AN EXAMINATION OF THE VARIABILITY OF DEFERRED ACTION FOR CHILDHOOD ARRIVALS *(DACA)* POLICY EFFECT IN THE UNITED STATES OF AMERICA LABOR-FORCE

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Abstract

It has been underscored by recent studies that ending DACA would place a severe economic strain on businesses around the country. In 2017, the United States of America's Citizenship and Immigration Services reported that a total of nearly 800,000 immigrants have obtained the status of Deferred Action for Childhood Arrivals (or DACA), thereby rapidly increasing or adding significantly to the total labor force in the United States of America. Therefore, the primary objective of this study is to examine and predict the variability of DACA policy effects on the United States of America labor-force. The study utilized secondary sources of immigration data on DACA immigrants between 2012 and 2015, coupled with labor-force data from 1995 to 2015. The study adopted the application of time series models from the perspective of the autocorrelation function of a time series data such as ACF, PACF, and ARIMA-models to enable a better understanding of DACA accepted data to policymakers. Furthermore, the best ARIMA-model was selected for forecasting based on each models' parameter estimates, coupled with the diagnostics test of residuals as well as their various AICs and BICs. The data was coded and analyzed with the help of R -statistical software. As part of the results, the study found that there is a systematic change in the time plot of ACF and PACF (i.e. trend component) in the accepted DACA data. Also after the introduction of the first differencing procedure, the U.S. employment DACA data was observed to be approximately stable, hence stationary. Based, on the appropriateness (checking and diagnostic testing) of ARIMA-model, the study forecasted that the accepted DACA will continue to vary by rising and falling seasonally in the next 60 months due to the policy repeal. The study has the conclusion that, for the continuous growth and survival of the labor force of the United States of America, there is the need for continuity and expansion of the DACA policy.

Keywords: Labor-Force, DACA, ARIMA, Autocorrelation, Immigration, and Employment

1.0 Introduction

According to Gillett (2017), repealing DACA policy could cost about 700,000 DACA recipients or workers to lose their jobs, and employers $6.3 billion in employee turnover costs. Additionally, Gillett (2017) has explicitly stated on September 5, 2017, that the loss of labor of DACA recipients will cost the country $460.3 billion in economic output over the next decade. Similarly, Center for American Progress (2017) has argued that if DACA recipients were deported and forced to leave the United States, the United States would stand to lose about $460 billion in the Gross Domestic Product (GDP) over the next ten years.

In 2017, the Center for American Progress (CAP) Survey indicated that, of the roughly 3,000 DACA recipients, nine-tenths of the respondents stated that they had jobs. The survey further specified that DACA recipients have been working in the United States since they were children, with most of them holding jobs in important sectors of the United States of America economy. However, the recent study of CAP (2017) reported that ending DACA would place severe economic damage on businesses around the country, putting them into the impossible and extremely costly position of having to fire productive employees for no other reason than arbitrary change in federal policy, potentially resulting in backlash from other employees or their broader community (Gillett, 2017; Adu-Frimpong, Jones, and Esedo, 2018).

In 2017, the United States of America's Citizenship and Immigration Services confirmed that a total of nearly 800,000 immigrants have obtained the status of Deferred Action for Childhood Arrivals (or DACA), thereby adding significantly to the total labor force in the country (Cato Institute, 2017; Adu-Frimpong, Jones, and Esedo, 2018). The Washington, DC-based think tank, Cato Institute (2017) asserted that the economy of United States has gained directly and indirectly from the collective skilled labor force from both legal and illegal immigrants. Furthermore, the conservative institute contended in its 2017 study that deporting American residents, who entered the country illegally as children, could cost the United States economy about $280 billion (Adu-Frimpong, Jones, and Esedo, 2018). Additionally, K. D'Onofrio (2017) reiterated that the deportation of DACA participants in the United States would cost the American economy billions of dollars, as well as billions of tax revenues that would be foregone, all other things being equal.

Meanwhile, a recent report released by the Center for American Progress (2017) also pointed out that 91 percent of DACA recipients are currently employed by American companies throughout the country (Adu-Frimpong, Jones, and Esedo, 2018). However, many economists and political scientists have predicted devastating consequences the DACA policy would inflict on U.S. labor force, as well as the dire far-reaching consequences to communities across the country as well as to employers, and to the American economy across all regions and sectors if the policy is not properly reviewed. In light of the foregoing details, it is part of the primary objective of this study to examine the variability of DACA policy towards the United States of America labor-force. Also, the study predicts the variability in the accepted DACA recipients' data between 2012 and 2016 to inform policymakers (Adu-Frimpong, Jones, and Esedo, 2018).

2.0 Historical Review of Deferred Action for Childhood Arrivals (DACA) Policy

Very importantly, the United States Migration Policy Institute revealed that there are more than forty-three (43) million immigrants in the United States of America. Out of the number, eleven (11) million are undocumented. Therefore, in the year 2012, President Barack Obama and his administration implemented the Deferred Action for Childhood Arrivals –DACA-DREAM ACT bill (DACA), an American immigration policy that allowed some individuals, who entered the country as minors and had either entered or remained in the country illegally, to receive a renewable two-year period of deferred action from deportation and to be eligible for work permits (Glum, 2017; Adu-Frimpong, Jones, and Esedo, 2018).

It is very important to note that DACA came into effect after the failed passing of the Dreamers Act in 2007 and in 2011, respectively. The so-called Dreamers Act would have provided a way for immigrants, brought into the United States after meeting certain qualifications, to be considered to become permanent residents of the United States of America. Nonetheless, after the passing of DACA policy in 2012, the immigrants had to satisfy certain qualifications before becoming accepted. Those qualifications were as follows: he/she had to be younger than 31 years old, must have entered the United States of America before turning 16 years, and lived in the United States before June 15, 2007 (Adu-Frimpong, Jones, and Esedo, 2018).

Interestingly, in 2014, President Obama indicated his intentions on expanding the DACA immigration policy. As a rest, in the year of 2016, the Migration Institute stated that about 1.9 million people were eligible for DACA status. However, while reviewing DACA records, many U.S. States disagreed with the expansion and, as a result, sued to prevent it. On September 5, 2017, under the presidency of Mr. Donald Trump and his administration, the DACA policy was rescinded, but it was delayed for six months to give Congress time to understand the policy fully and decide on how to deal with the issue. Indeed, the Trump administration wants tougher immigration and border security measures as well as crackdowns on sanctuary cities, green card restrictions and money for the President's border wall between the U.S. and Mexico. It is reported that 53% of immigrants that use DACA are women while 47% are men. In addition, 83% are either single or divorced (Lopez & Krogstad, 2017; Adu-Frimpong, Jones, and Esedo, 2018).

Also the study by Lopez & Krogstad (2017) in collaboration with Pew Research Center has stated that the average age of Dreamers enrolled in DACA is 24 years. Also, twenty-five year-olds of the dreamers make up 29%, while 37% are of ages 21 through 25; 24% are ages 26 through 30, and 10% are of ages 31 through 36.

Although it is a fact that DACA has a large number of immigrants as its recipients, many choose not to reapply or are no longer enrolled (Lopez & Krogstad, 2017; Adu-Frimpong, Jones, and Esedo, 2018).

3.0 Methodology

This current study employed an exploratory data analysis to ascertain the descriptive structure of the United States of America's Citizenship and Immigration Services, and U. S. Bureau of Labor Statistics data. The study utilizes secondary and extant sources of immigration data on DACA immigrants between 2012 and 2015, coupled with labor-force data from 1995 to 2015. The study adopted the application of time series models from the perspective of the autocorrelation function of a time series data such as ACF, PACF, ARIMA, etc to enable a better understanding of DACA accepted data. Finally, the best model is selected for forecasting based on each models' parameter estimates, coupled with the diagnostics test of residuals as well as their various AICs and BICs. The data was coded and analyzed with the help of R -statistical software.

Conceptual Framework of ARIMA-Model

Autoregressive Integrated Moving Averages (ARIMA) is one of the most widely used models to describe time series behavior. The ARIMA is an acronym with the first two letters, AR, meaning Autoregressive; following by I representing Integration, while the last two letters, MA, stands for Moving Average. ARIMA model is useful in this particular study because it has simple structures that enable researchers to model properly a data with time series characteristics. According to V. Gomez and A. Maravall (1998), ARIMA models can be successfully used in practice to express various economic time series, because: (1) they can represent many processes with parsimonious model, (2) they can be extended to incorporate the modeling of deterministic effects (intervention variables), outliers, calendar effects, and (3) a well-established procedure for modeling has been developed.

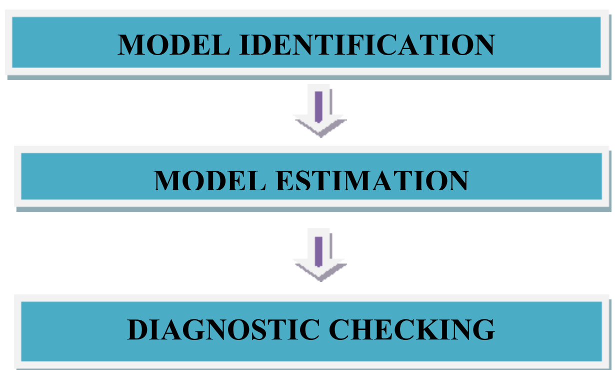
Very importantly, the ARIMA models are appropriate for modeling time series with trend characteristics, random walk processes, and seasonal and non-seasonal time series.

Model Specification

The study followed the ARIMA model developed by George Box, and Gwilym Jenkins (1976). The Box-Jenkins procedure involves identifying an appropriate ARIMA model, fitting it to the data, in order to perform checking and diagnostic testing of the model.

More specifically, the ARIMA (p,d,q)(P,D,Q) model describes the values of the time series as a function of the order of the autoregressive (p, P), integrated (d,D), and moving average (q,Q) parts of the model, where p, d, q, P, D, Q are non-negative integers. The number of values (lags and differences) involved in AR, I, and MA processes is referred to as the order of respective effects. Additionally, the number of parameters, as well as their values, determines the properties of the given ARIMA model. This algorithm is widely used for time series modeling. The procedure consists of three iterative steps: (1) identification (choice of parameters); (2) estimation (assessment of the parameters' values); and (3) checking and diagnostic of the model, going back to the model identification step if the previous assumptions are not satisfied. On this step, the assumption of ARIMA models is checked, for example, that the errors are independently and normally distributed.

Figure 3.1: Conceptual Framework of ARIMA-Model



Source of Diagram: George Box, and Gwilym Jenkins (1976)

According to George Box, and Gwilym Jenkins (1976), the major tools used in the identification step are autocorrelation function (ACF), and partial autocorrelation function (PACF). The ACF and PACF are used to confirm the presence of the autoregressive process in the time series data. The PACF is helpful in identifying the order of an autoregressive part of the ARIMA model. By following the properties of theoretical PACF, the number of significant lags determines the order of autoregressive process.

4.0 Data Presentation

Figure 4.1: Time plot of DACA accepted for 2012 through 2016 within the sixty months.

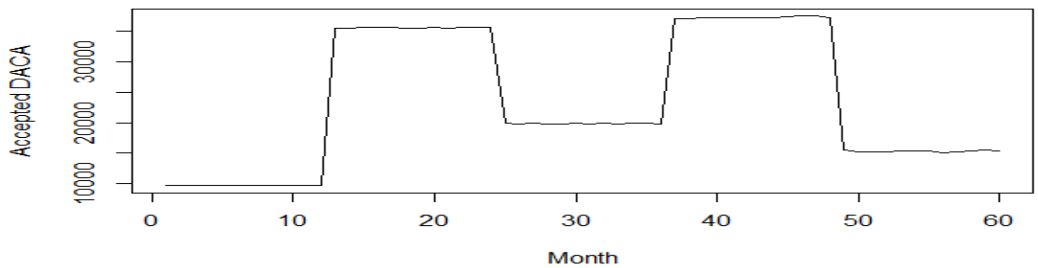
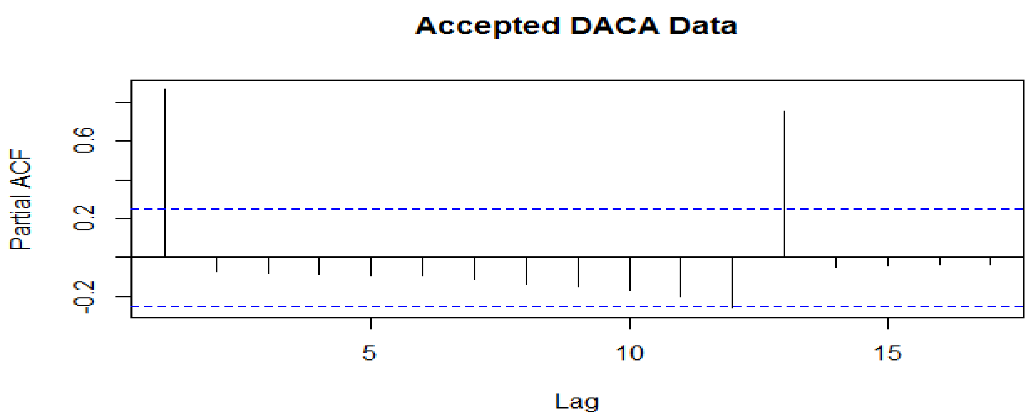
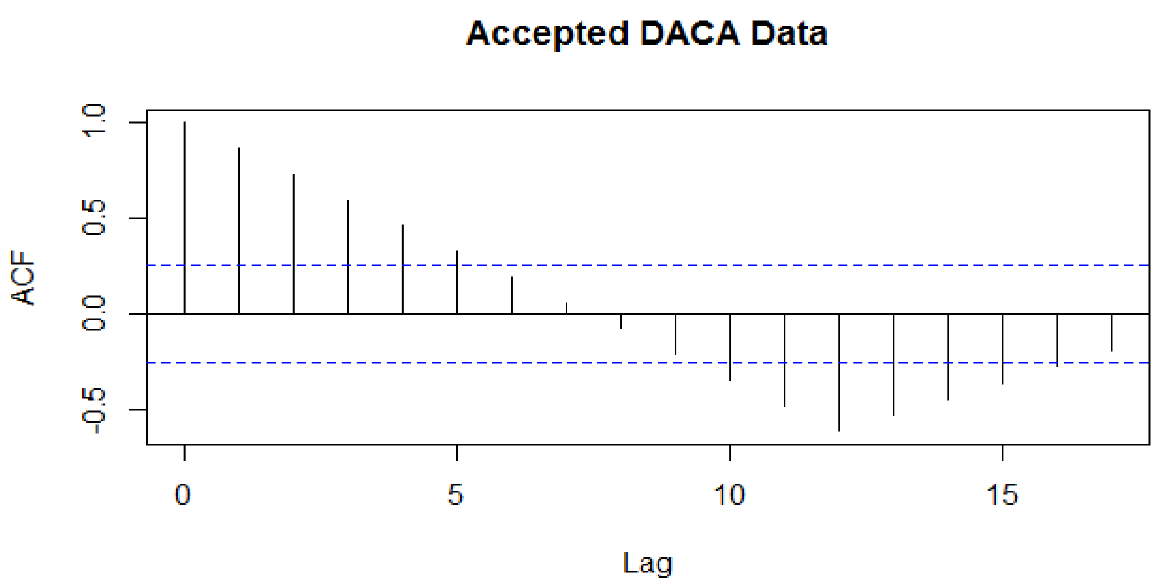


Figure 4.2: Partial Autocorrelation Function (PACF) and Autocorrelation Function (ACF) of U.S. Employment.





Trend Differencing

Figure 4.3: First difference of the U.S. employment data

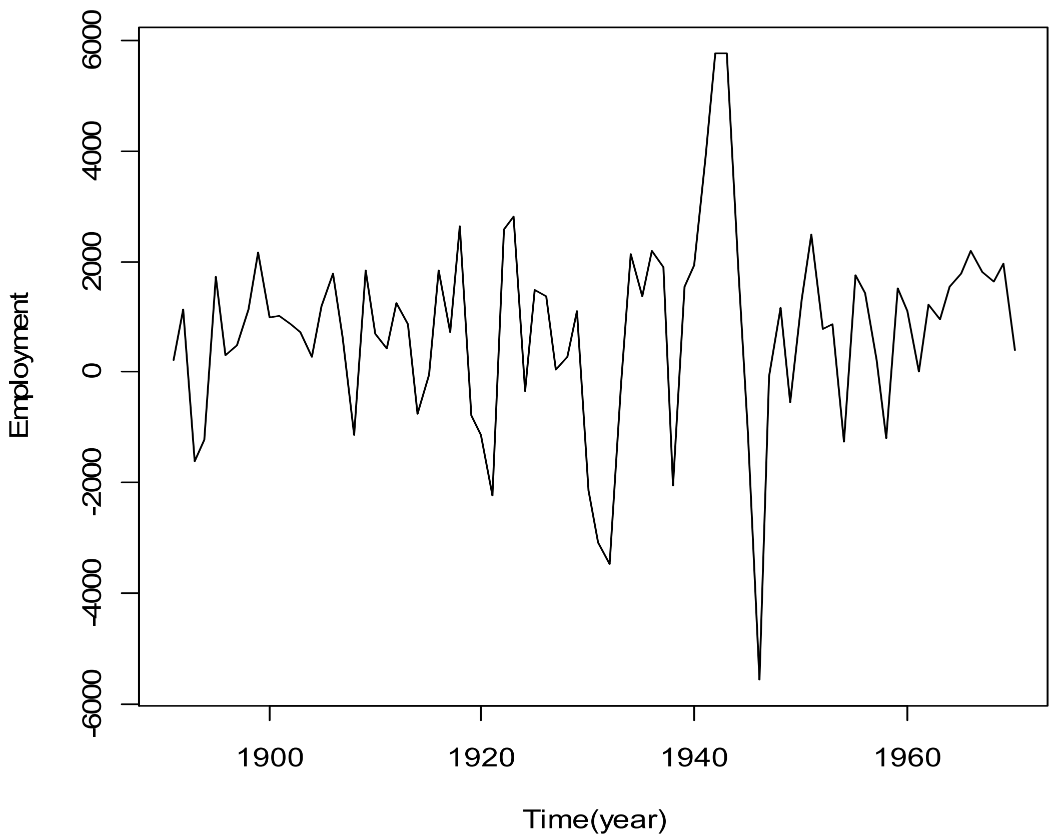
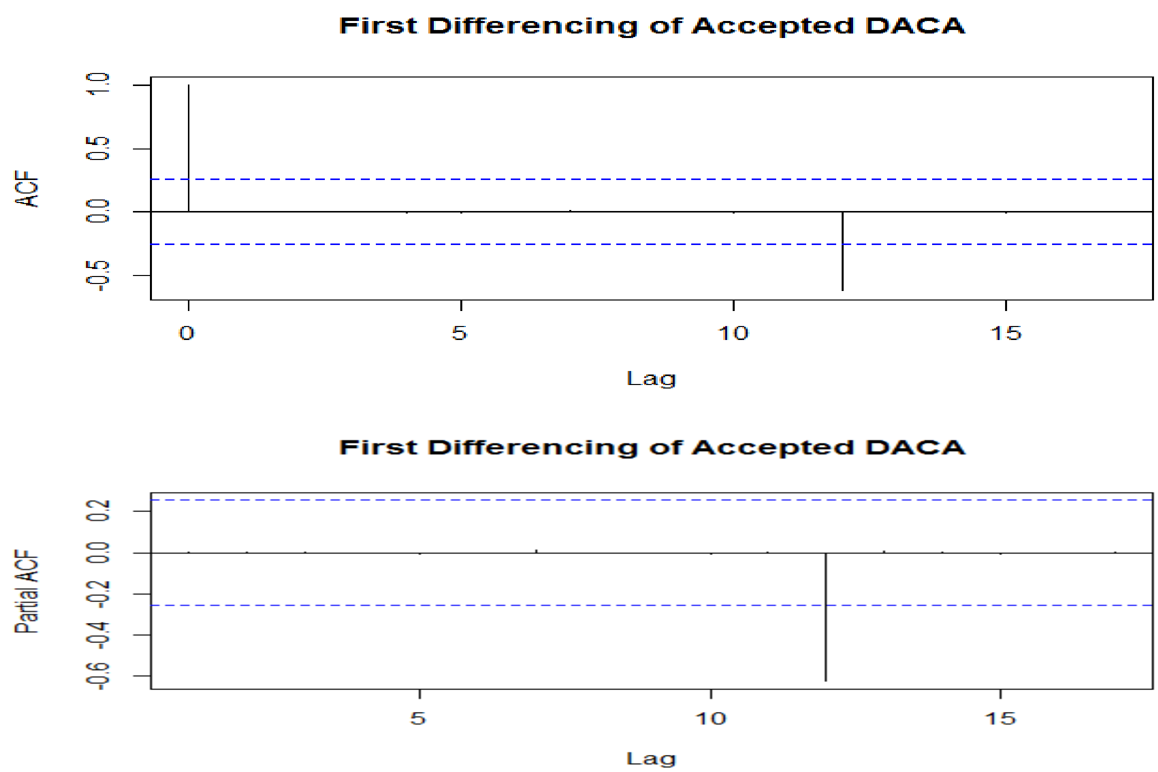


Figure 4.4: ACF and PACF of the first differencing of accepted DACA data



Very importantly, inspecting both the ACF and the PACF of the first differencing of the data, the following models are suggested;

- $ARIMA(1,1,0)$
- $ARIMA(0,1,1)$
- $ARIMA(1,1,1)$

To select the best model for forecasting into the future, each model is assessed based on its parameter estimates, the corresponding diagnostics of the residuals and the $AIC, and\ BIC$.

Model Selection

Figure 4.5 Parameter Estimates and Diagnostics of $ARIMA(1, 1, 0)$ Model

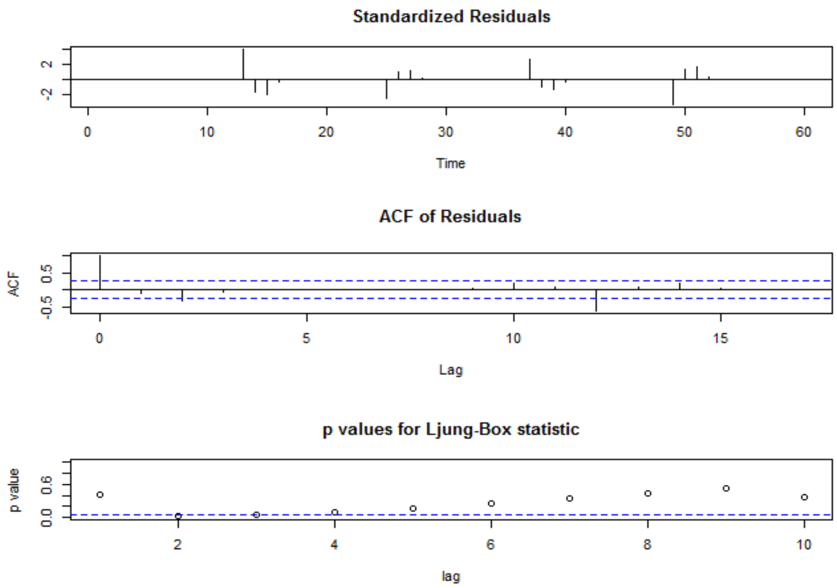


Figure 4.6 Parameter Estimates and Diagnostics of $ARIMA(1, 1, 1)$ Model

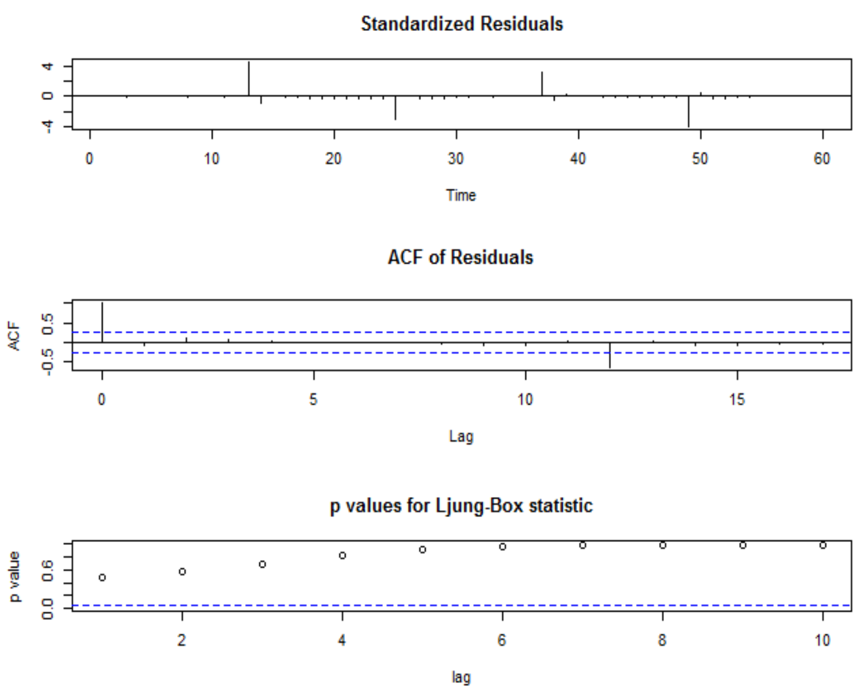
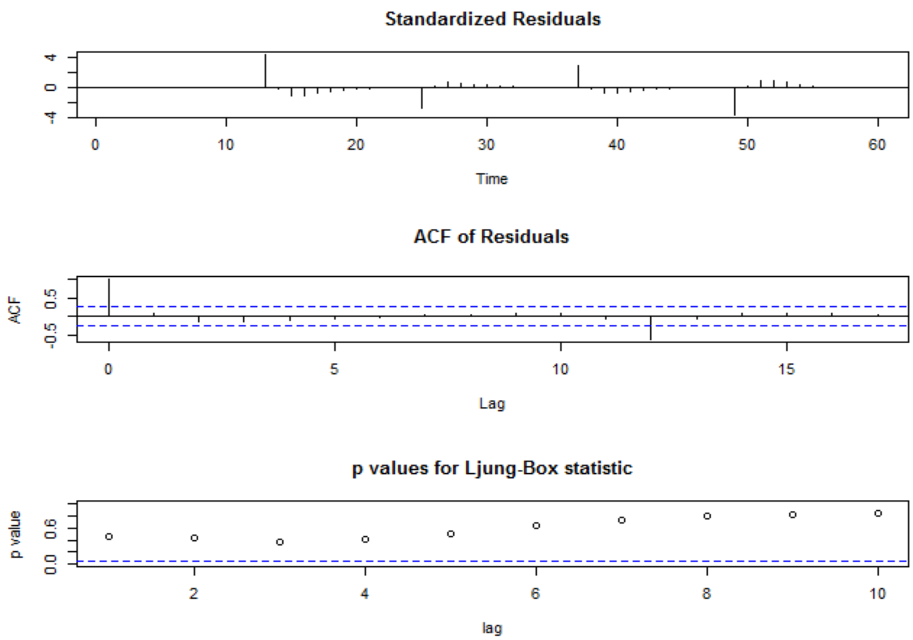


Figure 4.7 Parameter Estimates and Diagnostics of $ARIMA(0, 1, 1)$ Model



4.1 Data Discussion and Analysis

Figure 4.1 shows the time plot of the DACA accepted for 2012 to 2016. There is a systematic change in the time plot in Figure 4.1 which is seemingly periodic known as the trend. The trend factor shows the pattern of the accepted DACA whether it is decreasing or not. In general, the trend in accepted DACA is increasing but not always the case. This implies that both the legal and illegal immigrants always find the DACA policy interesting at the first time and get registers in the short-run, wherein somewhere along the line majority of the DACA recipients quit from the policy by refusing to renew their policy after expiration. Regarding figure 4.1, it is very important to note that the monthly (or annual) accepted DACA time plot does exhibit seasonal variation and it is not stationary due to the trend component.

Figure 4.2 demonstrates the autocorrelation function of accepted DACA made up of both employed and eligible DACA recipients who are more likely to supply labor. The ACF and PACF both describe the correlation between values of the accepted DACA at different points in time before deportation, as a function of the two times or of the time difference. The autocorrelation function in both the ACF and PACF are decreasing to some level and increase again with the certain terrain. However, the above plot of ACF and PACF further show that there exists a trend factor in the sampled DACA immigration data.

Figure 4.3 shows the transformation of the U.S employment data using the first differencing method. The data took into account both DACA employed and Citizens employed. The first differencing method is performed to remove the trend component in the original U.S employment data. The observations move irregularly but revert to its mean value and the variability is also approximately constant. After the introduction of the first differencing procedure, the U.S. employment data is observed now to be approximately stable, hence stationary.

The top part of **Figure 4.4** shows the autocorrelation function of the first differencing of the accepted DACA data at various lags and the bottom part is the partial autocorrelation function of the first differencing of the accepted DACA data also at different lags.

Figure 4.5 shows the diagnostics of the residuals from $ARIMA(1,1,0)$ above. Interestingly, the top part is the time plot of the standardized residuals of$ARIMA(1,1,0)$. Given the available DACA data, the standardized residuals plot shows no obvious pattern and look like an identical and independent distribution (i.i.d) sequence of mean zero with some few outliers. Also, the middle part of figure 4.5 shows the diagnostics checking plot of the ACF of the residuals. It revealed that there is no evidence of significant correlation in the residuals at any positive lag. Finally, the bottom part of the diagnostics is the time plot of the Ljung-Box statistics. It is observed that the Ljung-Box statistics plot is significant at any positive lag.

Figure 4.6 demonstrates the Diagnostics of the residuals from $ARIMA(1,1,1)$. The top part is the time plot of the standardized residuals of $ARIMA(1,1,1)$. The standardized residuals plot shows no obvious pattern and looks like an i.i.d sequence of mean zero with some few outliers. The middle part of figure 4.6 of the diagnostics is the plot of the ACF of the residuals. It revealed that there is no evidence of significant correlation in the residuals at any positive lag. Nonetheless, the bottom part of the diagnostics is the time plot of the Ljung-Box statistics. It is also observed that the Ljung-Box statistics plot is not significant at any positive lag.

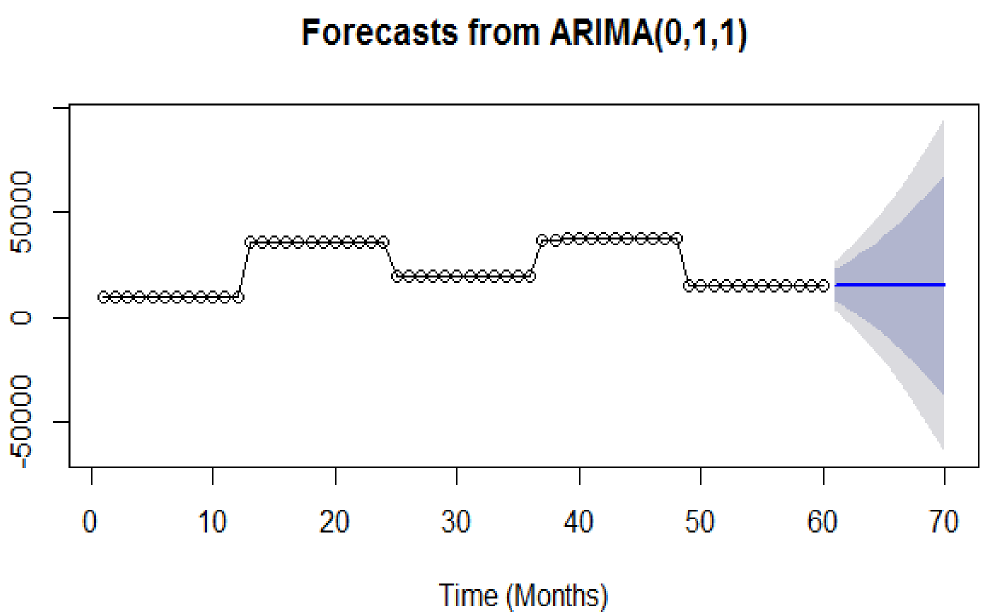
Figure 4.7 shows the diagnostics of the residuals from $ARIMA(0,1,1)$ which is made up of three parts diagrams. The first part is the time plot of the standardized residuals of $ARIMA(0,1,1)$. The standardized residuals plot shows no obvious pattern and looks like an i.i.d sequence of mean zero with some few outliers. The middle (or second) part of the diagnostics is the plot of the ACF of the residuals. There is no evidence of significant correlation in the residuals at any positive lag. However, the bottom (or third) part of the diagnostics is the time plot of the Ljung-Box statistics. It is observed that the Ljung-Box statistics plot is significant at any positive lag.

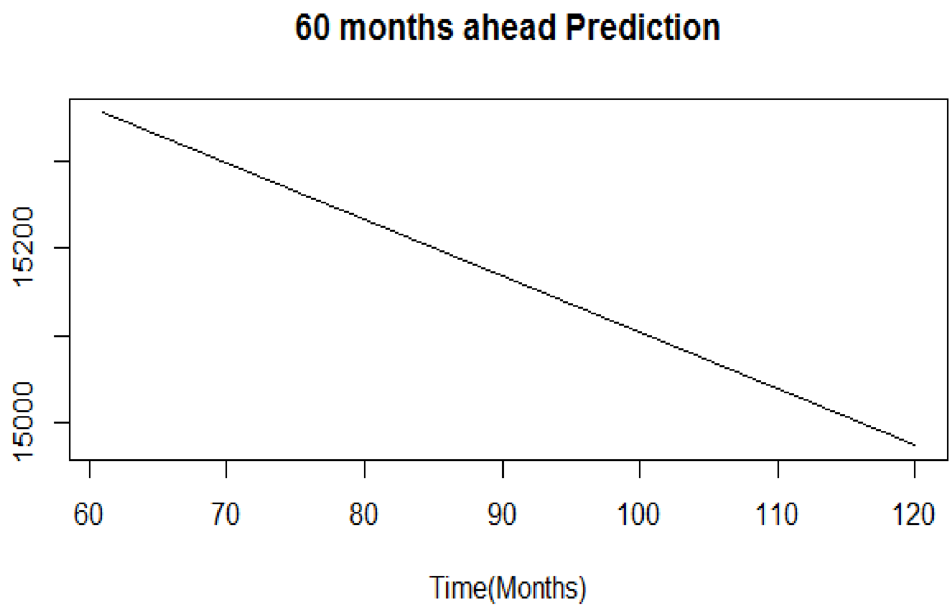
4.2 Selection of Best Model for Forecasting

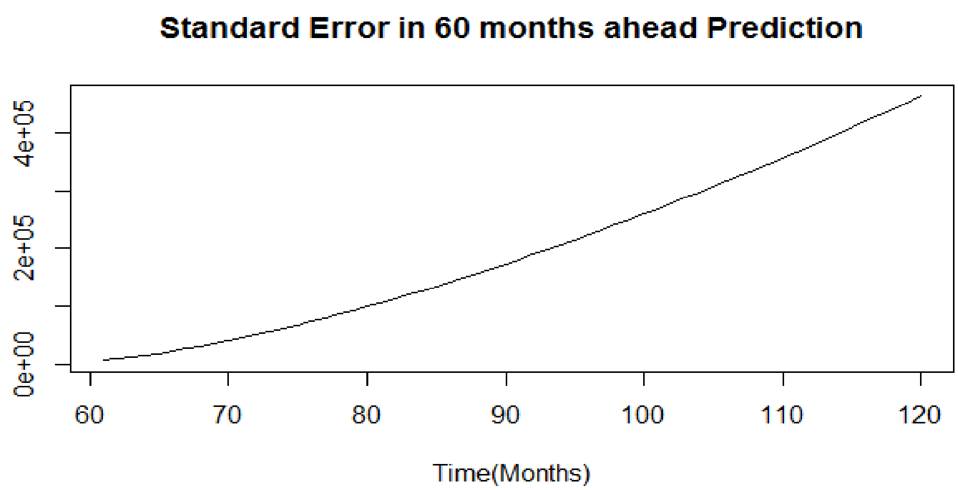
The standardized residual plots of all the models are independently and identically distributed (i.i.d) with mean zero and some few outliers. There is no evidence of significance in the autocorrelation functions of the residuals of all the models except one model and the residuals appear to be normally distributed in all the models. The Ljung-Box statistics are not significant at any positive lag for all the models

All the parameters in the $ARIMA(1,1,1)$model are not significant at 5% level of significance which could have a negative effect on the forecast if used for prediction while the parameters in the $ARIMA(1,1,0)$ and $ARIMA(0,1,1)$ models are significant. The AIC and the BIC are good for all the models but they favor $ARIMA(0,1,1)$, model. From the above discussion, it is clear that $ARIMA(0,1,1)$ model is the best model for forecasting.

Figure 4.8 Graph of the accepted DACA, its forecasts and confidence intervals







Towards this end, the 60 steps into the future forecasts are shown in Figure 4.8 by the grey-shading in the first diagram. The future forecast implies that the accepted DACA will continue to vary by rising and falling seasonally in the next 60 months due to the policy repeal.

5.0 Conclusion and Policy Recommendation

Toward this end, the study came out with interesting and important revelations to the policymakers. As part of the findings, the study revealed that there is a systematic change in the time plot of ACF and PACF (i.e. trend component) in the accepted DACA data. Also after the introduction of the first differencing de-trending procedure, the U.S. employment DACA data was observed to be approximately stable, hence stationary. Based, on the checking and diagnostic testing of ARIMA-models, the study forecasted that the accepted DACA will continue to vary by rising and falling seasonally in the next 60 months due to the policy repeal.

The study has the conclusion that, for the continuous growth and survival of the labor force of the United States of America, there is the need for continued existence and expansion of the DACA policy. It is not, therefore, surprising that President Obama decided to expand the DACA policy in 2014. However, the deportation of DACA recipients by the Trump administration is likely to inflict a devastating consequence on U.S. labor force, if the policy is not properly assessed.

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