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Impacts of Climate Factors on UK Insurance Companies: Evidence from the Stock Prices

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Abstract. Climate change poses significant risks to the insurance industry, particularly through increased frequency and severity of weather events. In this paper, we examine the extent to which temperature, wind speed, and rainfall influence the stock prices of companies listed on the UK stock market. By using data of 1. Andrews Sykes Group plc. (ANSY) 2. Aviva plc (AVIVA) 3. Legal & General Group plc (LGEN) 4. Prudential plc (PRU) 5. Direct Line Insurance Group plc (DLGD) and conducting the multiple linear regression model and random forest model, the findings, illustrated through scatterplots, indicate a weak relationship and correlation between the dependent (stock prices) and independent variables (weather data), as shown by the P-values and R-values.

Keywords: Climate Change, Stock Market, UK Insurance Company

1. Introduction

Weather impact on the economic sector, particularly insurance industries, is significant and multifaceted, along with tremendous financial losses, which inevitably prompts insurers to adjust their risk models and pricing strategies. It is highly believed by Stern that the fluctuation in the appearance of extreme weather and its uncertainty threatens insurance industries [1]. Thus, the industry itself must account for the rising costs associated with natural disasters, which can severely impact its profitability and stability. The UK's insurance industry, serving as one of the largest and most famous national insurance industries, suffers from the uncertainty of weather-related risks [2]. According to Roberts, the UK's insurance market has seen a significant increase in claims related to weather events over the past decade, forcing managers to re-evaluate their underwriting operations and consider the long-term effects of climate change [3]. In addition, Williams and Brown also suggest that the UK's insurance industry is leading the way in integrating climate risk into its business model [4]. The proposal of such proactive fiscal measures taken by the UK government can serve as a benchmark for other markets worldwide. Nevertheless, considering the negative impact of weather-related risks, a more comprehensive and efficient strategy is before us. In this research, the key is to explore the extent to which temperature, wind speed, and rainfall affect the share prices of 5 companies mentioned in the Abstract and to analyse historical weather data and related stock performance [5]. In addition, this study will also reveal a basic model of how environmental factors

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affect financial markets, laying the foundation for future research and policymaking for sustainable finance.

2. Literature review

In finance, Johnson indicates that the uncertainty of climate change inevitably influences investment decisions. As for the UK market, environmental regulations, particularly stringent carbon reduction, force companies to adjust their investment strategies to comply with the new regulatory environment [4]. Herring et al. mention that extreme weather events impact asset prices and investor sentiment due to the economic costs associated with events like floods, droughts, and hurricanes [6, 7]. Besides, Williams and Brown found an interesting phenomenon that companies with high exposure to climate risks are inclined to perform poorly in the stock market. One of the persuading explanations is that those companies who face higher operating costs and potential legal liabilities lack investor confidence and, therefore, increase stock price volatility [5]. Other economists, such as Anderson et al., emphasized the benefit of applying machine learning algorithms in predicting stock price time series, which proved efficient, especially in dealing with fluctuations caused by climate change. Scientists argue that machine learning algorithms bridge the gap between stock market performance and economic predictions, which can better capture and analyze complex market dynamics, providing more accurate investor forecasts [8]. According to Roberts who examined the impact of climate risk on financial market stability, he asserted that climate change is a critical component of financial risk management more than merely an environmental issue. What he suggested is that investors and companies as well are highly suggested to prioritize the identification and mitigation of climate risks to minimize the potential losses [3].

3. Methodology

By collecting UK weather data, focusing on rainfall, temperature and wind speed, and the stock prices of 5 public limited insurance companies. Firstly, the use of Linear Regression Model (LRM) to help us detect the relationship between dependent (stock prices) and independent variables (weather data). Subsequently, the Random Forest Model (RFM) is employed to examine non-linear relationships of independent variables on stock prices.

4. Data selection and process

To investigate the impact of climate change on the UK insurance sector, monthly average data on the UK's rainfall, temperature and windspeed from 2015 to 2023 [9], and daily stock prices at the same time range of the 5 insurance companies in the UK are extracted from the website --investing.com [10]. In addition, control variables were added to avoid the omitted variable bias (OBV), where the model ignores other relevant variables [11]. The interest rate (IR) is the cost of borrowing, playing a crucial role in investment and the stock market, meanwhile, the inflation rate is a key economic factor to indicate the economic environment, which to a great extent influences investors' decisions and so as stock prices. Thus, we decided to employ these two indicators as our control variables. Due to the limitation of the data resources, only the monthly average data of the above weather factors could be collected to match the stock prices with them, and the mean stock prices of every month for each company were computed.

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5. Linear Regression Model (LRM)

Since this paper aims to detect the relationship between the climate and the stock market of the insurance companies in the UK, the multilinear regression model is utilised. As shown in the equation below, we have constructed a multilinear regression on the stock price of each selected company with 5 independent variables.

$$y_i = \beta_0 + \beta_1 temperature + \beta_2 rainfall + \beta_3 windspeed + \beta_4 interest\ rates + \beta_5 inflation\ rate + \varepsilon \ldots \quad (1)$$

Where:

$$i = 1,2,3,4,5$$

y_i is the historical stock price of each insurance company.
β_0 is the intercept.
β_i is the slope of the slope of each variable.
The R-squared mean is employed to examine the fitness of the linear model. The R-squared (R^2) value of each company is listed in Table 1 below.

Table 1. R-squared of LRM

	ANSY	AVIVA	PRU	LGEN	DLGD
R^2 (LRM)	0.047	0.035	0.264	0.157	0.723

Correspondingly, the scatterplots show a similar trend in fitness. In this study, the investigated samples have been categorised into the poor-fitted, medium-fitted, and well-fitted groups. Here, ANSY and AVIVA are in the poor-fitted group (see Figure 1, Figure 2 and Figure 3), which means that the points are not closely aligned with the reference line, indicating significant deviations between actual and predicted stock prices. The rest of the samples' scatterplots follow the value of R^2 as well, thus, LGEN and PRU are distributed to the medium-fitted group, while GLGD with good fitness is counted as the well-fitted group.

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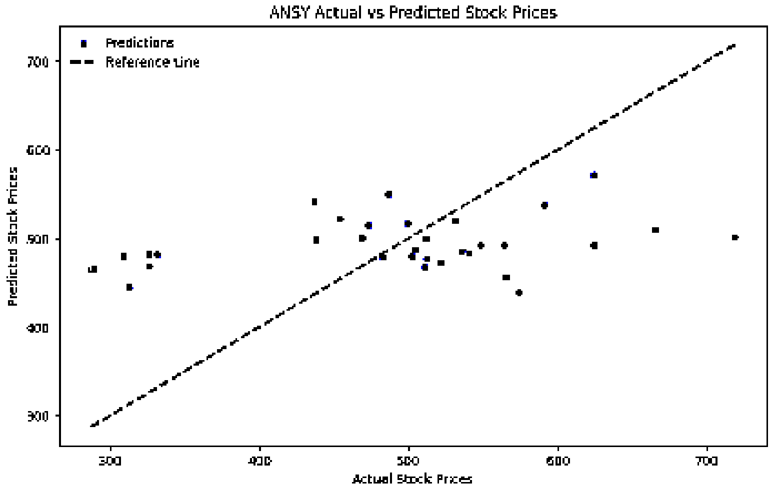

Figure 1. The scatterplot of LRM (ANSY)

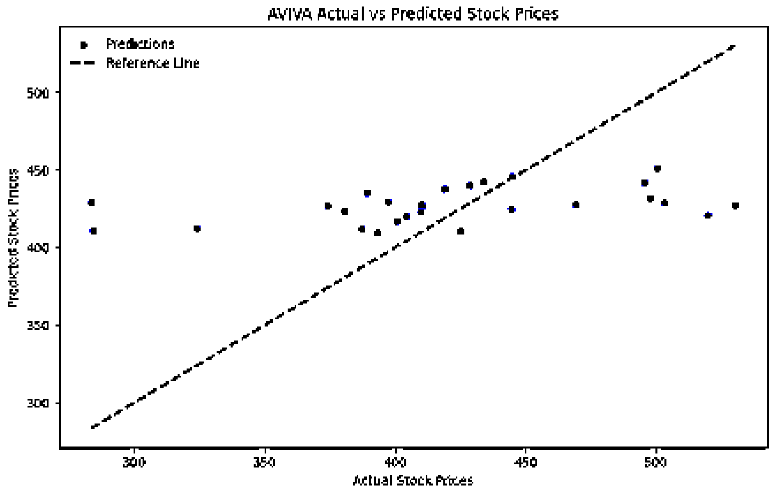

Figure 2. The scatterplot of LRM (AVIVA)

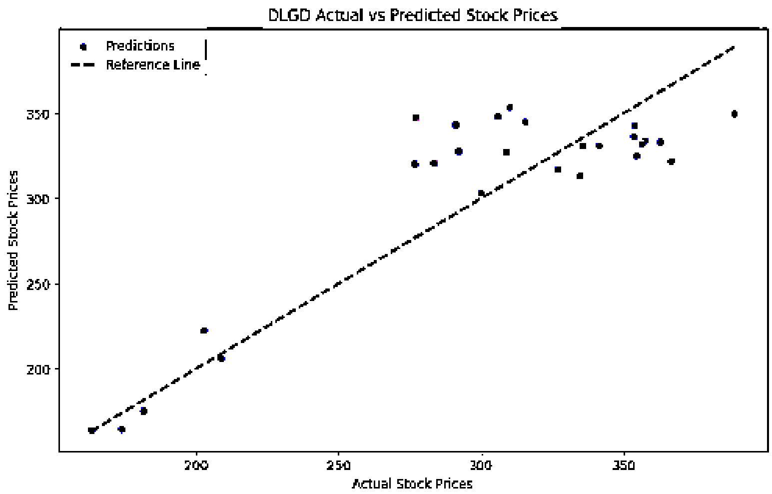

Figure 3. The scatterplot of LRM (DLGD)

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Therefore, only the well-fitted group, the DLGD company, is further analysed in the linear regression section; the other companies will be examined in the subsequent RFM about their non-linear relationship.

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...                              OLS Regression Results
==============================================================================
Dep. Variable:                   dlgd   R-squared:                       0.723
Model:                            OLS   Adj. R-squared:                  0.704
Method:                 Least Squares   F-statistic:                     39.10
Date:                Sat, 20 Jul 2024   Prob (F-statistic):           1.45e-19
Time:                        11:49:09   Log-Likelihood:                -399.17
No. Observations:                  81   AIC:                             810.3
Df Residuals:                      75   BIC:                             824.7
Df Model:                           5
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const        351.5168     12.985     27.071      0.000     325.650     377.384
tem          -15.6646     14.676     -1.067      0.289     -44.901      13.571
rainfall     -23.2528     23.549     -0.987      0.327     -70.165      23.659
windspeed     31.2694     27.528      1.136      0.260     -23.569      86.108
ir          -133.6810     20.620     -6.483      0.000    -174.758     -92.604
inf          -71.6045     22.478     -3.186      0.002    -116.382     -26.827
==============================================================================
Omnibus:                        1.298   Durbin-Watson:                   1.995
Prob(Omnibus):                  0.523   Jarque-Bera (JB):                1.215
Skew:                          -0.158   Prob(JB):                        0.545
Kurtosis:                       2.490   Cond. No.                         11.3
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
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Figure 4. OLS summary of DLGD

Figure 4 illustrates the empirical result of the DLGD company trained by the OLS model. However, the p-values of our targeted weather variables seem not ideal since they are greater than 0.05. This means there is insufficient evidence to reject the null hypothesis, and so the linear relationships are not significant. Thus, the non-linear relationship between the weather factors and the stock price of DLGD will be considered in RFM.

6. Random Forest Model (RFM)

6.1. Empirical results

Each company's RFM is trained in Python to research non-linear relationships. The result has improved significantly for every targeted company. The R^2 increased from the LRM to the RFM, as indicated in Table 2.

Table 2. R-squared of LRM and RFM

	ANSY	AVIVA	PRU	LGEN	DLGD
R^2 (LRM)	0.047	0.035	0.264	0.157	0.739
R^2 (RFM)	0.810	0.722	0.857	0.525	0.942

The scatterplots in Figure 5 and Figure 6 matched the improvement in R^2 as well.

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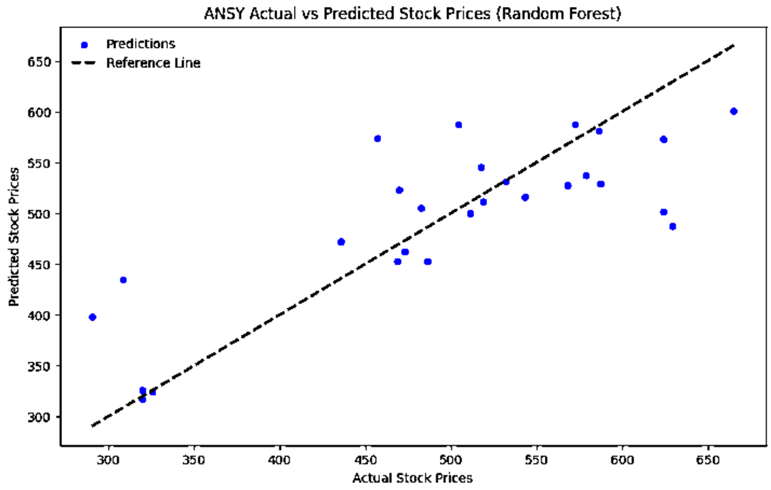

Figure 5. The scatterplot of RFM (ANSY)

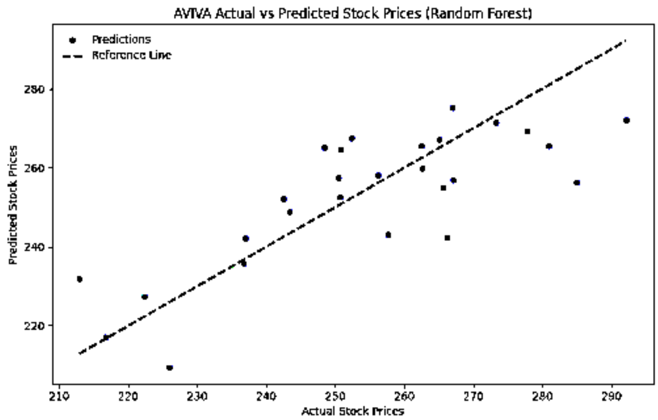

Figure 6. The scatterplot of RFM (AVIVA)

6.2. Data analysis

From Table 3, we know that although the relationship between weather factors is not as significant as the interest rate and inflation rate, they still contribute to the change in stock prices to some extent. Specifically, the weather factors accounted for around half of the importance of LGEN, and among the three weather factors, temperature and rainfall weighted more than the wind speed. This could be related to the extreme weather and disaster caused by the rise of the rise in temperature and rainfall more frequently or on a larger scale in the UK. According to the Environment Agency's Flood and Coastal Erosion Risk Management (FCERM) risk management report, there were around £333 million in economic losses in flood between November 2019 and March 2020 [12]. In addition to the statistics from the article 'Weather Damage Insurance Claims Worst on Record', the storm damage claims were around £133m, but flooding claims took up about half of all weather-related claims with a value of £286m. Also, the article recorded a slightly higher value (£153m) from burst pipes claims induced by the increasing temperature, which leads to a more significant impact on stock prices caused by the rainfall and temperature. These statistics are in line with our model results, demonstrating the effect of different weights of the weather factors on the stock prices.

Table 3. The table of feature importance

PLC. Importance	ANSY	AVIVA	PRU	LGEN	DLGD
Rainfall	0.0834	0.0561	0.0324	0.1595	0.0256
Temperature	0.0709	0.0740	0.0513	0.1637	0.0254
Windspeed	0.0426	0.0842	0.0458	0.1076	0.0194
Interest Rate	0.2811	0.5310	0.1987	0.1794	0.7090
Inflation Rate	0.5220	0.2547	0.6717	0.3896	0.2205

7. Evaluation

The empirical research and models used in this paper still have some drawbacks and need to be improved in the current research period. Firstly, the data limitation restricted our model as there is not much complete quantitative data for weather factors. The 3 factors we have used in our study cannot fully represent climate change, and the lack of daily data to some extent decreased the sensitivity reflected on stock prices. Also, climate change needs a more extended period to disclose its influences, but the historical data of the stock prices needs to be more capable of covering the large time range. Furthermore, the information gap is difficult to dismiss, and bounded rationality makes it hard to find the best-fitting model to capture the relationship perfectly. There might be other models with better results to show the relationship. Furthermore, the undercover corporate information of each company is not easy to access, which has hindered has from analysing our model results in depth.

8. Conclusion

In conclusion, there is a weak correlation in both linear and non-linear relationships. The effect of climate change on stock prices in the insurance stock market is insignificant. Nevertheless, we can still draw some information from our research, which is the different importance of three weather factors on stock prices, providing useful information in studying the causes of change in stock prices of the UK insurance sector.

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