Time Series Analysis of Unemployment Levels in the United States

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Abstract:

Unemployment levels serve as a critical metric in assessing the economic health of a nation, reflecting both challenges and opportunities for change. This study employs time series analysis to examine the dynamics of unemployment in the United States, utilizing data derived from the Current Population Survey spanning from January 1948 to February 2024. The dataset, measured monthly in thousands, offers insights into the total count of individuals actively seeking employment during the survey reference week. Through iterative modeling, incorporating various combinations of seasonal and non-seasonal parameters, the ARIMA(2,1,2)*$(0,1,1)_{12}$ model was identified as a reliable tool for forecasting future unemployment trends. This model demonstrates minimal violations of assumptions and produces significant estimates, instilling confidence in its predictive capabilities. Recognizing the significance of unemployment data as an early indicator of economic trends, the analysis underscores the importance of employing robust forecasting methodologies, such as SARIMA, to inform policy decisions, macroeconomic analyses, and interventions aimed at addressing labor market challenges.

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Introduction:

Unemployment stands as a significant measure in evaluating the economic well-being of a nation, encapsulating both its challenges and potential for change. In this analysis, I delve into the dynamics of unemployment levels within the United States, a topic of paramount importance in understanding the country's economic landscape. The dataset under examination originates from the Current Population Survey, providing a comprehensive record of monthly unemployment counts spanning from January 1948 to February 2024. Each data point represents the total number of individuals actively seeking employment during the respective survey reference week, which are measured in thousands. Understanding unemployment trends is vital as it offers critical insights into the labor market's health and reflects broader economic conditions. Just as a drop in unemployment rates can signify economic growth and prosperity, a rise may indicate downturns or challenges within the economy. By exploring this dataset, I aim to take a deeper dive on the patterns, trends, and underlying factors influencing unemployment levels in the United States. Overall, this analysis serves to deepen our understanding of the nation's economic dynamics and also lays the groundwork for informed policymaking, intervention strategies, and efforts to foster a more resilient and equitable labor market.

Model specification:

The dataset used in this study was plotted to check the temporal pattern of US unemployment levels. The temporal pattern (Plot1) suggested that the model was not stationary, as the mean did not remain constant around a variable, and the variance was highly fluctuating. It was essential to first make the model stationary to proceed with the time series analysis and forecasting of the dataset.

The initial ACF and PACF plots (Plot2) of the original dataset indicated that the Autocorrelation Function (ACF) plot demonstrated a gradual decline towards zero, while the Partial Autocorrelation Function (PACF) plot exhibited a sharp cut-off after lag 1. Looking at the ACF plot, there was autocorrelation even at lag 72, indicating a long-term memory and a linear trend involved, thus proving that the model was not stationary.

To gain a deeper understanding of these intricacies, we delved into the data, making it stationary and meticulously examining its nuances and complexities.

To make the dataset stationary, first differencing was performed on the dataset to remove the linear trend. The first differencing was done on the seasonal part (Plot3). The plot appeared to show that the mean was almost around 0; however, there were ample variations observed. Considering this, first differencing was performed on both the seasonal and non-seasonal parts (Plot4). This resulted in a stationary model, with a constant mean and variation, except for a spike during the years 2020-2022. It is understandable that this peak was due to the pandemic, and it was not just in the US; unemployment levels skyrocketed all around the world. This variation was unavoidable, even after taking transformation, so I moved forward without transforming the data. Additionally, this spike is crucial for future years, as it represents an unchangeable level, and future predictions depend on these three years as well.

The ACF and PACF plots were plotted for the differenced data (Plot5). Firstly, looking at the seasonal portion, the PACF plot suggested strong bars till lag 120, indicating an autoregressive (AR) order of 10. The ACF plot showed only one strong bar at lag 12, indicating the Moving Average (MA) to be 1. Secondly, for the non-seasonal part, at both the ACF and PACF plots, there wasn't a prominent peak at time point 1; however, there were two distinct peaks at time points 2 and 3. Considering these observations, I decided to include both the autoregressive (p) and moving average (q) terms for the non-seasonal component, each of order 3.

Initial Thoughts From the Plots:
Seasonal: AR(P) = 10, MA(Q) = 1
Non-Seasonal: AR(p) = 3, MA(q)= 3

Lastly, it is worth noting that the PACF and ACF plots resemble the theoretical concept for seasonal MA 1, wherein the ACF cuts off to 0 after a strong bar at the s-lag (here it is after 12), and the PACF tails off to 0. This closely aligns with the theoretical concepts, indicative of potential future model possibilities.

Fitting and Diagnostics:

The model fitting process began by exploring models with the highest possible order, which revealed violations of assumptions and insignificant estimates. To address this, a systematic approach was adopted, starting with the least orders possible and incrementally increasing based on the significance of the estimates. This iterative process resulted in the generation of approximately 30 different potential models, of which only five exhibited minimal violations and significant estimates. Notably, models $(0,1,0)(4,1,0)_{12}$(Plot6), $(0,1,0)(5,1,0)_{12}$(Plot7), and $(0,1,0)(6,1,0)_{12}$(Plot8) demonstrated striking similarities in their diagnostic evaluations.

Each of the above three models displayed a consistent pattern. The Ljung-Box-Pierce test unveiled a few significant groups of autocorrelations, while the ACF and PACF plots did not reveal any significant values. A discernible peak around two time points, particularly during the years 2020-2022 at the standardized residual plot, hinted at a clear outlier, albeit one considered reasonable within the context of the data pattern and the 95% Confidence Level. Additionally, the normality assumption appeared to be satisfied, with p-values less than 0.05, indicating that estimates significantly differ from zero and rendering these models favorable candidates for further consideration. Although minor violations in LB Statistics were noted, these deviations were deemed reasonable(Table1,2,3).

Focusing on the non-seasonal component along with the seasonal, Model:$(1,1,1)(0,1,1)_{12}$(Plot9) and Model:$(2,1,2)(0,1,1)_{12}$ (Plot10) displayed promising results. The former indicated a three significant groups of autocorrelations in the Ljung-Box-Pierce test, initially. The ACF & PACF plots did not exhibit any significant values. A notable peak around two time points at the standardized residual plot, suggested a clear outlier, which was considered reasonable given the data pattern and the 95% Confidence Level. Additionally, the normality assumption appeared to be satisfied. The p-values were less than 0.05, indicating that the models were good candidates for further consideration, despite a small violation in LB Statistics (Table4). Conversely, the latter model, Model:$(2,1,2)(0,1,1)_{12}$(Plot10), did not indicate any significant groups of autocorrelations in the Ljung-Box-Pierce test. The ACF & PACF plots also did not exhibit any significant values. A similar peak around two time points at the standardized residual plot , suggested a clear outlier, which was considered reasonable. Additionally, the normality assumption appeared to be satisfied. The p-values were less than 0.05, indicating that the model was a good candidate for further consideration, with no reasonable violations in the data model (Table5).

After careful consideration of the AIC and AICc criterion (Table6) and examining six different diagnostic plots for potential violations, the ARIMA(2,1,2)x(0,1,1)_12 model was selected for future forecasting endeavors. This decision was informed by a comprehensive evaluation of model performance and diagnostic indicators, ensuring a robust framework for forecasting unemployment levels in the United States.

Estimated Model:

$$\Phi(B)\phi(B)\,(1-B)^{D}(1-B^{S})^{D}x_t = \Theta(B)\theta(B)w_t$$

Based on ARIMA(2,1,2)x$(0,1,1)_{12}$:

$$\boxed{\begin{gathered} \mathbf{x_t = 1.2516x_{t-1} + 0.4283x_{t-2} - 0.6799x_{t-3} + x_{t-12} + 0.7484x_{t-13}} \\ \mathbf{-0.9315x_{t-14} - 0.6799x_{t-15} - 0.2012w_{t-1} - 0.7909w_{t-2}} \\ \mathbf{-0.9512w_{t-12} + 0.1914w_{t-13} + 0.7523w_{t-14} + w_t} \end{gathered}}$$

Forecasting:

The model was employed to forecast 24 months into the future (Plot11). The plot suggests that the unemployment level will continue to increase following a sharp decline in 2023. The years 2024, 2025, and 2026 were identified as resulting in increased layoffs, indicating potential economic challenges in the future. This projected growth in unemployment raises concerns about its implications for overall economic growth and stability. High unemployment rates can lead to reduced consumer spending, weakened demand for goods and services, and dampened investment, all of which can negatively impact economic growth. Furthermore, prolonged periods of high unemployment can strain government resources, increase social welfare expenditures, and hinder efforts to achieve long-term economic prosperity. This anticipated rise in unemployment may be attributed to various factors such as shifts in labor demand, changes in economic policies, or external shocks to the economy. For example, economic forecasts indicate that certain industries may experience layoffs due to technological advancements, changes in consumer preferences, or global market dynamics. Additionally, factors such as trade tensions, geopolitical instability, or natural disasters can also contribute to fluctuations in unemployment rates.

Furthermore, to assess the model's accuracy, the forecasted data points for each year were superimposed on the observed values (Plot12). The resulting plot indicates that the model fits well, accurately capturing the variations and trends in the dataset. However, it iss essential to remain vigilant and continuously monitor economic indicators to adapt to changing conditions and mitigate potential adverse effects on economic growth and stability.

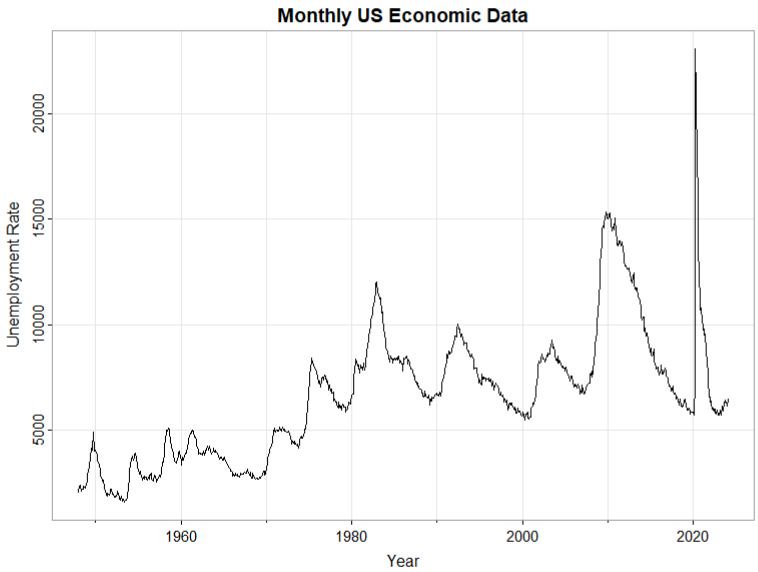
Discussion and Limitations:

From the data model, it is evident that the dataset is subject to certain limitations, particularly influenced by the disruptive impact of the pandemic. The unprecedented economic turbulence during 2020-2023, characterized by widespread layoffs and fluctuating job market conditions, led to pronounced peaks in unemployment levels. These irregularities may introduce challenges in modeling and forecasting, necessitating careful consideration and potentially impacting the model's accuracy. Furthermore, while the non-seasonal component of the data did not exhibit a strong peak at time point 1, subsequent time points displayed notable bars, prompting exploration of alternative parameter configurations such as p=3,q=3. This adjustment resulted in a model encompassing both seasonal and non-seasonal components, enhancing its adaptability to the dataset's nuances. Despite this finding a reliable SARIMA model, other alternatives like GARCH and ARCH could offer superior performance, especially when dealing with pronounced heteroscedasticity during events like the pandemic

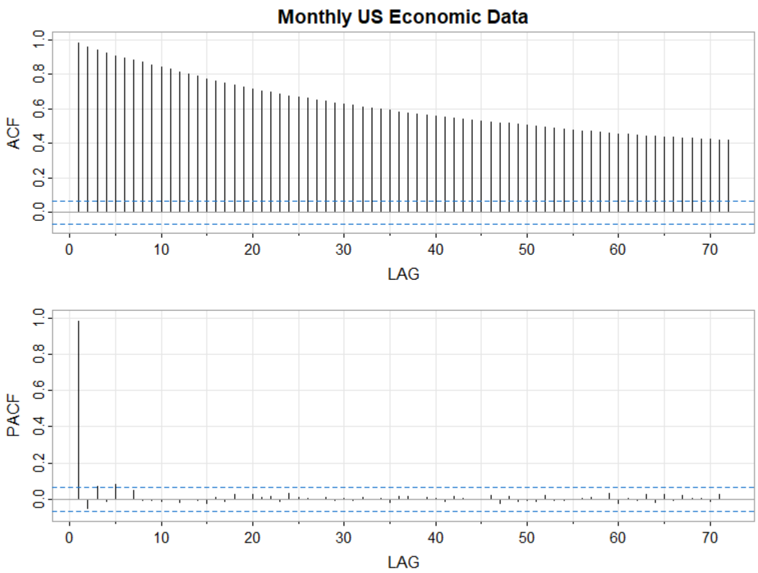
Conclusion:

The ARIMA(2,1,2)*(0,1,1)$_{12}$ model proves to be a reliable tool for forecasting future values and identifying trends within the dataset. The model's ability to maintain minimal violations and produce significant estimates instils confidence in its predictive capabilities. Understanding the importance of unemployment data as an early indicator of economic trends is paramount. By utilizing models like ARMA(2,1,2)*(0,1,1)$_{12}$, policymakers, economists, and researchers can gain valuable insights into the state of the labor market. These insights are instrumental in informing policy decisions, conducting macroeconomic analyses, and devising interventions to address unemployment challenges effectively. Its continued utilization will play a vital role in shaping strategies aimed at fostering a healthier and more resilient economy.

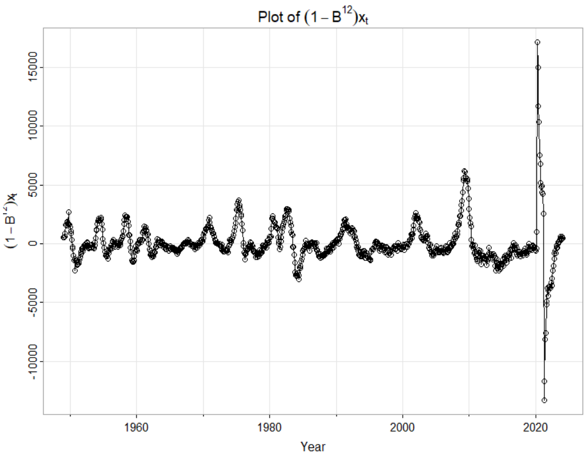
Appendix:



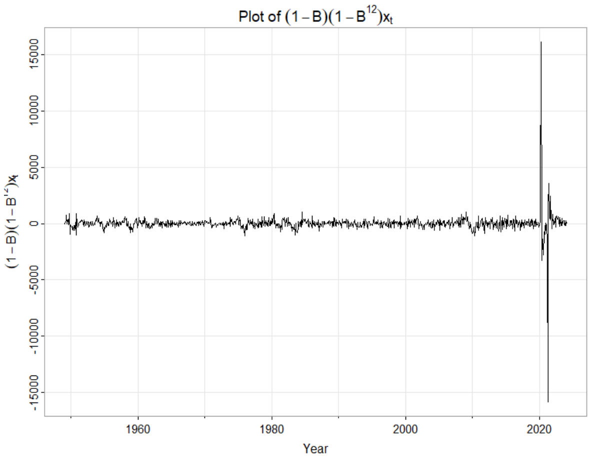
Plot1: Temporal Plot of the US Unemployment Level



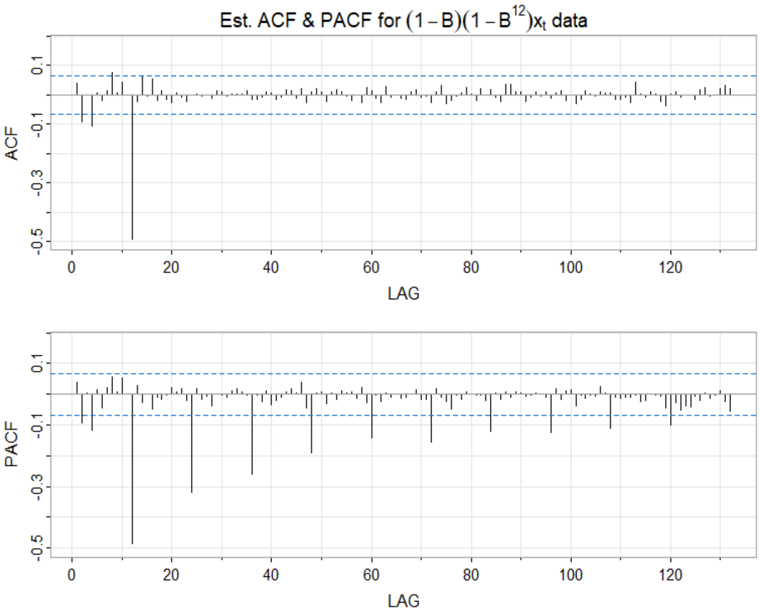
Plot2: Initial ACF and PACF Plots of the Original Data Set



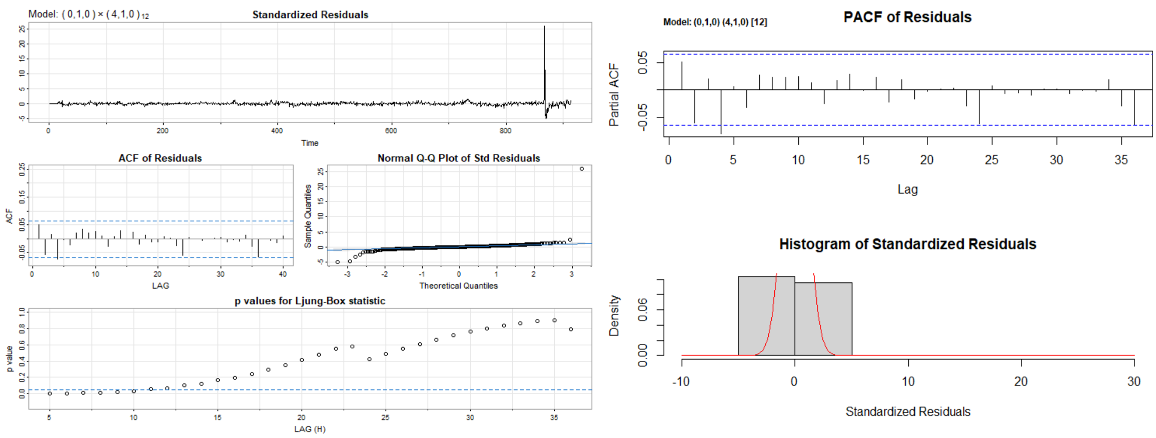
Plot3: First Differencing on the Seasonal Part



Plot4: First Differencing on Both Seasonal and Non-Seasonal Part



Plot5: ACF and PACF plot of the Differenced Data

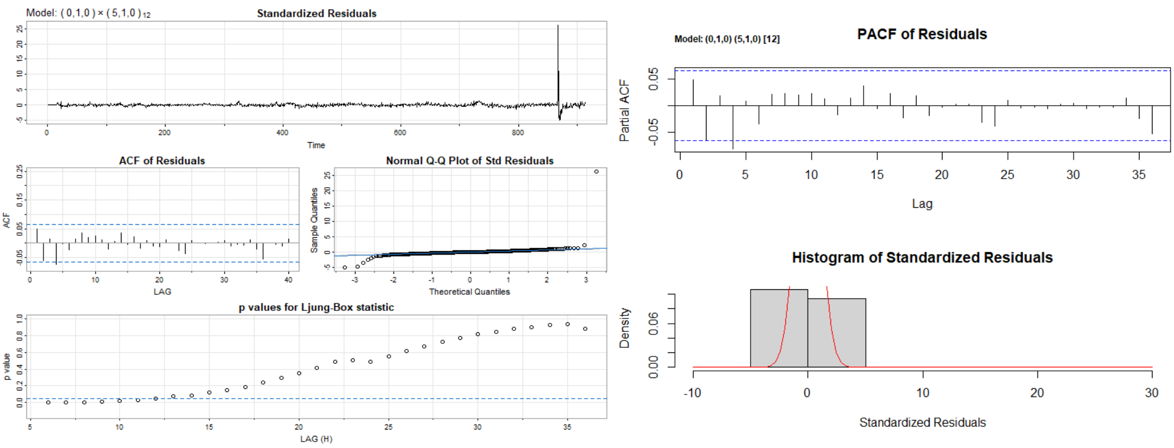


Plot 6: Model:$(0,1,0)(4,1,0)_{12}$ - Diagnostic Plots

AR/MA	Estimates	Std Error	t-value	p-value
sar1	-0.9406	0.033	-28.474	0
sar2	-0.8759	0.0432	-20.283	0
sar3	-0.8214	0.0486	-16.911	0
sar4	-0.3803	0.0618	-6.1499	0

The Ljung-Box-Pierce test does indicate a few significant groups of autocorrelations.
The ACF & PACF plots do not exhibit any significant values.
There is a high peak around two time points suggesting a clear outlier, however this outlier is considerable, given the pattern of the data and 95% Confidence Level.
The normality assumption appears to be satisfied.
The p- values are lesser than 0.05 indicating that the model is a good candidate to proceed further, although there is a small violation in LB Statistics, which is reasonable.

Table1: Model:$(0,1,0)(4,1,0)_{12}$



Plot7: Model:$(0,1,0)(5,1,0)_{12}$ - Diagnostic Plots

AR/MA	Estimates	Std Error	t-value	p-value
sar1	-0.9559	0.0335	-28.576	0
sar2	-0.914	0.046	-19.858	0
sar3	-0.8728	0.0532	-16.394	0
sar4	-0.4865	0.0742	-6.556	0
sar5	-0.1672	0.0652	-2.5625	0.0106

The Ljung-Box-Pierce test does indicate a few significant groups of autocorrelations.
The ACF & PACF plots do not exhibit any significant values.
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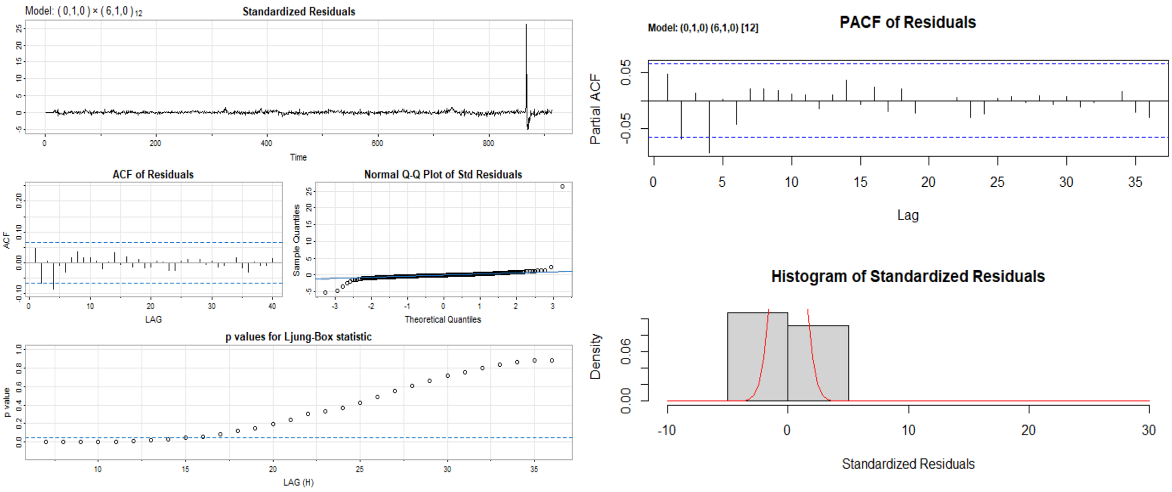
The normality assumption appears to be satisfied.
The p- values are lesser than 0.05 indicating that the model is a good candidate to proceed further, although there is a small violation in LB Statistics, which is reasonable.

Table 2: Model:$(0,1,0)(5,1,0)_{12}$

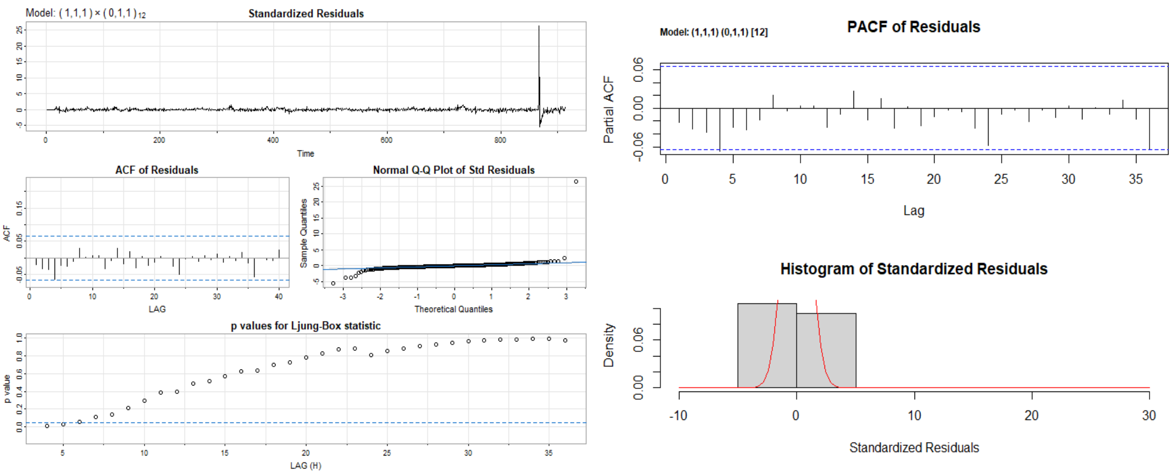


Plot8: Model:(0,1,0)(6,1,0)12 - Diagnostic Plots

AR/MA	Estimates	Std Error	t-value	p-value
sar1	-0.9621	0.0332	-28.95	0.00
sar2	-0.9398	0.0464	-20.254	0.00
sar3	-0.923	0.0555	-16.633	0.00
sar4	-0.6013	0.0806	-7.4646	0.00
sar5	-0.3321	0.081	-4.1	0.00
sar6	-0.234	0.0656	-3.5679	4.00E-04

The Ljung-Box-Pierce test does indicate a few significant groups of autocorrelations.
The ACF & PACF plots do not exhibit any significant values.
There is a high peak around two time points suggesting a clear outlier, however this outlier is considerable, given the pattern of the data and 95% Confidence Level.
The normality assumption appears to be satisfied.
The p- values are lesser than 0.05 indicating that the model is a good candidate to proceed further, although there is a small violation in LB Statistics, which is reasonable.

Table3: Model:(0,1,0)(6,1,0)12

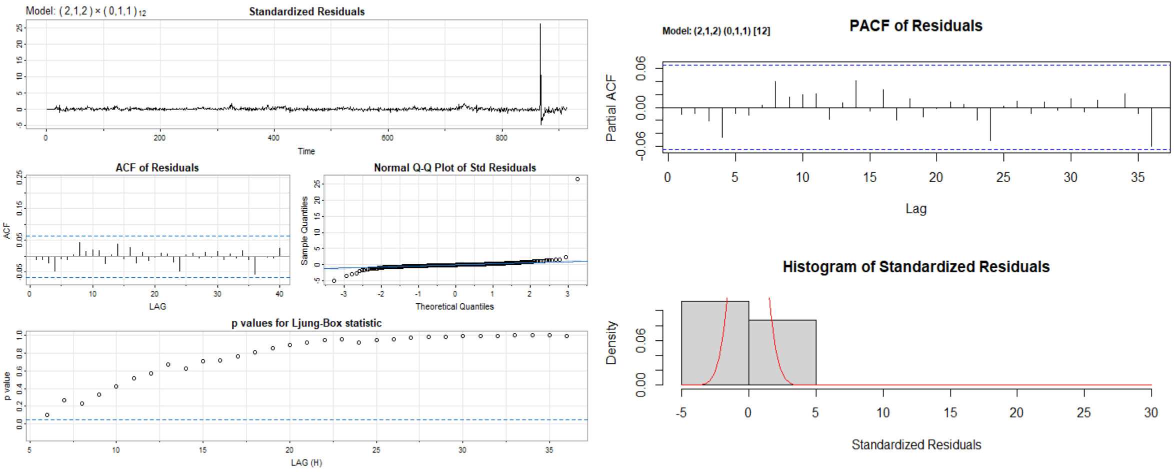


Plot 9: Model:(1,1,1)(0,1,1)12 - Diagnostic Plots

AR/MA	Estimates	Std Error	t-value	p-value
ar1	-0.7267	0.0925	-7.8599	0
ma1	0.8054	0.0788	10.221	0
sma1	-0.9569	0.0158	-60.458	0

The Ljung-Box-Pierce test does indicate a few significant groups of autocorrelations.
The ACF & PACF plots do not exhibit any significant values.
There is a high peak around two time points suggesting a clear outlier, however this outlier is considerable, given the pattern of the data and 95% Confidence Level.
The normality assumption appears to be satisfied.
The p- values are lesser than 0.05 indicating that the model is a good candidate to proceed further, although there is a small violation in LB Statistics, which is reasonable.

Table4: Model:(1,1,1)(0,1,1)12



Plot10: Model:(2,1,2)(0,1,1)12 - Diagnostic Plots

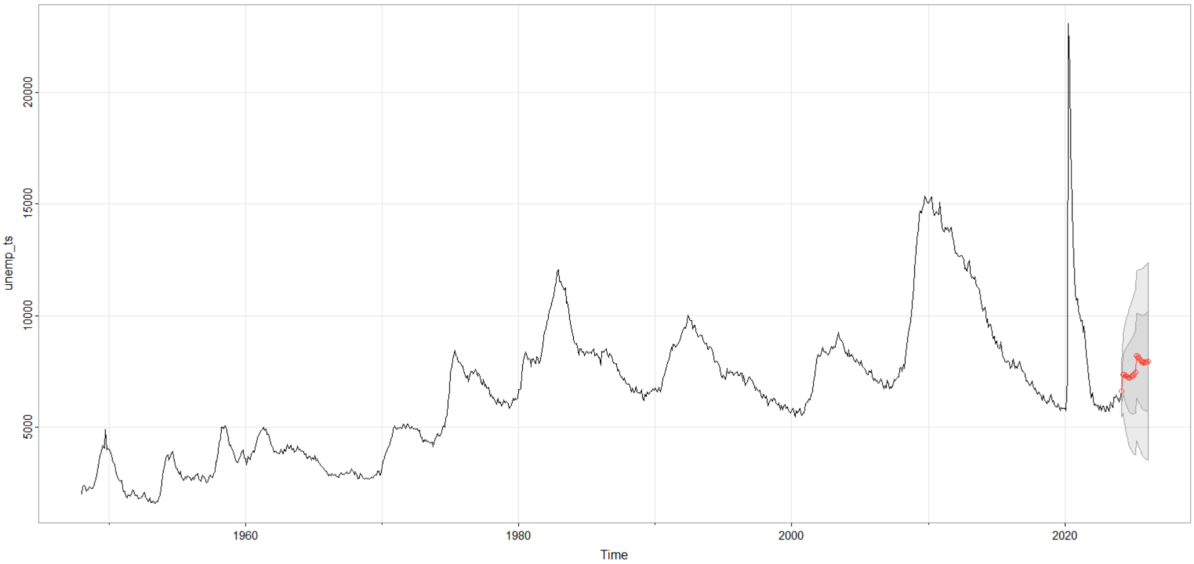
AR/MA	Estimates	Std Error	t-value	p-value
ar1	0.2516	0.0967	2.6019	0.0094
ar2	0.6799	0.0946	7.1841	0
ma1	-0.2012	0.0829	-2.4266	0.0154
ma2	-0.7909	0.0829	-9.5375	0
sma1	-0.9517	0.0166	-57.24	0

The Ljung-Box-Pierce test does not indicate any significant groups of autocorrelations.
The ACF & PACF plots do not exhibit any significant values.
There is a high peak around two time points suggesting a clear outlier, however this outlier is considerable, given the pattern of the data and 95% Confidence Level.
The normality assumption appears to be satisfied.
The p- values are lesser than 0.05 indicating that the model is a good candidate to proceed further, with no reasonable violations in the data model.

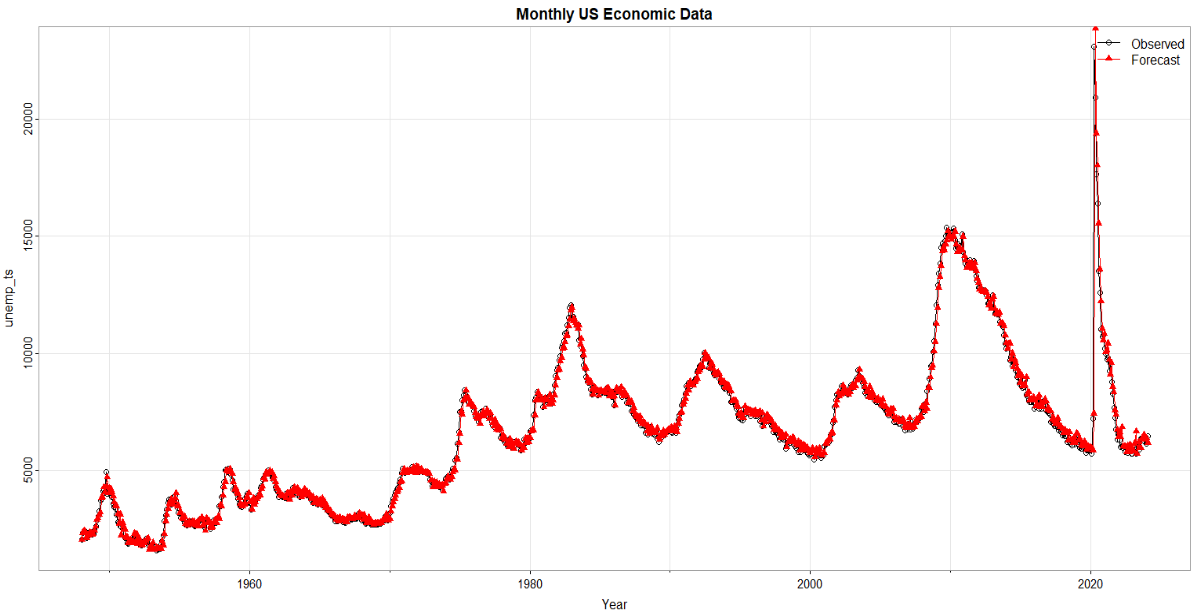
Table5: Model:(2,1,2)(0,1,1)12

Index	Models	AIC	AICc	BIC
1	ARIMA(2,1,2)x(0,1,1)_12	15.6573	15.65737	15.68928
2	ARIMA(1,1,1)x(0,1,1)_12	15.66522	15.66525	15.68654
3	ARIMA(0,1,0)x(4,1,0)_12	15.70105	15.7011	15.72771
4	ARIMA(0,1,0)x(5,1,0)_12	15.69582	15.6959	15.72781
5	ARIMA(0,1,0)x(6,1,0)_12	15.68401	15.68411	15.72133

Table6: AIC, AICc, BIC Criterion Comparisons



Plot11: Forecasting 24 months into the future



Plot12: Model Validity Prediction