Forecasting Accounts Receivable in Domestic Agriculture

A project presented to the

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and the

Faculty of the Graduate College

University of Nebraska

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Master of Science

University of Nebraska at Omaha

by

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<u>Supervisory Committee</u>

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1. Abstract

This project focuses on developing a robust forecasting framework for Valmont's domestic agriculture accounts receivable for the Treasury Department to help improve business operations and rigorize the forecasting process. Due to Valmont's nascent development in data science, there was limited immediate data to be utilized. Given the limited dataset—only a few years of daily records—time series modeling was employed to generate predictions on weekly and monthly timeframes. Initial efforts involved using a Seasonal AutoRegressive Integrated Moving Average (SARIMA) model to forecast the cash flows of a single bank account that contained the bulk of transactions. The model demonstrated high diagnostic reliability and was subsequently generalized to a group of accounts encompassing almost all of the receivables. To further enhance the predictive accuracy, the SARIMA-generated forecasts were integrated with additional temporal features and processed using an Extreme Gradient Boosting (XGBoost) machine learning model. The hybrid approach effectively combined the strengths of traditional time series analysis with advanced predictive analytics. This framework offers a scalable methodology for financial forecasting in the context of sparse data, with potential applications in broader operational and strategic financial planning across all of Valmont's areas of production.

2. Acknowledgements

First, I would like to thank the excellent teachers at UNO who have helped me through this process: Dr. Xiaoyue Cheng and Dr. Andrew Swift. I am grateful to Dr. Cheng for the opportunities she has provided me and for her investment in my professional development. I deeply appreciate Dr. Swift for his patience, guidance, and for being a much-needed lighthouse of sanity. Finally, I would like to thank my mom, who has only shown me unending compassion and unwavering support.

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3. Background

3.1 Valmont Industries Overview

Valmont Industries, Inc. is a globally recognized leader in the design and manufacture of engineered metal structures and advanced water management solutions. The company operates across multiple sectors, with a significant focus on infrastructure and agriculture. Within its agricultural division, Valmont is a pioneer in precision irrigation technologies, offering systems such as center pivot and linear irrigation solutions that optimize water usage, enhance crop yields, and promote sustainable agricultural practices. These systems play a critical role in addressing global challenges such as water scarcity, food security, and climate variability.

3.2 Importance of Financial Forecasting

Effective financial forecasting is a cornerstone of strategic decision-making within the agricultural and irrigation industries. The seasonal and cyclical nature of agricultural production, coupled with market volatility and variable payment terms, underscores the need for precise financial projections. For a company like Valmont, accurate forecasting of accounts receivable is particularly vital for several reasons:

1. **Optimizing Working Capital**: Reliable forecasts enable efficient cash flow management, ensuring the availability of liquidity to meet operational demands while minimizing excess reserves.

2. **Informing Strategic Decisions**: Anticipating financial inflows provides critical insights for resource allocation, production scaling, and investment planning, aligning operational capabilities with market demands.

3. **Risk Mitigation**: Advanced forecasting techniques help identify potential disruptions in financial flows, allowing the organization to implement proactive risk management strategies.

4. **Enhancing Stakeholder Confidence**: Precise financial projections strengthen the company's position with investors, creditors, and other stakeholders by demonstrating fiscal responsibility and operational resilience.

Given the criticality of these factors, developing an advanced forecasting model for Valmont's domestic agriculture accounts receivable is a necessary step toward improving financial efficiency and resilience.

3.3 Project Objectives

The project aims to integrate traditional time series modeling and advanced machine learning techniques in a way that is accessible to employees that lack the technical training to implement these models. The ultimate goal of this study is to provide accurate forecasts on weekly and monthly timeframes. Longer timeframes move outside of cash flow forecasting and into the realm of revenue forecasting while daily forecasts are too granular; the variance is too high to get meaningful results and the use of these forecasts is limited to Treasury at a company the size of Valmont. Initially, a Seasonal AutoRegressive Integrated Moving Average (SARIMA) model is employed to capture temporal patterns and seasonality in the data. Predictions generated by the SARIMA model are then combined with additional temporal features, such as fiscal and calendar variables, and used as inputs for an Extreme Gradient Boosting (XGBoost) model. This hybrid approach leverages the strengths of both methodologies: SARIMA's ability to capture the autocorrelation patterns in the seasonal agricultural cash flow, and XGBoost's capacity to handle multiple patterns over longer time periods.

4. Methodology

4.1 Data Overview

The data consists of weekday deposits into a bank account(later a group of bank accounts) dating back to May 2nd, 2022. The data was aggregated by taking weekly sums where the first day of the week is Monday and the last is Friday. There are no deposits on weekends or bank holidays, resulting in those days having a value of 0. Since the most granular prediction was on a weekly level, holidays didn’t affect the process much beyond implementing a flag later on for if a given week contained a bank holiday.

4.2 Seasonal AutoRegressive Integrated Moving Average (SARIMA) Model

Given the univariate structure, the initial methodology used was a SARIMA model. ARIMA models are widely used in time series analysis to model and forecast data by combining three components: autoregression (AR), differencing (I), and moving averages (MA). The AR component captures the relationship between a variable and its lagged values, the I component removes trends to make the data stationary, and the MA component models the relationship between a variable and past forecast errors. However, when data exhibit repeating seasonal patterns, ARIMA alone may not suffice. Seasonal AutoRegressive Integrated Moving Average (SARIMA) models are an extension of the ARIMA framework designed to handle time series data that exhibit both non-seasonal and seasonal patterns.

SARIMA incorporates additional terms to specifically address seasonality. These include seasonal autoregression (PP), seasonal differencing (DD), seasonal moving averages (QQ), and a seasonal period (ss) that defines the length of the seasonal cycle. The resulting SARIMA model is expressed as (p,d,q)×(P,D,Q,s), where p, d, and q represent the non-seasonal parameters, and P, D, Q, and s define the seasonal parameters. Seasonal differencing removes cyclical trends, such as yearly fluctuations, ensuring the data meet the stationarity assumption required for time series modeling.

SARIMA models are particularly useful in applications where cyclical patterns are strongly tied to specific intervals, such as weekly, monthly, or yearly sales or cash flows. The parameters of SARIMA are typically chosen based on diagnostic tools like autocorrelation function (ACF) and partial autocorrelation function (PACF) plots, as well as trial-and-error processes to minimize error metrics like Akaike Information Criterion (AIC) or Bayesian Information Criterion (BIC).

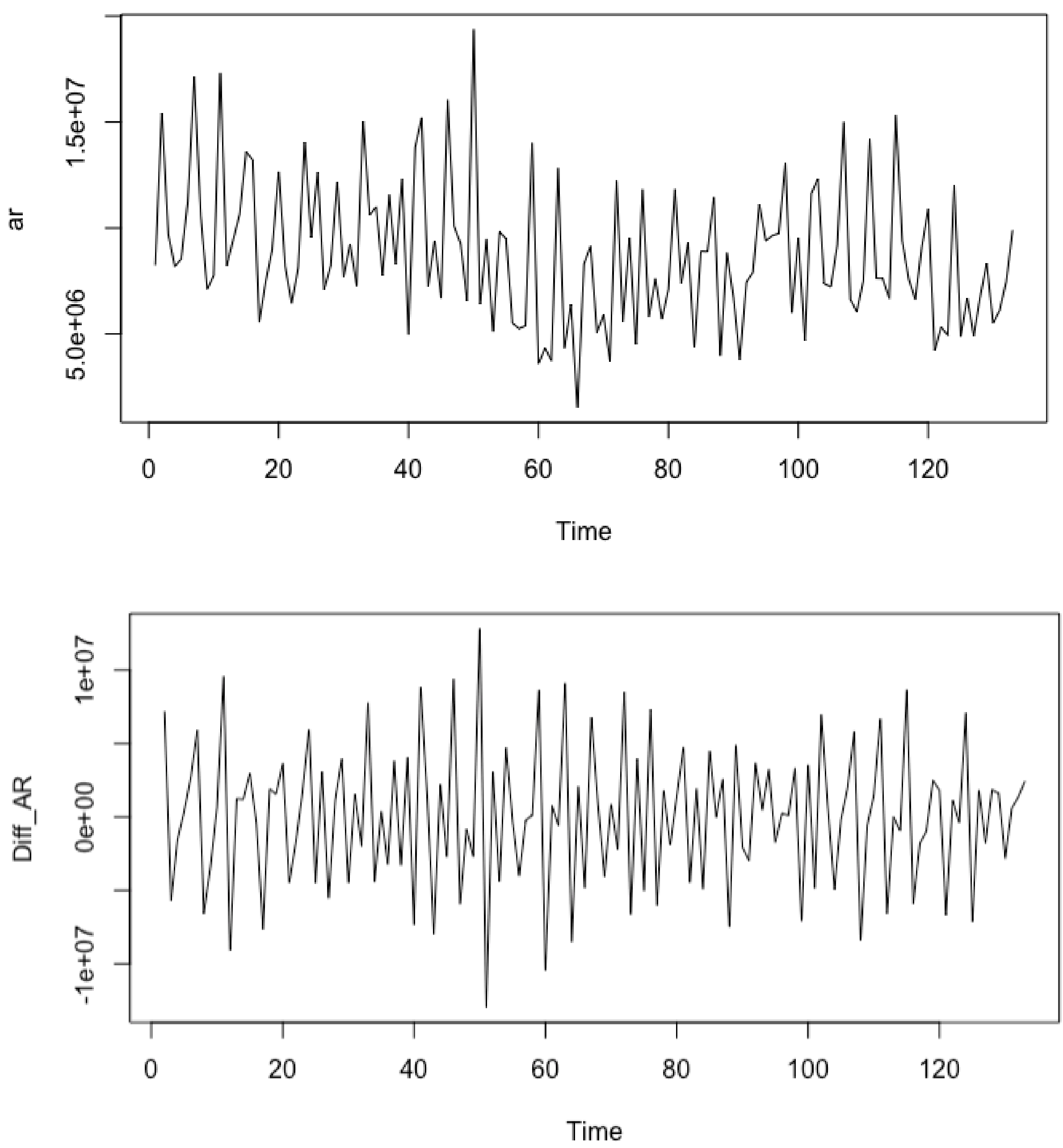
4.3 Model Selection And Diagnostics

To decide the model parameters, the data was plotted as a time series and then the augmented dickey-fuller root test was used to determine if differencing was necessary. Then the ACF, PACF, and EACF were checked to give a starting point for parameter selection. Models were then diagnosed via outlier detection and residual analysis, and compared via AIC. Residual analysis included checking the plot of standardized residuals, checking the ACF of residuals, the Ljung-Box test, the Shapiro-Wilks test for normality, checking the qq plot of the residuals, plotting a histogram of the residuals against a standard normal curve, and the McLeod-Li test for volatility clustering.

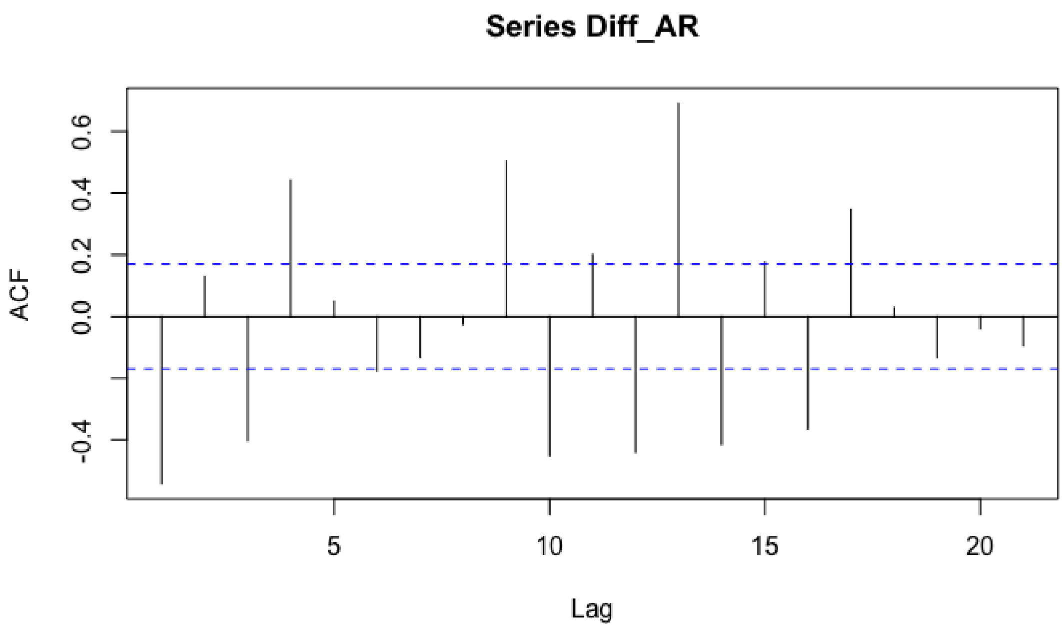
4.3.1 Singular Bank Account

The first attempt at modeling was on an account containing approximately 75% of domestic agriculture's receivables.

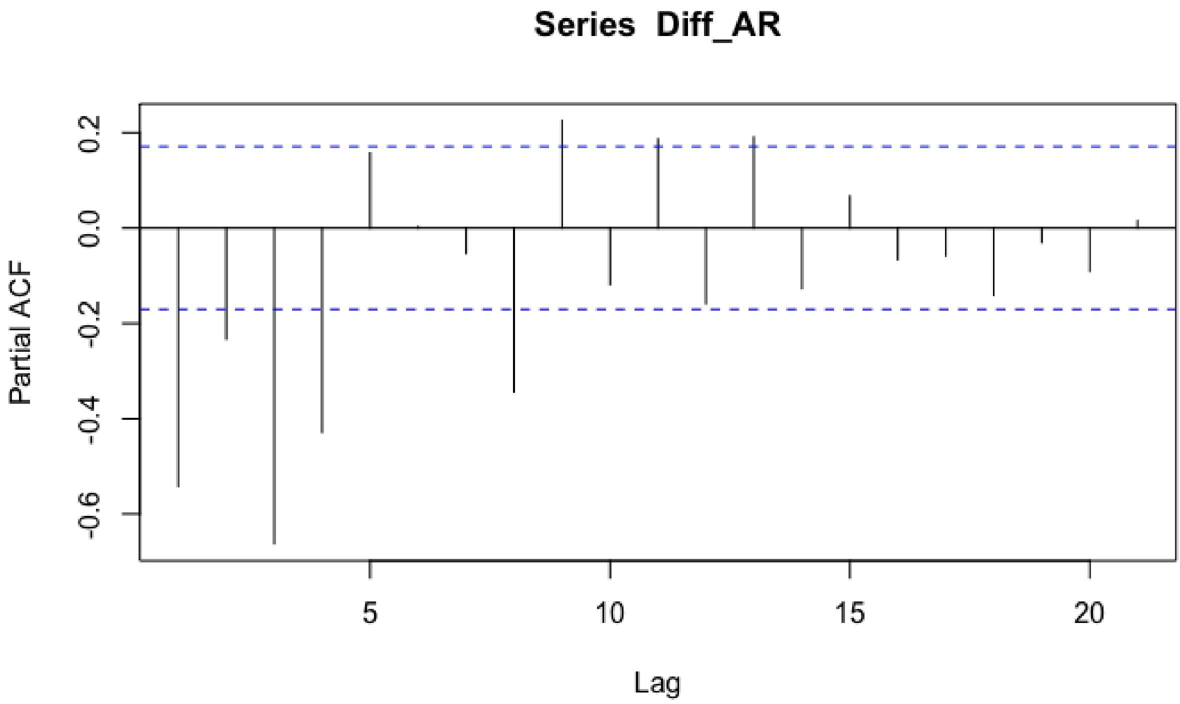
Singular Bank Account Weekly and Differenced Amounts Over Time



The data appeared non-stationary and the ADF test returned a p-value of .24, which also implies the data is not stationary. After differencing, the ADF test returned a p-value of less than .01 and the plot looked reasonable, so a first-differenced model was applied. Following this, plots of the ACF, PACF, and EACF were generated.



ACF of Weekly Amounts from Singular Account



PACF of Weekly Amounts from Singular Account

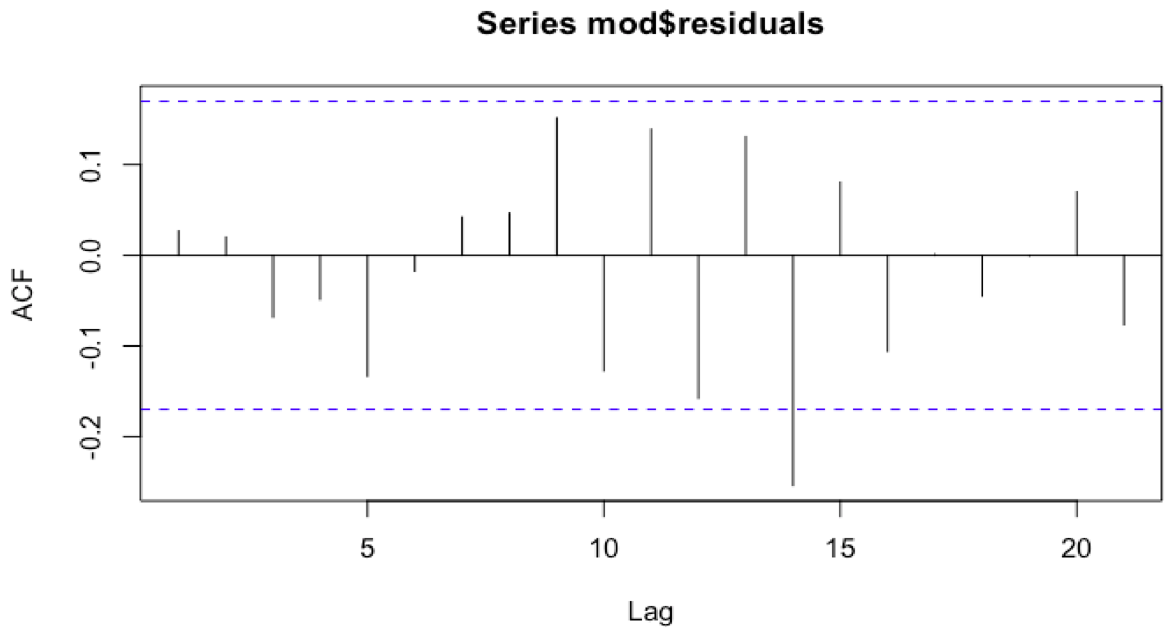
AR/MA	0	1	2	3	4	5	6	7	8	9	10	11	12	13
0	x	o	x	x	o	o	o	o	x	x	x	x	x	x
1	x	x	x	x	o	o	o	o	x	x	x	o	x	o
2	x	x	x	x	o	o	o	o	x	x	x	o	x	o
3	x	x	x	x	o	o	o	o	x	x	x	x	x	x
4	x	o	o	x	x	o	o	o	o	o	o	o	o	o
5	o	o	o	x	x	o	o	o	o	o	o	o	o	o
6	o	o	o	x	x	o	o	o	o	o	o	o	o	o
7	o	o	x	x	o	o	o	o	o	o	o	o	o	o

EACF of Weekly Amounts from Singular Account

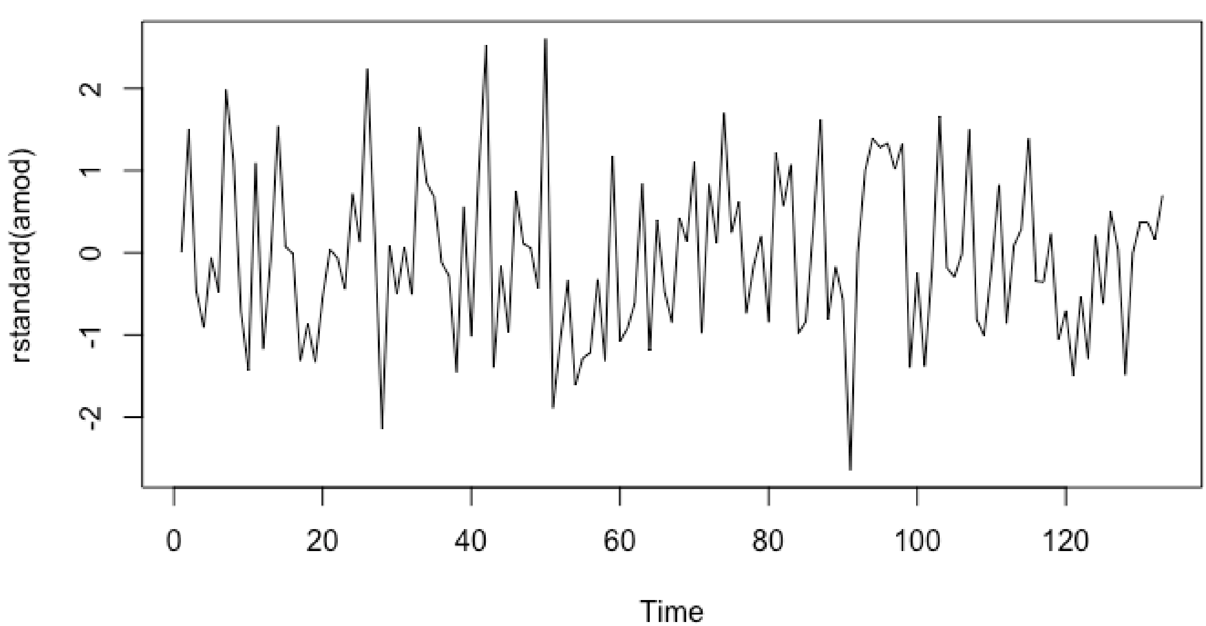
These results suggested p and q values in the range of 3-5 with clear seasonality present at further lags to be examined later. Several ARIMA models with varying parameter configurations were then examined and compared via AIC and were virtually identical with values of around 4272 . No outliers were detected via the detectAO and detectIO functions from the TSA R package, the standardized residuals and ACF of the residuals were checked, and the Ljung-Box and McLeod-Li tests were applied. The residuals were also run through the

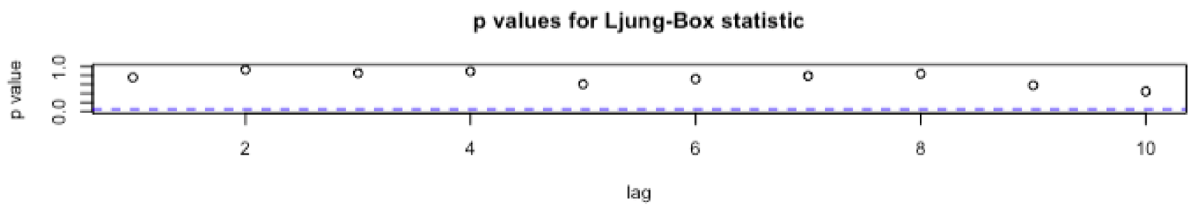
Shapiro-Wilks test for normality and compared to a qq-plot/line and a histogram was compared to the appropriate normal density curve. Below are the diagnostic results for the (3,1,3) model:

ACF of Model Residuals



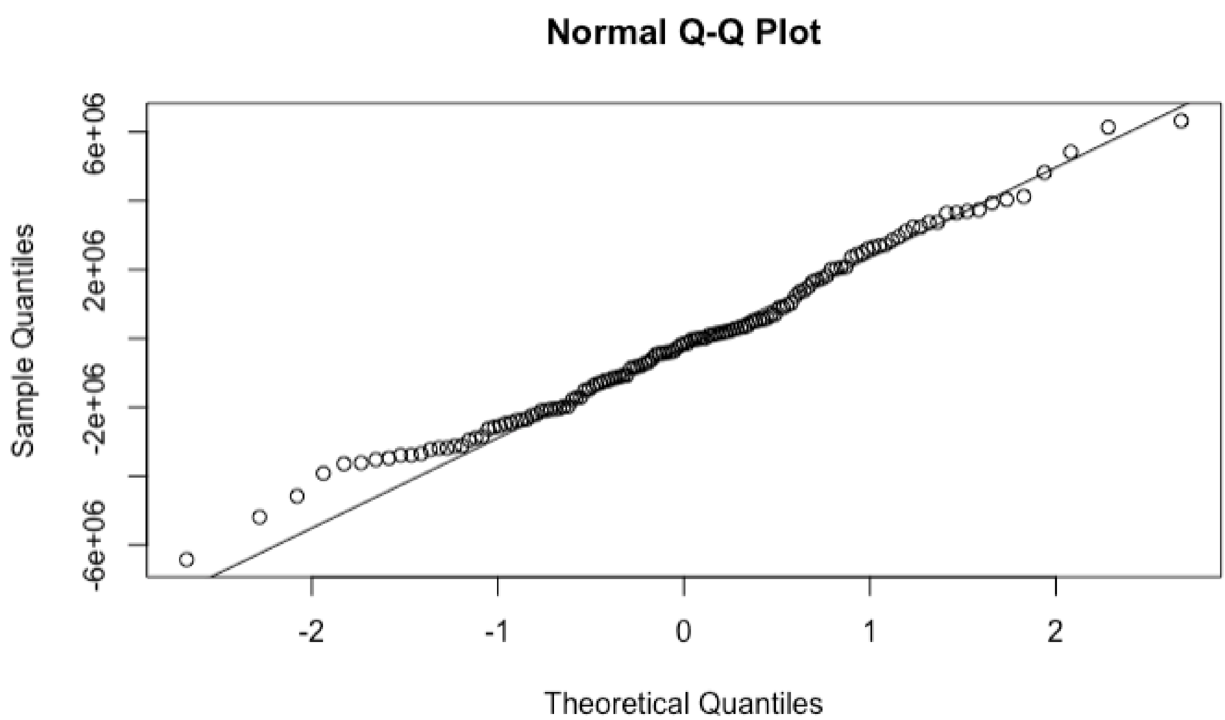
Standardized Residuals



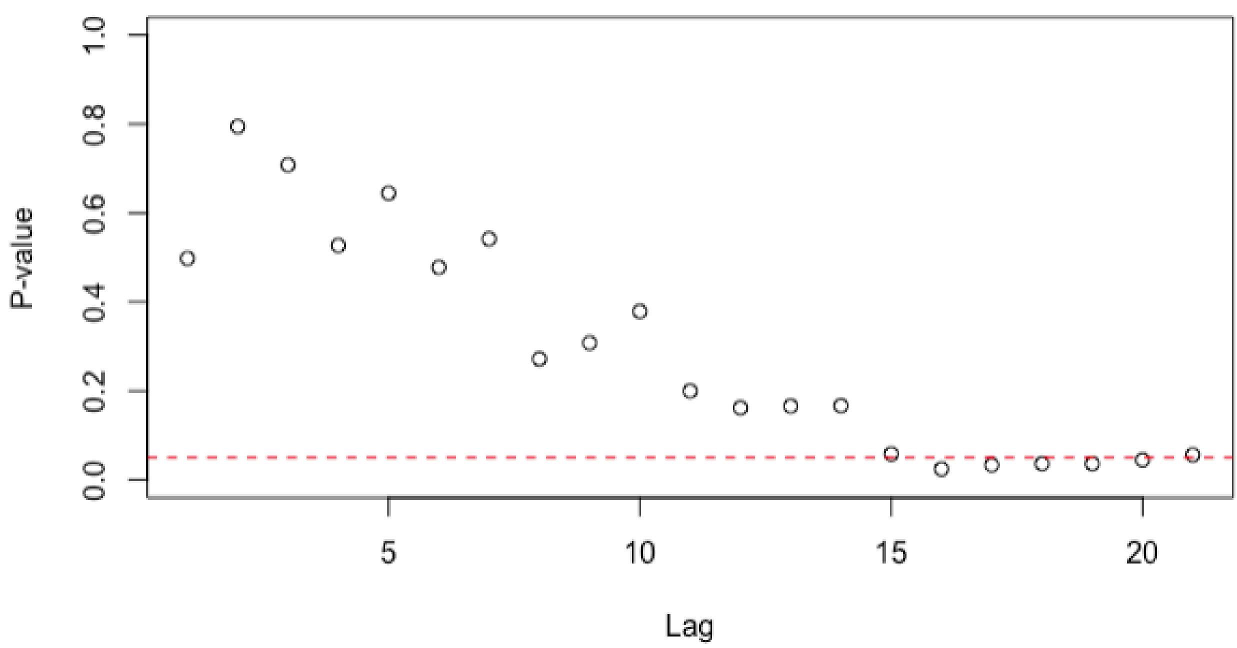


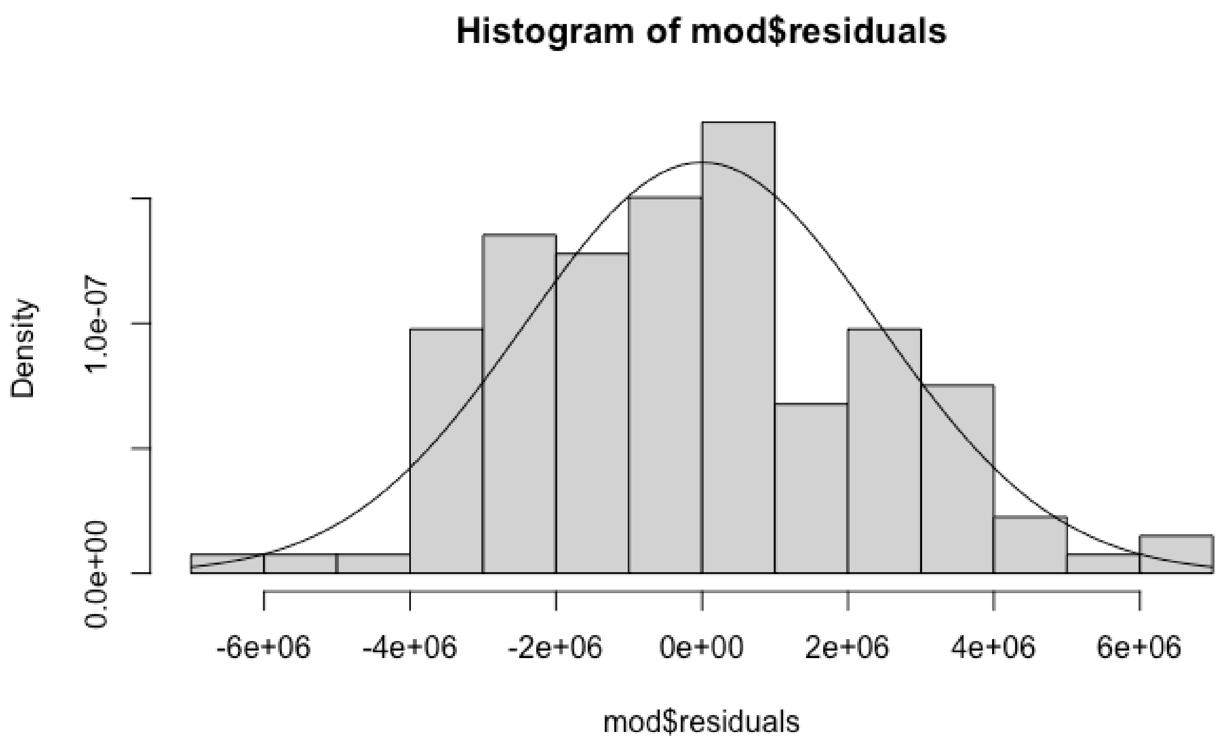

```
        Shapiro-Wilk normality test

data:  mod$residuals
W = 0.98828, p-value = 0.3199
```



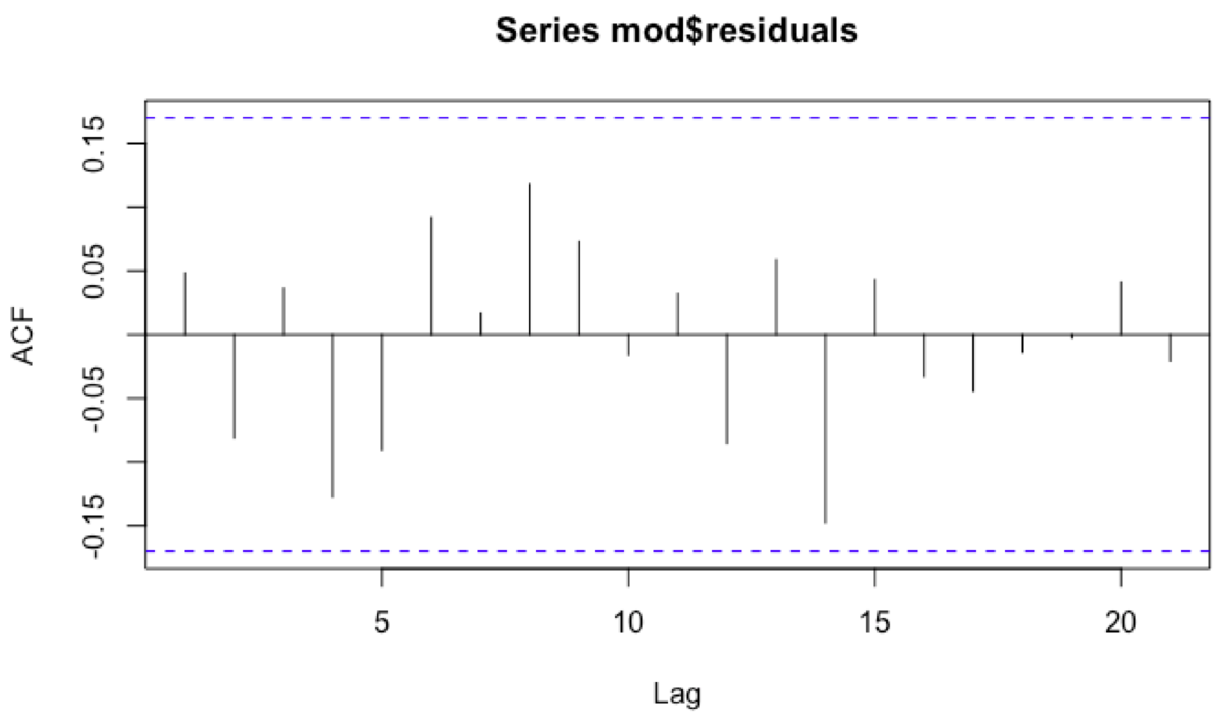
McLeod-Li Test



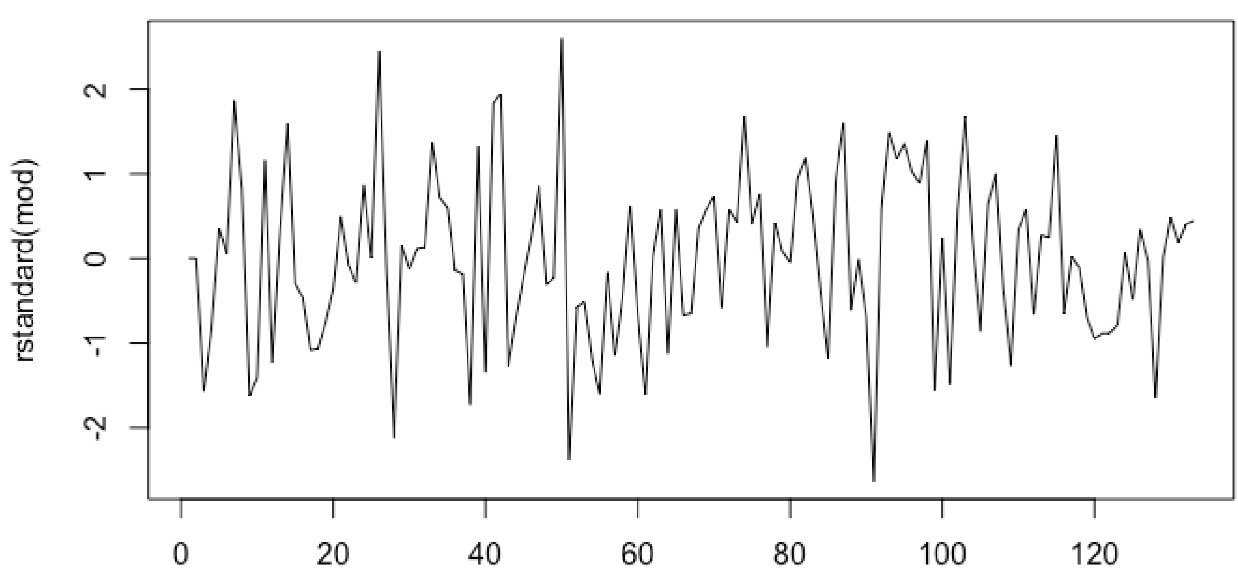


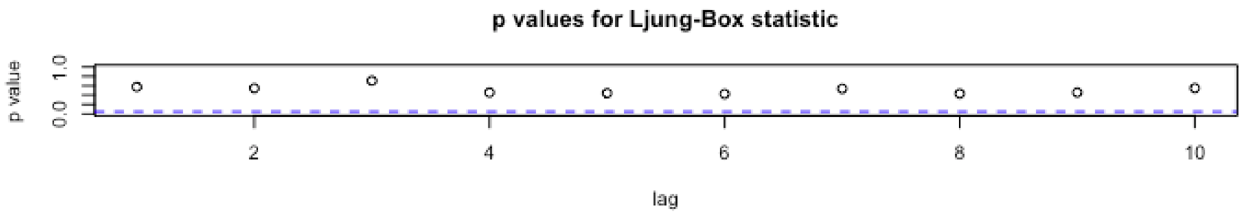
Overall, the diagnostic results were mostly positive, but showed some areas in need of improvement. The main result was that there was clear seasonality at lag 14, and a seasonal component needed to be implemented. Here are the results of the SARIMA (3,1,3) x $(2,1,2)_{14}$:

ACF of Model Residuals



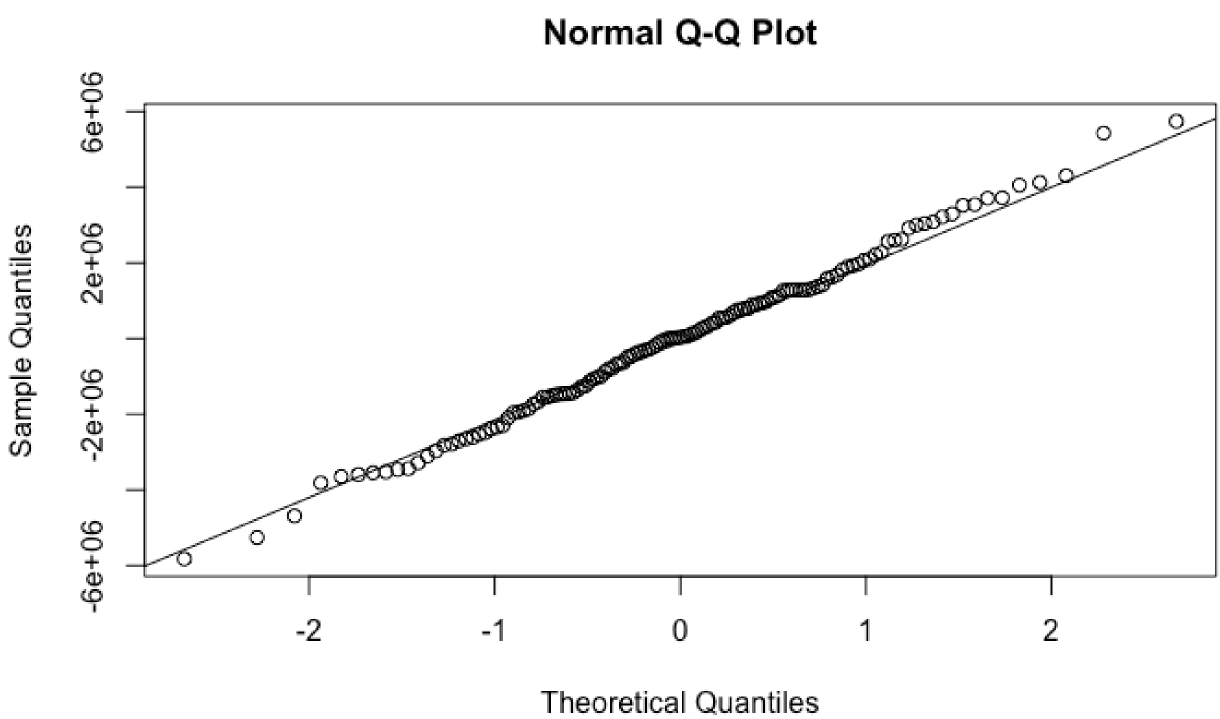
Standardized Residuals

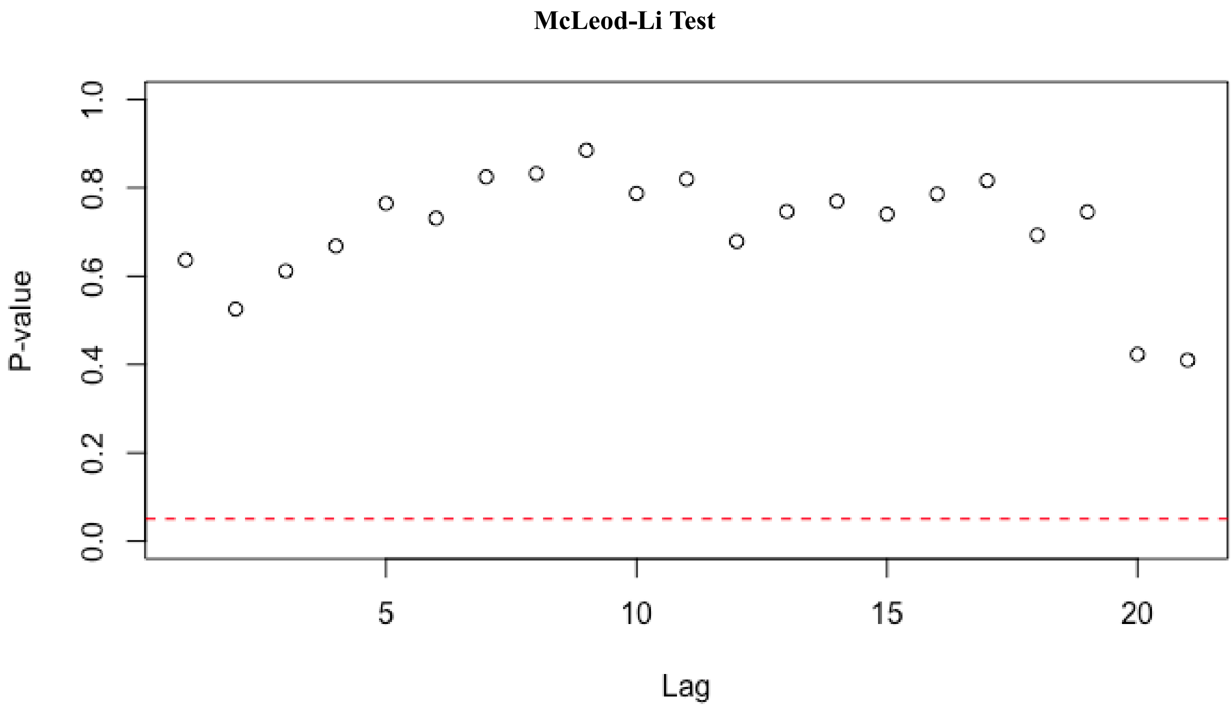


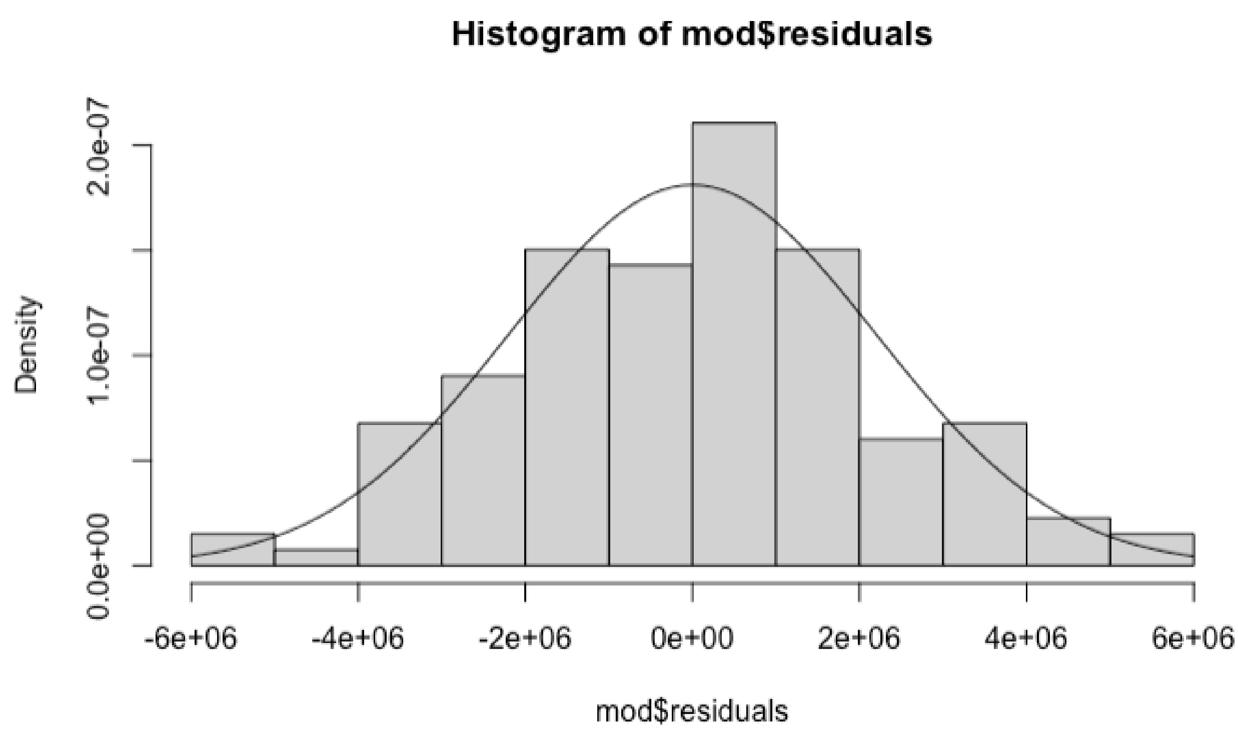



```
        Shapiro-Wilk normality test

data:  mod$residuals
W = 0.99621, p-value = 0.9812
```




McLeod-Li Test
P-value
1.0
0.8
0.6
0.4
0.2
0.0
5
10
15
20
Lag


Histogram of mod$residuals
Density
2.0e-07
1.0e-07
0.0e+00
-6e+06
-4e+06
-2e+06
0e+00
2e+06
4e+06
6e+06
mod$residuals

These results suggest a near perfect fit. The histogram shows some deviation from the theoretical curve, but this is to be expected from the stochastic nature of the underlying data.

Once a model had been established, the next step was to test it against new data. Predictions were made every week for the next four weeks out and the running mean absolute error for each timeframe was calculated. The results (in millions) from the last 21 weeks can be found below:

Kyriba Results in Millions - US Bank Accounts *Standard Error is ~2.5						
Week.Starting.On	Actuals		One Week Out Pred	Two Weeks Out Pred	Three Week Out Pred	Four Week Out Pred
7/1/24	6.67		6.15	6.19	6.49	6.41
7/8/24	15.31		11.48	11.53	11.46	11.58
7/15/24	9.39		10.83	11.22	11.13	11.1
7/22/24	7.58		7.57	7.44	6.9	6.88
7/29/24	6.61		6.55	6.56	6.78	6.62
8/5/24	9.09		11.09	11.1	11.09	11.11
8/12/24	10.91		13.13	12.89	12.88	12.88
8/19/24	4.21		7.23	7.05	7.31	7.31
8/26/24	5.33		6.84	6.57	6.89	6.98
9/2/24	4.93		7.82	7.79	8.15	8.22
9/9/24	12		11.37	11.27	11.52	11.67
9/16/24	4.88		5.95	5.95	6.36	7.41
9/23/24	6.68		5.63	5.85	5.84	5.93
9/30/24	4.89		4.73	4.86	5.19	5.18
10/7/24	6.74		10.75	10.77	10.41	10.39
10/14/24	8.34		8.42	7.87	7.82	7.89
10/21/24	5.52		4.39	4.53	5.8	5.81
10/28/24	6.11		4.86	5.67	5.05	4.82
11/4/24	7.47		6.49	7.13	6.27	6.81
11/11/24	9.9		8.67	8.83	8.39	8.68
11/18/24	6.1		6.29	6.41	6.07	6.33

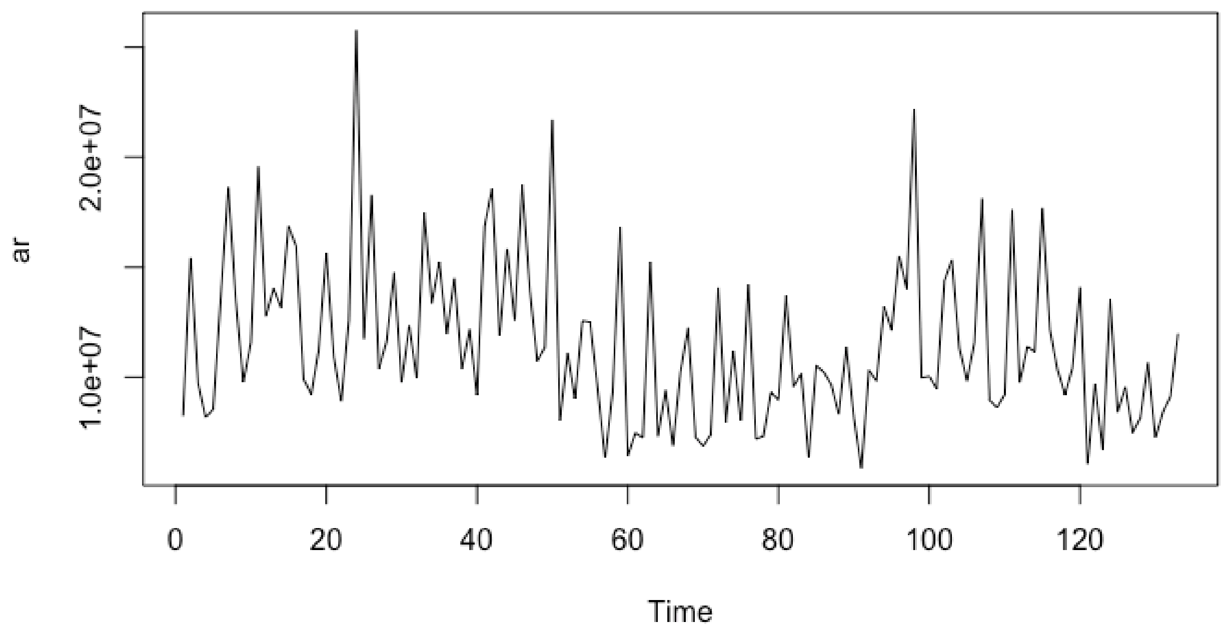
The MAE for the one, two, three, and four week predictions are: 1.394, 1.310, 1.421, and 1.435 respectively. The average amount for AR by week is 7.55 million which means the MAPE is approximately 17.5% - 19%. The average residuals are: -.361, -.42, -.435, and -.540, respectively. Some issues are that the model seems to be slightly, but consistently, over predicting and has trouble accurately predicting weeks that are much higher or lower than average. However, given the standard error for the predictions is roughly 2.5 million, the model is behaving quite well.

4.3.2 Domestic Account Group

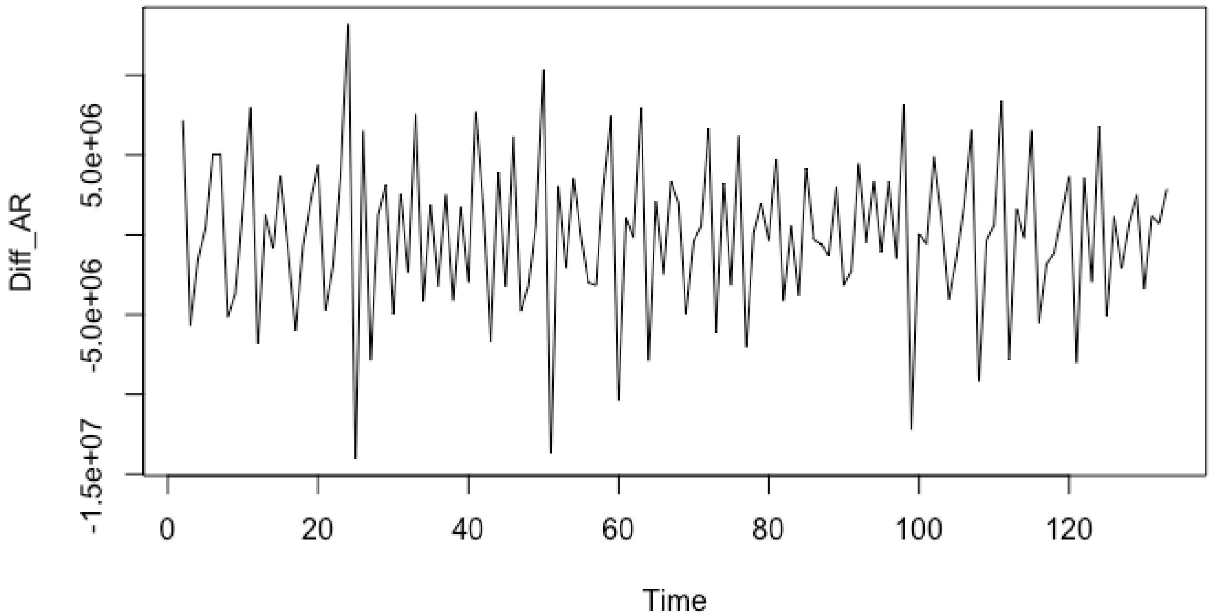
From here, the next step was to expand the model from one bank account containing ~75% of AR from domestic agriculture to the group of four accounts that comprises ~99%. This is a harder task for a variety of reasons. The first is that the first bank account modeled has relatively stable and consistent incoming revenue while the other three are more sporadic. The second is that during the first attempts at modeling the secondary accounts showed that it was unlikely to get a somewhat reliable forecast with usable error bounds outside of one to two weeks away. This horizon is not particularly useful to the Treasury department. For their purposes the minimum horizon to be useful, outside of a sanity check, is one month. Thus, the decision was made to focus on modeling the group as a whole instead of individual accounts.

The process in modeling was the same as the one described previously. The data was found to be non-stationary and all analysis was done on the first difference of the data. The results indicated that the best course of action would be to keep the same model structure that was found for the singular account and accept the increased variance/number of points with abnormal behavior. This increase as well as a worsening in the tendency to overpredict can be seen in the diagnostic results and test results against new data below:

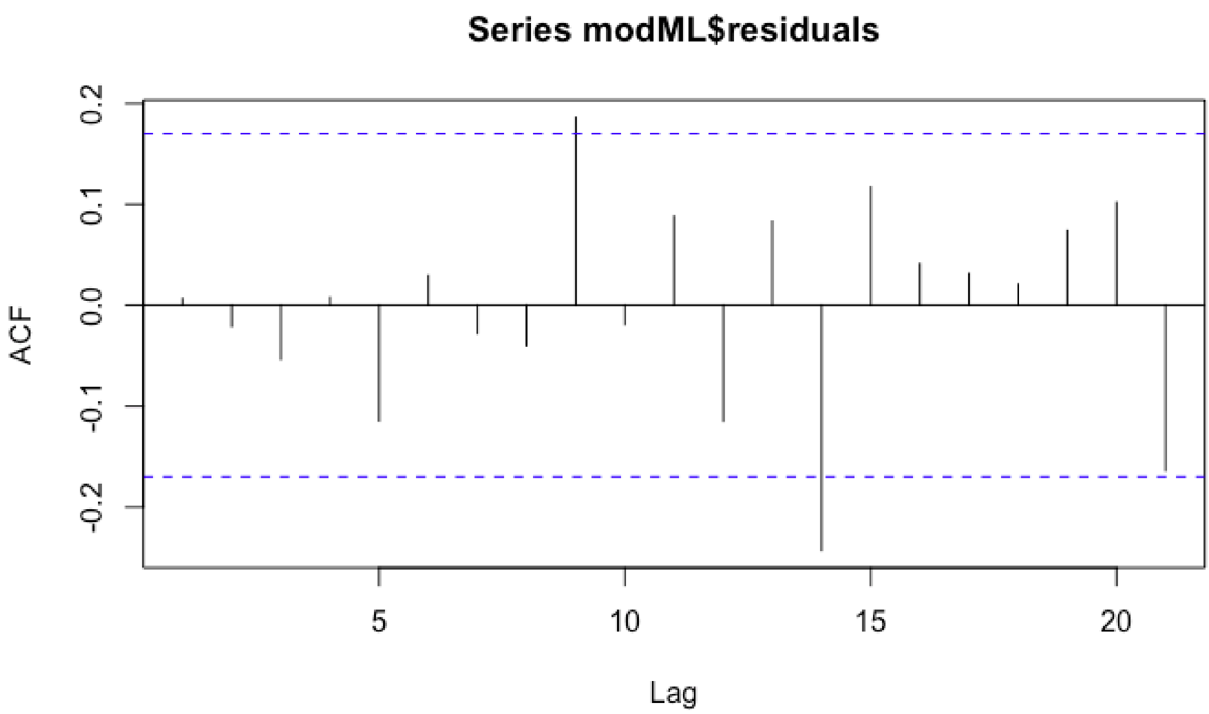
Weekly AR from Domestic Agriculture

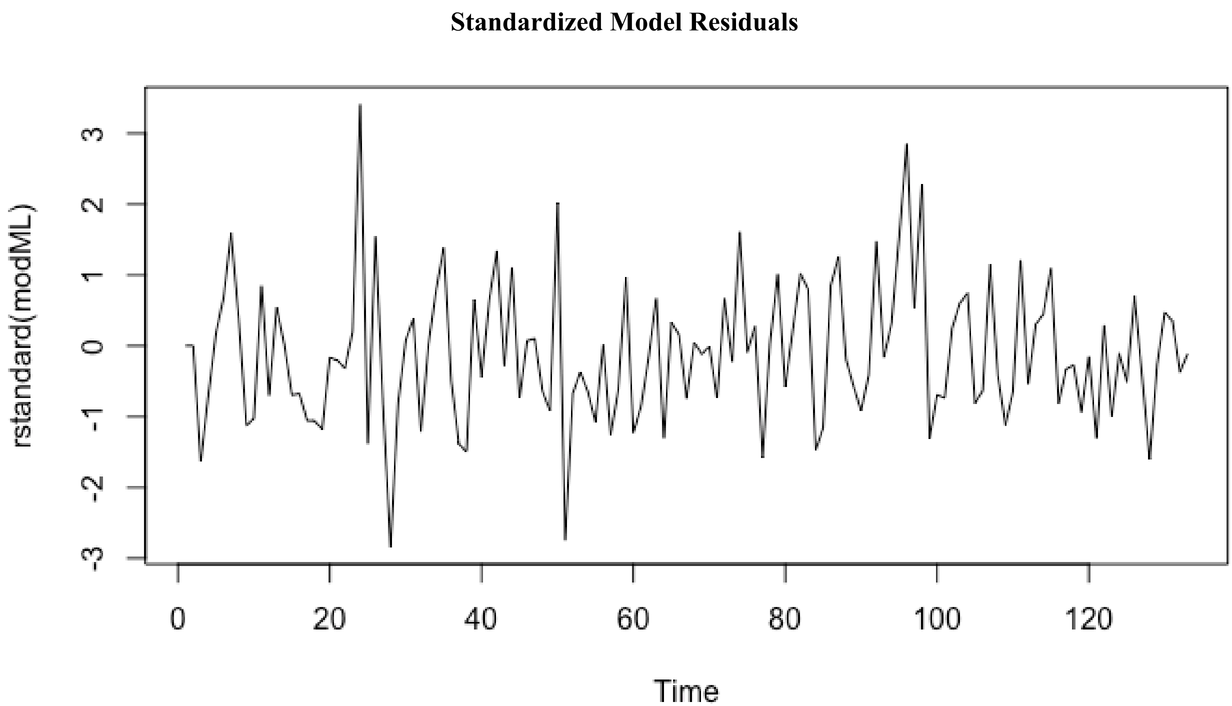


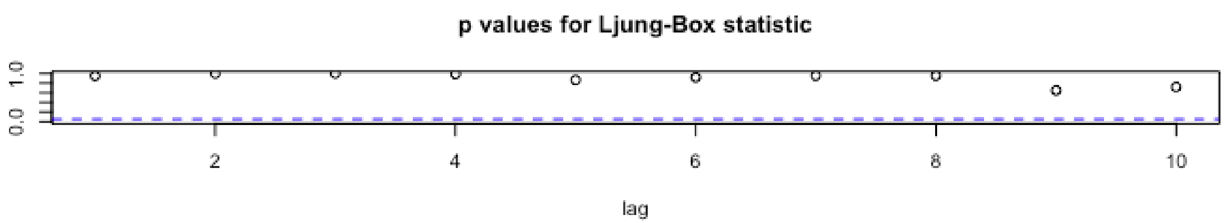
Differenced Weekly AR from Domestic Agriculture



ACF of Model Residuals

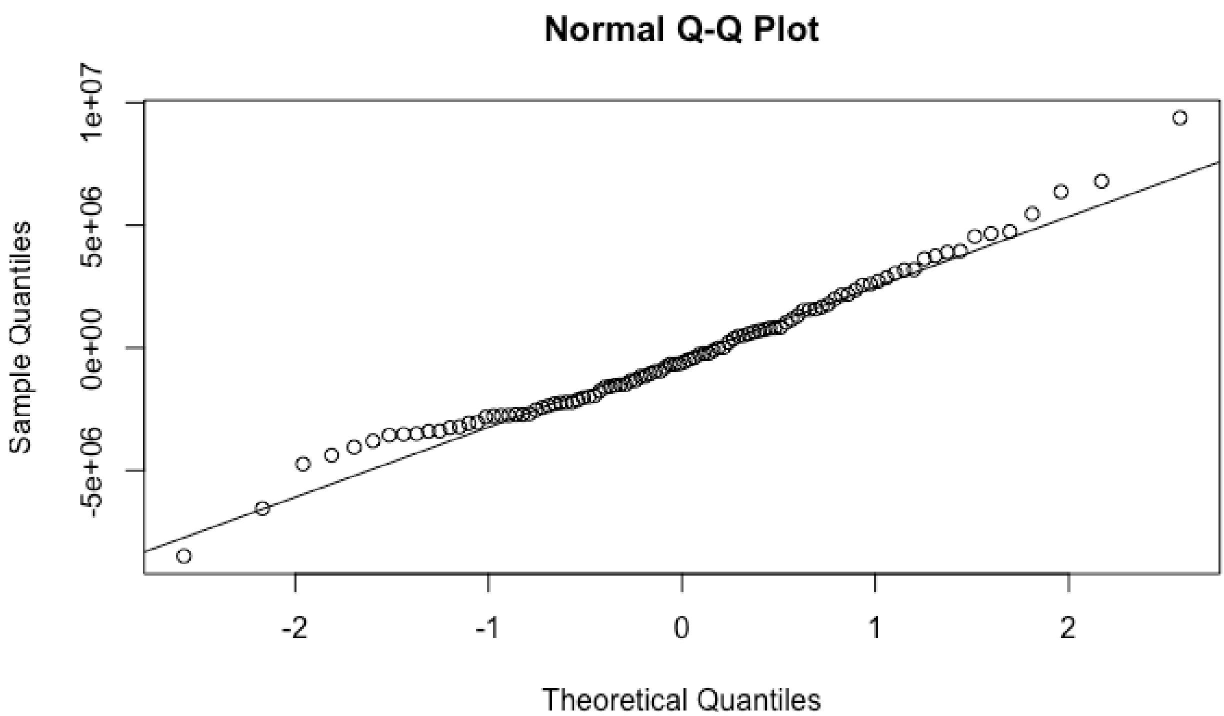


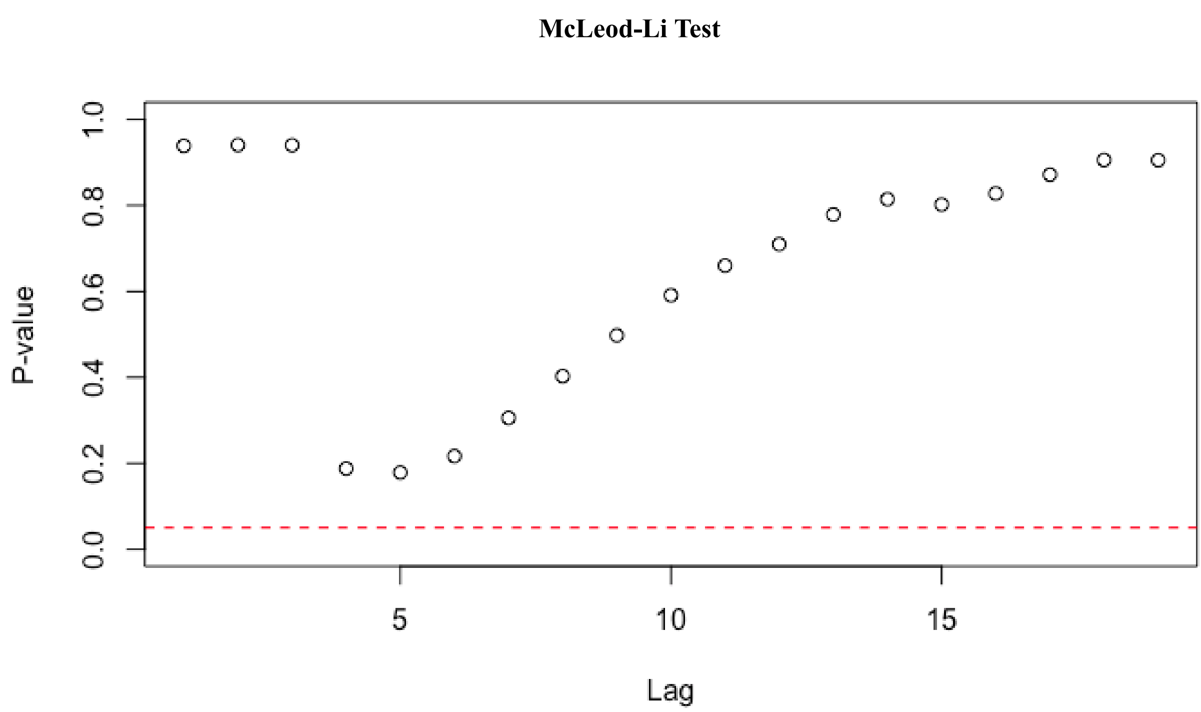


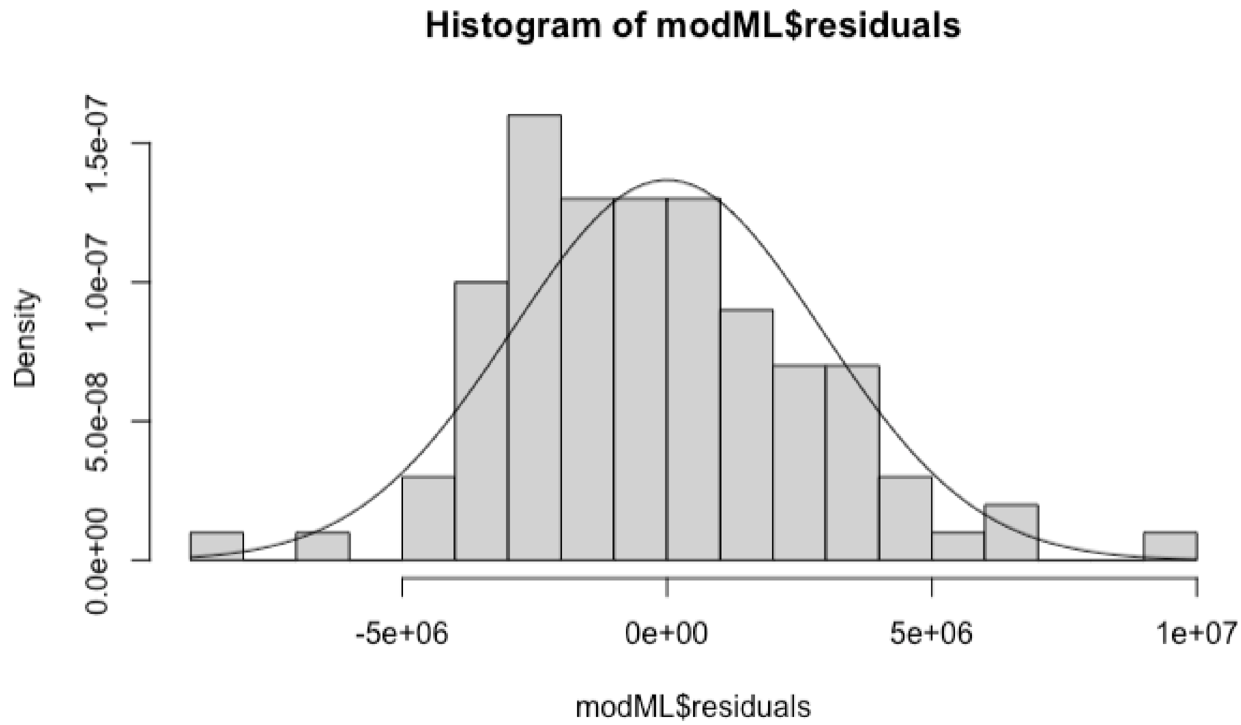



```
        Shapiro-Wilk normality test

data:  modML$residuals
W = 0.97831, p-value = 0.09805
```


Normal Q-Q Plot
Sample Quantiles
Theoretical Quantiles
1e+07
5e+06
0e+00
-5e+06
-2
-1
0
1
2


McLeod-Li Test
P-value
Lag
1.0
0.8
0.6
0.4
0.2
0.0
5
10
15



While the diagnostics from the model being applied to this data are worse than those of the previous, there are no true red flags. There is an odd result in the acf chart of the residuals in that lag 14 persisted as significant despite it being used as the seasonal component and in depth examination of different hyperparameter values, but ultimately the results when used on new data are quite good.

Kyriba Results - AG Bank Accounts *Standard Error is ~2.9, all values in Millions						
Week.Starting.On	Actuals		One Week Out Pred	Two Weeks Out Pred	Three Week Out Pred	Four Week Out Pred
7/1/24	11.17		9.43	9.39	10.35	9.95
7/8/24	17.69		14.68	14.89	14.55	14.41
7/15/24	12.17		14.46	14.21	13.15	13.09
7/22/24	10.36		11.31	11.56	10.27	10.58
7/29/24	9.2		9.88	9.94	10.86	10.33
8/5/24	10.43		13.02	13.1	13.5	13.84
8/12/24	14.08		14.56	14.75	15.02	15.19
8/19/24	6.06		10.12	9.74	10.77	10.86
8/26/24	9.67		8.89	9.04	9.42	9.88
9/2/24	6.71		9.52	9.43	11.23	10.88
9/9/24	13.52		13.87	14.14	13.8	14.24
9/16/24	8.42		9.57	9.88	10.98	10.82
9/23/24	9.55		8.12	8.13	7.97	8.47
9/30/24	7.47		8.64	7.97	8.54	9.03
10/7/24	8.16		13.22	12.82	12.56	12.61
10/14/24	10.66		11.35	11.22	12.31	11.32
10/21/24	7.26		5.95	6.04	8.82	8.24
10/28/24	8.42		7.39	7.3	7.6	7.66
11/4/24	9.12		10.18	10.01	9.48	9.59
11/11/24	11.98		12.37	12.4	12.01	11.75
11/18/24	8.45		7.92	7.99	8.42	8.25

The MAE for the one, two, three, and four week predictions are: 1.598, 1.536, 1.644, and 1.618 respectively. The average amount for AR by week is 10.03 million which means the MAPE is approximately 15% - 16%, which is better than the results from the singular bank account model. The average residuals are: -.66, -.64, -1.0, and -.97 respectively. So, this model tends to overpredict worse than the other both relatively and overall. However, the main issue is that this model tends to go on runs. That is, it will have periods of time where it will over or under predict for 4-5 weeks in a row. This causes issues in forecasting as we would like to simply take the relevant sums to produce a monthly forecast because we don't have enough data points to employ time series methods reliably on those timeframes. Of course, given the relatively small sets of results these runs could be random chance. However, since the underlying data is agricultural and heavily seasonal this seems unlikely. Rather, it seems that due to the structure of the SARIMA model, it is having a hard time picking up on level shifts.

4.3.3 Hybrid Ensemble Model

This takes us to our final step in our current modeling efforts. By taking our predictions and feeding them through XGBoost along with datetime data, we hope to pick up on these trends that take place over a larger time frame than what the base model can effectively track. To do this we generate a dataframe of predictions from n to n + i weeks out for each data point, join the calendar data, then generate the interaction effects between week of the year and the prediction amount as well as a binary flag to signify if a week contains at least one bank holiday. How many predictions to include is a hyperparameter that is usually kept between 3 to 6. For example, if generating predictions from two weeks out, one might feed in SARIMA predictions from two to six weeks out.

Unfortunately, we found that this model is not yet generally stable. In testing, we had very promising results only to see that when introduced to new data week by week the model started to degenerate. This could likely be because of the lack of data we have since when performing regression XGBoost takes the average of the data points that populate each node. Fortunately, as it stands this framework is consistent in underestimating. When forecasting cash flow, one generally would prefer to underpredict than overpredict, but we can also ensemble these predictions with our base SARIMA model which has a tendency to overpredict. The results over the last 13 weeks (in millions) can be seen below:

Date	Actual	1wk XGB	2wk XGB	3wk XGB	4wk XGB	1wk Ensem	2wk Ensem	3wk Ensem	4wk Ensem
8/26	9.67	7.00	6.83	6.88	7.52	7.95	7.94	8.15	8.70
9/2	6.71	6.59	6.88	8.48	8.74	8.06	8.16	9.86	9.81
9/9	13.52	11.71	11.7	11.41	11.65	12.79	12.92	12.61	12.95
9/16	8.42	6.84	6.88	7.26	8.74	8.21	8.38	9.12	9.78
9/23	9.55	6.72	6.91	6.78	6.83	7.42	7.52	7.38	7.65
9/30	7.47	6.72	6.72	6.05	7.20	7.68	7.35	7.30	8.12
10/7	8.16	10.77	9.97	9.69	9.35	12.0	11.40	11.13	10.98
10/14	10.66	8.31	7.18	8.78	9.22	9.83	9.2	10.55	10.27
10/21	7.26	6.02	6.96	6.61	6.83	5.99	6.5	7.72	7.54
10/28	8.42	7.05	6.72	6.11	6.98	7.22	7.01	6.86	7.32
11/4	9.12	7.45	7.07	7.51	7.79	8.82	8.54	8.50	8.69
11/11	11.98	9.54	9.49	9.00	9.22	10.96	10.95	10.51	10.49
11/18	8.45	6.82	6.96	6.61	7.10	7.37	7.48	7.52	7.68

The MAE for the one, two, three, and four week predictions are: 1.22, 1.21, 1.29, and 1.22 respectively. The average amount for AR by week over this time period is 9.01 million which means the MAPE is approximately 13.5%. The average residuals are: .394, -.466, .172, and -.043 respectively. We can see a significant reduction in both MAE and MAPE, and the tendency to overpredict has been eliminated. Most importantly, at least for this batch of predictions, we have no meaningful runs of over or underpredicting. This lets us have more faith in predicting monthly values simply by summing weekly predictions. Valmont follows a standard 4-5-4 financial calendar, so these would be the results of each month's prediction if the quarter started on 8/26 and we summed the 4 week out predictions:

Month	Actual	Prediction	Difference
1	38.32	41.24	-2.92
2	43.1	44.56	-1.46
3	37.97	34.18	3.79

Conclusion and Future Work

This study successfully developed and implemented a forecasting framework for Valmont's domestic agriculture accounts receivable, leveraging a combination of traditional SARIMA models and advanced machine learning techniques. The SARIMA model effectively captured the autocorrelation and seasonality inherent in the data, providing reliable predictions for individual and aggregated accounts on a weekly basis. Expanding to XGBoost allowed for the incorporation of additional temporal features and interaction effects, addressing limitations in capturing level shifts and trends over extended time frames. The ensemble approach further improved forecast accuracy, balancing the tendencies of the SARIMA and XGBoost models. Overall, the results demonstrated a significant reduction in error rates and an improvement in stability, providing actionable insights for financial planning and operational efficiency at Valmont.

As the dataset grows with time, there are several opportunities to refine and expand the forecasting framework:

1. **Refining the Model with Additional Data**: With more data points becoming available, the accuracy and reliability of both SARIMA and XGBoost models can be further enhanced. This will allow for better handling of anomalies, level shifts, and seasonal patterns that are currently challenging to model.

2. **Quarterly Forecasting**: The current framework focuses primarily on weekly and monthly predictions. Expanding the methodology to reliably forecast on a quarterly basis will address broader financial planning needs, aligning with Valmont's standard financial decision-making needs.

3. **Application Across Business Sectors**: While this project concentrated on domestic agriculture accounts, the methodology can be extended to other sectors of Valmont’s operations. By tailoring the model to the specific cash flow characteristics of different divisions, this approach could provide comprehensive forecasting capabilities across the organization.

These future developments will ensure that the forecasting framework remains robust, scalable, and integral to Valmont's financial operations, supporting both short-term decision-making and long-term strategic planning.