Delinquency on Credit Card Debt Across all Banks in the United States:

A Time Series Forecasting Report

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Executive Summary

This report aims to provide an analysis of the time series modeling and forecasting of the data titled "Delinquency Rate on Credit Card Loans, All Commercial Banks," from the Federal Reserve Economic Data (FRED)[i]. The delinquency rate is a quarterly data and not seasonally adjusted.

The benchmark models fitted on the dataset are not suitable for forecasting as there is information left uncaptured in those models. On the other hand, ARIMA and Exponential Smoothing models fit well and demonstrate good forecasting accuracy. We selected the ARIMA (1,1,1)(0,1,1) model to be the one that best fits and gives a better forecasting than exponential smoothing, as it captures the trends and seasonality of the date better.

From the model and forecasting, considering the significant increase in delinquency rates during the previous recession period (2008-2010), it is plausible to anticipate a similar surge if the US faces an impending recession due to the Fed's measures to control inflation. Such potential economic conditions can be captured by the model, adding further value to the ARIMA model's forecasting accuracy.

Introduction

Dataset Overview

The dataset consists of a time series data on the delinquency rate on credit card debt, downloaded from the FRED. The dataset has two variables: time and rate of delinquency. The dataset is a quarterly data of the delinquency rate on credit card loans in the United States. Delinquency rate is calculated as the principal amount which is delinquent by at least 30 days over the total principal amount of credit card debt outstanding[ii]. The dataset is not adjusted for seasonality as we want to show the effect of seasonality on the debt outstanding in the US. The dataset ranges from Q1 1991 to Q1 2023. Each row represents one time point or one quarter in the data along with the delinquency rate of all credit cards loans across all the banks in the US and the delinquency rate is a continuous random variable.

Importance and Significance

The delinquency rate of credit cards loans is a crucial metric in the decision making by the Federal Reserve (Fed) and the Department of Treasury of the United States government. Delinquency rates also play an important part in determining the interest rates during the Federal Open Market Committee meetings of the Fed.

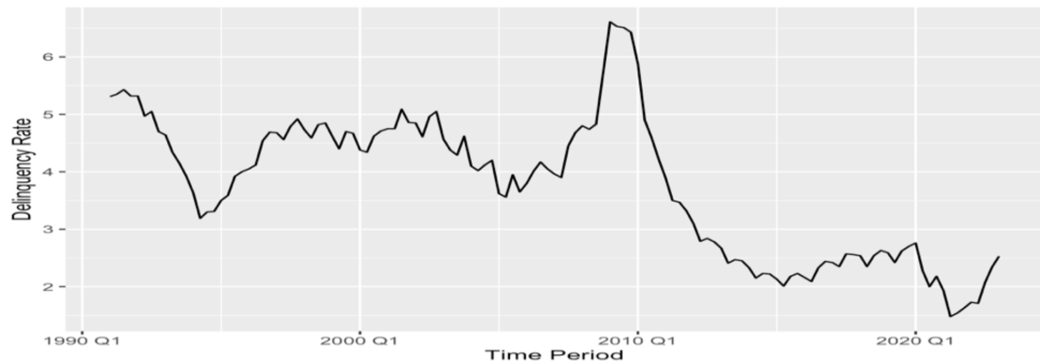
Exploratory Analysis

The entire statistical analysis and modeling is done in RStudio using the library package 'fpp3'[iii] developed by Rob Hyndman and George Athanasopoulos. The R Markdown file is attached as a link in the appendix.

Time Plot

As a first step in analysis of time series data is to plot the time plot. We use the 'autoplot' function in the fpp3 library. Exhibit A displays the time series plot of the dataset.

Exhibit A- Time Plot of the Delinquency Rate of Credit Card Loans

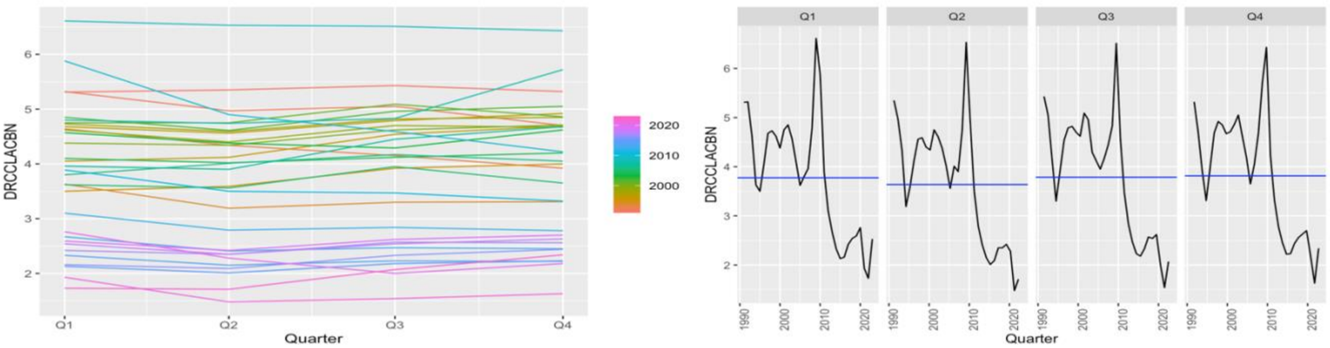


There is no evident trend in the plot as the delinquency rate is usually a factor of economic cyclicity. There are, however, quarters with very high delinquency rates, usually during the periods of recession and troughs with low rates during the periods of high liquidity in the economy.

Seasonal and Subseries Plots

We observe the seasonal plot using the 'gg_seasonal' and 'gg_subseries' functions. In a seasonal plot the observations are plotted against seasons in the Exhibit B, quarters in our case. We can observe a higher rate in Q1 across most years which reduces in Q2 and Q3 and then slightly rises in Q4.

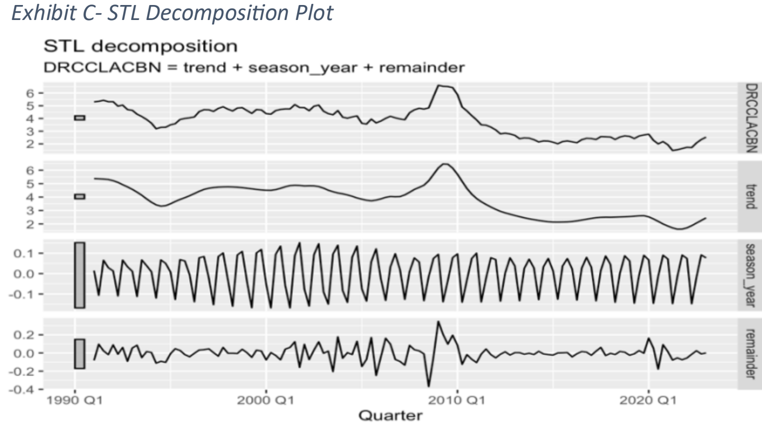
Exhibit B- Seasonal Plot and Subseries Plot of the Delinquency Rate of Credit Card Loans



This is likely due to the fact that people tend to spend more money during the holidays, which can lead to more credit card debt.

Seasonal and Trend Decomposition using Loess

Exhibit C- STL Decomposition Plot



Seasonal and Trend decomposition using Loess (STL) is a versatile and robust method for decomposing time series. The data has been decomposed into three components: trend, seasonality, and remainder in Exhibit C. The trend component of the graph shows overall the delinquency rate has decreased over the years. There was a major rise in the years 2008-2010 due to the global financial crisis and has been on a steady decrease ever since and rising recently as the Fed continues to raise interest rates. The seasonality component is mostly steady with an increase until 2002 and a decrease thereafter. The seasonality remains steady post the rise. The remainder component of a time series is the random variation in the data. We can see an increase in variation of the remainder component between the years 2001 to 2010 with its peak around 2008-2010.

Modeling and Forecasting

Transformation

It was observed that the original data and the log transformed data were very identical in the features. Therefore, we decided to pursue the modeling with the untransformed data as we believe it will not affect the models that will fit best.

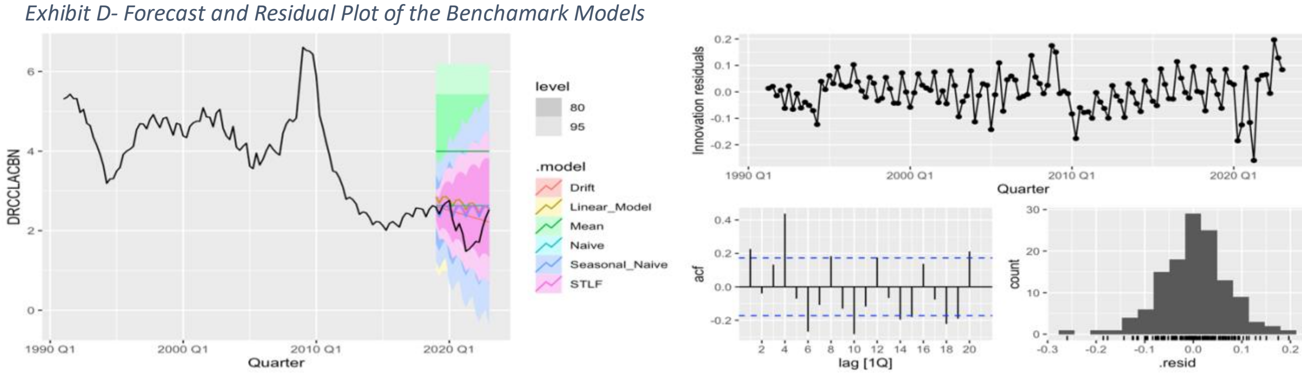
Training and Test Dataset

All observations till Q4 of 2018 are considered to be training set and remaining data will be test set. The training set comprises of 85% of the total dataset. The test data is mostly during the period of COVID-19 and after it when there was cheap liquidity in the market resulting in high inflation and later period of rising interest rates to control the inflation (current times).

Benchmark Models

Benchmark models specifically the Mean, Naïve, SNAIVE, Random Walk with Drift, Linear Model, and STLF model. The models demonstrate good fit and amongst these models, the Random Walk with Drift demonstrates the lowest root mean squared error (RMSE), followed by SNAIVE and STLF models indicating good forecasting accuracy. The forecast plots for each of the benchmark models are given in Exhibit D.

Exhibit D- Forecast and Residual Plot of the Benchamark Models

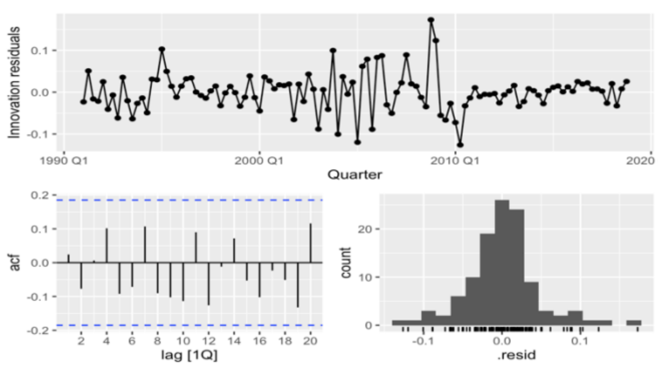


However, after testing the residuals generated with 'gg_tsresiduals,' using the ACF and PACF plots in Exhibit D of the Random Walk with Drift model, we observe that the residuals are not white noise and p-value from Ljung-Box test suggests the same. This means that there is information left uncaptured in the residuals. Therefore, it will be best not to proceed ahead with the benchmark models. Therefore, we will proceed ahead with Exponential Smoothing and ARIMA.

Exponential Smoothing

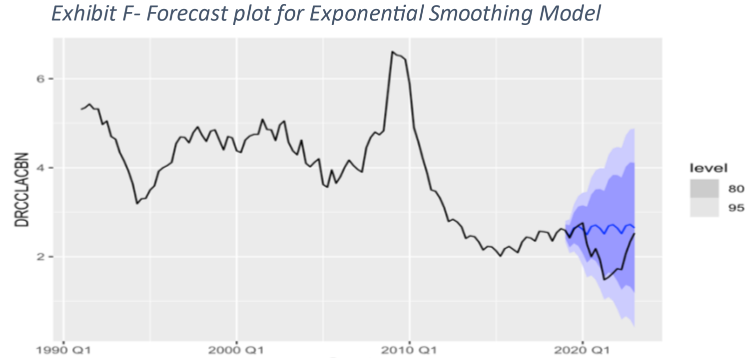
Exponential Smoothing (ES) models captures the underlying trends, seasonality and the movement in the error term in the data to help forecast for the future. We have used the ETS function in the fpp3 package to fit the models. ES models requires the modeler to identify whether the error, trend and seasonality are additive or multiplicative in nature and hence it becomes important to refer the STL decomposition. Furthermore, we can also input the argument for ETS to be damped additive as well.

Exhibit E- Residual Plot for Exponential Smoothing



From the STL decomposition of the data, we observe that the trend is additive and it has to be damped so that the forecasts don't either keep rising or falling. For the seasonality, we observe that the additive and the error term can be additive or multiplicative. So, we will try both the options. We also fit various other models such as the Simple Exponential Smoothing (SES), Holt's model, Holt-Winter's (HW) additive and multiplicative models, and also try variations on the HW models with damped trend. We also fit one model where R decides the best one. Total, we try a total of 8 models in Exponential Smoothing. We fit the models on the training dataset. We observe that the model fit by R i.e., ETS(M,Ad,A) gives the lowest AICc score of 159 and indicates that to be the best fit model. However, on observing the RMSE scores, we find

Exhibit F- Forecast plot for Exponential Smoothing Model



that ETS(A,Ad,A) gives the lowest RMSE of 0.607, indicating that it gives the best forecasting accuracy but it has a pretty high AICc score. Therefore, we decide to strike a balance between the AICc and RMSE and decide to go ahead with the model generated by R ETS(M,Ad,A). Also, on observing the residual plot in Exhibit E, we see that the residuals are white noise and means that there is no information uncaptured.

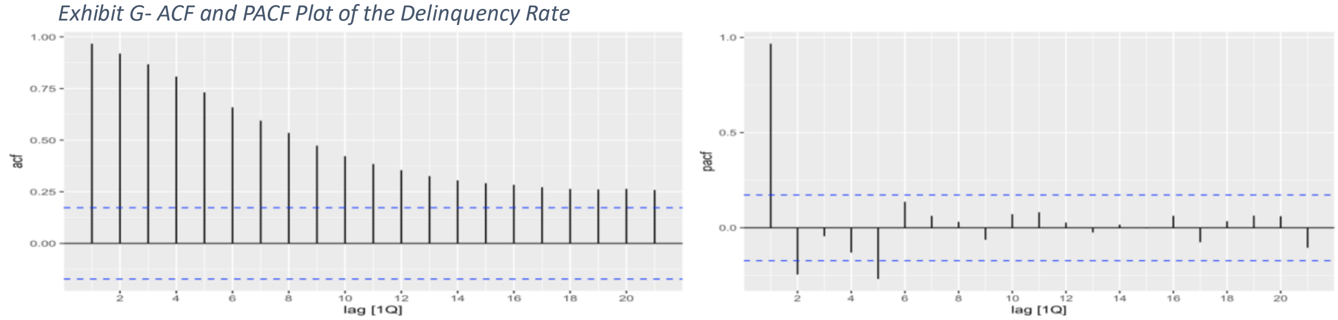
On forecasting with the ETS(M,Ad,A) model on the test data, we obtain the above plot in Exhibit F shows the forecast. This looks a good forecast and is a model that can be considered. However, a drawback in the forecast plot is that the forecast intervals are quite wide. Therefore, the model can be used to forecast values of a few quarters in the future.

Autoregressive Integrated Moving Average (ARIMA)

Stationarity and Order of Differencing

ARIMA models require the data to be stationary and we check the stationarity of the data using the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots. The Exhibit G shows the ACF plot and PACF plot of the raw time series data for the delinquency rates in credit card debt across the US.

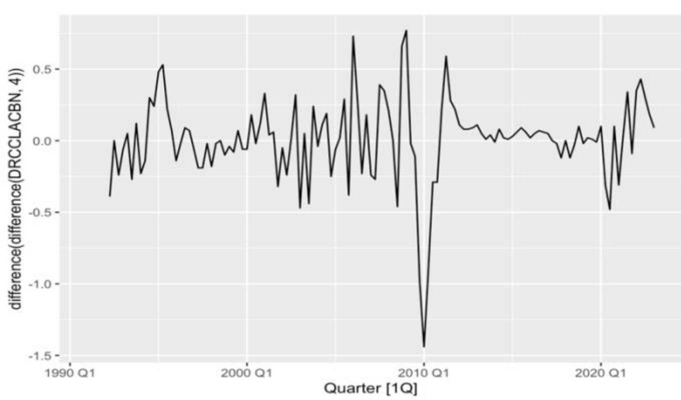
Exhibit G- ACF and PACF Plot of the Delinquency Rate



The ACF plot shows that the decrease in the lag order spikes is really slow and the PACF plot shows a significant spike in the first lag order. From both the plots, it is clear that the data is non stationary and we will need to make it stationary.

We also check for stationarity using the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test. The KPSS test uses a hypothesis test where the null hypothesis means that the data is stationary. From the KPSS test, we find that the p-value is less than 0.05, meaning that the data is not stationary. To make the data stationary, we take the first order difference for both the seasonal and non-seasonal components. Exhibit H shows the plot of the time series after first order differencing.

Exhibit H- Stationarity Plot after 1st Order Differencing



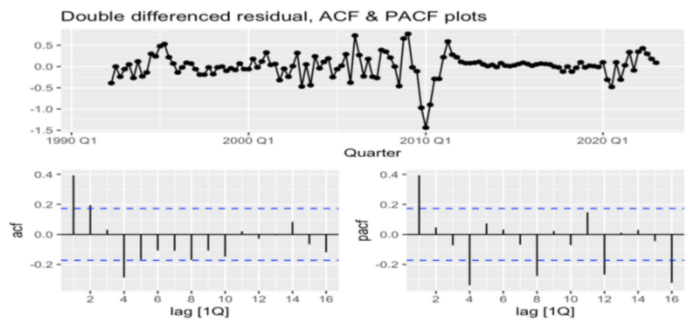
We can also let R decide the order of seasonal and non-seasonal differencing order using the ‘unitroot_nsdiffs’ and ‘unitroot_nsdiffs’ arguments in the features function. However, using those arguments gave a result of 0, meaning that we don’t need any differencing at all, which is counter-intuitive to the ACF and PACF plots. Therefore, we determine that the seasonal differencing order (D) and non-seasonal differencing order (d) are 1.

Seasonal and Non-Seasonal Autoregression (AR) and Moving Average (MA)

The residual plots of the double differenced time series is shown in Exhibit I. We will try to estimate an ARIMA(p,d,q)(P,D,Q) model based on the order of differencing and ACF and PACF plots. The residuals plot is generated in R, gives the double differenced innovation residuals after differencing for seasonal and non-seasonal components of the data.

From the ACF plot, we observe we can use a seasonal MA (1) model as there is only one significant spike on the lag order = 4 and nothing after that on 8, 12, 16 & 20. Also, we can use a non-seasonal MA(2) model as there is significant spike on lag order = 2. We will also test for non-seasonal MA(1). From the PACF plot, we observe that there is a significant spike at lag order 1, non-seasonal AR(1) model and it is difficult to identify the seasonal AR model. So, we will try a bunch of them. Hence, our initial ARIMA candidate model is ARIMA(1,1,2)(0,1,1). Also, the residuals appear to be homoscedastic, which is a good sign.

Exhibit I- Residual Plot of the Stationary Data



ARIMA Models

We try to fit a bunch of ARIMA models, including a model auto-generated by R, with D & d = 1 so that it is easy to compare the goodness of fit on the basis of AICc. The model ARIMA(1,1,1)(1,1,1) gives the lowest AICc and demonstrates the best goodness of fit. However, on checking the RMSE scores, ARIMA(1,1,2)(2,1,1) displays the lowest RMSE and best forecasting accuracy. From both the AICc and RMSE scores, we see contrasting results. So, we decided to strike a balance between AICc and RMSE. Therefore, we see that ARIMA(1,1,1)(0,1,1) is giving the best balance with a slight trade off in AICc.

Forecasting with ARIMA(1,1,1)(0,1,1)

The plots for the forecast in Exhibit J shows a good forecast capturing the trend and seasonality of the data. Also, from the residual plot in Exhibit K, we observe that the residuals are homoscedastic and are white noise. We can confirm the same from the Ljung-Box Test where the p-value is high enough to interpret that there is no uncaptured information in the residuals and that it is a good model.

Exhibit K- Forecast Plot Using ARIMA Model

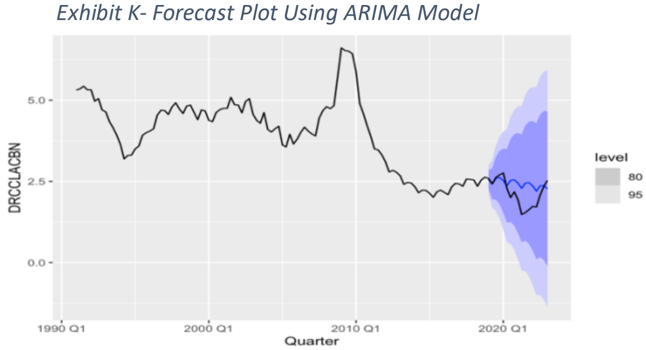
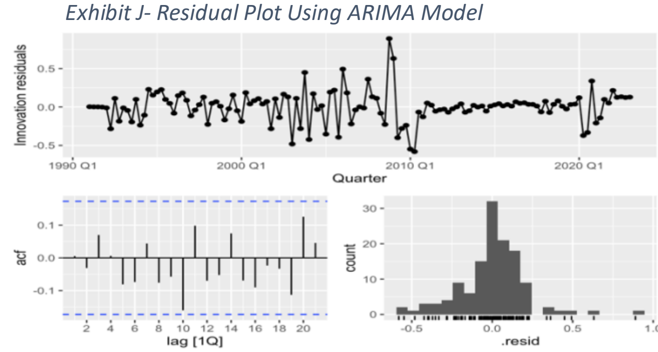


Exhibit J- Residual Plot Using ARIMA Model



The forecast intervals are quite wide, just like in exponential smoothing model forecast. Therefore, we can use this ARIMA model for forecasting for near term future.

Conclusion

The forecasting of the delinquency rates of credit cards loans in the US was conducted using a range of models, including benchmark models, exponential smoothing, and ARIMA. The benchmark models exhibited limited performance in capturing the underlying trend and seasonality of the data. However, both Exponential Smoothing and ARIMA models demonstrated strong forecasting capabilities, with the ARIMA model yielding superior results and closely aligning with the actual data. It is worth mentioning that given the evaluation of the models was conducted using test data during and after the COVID-19 period, hence wider prediction intervals were expected, as some part of the test data coincides with a recessionary period in the United States. Overall, the ARIMA model gives good forecasts to be used in short term forecasting of credit card delinquencies and defaults.

Appendix

Link to the OneDrive containing the R Markdown file used to model and forecast the Delinquency Rate of Credit Card Loans across all the banks in the US: Link to OneDrive

References:

[i] https://fred.stlouisfed.org/series/DRCCLACBN
[ii] https://www.investopedia.com/terms/d/delinquency-rate.asp
[iii] https://otexts.com/fpp3/