United Airlines Time Series Analysis

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Abstract

In this paper, we will discuss a time series analysis approach on United Airlines stock data. A few different approaches will be taken in analyzing this data. To start, we will be investigating a subset of the data that predates the start of COVID-19 (2020). With this subset of the data, we will discuss an appropriate ARIMA (Auto-Regressive Integrated Moving-Average) modeling process. We will investigate the appropriate model diagnostics, assess the fit of our model, and compare this to an exponential smoothing model. Additionally, we will compare the forecasts from each class of models. This process will then be repeated on the full data, and we will investigate the effect that COVID-19 had on fitting time series models to United stock data. Lastly, we will compare the GARCH (Generalized Auto-Regressive Conditional Heteroskedasticity) models on each set of data.

Keywords: Time Series Analysis, Stock Data, ARIMA

1 Introduction

Stock market predictions are one of the most utilized time series analysis applications. However, this particular application of a time series problem presents its own unique challenges. Stock market data can take many forms, but something it is highly known for is its incredible volatility. When the COVID-19 pandemic introduced itself in early 2020, there were many stocks that were highly effected. The challenge COVID-19 presents is that it introduced an incredible amount of unexpected variance to the stock market, something that is already incredibly volatile. In this paper, we will investigate the effect that this unexpected variance had on one of the most effected companies, United Airlines. The goal of this analysis is to investigate the effect of COVID-19 in fitting ARIMA, Exponential Smoothing, and GARCH time series models to existing data.

The benefit of using ARIMA in this instance is that we can express the price at any given time point as a linear combination of a set number of previous observations and white noise. Additionally, ARIMA requires us to create a stationary process. This indicates that we can adjust our data so that its behavior remains consistent over time. As we rarely observe stationary processes in stock market data, this necessity of an ARIMA model to assume a constant mean and variance can add a degree of accuracy to estimating the data generative process and forecasted predictions. Exponential smoothing is valuable in the sense that is allows us to apply different weights to past observations. We can place higher weights on more recent observations, and these weights exponentially decrease as we go back in time (thus, *exponential* smoothing).

Lastly, fitting GARCH models allows us to assess the variance in our models. This becomes appropriate because it allows us to interpret the accuracy of the models we fit to the data, and how much we can anticipate the expected value of time series data points to change. In this particular problem scope, it is applicable in the sense that it allows us to compare the risk of investing in United Airlines before and after COVID-19.

2 Data Description

The data used in this paper contains United Airlines daily stock price information from January 2, 2014 to December 4, 2024. This data was collected using the *quantmod* package in the programming language *R*. The data contains 2,750 entries and contains information on the opening, high, low, closing, and adjusted stock prices. It also contains information on the total number of shares traded over a given day. For our purposes, we will be utilizing and investigating the trend in closing price. For our analysis, we will also be examining a subset of the data with closing stock prices from January 2, 2014 to December 31, 2019. This subset has 1,510 observations.

Some particular challenges involved with data of this type is the unexplained variance that commonly occurs in the stock market. Additionally, stock price data is often non-stationary, which presents challenges in the sense that some modeling procedures require stationary data. Lastly, it is important to note that we do not have available data on each individual day. For example, our data only has available information on trading days, which excludes weekends and holidays. It is also important to note that there is often little to no seasonality in stock market data.

3 Methodology

The first method we investigate in attempts to model our data is an ARIMA process. ARIMA stands for Auto-Regressive Integrated Moving-Average, and it is made up of three separate components. To start, let's discuss an auto-regressive process. If Y_t is the observed value at time t, we can express Y_t in terms of previous observed values. That is,

$$Y_t = \phi Y_{t-1} + \epsilon_t, \tag{1}$$

where ϕ is a constant and ϵ_t is white noise. This is commonly known as an AR(1) model, where we only utilize that last observed value. This can be generalized to an AR(p) model in which

$$Y_t = \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + ... + \phi_p Y_{t-p} + \epsilon_t. \tag{2}$$

In this case, the last p observed values are used to express Y_t. This is very similar to how the moving average (MA) process is explained. However, in this case, we use previous white noises to express Y_t. Note that white noises (e_i) come from a normal distribution with mean 0 and variance of 1. In an MA process of order q, we have

$$Y_t = \phi_1 \epsilon_{t-1} + \phi_2 \epsilon_{t-2} + ... + \phi_q \epsilon_{t-p} + \epsilon_t. \tag{3}$$

The last component of an ARIMA model is the order of integration. In order to understand integration, we must first understand some underlying assumptions of ARIMA modeling. In order to apply an ARIMA model to a set of data, the observed values must exhibit behavior that is *stationary*. A stationary process is one who's behavior does not change over time. In short, we assume that a stationary process is one with a constant mean and variance. If our data proves to be non-stationary, we must transform the time series to be stationary. This is where integration becomes important. All ARIMA analysis in this paper will contain first order integration, also known as differencing. In this case, define

$$W_t = Y_t - Y_{t-1}, \tag{4}$$

and reevaluate the newly differenced time series to check for stationary behavior. We combine all three of these components to formulate an ARIMA(p, d, q) model, where p is the order of auto-regressive terms, d is the order of differencing, and q is the order of moving average.

Another modeling technique utilized in this analysis is exponential smoothing. This method has many different variations, but for our purposes, we will focus on Simple Exponential Smoothing (SES). SES is a method that works especially well when there is no trend or seasonality in the data. In SES, we express the current time observation Y_t in terms of previous observations, similar to an AR process. However, in this case, we assign exponentially decreasing weights to past terms. Thus, observations further back in time are less influential on the predicted value. We determine the weight on each past observation by defining the smoothing parameter α, such that the smoothing equation is expressed as

$$\hat{Y}_t = \alpha Y_{t-1} + \alpha(1-\alpha)Y_{t-2} + \alpha(1-\alpha)^2 Y_{t-3} + ..., \tag{5}$$

where $0 < \alpha < 1$. We can set the value of α based on if we want a slow or fast learning model. Slow learning models, where α is typically between 0.1 and 0.2, usually perform better. This is because we don't put as large of weights on recent observations and allow more influence to historical data. Fast learning models have α values closer to 1 and place a lot of importance on recent observations. There is little seasonality in United Airlines closing stock price, so exponential smoothing is a method that could work well if there proves to be minimal trend.

Lastly, we will be investigating the application of GARCH (generalized auto-regressive conditionally heteroskedastic) models in estimating the volatility of our data. GARCH models also have a stationarity assumption, so when used in practice, they are often applied to stock returns. We will perform a similar analysis in this paper, as we attempt to investigate the impact of COVID-19 on the volatility on observed values of stock returns. A GARCH model uses both past squared observations and past variances to explain the variance at the current time point. We can define the order of our GARCH model, similar to defining order in an ARIMA process, by specifying the number of past observations and variances that contribute to the current value. We can express the variance at time t using a GARCH(1,1) model as

$$\sigma_t^2 = \alpha_0 + \alpha_1 Y_{t-1}^2 + \beta_1 \sigma_{t-1}^2, \tag{6}$$

where $\alpha_0 > 0$. Similar to an ARIMA process, this can be expanded to higher order to include more past squared observations and past variances.

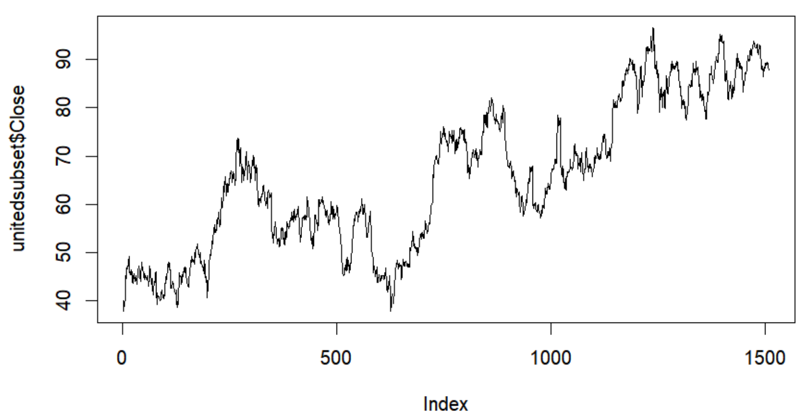


Figure 1: Pre-COVID-19 United Airlines Closing Price

When we begin analysis on the actual data, we must first check the assumption that it is stationary. Figure 1 displays the closing price of United Airlines stock prior to COVID-19. Stock data is commonly non-stationary, and this appears to be the case here. While the variance appears to be fairly consistent across all time indexes, there is an apparent shift in mean as we increase in time index. Visually, it appears that this time series is not stationary. This is confirmed with the results of an Augmented Dickey-Fuller (ADF) test. The ADF tests checks the roots of the characteristic polynomial and has a null hypothesis that our time series has a unit root. This would indicate that it is non-staionary. When we run the ADF test on the unedited data, we are returned a p-value of roughly 0.09. If we set $\alpha = 0.05$, this p-value is not small enough to reject the null hypothesis and conclude our data is stationary.

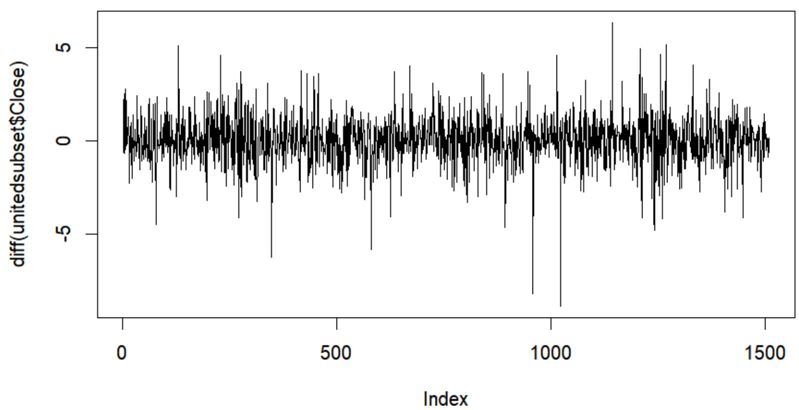


Figure 2: Differenced United Airlines Closing Price

Thus, we will difference our data in an attempt to make it stationary. Figure 2 displays our differenced data, and visually, it appears to have constant mean and variance. This is confirmed with an ADF p-value of less than 0.01. Now that our data is stationary, we can begin the model fitting process.

The fitting criterion we will be utilizing in this paper is Akaike's Information Criteria (AIC). AIC is commonly used in model specification when the goal is to make the most accurate predictions. Our goal is to minimize the AIC value in order to create the model with the most predictive power. To do this, many different ordered ARIMA models were tested, and the model with the minimum AIC value proved to be an ARIMA(5,1,5) model. The fitted values can be seen in Figure 3.

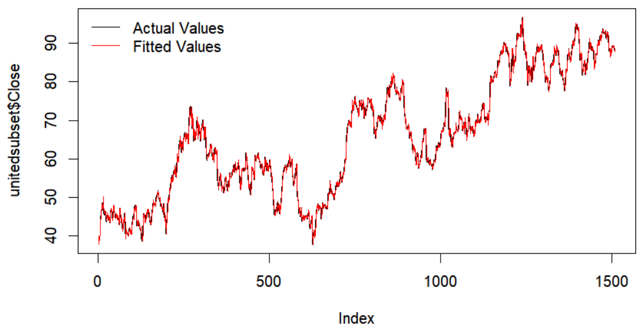


Figure 3: SES Fitted vs. Actual Values

An exponential smoothing model will now be fit to the data prior to COVID-19. As discussed above, SES works well on data with no consistent trend or seasonality. Based on Figure 1, there is a possibility that there is an increasing trend, so model diagnostics will be key in assessing the reliability of SES. We will set $\alpha = 0.2$ and create a slow learning model. This is done in attempt to create a better fitting, more accurate SES model. The fitted values can be seen in Figure 4.

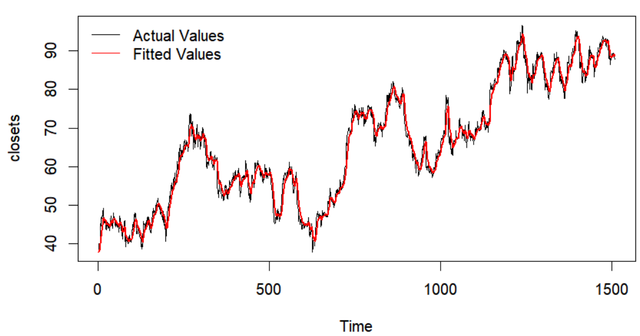
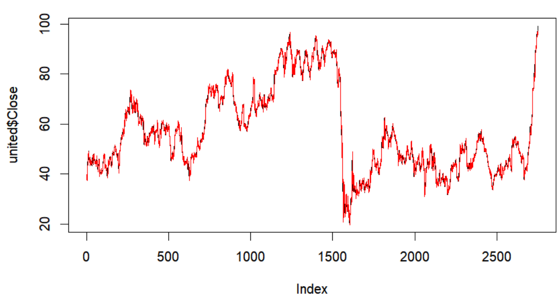
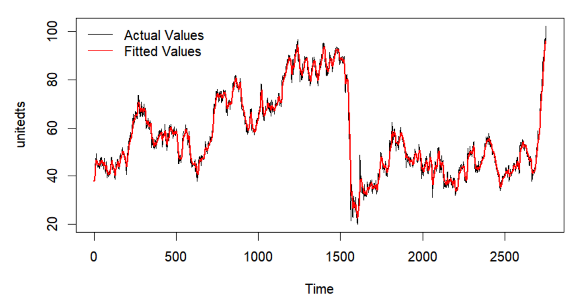


Figure 4: SES Fitted vs. Actual Values

Next, we will compare the ARIMA and SES fits on the full data ranging from 2014-2024. For the ARIMA model, we must first assert that the data is stationary. An ADF test reveals that while the unaltered data is not stationary, the differenced data does have constant mean and variance. We now undergo the same modeling process as described above and test different ordered models on the data. We then select the model with the minimum AIC value, and ARIMA(2,1,4) model. We also take a similar approach in fitting an SES model. We will once again use $\alpha = 0.2$. The respective model fits can be seen in Figure 5. Next, we will fit a GARCH model to the full



(a) ARIMA Fit



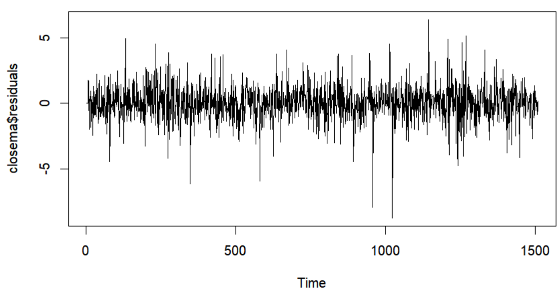
(b) SES Fit

Figure 5: Full Data ARIMA and SES Fits

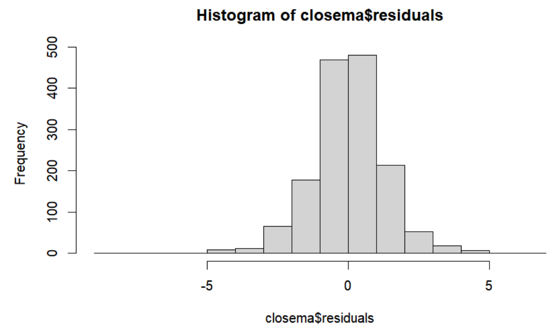
data. This is done to assess the volatility of United stock and fitting this model to the full data allows us to assess how COVID-19 affected the volatility of the stock. Our strategy for fitting a GARCH model will slightly differ from that in ARIMA and SES. Since we are now fitting a volatility estimate to stock returns, we will attempt to create an accurate fit with the simplest model possible. To start, a standard GARCH(1,1) model was fitted to United Airlines stock returns from 2014-2024. We will assess its fit in the *Data Analysis and Results* section.

4 Data Analysis and Results

In order to determine the effect of COVID-19 on fitting time series models to United Airlines stock data, we want to compare the error of fitted values from the subset data and the full data. In addition, we want to compare the patterns in each model's forecasted values. However, if we want to provide reliable interpretations of each model, we must first investigate model diagnostics. In particular, we are looking for randomly patterned, uncorrelated, normally distributed residuals from each model.



(a) Plotted Residuals



(b) Residual Distribution

Figure 6: Pre-COVID-19 Diagnostics

Figure 6 displays some of the diagnostic plots on the residuals from the ARIMA(5,1,5) model applied to subset of data prior to COVID-19. As we can see, the residuals appear to be normally distributed and have no apparent pattern. Additionally, PACF and ACF plots show that there is no auto-correlation among the residuals. This is confirmed with the Ljung-Box Test, which yielded a p-value of roughly 0.99. As this statistical test has a null hypothesis that the residuals are uncorrelated, we fail to reject the null and confirm no correlation among residual terms. The same analysis proves to be true for an ARIMA(2,1,4) model on the full data. The residuals appear to be normally distributed, and the Ljung-Box Test confirms that they are uncorrelated from one another.

Figure 7 displays the residual ACF plot from the SES model fit to the data prior to COVID-19. This plot provides evidence that there is cause for concern with this model, as it appears there is correlation among our residuals. This is confirmed with a Ljung-Box Test returning a p-value of approximately 0. This indicates that there is most certainly correlation among residual terms, and we cannot trust this model's fit and predictions. When the SES model on the full data is tested diagnostically, we find the same results. Both SES models need to be adjusted as they do not capture all the patterns in our data. Because of this fact, we will focus on comparing each ARIMA model's fits and predictions.

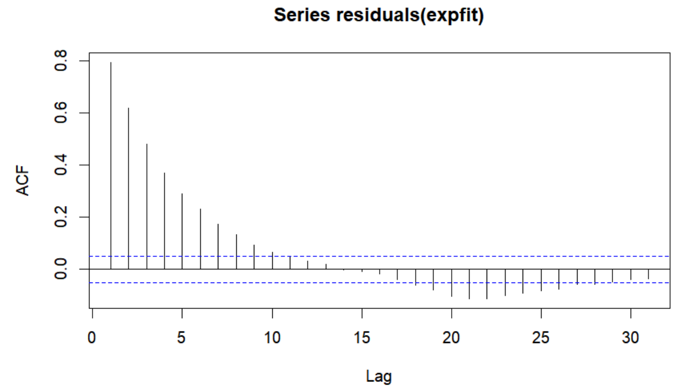


Figure 7: Pre-COVID-19 SES Residual ACF

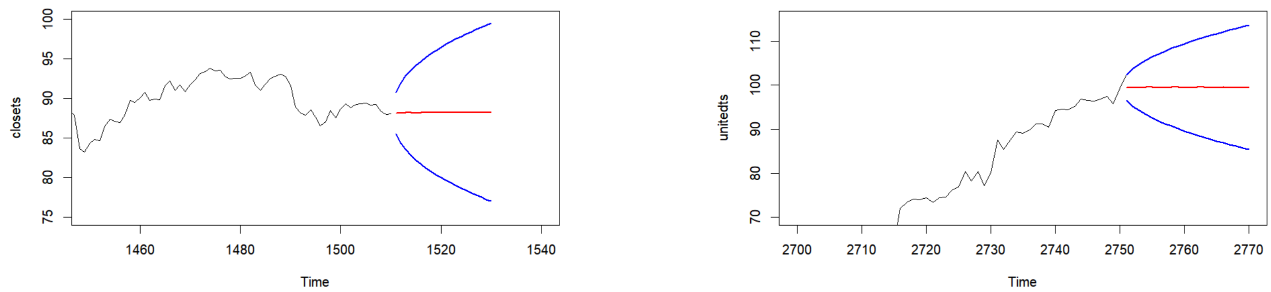
When comparing ARIMA fits, a visual interpretation is insufficient in this case. If we compare Figures 3 and 5a, it appears that each model performs similarly. To look at this from a statistical standpoint, we will compare RMSE values (Root Mean Squared Error). This is a commonly used method in comparing the fit of models on continuous data. Table 1 displays the RMSE score comparisons. So, while the model fit to data previous to COVID-19 is more

Table 1: RMSE Comparison

Model	Data Applied To	RMSE
ARIMA(5,1,5)	Pre-COVID-19	1.32
ARIMA(2,1,4)	Full Data	1.46

accurate, it does not outperform the full model by an overwhelming amount. We are still able to generate a comparably good fitted model to data including COVID-19 observations. When we analyze the pattern in the 20-day prediction window, we also see similarities. There is very little fluctuation in the actual forecasted values over the course of each prediction window. Additionally, when we take the scale of each graph in Figure 8 into account, it appears that there is similar variance as well.

Lastly, let's investigate the results of our GARCH model on stock returns. Figure 9a displays the stock returns over time with a confidence bound created from the fitted standard deviations of our GARCH model. It appears that our GARCH model does a fairly good job, as the confi-

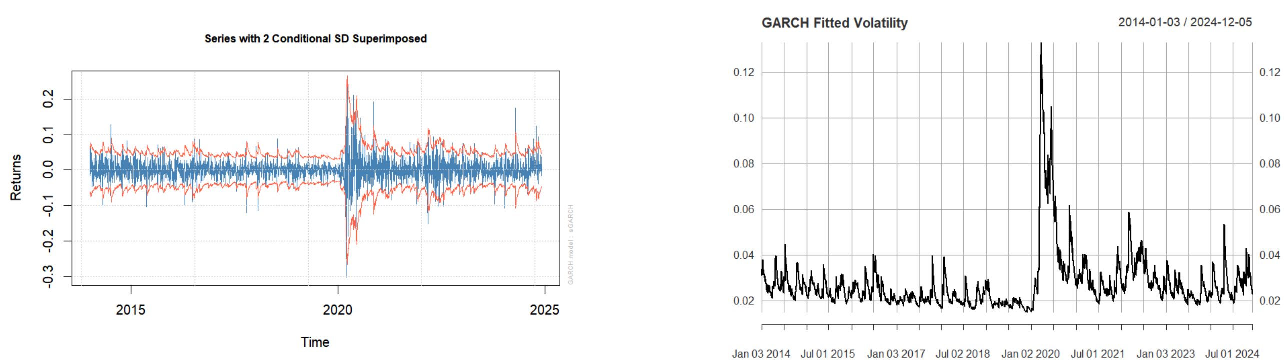


(a) Pre-COVID-19 Predictions

(b) Full Model Predictions

Figure 8: 20-Day Predictions

dence bound exceeds the stock return at almost all given time points. There are a few outlying return values, but with so much data, this can be expected with a 95% interval. Additionally, Figure 9b displays the fitted volatility across all time points contained in our data. As we can see, our model captures the large variance that we expected to see during COVID-19. We can also see that, after COVID-19, the GARCH model fits an average volatility that is higher than the average volatility before COVID-19. This tells us that perhaps COVID-19 is still having an impact on how we predict and fit the volatility of certain stock data.



(a) GARCH Return, 95% CI

(b) Fitted Volatility

Figure 9: GARCH Model Plots

5 Conclusion

Throughout this analysis, we learned that even with the unexplained variance that COVID-19 introduced into our data set, we were still able to create models that had similar accuracy and prediction trends. We were also able to discover that COVID-19 does affect how we fit volatility to stock market data, but the GARCH model was able to capture this increased variance after 2020. Suggestions for further analysis include making adjustments to exponential smoothing models in order to have trusted fitted and forecasted values, as well as repeating this analysis on stocks less affected by COVID-19.

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