Analyzing Louis Vuitton's Stock Prices Through the SARIMA Model and Spectral Analysis

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PSTAT 174: Spring 2024

Abstract

This report employs time series data analysis techniques to gain a comprehensive analysis of Louis Vuitton's stock prices. By utilizing various statistical models, which include the SARIMA model and spectral analysis methods, this project aims to discover any patterns or findings within this vast dataset. This analysis bridges my interest in the fashion industry and financial markets, which can offer insight into the economic influences and market behavior. This project contributes to understanding the financial dynamics of one of the most powerful luxury brands in the world, as well as gaining valuable insights into stock market strategies and the economic impacts in the fashion industry.

1 Introduction

The objective of this project is to conduct a thorough analysis of Louis Vuitton's stock prices using advanced time series analysis methods. The main goal is to discover any significant patterns or insights to gain a deeper understanding of how stock performance can tell us about how fashion trends and economic factors can influence stock prices. Louis Vuitton is one of the largest fashion brands in the world, which makes it especially appealing for financial analysis due to its significant influence in the fashion industry and the global market.

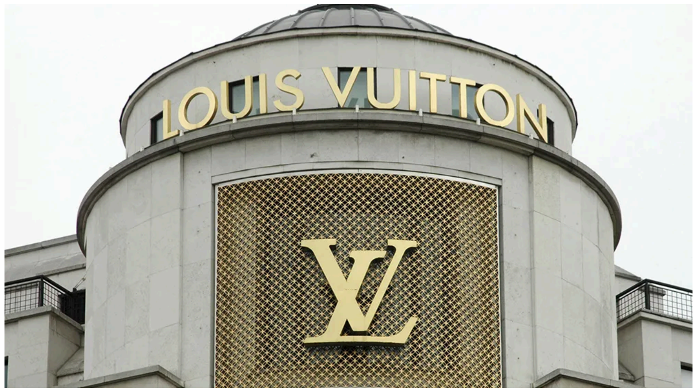
I chose this topic and dataset, because of my interest in the fashion industry and my desire to gain a deeper understanding of financial markets. This project combines my academic interests and my passions, which has allowed me to explore the intersection between fashion trends and the stock market. This dataset, which spans from January 27th, 2006 to December 15th, 2023, provides some historical insight into Louis Vuitton's stock prices.

Louis Vuitton's parent company LVMH (Moët Hennessy Louis Vuitton) has consistently demonstrated strong financial performance. In 2023, LVMH achieved a record year, which shows its strong position in the luxury goods sector. According to LVMH, "the Group recorded revenue of €64.2 billion in 2023, up 23% compared to the previous year, driven by the excellent performance of all business sectors." The brand's timeless appeal and cultural influence has also played a significant role into its strong market presence. The Île-de-France region in Paris, where the brand originates, is one of the most economically powerful regions in the world, and has significantly contributed to France's GDP. As noted in a Medium article, "Louis Vuitton's legacy is not just about fashion; it's a symbol of status, heritage, and timeless luxury."

Previously, this dataset has been used to conduct more basic trend analysis, but this project employs more sophisticated techniques, including SARIMA modeling and spectral analysis. SARIMA modeling is effective to discover seasonal trends, while spectral analysis helps to gain a deeper understanding of the periodicities underlying the data. My analysis revealed that the SARIMA(1, 0, 5) model best fits the data, indicating stable stock prices with minor fluctuations, while the spectral analysis identified significant periodic components, suggesting the presence of annual and shorter-term cycles in the stock prices.

Overall, this project has not only helped me explore the world of luxury fashion and financial markets, but it has also allowed me to practice advanced statistical methods to make discoveries about the stock market. By bridging the gap between fashion and finance, this analysis has helped me to gain a deeper perspective into the economic factors that have shaped one of the world's most powerful luxury brands.

2 Data



For my analysis, I used the LVMUY dataset, which contains historical stock prices from Louis Vuitton. The dataset ranges from January 27th, 2006 to December 15th, 2023, which provides almost 15 years of the company's stock performance. The data is recorded daily, and the values represent the closing stock prices of Louis Vuitton in stock units, which are positive values.

- Time Range: January 27th, 2006 - December 15th, 2023
- Frequency: Daily
- Values; Closing stock prices in stock units
- Size: 3436 observations

I chose this dataset, because of my interest in the fashion industry and desire to gain a deeper understanding of the financial markets. Louis Vuitton is one of the largest luxury fashion brands in the world, and analyzing its stock performance can provide insight into how fashion trends and economic factors can influence stock prices. I have also been learning about stocks from my dad, and this project has given me the opportunity to apply that knowledge in a practical setting.

The dataset was sourced from Kaggle, which is a well-known platform for data science projects and dataset exploration. The LVMUY dataset was compiled by Dhruv Shan and includes data that was collected from public financial market records and stock exchanges where LVMUY stock is traded. **The dataset can be accessed and downloaded here:**

https://www.kaggle.com/datasets/dhruvshan/louis-vuitton-stock-data-all-time

The data itself was collected from historical stock price data from different financial market databases and APIs. Louis Vuitton, and its parent company LVMH, has long had a significant impact on the global market. Understanding its stock performance is valuable for financial analysis and gaining a broader perspective on the impacts that economic factors and the fashion industry have had on each other. By analyzing this dataset, I hope to have a better understanding of the stock market of one of the world's largest luxury brands and its influences on the fashion industry.

3 Methodology

First, I plotted the original time series data, ACF, and PACF to look at trends and to see if the data needed any adjusting. After analyzing these plots, the dataset was log-transformed and differenced to achieve more stationarity and stabilized variance. I then plotted the ACF and PACF of the differenced log-transformed data. Using the Box-Jenkins approach for SARIMA modeling, several ARIMA models were fitted in order to determine the best model. Diagnostic plots, which included standardized residuals, ACF of residuals, normal Q-Q plots, and the Ljung-Box test, were used to ensure that the model's results were valid. The selected model was then used to forecast future values over 12 periods, which were visualized through forecast plots.

In addition to SARIMA modeling, I also applied spectral analysis. This involved calculating the periodogram of the differenced log-transformed data and plotting both the periodogram and log-periodogram to identify any significant frequencies. The Daniell kernel method was used to compute the smoothed periodogram, reducing any noise and visualizing these frequencies. Finally, a linear model was fitted onto the log-periodogram to analyze the relationship between frequency and log-spectral density.

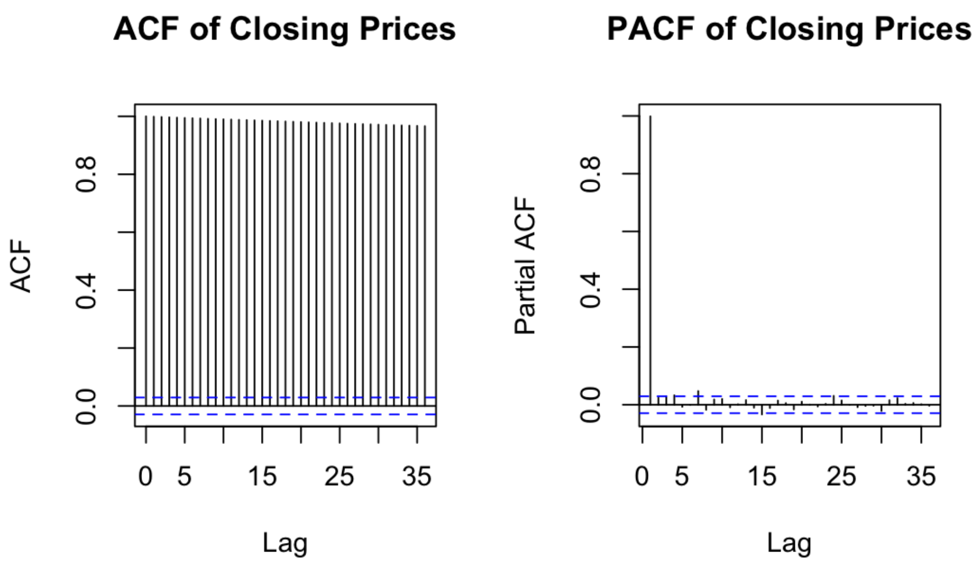
4 Results

4.1 SARIMA Modeling

First, the original data of Louis Vuitton's stock prices were plotted over time.

We can see a clear upward trend, especially since 2015. The stock prices have increased dramatically, with some volatility.

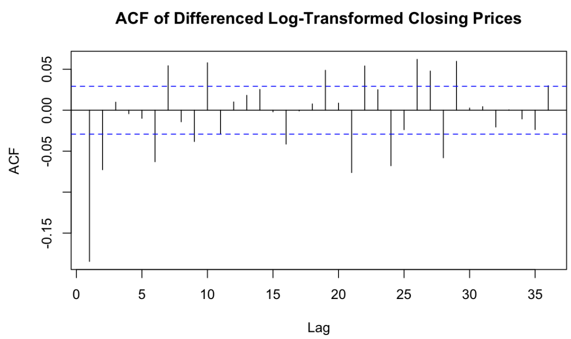
Next, the ACF and PACF of this original data was plotted below:

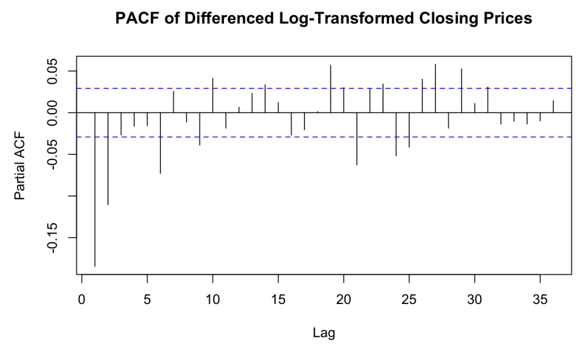


We can see that there is a strong correlation at many lags, as seen by the slow decay in the ACF plot and significant spike at lag 1 in the PACF plot. This shows that the data is non-stationary, indicating that the mean and variance of the stock prices change over time. As a result, I applied a log transformation to stabilize the variance and then differencing to make the data more stationary.

Aftering applying these transformations, I plotted the differenced log-transformed closing prices (now a more stationary time series), which shows reduced heteroscedasticity and volatility compared to the original graph.

The ACF and PACF plots of the differenced log-transformed data also show more stationary behavior. The ACF plot has a sharp drop after the first lag, and the PACF plot shows reduced significance of partial autocorrelation at higher lags. Both plots show significant peaks at lag 1. This shows that the transformation in the data was effective to gain more stationarity. Now, the Louis Vuitton stock price data is ready for further analysis using SARIMA models and spectral analysis.





The next step in analysis is to fit various SARIMA models using several combinations of the ARIMA parameters (p, d, q) to identify the most ideal SARIMA model. The Box-Jenkins method is used in this process, which is a forecasting method that includes model identification, parameter estimation, and diagnostics. Four models were chosen based on the patterns in the ACF and PACF plots. The goal is to choose the model with the best fit, which was based on criteria that includes: Akaike Information Criterion (AIC), Corrected Akaike Information Criterion (AICc), and Bayesian Information Criterion (BIC).

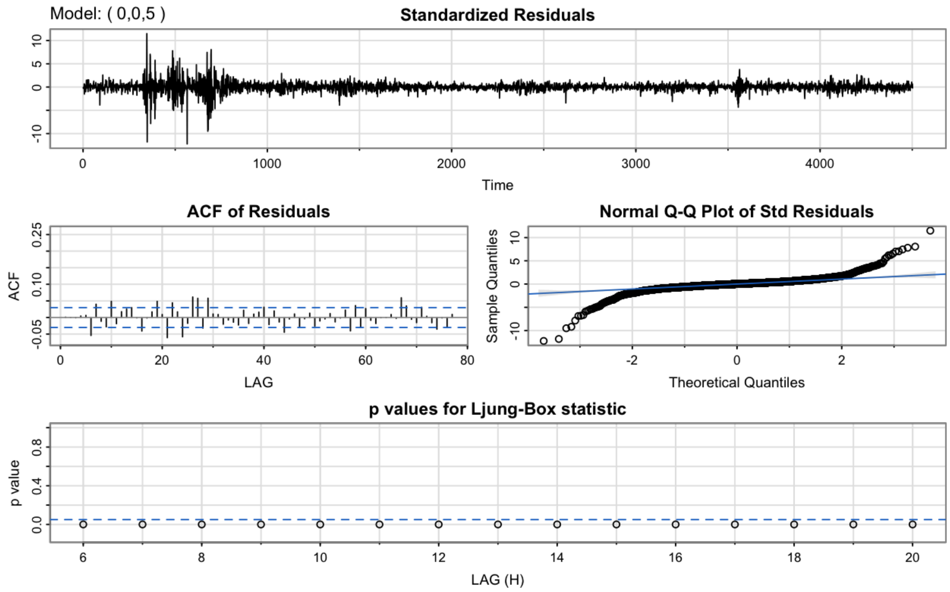
Among these tested models, the SARIMA(1, 0, 5) model was determined to be the best model. This was because it had the lowest AIC, AICc, and BIC values, which indicates that it best fits our data. The coefficients of this model are shown in the output below, which shows the significance of the parameters.

```
Coefficients:
      Estimate     SE t.value p.value
ar1     0.3854 0.2259  1.7065  0.0880
ma1    -0.5963 0.2256 -2.6433  0.0082
ma2     0.0064 0.0503  0.1280  0.8982
ma3     0.0371 0.0251  1.4782  0.1394
ma4    -0.0183 0.0186 -0.9875  0.3235
ma5    -0.0204 0.0165 -1.2346  0.2170
xmean   0.0005 0.0003  1.6099  0.1075

sigma^2 estimated as 0.0009224227 on 4495 degrees of freedom

AIC = -4.14706  AICc = -4.147054  BIC = -4.135665
```

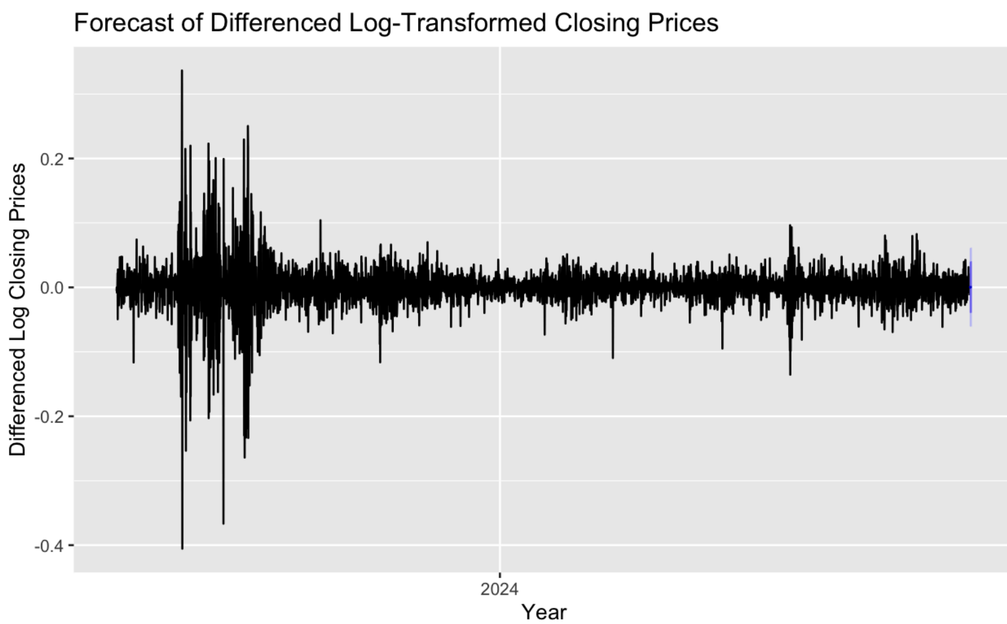
The diagnostics plots for the SARIMA(1, 0, 5) model are also shown below to validate its fit:



- **Standardized Residuals Plot**: This shows that the residuals are randomly distributed around 0, which indicates that it is a good fit for our data.
- **ACF of Residuals**: This shows there is no significant autocorrelation, confirming that the model has adequately captured the structure in the data.
- **Normal Q-Q Plot**: This plot checks the normality of our standard residuals. Since most of the points lie around the reference line, the residuals are normally distributed.
- **Ljung-Box Test**: The p-values are fairly small, which suggests that there is no significant autocorrelation in the residuals.

These diagnostic tests validate that the SARIMA(1, 0, 5) model is the most fitting for our data, as it shows that the residuals are normally distributed and uncorrelated. This suggests that the model has successfully been able to obtain any patterns underlying in the data and can be used for reliable forecasting.

The last step is to now use the SARIMA(1, 0, 5) model for forecasting. I forecasted the future values of the differenced log-transformed closing prices over the next 12 periods. The forecasted values can be seen below:

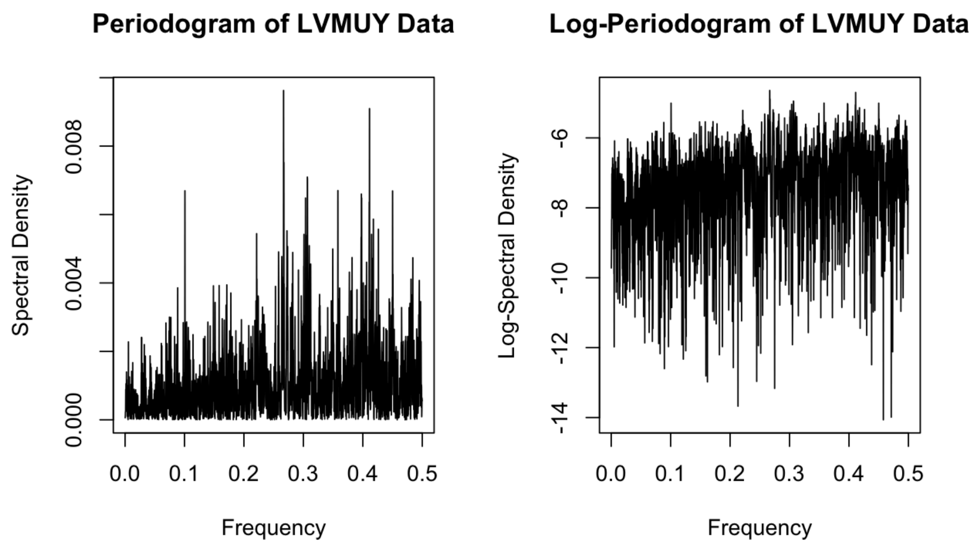


The forecast plot shows predicted values and its confidence intervals, which shows us the range in which future values will most likely fall. The forecast suggests that the differenced log-transformed closing prices will remain relatively stable over the next few periods, with some small fluctuations within the confidence intervals. This stability implies that Louis Vuitton's stock prices are not expected to have extreme volatility in the near future, which is important information for investors and analysts.

4.2 Spectral Analysis

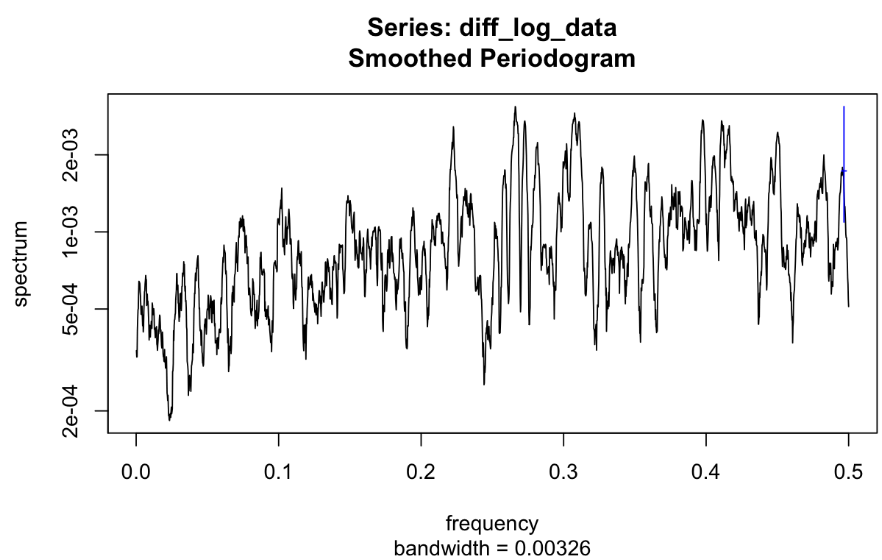
The next method that I will use is spectral analysis. Spectral analysis can help identify periodicities in our data. This includes the periodogram and smoothed periodogram. If there are significant frequencies present in these spectral density plots, then this could indicate any cycles or periodic behavior in the stock prices. This information can be useful to understand and anticipate trends in the financial market and fashion industry.

I first calculated the periodogram to estimate the spectral density of the data, which can show us how the variance of the data is distributed across different frequencies. Afterwards, I did a log transformation of these periodogram values to make it easier to identify any patterns or significant peaks in the spectral density. These results were then plotted side by side below:



- **Periodogram:** We can see several peaks at many different frequencies, especially at around 0.1, 0.2, 0.3, and 0.4. This could suggest that there are periodic components present in the stock price data at these frequencies. These are also the highest peaks, which indicates the strength of these periodic components.
- **Log-Periodogram:** Similarly, the log-periodogram has the highest peaks at around the same frequencies. This shows the dominant frequencies that correlate to any underlying periodic patterns in the stock prices.

The Daniell kernel method was then used to calculate the smoothed periodogram, which helps to reduce the noise in the raw periodogram by averaging out the spectral densities. This makes it easier to identify significant frequency components. This was then plotted below, with a vertical line added at 1/12 to show the frequency corresponding to a 12 month cycle:



- **Smoothed Periodogram:** The peaks in the smoothed periodogram shows us important periodic components in the stock closing price data. The most significant peaks can be seen at around the frequencies of 0.1, 0.2, 0.3, and close to 0.5. The peak around the 0.083 frequency, corresponds to a 12 month cycle. Therefore, there may be a yearly periodic component in the stock prices, which could be influenced by seasonality or some other factor in the luxury goods market. On the other hand, the peaks at the higher frequencies show us that there may be shorter term periodicities, which means that there could be quarterly or semi-annual patterns in the stock market. This could be related to market trends or other economic factors.

To better understand the relationship between frequency and log-spectral density, I fit a linear model to the log-periodogram data. The summary of this linear model can be seen below:

```
Call:
lm(formula = log_spec ~ freq)

Residuals:
    Min      1Q  Median      3Q     Max 
-7.0137 -0.6151  0.2394  0.8904  2.8344 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept) -8.06354    0.05415  -148.9   <2e-16 ***
freq         2.21243    0.18752    11.8   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 1.299 on 2302 degrees of freedom
Multiple R-squared:  0.05702,	Adjusted R-squared:  0.05661 
F-statistic: 139.2 on 1 and 2302 DF,  p-value: < 2.2e-16
```

From this summary, we can see that there is a significant relationship between frequency and log-spectral density. This can be proven by the p-value being very small. The residuals range from -7.0137 to 2.8344, with a median close to 0. This indicates that the model's predictions are mostly unbiased, but there is some slight variation in the residuals. The adjusted R-squared value of 0.05661 is very close to the R-square value of 0.05702, which means that the model is not overfitted. However, not a lot of the variability in the log-spectral density can be explained by the frequency. Overall, the F-statistic and small-value show that the model is statistically significant. The positive slope of 2.21243 suggests that as frequency increases, the log-spectral density also increases. This could indicate that there are higher frequency components in the stock price data, which can correspond to shorter-term cycles or fluctuations in the market.

Using spectral analysis was valuable to help identify dominant cycles in the stock price data. This can help to find insights into the market behavior and any economic factors that influence the stock price.

5 Conclusion and Future Study

In this project, I utilized advanced time series analysis techniques to explore Louis Vuitton's stock prices. My main goal was to find any significant patterns and insights that could provide a deeper understanding of how fashion trends and economic factors influence stock prices, especially in the luxury goods market. By using SARIMA modeling and spectral analysis, I was able to do a more comprehensive analysis of this dataset.

The SARIMA model was able to capture patterns within the stock prices, which was validated through the diagnostic plots. The forecasted values showed us that the closing prices would remain relatively stable over the next few periods, with some minor fluctuations. This showed that Louis Vuitton's stock prices are not expected to display extreme volatility in the upcoming future. This is valuable information for any investors and analysts.

The spectral analysis helped to identify dominant cycles in the stock price data. The significant peaks in the periodogram and log-periodogram revealed the presence of periodic components at the given frequencies. The smoothed periodogram further confirmed these findings and suggested that there may be annual and shorter-term periodicities in the stock prices. Finally, the linear model that was fitted to the log-periodogram data indicated that there is a significant relationship between frequency and log-spectral density. The high frequency components showed that there may be shorter term cycles or fluctuations in the stock market.

Overall, I believe that this project was able to utilize advanced time series analysis methods to gain some insight into the stock prices of one of the largest luxury brands in the world. I was able to find valuable information relating to the stability and periodic behavior of Louis Vuitton's stock prices. This could be useful when making investment strategies or to understand the impacts of the fashion industry.

For future studies, I believe that I could incorporate external factors, such as market trends or major fashion industry events that could explain this stability and periodic behavior of the stock prices. In addition, I would like to analyze other major luxury brands and compare their stock performances to help identify more specific trends and patterns in the industry.

6 References

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Lefèvre, C. (2022). *The economy of Île-de-France: From national capital to global metropolis*. In *Paris*. Agenda Publishing. Retrieved from https://www.jstor.org/stable/j.ctv25tnx1t.9

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7 Appendix: R Code

```
# Load Data and Packages
```{r }
# Load libraries
library(readr)
library(forecast)
library(ggplot2)
library(astsa)

# Load dataset
LVMUY <- read_csv("/Users/catherineli/Downloads/LVMUY.csv")

# Preview dataset
head(LVMUY)
str(LVMUY)
```
```

```
# 4.1 Results from SARIMA (p,d,q) x (P,D,Q)
```{r }
# Plot Time Series Data
# Convert date column to Date type
LVMUY$Date <- as.Date(LVMUY$Date, format="%Y-%m-%d")

# Plot the time series data
og_plot <- ggplot(LVMUY, aes(x=Date, y=Close)) +
  geom_line() +
  labs(title="LVMUY Stock Prices Over Time", x="Year", y="Closing Price") +
  scale_x_date(date_labels="%Y", date_breaks="5 years") +
  theme_minimal()
print(og_plot)

# Plot ACF and PACF on original data
par(mfrow=c(1, 2))
acf(LVMUY$Close, main = "ACF of Closing Prices")
pacf(LVMUY$Close, main = "PACF of Closing Prices")
```
```

```
```{r }
# Apply log transformation
log_data <- log(LVMUY$Close)
print(head(log_data))

# Differencing the log-transformed data
diff_log_data <- diff(log_data)
print(head(diff_log_data))

# Create new data frame with difference log values
LVMUY_diff <- data.frame(Date=LVMUY$Date[-1], Log_Close_Diff = diff_log_data)

# Plot time series with new log-transformed data
log_plot <- ggplot(LVMUY_diff, aes(x=Date, y=Log_Close_Diff)) + geom_line() +
  labs(title="Differenced Log-Transformed Closing Prices", x="Year", y="Differenced Log Closing Prices")
print(log_plot)
```
```

```
# Plot
acf(LVMUY_diff$Log_Close_Diff, main = "ACF of Differenced Log-Transformed Closing Prices")
pacf(LVMUY_diff$Log_Close_Diff, main = "PACF of Differenced Log-Transformed Closing Prices")
```
```
```

```
acf2(diff_log_data, max.lag=100)
acf2(diff(log_data, lag=1))
acf2(diff(log_data, lag=2))
acf2(diff(log_data, lag=3))
```

```
# Fit various SARIMA models
```{r }
sarima(diff_log_data, 0, 0, 5, 0, 0, 0)
sarima(diff_log_data, 1, 0, 5, 0, 0, 0)
sarima(diff_log_data, 0, 1, 1, 0, 0, 0)
sarima(diff_log_data, 1, 1, 1, 0, 0, 0)
```
```

```
# SARIMA Model
```{r }
best_model <- arima(diff_log_data, order=c(1,0,5))
summary(best_model)
```
```

```
# Forecast future values
```{r }
# Forecast future values over 12 periods
forecasted_values <- forecast(best_model, h=12)

# Plot forecasted values
autoplot(forecasted_values) +
  ggtitle("Forecast of Differenced Log-Transformed Closing Prices") + xlab("Year") + ylab("Differenced Log
Closing Prices") + scale_x_continuous(breaks = seq(2024, 2030, by = 8))
```
```

```
# 4.2 Spectral Analysis
```{r }
library(TSA)

# Calculate the periodogram of the differenced log-transformed data
spec_LVMUY <- spectrum(diff_log_data, plot = FALSE)
log_spec_LVMUY <- log(spec_LVMUY$spec)

# Plotting the periodogram and log periodogram
par(mfrow = c(1, 2))
plot(spec_LVMUY$freq, spec_LVMUY$spec, type = "l", main = "Periodogram of LVMUY Data", xlab = "Frequency", ylab
= "Spectral Density")
plot(spec_LVMUY$freq, log_spec_LVMUY, type = "l", main = "Log-Periodogram of LVMUY Data", xlab = "Frequency",
ylab = "Log-Spectral Density")
```
```

```
# Compute the smoothed periodogram with the Daniell kernel
spec_LVMUY_smoothed <- mvspec(diff_log_data, kernel = kernel("daniell", 7), log = "no")

# Plot the smoothed periodogram
plot(spec_LVMUY_smoothed)
abline(v = 1/12, lty = 2)
```
```
```

```r
# Fit the linear model on the log-periodogram
freq <- spec_LVMUY$freq
log_spec <- log(spec_LVMUY$spec)
lm_spec <- lm(log_spec ~ freq)
summary(lm_spec)
```