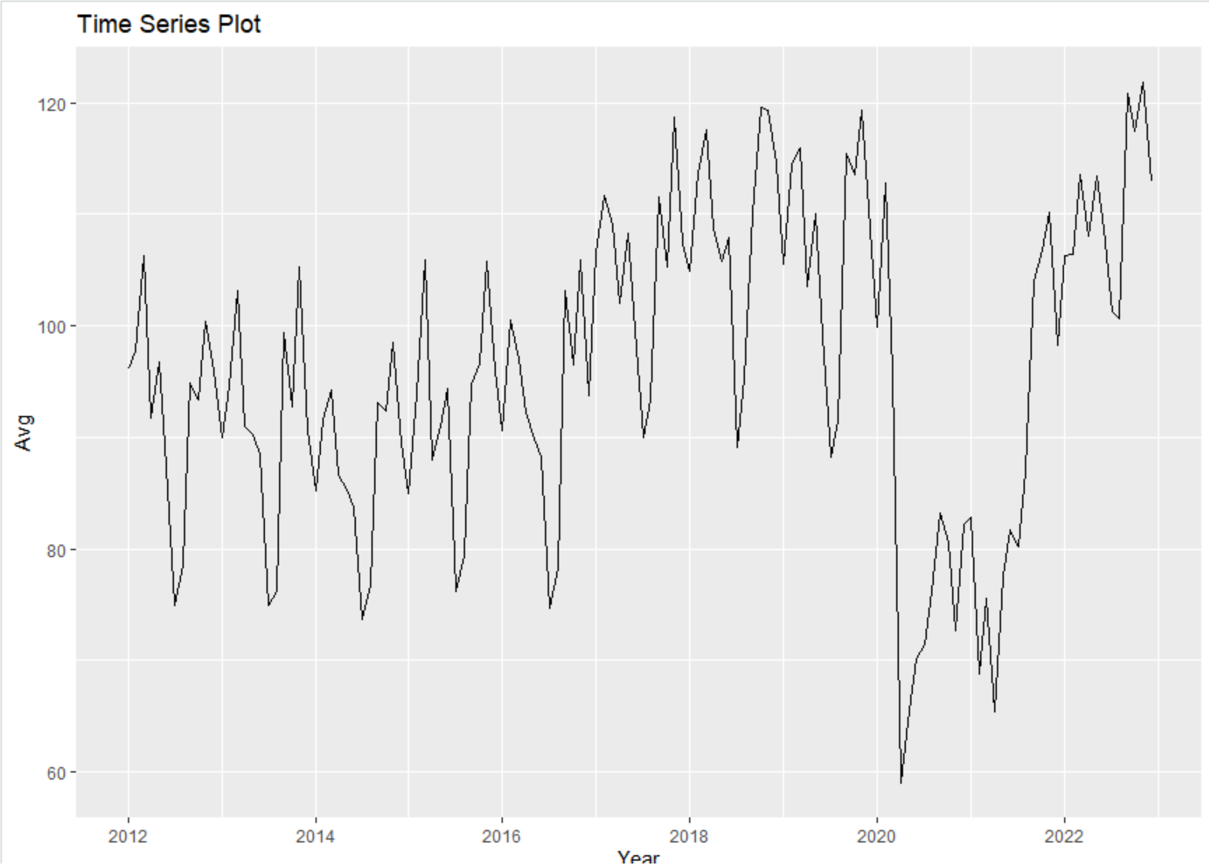
Forecasting the EU Travel Expenditure.

1) Data Exploration:



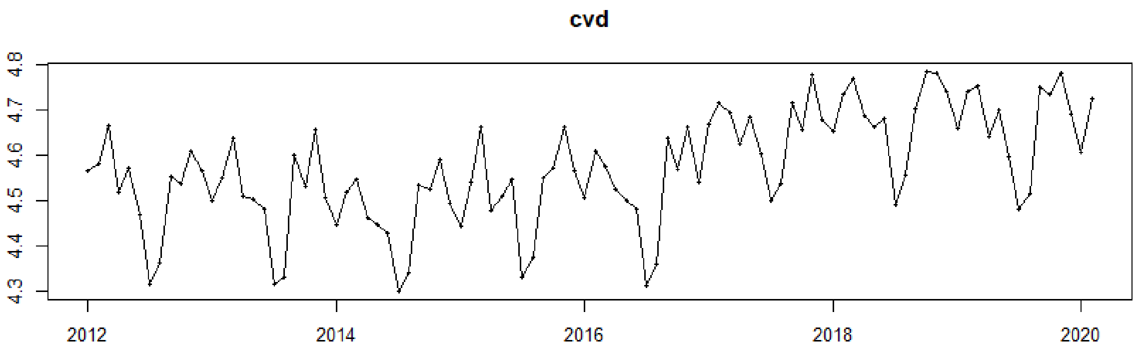
The above picture is the time series plot of the EU travel Expenditure.

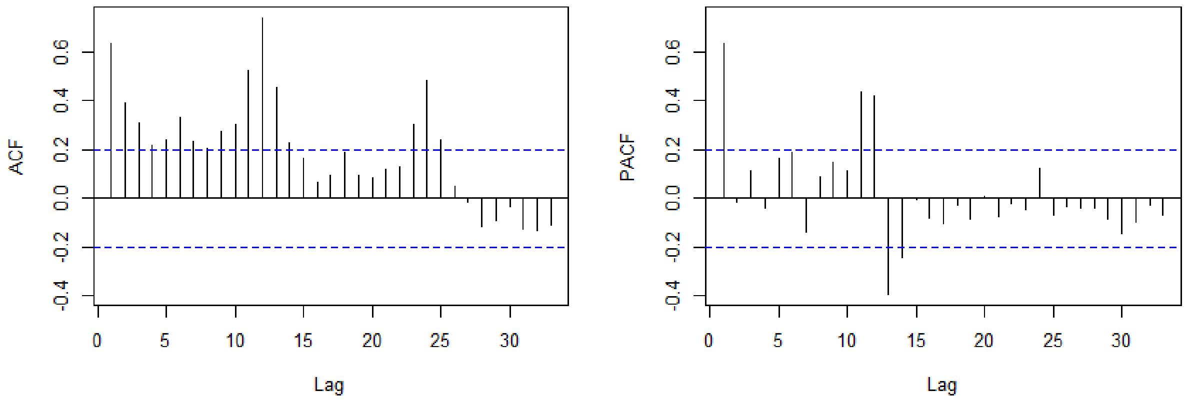
Data Period : 2012 January – 2022 December

Train set : 2012 January – 2017 March

Test set : 2017 April – 2020 March

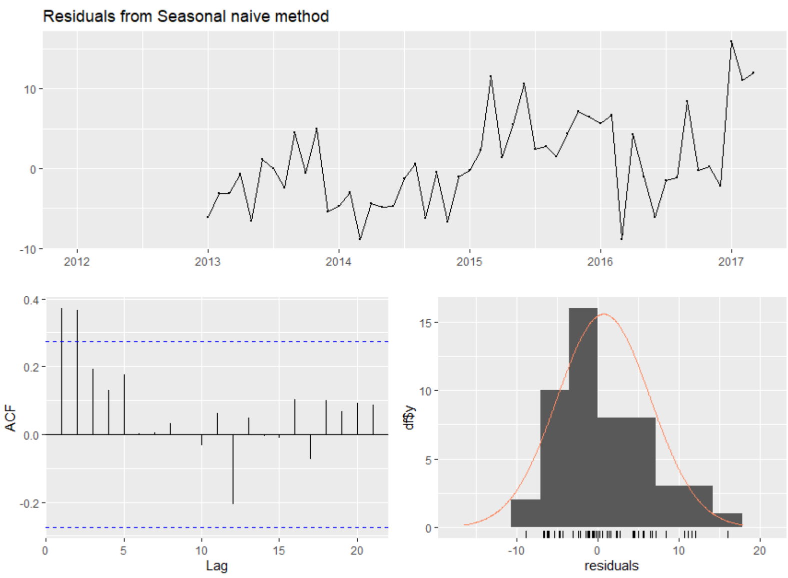
2) DATA TRANSFORMATION:





The time series data exhibits a non-linear trend, seasonal pattern, and non-constant variance over time. To address these issues and achieve stationarity, a Box-Cox transformation with an optimal λ value of 0.6385768 is recommended. This transformation can stabilize the variance and potentially linearize the trend, making the data suitable for time series forecasting models like ARIMA.

3) Bench Mark Model (Seasonal Naïve)

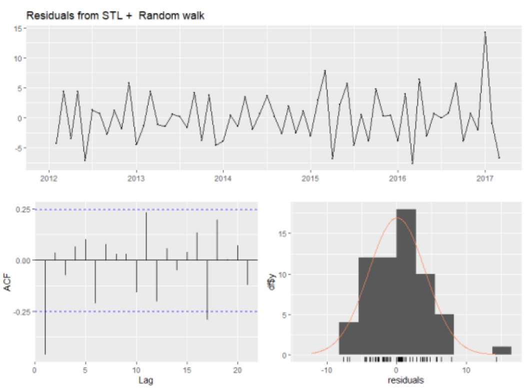


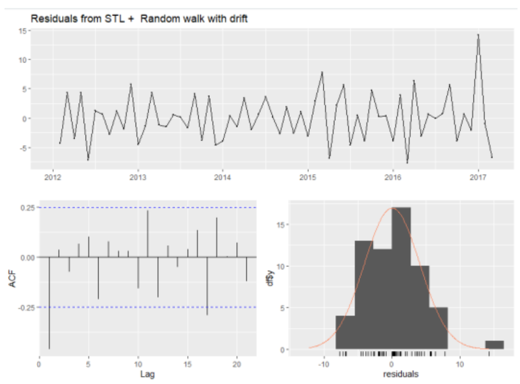
The seasonal naive method demonstrates a mixed performance in forecasting travel expenditures in the EU. While the model appears to fit well with the training data, as indicated by an MASE of 1.00000, its accuracy declines when applied to the test set, resulting in higher RMSE, MAE, MPE, MAPE, and MASE values. This discrepancy between training and test sets suggests potential overfitting or limitations in the model's ability to generalize to unseen data. Furthermore, the presence of significant autocorrelation in the residuals, confirmed by p-values below the 0.05 significance level, highlights a deficiency in capturing all the underlying data patterns. This autocorrelation can compromise forecast reliability and accuracy, underscoring the need for model refinement or exploration of alternative forecasting methods.

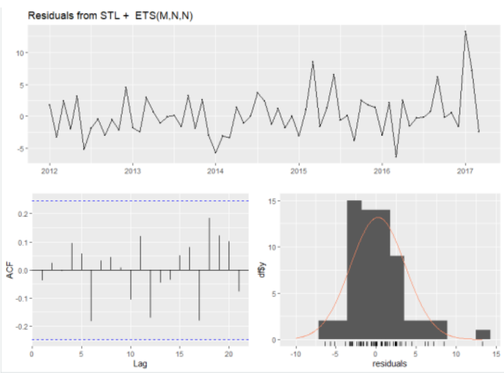
4) Decomposition

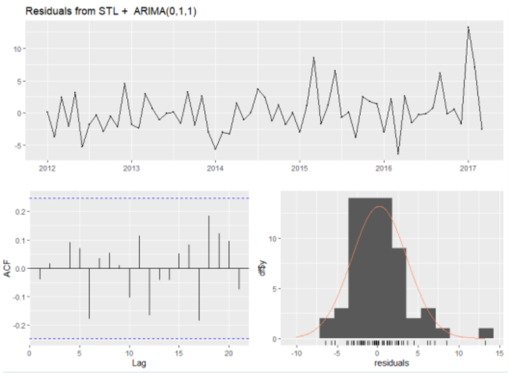
Forecasting Method	Dataset	RMSE	MAE	MAPE	MASE	Ljung-Box p-value	Autocorrelation
Naive	Training	4.038	3.161	3.357	0.710	0.0074	Significant
	Test	4.038	3.161	3.357	0.710		Autocorrelation
RW Drift	Training	4.038	3.158	3.353	0.709	0.0074	Significant
	Test	4.038	3.158	3.353	0.709		Autocorrelation
ETS	Training	3.388	2.485	2.616	0.558	0.834	No Significant
	Test	3.388	2.485	2.616	0.558		Autocorrelation
ARIMA	Training	3.388	2.470	2.601	0.555	0.797	No Significant
	Test	3.388	2.470	2.601	0.555		Autocorrelation

ETS and ARIMA models have the lowest RMSE, MAE, MAPE, and MASE values on both the training and test sets compared to the Naive and RW Drift models. ETS and ARIMA models also have higher p-values in the Ljung-Box test, indicating no significant autocorrelation in their residuals, unlike the Naive and RW Drift models which show significant autocorrelation. Therefore, based on both the accuracy metrics and residual diagnostics, ETS and ARIMA models seem to perform better than Naive and RW Drift models for the given time series data. Among ETS and ARIMA, both models are comparable, but ETS has slightly better performance with higher p-values in the Ljung-Box test and slightly lower RMSE, MAE, MAPE, and MASE values.









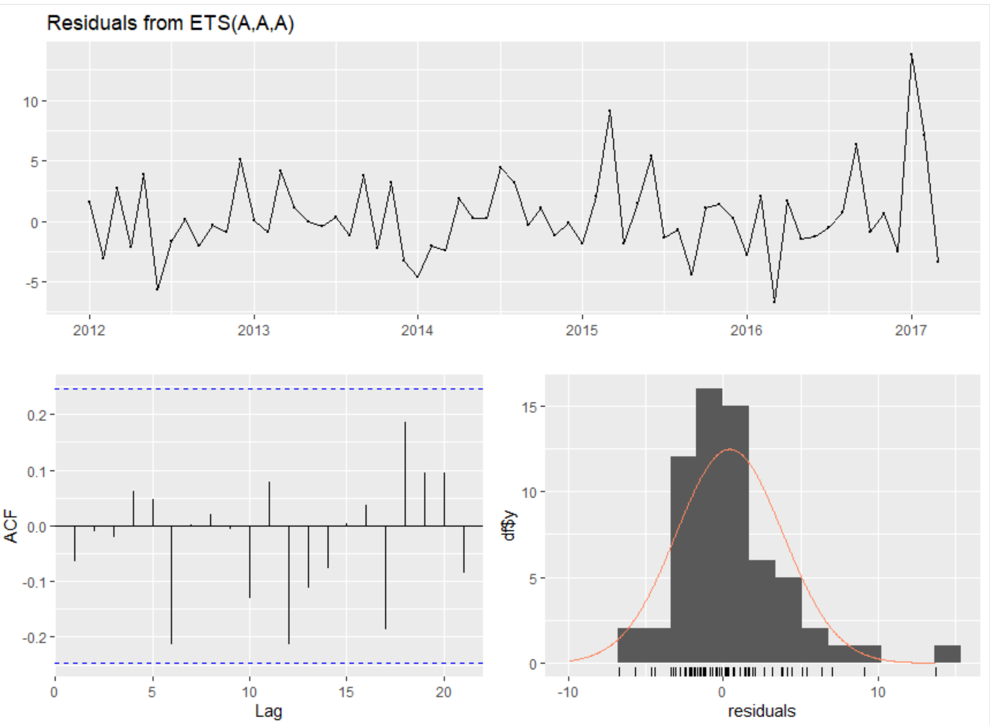
5) ETS and AUTO ETS

AUTO ETS:

The values of alpha and gamma suggest moderate level and minimal seasonal smoothing, respectively. These initial estimates provide a starting point for forecasting the level and seasonal components of the time series. The low value of sigma indicates that the residuals have low variability around the predicted values, suggesting a good model fit. The AIC, AICc, and BIC values can be used for model comparison, with lower values indicating better model fit. The error measures provide insights into the model's performance on the training data. The RMSE, MAE, and MASE values are relatively low, suggesting that the model's predictions are reasonably close to the actual values. However, the ME and MPE indicate some bias in the predictions. Overall, the ETS model seems to provide a reasonably good fit to the training data based on the error measures and information criteria

MANUAL ETS:

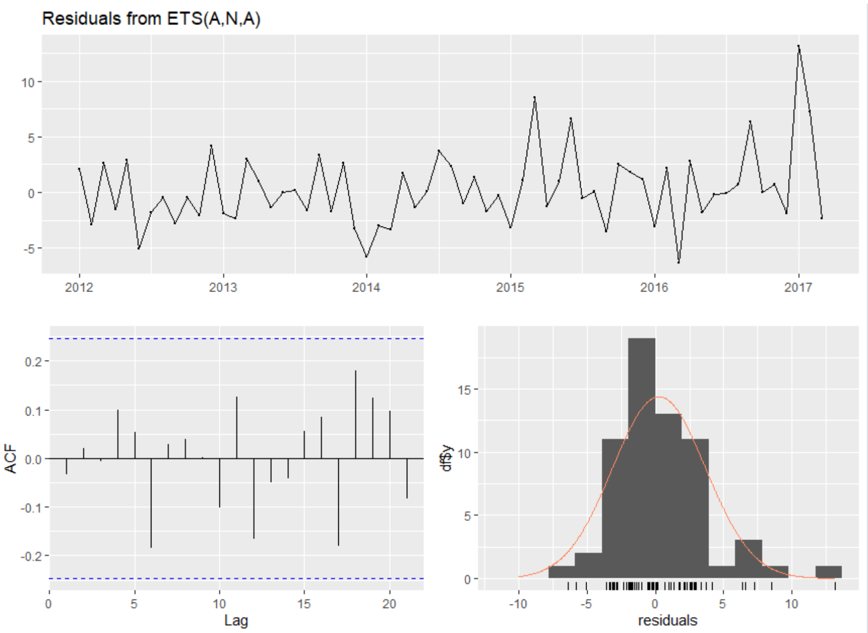
AAA



The values of alpha, beta, and gamma suggest moderate level smoothing, minimal trend smoothing, and minimal seasonal smoothing, respectively. These initial estimates provide a starting point for forecasting the level, trend, and seasonal components of the time series. The high value of sigma indicates that the residuals have higher variability around the predicted values compared to the previous model, suggesting a poorer model fit. The AIC, AICc, and BIC values are higher compared to the previous model, indicating a worse model fit based on these criteria. The error measures provide insights into the model's performance on the training data. The RMSE, MAE, and MASE values are relatively high compared to the previous model, suggesting that the model's predictions are farther away from the actual values. The ME and MPE also indicate bias in the predictions.

The ETS model with a "AAA" specification does not seem to provide as good a fit to the training data as the previous model based on the error measures and information criteria. It has higher errors, higher sigma (indicating more variability in residuals), and higher AIC, AICc, and BIC values (indicating worse model fit).

ANA



The values of alpha and gamma suggest moderate level smoothing and minimal seasonal smoothing, respectively. These initial estimates provide a starting point for forecasting the level and seasonal components of the time series. The high value of sigma indicates that the residuals have higher variability around the predicted values compared to the previous model but slightly better than the "AAA" model. The AIC, AICc, and BIC values are slightly lower compared to the "AAA" model, indicating a better model fit based on these criteria. The error measures provide insights into the model's performance on the training data. The RMSE, MAE, and MASE values are relatively high compared to the initial ETS model but slightly better than the "AAA" model. The ME and MPE also indicate bias in the predictions, but it's slightly reduced compared to the previous models.

The ETS model with an "ANA" specification seems to provide a better fit to the training data compared to the "AAA" model but is slightly inferior to the initial ETS model based on the error measures and information criteria. It has lower errors, lower sigma (indicating less variability in residuals), and slightly lower AIC, AICc, and BIC values (indicating better model fit) compared to the "AAA" model but higher errors and higher AIC, AICc, and BIC values compared to the initial ETS model.

Both ETS(A,A,A) and ETS(A,N,A) models appear to have residuals that are not significantly autocorrelated based on the Ljung-Box test results. This suggests that both models are doing a reasonably good job of capturing the temporal dependencies in the data.

Based on the forecast accuracy measures and diagnostic checks, the ETS(A,N,A) model appears to be a better choice for forecasting the time series data compared to the ETS(A,A,A) model. The ETS(A,N,A) model generally demonstrates lower forecast errors, lower ACF1 values, and a lower Theil's U statistic on the test set, indicating better accuracy, less autocorrelation in residuals, and overall superior performance in out-of-sample forecasting.

6) ARIMA and AUTO ARIMA

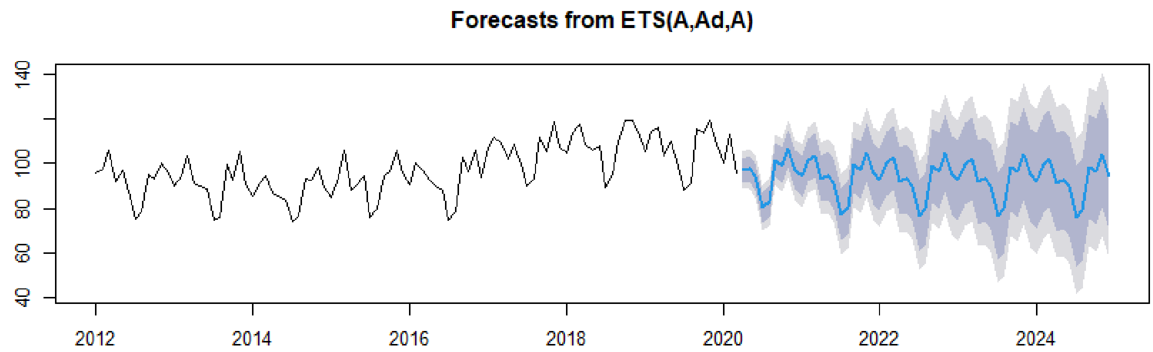
$(1-\phi_1 B)(1-\Phi_1 B^{12})(1-B)(y_t-\mu)=(1+\theta_1 B)\epsilon_t$
So, the estimated model using the backward shift operator is:

$(1+0.6371B)(1+0.5476B^{12})(1-B)(y_t-\mu)=\epsilon_t$

Model	ME	RMSE	MAE	MPE	MAPE	MASE	ACF1	Theil's U
SARIMA(1,1,1)(1,1,1)[12]	-2.662	8.863	6.42	-2.569	6.14	1.442	0.493	0.831
SARIMA(0,1,2)(0,1,2)[12]	-3.46	9.429	6.673	-3.319	6.377	1.498	0.523	0.885
SARIMA(2,1,1)(1,1,2)[12]	-2.731	8.796	6.366	-2.634	6.089	1.43	0.489	0.824
ARIMA(1,0,0)(1,1,0)[12]	0.335	4.195	2.803	0.228	2.957	0.629	-0.164	1.228

The analysis suggests SARIMA(0,1,2)(0,1,2)[12] as the best model for forecasting this time series data. It has the lowest error (RMSE, MAE) and outperforms a naive forecast (Theil's U). Despite being simpler, it captures the data's patterns effectively. All models underestimate values, but SARIMA(0,1,2)(0,1,2)[12] does so the least. While all models fit the data well (ACF1), SARIMA(0,1,2)(0,1,2)[12] offers the best balance of accuracy and simplicity.

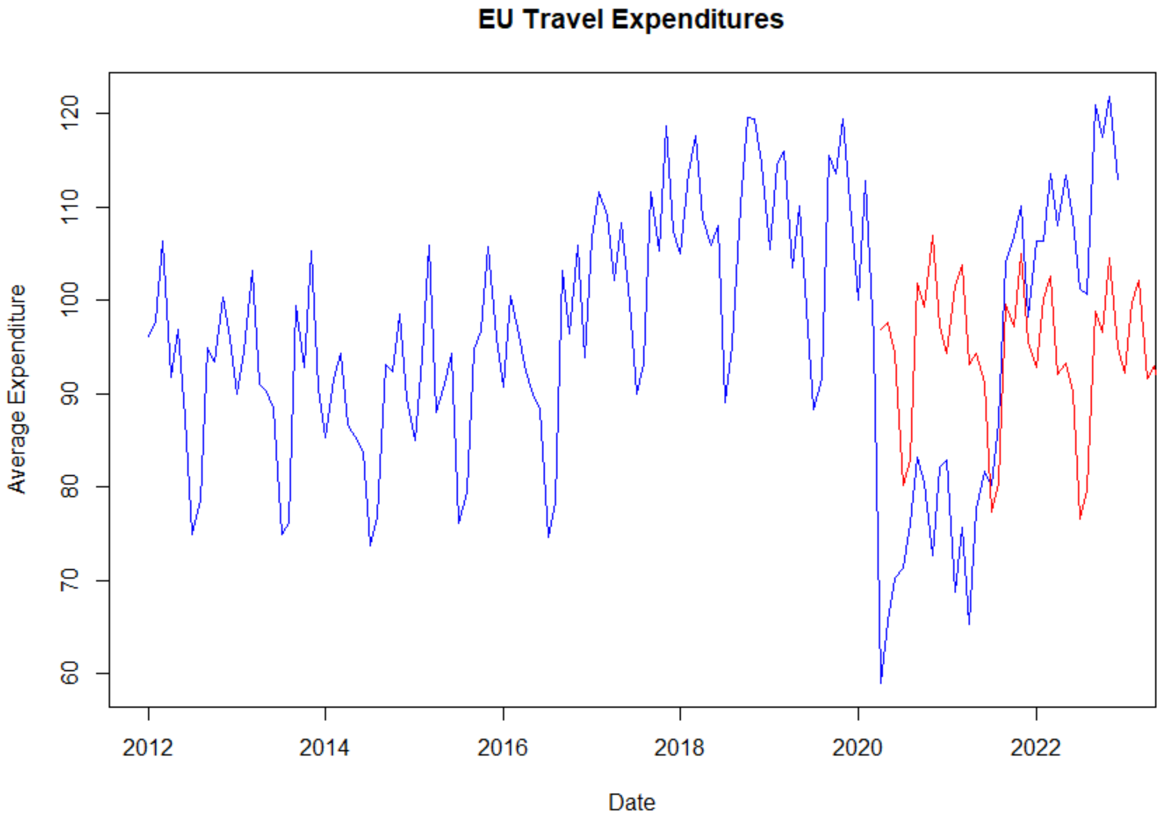
7) Generate out of sample forecasts up to December 2024, based on the complete time series (January 2012- March 2020).



Here are some key things you can interpret from the graph:

- **Overall Trend:** The forecast suggests a gradual increase in EU travel expenditure over the entire period, from January 2012 to December 2024.
- **Seasonality:** There appears to be a seasonal pattern in the data, with travel expenditure likely to be higher during the summer months (around June to August) and lower during the winter months (around December to February).

8) **Impact of the pandemic on travel expenditures in the EU**



Analysis:

Statistic	Value	Description
Minimum	-37.829	Underestimated travel expenditures by most (37.829 units).
Median	-10.449	Half of forecasts underestimated by around (10.449 units) during the pandemic.
Mean	-10.843	On average, underestimated travel expenditures by (10.843 units).
Maximum	13.525	Overestimated travel expenditures by most (13.525 units).

The negative values across the quartiles and the mean indicate that, on average, the travel expenditures during the COVID-19 pandemic were lower than what was forecasted. The pandemic had a negative impact on travel expenditures in the EU, with the forecast generally underestimating the decline. However, it's essential to note that there were instances where the forecast overestimated the expenditures, especially seen in the maximum value.

Forecasting Consumer Price Index of USA

Using the Consumer Price Index of USA we are going to forecast the data upto February 2024.

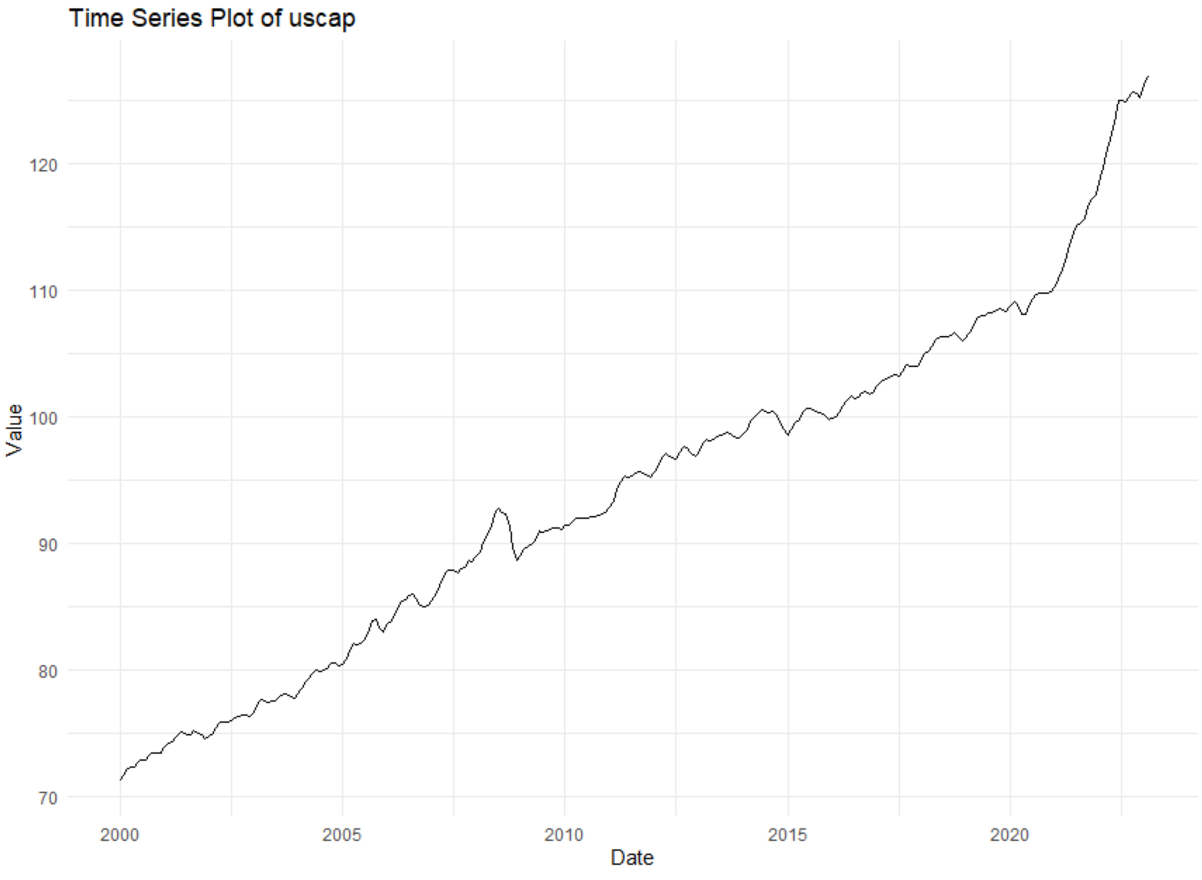
Data source: : https://fred.stlouisfed.org/series/USACPIALLMINMEI

Timeline: 2000 January – 2023 February

Training Set: 2000 January – 2021 December

Test Set: 2021 January – 2023 February

Time Series Plot

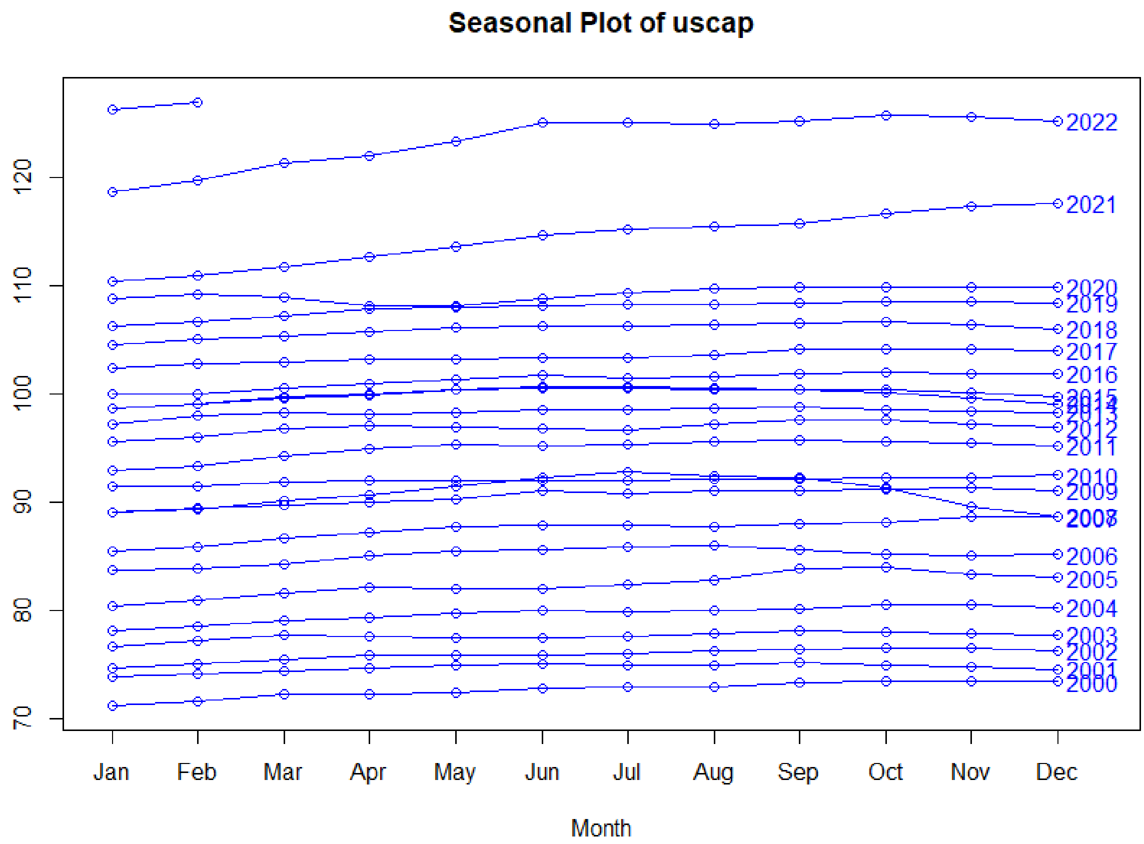


The y-axis likely represents the index value, where a baseline value (often 100 for a specific year) is set. An increase in the index value signifies inflation, while a decrease indicates deflation.

The upward trend in the plot suggests that prices for a basket of goods and services typically consumed by Americans have generally increased over time. This aligns with the concept of inflation.

The dip around 2005 could be a period of lower inflation or even deflation.

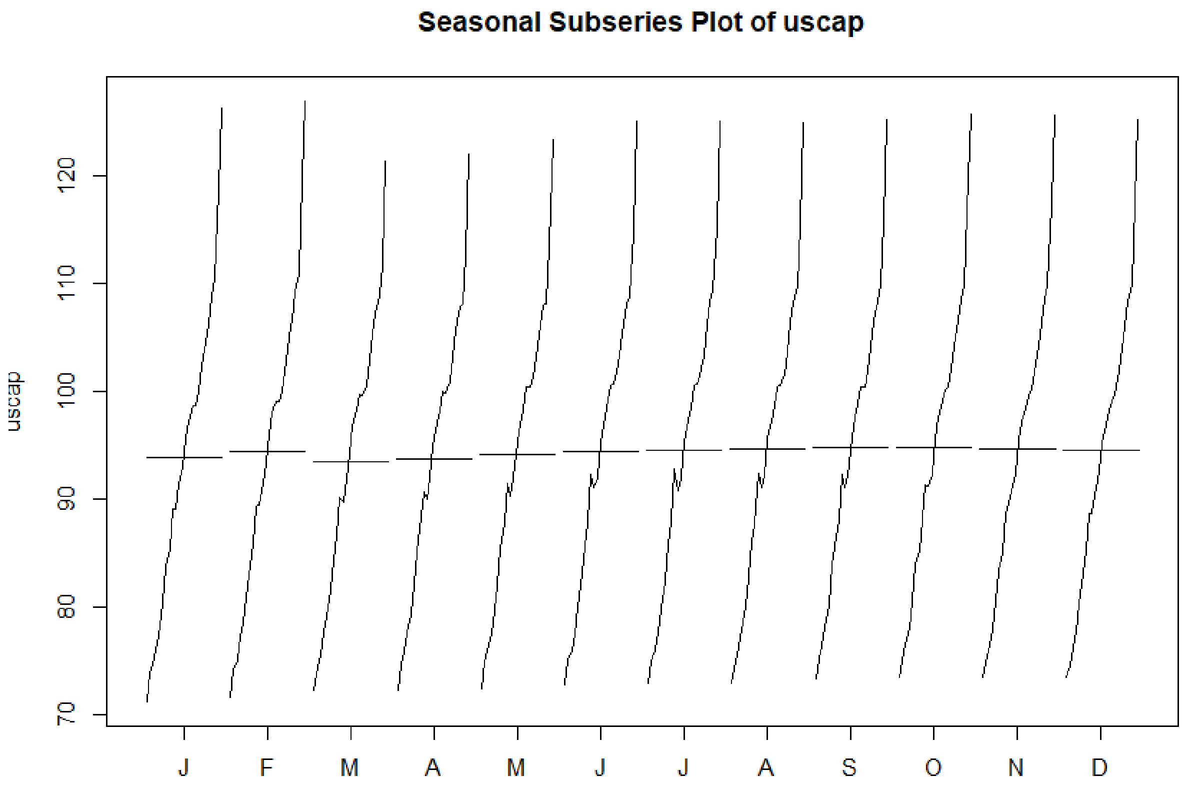
Seasonal Plot



There is a seasonal pattern to USCAP, with prices generally peaking in December and January and dipping in the summer months. This could be due to factors such as holiday shopping and increased demand for energy during the summer.

There is a general upward trend in USCAP over time, which suggests inflation. However, the rate of inflation appears to vary from year to year.

For example, the increase in USCAP seems to be sharper in 2021 and 2022 compared to previous years.


Seasonal Subseries Plot of uscap
uscap
70
80
90
100
110
120
J
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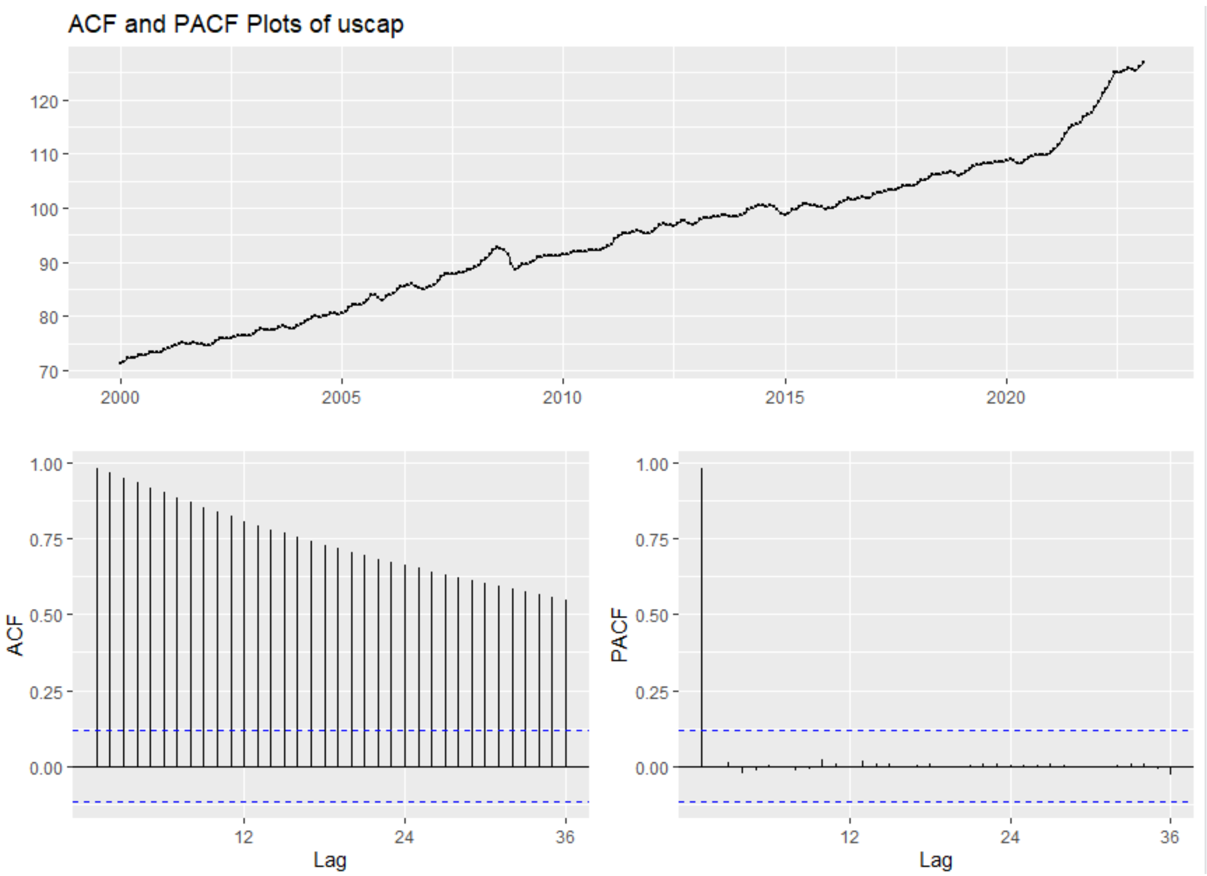
ACF and PACF Plots of uscap
70
80
90
100
110
120
2000
2005
2010
2015
2020
ACF
1.00
0.75
0.50
0.25
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24
36
Lag
PACF
1.00
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24
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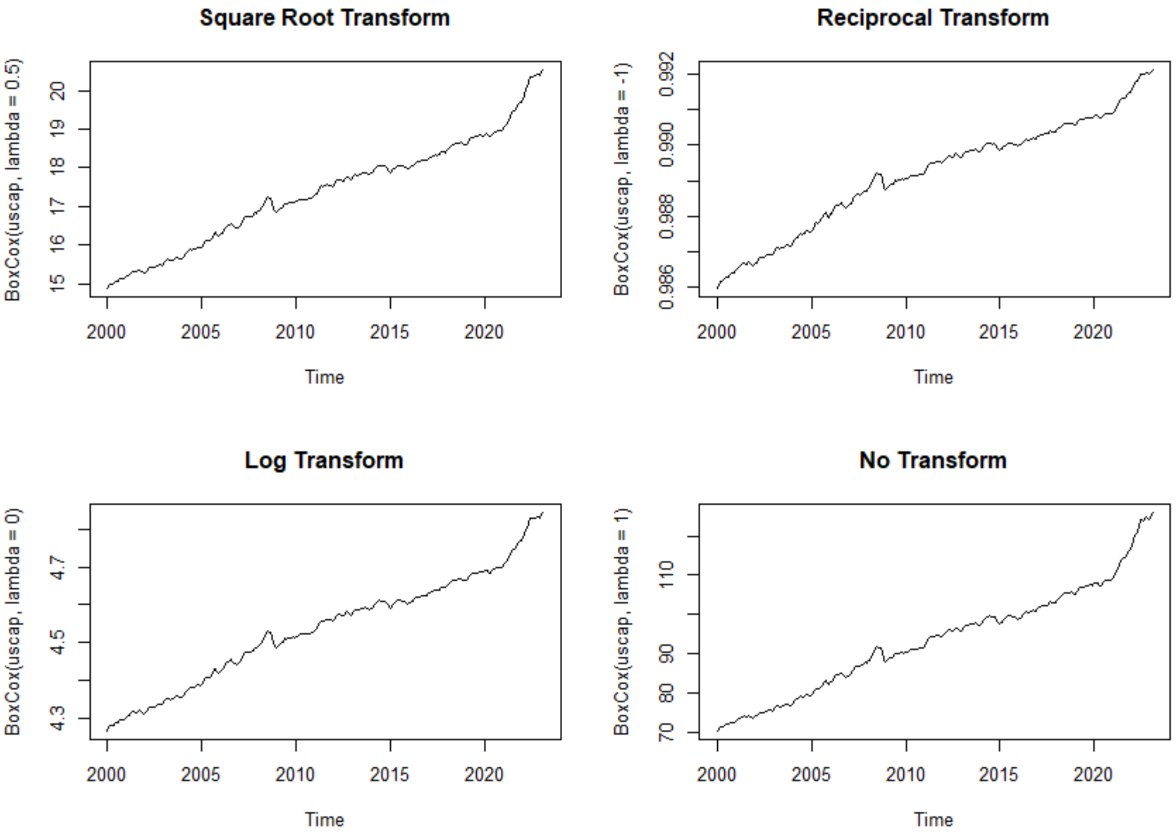
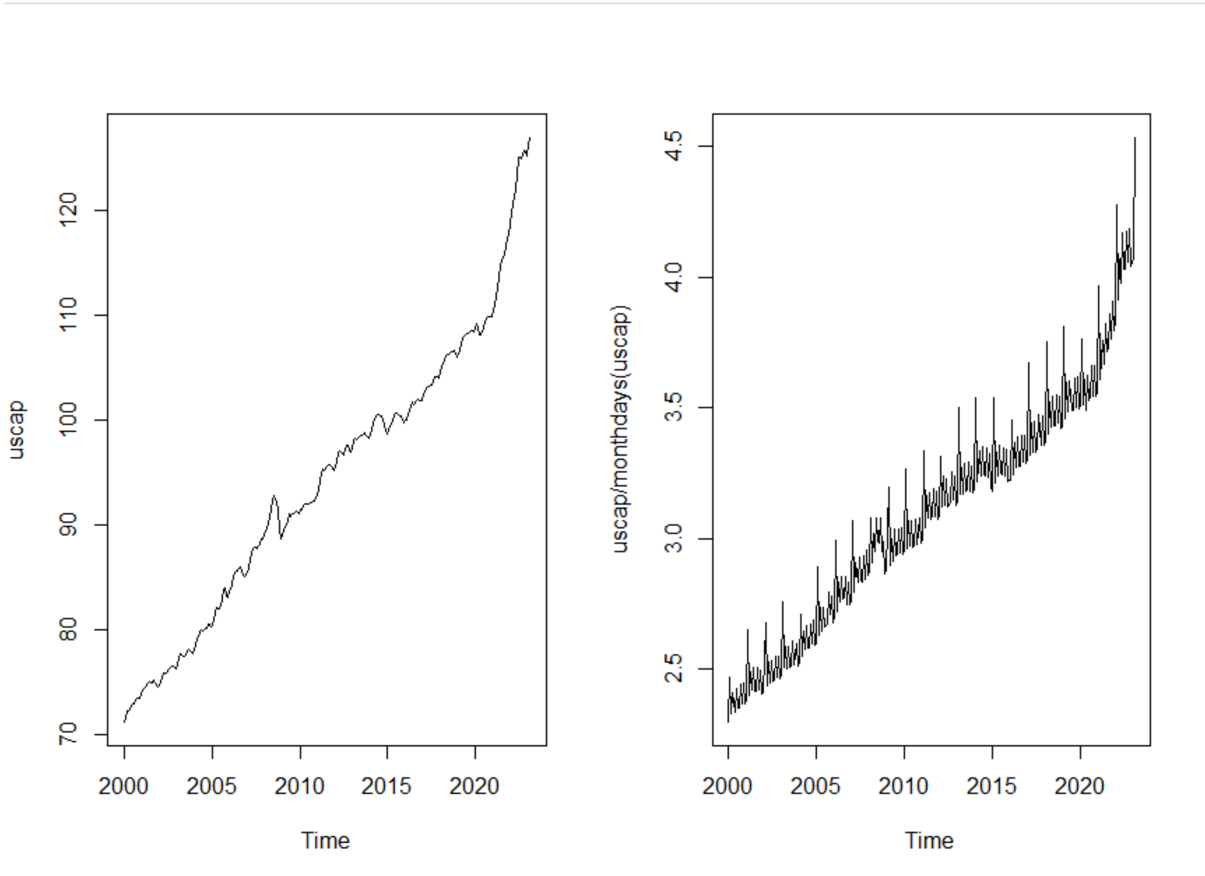
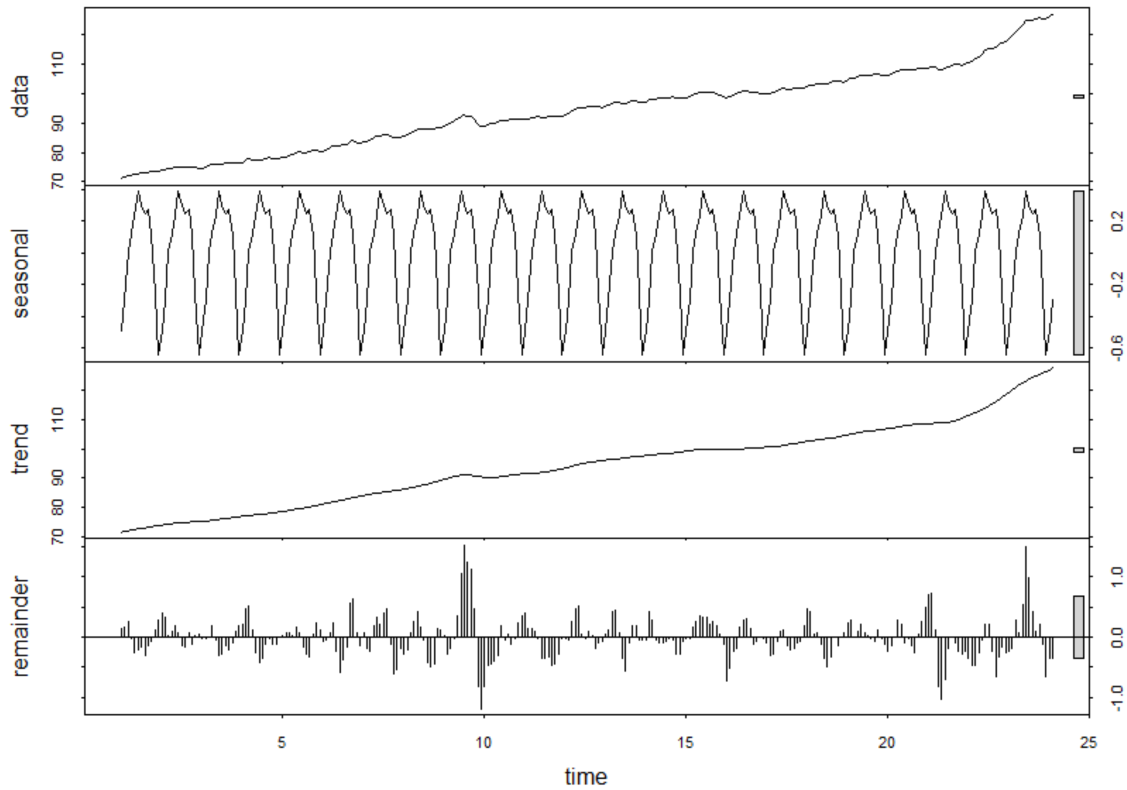
Lag


Square Root Transform
BoxCox(uscap, lambda = 0.5)
Time
Reciprocal Transform
BoxCox(uscap, lambda = -1)
Time
Log Transform
BoxCox(uscap, lambda = 0)
Time
No Transform
BoxCox(uscap, lambda = 1)
Time


uscap
Time
uscap/monthdays(uscap)
Time



Model m9

ARIMA Specification: ARIMA(0,1,3)(2,0,0)[12] with drift.

Ljung-Box Test:

Test statistic (Q*): 7.4522

Degrees of freedom (df): 19

P-value: 0.9914

Model Degrees of Freedom: 5

Total lags used: 24

Model m10

ARIMA Specification: ARIMA(0,1,2)(0,1,2)[12].

Ljung-Box Test:

Test statistic (Q*): 16.173

Degrees of freedom (df): 20

P-value: 0.7059

Model Degrees of Freedom: 4

Total lags used: 24

Both models seem to be reasonably good fits to the data as indicated by the high p-values in the Ljung-Box test, suggesting no significant autocorrelation in the residuals. Model m9 has a higher degree of freedom (5) compared to m10 (4). This suggests that m9 might capture the underlying patterns in the data with slightly more flexibility. Model m10 incorporates an additional differencing parameter (d=1, D=1) compared to m9. This indicates that m10 uses a more aggressively differenced series. Both models have a seasonal component with a period of 12. Both models use the same number of total lags (24), suggesting similar memory or persistence in the model residuals.

In conclusion, while both models appear to be reasonable, the choice between them might depend on other factors like forecasting accuracy on a validation set or the simplicity of the model. Further diagnostic tests and validation on out-of-sample data would be beneficial to make a final model selection.

Model Description	Q*	df	p-value
Seasonal naive method	831.33	24	< 2.2e-16
STL + Random walk	116.92	24	3.419e-14
STL + Random walk with drift	116.92	24	3.419e-14
STL + ETS(A,A,N)	133.75	24	< 2.2e-16
STL + ARIMA(2,1,2) with drift	5.6422	20	0.9993
ETS(A,Ad,N)	207.34	24	< 2.2e-16
ETS(A,A,A)	517.83	24	< 2.2e-16
ETS(A,Ad,A)	566.81	24	< 2.2e-16
ARIMA(0,1,3)(2,0,0)[12] with drift	7.4522	19	0.9914
ARIMA(0,1,2)(0,1,2)[12]	16.173	20	0.7059

White Noise Residuals: Models with p-values less than 0.05 indicate significant autocorrelation in the residuals, suggesting that these models might not adequately capture the underlying patterns in the data. Models like "Seasonal naive method," "STL + Random walk," "STL + Random walk with drift," "STL + ETS(A,A,N)," "ETS(A,Ad,N)," "ETS(A,A,A)," and "ETS(A,Ad,A)" seem to exhibit significant autocorrelation. Models with high p-values (>0.05) in the Ljung-Box test are preferable as they suggest that the residuals are white noise and the model captures the data's patterns well. Examples include "STL + ARIMA(2,1,2) with drift" and "ARIMA(0,1,3)(2,0,0)[12] with drift." More complex models (with higher df) do not necessarily perform better, as seen in the contrast between ARIMA models with different specifications. All models have used the same number of total lags (24), indicating similar memory or persistence in the model residuals.

In conclusion, models like "STL + ARIMA(2,1,2) with drift" and "ARIMA(0,1,3)(2,0,0)[12] with drift" appear to perform relatively better based on the Ljung-Box test results. However, it is essential to validate these models further using out-of-sample forecasting accuracy and other diagnostic checks.

Training Set Performance:

Model	RMSE	MAE	MAPE	MASE
Seasonal Naive	2.3824	2.0529	2.2011	1.0000
STL naive lambda	0.3257	0.2541	0.2728	0.1238
STL rwdrift lambda	0.2717	0.1964	0.2117	0.0957
STL ets lambda	0.2632	0.1930	0.2086	0.0940
STL arima lambda	0.3682	0.1861	0.2071	0.0907
Auto ETS lambda	0.3496	0.2661	0.2890	0.1296
AAA lambda	0.7567	0.5328	0.5614	0.2596
AAdA lambda	0.7581	0.5182	0.5468	0.2524
ARIMA lambda	0.3974	0.2245	0.2499	0.1094
ARIMA dD lambda	1.6037	0.3332	0.3974	0.1623

The STL models (especially with drift) and the ETS models (with and without drift) perform relatively well with lower RMSE, MAE, MAPE, and MASE values. The ARIMA models show mixed performance with ARIMA lambda having the lowest values among the ARIMA models.

Test Set Performance:

Model	RMSE	MAE	MAPE	MASE
Seasonal Naive	10.4113	10.1149	8.1471	4.9271
STL naive lambda	6.2543	5.7835	4.6308	2.8172
STL rwdrift lambda	3.7605	3.5424	2.8395	1.7255
STL ets lambda	1.0737	0.9224	0.7433	0.4493
STL arima lambda	3.5405	3.3295	2.6687	1.6218
Auto ETS lambda	3.8384	3.6139	2.8982	1.7604
AAA lambda	6.1916	6.0496	4.8629	2.9468
AAdA lambda	3.4475	3.4061	2.7441	1.6592
ARIMA lambda	3.7372	3.5268	2.8297	1.7179
ARIMA dD lambda	1.9834	1.8279	1.4653	0.8904

The STL model with ETS lambda outperforms others with the lowest RMSE, MAE, MAPE, and MASE values. The Seasonal Naive model performs the worst, highlighting the need for more sophisticated models.

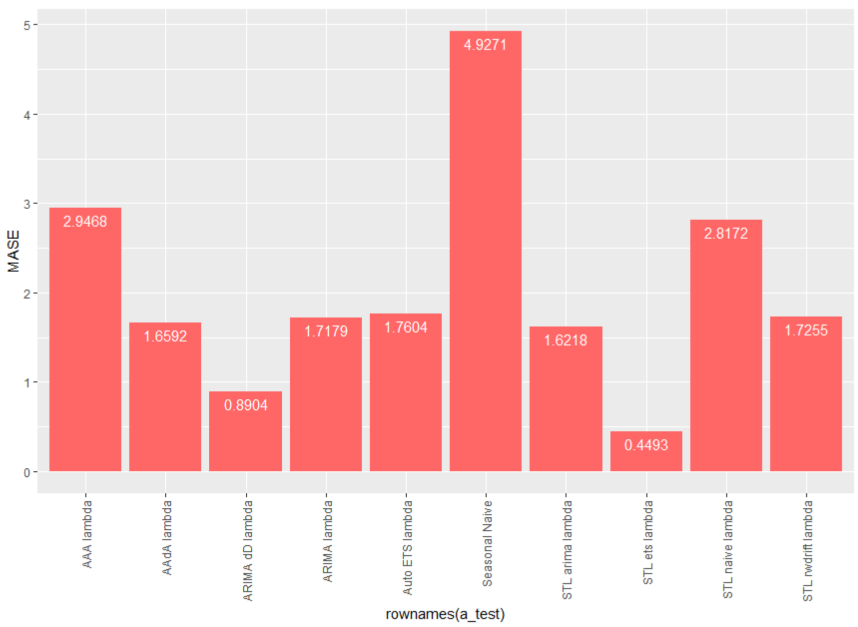
Overall, the STL model with ETS lambda appears to be the best-performing model based on the testing set metrics.

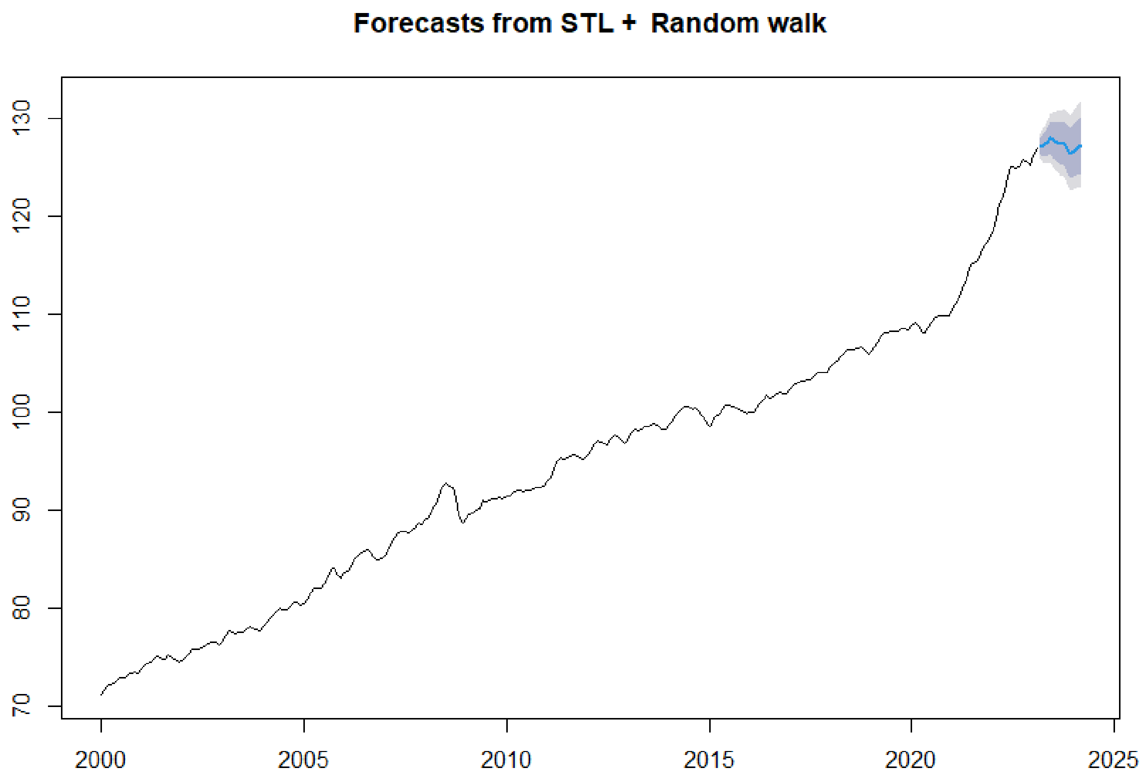
Ljung-Box Test Result:

Model	Q*	df	p-value
Seasonal Naive	831.3306	24	0.0000
STL naive lambda	116.9181	24	0.0000
STL rwdrift lambda	116.9181	24	0.0000
STL ets lambda	133.7532	24	0.0000
STL arima lambda	5.6422	20	0.9993
Auto ETS lambda	207.3371	24	0.0000
AAA lambda	517.8340	24	0.0000
AAdA lambda	566.8111	24	0.0000
ARIMA lambda	7.4522	19	0.9914
ARIMA dD lambda	16.1726	20	0.7059

Models with a low p-value (typically < 0.05) indicate that the residuals are not white noise, meaning there's some autocorrelation present. Models like Seasonal Naive, STL models, Auto ETS, AAA lambda, and AAdA lambda show significant autocorrelation. Models with high p-values (close to 1) suggest that the residuals are close to white noise, indicating good model fit in terms of capturing patterns. ARIMA lambda and ARIMA dD lambda have higher p-values, suggesting a better fit in terms of residual autocorrelation.

The ARIMA lambda and ARIMA dD lambda models exhibit the least autocorrelation in residuals, suggesting they might be the best-fitted models among the listed ones.





As you can see that the trend appears to be increasing a bit in the future and might take a slight dip in terms of consumer price index of the united states of America.