**Forecasting Sticky Price CPI**

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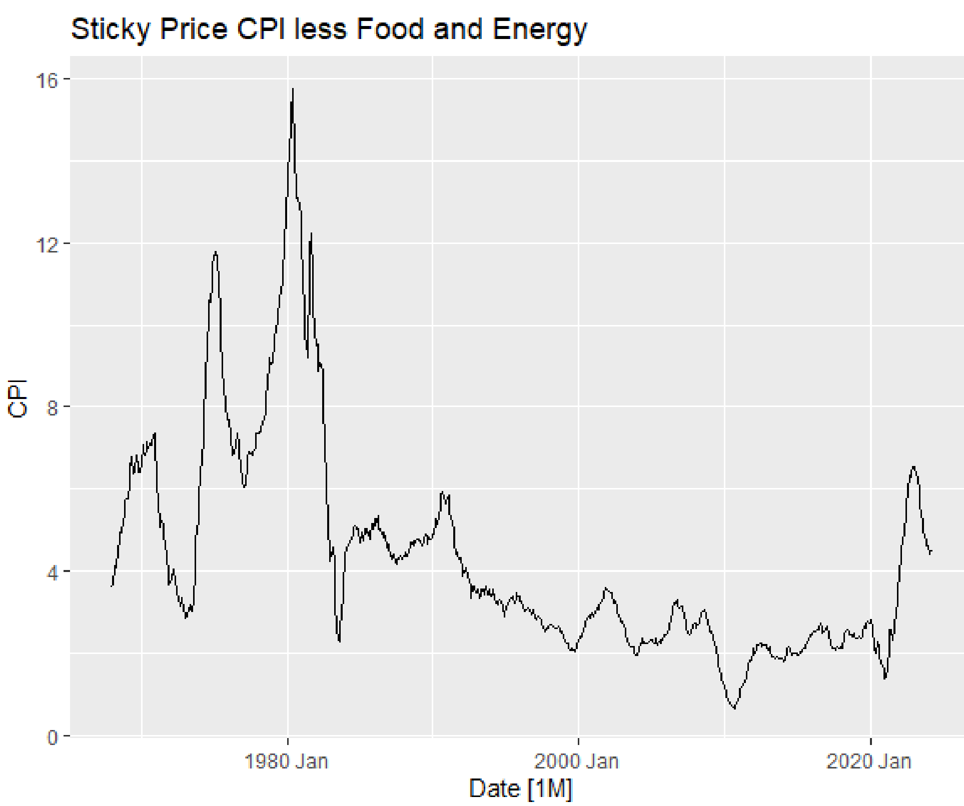
**Business Understanding**

Inflation is a general increase in the prices of goods and services in an economy. It's measured by a metric called the Consumer Price Index (CPI). There are many ways to measure inflation, each having a different purpose. Two of these metrics that the Bureau of Labor Statistics uses are:

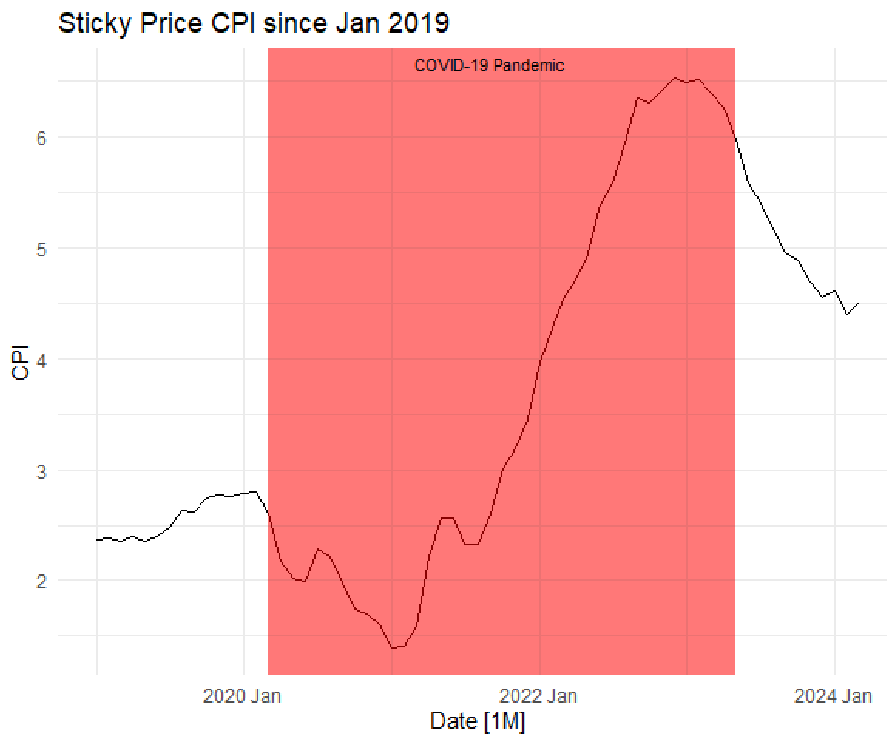
- CPI for All Urban Consumers (CPI-U).
    - This is the most commonly used version of CPI. It measures the average change over time in prices paid by urban consumers. It's the most comprehensive measure of CPI for most goods and services in the US [1].
- Sticky Price CPI less Food and Energy
    - This specialized version of CPI measures the price changes of goods and services that are slow to change prices. It provides a long-term view of inflation, focusing on the part of the economy less affected by short-term volatility [2].

This project will deal with the Sticky Price CPI less Food and Energy found on the Federal Reserve Economic Database (FRED) [3]. The data tracks CPI from January 1968 on a monthly basis. For the purpose of this forecast, the analysis will focus exclusively on the most recent 5 years of data, from January 2019 to February 2024—the goal will be to forecast the month of March 2024 as accurately as possible.



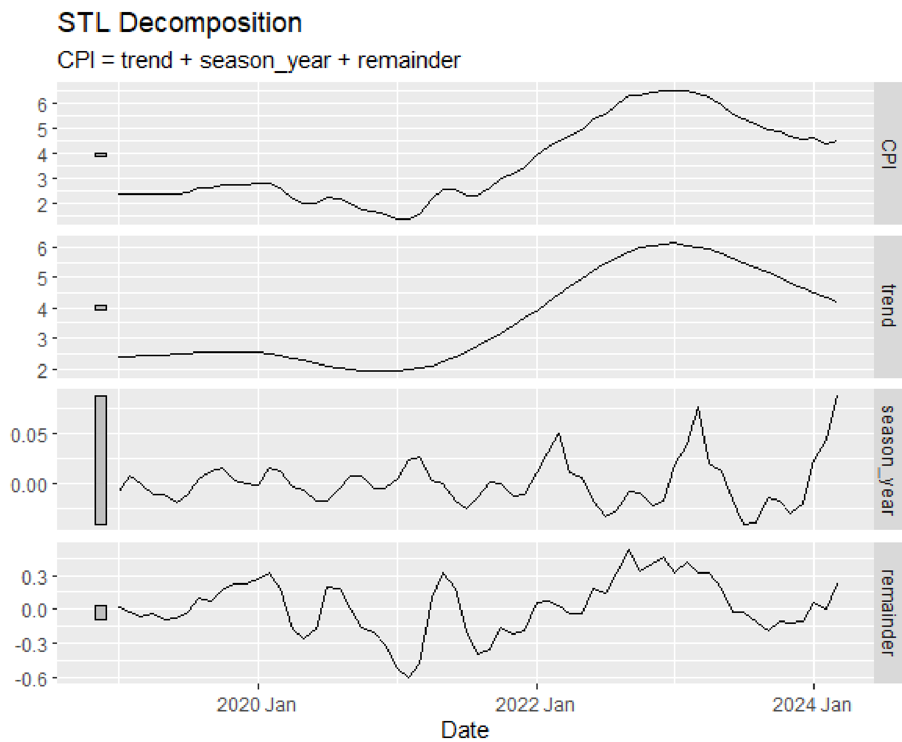

**Potential Outliers**

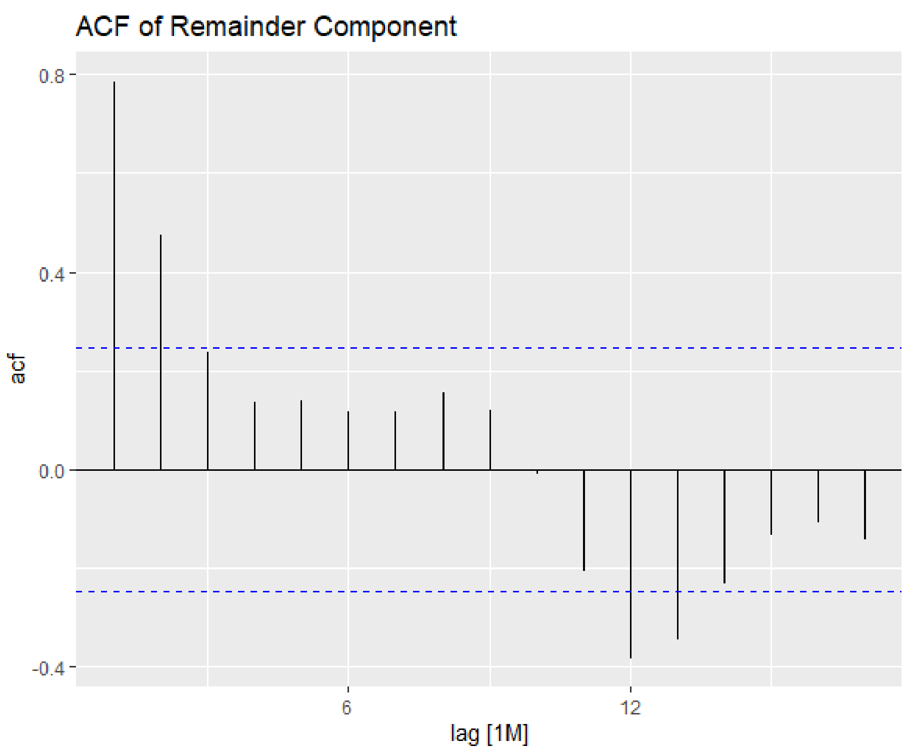
In March 2020, the World Health Organization characterized the outbreak of COVID-19 as a worldwide pandemic [4]. This led to a decline in CPI due to decreased demand for services like transportation, airfare, and hotels. It also disrupted supply chains and forced many companies to lay off a significant portion of their staff. As the economy recovered, labor shortages led to wage increases which were passed on to consumers in the form of higher prices—this coupled with ongoing supply chain issues led to a spike in CPI not seen since the early 1970's. The pandemic persisted for 3 years, until the Biden Administration announced it would end the public health emergency declarations in May 2023 [4]. The unique economic conditions created by the pandemic make it an important outlier to consider when analyzing inflation trends during this period, as it clearly distorts the underlying economic signals normally observed in the CPI data.




**Model Selection**

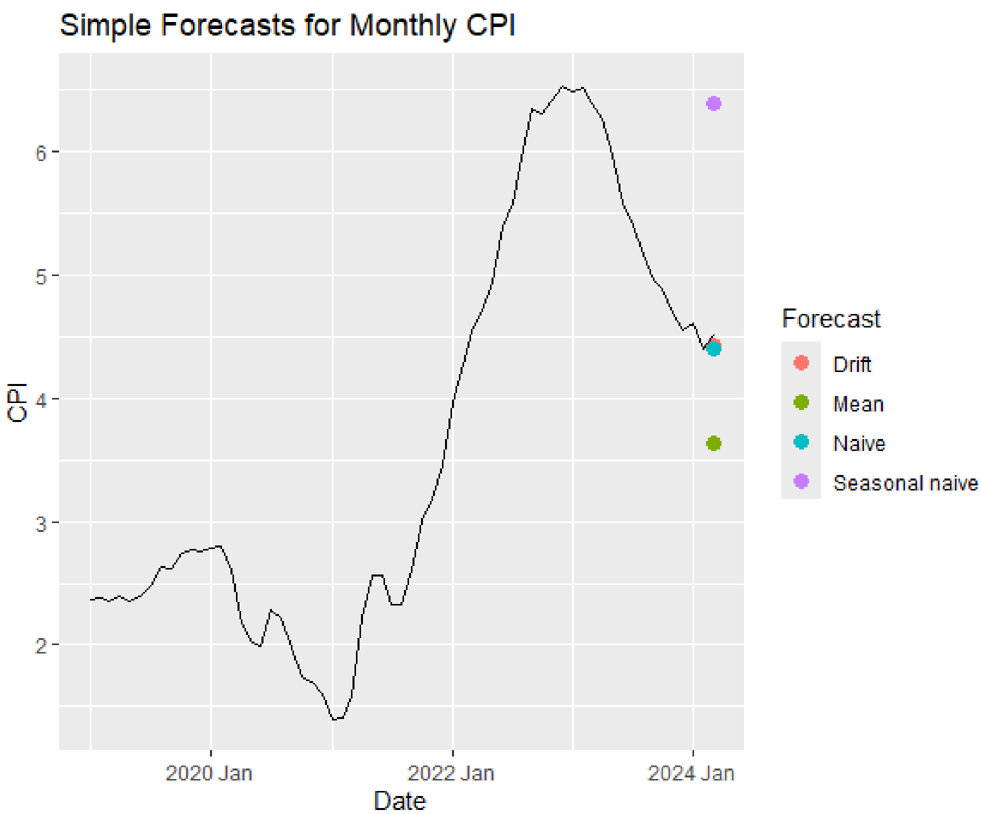
To begin, an STL decomposition was used to determine if there were underlying patterns in the data such as trend and seasonality. None of the components contained particularly useful information. The trend was neither linear nor exponential in nature. The variance in the seasonal component increased slightly over time, but it only accounted for a small portion of the variability of the series—this is likely due to the fact that the Sticky Price CPI is seasonally adjusted by the Federal Reserve.



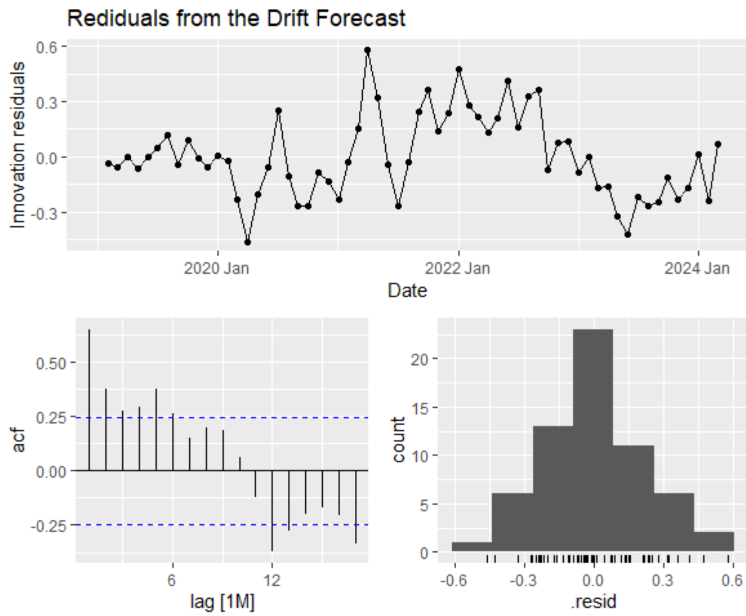

The ACF plot of the remainder component shows significant positive spikes at lags 1 and 2, and significant negative spikes at lags 12 and 13. This indicates there was autocorrelation remaining in the data that wasn't captured by the trend or seasonal components. This could be due to over-correction in the seasonal adjustments made by the Federal Reserve, or it might point to more complex seasonal patterns. This cyclic behavior—which is not uncommon in economic data—can make it particularly difficult to fit forecasts.

4 basic models (Drift, Mean, Naïve, and Seasonal Naïve) were fit to the series and used to forecast the next month as a baseline. The drift model performed the best by all metrics, followed closely by the naïve model. It makes sense that the mean method performed poorly since the mean of the series was skewed by the pandemic. It also makes sense that the seasonal naïve method performed poorly because there is little seasonality in the data.

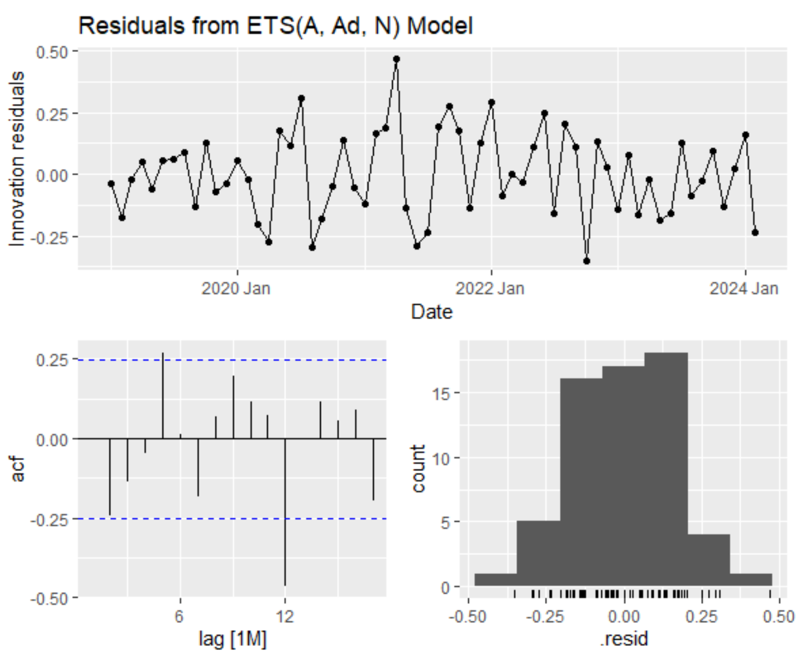



```
> accuracy(fc, cpi_5) |>
+   arrange(RMSE)
# A tibble: 4 × 10
  .model         .type      ME   RMSE    MAE    MPE  MAPE   MASE  RMSSE  ACF1
  <chr>          <chr>   <dbl>  <dbl>  <dbl>  <dbl> <dbl>  <dbl>  <dbl> <dbl>
1 Drift          Test   0.0729 0.0729 0.0729   1.62  1.62 0.0492 0.0397    NA
2 Naive          Test   0.106  0.106  0.106    2.35  2.35 0.0716 0.0579    NA
3 Mean           Test   0.869  0.869  0.869   19.3  19.3  0.586  0.474     NA
4 Seasonal naive Test  -1.88   1.88   1.88   -41.7  41.7  1.27   1.03      NA
```

The residuals from the drift method didn't look great. Although they were normally distributed, there were many significant autocorrelations, and the variance was not very consistent.

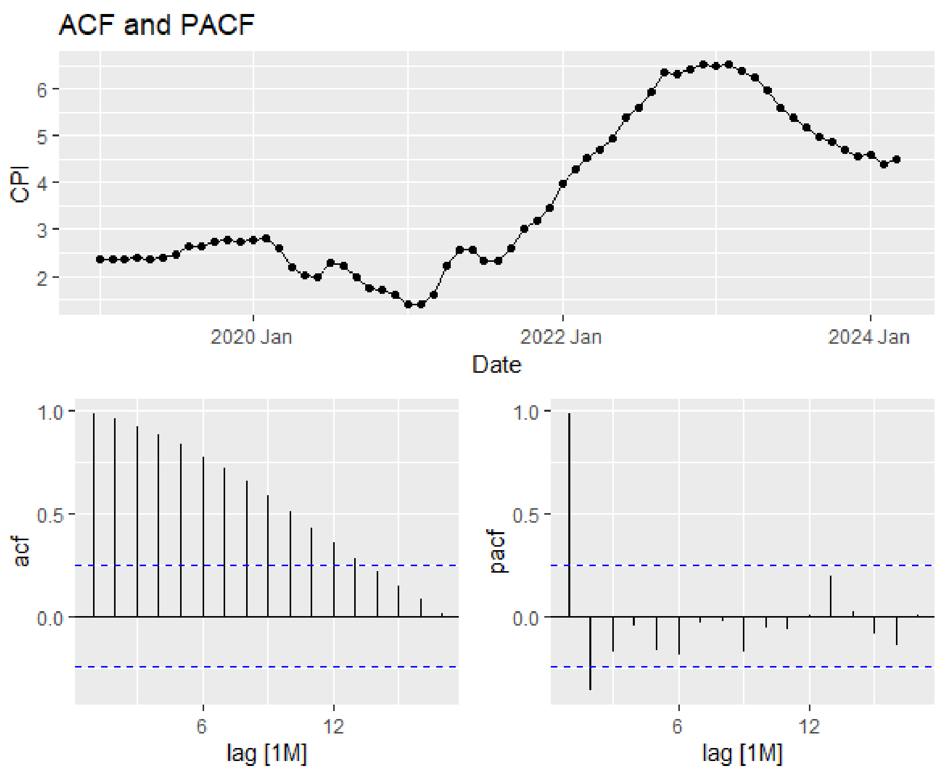



An ETS(A, Ad, N) model was fit to the data as well to see if it could outperform the simple methods. The residuals were much better: their variance was relatively stable, they were roughly normal, and there were only 2 significant spikes on the ACF plot. However, when it came to forecast accuracy, the ETS(A, Ad, N) model had an RMSE greater than both the drift and naïve models, and taking a Box-Cox transform (lambda = 0.515) actually made the ETS forecast accuracy worse than any model so far.

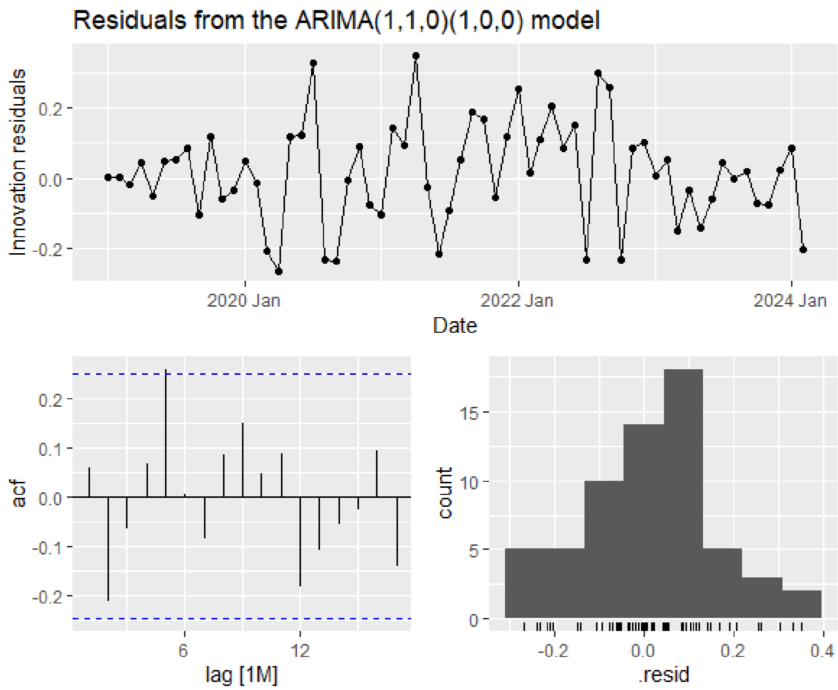


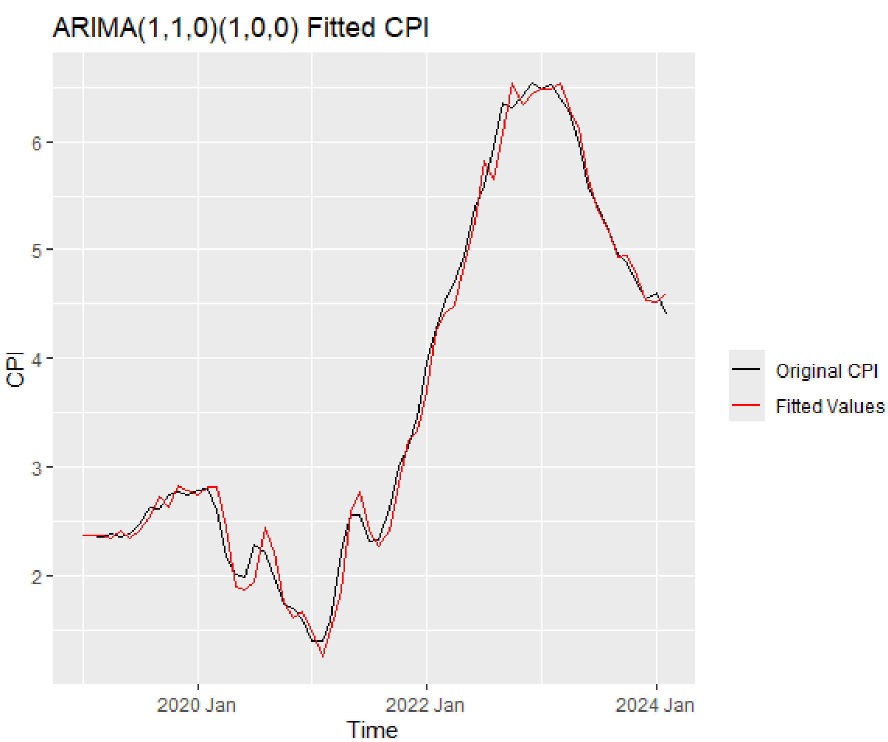

```
> accuracy(ets_fc, cpi_5)
# A tibble: 1 × 10
  .model    .type    ME  RMSE   MAE   MPE  MAPE  MASE RMSSE  ACF1
  <chr>     <chr> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl>
1 ETS(CPI)  Test  0.264 0.264 0.264  5.85  5.85 0.178 0.144    NA
```

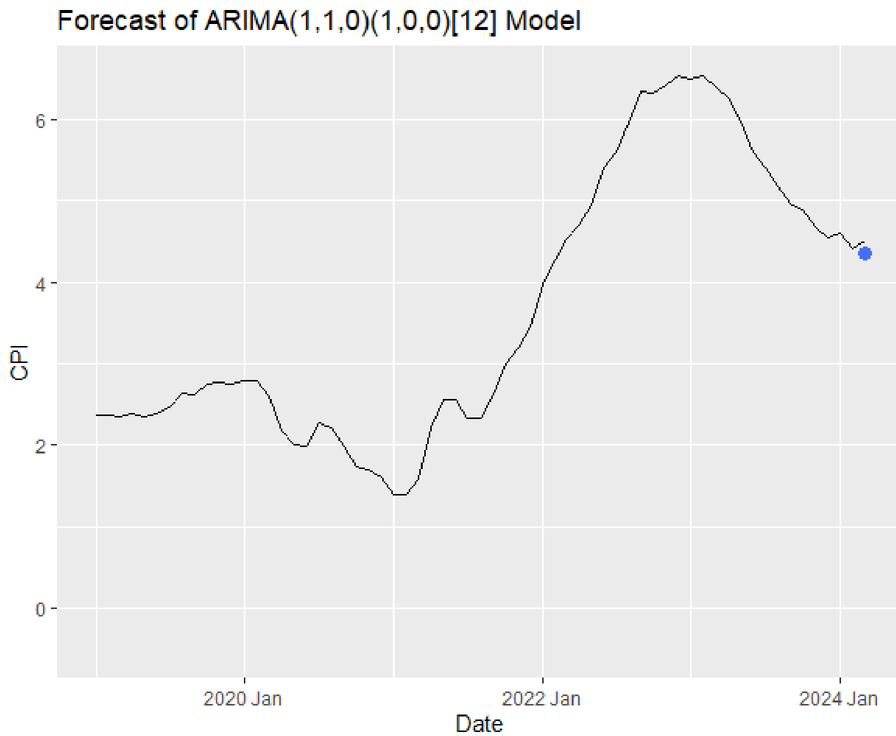
The ACF and PACF plots for the series showed characteristics of non-stationarity. The ACF showed a gradual decline of significant spikes, and the PACF showed a significant spike at lag 1. This was confirmed by a KPSS test (p-value = 0.01 < 0.05). Thus, it was determined that the series would require differencing to achieve stationarity. The order of differencing was determined by using the `unitroot_ndiffs` function in R; it showed that the series required a 1$^{st}$-order difference to achieve stationarity.




A binary indicator series was also used in conjunction with the CPI series to account for the pandemic. The indicator series had 1's from March 2020 to May 2023, and 0's everywhere else. An ARIMA model was automatically selected using R's `ARIMA` function. The model selected was an ARIMA(1,1,0)(1,0,0)[12]. This model uses 1 autoregressive term, 1$^{st}$-order differencing, no lagged forecast error terms, and 1 seasonal autoregressive term. Since there are 12 months in a year, 12 is the seasonal period. The residuals from this model were better than the ETS(A, Ad, N) model: roughly normally distributed and an arguably significant autocorrelation at lag 5.


Residuals from the ARIMA(1,1,0)(1,0,0) model
Innovation residuals
0.2
0.0
-0.2
2020 Jan
2022 Jan
2024 Jan
Date
acf
0.2
0.1
0.0
-0.1
-0.2
6
12
lag [1M]
count
15
10
5
0
-0.2
0.0
0.2
0.4
.resid


ARIMA(1,1,0)(1,0,0) Fitted CPI
CPI
6
5
4
3
2
2020 Jan
2022 Jan
2024 Jan
Time
Original CPI
Fitted Values




```
> accuracy(arima_fc, cpi_5)
# A tibble: 1 × 10
  .model      .type     ME  RMSE   MAE   MPE  MAPE  MASE  RMSSE  ACF1
  <chr>       <chr>  <dbl> <dbl> <dbl> <dbl> <dbl> <dbl>  <dbl> <dbl>
1 ARIMA(CPI) Test   0.161 0.161 0.161  3.57  3.57 0.109 0.0879    NA
```

**Fitness for Purpose**

While the RMSE of the Drift model is slightly better, there are good reasons to use the ARIMA model in this case. The autocorrelations present in the remainder component of the STL decomposition are good reason to think about using an ARIMA model because it will take advantage of these autocorrelations. The residuals from the ARIMA model are much better than the Drift model, with only 1 small significant spike on the ACF plot compared to 8. The Drift model is suitable for series with linear trends, which this series does not have, as the trend is clearly nonlinear. Since the forecast is only 1-step ahead, it's likely that if there were more datapoints in the test set that the ARIMA model would outperform the Drift model. Further, since ARIMA models consider autocorrelation in the series, they are less sensitive to violations of assumptions compared to a Drift model, which relies heavily on the continuation of observed trends. For these reasons, the ARIMA model was selected as the best choice for forecasting Sticky Price CPI.

**References**

[1] https://www.bls.gov/cpi/questions-and-answers.htm#:~:text=National%20(or%20U.S.%20City%20Average,published%20for%20the%20CPI%2DW

[2] https://www.clevelandfed.org/publications/economic-commentary/2010/ec-201002-are-some-prices-in-the-cpi-more-forward-looking-than-others-we-think-so

[3] https://fred.stlouisfed.org/series/CORESTICKM159SFRBATL

[4] https://www.nm.org/healthbeat/medical-advances/new-therapies-and-drug-trials/covid-19-pandemic-timeline#:~:text=By%20March%202020%2C%20the%20World,COVID%2D19%20outbreak%20a%20pandemic.