**7COM1079-0901-2024 - Team Research and Development Project**

**Analyzing the Correlation Between Simple Moving Average of Close Prices and the Price Volatility (Difference Between High and Low Prices) in Hyundai’s Stock Data**

**Group ID:** A 246  
**Dataset number:** DS327 - Hyundai Motor Company Stock Historical Price  
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**Abstract**

This research investigates the relationship between the Simple Moving Average (SMA) of closing prices and the difference between the highest and lowest prices of Hyundai’s stock. The goal is to understand how these two factors are related and whether one can help predict the other. To analyze this, we used two visualizations: a histogram and a scatter plot. The histogram showed that the price differences were not normally distributed, with most values clustering around smaller differences, and fewer occurrences of large price changes. The scatter plot illustrated a positive relationship between SMA and price differences, though there was considerable variability and outliers, suggesting that the relationship is not straightforward. Due to the non-normal distribution of the data, non-parametric methods, such as Spearman’s Rho and Kendall’s Tau, were used to measure the correlation between these two factors. The results indicated a moderate correlation, but also highlighted the importance of considering outliers and variability when interpreting market data. Overall, this research provides insights into how SMA and price differences can be used together to better understand Hyundai’s stock behavior, guiding future analysis and investment strategies.

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**1. Introduction**

**1.1. Problem Statement and Research Motivation**

In the financial world, stock data refers to information about the performance of a company’s shares on the stock market. This data typically includes details like the prices at which shares were bought and sold, how much the prices fluctuated, and how many shares were traded. Studying stock data helps investors, analysts, and stakeholders make better decisions by identifying patterns or trends in how the stock behaves.

For this research, we focus on the stock data of Hyundai Motor Company, a global leader in the automotive industry. Hyundai Motor Company, based in Seoul, South Korea, is a global leader in vehicle manufacturing, offering cars, SUVs, and eco-friendly models like electric and hybrid vehicles. Investing in Hyundai stocks means owning a part of a company involved in diverse areas like car production, financing, and mobility services. The stock's performance depends on factors like global vehicle demand and advancements in green technology, making it an exciting option for this Research. The goal is to investigate if there is a relationship between two key aspects of its stock performance:

1. The Simple Moving Average (SMA) of Closing Prices: This is the average of a stock's closing prices over a specific time frame. It smooths out price fluctuations to help identify trends.
2. The Price Volatility (Difference Between High and Low Prices): This shows how much the stock's price changes within a single day, capturing the range of volatility.

By analyzing this relationship, we aim to uncover patterns that could guide investment decisions or provide insights into market behavior.

**1.2.** **Dataset Description**

The dataset shown in Fig 1.1. is titled “Hyundai Motor Company Stock Historical Price” and is sourced from Kaggle [5], with data originally taken from Yahoo Finance. It contains daily stock price records from January 2016 to the present. Each record in the dataset has several columns, and here is what they represent:

* **Date:** The specific day the stock prices were recorded.
* **Open:** The price at which Hyundai’s stock started trading that day.
* **High:** The highest price the stock reached during the day.
* **Low:** The lowest price the stock fell to during the day.
* **Close:** The price at which the stock finished trading that day.
* **Adjusted Close (Adj Close):** The stock’s closing price adjusted for corporate actions like dividends, stock splits, or other events.
* **Volume:** The total number of shares traded during the day.

For this study, to examine this relationship, we will focus on the following:

* SMA of Closing Prices (dependent variable) calculated by the following formula:

Where,

* : Simple Moving Average at time .
* : Number of periods for the moving average.
* : The Close price at time .
* : The current time period.
* the Price Volatility (independent variable) which is calculated as follows.

Where,

* : Price Volatility at time .
* : High Price at time .
* : Low Price at time.
* : The current time period.

A close-up of numbers

Description automatically generated

**Fig 1.1. Modified Hyundai Stock Dataset**

**1.3. Research Question**

This study investigates:

***“Is there a correlation between the Simple Moving Average of Closing Prices and the Price Volatility (Difference Between High and Low Prices) in Hyundai’s stock data?”***

This question explores whether the average of past closing prices (SMA) is connected to the daily price range volatility. Answering this can provide insights into how historical trends in closing prices relate to the stock's daily volatility.

**1.4. Null Hypothesis and Alternative Hypothesis (H₀/H₁)**

* **Null Hypothesis (H₀):** There is no correlation between the Price Volatility (Difference Between High and Low Prices) and the Simple Moving Average of Closing Prices.
* **Alternative Hypothesis (H₁):** There is a correlation between the Price Volatility (Difference Between High and Low Prices) and the Simple Moving Average of Closing Prices.

The hypotheses will be tested using statistical methods to understand the relationship between these two variables. By exploring this relationship, we aim to contribute to the understanding of stock behavior and provide useful insights to stakeholders, even for those new to the world of finance or data analysis.

**2. Background Research**

**2.1.** **Literature Review**

Understanding financial markets often relies on identifying patterns and trends that inform investment decisions. A widely used tool in this process is the Simple Moving Average (SMA), which helps smooth out price fluctuations over time by averaging an asset's closing prices for a given period. Several studies have explored the utility of SMA in improving trading strategies and mitigating risks associated with market volatility. However, the specific relationship between SMA and the Price Volatility for Hyundai’s stock has received limited attention. This study seeks to fill this gap by investigating how these factors interact and contribute to more effective trading strategies, addressing the Research Question (RQ): How does the interplay between SMA and Price Volatility affect trading strategies for Hyundai’s stock?

Research has demonstrated the versatility of SMA as a tool for trend identification and risk reduction. A study found that using SMA as a trend indicator for main stock and real estate indices significantly reduced standard deviation and maximum drawdown, measures commonly used to assess investment risk [1]. Additionally, it highlighted that longer-term SMAs, spanning 9 to 20 months, were particularly effective for these purposes, offering insights into broader market trends and reducing the influence of short-term volatility.

The difference between an asset's high and low prices during a trading session provides a measure of its price volatility, which is influenced by factors such as liquidity constraints, transaction costs, and market shocks. Research indicates that these price extremes—high prices often representing the highest asking prices and low prices the lowest bids—can be subject to unexpected influences such as unanticipated news events or systemic market changes [2]. Accurate forecasting of these high-low price dynamics has been shown to improve trading performance by offering timely buy and sell signals. For example, if the intraday price crosses the upper predicted range, it may signal an optimal point to sell, whereas crossing the lower range might indicate a buying opportunity [2].

In addition to high-low price analysis, SMA has been widely used to identify trend changes and optimize trading strategies. Its application extends to techniques such as the moving average crossover, where traders compare short-term and long-term SMAs to detect trend reversals and potential trading opportunities [3][4]. These methods are particularly favoured by long-term traders who seek stability and wish to avoid reacting to short-term market fluctuations [4]. SMA thus serves as a robust tool for identifying opportunities and minimizing risks across different market conditions.

Despite these advancements, there remains a significant gap in the literature concerning the specific application of SMA in combination with high-low price dynamics for individual stocks such as Hyundai’s. This study aims to address this gap by investigating the correlation between SMA signals and high-low price differences. Understanding this relationship is crucial for technical analysts and investors, as it could provide actionable insights for predicting market movements and refining trading strategies.

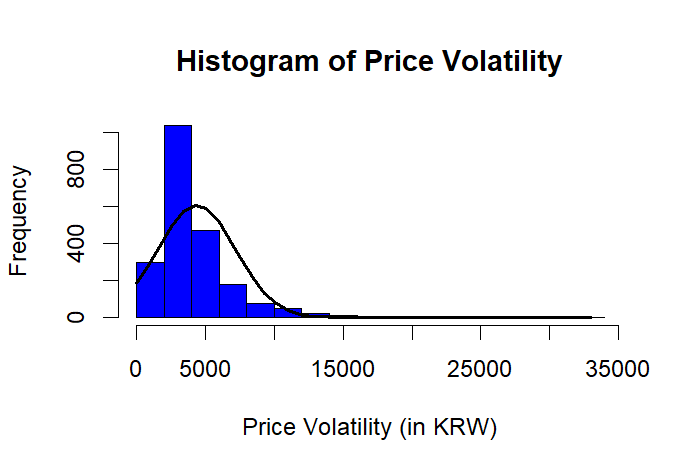
**2.2.** **Why RQ is of Interest.**

The significance of this research lies in its potential to contribute both to academic understanding and practical application. By focusing on Hyundai’s stock, the study provides a targeted analysis that can serve as a foundation for future research in this area. Additionally, the insights gained may help traders and investors better navigate market complexities, thereby improving their decision-making processes and enhancing overall market efficiency.

**3. Visualization**

To better understand the relationship between the Simple Moving Average (SMA) of closing prices and the Price Volatility in Hyundai’s stock data, two visualizations were used: a histogram and a scatter plot. These visualizations provide foundational insights into the data and guide the selection of appropriate statistical methods.

**3.1.** **Histogram: Distribution of High-Low Price Differences**

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**Fig 4.1. Histogram of Price Volatility**

The histogram shown in Fig 4.1. reveals the frequency distribution of the differences between high and low prices. The data shows a strong concentration of smaller price differences, with fewer instances of larger differences. This right-skewed distribution is non-normal, as indicated by the tail stretching towards higher price differences. This skewness suggests the presence of outliers, potentially arising from significant market events or abnormal trading activity.

The lack of normality in the data distribution is an important finding, as it directly influences the choice of statistical methods for further analysis. Traditional parametric tests, which assume normality, would be inappropriate here, leading to the selection of rank-based methods like Spearman’s Rho and Kendall’s Tau.

**3.2.** **Scatter Plot: SMA vs. High-Low Price Differences**

**A graph of a price volatility

Description automatically generated**

**Fig 4.2. Scatterplot of Price Volatility vs 20-Day Simple Moving Average**

The scatter plot in Fig 4.2. depicts the relationship between the SMA (x-axis) and the high-low price differences (y-axis). A fitted regression line provides a clear indication of a positive trend, suggesting that as SMA values increase, the differences between high and low prices also tend to rise.

However, the spread of data points around the regression line is considerable, indicating variability in the relationship. The presence of outliers, visible as points deviating significantly from the general trend, further emphasizes the complexity of the relationship. This variability necessitates robust statistical methods that can handle such irregularities without being unduly influenced by extreme values.

**3.3.** **Why the Data Distribution Influences Method Selection**

The non-normal distribution observed in the histogram justifies the choice of Spearman’s Rho and Kendall’s Tau for correlation analysis. Both methods are non-parametric and rank-based, making them ideal for datasets with skewed distributions and outliers. Spearman’s Rho measures the strength and direction of the monotonic relationship, while Kendall’s Tau assesses the agreement between data rankings. Their robustness ensures reliable results even when normality assumptions are violated.

**4. Analysis**

In financial markets, identifying relationships between various price metrics is crucial for understanding trends and making informed decisions. This study explores whether there is a meaningful correlation between the Simple Moving Average (SMA) of closing prices and the Price Volatility prices in Hyundai’s stock data. To assess this, statistical methods were employed to determine the strength and significance of the relationship between these two variables.

By examining the relationship between these two measures, this study aims to uncover whether trends observed in SMA align with variations in daily price ranges. Such a relationship, if present, could help traders refine their strategies by combining long-term trend analysis (SMA) with real-time price movement data.

**4.1.** **Results from Statistical Analysis**

Two statistical tools, Spearman's rank correlation (rho) and Kendall's rank correlation (tau), were used to analyze the relationship between SMA and the high-low price difference. These methods are particularly useful because they measure the strength and direction of associations between variables without assuming any specific type of relationship (linear or otherwise).

|  |  |  |
| --- | --- | --- |
|  | **Spearman Test** | **Kendall Test** |
|  | S = 975949783 | z = 19.642 |
| p-value | < 2.2e-16 | < 2.2e-16 |
| Rank Correlation | rho = 0.4083257 | tau = 0.2914608 |

**Table 1 – Statistical Test Findings**

* **Spearman's rho:** From Table 1, we can see that the analysis yielded a rho value of 0.408, which suggests a moderate positive correlation. This means that, generally, as the SMA of closing prices increases, there is a tendency for the high-low price difference to increase as well. The associated p-value was less than 2.2e-16, indicating that this result is statistically significant and highly unlikely to be due to random chance.
* **Kendall's tau:** Similarly, Table 1 shows that the Kendall’s tau analysis produced a tau value of 0.291, also pointing to a positive correlation. Although this value is slightly lower than rho, it reinforces the finding that there is a meaningful association between the two variables. The p-value, once again less than 2.2e-16, confirms the significance of this result.

**4.2. Interpretation of Findings**

The results suggest that there is a consistent relationship between the SMA of closing prices and the Price Volatility in Hyundai’s stock. A positive correlation indicates that these two measures tend to move in the same direction. In simpler terms, when the SMA, which represents the long-term trend of closing prices, increases, it is often accompanied by a larger range of daily price movement.

This relationship is not only statistically significant but also relevant for traders and analysts. It implies that the SMA could be a useful tool for predicting changes in price volatility. For instance, if an increasing SMA trend is observed, it may signal that the stock is experiencing broader price swings, which could influence decisions on when to buy or sell.

**5. Conclusions**

**5.1. Key Findings**

Our analysis of Hyundai's stock data revealed valuable insights that can help investors and traders better understand market trends. Specifically, we found a meaningful and moderate positive correlation between the 20-day Simple Moving Average (SMA) and the Price Volatility (Difference between High and Low Prices). This suggests that when the SMA increases, the variability in daily prices also tends to rise, highlighting a relationship between long-term trends and daily price movements.

Additionally, we discovered a statistically significant positive correlation between the SMA of closing prices and Price Volatility. This means that as the SMA rises, trading activity tends to increase. This behavior aligns with the way technical indicators influence market participation.

**5.2.** **What This Means for Investors**

These findings provide a practical understanding of stock market behavior. For example:

* **Price Trends and Variability:** Recognizing the connection between the SMA and Price Volatility allows investors to use SMA as a tool to gauge market momentum while also considering potential daily fluctuations.
* **SMA and Trading Activity:** The relationship between SMA and trading volumes indicates that traders often react to SMA trends, driving higher activity in the market.

However, the presence of outliers and variability in the data reminds us that market trends are influenced by many factors beyond just SMA, such as economic events and news.

**5.3. Implications and Future Directions**

While our findings highlight significant correlations, they are not the sole determinants of stock performance. Other factors like company announcements, global market conditions, and investor sentiment also play crucial roles. Future research could integrate these external factors to build more robust predictive models.

Moreover, while correlation suggests a relationship, it does not confirm causation. For instance, the rise in trading volumes alongside SMA trends may be influenced by broader market dynamics. Investigating these causes can lead to a deeper understanding of market behaviours.

**5.4. Concluding Remarks**

In summary, this research demonstrates the value of using SMA and Price Volatility as tools to understand stock trends. By applying these insights, investors can enhance their strategies, reduce uncertainty, and make more informed trading decisions. However, as always in financial markets, caution and comprehensive analysis remain key to successful investing.

**6. Reference list**

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**7. Appendices**

**A. R code used for analysis and visualization.**

library(TTR)

data = read.csv("005380.KS.csv")

data

data$sma = SMA(data$Close, n = 20) # Calculation of 20-Day Simple Moving Average

data$pricevolatility = data$High - data$Low # Caculation of Price Volatility

data

write.csv(data, "Dataset\_SMA.csv", row.names = FALSE) # Saving the modified dataset for further Visualisation and Analysis

library(ggplot2)

library(dplyr)

data = read.csv("Dataset\_SMA.csv")

data

summary(data)

# Data Cleaning - Removing Null values

sum(!is.finite(data$sma))

data\_cleaned <- data[!is.na(data$sma) & !is.nan(data$sma) & !is.infinite(data$sma), ]

sum(!is.finite(data\_cleaned$sma))

y <- data\_cleaned$pricevolatility

x <- data\_cleaned$sma

# Histogram of Price Volatility

h <- hist(y

, 12

, main = "Histogram of Price Volatility"

, xlab = "Price Volatility (in KRW)"

, ylab = "Frequency"

, col = "blue"

)

xfit <- seq(min(y), max(y), length = 40)

yfit <- dnorm(xfit, mean = mean(y), sd = sd(y))

yfit <- yfit \* diff(h$mids[1:2]) \* length(y)

lines(xfit, yfit, col = "black", lwd = 2)

# Scatterplot of Price Volatility vs. 20-Day Simple Moving Average

plot(x,y,main = "Scatterplot of Price Volatility vs. 20-Day Simple Moving Average" , xlab = "Price Volatility (in KRW)" , ylab = "20-day SMA (in KRW)" , pch = 19, frame = T)

model <- lm(y ~ x, data = data\_cleaned)

abline(model, col = "blue")

# Kendall Statistical Test

cor\_test\_result <- cor.test(x, y, method = "kendall")

print(cor\_test\_result)

# Spearman Statistical Test

cor\_test\_result <- cor.test(x, y, method = "spearman")

print(cor\_test\_result)

**B. GitHub log output**  
(ithu sample dhan)