The Relationship Between Weather Factors and Stock Exchange Trading Based in Istanbul

MSc Research Project
MSc in Data Analytics

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MSc Project Submission Sheet

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THE RELATIONSHIP BETWEEN WEATHER FACTORS AND STOCK EXCHANGE TRADING BASED IN ISTANBUL

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Abstract

This paper investigates the relationship between weather conditions and the performance of the Istanbul Stock Exchange (ISE). Istanbul offers a good case study due to its underrepresentation in finance literature, as most studies tend to focus on developed markets such as the U.S. and Europe. The study addresses gaps in prior research by focusing on an emerging market and incorporating multiple weather variables, such as temperatures, humidity, and rainfall, over three years (2009-2011) due to data access. Utilising advanced statistical techniques, including regression analysis, ANOVA, and GARCH modelling, the research evaluates the impact of both daily weather fluctuations and seasonal patterns on stock returns and volatility. The findings reveal no significant relationship between temperature and stock returns, aligning with some prior studies but contrasting with others conducted in different markets. Similarly, ANOVA results indicate no meaningful seasonal variations in stock returns, although descriptive statistics suggest higher returns during spring and summer. Notably, the GARCH model highlights periods where rainfall and humidity coincide with increased market volatility, although these effects are inconsistent. While direct links between and stock returns remain limited, the observed effects on volatility suggest potential implications for investors and policymakers. The research provides a foundation for further research, supporting comparative analysis with expanded datasets, additional weather variables and across markets.

1. Introduction

Stocks are one of the most popular investment choices for individuals. Although they carry inherent risks, they do potentially offer higher returns than other investment types, such as property. Stock market returns are generally linked to economic conditions, supply and demand trends, or the performance of individual companies. However, it is less common for people to connect stock market returns with weather or temperature changes. Since weather can affect people's moods and behaviour, it raises the question of whether it could also influence financial decisions and, as a result, stock market returns.

The weather can affect investors' moods and behaviour. Depending on their mood, investors may respond differently in the stock market. Previous studies have shown that the subject provides mixed results. While some studies find a relationship between weather and investor behaviour, the findings are largely based on international markets (Sigo, 2017). Moreover, previous research often focuses on a single weather variable, such as temperature, without considering the combined effects of factors, such as wind speed and humidity (Floros, 2011). These gaps offer an opportunity for a localised, comprehensive study that examines multiple weather variables to understand their potential impact on market volatility and investor behaviour.

This project aims to explore whether there is a link between weather and the Istanbul Stock Exchange (ISE). The Istanbul Stock Exchange, as an important emerging market, is a good example for studying these dynamics in a specific economic and cultural setting. Most existing studies have concentrated on developed stock markets like those in the U.S. or Europe. There's a lack of research on emerging markets, such as Turkey's Istanbul Stock Exchange (ISE). Which may behave differently due to economic, cultural, and investor behaviour differences. Therefore, this study tries to determine if there is a connection between weather and the Istanbul Stock Exchange are connected. Weather and financial data from 2009 to 2011 were collected. Weather factors like maximum temperature, minimum temperature, humidity, conditions, and average wind speed are considered. The financial assets analysed are TL-based ISE, USD-based ISE, SP and DAX. If significant relationships are found, this could have important implications for investors. New investment strategies could be developed based on weather forecasts. For example, if a weather variable has a positive effect on returns, might decide to invest on days when that weather condition is strong, believing it will impact the returns for that trading day.

This thesis contributes to the literature by being innovative in several areas. The core research question driving this study is: How do weather conditions influence the performance of the Istanbul Stock Exchange? To answer this, the research will employ advanced statistical models such as regression analysis, ANOVA test on time series, and GARCH (Generalized Autoregressive Conditional Heteroskedasticity) to assess the relationship between weather data and stock market performance. By doing so, this study seeks to contribute valuable insights into the behavioural economics of financial markets, offering practical implications for investors, traders, and policymakers.

The article is organised as follows. The next section presents an overview of the existing literature. The third section outlines the data variables and explains the methodology. An implementation is provided in the fourth section. The results of the evaluation and regression are discussed in the fifth section. The sixth section covers the conclusions and suggestions for future research. Finally, the references are included at the end.

2. Related Work

Weather can affect stock market prices in different ways. One obvious way is through its direct impact on companies like those involved in agriculture. However, most research focuses on how daily weather influences investors' behaviour and mood. When investors' moods change due to the weather, it can affect how they act in the stock market. Below is a summary of what previous studies have found about these connections. First, we will look at how weather affects investors' moods. Then, we will discuss how this impacts their decisions and the returns in financial markets.

2.1. Impact of mood on decision-making and human behaviour

First, it is important to examine the link between people's moods and the behaviours that come with them. The key question is whether a person's state of mind influences their behaviour. If it does, which specific moods lead to certain behaviours? Additionally, we must consider what types of weather trigger particular moods. These topics have been widely researched in the past. Below is a summary of the key findings from this area of study. This section will focus on how mood affects judgment, decision-making, and risk-taking behaviour.

An initial study by (Etzioni, 1999) argues that mood plays a key role as a focusing mechanism in economic decision-making. He suggests that most decisions are driven by emotional and value-based commitments. Mood can lead people to make decisions that are not optimal or rational. Later research by (Leowenstein, et al., 2001) suggests that emotional reactions can influence and even override logical thinking, especially when making risky or uncertain decisions. It's fascinating how often we misattribute our emotions to wrong things. As early studies by (Schwarz & Clore, 1983) highlighted, this can lead to skewed judgments and perceptions. For instance, a warm, sunny day can put us in a good mood, and we might unconsciously link this positive feeling to a brighter future. (Forgas & Ciarrochi, 2001) discovered that people in a good mood tend to value both their current and potential wealth more highly. This might explain why an inquiry by (Nofsinger, 2005) observed that happy people are more likely to invest in risky assets compared to those feeling unhappy.

As a result, psychological research demonstrates that mood, often unconsciously, significantly influences our judgments and decision-making. The degree to which mood affects our choices is linked to the complexity and uncertainty involved in the decisions. When faced with greater ambiguity and complexity, our mood exerts a more pronounced impact. Individuals in a positive mood tend to be more optimistic about their future and rely more on intuitive thinking than those in a negative mood. They are more likely to invest in risky ventures and are more susceptible to mood-driven biases.

2.2. The impact of weather on stock returns.

Weather conditions can influence mood, leading to misallocation and potentially affecting investors' risk aversion, perceptions, and actions.

Psychological studies show that temperature is an important weather factor that affects people's mood, and mood, in turn, influences behaviour. According to (Cao & Wei, 2005), there is a negative relationship between temperature and stock returns. When the temperature is lower, stock market returns tend to increase because people are more likely to take risks. Alternatively, when the temperature rises, stock market returns tend to decrease as people become less aggressive and more indifferent. Research has further shown that stock market index returns in Chennai, Mumbai, Kolkata, and Hyderabad in India were affected by temperature (Sigo, 2017). Higher wind speeds help disperse emissions and prevent the build-up of toxic substances, which makes socially responsible investors feel more secure about the stability of the economy.

This, in turn, leads to reduced stock return volatility (Sariannidis, et al., 2016). The authors (Shu & Hung, 2009) explored the link between wind speed and daily stock market returns in 18 European countries. Their findings highlight that wind speed negatively affects stock returns. More recent inquiries by (Dong & Tremblay, 2022) noted that wind in cold and mild regions negatively impacts returns during the summer but not during the winter.

The authors collectively suggested that weather conditions can impact stock markets, with humidity affecting investors' psychology, leading them to act contrary to the efficient market hypothesis (Zeren & Gumus, 2015). However, in contrast, (Tuna, 2014) analysed the effect of humidity and cloudy days on the Istanbul Stock Market index returns between 11 January 1987 and 31 December 2006 and found no significant impact. It must be noted that it has not been investigated whether the relationship between Istanbul weather and Istanbul stock market performance varies across seasons.

When considering another weather factor, the number of cloudy days, it appears that cloudy conditions lead to a perception of overpricing in individual stock and the Dow Jones Industrial Average (Goetzmann, et al., 2015). The Dow Jones Industrial Average (The Dow) is a price-weighted measure of 30 US blue-chip companies (S&P Global, 2024). Sunshine is the most extensively studied weather variable, with psychological research and common sense indicating that sunny weather tends to make people happier. (Geotzmann, et al., 2015)and Saunders (1993) also found a positive correlation between sunshine and stock market returns. Dong &Tremblay (2018) suggested that the effects of sunshine may vary by region, but their results showed that this positive effect was consistent across all regions and seasons. Additionally, Bassi, Colacito, and Fulghieri (2013)concluded that there is a positive link between sunlight and risk-taking behaviour.

2.3. Stock Market Volatility

The relationship between weather and stock exchange volatility has garnered increasing attention in academic literature, highlighting how environmental factors can influence investor behaviour and market dynamics. For instance, (Shim, et al., 2015) they examined how weather affects stock market volatilities in a leading emerging market, revealing that cloudy, wet, and windless conditions increase volatility and that investors respond asymmetrically to extreme weather conditions. Similarly, (Shahzad, 2019) explored the impact of meteorological conditions on stock returns and volatility, providing empirical evidence of a significant relationship between adverse weather and increased market volatility.

Further investigations have supported the notion that positive weather conditions can decrease volatility, as investors tend to exhibit more risk-averse behaviour during pleasant weather. Focusing on the psychological underpinnings of this phenomenon, research has revealed that weather-induced mood changes significantly affect investment decisions (Chen, et al., 2022). Additionally, weather effects across South Asian markets and the authors found a clear correlation between weather patterns and market fluctuations (Kathiravan, et al., 2021). Expanding on these findings, studies by (Choi, et al., 2021) highlighted the role of temperature and precipitation in shaping investor sentiment, further reinforcing the impact of weather on volatility. A comprehensive analysis (Zhang, et al., 2023) examined the interplay between climate change, economic uncertainty, and market volatility, demonstrating that extreme weather events can exacerbate financial instability.

These collective findings underscore the significance of interdisciplinary approaches in understanding the complex dynamics between weather and stock market behaviour. The influence of weather on market volatility is not merely an anomaly but rather a critical factor that necessitates consideration in financial analyses and economic forecasting.

2.4. Empirical Review (GARCH)

The relationship between weather and stock market behaviour has been explored extensively through models such as GARCH (Generalized Autoregressive Conditional Heteroskedasticity). Several studies suggest that weather conditions, such as temperature fluctuations and extreme climate events, can influence market volatility and returns. Using GARCH models, researchers analyse how weather impacts stock returns by capturing volatility patterns that adjust for time-varying risks.

For instance, GARCH and GARCHX models have been applied using South African data (Wu, et al., 2024). revealing that temperature anomalies significantly affect stock market volatility. It emphasised that climate risks, such as temperature deviations, can be incorporated into models to improve predictions of stock return volatility over long periods. Similarly, another study on Asian stock markets employed the GARCH-MIDAS approach, showing that climate change increases long-term volatility in %40 of the examined markets, with weather fluctuations being critical predictors (Oloko, et al., 2022). In another instance, researchers investigated SPY data (an ETF that tracks the S&P 500) to study how specific weather conditions, such as temperature and precipitation, correlate with stock market performance in New York and Chicago. By analysing data from weather stations near the stock exchanges, they identified significant links between weather variables and trading volume, suggesting that weather can influence investor behaviour (Jeong, 2020).

These studies demonstrate that weather conditions whether through gradual climate change or daily weather variations have a measurable impact on stock market behaviour, particularly through the lens of volatility, as captured by GARCH models.

3. Methodology

This research aims to investigate whether there is a relationship between Istanbul's stock market data and its weather conditions and to determine how such weather conditions can potentially influence the performance of the Istanbul Stock Exchange. The weather data adopted in the study covers the years 2009 to 2019 and was collected from Kaggle. The Istanbul Stock Exchange data is from 2009 to 2011 and was obtained from imkb.gov.tr. to address the difference in time ranges between the datasets, the two datasets were merged, and the focus was set on the years 2009 to 2011. A quantitative research design was adopted, applying statistical methods to study any possible link between the weather conditions and stock exchange performance.

The Knowledge Discovery in Databases (KDD) process was used to get useful insights from the datasets. The KDD steps, shown in the diagram below, include data selection, pre-processing, transformation, data mining, and interpretation. This process ensures that the data is handled in a way that helps produce meaningful insights, analysis, and conclusions.

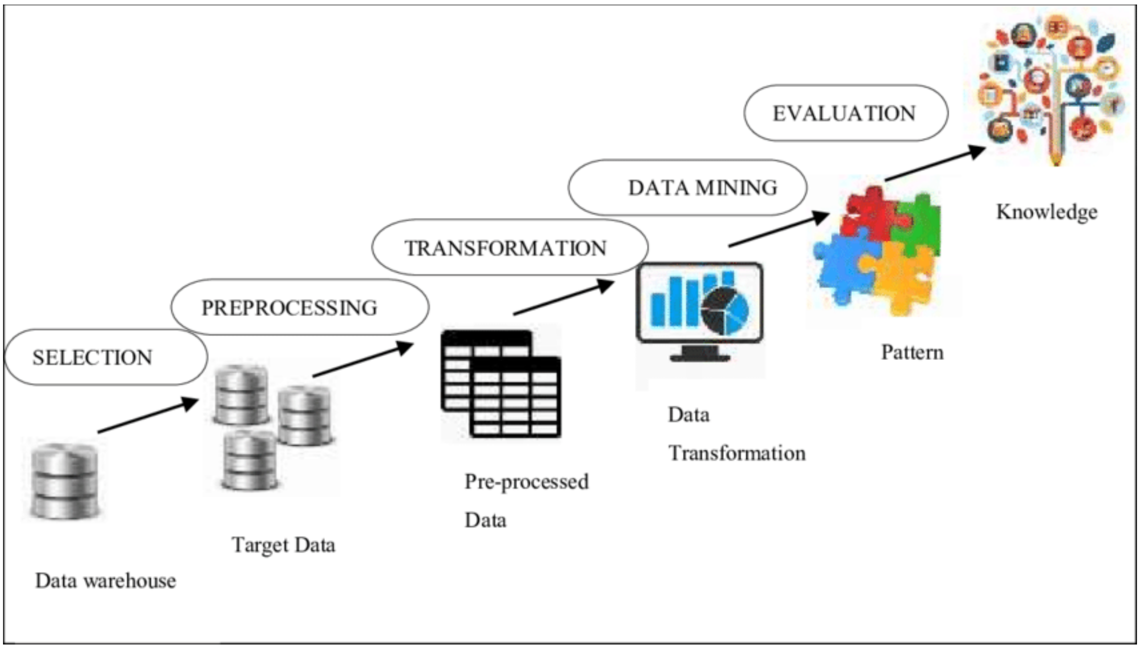

Figure 1: KDD

3.1. Data

The study utilises two main datasets: Istanbul Weather Data (2009-2019): This dataset includes daily weather variables such as temperature, humidity, precipitation, wind speed, and cloud cover. Istanbul Stock Exchange Data (2009-2011): This dataset provides daily stock market metrics, including stock prices, trading volume, and indices. Stock Exchange data is collected from imkb.gov.tr and finance.yahoo.com. Data is organised about working days in the Istanbul Stock Exchange. The weather data was collected from Kaggle, daily observations were taken from the worldweatheronline.com website.

3.2. Data Preparation

The data collected for analysis may be inconsistent, containing invalid structures, missing values, or irrelevant variables. These inconsistencies can lead to errors in the final results. Data preparation is, therefore a crucial step in the Knowledge Discovery in Databases (KDD) process. It involves transforming the inconsistent dataset into a structured and reliable form to ensure accurate analysis.

3.3. Model Development

3.3.1. The Regression Model

The objective of this study is to examine the impact of temperature fluctuations on the daily returns of the Istanbul Stock Exchange (ISE). During data preparation, the weather data was merged with the stock data based on matching dates, ensuring that the date formats were consistent across both datasets.

Simple linear regression involves a single explanatory variable (regressor) and is used to describe the linear relationship between the dependent variable and the relationship. The regression model serves as an approximation, as the true underlying relationship between Y (dependent variable) and X (regressor) is unknown. Mathematically, simple linear regression can be expressed as

$$Y = \beta_0 + \beta_1 X + \varepsilon$$

Y= Dependent Variable β_0= Constant/Intercept. β_1= Slope/Intercept

X= Independent Variable ε= Error term, a vector of values

In this model, Y represents the dependent. Variable, which is the TL-based daily returns of Istanbul Stock Exchange (ISE). The regression coefficient is used to test the null hypothesis that " temperature has an effect." If the p-value is lower than the specified significance level (0,5), the null hypothesis that "temperature has an effect" is rejected; otherwise, it cannot be rejected. The independent variables, X, are the daily maximum temperature (MaxTemp) and minimum temperature (MinTemp).

H_0= Temperature has an effect

H_1= Temperature has no effect

Why apply Regression Analysis? Once relationships are established, regression models can be used to predict future outcomes. This is beneficial if you want to forecast stock prices based on weather patterns or any other relevant variable. Regression quantifies the strength of the relationship between variables. For instance, you can identify and quantify how much a 1-degree change in temperature could potentially affect stock exchange performance. Compared to other analyses, while correlation analysis only tells you the strength and direction of a relationship between two variables, regression gives a more detailed insight into how one variable influences another and to what extent (Freedman, 2009).

3.3.2. GARCH

The challenge in modelling financial time series often lies in the presence of heteroscedasticity, where the error variance is not constant over time. This violates the assumption of homoscedasticity (constant variance of the error term) required by traditional models such as Moving Average (MA), Autoregressive (AR), and Autoregressive Moving Average (ARMA), making them less suitable for financial data. to address this, Engle (1982) introduced the Autoregressive Conditional Heteroscedasticity (ARCH) model, which captures time-varying volatility by modelling the conditional variance.

Building upon this, Bollerslev (1986) developed the Generalized ARCH (GARCH) model, which extends ARCH by incorporating both past errors and past variances, resulting in a more efficient and parsimonious model for handling heteroscedasticity in financial time series.

The GARCH (p, q) model incorporates conditional variance by extending the ARCH (q) model. It accounts for both previous residuals and past conditional variances to model the current conditional variance. In the GARCH (p, q) framework, the order (p, q) specifies the number of lagged conditional variances (p) and lagged residuals (q) included in the model.

$$\sigma_t^2 = \omega + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2$$

(Costa, 2017)

In this context, the parameters are defined as $\alpha_0 > 0$, $\alpha_i \geq 0$ for $1 \leq I \leq p$, and $\beta_j \geq 0$ for $1 \leq j \leq q$. The error terms, denoted as ε_t, are assumed to be independently and identically distributed, following a parametric distribution such as the normal distribution, generalised error distribution (GED), Student's t-distribution, or their skewed variants. While ARMA models are designed to address nonconstant conditional mean values, GARCH models are specifically used to handle nonconstant conditional variance (Mcleod, et al., 2012).

In this study, the impact of various weather conditions, such as rainfall and humidity, on the volatility of the Istanbul Stock Exchange was analysed. Compared to simpler time series models like ARMA or linear regression, GARCH models provide a distinct advantage when modelling data with non-constant variance. Standard models like ARMA assume constant variance, which might lead to incorrect predictions and underestimated risks in financial applications. GARCH models handle dynamic variance, which results in better predictions and a more realistic understanding of market risks.

Other models, such as ARMA or exponential smoothing, focus more on mean-level predictions and assume that the variance remains constant. However, in financial time series, variance often fluctuates significantly, making models like GARCH more appropriate.

3.3.3. Time Series (ANOVA)

The study examined the impact of seasonal weather conditions on the performance of the Istanbul Stock Exchange over the year. ANOVA is used to compare stock returns across different seasons. Key seasonal patterns in stock returns were identified and their connection to seasonal weather changes was explored.

H_0: There is no significant effect of seasonal conditions on the stock exchange

H_1: There is a significant effect of seasonal conditions on the stock exchange

The formula for the F-statistic is:

$$F = \frac{\text{Mean Square Between (Factor/Interaction)}}{\text{Mean Square Within (Error)}}$$

Source	Degrees of Freedom	Sum of Squares	Mean Square	F
Factor A	$a - 1$	SSA	$MSA = SSA/(a-1)$	MSA/MSE
Factor B	$b - 1$	SSB	$MSB = SSB/(b-1)$	MSB/MSE
AB interaction	$(a-1)(b-1)$	SSAB	$MSAB = SSAB/(a-1)(b-1)$	$MSAB/MSE$
Error	$N - ab$	SSE	$MSE = SSE/(N-ab)$	
Total	$N - 1$	SSTO		

ANOVA is ideal when you want to test whether there are statistically significant differences in the means of more than two groups. In my case, data is categorised to different weather conditions (such as summer, autumn, winter, and spring). And then tested whether the change in the stock exchange differed significantly between these seasons. When you compare more than two groups using multiple t-tests, the possibility of making a Type-1 error (false positive) increases. ANOVA was preferred in this study because it controls this by testing all groups simultaneously under a single hypothesis, thus preserving the level of significance.

While regression can help establish relationships between independent and dependent variables and quantify the strength of these relationships, ANOVA focuses on comparing group means. ANOVA does not necessarily model a direct causal relationship but emphasises testing differences between group effects. Additionally, while regression accounts for the impact of predictors on the outcome, it may not clearly identify group-based differences without steps, like encoding categorical variables.

3.4. Evaluation

3.4.1. Regression Model

T-test

The T-test will be employed to test the hypothesis that a regression coefficient is not statistically significant. If the p-value obtained from the test is less than the chosen significance level (0.05), we reject the hypothesis that the coefficient is not significant. Otherwise, we fail to reject the hypothesis, indicating that the coefficient may not be significantly different from zero.

F-test

The F-test will be utilised to evaluate the overall significance of the regression model. It tests the hypothesis that the model's explanatory variables do not affect the dependent variable. If the p-value for the F-test is less than the significance level, the hypothesis of "no significance" is rejected, suggesting that the model as a whole is statistically significant.

Coefficient of Determination (R^2)

The R^2 value is a measure of how well the regression model fits the data. it indicates the proportion of variation in the dependent variable (Y) that is explained by the independent variable(s) (X). The R^2 value ranges between o and 1, with values closer to 1 indicating a better fit.

3.4.2. GARCH Model

In this analysis, Both AIC and BIC were used to evaluate and compare the performance of GARCH models to determine the most appropriate model.

Akaike Information Criterion (AIC) is a statistical measure used to estimate the quality of a model for predicting future values. It balances the complexity and goodness of fit of a model. Among different models, the one with the lowest AIC is considered the best for the given dataset.

Bayesian Information Criterion (BIC) is a statistical measure that also helps in model selection. It considers both the fit of the model and its complexity, with a focus on penalising more complex models. A lower BIC value indicates a better model fit.

3.4.3. ANOVA Model

The calculated F statistic is compared to a critical value from the F distribution table (based on the chosen significance level (0.05), and the degrees of freedom. Alternatively, the p-value of the F statistic is compared to the chosen significance level.

- If the p-value is less than the significance level, we reject the null hypothesis (H_0) and conclude that there is a statistically significant difference between the group means.
- If the p-value is greater than the significance level (0.05), we fail to reject the null hypothesis (H_0), indicating that there is no evidence of a significant difference between the group means.

The following part examines the application and analysis of the statistical model introduced in this methodology section. Specifically, this part discusses the application of regression analysis, GARCH model and ANOVA to investigate the relationship between variables and stock exchange performance in the Istanbul Stock Exchange. The analysis will be structured to provide insights into the effects of seasonal weather patterns, individual weather conditions and volatility on Istanbul stock.

4. Implementation

The implementation of data modelling, analysis, interpretation, and evaluation was conducted through the following steps:

First: The datasets selected for this study are sourced from Kaggle and include information on the Istanbul Stock Exchange (ISE) and Istanbul Weather. These datasets cover the period from 2009 to 2011.

Second: The data columns were converted to date format to ensure consistency across the CSV datasets. Both datasets were then filtered to include only data from 2009 to 2011. Missing values were checked and addressed for datasets. Dashes in the data columns were consolidated and unnecessary columns, such as “moonrise” and ”moonset” were removed to streamline the data.

Third: The regression analysis focuses on estimating the relationship between stock variables and weather variables, specifically “maxtemp” and ”mintemp”. Descriptive statistics, including minimum, maximum, mean, median, variance, standard deviation, kurtosis, and skewness were examined. Additionally, a histogram was used to create a density plot, visualising the statistical distribution of the return series.

Fourth: At this stage, ANOVA was conducted, and the *classify_season* function was implemented to categorise each date by season. The season classification was applied to the ‘date’ column, allowing the stock exchange to be grouped seasonally. Based on the ANOVA results, a plot chart was generated to visualise the findings. Descriptive statistics were presented for each season. A histogram was used to assess normality, while the Kruskal-Wallis test was employed to check for variance homogeneity. Following normalization, a log transformation was applied to stabilize variance, and the final ANOVA results were obtained.

Fifth: The fifth step in the implementation phase is the GARCH model. At this stage, the relationship between volatility and the weather variables, rain and humidity, was analysed for significance. Conditional volatility and selected weather variables were plotted over time to visualise their pattern. Models including GARCH (1,1), EGARCH (1,1), and AR-GARCH (1,1) were estimated. Based on AIC and BIC values, GARCH (1,1) was identified as the most suitable model and was further analysed.

5. Evaluation/Findings

In this section, we present the results obtained from applying our algorithms and models. The dataset used for modelling consists of Istanbul Stock Exchange (ISE) and weather data from 2009 to 2011. The outputs from the regression analysis, ANOVA analysis, and GARCH model will be interpreted sequentially.

5.1. Regression Analysis

5.1.1 Descriptive Summary/Distribution

To select the independent and dependent variable (TL BASED ISE), X and Y were defined accordingly.

```
x = merged_data[['MaxTemp', 'MinTemp']]
y = merged_data['TL BASED ISE']
```

	MaxTemp	MinTemp
Count	536.000000	536.000000
Mean	18.164179	11.886194
Std	8.313209	6.781235
Min	-3.000000	-4.000000
Max	35.000000	26.000000
25%	12.000000	6.000000
50%	18.000000	12.000000
75%	25.000000	18.000000

Table 1: Descriptive Statistics for MaxTemp and MinTemp

As highlighted above in Table 1, there are 536 recorded values for both MaxTemp and MinTemp, indicating no missing data for these variables over the selected period. The average maximum temperature is approximately 18.16°C, while the average minimum temperature is around 11.89°C. The standard deviation values of 8.31°C for MaxTemp and 6.78°C for MinTemp suggest moderate variability, with maximum temperatures showing slightly more fluctuation than minimum temperatures. The temperature range is broad, with maximum temperatures spanning from a low of -3°C to a high of 35°C and minimum temperatures ranging from -4°C to 26°C. These extremes likely reflect seasonal changes, with the coldest minimums occurring in winter and the highest maximums in summer. Percentile statistics reveal further insights: 25% of max. temperatures are below 12°C, and 75% are below 25°C, indicating that most high temperatures are clustered within a moderate range. Similarly, min. temperatures are below 6°C for the lower quartile and below 18°C for the upper quartile, showing that cool nights are common, with occasional warmer ones.

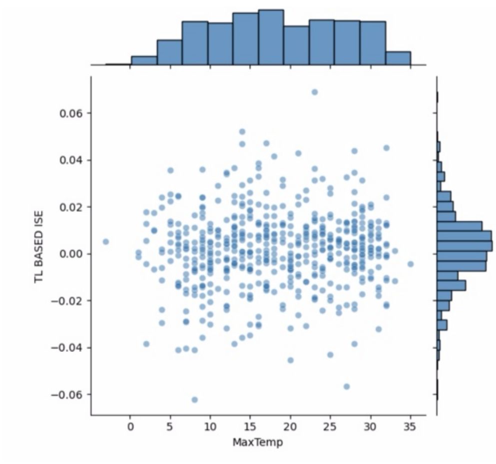

Figure 2: Scatter plot relationship between MaxTemp and TL BASED ISE.

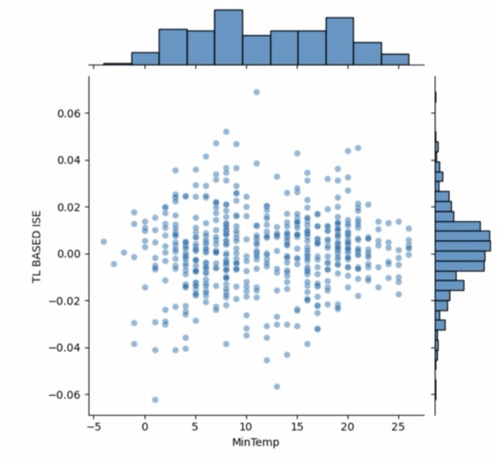

Figure 3: Scatter plot relationship between MinTemp and TL BASED ISE

The Figure 2 scatter plot, as shown above, explains the relationship between MaxTemp and TL BASED ISE. The data points are widely scattered, suggesting a low or possibly non-linear correlation between the maximum temperature and ISE values. The histogram at the top shows the distribution of MaxTemp values. It appears relatively uniform, with a higher frequency of occurrences around the mid-range temperatures, indicating that these are the most common maximum temperatures in the dataset. The histogram on the right displays the distribution of TL BASED ISE values, which is centred around zero with a normal like spread on both sides. This distribution suggests that ISE returns are centred around a mean close to zero, with a symmetrical spread typical for financial return data. Figure 3, explains the scatter of data points with no clear pattern or strong linear relationship between minimum temperature and ISE values, suggesting that MinTemp does not have a direct impact on the stock exchange.

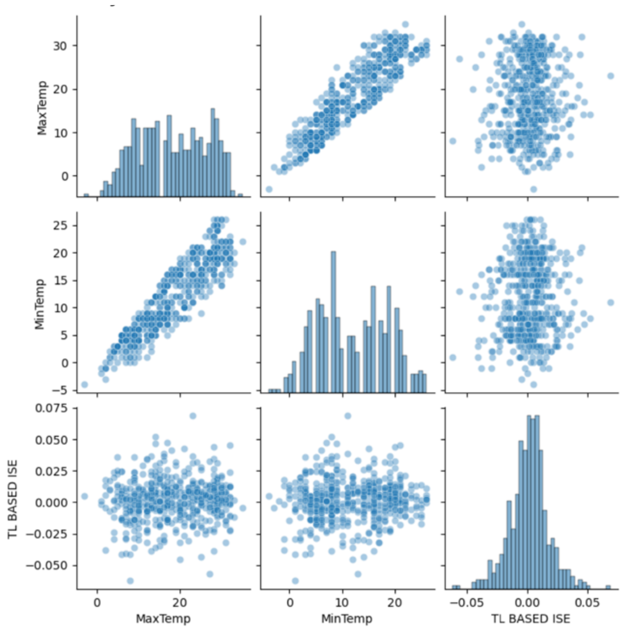

Figure 4

In Figure 4, The plot confirms that while MaxTemp and MinTemp are closely correlated with each other, neither of these temperature variables shows any significant association with TL-based ISE. This reinforces the finding that temperature does not appear to impact the stock exchange directly in this dataset.

5.1.2 Splitting The Data

```
# Split the data into train and test sets (80% train, 20% test)
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random

# Display the shapes of the train and test sets
print("Training set size:", X_train.shape, y_train.shape)
print("Test set size:", X_test.shape, y_test.shape)

Training set size: (428, 3) (428,)
Test set size: (108, 3) (108,)
```

Figure 5: Splitting The Data

In this section, the dataset is split into training and testing sets to prepare for model training and evaluation. Using *the train_test_split* function from *sklearn.model_selection*, the data is divided with 80% allocated to the training set and 20% to the testing set. The code specifies a *random_state* parameter to ensure reproducibility of results.

As depicted above, Figure 5 highlights that the training set contains 428 samples, with each sample having three features, while the testing set has 108 samples, also with three features. This split enables the model to learn from the training data and then be evaluated on the test data, ensuring the model's performance is generalised and not overly fitted to the training set.

5.1.3 Training The Model With Regression

After training the model, all values were considered statistically. After comparing the two models, the correct model was decided by looking at R-square values, T-test, F-test, and which are the decision variable criteria.

Before splitting, the R-squared decreases to 0.004, with an adjusted R-squared of 0.001, meaning that the model explains even less variance (0.4%) when using the entire dataset. This reinforces the weak explanatory power of temperature variables for the stock exchange. After splitting, the R-squared value is 0.008, and the adjusted R-squared is 0.004, indicating that only 0.8% of the variance in TL-based ISE is explained by the model. This suggests very low predictive power.

	R-squared	Adj. R-squared
Normal Model	0.004	0.001
Training Model	0.008	0.004

Table 2: R-squared/Adj. R-squared

In the normal model, the coefficients for MaxTemp and MinTemp change slightly to 6.452 and 8.493, respectively, and the p-values increase to 0.752 for MaxTemp and 0.735 for MinTemp, further emphasizing their insignificance. This suggests that using the full dataset confirms the lack of a relationship between temperature and the stock exchange. After training the model, the coefficients for MaxTemp and MinTemp are -0.0002 and 0.0004, respectively. However, both p-values (0.503 for MaxTemp and 0.185 for MinTemp) are not statistically significant, indicating that these variables do not contribute meaningfully to predicting TL-based ISE.

	MaxTemp	MinTemp
Normal Model	6.452	8.493
P-value	0.752	0.735
Training Model	-0.0002	0.0004
P-value	0.503	0.185

Table 3: Coefficients and P-values

H_0: All coefficients for weather variables are equal to zero
(There is no relationship between weather and stock exchange)

$\beta_{Maxtemp} = 0 \quad \beta_{MinTemp} = 0$

H_1: At least one of the coefficients for weather variables is not equal to zero (There is a relationship between weather and stock exchange)

$\beta_{Maxtemp} \neq 0 \quad \beta_{MinTemp} \neq 0$

The p-values for the weather variables (MaxTemp and MinTemp) are high (above a significance level such as 0.05), so the null hypothesis cannot be rejected. This suggests that there is no significant evidence of a relationship between weather and the stock exchange.

Before splitting the data, the F-statistic is 1.196 with a p-value of 0.303, further confirming that the model remains statistically insignificant even with more data. After training the data, the F-statistic is 1.796 with a p-value of 0.167, suggesting that the model as a whole is not statistically significant.

	F-statistic	P-value
Normal Model	1.196	0.303
Training Model	1.796	0.167

Table 4: F-statistic

In conclusion, whether using the full dataset or a training version, the results consistently indicate that temperature variables have no meaningful relationship with stock in the dataset. The training model has only a slight impact on the values but does not alter the overall interpretation or findings.

5.2 ANOVA Test

This section of the analysis centres on the results of the ANOVA test, a statistical method employed to examine whether there are significant differences in the stock exchange performance across various seasons, namely winter, summer, spring, and autumn. The primary motivation for incorporating ANOVA into this project is its ability to compare the means of multiple groups and determine if variations in the stock exchange returns can be attributed to seasonal changes.

5.2.1 Descriptive Summary

	Count	Mean	Std.	Min.	Max.	25%	50%
Autumn	116.0	0.000396	0.014998	-0.035850	0.038613	-0.007720	0.000982
Spring	126.0	0.003706	0.019113	-0.056753	0.068952	-0.006215	0.003409
Summer	130.0	0.003060	0.012603	-0.025344	0.045220	-0.004546	0.002510
Winter	164.0	-0.000229	0.017151	-0.062208	0.046831	-0.008071	0.000960

Table 5: Descriptive Statistics

Table 5 above, provides descriptive statistics of the stock exchange categorised by seasons: Autumn, Spring, Summer, and Winter. Mean returns are highest in Spring (0.0037) and lowest in Winter (-0.0002), indicating a potential seasonal variation in the stock performance. The standard deviation is largest in Winter (0.0172), suggesting higher variability in returns compared to other seasons, while summer exhibits the lowest variability (0.0126). The minimum and maximum values reveal that Spring has the widest of returns (-0.0568 to 0.0690), while Autumn has a smaller range. Median returns (50%) are positive for all seasons except Winter, further supporting the idea that Winter might have a unique impact on stock exchange performance. This seasonal breakdown highlights the potential influence of seasons on stock exchange returns, with Spring and Summer generally showing more favourable mean performance and winter demonstrating higher variability and lower average returns.

5.2.2 Assumptions

After evaluating the normality assumption using the Shapiro-Wilk test, the following results were obtained.

	Statistics	P-value
Winter	0.9819088994377	0.030750346802652
Spring	0.9777476964314	0.035686985136607
Summer	0.9699436481067	0.005508002801511
Autumn	0.9863249182737	0.291178170437046

Table 6: Shapiro-Wilk test results

The p-values indicate the likelihood that the data are normally distributed. A p-value less than the significance level (0.05) suggests a rejection of the null hypothesis, meaning the data deviate significantly from normality. For Winter, Spring, and Summer, the p-values are below 0.05, suggesting that the distributions for these seasons deviate from normality to some extent. In contrast, the p-value for Autumn (0.2912) exceeds 0.05, indicating no significant evidence against normality for this season.

After assessing the normality assumption, Levene's test was conducted to evaluate the assumption of variance homogeneity. According to the test result, **Levene's statistic** is 4.799837 and the **P-value** is 0.0026. In this analysis, the p-value of 0.0026 is well below 0.05, suggesting that the assumption of equal variances is violated.

5.2.3 Normalization and Stabilising Variance

To address the non-normality in the stock exchange data across seasons, a log transformation was applied as an initial normalisation technique. Log transformation is commonly used to reduce skewness and stabilise variance, thereby making the data more suitable for parametric statistical tests such as ANOVA. Following the transformation, the Shapiro-Wilk test was conducted to evaluate whether the data conformed to a normal distribution. However, the results revealed that all p-values in Table 7 were below the threshold of 0.005, indicating that the null hypothesis of normality was rejected for all seasons (Winter, Spring, and Summer). This outcome suggests that the log transformation was insufficient in normalising the data.

	P-value
Winter	0.013066771933123365
Spring	0.03711084459517738
Summer	0.00874685773530104

Table 7: P-values after normalisation

Levene's test was re-applied after normalisation to test the homogeneity of variance. As a result, the p-value (0.0802) is greater than the commonly used significance level of 0.05. Therefore, the null hypothesis was not rejected, meaning there is no significant evidence to suggest that the variances of the groups are unequal. In other words, the data meets the assumption of homogeneity of variances after normalisation.

This result indicates that the assumption of equal variances is satisfied, which supports the use of parametric tests like ANOVA. If normality is still not satisfied, like in this project, non-parametric tests (e.g. Friedman) can be considered.

5.2.4 Applying ANOVA with Log Transformation Results

After applying a log transformation to stabilise variance and address skewness, an ANOVA test was conducted to examine the differences in the stock exchange across the four seasons (Winter, Spring, Summer, and Autumn). The test produces an **F-statistics** of 1.9660 and a **p-value** of 0.1181. As the p-value exceeds the significance threshold of 0.05, the null hypothesis cannot be rejected.

H_0 : The mean log-transformed stock exchange is equal across all seasons.

H_1 : At least one season has a significantly different mean log-transformed stock exchange.

This suggests that the mean log-transformed stock exchange returns do not differ significantly among the seasons. While the log transformation improved data distribution and variance homogeneity, it did not reveal any significant seasonal variation in the stock exchange. This outcome implies that seasonal effects may not play a significant role in influencing the returns, or the chosen transformation and analysis may not fully capture subtle seasonal dynamics.

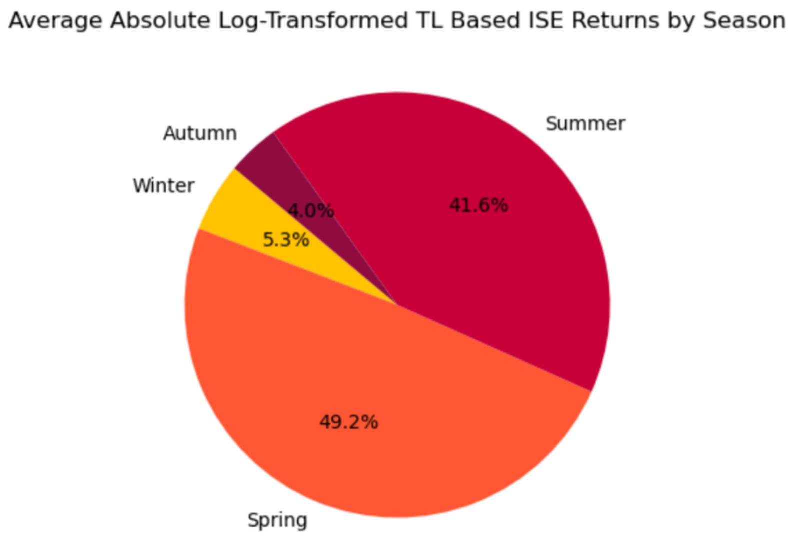

Figure 6

The pie chart in Figure 6 displays the distribution of average absolute log-transformed TL-BASED ISE returns by season, highlighting the seasonal contribution to stock market performance. The largest segment belongs to Spring, which accounts for 49.2%, indicating that it has the highest average absolute returns among all seasons. Summer follows with a significant contribution of 41.6%, reflecting notable activity during this period. In contrast, Winter and Autumn contribute much less, with 5.3% and 4.0%, respectively. This stark contrast suggests that stock exchanges exhibit strong seasonal variation, with Spring and Summer dominating market activity and winter and Autumn experiencing considerably lower levels.

5.3 GARCH Model

In this section, the GARCH model is utilized to analyse the impact of various weather conditions, such as rainfall and humidity, on the volatility of the Istanbul Stock Exchange. To enhance model performance and convergence, the returns series is scaled by multiplying it by 100. This transformation adjusts the scale of the data without altering the inherent characteristics of the volatility model, ensuring consistent and reliable results. After selecting the relevant weather variables, the GARCH model results with exogenous variables in the variance equation were obtained.

The results from the GARCH model reveal several insights about the volatility of the Istanbul Stock Exchange returns. The mean model includes a constant term (μ) with a statistically significant coefficient (**p-value**=0.0012), indicating that the returns exhibit a consistent average behaviour over the period. The volatility model parameters, including ω (the baseline variance), α_1 (the impact of past shocks), and β_1 (the persistence of volatility), are all statistically significant. Specifically, $\alpha_1 = 0.0796$ suggests that past shocks have a moderate impact on current volatility, while $\beta_1 = 0.8653$ indicates high persistence, meaning that volatility tends to persist over time. The model's fit statistics, such as the Log-Likelihood (-996.206), AIC(2000.41), and BIC (2017.55), provide benchmarks for comparison with alternative specifications.

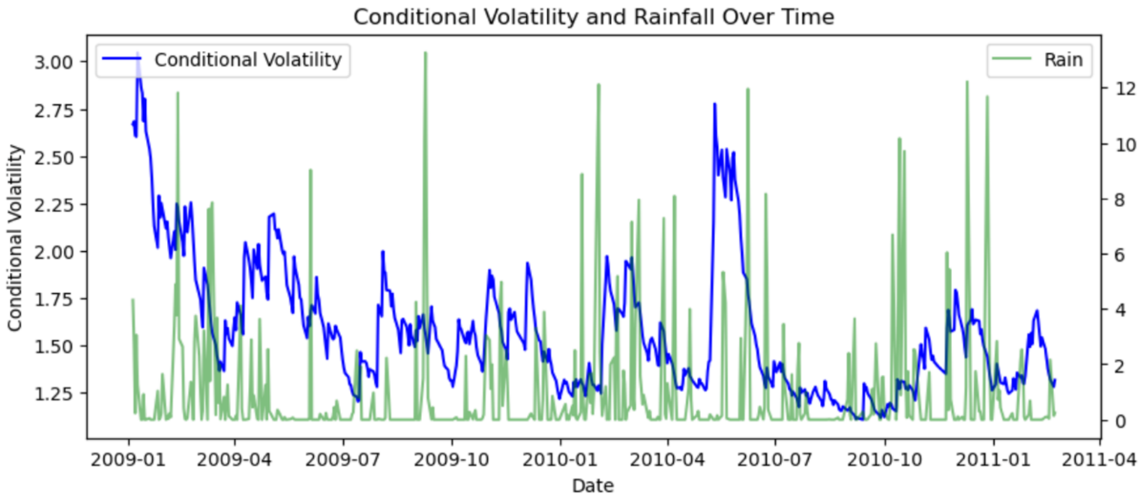

Figure 7: Conditional Volatility and Rainfall Over Time

Figure 7 above illustrates the relationship between conditional volatility of the Istanbul Stock Exchange (blue line) and rainfall (green line) over time. The conditional volatility represents the time-varying uncertainty or risk in stock returns, as modelled by the GARCH process, while the rainfall variable indicates the amount of precipitation. There are noticeable peaks in conditional volatility during certain periods, suggesting increased uncertainty in the stock market during those times. For instance, the beginning of 2009 and mid-2010 show significant spikes in volatility.

The graph suggests that rainfall may have some influence on stock market volatility, as periods of high precipitation seem to align with increased volatility at certain points. However, this relationship appears inconsistent, highlighting the need for further statistical analysis (e.g., regression or hypothesis testing) to determine whether the observed patterns are statistically significant or coincidental.

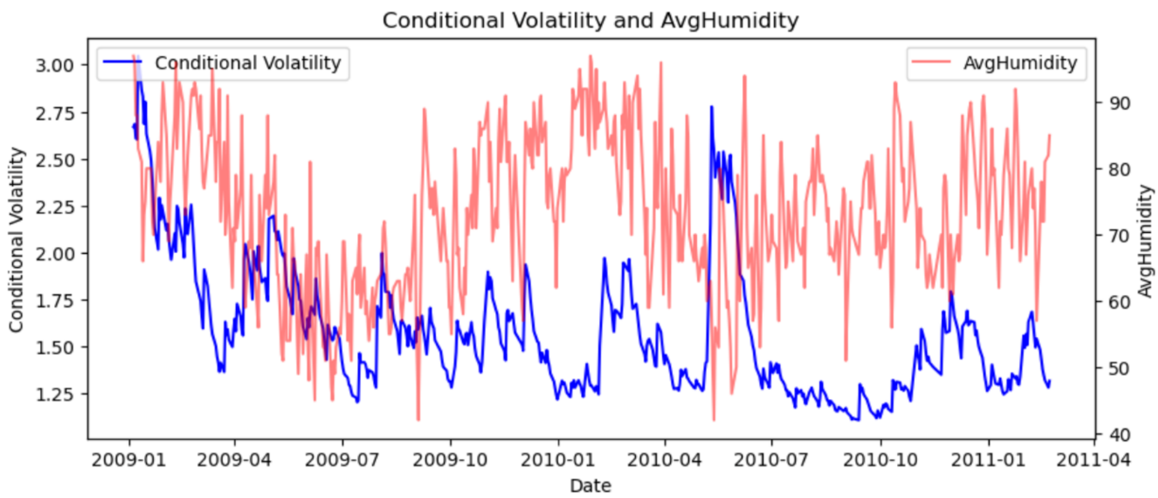

Figure 8: Conditional Volatility and Humidity

The blue line demonstrates declining volatility from early 2009 to mid-2010, followed by intermittent spikes, especially around early 2010 and early 2011. These fluctuations indicate periods of varying market risk. The red line shows a relatively stable but oscillatory pattern in average humidity, with frequent short-term increases and decreases. Humidity remains within a narrower range, with values generally between 60% and 90%.

This graph suggests that while average humidity and market volatility vary over time, their relationship is not immediately apparent or consistent. Some periods may suggest alignment (e.g., volatility dips when humidity stabilizes), but overall, the connection is weak.

A comparison of another model applied to achieve better AIC and BIC values is given in the table below.

	AIC	BIC
GARCH(1,1)	2000.41	2017.55
GARCH(2,2)	2004.18	2029.89

Table 8

The GARCH(1,1) model achieves both a lower AIC and BIC compared to GARCH(2,2), implying that it fits the data well while being more parsimonious(fewer parameters).

6. Discussion

This project investigates the interplay between weather conditions and the performance of the Istanbul Stock Exchange (ISE), shedding light on a largely unexplored area within behavioural finance and market dynamics. The findings, derived from regression analysis, ANOVA tests, and GARCH modelling, provide valuable insights into the impact or lack thereof of weather variables on the stock market and volatility. This section situates the findings of the study within the broader academic context and compares them with articles in the existing literature.

The limitation of this study is that the weather dataset (2009-2019) and stock exchange dataset (2009-2011) only cover the intersecting years (2009-2011) due to the different time intervals of the datasets used. Regression analysis was additionally conducted to assess the relationship between temperature as a weather variable and stock market performance. ANOVA was applied to examine the seasonal effects on the stock exchange. Additionally, the GARCH model was utilised to explore the impact of weather conditions on stock exchange volatility.

One of the main findings from the regression analysis was the lack of significant correlations between temperature (both maximum and minimum) and TL-based ISE returns. This aligns with the work of Tuna (2014), who found no substantial relationship between humidity and Istanbul's stock market returns. Descriptive statistics revealed moderate variability in maximum and minimum temperatures, but scatter plots showed no significant linear correlation between temperature and TL-based ISE returns. Regression coefficients for both maximum and minimum temperatures were insignificant (p-values>0.05), confirming no meaningful relationship. R-squared values were low (below 1%), indicating the temperature variables could explain very little variance in the stock.

ANOVA assumptions were tested, and the Shapiro-Wilk test was used to evaluate the normality assumption. The results indicated that the Winter, Spring, and Summer seasons were not normally distributed, while the Autumn season followed a normal distribution. Regarding the assumption of equal variances, Levene's test revealed a violation, indicating that homogeneity of variance was not achieved in this study. If homogeneity were satisfied, the Friedman test could have been applied; however, this requires equal group sizes, which was not case in this study. To address the lack of normality, a log transformation was applied to normalise the non-normally distributed variables. The results showed that the log-transformed stock exchange returns did not differ significantly between seasons. Although the logarithmic transformation improved data distribution and variance homogeneity, it did not reveal any significant seasonal variations in stock exchange returns.

The GARCH model provided some of the most compelling insights by highlighting the potential influence of rainfall and humidity on market volatility. To improve model performance and convergence, the return series was scaled by multiplying by 100. While the overall relationship between these variables and volatility was inconsistent, certain periods displayed notable spikes in conditional volatility coinciding with extreme weather conditions. The GARCH (1,1) model was selected for its lower Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC), demonstrating a better fit for capturing volatility dynamics. Results indicated high volatility persistence but inconsistent relationships between weather variables like rain and humidity and stock exchange volatility.

This study contributes to the growing body of literature on the intersection of weather and financial markets by providing evidence from an emerging market context. While the direct relationship between conditions and stock returns in the Istanbul Stock Exchange appears limited, the observed effects on market volatility underscore the complex interplay between environmental factors and investor behaviour. Despite its contributions, this study is not without limitations. The dataset covers only three years (2009-2011), which may not fully capture long-term patterns or the potential impact of extreme weather events such as heat waves or floods. Moreover, extending the analysis to longer and more comprehensive time periods or periods of extreme weather events may potentially provide additional deeper insights.

7. Conclusion and Future Work

In this study, the potential effects of weather conditions on the Istanbul Stock Exchange (ISE) were investigated, and the relationships between them were revealed by using advanced statistical techniques such as regression analysis, ANOVA and GARCH model.

The regression analysis revealed no significant correlation between daily temperature fluctuations and stock returns, aligning with some prior studies while contrasting with research in other markets that found notable weather-related effects. Similarly, the ANOVA test did not demonstrate meaningful seasonal variations in stock returns, despite descriptive statistics suggesting minor trends, such as slightly higher returns in spring and summer these outcomes indicate that seasonal weather conditions do not substantially influence stock performance in the Turkish market. On the other hand, the GARCH model highlighted the persistence of market volatility over time but revealed the limited and inconsistent relationship between weather variables and volatility. While rainfall and humidity occasionally appeared to coincide with changes in volatility, these patterns were neither strong nor consistent enough to establish a robust link.

Future Work

Future research could expand on this study by including longer time periods and datasets to capture more comprehensive trends and the effects of rare or extreme weather events, such as storms, heatwaves, or prolonged precipitation. Furthermore, conducting comparative studies across multiple emerging and developed markets could uncover regional differences in the weather-stock market relationship, shedding light on cultural, economic, or structural factors influencing these dynamics. Polynomial Regression or Spline Regression can be applied to identify and model possible non-linear relationships between weather conditions and stock market performance. Lastly, integrating behavioural finance perspectives, such as investor sentiment analysis derived from social media or surveys, could help link weather-induced mood changes with financial decision-making more directly.

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“Go raibh maith agat”

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