Exchange rate between the Vietnamese Dong and US Dollar: An investigation into seasonal trends and key drivers

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Abstract

This study investigates the dynamics of the exchange rate between the Vietnamese Dong (VND) and the US Dollar (USD) from 2000 to 2024, emphasizing the impact of economic and consumer behaviors as well as exploring seasonal patterns. Our initial findings revealed an overall depreciation trend in the VND. However, when adjusted for inflation, it indicated a real appreciation, highlighting the complex nature of exchange rate movements. We then preprocessed the data using the Box-Cox transformation to stabilize variance for subsequent time series analysis.

Using LOESS additive decomposition, we analyzed the seasonality of the exchange rate, which revealed no consistent seasonal pattern across the entire 24-year period. However, we detected micro-periodic patterns occurring approximately every six years, with peaks typically in late summer to late fall and troughs around March. Despite these variations being subtle—often less than one cent—they hold significant implications for large-scale currency exchanges.

In our forecasting efforts, contrary to previous literature, the Random Walk model underperformed in predicting the VND-USD exchange rates. Instead, the ‘auto.arima‘ function in R provided a more robust model, although the wide confidence intervals due to previous rate shocks offered limited directional predictability. Integrating exogenous factors representing human behaviors into our models enhanced their predictive accuracy, highlighting the significant impact of non-economic factors on exchange rate fluctuations. In contrast, economic factors proved unsuitable for incorporation into the SARIMA model.

This paper extends beyond traditional economic analyses by incorporating consumer behaviors and other non-economic influences, offering a comprehensive view of the factors affecting exchange rates. The findings not only shed light on the intricate interactions influencing the VND-USD rates but also aid in forecasting short-term future movements, thus providing valuable insights for policymakers, investors, economic researchers, and speculators.

Keywords: seasonality, vnd-usd exchange rate, human impact, time series forecasting, arima, sarima

Exchange rate between the Vietnamese Dong and US Dollar: An investigation into seasonal trends and key drivers

In an increasingly interconnected global economy, exchange rates play a critical role in shaping international trade, investment flows, and economic stability. By determining the relative value of one currency against another, exchange rates impact the competitiveness of exports, the cost of imports, and the movement of capital. This paper examines fluctuations in Vietnam's exchange rate against the USD and explores the factors driving these changes, including economic variables such as capital flows and trade balances, as well as non-economic influences such as the number of foreign tourists, to understand how human behaviors impact exchange rate dynamics. Our dependent variable for this study is the VND-USD exchange rate, with the exchange rate expressed in VND. Consequently, an increase in the exchange rate indicates depreciation of the Dong, potentially reflecting increased demand for USD, and vice versa.

An initial analysis of the VND-USD exchange rate from 2000 to 2024 revealed a consistent upward trend, indicating a depreciation of the Vietnamese Dong over time. This trend appeared counterintuitive for a rapidly developing country like Vietnam. However, after adjusting for inflation, the data showed a decrease in the exchange rate over time, suggesting that the real value of the Dong had appreciated when accounting for inflation.

To explore fluctuations in the VND-USD exchange rate, we analyzed its seasonality using LOESS additive decomposition. While no consistent pattern spanned the entire 24-year period, we observed periodic trends occurring approximately every six years. These patterns exhibited relatively consistent peak and trough months before gradually transitioning to new patterns. Although predicting future periodic patterns remained challenging, identifying these trends as they emerged could help forecast short-term exchange rate movements.

We further investigated the determinants of the exchange rate by employing predictive time series models. Beginning with time-independent ARIMA models, we tested the Random Walk model commonly suggested in previous literature, alongside models generated using the ‘auto.arima‘ function in R to find the best fit for our data. Subsequently, we extended the analysis with SARIMA models, incorporating exogenous factors such as economic variables and non-economic factors, including the number of foreign tourists. This allowed us to assess which factors enhanced predictive power when modeling the short-term VND-USD exchange rate.

This introduction proceeds with a literature review of factors influencing short-term exchange rates, previous researches done on the movement and seasonality of exchange rate of the VND against other currencies, and a discussion of ethical considerations relevant to this research. Data & Methods section describes the datasets collected and variable creations, and justifies the chosen methodologies. Results section outlines the steps taken during the analysis and presents the results, while Discussion & Interpretations talks about the implications of the findings. The conclusion of this paper summarizes the key results, acknowledging limitations, and offering suggestions for future research.

Literature Review

In the globally integrated economic landscape, exchange rates are pivotal in directing the flow of international trade, investments, and maintaining economic equilibrium. They dictate the relative worth of currencies, influencing export competitiveness, import costs, and capital transfers. An appreciation in exchange rate occurs when the demand for a currency surpasses its supply, which alters its value relative to others. This literature review explores the oscillations of Vietnam's exchange rate against the USD and examines the factors driving these fluctuations.

Exchange rates are foundational in international finance, essential for transactions ranging from local dealings to global investments (Stockman, 1980). They are influenced by various determinants including interest rates, inflation, GDP, political conditions, and capital flows, which in turn affect global trade and economic stability (Evans & Tawiah, 2015). For example, Japan's domestic production surge during its technological boom reduced the need for imports, thereby increasing the yen's value due to heightened demand for Japanese exports (Stockman, 1980). Conversely, currency depreciation can reduce import purchasing power but boost export appeal as domestic goods become cheaper for foreign markets (Dinh, 2022). Stable currencies attract foreign investment, whereas volatile ones deter investors due to potential risks associated with rapid value changes (Dinh, 2022).

The complexity of predicting exchange rates fascinates economists, offering crucial insights for investors and policymakers. Many economists use the purchasing power parity (PPP) hypothesis, suggesting that exchange rates equilibrate the price levels between two countries, simplifying the assessment of currency values (Dinh, 2022). Seasonal variations also affect exchange rates, particularly in economies with robust export sectors like Ukraine and Ghana, where currency values fluctuate in sync with commodity prices and economic activities (Roshylo & Long, 2022).

In Vietnam, a burgeoning economy with significant agricultural and industrial exports, exchange rate dynamics are similarly influenced by trade balances and price indexes (Le, 2015). Tourism also plays a critical role in shaping the Vietnamese Dong's value as foreign visitors increase demand for the currency (L. Tran & Dao, 2020). This research focuses on the VND to USD exchange rate from 2000 to 2024, aiming to discern potential seasonality in the VND-USD exchange rate and identify the various economic and non-economic factors impacting it. Our approach analyzes the behavior of market participants during periods of perceived currency risks, offering a comprehensive view of the dynamics influencing the Vietnamese Dong's value against the USD. This multifaceted analysis aims to provide a nuanced understanding of the factors affecting the VND-USD exchange rate, aiding in the prediction and management of economic policies.

Ethical Considerations

Given that this is a non-experimental study, we do not manipulate variables directly but instead rely on observational data. Therefore, any conclusions drawn about causality must be approached cautiously. The challenge in this context is that even if the models we build are not statistically significant, it does not imply that no factors are influencing the exchange rate. Specifically, certain variables, such as consumer expectations, are difficult to measure and incorporate into models.

In conducting this research, several ethical considerations were taken into account. We ensured that all data used in the analysis was publicly available and sourced from reputable institutions, such as government agencies and financial databases, to maintain transparency and accountability. Given that this is a non-experimental study, we do not manipulate variables directly but instead rely on observational data. Therefore, any conclusions drawn about causality must be approached cautiously. The challenge in this context is that even if the models we build are not statistically significant, it does not imply that the involved factors are not influencing the exchange rate. Specifically, finding variables to represent consumer behavior is hard to identify and incorporate into models, especially if we want the data to be monthly. Some of the data we found, such as the number of foreigners traveling to Vietnam and the number of Vietnamese international students in the U.S., were collected as a measure of human movement to observe patterns that could influence exchange rates.

Moreover, while the research explores various macroeconomic factors, it does not seek to make assumptions or inferences about the internal politics or policies of Vietnam or the United States. The intention of this study is purely to examine how non-economic variables such as international travel, social movements, or different types of policy affect exchange rates, not to serve as a commentary on the bilateral relations of the two nations. We also ensured that any personal data used in the study was anonymized, with no identifiable information about individuals, such as data on foreign travelers coming into Vietnam, being disclosed. Throughout the research process, we adhered to academic integrity by properly citing all sources and avoiding any manipulation of data or results. We acknowledge the limitations of our models and emphasize that our conclusions are based on the available data, which should not be used for political or policy interpretation.

Data & Methods

The primary dependent variable is the monthly average exchange rate between the USD and VND, measured in VND, spanning from 2000 to 2024. Independent variables include traditional economic indicators (price indexes, interest rates, inflation rates) and the hypothesized seasonal non-economic factors influencing USD demand. Data sources comprise the International

Monetary Fund (IMF), Federal Reserve Economic Data (FRED), and Vietnamese government statistics (GSO), spanning from early 2000 (the stock volatility rate for Vietnam starts from August 2000), to around May 2024. All variables are numerical. For the consumer behavior-related data, we plan to use the yearly number of Vietnamese students studying abroad, indicating the need to buy USD in Vietnam to pay tuition, and also the monthly tourism rate of foreigners coming into Vietnam for traveling, indicating the demand to buy the Dong for local transactions, which appreciate the Dong.

The methodology employs time series analysis to identify seasonal patterns and ARIMA and SARIMA modeling to assess the impact of both economic and non-economic factors on exchange rate fluctuations, aiming to isolate the effects of seasonal variations on the currency market.

Data

As research on the USD-VND exchange rate is limited, the data had been self-collected specifically for this project using mainly historical data. Our primary dependent variable is the monthly exchange rate *ExRate* [1], defined as the value of 1 USD measured in Vietnamese Dong (VND). This decision was made because the exchange rate of VND against USD fluctuates within the range of 20,000-27,000 VND for 1 USD, which makes the changes reflected in the exchange rate easier to see and interpret.

To identify the key independent variables, I consulted with two professors: Professor Alex Scarciofollor from the Denison Data Analytics department and Professor Adam Walke from the Denison Economics department. Based on their recommendations and other previous research, nominal macroeconomic variables are used to build the forecasting model, with the following variables identified as significant predictors:

1. **Price Index**[2]: The price index indicates the currency value of buying good power. For example, if you need more money to buy the same thing, then the currency value must have

[1] (IMF, 2024a)

[2] (IMF, 2024c)

depreciated. The log of the price index in Vietnam divided by that of the US is one of our economic indicator, as Le (2015) has indicated that the log of the price index fraction is a key determinant of the exchange rate in Vietnam.

$$log\_PI = \ln\left(\frac{P_{VN}}{P_{USA}}\right),$$

where P_{VN} is the price index of Vietnam and P_{USA} is the price index of USA.

2. **Interest Rate**[3]: The interest rate of a country affects the currency demand, as an increase in interest rate increases the exchange rate (Pandey et al., 2020). In his research, Le (2015) showed that the difference between interest rates in the US and Vietnam statistically significantly impacts the exchange rate between VND and USD.

$$Difference\_In\_IR = I_{VN} - I_{USA},$$

where I_{VN} is the interest rate of Vietnam and I_{USA} is the interest rate of USA.

3. **Capital Flows**: Capital flows is measured using each country's volatility of stock prices. Higher capital flows indicate higher interest in foreign investors coming into the domestic market and thus appreciating the domestic currency value. The US capital flow is be represented by the *VIX*[4] index, while for Vietnam, we use data from the stock price volatility index called *VNINDEX*[5].

For non-economic data, we incorporated the **number of foreign tourists visiting Vietnam**[6] (*Num_of_Tourists*). It is important to notice that this dataset is limited to observations starting from January 2008, which constrained the available training data for our SARIMA model. Additionally, we included data on **Vietnamese international college students in the USA**[7].

[3] (IMF, 2024b)

[4] (FRED, 2024)

[5] (TradingView, 2024)

[6] (GSO, 2024)

[7] (OpenDoors, 2024)

However, this data is available only on an annual basis, as student enrollment is recorded by academic year.

Methods

This research design followed a systematic approach to uncovering both economic and non-economic factors that drove the exchange rate between the USD and the Vietnamese Dong. By first identifying trends and seasonality through time series analysis and then incorporating broader macroeconomic and non-economic variables into prediction models, we aimed to provide a nuanced understanding of the factors that impacted exchange rate movements.

We developed models to examine the predictive power of our independent variables on short-run exchange rate movements and assess their effects on the exchange rate. We decided to focus on the short run, as it had been found that market sentiments were more influential in short-run exchange rate movements (Hopper, 1997). M. U. N. Tran (2016) used an ARIMA model to predict the exchange rate between USD and VND and found that this method was suitable for forecasting the short-term exchange rate in Vietnam. Moosa and Kelly (2014) further indicated that the random walk model had the lowest magnitude of error compared to other possible methods. Thus, we started with a model that used time as the only independent variable, employing an ARIMA (AutoRegressive Integrated Moving Average) model to capture time-dependent changes. We performed multiple ARIMA models, including a random walk forecast, to validate whether the random walk model was the best to use and to establish a baseline forecast based solely on past exchange rate data.

To ensure our data was suitable for ARIMA models, we employed different methods to stabilize its mean, such as differencing and detrending, and its variance, such as the Box-Cox transformation. To assess seasonality, we used LOESS decomposition (SLT), which allowed us to identify cyclical patterns over time. For model validation, we analyzed the ACF and PACF plots, addressed the residuals distribution, and checked for autocorrelation using the Ljung-Box test.

To improve prediction accuracy, we extended the model using SARIMA (ARIMA with exogenous variables). This approach allowed us to incorporate additional factors beyond time, particularly focusing on economic variables. Initially, we concentrated on financial and macroeconomic factors such as GDP growth, inflation rates, and trade balances from both the US and Vietnam. Since we aimed for a short-term prediction, using nominal economic variables that reflected immediate market conditions was most appropriate. We also built a model incorporating human factors.

In the final step, we ran another SARIMA model that incorporated both financial factors and non-economic variables. By including these broader factors, we aimed to assess whether their inclusion improved the predictive power of the model and better explained short-term fluctuations in the exchange rate.

Results

Seasonality trends

First, we plotted the values of *ExRate* over the 24 years to observe its past movement and identify any seasonal pattern of the exchange rate between the USD and VND. By plotting the nominal exchange rate over time in Figure 1, we observed a steady increase, suggesting that, on the surface, the VND weakens and depreciates against the USD. Given that Vietnam is a rapidly growing country with a strong investment appeal, this nominal depreciation is unexpected. Thus, we took a further step to find the real exchange rate that accounts for inflation's effect, introducing the adjusted exchange rate variable. Since our nominal exchange rate variable (*ExRate*) is in Vietnam Dong, we can adjust it by dividing the rate by the Consumer Price Index in Vietnam (*VN_CPI*). The discontinuity in the red line is due to months that have NA values for CPI. The real exchange rate's downward trend suggests that inflation significantly shapes the nominal exchange rate, revealing the VND's stability or even real appreciation over time.

Next, we applied a Box-Cox transformation to stabilize the variance of our dependent variable, *ExRate*. Using the Guerrero method, we identified the optimal lambda value as 0.72. This transformation effectively rescaled the data with minimal impact on its movement pattern (see Figure 2).

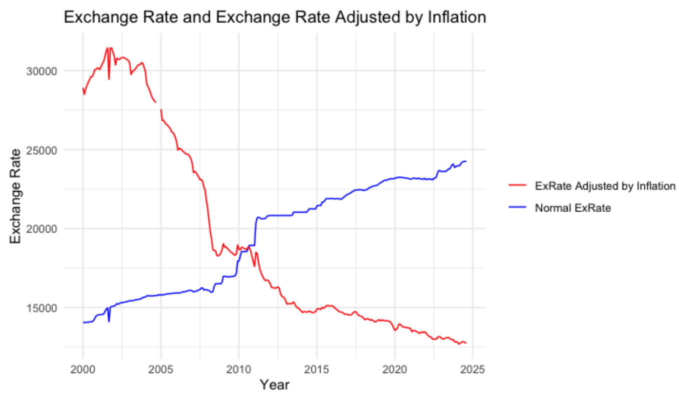

Figure 1

Line plot showing (blue) the VND-USD exchange rate ExRate in Vietnamese Dong from 2000 to 2024 and (red) the real exchange rate adjusted by the consumer price index of Vietnam, which indicates the inflation rate of the Vietnam economy.

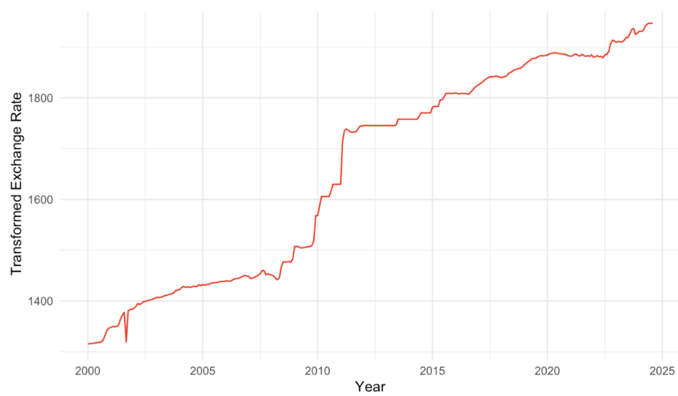

Figure 2

Line plot showing the Box-Cox transformed ExRate from 2000 to 2024. Notice that the values are smaller but the movement remains the same.

Next, we aimed to stabilize the mean of our dependent variable, *ExRate*, to achieve stationarity. We tested both detrending and differencing techniques and found that detrending more effectively stabilized the mean. Upon examining the detrended *ExRate* graph, we identified several periods with distinct shocks in the data, evidenced by the rapid and continuous jumps over time. Using the basic quartiles and IQR method, we found the outliers which are the following identified months:

1. September 2001
2. October 2009
3. December 2010
4. April 2008
5. November 2009
6. January 2011
7. August 2009
8. March 2010
9. September 2009
10. November 2010

We noted the specific months where these shocks occurred and mapped them onto both the detrended *ExRate* (Figure 3) and the original *ExRate* distribution graph for further analysis (Figure 4).

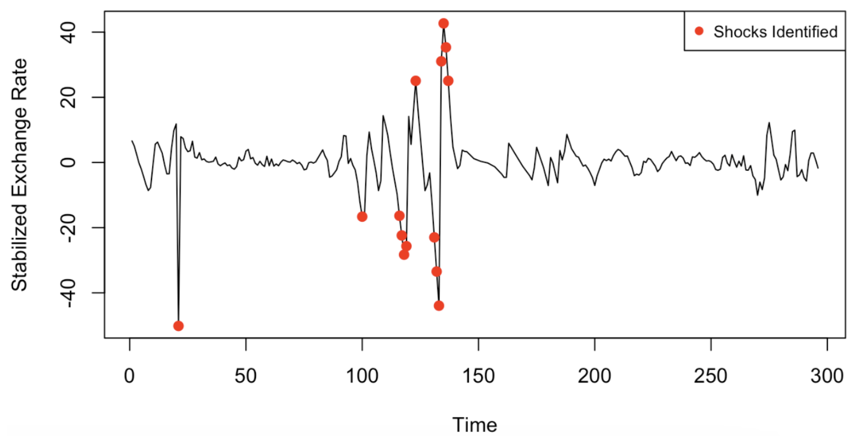

Figure 3

Stablized Exchange Rate using Box-Cox transformation and Detrending. The red dots are shocks identified using variance.

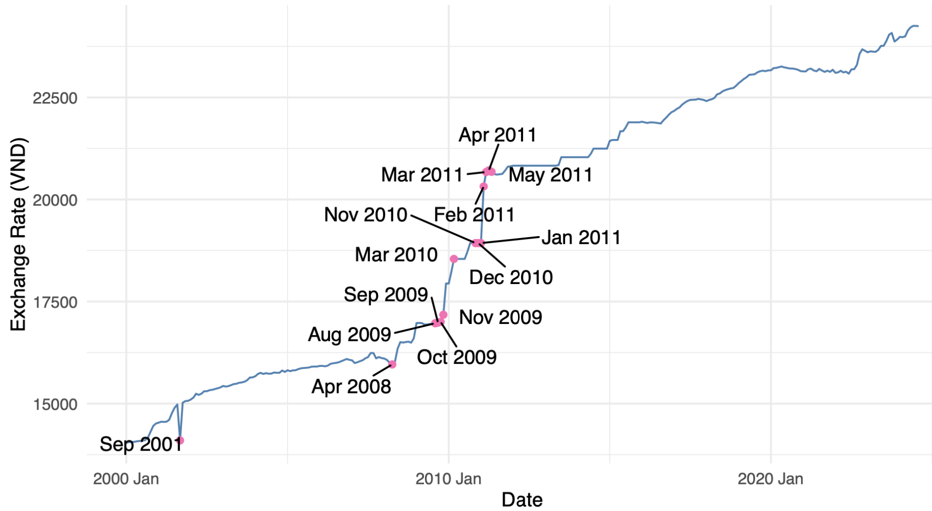

Figure 4

Exchange rate with shock points identified and labeled.

Next, we investigated the presence of seasonality within our data. To do this, we conducted a LOESS additive decomposition (also called as STL decomposition) to observe the overall seasonal patterns in the *ExRate* data. Although no consistent seasonality was observed across the entire 24-year period (2000–2024), a recurring pattern appeared approximately every 4-6 years, with shifts in the pattern after each interval (see season_year graph in Figure 5).

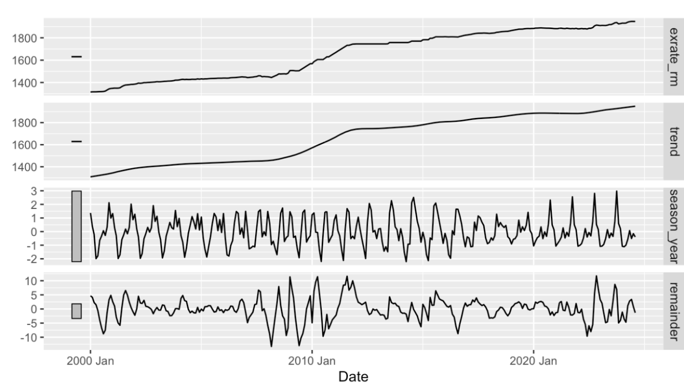

Figure 5

Graph of the STL Additive Decomposition components of Box-Cox Transformed ExRate from 2000-2024.

Based on this observation, we divided the data into subsets spanning 3, 4, 5, 6, and 7 years. Our analysis suggested a notable seasonality pattern approximately every 6 years, although the seasonal span diminished slightly each year. For example, the SLT decomposition of the years 2012 to 2018 illustrated this pattern. As shown in the *season_year* plot in Figure 6, the peaks were higher in the early years and gradually decreased over time. To better understand these variations, we applied a de-Box-Cox transformation to the seasonality values, allowing us to quantify the differences between the minimum and maximum months in terms of USD. The peaks months and the difference between the min and max points are illustrated in Figures 7, 8, 9, and 10, shown below. Graphs of SLT decompositions for other periods are provided in the appendix (see Fig. 18, 19, 20).

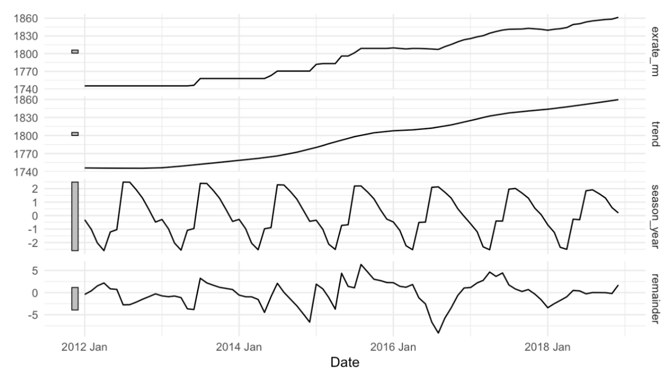

Figure 6

Graph of the STL Additive Decomposition components of Box-Cox Transformed ExRate from 2012-2018.

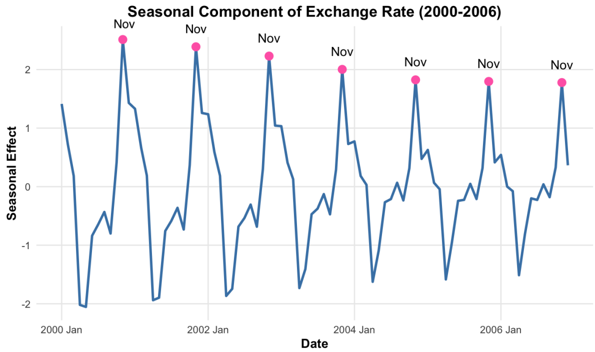

Figure 7

Seasonal component of exchange rate from 2000 to 2006. The highest peak of each year is November. The difference between the maximum and the minimum is about 0.90 cent.

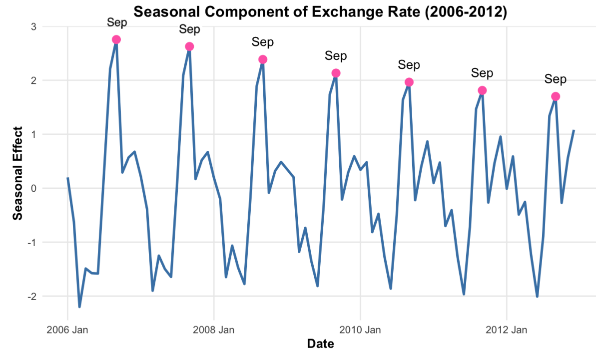

Figure 8

Seasonal component of exchange rate from 2006 to 2012. The highest peak of each year is September. The difference between the maximum and the minimum is about 0.93 cent.

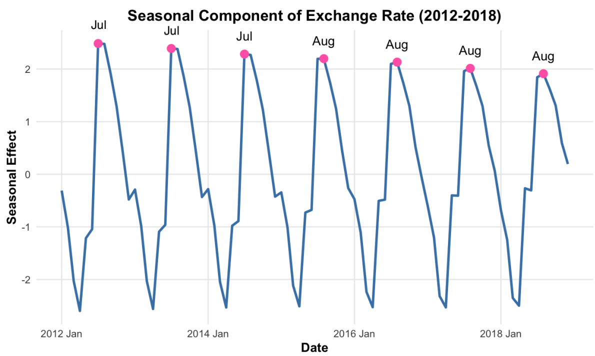

Figure 9

Seasonal component of exchange rate from 2012 to 2019. The highest peak of each year is either July or August, but the difference between the two months is not significant. The difference between the maximum and the minimum is about 0.89 cent.

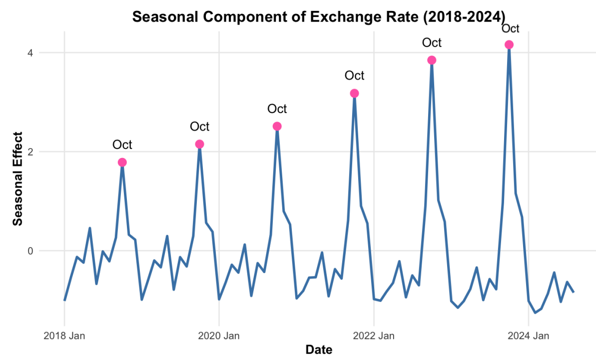

Figure 10

Seasonal component of exchange rate from 2018 to 2024. The highest peak of each year is Octobor. The difference between the maximum and the minimum increases throughout the year, with a mean of 0.74 cent.

Times Series Models

Following this, we implemented several models to forecast the *ExRate*. Starting with our box-cox transformed and detrended data, which we adjusted for stationarity, we applied the ARIMA model. Using the ‘auto.arima‘ function, the model recommended an ARIMA(3,0,2) configuration. We validated this recommendation by examining the ACF and PACF plots, which indicated a lag of 3, suggesting an autoregressive term (AR) of 3 would be optimal. The differencing term was set to 0, as detrending had already stabilized the mean, while a moving average (MA) of 2 effectively captured the primary trend without excessive sensitivity to minor fluctuations. Since our analysis did not reveal significant seasonality in the *ExRate* variable, the forecasted line from this ARIMA model appeared smooth with minimal fluctuation over time. The model performed well, with most of the actual exchange rate values falling within the 95% confidence interval, and some within the 80% interval (as shown in Fig. 11).

However, given the high frequency of fluctuations in the data, our ARIMA(3,0,2) model does not give us any prediction power, meaning we cannot tell whether the exchange rate would go up or down in the future using our model. Thus we decided to go beyond interval-capturing for more detailed forecasting by using the original *ExRate* data with only the Box-Cox transformation applied and analyze it with drift to account for the observed upward trend in the mean over time.

Given that our data is non-stationary, prior research, Moosa and Kelly (2014), suggests that a Random Walk model is well-suited for forecasting in this context. Therefore, we applied an ARIMA(0,1,0) model, which is Random Walk coefficients in ARIMA, to our data. As before, the absence of seasonality means that the forecasted line is expected to be smooth, reflecting the gradual trend without seasonal fluctuations.

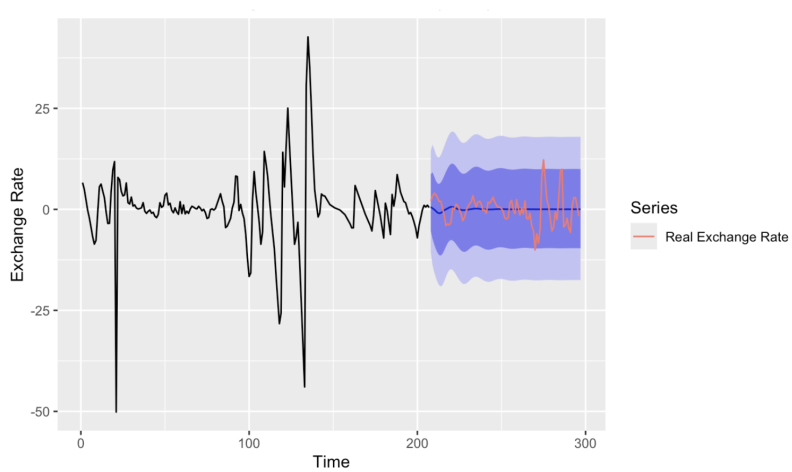

Figure 11

Line plot showing the forecasts for stabilized ExRate using ARIMA(3,0,2) against the observed and stablized exchange rate.

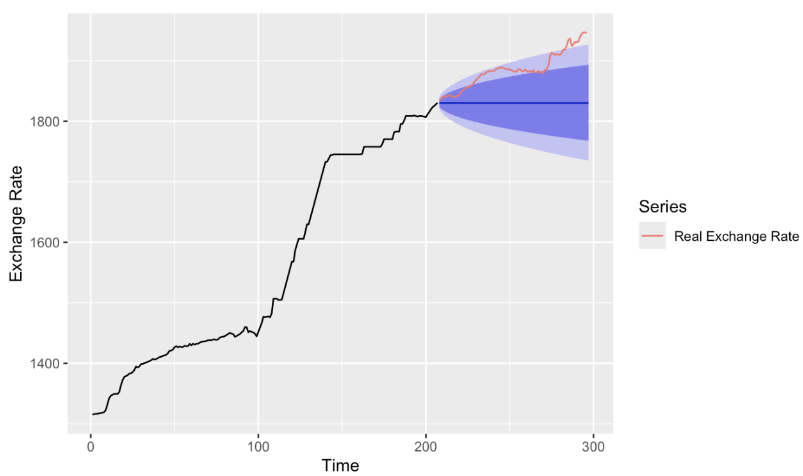

Figure 12

Line plot showing the forecast for Box-Cox transformed Exchange Rate using Random Walk.

Unexpectedly, the Random Walk model did not perform well with our data. Most of our historical test data points fell outside the 0.95 confidence interval and even diverged from the prediction range, indicating that the Random Walk model was not suitable for our data.

As an alternative, we explored an ARIMA model for our data. Using the ‘auto.arima‘

function, we identified ARIMA(1,1,2) as the optimal model. This recommendation aligns with the analysis of our variable which displays an upward linear trend through time, justifying the need for first-order differencing to stablize the mean. We further validated this choice by examining the ACF plot, where a lag of 1 appeared positive and outside the confidence interval. We proceeded with the ARIMA(1,1,2) model, which provided a relatively accurate forecast with an AIC of 1607, as shown below.

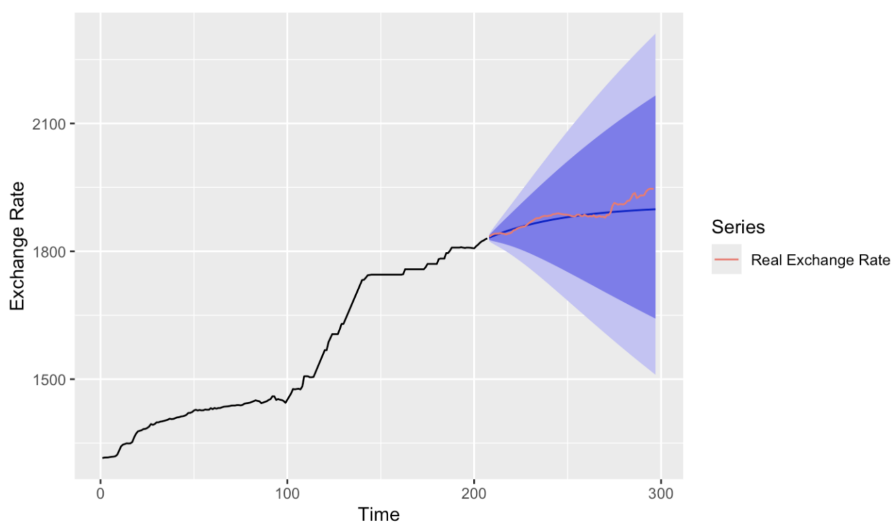

Figure 13

Line plot showing the forecast for Box-Cox transformed Exchange Rate using ARIMA(2,1,1). Although the mean prediction is close to the real transformed exchange rate, the confidence interval is wide and does not give us any suggestion on whether the exchange rate would increase or decrease in the future. This wide interval is due to the previous shocks in the past.

The next logical step is to assess the stability of our model. We began by examining the residuals' ACF and histogram plots. The histogram indicates that the residuals follow a normal distribution, which is a positive sign. However, the ACF plot reveals a small peak at a lag of 7 that slightly exceeds the confidence interval. This anomaly may be due to outliers in our data, which could influence the ACF at specific lags.

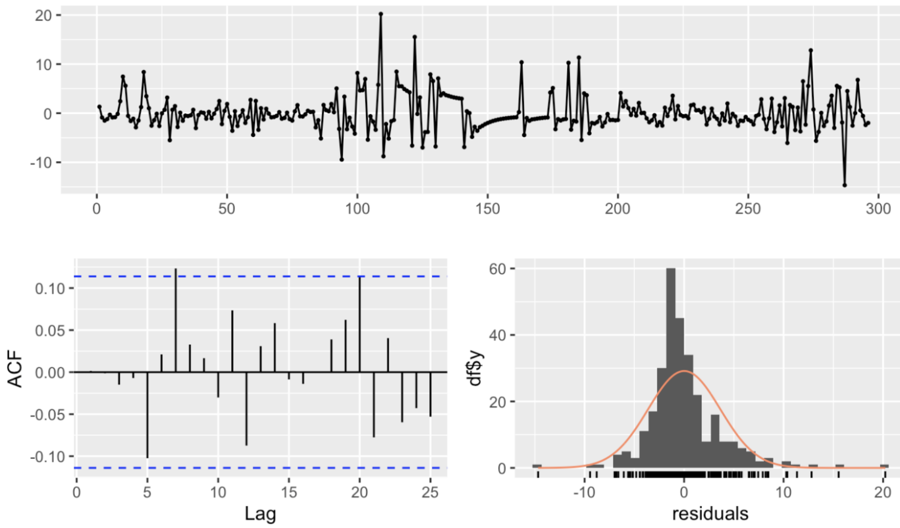

Figure 14

Line plot showing the forecast for Box-Cox transformed Exchange Rate using Random Walk.

The Ljung-Box test with p-value of 0.2726 indicates that our residuals do not have autocorrelation, thus our model is adequate to use. We also conducted a unit root test and confirmed that all characteristic roots lie within the unit circle and are distinct from each other, further supporting the stability of our model (see Figure 21 in Appendix). This result aligns with expectations, given that we used the values suggested by ‘auto.arima‘, which should always give the model that satisfy all requirements needed for ARIMA models.

Next, we incorporated exogenous variables to identify which factors demonstrated strong predictive power over exchange rate movements over time. The first approach involved using a SARIMA model with only economic factors. Specifically, we includd the difference in interest rates between the two countries (*Difference_In_IR*), the log of the price index (*Log_PI*) to represent inflation rates, and the stock indices (*VIX* and *VNINDEX*) of both countries to capture the flow of foreign investment.

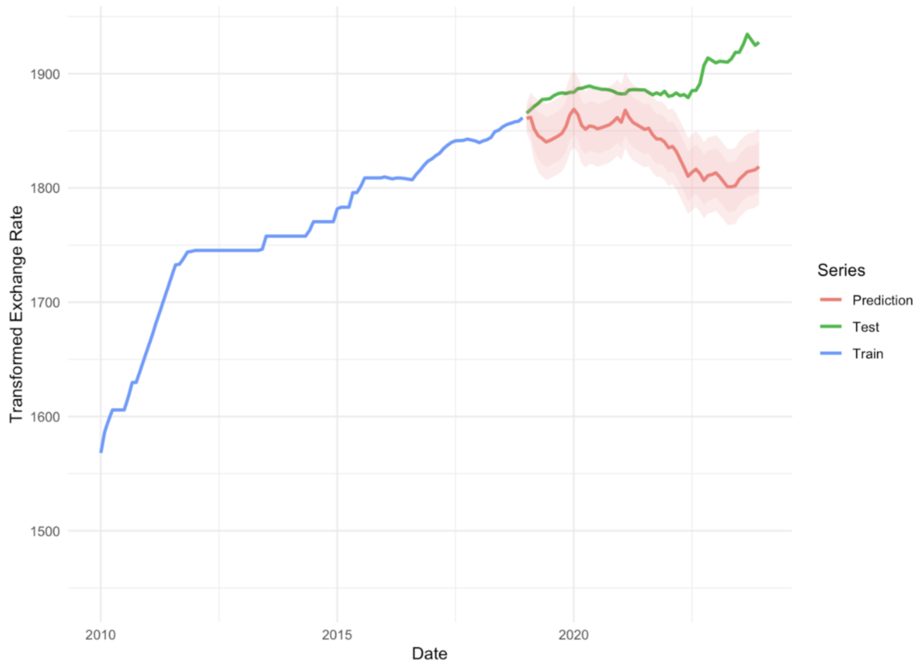

Figure 15

SARIMA model incorporating economic variables (log_PI, Difference_In_IR, and stock indices) as exogenous factors shows reduced predictive accuracy. Predictions deviate significantly from the observed data compared to a model that uses only time as the independent variable.

We also developed a SARIMA model using the number of foreign tourists as an exogenous variable to represent human factor. While the model slightly overestimated the actual observations, all observed data points remained within the 95% confidence interval (see Figure 16). Additionally, the model successfully captured the upward trend in the observed values. The residual, ACF, and PACF plots are in Figure 22 in the Appendix.

We further enhanced our SARIMA model by incorporating both economic and non-economic variables, and the predictions are shown in Fig. 17. However, the imbalance between the number of economic variables and non-economic variables (3:1) caused the predictions to be predominantly influenced by the economic variables. As a result, the model produced outcomes similar to those of the SARIMA model with only economic variables.

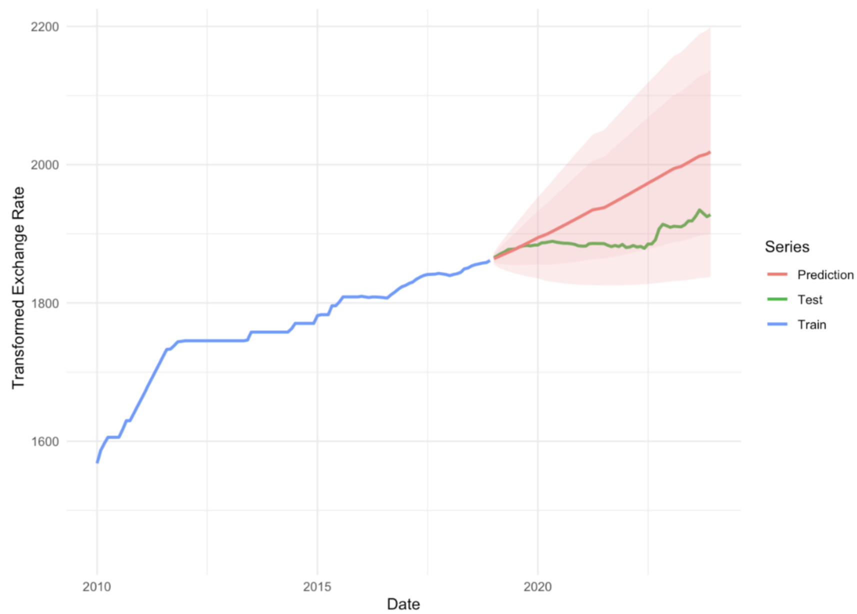

Figure 16

SARIMA model using the variable Num_of_Tourists as an exogeneous factor. All real observations is within the 0.95 C.I.

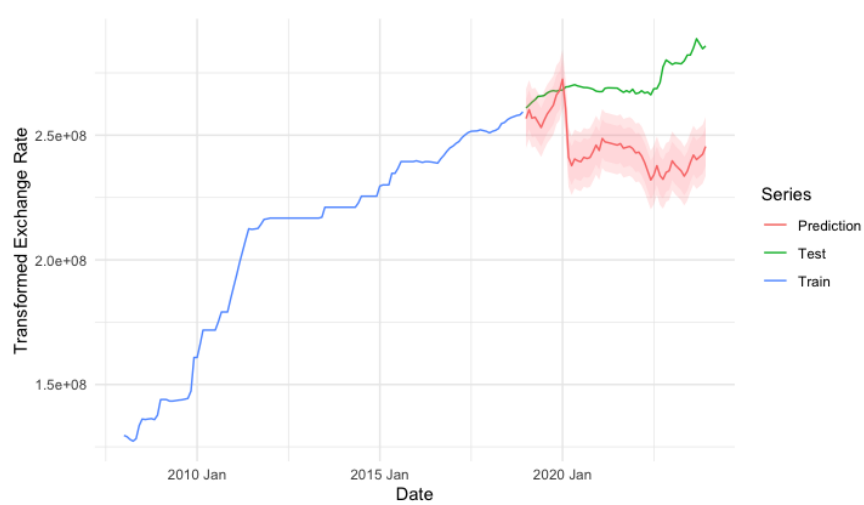

Figure 17

SARIMA model with all three economic factors and Num_of_Tourists as exogeneous factor. The prediction is similar to that of just economic factors, specifically after January of 2020.

Discussion & Intepretation

Our analysis highlights that the exchange rate is significantly influenced by macroeconomic factors, particularly the Consumer Price Index (CPI), which serves as a proxy for inflation in this research. Given Vietnam's status as a rapidly developing economy, one might expect the Vietnamese Dong (VND) to appreciate over time. However, historical data reveals the opposite trend, with an increasing amount of VND required to purchase one USD. Adjusting for inflation shows that the real exchange rate reflects an appreciation of the VND over time, aligning with expectations given the rapid growth of Vietnam economy in recent years. This disparity underscores the substantial impact of inflation on the exchange rate, suggesting that in order to raise the appreciation of the Vietnamese Dong, the government of Vietnam must prioritize stabilizing the domestic inflation rate.

We also observed that most identified "shocks" months correspond to global financial events, such as 9/11, the Great Recession, and the Eurozone debt crisis of 2008–2012. However, certain shocks diverged from expected outcomes. For instance, during the Eurozone debt crisis (late 2009 to early 2010), several countries, including the U.S., lowered interest rates to facilitate borrowing in Europe. According to Pandey et al. (2020), lower interest rates typically reduce a currency's exchange rate. Surprisingly, our data indicates an increase in the USD price in VND during this period. This could be attributed to instability in the Euro, prompting Vietnamese individuals to shift towards holding USD, increasing local demand and, consequently, the USD price in VND. Political factors may also have played a role in this anomaly.

While no long-term seasonality spanned the whole 24 years of data, we identified a recurring pattern approximately every six years. Subset plots reveal that the USD often peaks during late summer to fall, likely driven by seasonal behaviors such as travel or tuition payments. These findings suggest that once seasonality patterns are established, they can be incorporated to improve short-term exchange rate predictions over six-year cycles. While the magnitude of this seasonality is relatively minor—around 0.86 cents or approximately 212 VND—it may still be significant for those making large transactions like tuition payments. For smaller transactions, such as those related to travel, this variation is likely negligible.

To forecast the exchange rate, we developed several time series models. While efforts to stabilize the mean through detrending and differencing proved insufficient due to simultaneous upward and downward shifts, we successfully adjusted the variance using the Box-Cox transformation. We then employed models with drift to account for the upward movement of *ExRate*. Although Random Walk models work well for non-stationary exchange rate data according to Moosa and Kelly (2014), ours showed limited predictive power. In contrast, the ARIMA model generated by ‘auto.arima‘ performed better, as validated by residual histograms, characteristic roots, and Ljung-Box tests, making it a more robust choice for our data. Therefore, when running forecast for the USD-VND exchange rate, the built-in ‘auto.arima‘ function produced better results than the Random Walk model. All together, these findings align with the findings of M. U. N. Tran (2016) that ARIMA models are suitable for modeling the exchange rate of the VND against the USD.

Despite effectively capturing the fluctuation range of the stabilized data, our time series models offered limited insight into directional trends—that is, predicting whether the rate would increase or decrease in the future. To address this limitation, we incorporated exogenous variables into our SARIMA model to see if additional factors would help us capture the directional movements. Interestingly, non-economic factors, such as foreign travelers, exhibited stronger predictive power for forecasting exchange rates compared to economic factors. This finding suggests that consumer-driven variables can significantly influence a country’s exchange rate.

However, this does not imply that economic factors are irrelevant in determining exchange rates. Fundamentally, a country’s currency reflects the strength of its economy, and existing literature has consistently demonstrated the impact of economic factors on currency valuation. The observed discrepancy may instead indicate that economic factors are less compatible with SARIMA models, rather than lacking overall predictive utility.

Conclusion

This study provides valuable insights into the factors influencing the exchange rate between the Vietnamese Dong (VND) and the US Dollar (USD). Our analysis reveals that macroeconomic factors, particularly inflation represented by the log of the price index fraction (*log_PI*), play a critical role in shaping the exchange rate. While the nominal exchange rate shows a consistent depreciation of the VND against the USD over time, adjusting for inflation presents a more nuanced picture, indicating an appreciation of the VND in real terms.

The study also uncovered unexpected trends, particularly during the Eurozone debt crisis. Economic theory suggests that lower interest rates typically lead to currency depreciation. However, our findings show an increase in the price of USD in VND during this period, likely driven by speculative demand for USD in Vietnam. This anomaly highlights the complexity of exchange rate dynamics, where non-traditional factors, such as investor behavior and speculative demand, can significantly influence outcomes.

Our time series models, including ARIMA and Random Walk approaches, provided meaningful insights into exchange rate fluctuations but also revealed certain limitations. The ARIMA model performed well in capturing the range of fluctuations but struggled to accurately predict directional trends. Similarly, the Random Walk model, while commonly used for forecasting non-stationary exchange rate data, demonstrated limited predictive power in this context. These findings underscore the challenges of modeling exchange rates and the potential need for more complex or hybrid approaches to improve predictive accuracy.

Limitations

This study has several limitations. First, the exogenous factors included in the linear regression model (CPI, interest rates, and stock indices) are relatively few, and there may be other relevant variables not captured in this analysis, such as political events, trade policies, or investor sentiment, which could influence the exchange rate. Second, while we adjusted for inflation, we did not account for potential structural breaks or other irregularities in the data that could affect the stability of the models. Additionally, the time series models, though useful in capturing broad trends, may not be fully equipped to predict sudden, large-scale fluctuations, especially in response to unforeseen economic or geopolitical shocks.

Future Work

Future research could benefit from incorporating a broader range of exogenous factors. On the economic side, including Vietnam's import and export data could provide valuable insights, as previous literature has demonstrated the influence of these variables on exchange rates in other countries. Unfortunately, monthly import and export data for Vietnam are not publicly available, and although we have contacted relevant authorities, access to this data remains pending. Addressing this limitation could significantly enhance future analyses.

Finding additional variables to represent human activity could also advance this research. With only one non-economic variable included in our study, we observed strong predictive power, suggesting that expanding this category could yield meaningful results. Incorporating more non-economic factors would also balance the ratio of economic to non-economic variables, potentially improving the performance of integrated models.

Exploring more sophisticated modeling techniques, such as machine learning algorithms, offers another promising avenue for future work. Machine learning approaches could better capture complex, non-linear relationships that traditional models may overlook. Additionally, conducting a more granular analysis of high-volatility periods or financial crises could improve the models' ability to forecast during times of significant market stress.

Finally, extending the time frame of the data to include more recent events or utilizing real-time data could provide valuable insights into the evolving dynamics of the exchange rate. Events such as the COVID-19 pandemic and other global macroeconomic shifts offer unique contexts that could refine our understanding and improve the robustness of future predictions.

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Appendix

GitHub Repository: https://github.com/celine1712/da401_project.git

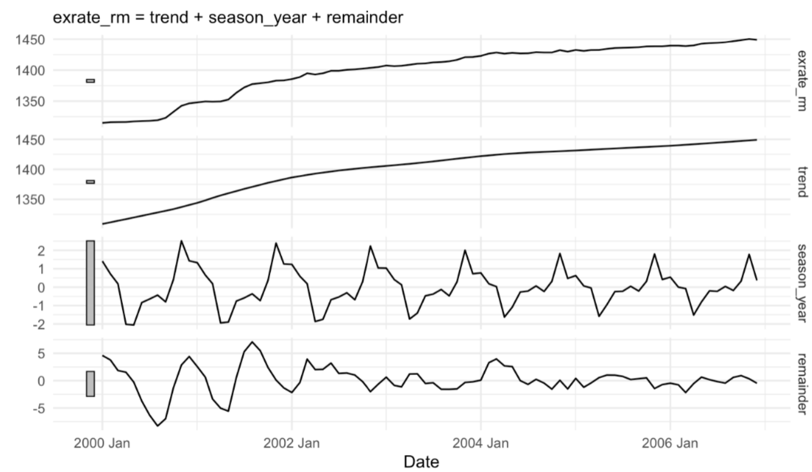

Figure 18

Graph of the STL Additive Decomposition components of Box-Cox Transformed ExRate from 2000-2006

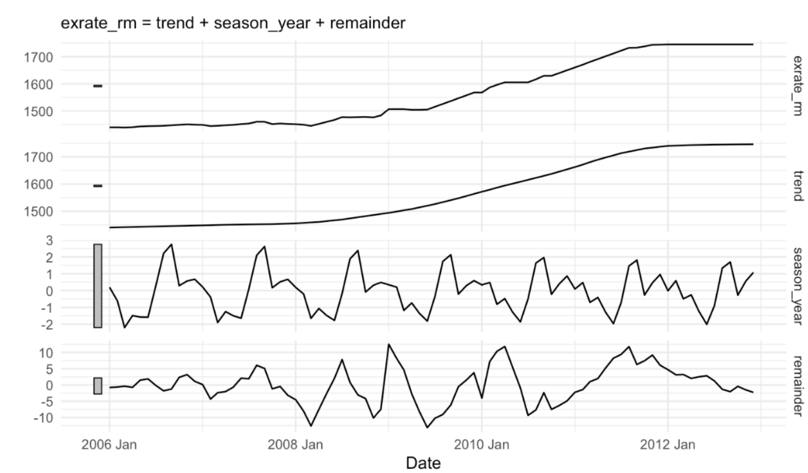

Figure 19

Graph of the STL Additive Decomposition components of Box-Cox Transformed ExRate from 2006-2012

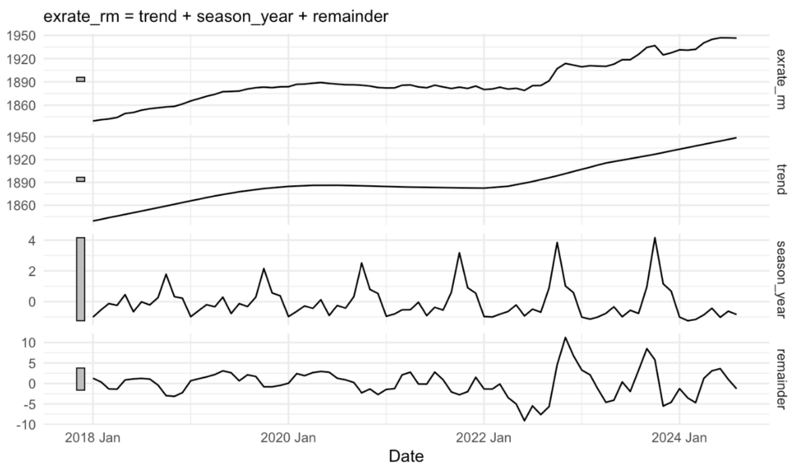

Figure 20

Graph of the STL Additive Decomposition components of Box-Cox Transformed ExRate from 2018-2024.

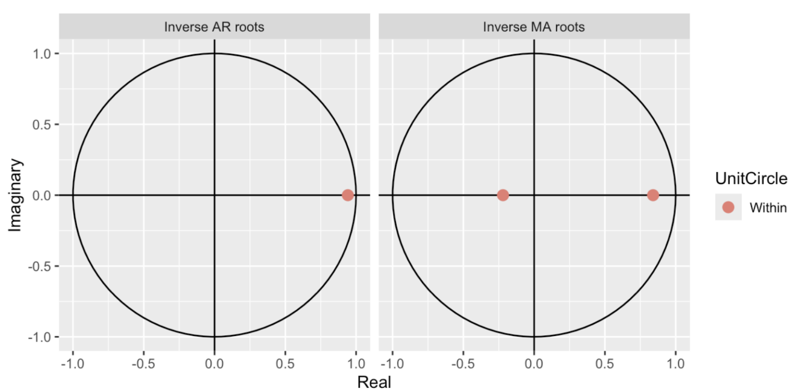

Figure 21

Plot showing the characteristic roots of ARIMA(1,1,2). No repeated roots, no roots outside of the unit circle.

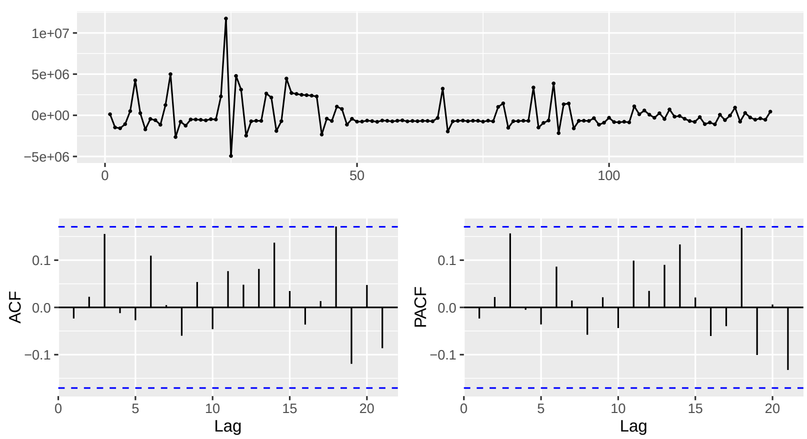

Figure 22

Plot showing the residuals, ACF, and PACF values of the SARIMA model with Num_of_Tourists as exogenous factor.