significant impact on the ASPI sector index.

Accordingly, the energy sector's adjusted R squared depicts a value of 0.09%. At the same time, drought and Lightning significantly impact this sector and the food and staples retailing sector, which has no significant impact on the ASPI sector index. The adjusted R squared of the model is -0.4%. In the food, beverage, and tobacco sectors, the adjusted R squared is 0.2%, and high wind significantly impacts the ASPI sector index. For the Healthcare equipment and services sector, the adjusted R squared of the regression model is 1.9%, and here, high wind and drought significantly impact ASPI.

The adjusted R squared value is 1.8% in the household and personal products sector, and high wind and drought significantly impact the sector index. For the Insurance sector, the adjusted R squared of the regression model run for the sector is -0.2%. Among all the independent variables of climate risk variabilities, no climate change variable has a significant impact on the ASPI sector index. For the materials sector, the adjusted R squared for the sector is 3.6%, and drought and high wind significantly impact ASPI. For the retail sector, the adjusted R squared of the regression model run for the sector is 0.7%. In comparison, drought and high wind significantly impact the ASPI retail sector under the 5% level of significance.

The telecommunications sector's adjusted R squared value is -0.7%. However, there is not any climate change variable that has a significant impact on the ASPI sector, and for the utility sector, the adjusted R squared of the regression model is 2.9%, drought and high wind have a significant impact on ASPI sector index. For the real estate sector, the adjusted R squared of the regression model that was run for the sector is -0.5 % and no climate change variable has a significant impact on the ASPI sector real estate sector. Finally, the Pharmacy and biotech sector test results depicted that drought, heavy rain, high wind, landslide risk and lightning significantly impact the ASPI sector index under the 5% significance level.

Discussion

As the key findings of the study, the two dependent variables, ASPI and S&P SL 20 and the independent variables comprise six variables relevant to climate risk in Sri Lanka, such as flood, drought, lightning, heavy rain, high wind and landslide risk.

According to the descriptive analysis, all the kurtosis values are greater than three test results, indicating that both dependent and independent variables have a long right tail, positive skewness and leptokurtic. The statistic, which measures the difference of the skewness and kurtosis of the series with those from the normal distribution Jarque-Bera test, proved that the model can reject the null hypothesis of normally distributed and statistics if there are outliers in the flood regarding the level of peaked curve.

Further, the stationarity test depicts that they don't have nonstationary problems at the first difference, while all other independent variables are stationary at the level form of data. As per the multicollinearity test, which refers to the dependent variables not being perfectly collinear, one repressor cannot be a linear function of another, showing no correlation among the variables considered for the study. The greater accuracy of the above test was ensured after doing the Variance Inflation Factors (VIF) test too, with values less than 5.

According to the results of the regressions, the ARIMA model for ASPI test results shows that, in the multiple regression using more than one dependent variable, adjusted R squared value 6.4% depicts the weight of independent variables collectively interpreting the dependent variable ASPI. In contrast, the ARIMA model for S&P SL 20 proved that the adjusted R squared value of 7.99% depicts the weight of independent variables collectively interpreting

the dependent variable S&P SL 20 too. Thus, in both incidents, the explanatory power of the ARIMA models is very low, leading to running the ARIMAX model for the study.

The regression results of the ARIMAX model depict this variability in the dependent variable due to the one-unit change in the independent variable. To the interpretation results, drought, flood and landslide risk provided variability in the opposite direction. At the same time, the heavy rain, high wind, and lightning depicted the same direction in ASPI. However, S&P SL 20 test results show that drought and landslide risk have variability in the opposite direction.

In the normality assumption. Which checks whether the error term has been normally distributed and whether the behavior of residuals is normal. Accordingly, Jarque-Bera's probability is less than the significance level; hence, it is proved that it fails to reject the null hypothesis (Residuals are normally distributed) at a 5% significance level. Moreover, homoscedasticity refers to the variance in the residuals having to be constant or cannot be varied for lower or higher values of independent variables, and the hypothesis and test results show homoscedasticity in the residuals at the 95% confidence level. In the autocorrelation assumption, it is revealed that there is no systematic relationship between the two error terms of the model. Test results for ASPI and the S & P SL20, which have Durbin-Watson statistics less than 2, showed enough evidence to conclude that the model has positive autocorrelation.

After testing the significance of the overall model, analyses done for two indices concluded that there is no statistically significant relationship between dependent and independent variables.

According to the analysis done to identify the Climate risk effect on industry groups according to the GICS classification in Sri Lanka, the studies were done separately for twenty subcategories of GICS industry groups. Hence, the data have been analyzed under the time series regression. According to the test results, for automobiles and components, drought significantly affects the banking and transport sectors. As well as drought and high wind, they greatly impacted the following sectors: capital goods, utilities, consumer durables and apparel, consumer services, healthcare, equipment and services, materials and household and personal products. Apart from that, drought and lightning significantly affected the commercial and professional services sector and the energy sector. Climate change variabilities such as drought, high wind, and heavy rain impact the diversified financial sector. At the same time, the test results indicate that high wind is the only factor affecting the food, beverage and tobacco industry group. According to the test results, some industry groups like food and staples, retailing, insurance, real estate, and telecommunication are not significantly impacted by climate change variability; however, the pharmacy and biotech industries are significantly impacted by all the climate risk factors except floods.

(Cheng, Wang, & Wu, the effect of drought on stock price: An industry-specific perspective, 2022) examined the drought on industry stock prices through a balanced panel of 15 industries every month, which was classified by the China Securities Regulatory Commission in 2012. In order to combine the results of Ordinary Least Square (OLS) regression models in both estimation and quartile models, results revealed that drought has negatively correlated with industry stock prices and the effect of drought varies from positive to negative from the lowest to the highest stock price quartile. In addition, the researchers have expanded the study to include moderate variables that can impact the relationship between drought and stock prices in China. The sentiment of investors can be identified in two regimes. Test results showed that under the low sentiment regime, drought has a significant positive effect on stock prices and under the high sentiment regime showed that drought has a significant negative impact. Further, the research showed that drought is a frequent natural disaster with a relatively long

duration and a wide range of effects. Two factors have significantly affected the drought trend in China recently, such as changes to atmospheric circulation patterns and increased global warming.

However, in order for this study, it is proven that in the Sri Lankan context, the drought variable of climate risk has a positive and significant effect on the dependent variable industry group, according to the GICS.

(Pan & Qui, 2022) research was conducted to determine the impact of flooding on firm performance and economic growth, which used flood data in China and concluded that flooding has a negative impact on firm performance, this impact is more related to the firms with more tangible asset investments, firms located in areas with low government quality, controlled by non-government entities, facing tight financial constraints and with low geographical diversification. (Fang, Noe, & Tice, 2008) Investigated the relationship between stock liquidity and firm performance and concluded that stocks with high liquidity have better performance; accordingly, the negative impact of flooding on firm performance will end up with a low level of stock market liquidity. However, in the Sri Lankan context, the insignificance of the impact of flooding on stock performance can be seen.

Further, (Lucas, Da Silva, & Araujo, 2017) analyzed the economic impact of extreme rainfall on the food industry in an emerging economy. Natural extreme events that occur frequently in an emerging economy with some growing consequences. This study was done at the corporate level and researchers analyzed six companies from the Brazilian food sector listed on the Brazilian stock exchange. The results depict a substantial impact on stock returns, as five out of six companies' stocks showed that more than 50% of extreme rainfall had a significant impact. Finally, the researchers have emphasized that the above results were used to encourage the companies in Brazil to use derivatives. However, according to the test results of this research, heavy rain has an insignificant impact on stock market performance in Sri Lanka.

The effect of wind on stock market returns: Evidence from the European market was identified by (Shu & Hung, 2009), who analyzed the relationship between stock market returns daily and wind speed using data from 1994 to 2004 from 18 European countries. However, the study revealed a significant and pervasive wind effect on stock returns. In addition, the results found that wind strongly impacts mood and comfort, seasonality effect and temperature effect in European stock markets. However, in Sri Lankan stock performance, an insignificant impact (but very close to the significance level) can be identified from the high wind as a climate risk variable.

Conclusion

The analysis done for the study mainly addressed the three primary research questions for climate risk's effect on stock market performance: the All-Share Price Index, Standard and Poor's Index and industry group according to the GICS classification. The independent variables for the research tests include climate risk variables which are more relevant to Sri Lanka, such as flood, landslide, heavy rain, high wind and lightning and drought. Several tests have been done for the two data types using time series data analysis. The tests and analyses done for the time series data regressions are mainly comprised of descriptive analysis, stationary tests, and variance Inflation test (VIF). The regression analyses include the ARIMA model and the ARIMAX model. Both tests done for the ASPI and S&P SL 20 according to the *ARIMA model concluded that the weight of independent variables are collectively interpreted as the dependent variables.*

Based on the results of ARIMAX regression analysis, the probability value for estimated coefficients for each independent variable is greater than 0.05 level of significance. Hence, *the suggested hypotheses of each independent variable haven't any impact on the performance of the stock market as to the ASPI of Sri Lanka, which can't be accepted at the 5% level of significance criteria.*

Also, according to the results of ARIMAX regression analysis, the probability value for estimated coefficients for each independent variable is more than 0.05 level of significance. Hence, *the suggested hypotheses of each independent variable haven't any impact on the performance of the stock market as per the Standard and Poor's Index of Sri Lanka, which can't be accepted at the 5% level of significance criteria.*

Moreover, the time series data regression was done to identify the climate risk effect on the industry group according to the GICS classification in Sri Lanka. Under the method of time series data regression, test results concluded that climate risk variables, *drought and high wind significantly affect ASPI for most industry groups considered under the GICS classification.*

Implication

Based on the above conclusions, several implications can be drawn for *policymakers and market participants* in Sri Lanka. As the country is in a crisis, policymakers must be concerned about the risks related to climate change and take action to ensure the climate risk does not overly worsen the economy and financial activities. Financial regulation authorities should also provide motives to disclose more climate-related information. The disclosures of firm-specific climate risk can evaluate the underlying stock efficiently. Thus, it is a compelling necessity to impose stringent regulations to disclose climate-related information and it provides some directions for investors to allocate a reasonable portion of their investments in stocks that are less sensitive to climate risk.

Moreover, as a country with more government intervention in the economy, the role of *government* is more important. Strong government leadership can make prerequisites of market-based solutions, including adoptions and mitigating techniques, at an appropriate level. For example, the government can provide a sound basis for making political commitments by granting grants for scientific research and enhancing the efforts to educate the public.

Recommendations

To address the above-revealed facts, countries can take some recommended actions against currently affected climate risk variables and future predicted climate risk factors.

Policymakers can emphasize the importance of attaining long-term climate stability through the United Nations Framework Convention on Climate Change and the long-term policy framework related to climate change in Sri Lanka. The government should take the necessary steps to develop strategies to produce market-based solutions against current and future climate risk variables, such as low-carbon technologies and clean technology research. In addition, institutes, associations, and professionals should be more aware of the threats and opportunities arising from climate change issues and incorporate climate change factors related to their business processes.

However, the proactive stance of relevant participants in the economy will help to reduce the threat of climate change to the economy while generating opportunities. Therefore, relevant authorities can take steps to control the climate risk factors to keep the stock performance at

an optimal level for the country's growth. Therefore, paying more attention to climate risk on an island like Sri Lanka is necessary.

Limitations

This research only addresses one category of climate risk, natural disasters due to the resources and information available in the country. As an island, a nation is regularly affected by climate change. In the Sri Lankan context, the country is not industrialized at a considerable level, so some crucial factors for climate change like carbon emission are excluded from this research. As well as the unavailability of data about disasters daily before 2017, this is a major limitation for the study. Apart from that, for the sector-wise analysis, ASPI data is available from January 20, 2020, and the lack of early research studies on the topic in the country was a major issue in conducting the research.

Suggestions for Future Research

The objective of this study is to identify the effect of climate risk on the stock market performance of Sri Lanka. According to the regression results in the time series, the six considered climate risk variables concluded that there is no statistically significant impact on stock market performances in both stock indices, ASPI and S&P SL 20, but according to the sector analysis, drought and high wind have a significant effect on the majority of industry groups in the stock market.

According to the post-analysis of the study, the following facts may have contributed to the above results.

The stock market data considered for the study is from 2018 to 2022. Throughout this period, the country faced several significant reasons that may have affected the stock performance other than the climate risk factors, such as the 2019 Easter bombing, the COVID-19 pandemic, the economic crisis with political uncertainty, and some external factors such as the Russian-Ukraine war situation. Therefore, it is better to use a smooth period to conduct the research for further studies.

As well as the climate change variable data used for tests, with approximately 1130 observations in the last five years. However, it is better to extend the considered period to the long term to identify the effect of climate risk.

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