Analyzing Global Ongoing Covid-19 Depression

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Introduction

Background

The Coronavirus pandemic has led to countries' governments issuing lots of restrictions to limit the spread of the virus, and these policies have strong effects on the global economy. Therefore, citizens' lives have also been greatly affected by the economic crisis. At the beginning of the COVID-19 period (April 2019), there were more than 20 million jobs swept away which caused an increase in the unemployment rate. (An Unemployment Crisis after the Onset of COVID-19, 2020) Unemployment is defined as a person who loses a job, but actively searches for jobs for four weeks, and is available for work. The U.S. unemployment rate during the Coronativrus period reached its peak throughout the American historical unemployment rate. According to the U.S. Employment and Training Administration(ETA), during the COVID-19 period unemployment was even higher than during the Great Recession of the 1930s.

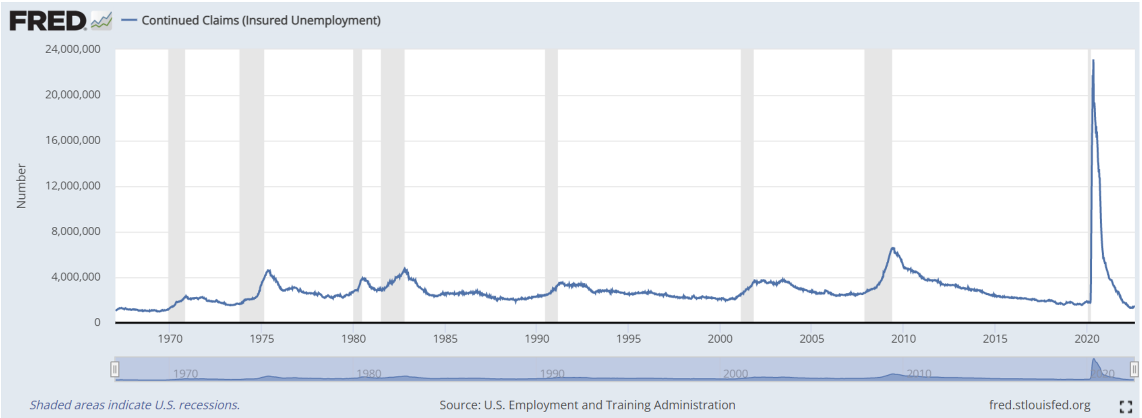

Figure 1. U.S. Employment and Training Administration, Continued Claims (Insured Unemployment) [CCSA], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/CCSA, August 25, 2022.

Motivation

The Economist Elvis Picardo claims that the national unemployment rate is the key indicator to measure a country's labor force market. Governors and economists would pay more attention to the national economic rate, especially during huge economic recession periods and special economic events. This is because the unemployment rate not only has an impact on personal life but also has over-widening effects on the whole economy. Therefore, this is why our group focuses on the topic of the U.S. unemployment rate problem because the U.S. labor market is now under tremendous stress as a result of the COVID-19 outbreak and subsequent mitigation measures. Besides, researching the U.S. unemployment rate enables us to have a deeper understanding of other countries' unemployment models. It is well known that the U.S. is the world's largest economy, and studying the unemployment rate in the U.S. in the

Covid19 gives us a good model to study other economies. The conclusions and recommendations of the study will also be useful for other countries.

Data Selection

We choose the Continued Claims as the key indicator to measure the U.S. unemployment model. Continued Claims are defined as the number of people who have already filed an initial claim and who have experienced a week of unemployment and then filed a continued claim to claim benefits for that week of unemployment.

In order to determine the best model to forecast the US unemployment rate at the post covid, we have investigated the weekly continued claims (Insured Unemployment rate) covering two separate time periods: 2000/01/01 to 2022/08/06; 2010/1/2 to 2022/08/06. The data were provided by FRED(Federal Reserve Economic Data, US-STL). The reason we choose the 2010 to 2022 period is that 2010 is the time to recover from the great economic recession of 2008. The continued claims from 2000 to 2022 could give us an overview of the trend of the overall unemployment rate. By comparing and contrasting these two periods' claimed data, we could make more accurate predictions.

The benefit of weekly data is that These data are on a weekly basis, which is different from many data that are on a monthly or quarterly basis. We can capture the changes in the number of unemployed people from the weekly data and make more accurate predictions. Besides, Our data is based on the Unemployment Insurance Weekly Claims Report by the U.S. Employment and

Training Administration(ETA).they collect data that measure the state of the nation's workforce, including employment and unemployment levels, as well as weeks and hours worked. We chose these data sources to ensure the authority of the data.

Methodology

The report's main objective is to compare the forecasting potential of two models: exponential smoothing models (ETS model specifically), and the ARIMA model, and to predict future values of the unemployment rate beyond the period under consideration.

Therefore, with the study, the forecasting performance was derived from the two models in view of identifying the best-suited forecasting procedure for the weekly continued claims, taking into account the following steps:

1. Fit the ETS model on the dataset
2. Fit the ARIMA model on the dataset
3. Compare the in-sample forecast accuracy measures for two models
4. Compare the forecast projections of the unemployment rate for all models over the period of September 2022 to December 2022.

Stationary

Time-series data should be stationary. A stationary series means that the properties [means, variance, and covariance] do not change over time. Note that seasonality and trends are not stationary because they demonstrate the value of the time series at different times.

Hypothetically, time-series data should be stationary to run the ARIMA forecasting model. Autocorrelation and order differencing to visualize the stationary status. As displayed in Figure 2, the first Autocorrelation of the Continued claims is nonstationary data for both time periods. This means that this dataset changes over time, and it plays a key role to determine the criteria. Therefore, this issue which is called the stationarity attribute should be solved before employing data. The first order of differencing was applied to display the stationarity situation among the dataset. According to the ACF, after 1st-order differencing, the data set becomes stationary for both time periods. To better visualize through numbers, the augmented Dickey-Fuller test (ADF) was also applied to the dataset after first-order differencing.

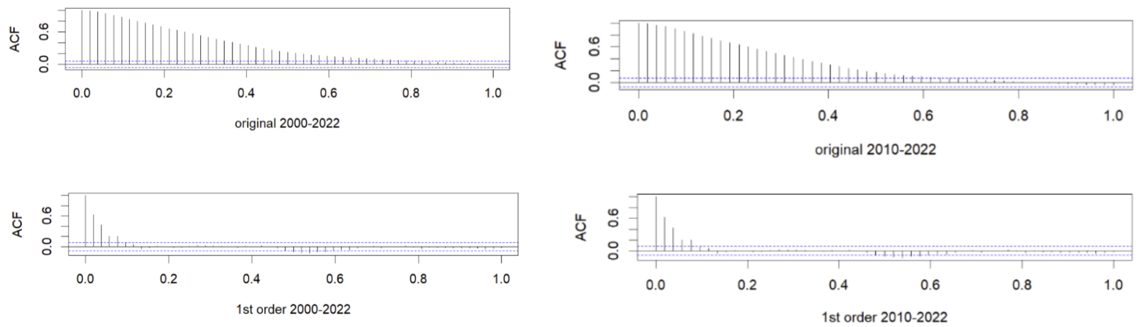

Figure 2. ACF for original and 1st order differencing time series

The ADF tests the null hypothesis that a unit root is present in a time series sample. The alternative hypothesis is different depending on which version of the test is used but is usually stationarity or trend-stationarity. (Augmented dickey–fuller test, 2022). Based on Figure 3, our small p-values(< 0.05) suggested rejecting and null hypothesis and confirming the stationary. Furthermore, time series when stationary was not white noise based on the ACF, which proved the significance of our continuing research on these time series.

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        Augmented Dickey-Fuller Test

data:  beforecovid_0022.diff
Dickey-Fuller = -9.2745, Lag order = 10, p-value = 0.01
alternative hypothesis: stationary
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```
        Augmented Dickey-Fuller Test

data:  beforecovid_1022.diff
Dickey-Fuller = -6.9674, Lag order = 8, p-value = 0.01
alternative hypothesis: stationary
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Figure 3. ADF test results for 2000-2022 & 2010-2022 time series

ETS Model

The ETS (error, trend, seasonal) model represents time series models that support the exponential smoothing methods, consisting of a trend component (T), a seasonal component (S), and an error term (E). These are based on error–trend–season probabilities of Hyndman, which is defined as an extended class of ETS methods using probability calculations based on the state space, with support for model selection and the calculation of standard forecast errors (Hyndman et al., 2002).

The long-term movement is characterized by the trend term, the pattern with known periodicity is reflected by the seasonal term, and the error term represents the irregular, unpredictable component of the series.

ETS models generate both point forecasts and prediction intervals (or forecasts). If the same values of the smoothing parameters are used, the point forecasts are identical but will generate different prediction intervals. The individual components of an ETS specification may be specified as being of the following form: N = none, A = additive, M = multiplicative:

E: A, M

T: N, A, M

S: N, A, M.

Our selection of the best method under the ETS family was mainly based on the Root Mean Square Error (RMSE). Root Mean Square Error (RMSE) is the standard deviation of the residuals (prediction errors). Residuals are a measure of how far from the regression line data points are; RMSE is a measure of how spread out these residuals are. (RMSE, 2021) In other words, it tells you how concentrated the data is around the line of best fit. Root mean square error is commonly used in forecasting, and regression analysis to verify experimental results. The better forecast performance of the model is that with the smaller error statistics.

ARIMA model

ARIMA (Autoregressive Integrated Moving Average) models provide another approach to time series forecasting, which aims to describe the autocorrelations in the data. ARIMA model is a form of regression analysis that gauges the strength of one dependent variable relative to other changing variables. An ARIMA model can be understood by outlining each of its components as follows:

Autoregression (AR): refers to a model that shows a changing variable that regresses on its own lagged, or prior, values.

Integrated (I): represents the differencing of raw observations to allow for the time series to become stationary (i.e., data values are replaced by the difference between the data values and the previous values).

Moving average (MA): incorporates the dependency between an observation and a residual error from a moving average model applied to lagged observations.

Each component in ARIMA functions as a parameter with a standard notation. For ARIMA models, a standard notation would be ARIMA (p, d, q), where integer values substitute for the parameters to indicate the type of ARIMA model used. The parameters can be defined as:

p: the number of lag observations in the model.

d: the number of times that the raw observations are differenced.

q: the size of the moving average window.

Our study used the R program to automatically select the best-fitted ARIMA model. The auto.arima() function in R uses a variation of the Hyndman-Khandakar algorithm, which combines unit root tests, minimisation of the AICc and MLE to obtain an ARIMA model (Hyndman & Khandakar, 2008).

Forecasting Performance Comparison

Forecasting accuracy offers valuable information about the best fit of the forecasting model and shows the capacity of the model to predict future values of the unemployment rate. Similar to the ETS model selection, RMSE has been used to evaluate the performance of models on in-sample data(training data). The better forecast performance of the model is that with the smaller error statistics.

Another method we also applied to model selection is AIC & BIC. Akaike Information Criterion (AIC), and the Bayesian Information Criterion (BIC) are chosen as the optimal models (Mutairu Oyewale, 2017). The model with the smallest values of AIC, and BIC are deemed to be the best fitting models.

Results and Limitations

The research used the ETS model and the ARIMA model to project numbers of continued claims after the latest reported claims ending Aug 16, 2022. The projections span 12 weeks, and are based on two series of weekly data of US continued claims: the first one from Jan 1, 2000 to Aug 16, 2022, and the second one from Jan 2, 2010 to Aug 16, 2022.

The research compared the different ETS models and used RMSE values to select the best fitting model; for the ARIMA models, the research used Auto ARIMA function in RStudio to identify the best fitting model with the smallest AIC value. The research concluded the best fitting ETS model for both the

2000-2022 series and the 2010-2022 series is ETS (A, Ad, N), while the best fitting ARIMA models for the 2000-2022 series and the 2010-2022 series are ARIMA (3,1,2) and ARIMA (2,1,3), respectively.

Table 1 below shows the 4 sets of projections based on the best fitting models selected. Figures 4-7 below visualize the projection results based on the different models. The projections based on ETS (2000-2022) and ETS (2010-2022) have extremely similar projections, while the projections based on ARIMA (2000-2022) and ARIMA (2010-2022) have more variation. The difference in projection variation may be attributed to the same best-fitting model, ETS (A, Ad, N), applied to both time series analyzed, while different ARIMA models fit best for the two time series.

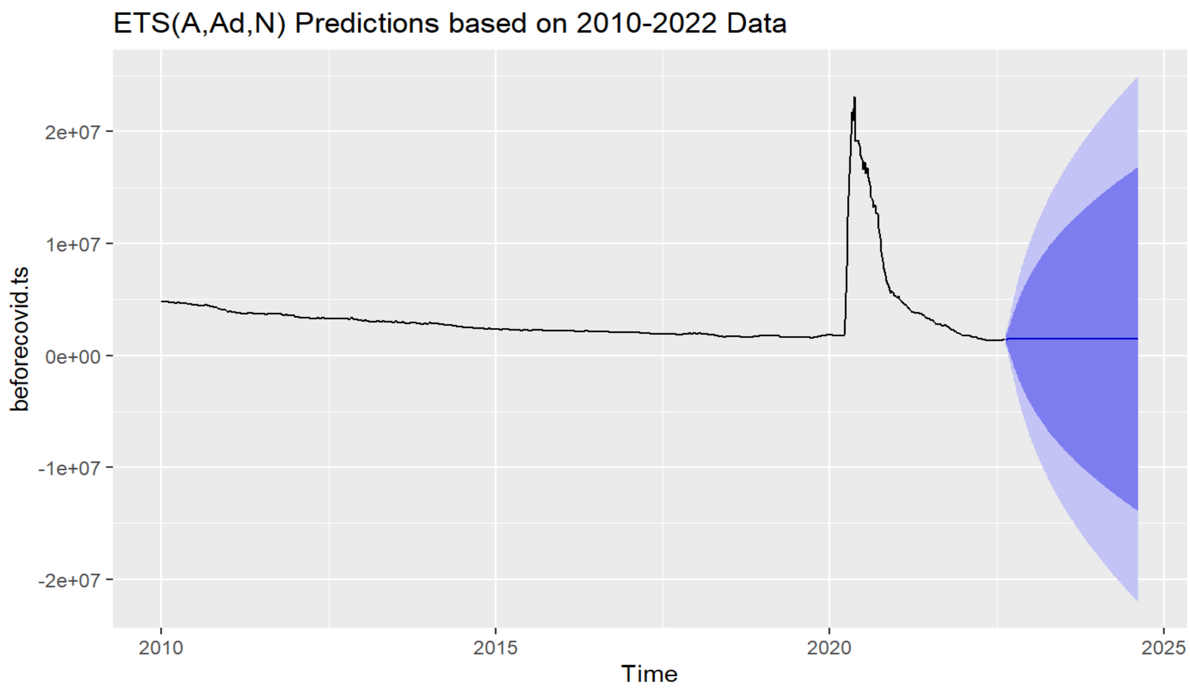

Figure 4. ETS 2010-2022 Projections

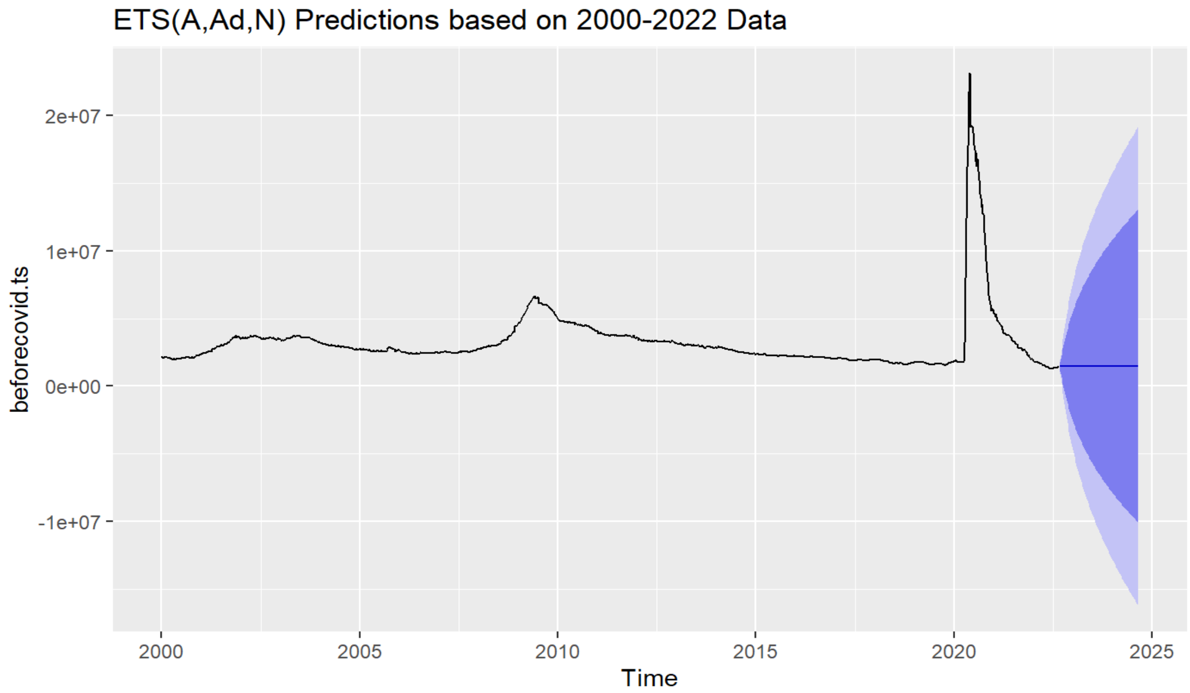

Figure 5. ETS 2000-2022 Projections

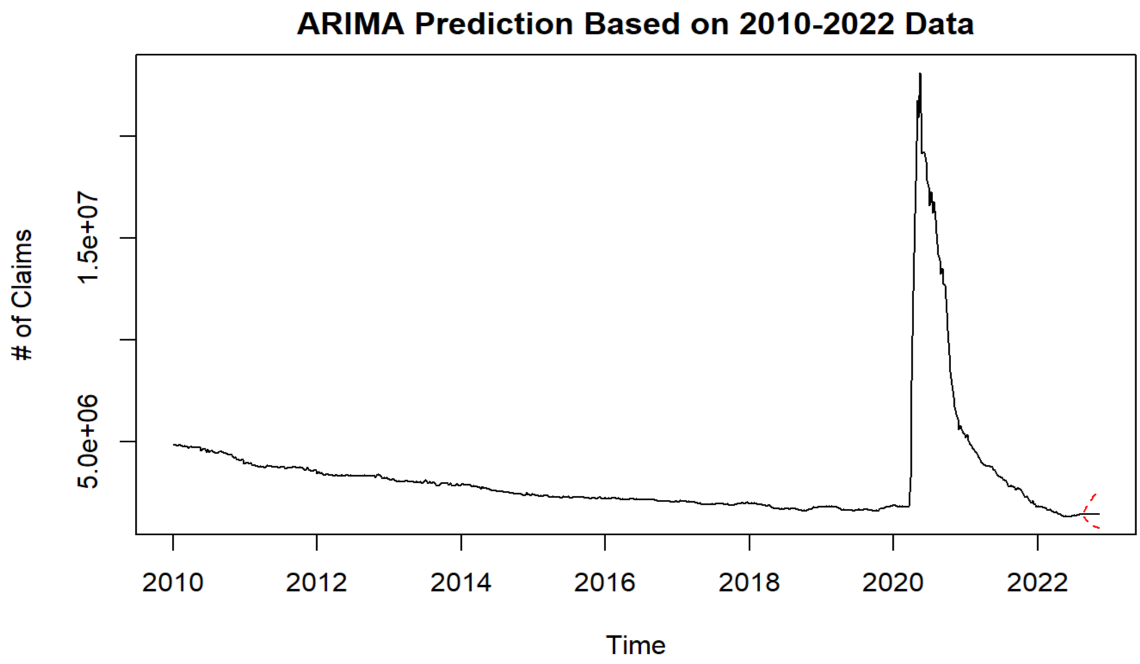

Figure 6. ARIMA 2010-2022 Projections

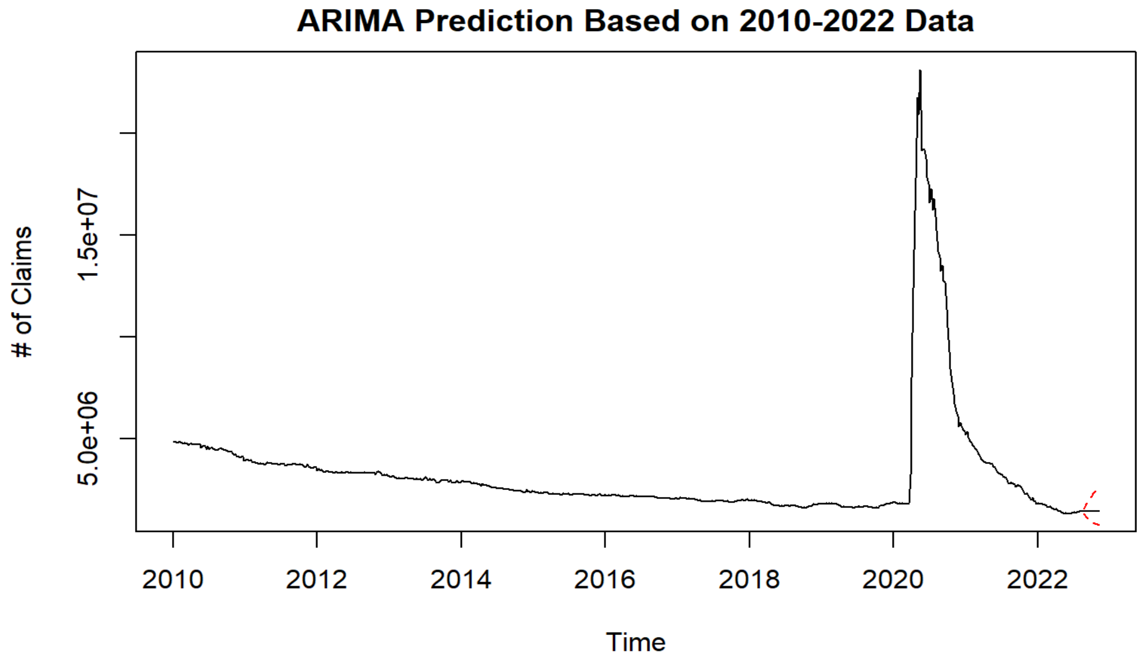

Figure 7. ARIMA 2000-2022 Projections

	Model												
Projection Period		1	2	3	4	5	6	7	8	9	10	11	12
	ARIMA(3,1,2) 10-22	1,412,609	1,413,950	1,408,385	1,405,152	1,406,330	1,402,840	1,404,650	1,402,747	1,403,519	1,403,002	1,402,990	1,403,097
	ARIMA(2,1,3) 00-22	1,418,312	1,424,283	1,417,554	1,421,322	1,417,399	1,419,751	1,417,450	1,418,906	1,417,550	1,418,445	1,417,642	1,418,191
	ETS(A,Ad,N) 10-22	1,448,535	1,454,663	1,459,564	1,463,486	1,466,623	1,469,133	1,471,140	1,472,747	1,474,032	1,475,060	1,475,882	1,476,540
	ETS (A,Ad,N) 00-22	1,448,623	1,454,795	1,459,732	1,463,682	1,466,842	1,469,370	1,471,393	1,473,011	1,474,305	1,475,340	1,476,169	1,476,831

Table 1. 12-Week projections based on four projection models

The research then compared the accuracies of the 4 projection models. Table 2 below shows the RMSE values for the four models, and regardless of the model selected, the best-fitting models for the 2000-2022 series had better fits than the models for the 2010-2022 series. When comparing the two models for the same time series, the ARIMA models had lower RMSE values, indicating higher accuracy.

Model	RMSE
ARIMA(3,1,2) 10-22	256,812.80
ARIMA(2,1,3) 00-22	334,910.90
ETS(A,Ad,N) 10-22	235,461.50
ETS (A,Ad,N) 00-22	308,808.80

Table 2. RMSE values for the four projection models

Figures 8-11 compare the residuals from the four projections. Both ETS models have a p-value < 0.05 when performing the Ljung-Box test, indicating the residuals are not white noise. The Ljung-Box tests for the residuals for ARIMA (2000-2022) and ARIMA (2010-2022) have p values of 0.3321 and 0.9731 respectively. The p-values are both larger than 0.05, meaning the residuals for both ARIMA models could be white noise, and the ARIMA models are more adequate in capturing all the correlations within the studied time series.

Ljung-Box test

data: Residuals from ETS(A,Ad,N)

Q* = 256.41, df = 99, p-value = 6.661e-16

Model df: 5. Total lags used: 104

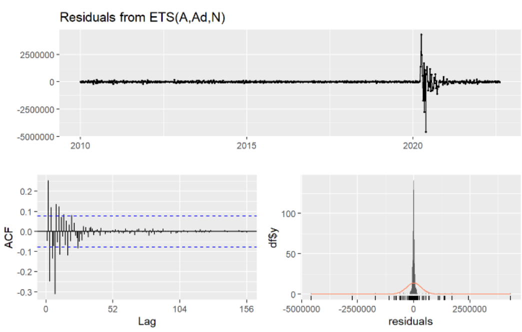

Figure 8. Residuals from ETS 2010-2022

Ljung-Box test

data: Residuals from ETS(A,Ad,N)

Q* = 437.62, df = 99, p-value < 2.2e-16

Model df: 5.   Total lags used: 104

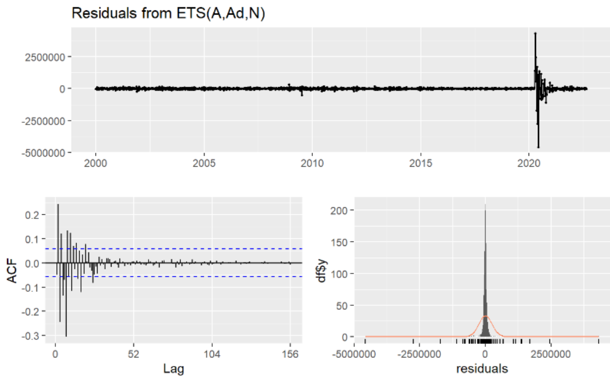

Figure 9. Residuals from ETS 2000-2022

Ljung-Box test

data: Residuals from ARIMA(3,1,2)

Q* = 73.715, df = 99, p-value = 0.9731

Model df: 5.   Total lags used: 104

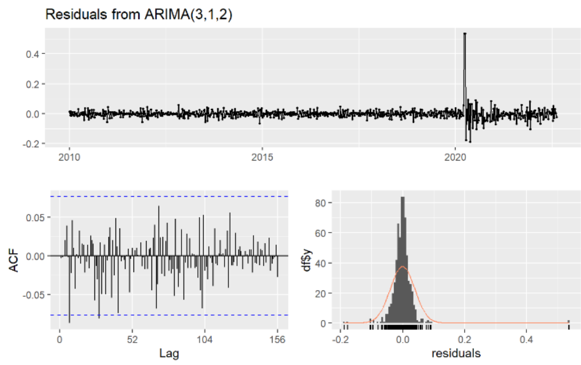

Figure 10. Residuals from ARIMA 2010-2022

Ljung-Box test

data: Residuals from ARIMA(2,1,3)

Q* = 104.55, df = 99, p-value = 0.3321

Model df: 5.   Total lags used: 104

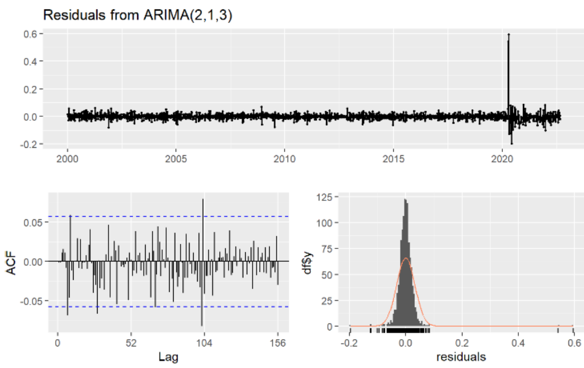

Figure 11. Residuals from ARIMA 2000-2022

Both the accuracy tests and the Ljung-Box tests for the residuals show the ARIMA models are better models for fitting and projecting the continued claims data. Based on the projection results, the number of continued claims will stay stable at around 1.4 million, within the next 12-week period. Even though the number of continued claims spiked in March 2020 following the outbreak of COVID-19, the projections show the sudden increase will not likely recur from September to November 2022.

Limitations of Study

One limitation of the study is that both ETS models had residuals that are not white noise, indicating further correlations can be summarized to advance the projection models. The low p-values of the Ljung-Box test on the models undermine the credibility of the projections resulting from the models. Another limitation is that the ETS models worked with the original data, while both ARIMA models, as best selected models, had a d value of 1, indicating they worked with the first order differencing of the original data. The different nature of the data used for projection means the AICs of the methods cannot be meaningfully compared to determine the methods' accuracies.

Recommendations for Future Research

The study focused on weekly continued claims data from 2000-2022 and 2010-2022, with the intention to compare how different time span selections will impact the projection results. The ARIMA models show when selecting different time periods, the best-fitting models are different. Future research can compare other time periods and identify social and economic events that may have impacted the number of claims in the US, to see if the best fitting models would change.

Another direction for future studies is to apply the method to other countries. Weekly data of continued claims, or people getting unemployment insurance, are meaningful tools to monitor an economy's employment performance, a critical contributing factor to an economic system's operation. COVID-19 as a global pandemic had worldwide economic impacts, and an unemployment spike occurred in many countries other than the US. Time series analysis and prediction of the number of continued claims for other countries and economies may benefit policy makers across the world.

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