

# US Unemployment Trends

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## Abstract

*The information from above is from the original presentation. The links as to who did what should be modified probably at the end. This is just a starting point. Also the abstract should be written last so I thought it was a good place to put this information.*

*The writeup below has dummy text so I could set up the sections. I also moved some of the older write-up text to this document to start it all up.*

## 1 Introduction

Unemployment has been a topic of concern throughout the United States in recent years. The Great Recession of 2007 was accompanied the worst unemployment crises seen since the 1930s (Wanberg, 2012). The results have been enduring, in 2010 the US job deficit was estimated to be over 10 million (Katz, 2010). Graduate and Undergraduate college students alike are concerned over their employment prospects, wondering if their degrees will be enough to gain them a job after graduation. These worries are well-founded as full-recovery of college graduate employment rates and earning is expected to be a slow process Carnevale and Cheah (2015). In these times of economic uncertainty, obtaining an income generating position is not the guarantee it has seemed to be in generations past.

Unemployment has far-reaching consequences that extends beyond financial security. Unemployment is linked to psychological difficulties, including depression and suicide, and even physical deterioration (Wanberg, 2012; Kim and von dem Knesebeck, 2015; DeFina and Hannon, 2015). A study of Greek students found a relationship between parental unemployment and PTSD symptoms related to bullying (Kanellopoulos et al., 2014). In Nigeria, unemployment has been linked to insurgency and terrorism (Akanni, 2014). Given the impact

that unemployment has on fiscal, mental, and physical health, reasearch into unemployment patterns an important part of developing policies to improve the welfare of the local, national, and global populace.

### 1.1 Goal

The purpose of our project is to examine trends in unemployment in the United States. We will focus on the years surrounding the Great Recession of 2007, 1992 to 2015. Our goal is to forcast unemployment into 2016.

### 1.2 Data

The unemployment data being examined was obtained from the seasonally adjusted, monthly, Civilian Unemployment Rate Series (UNRATE), published by the Bureau of Labor Statistics (BLS). This series includes unemployment figures from January of 1948 to May of 2016 (U.S. Bureau of Labor Statistics, 2016b,a). The response variable being analyzed is the unemployment rate defined as the percentage of the labor force that is unemployed. In defining this variable, the BLS restricts this to, “people 16 years of age and older, who currently reside in 1 of the 50 states or the District of Columbia, who do not reside in institutions (e.g., penal and mental facilities, homes for the aged), and who are not on active duty in the Armed Forces”.

Resession dates were obtained from the National Bureau of Economic Research (NBER) (The National Bureau of Economic Research, 2016). The NBER identifies recessions and US business cycles based upon a variety of economic indicators. These include Gross Domestic

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§Write-up

¶Diagnostics

||Model fitting and plots

Product (GDP), Gross Domestic Income (GDI), and a variety of less well known indicators such as Aggregate hours of work in the total economy.

We also explored several potential predictor variables that are potentially related to unemployment. Industrial Production measures enterprise output of the U.S. establishments (The Board of Governors of the Federal Reserve System, 2016). Value of Manufacturers' New Orders for All Manufacturing Industries refers to manufacturer's sales and inventory, except for New Orders from the Semiconductor Industry (US. Bureau of the Census, 2016c). The Purchase Only House Price Index for the United States follows sales for a specific set of single-family homes (US. Federal Housing Finance Agency, 2016). We also included Retailers Sales (US. Bureau of the Census, 2016a) and Total Construction Spending (US. Bureau of the Census, 2016b).

## 2 Exploratory Analysis

Figure 1: Plot of the original data

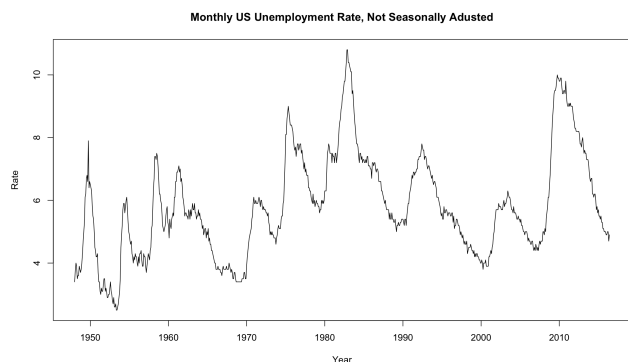


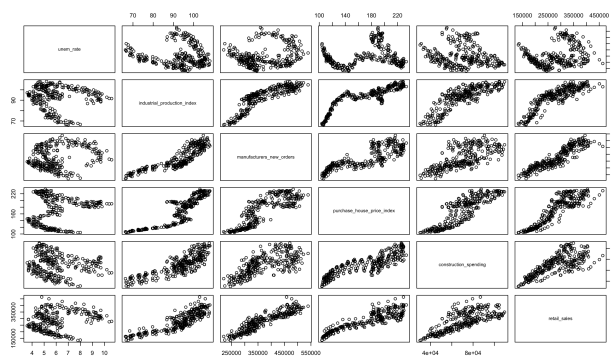
Figure 2: Seasonally adjusted unemployment for the study time period



As a first step, the data was plotted over time to identify any obvious patterns visually, considering both seasonally adjusted and non-seasonally adjusted versions of the unemployment rate, see Figure 1. Overall, unemployment appears relatively volatile. There are several time periods of sudden spikes in the unemployment rate, followed by a slower recovery period. This countercyclical movement is consistent with the descriptions of unemployment data found in the literature (Katz, 2010; Montgomery et al., 1998; Shimer, 2012).

Due to marked potential differences in the trend surrounding times of economic downturn, such as those that occurred after World War II and in the 70s and the 80s, we have chosen to limit our analysis on a more recent set of unemployment data. Ultimately, we decided to focus the time preceeding and following the Great Recession of 2007. We limited our initial analysis to 1992 to 2015, which encompasses the presidential terms of Bill Clinton, George W. Bush, and Barack Obama, each serving eight years in office. Initial graphs of the data seem to indicate that, in general, unemployment spiked at the beginning of each president's term and fell gradually over the time he was in office, see Figure 2. There are also two noticeable spikes that represent the recessions of 2001 and 2008, respectively. The 2008 recession also follows the burst of a housing market bubble. These are all explanatory variables that can potentially inform unemployment patterns. A scatterplot of these predictors can be seen in Figure 3.

Figure 3: Scatterplot of unemployment and potential predictors



## 3 Achieving Stationarity

After the initial exploration of the time series graphs, the team has chosen to focus on building preliminary models which will serve as the foundation of further analysis. In looking at the initial plots, it appears that the series could benefit from detrending. As such, one of the pri-

many goals has been to transform the data to stationarity.

An Augmented Dickey-Fuller (ADF) test for stationarity was conducted to verify the nonstationarity of the unemployment data. The ADF test tests the null hypothesis that the time series data has a unit root against the alternative that the data are stationary (Shumway and Stoffer, 2006). For the non-seasonally adjusted data the Dickey-Fuller test statistic was -1.4266, with a lag order of 6, and a p-value of 0.8176. Additionally, the seasonally adjusted data had a Dickey-Fuller test statistic of -2.1377, also with a lag order of 6, and a p-value of 0.518. The high p-values suggest that we do not have a stationary model with just the raw unemployment data, whether or not the data are seasonally adjusted.

Figure 4: Autocorrelation of unemployment data

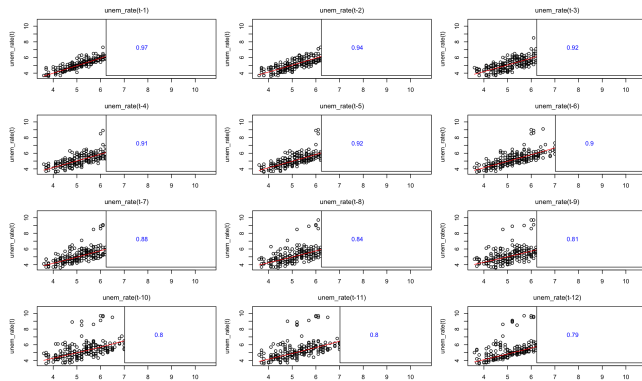
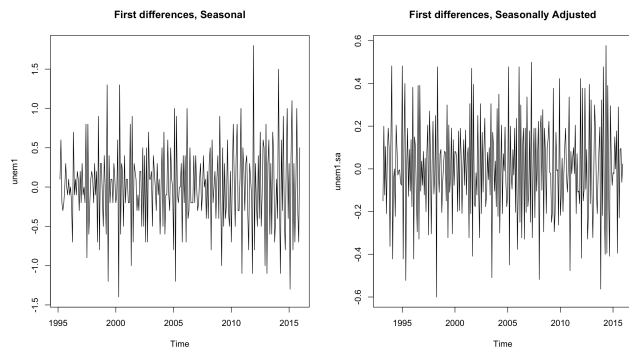


Figure 5: First differences of unemployment rate



A graph of various potential lagged values for unemployment can be seen in Figure 4. The first and second differences of the unemployment data were plotted for both the seasonal and seasonally adjusted unemployment data, see Figures 5 and 6. Both the first and second differences appear considerably more stationary when compared to the original data. The associated ADF test results are given in Table 1. Based on the p-

values, there is significant evidence of stationarity with each of the 4 differenced models. The consensus in the group was to continue the model building using second differences.

Figure 6: Second differences of unemployment rate

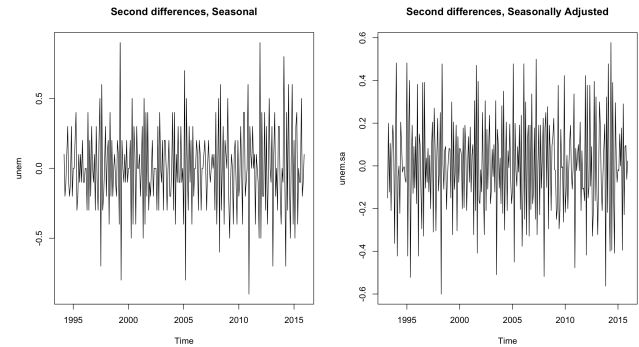


Table 1: ADF Test Results

Model	Statistic	Lag order	p-value
1 <sup>st</sup> difference	-7.6799	6	< 0.01
1 <sup>st</sup> difference, SA	-9.3595	6	< 0.01
2 <sup>nd</sup> difference	-8.4515	6	< 0.01
2 <sup>nd</sup> difference, SA	-9.3595	6	< 0.01

## 4 Model Building

### 4.1 ACF and PACF Plots

The team visually analyzed the ACF and PACF plots within the first season ( $h = 1, 2, \dots, 12$ ), see Figure ?? . The PACF appears to decline slowly, while the ACF seems to fall off after 1. Therefore we began by letting  $p = 0$ , and  $q = 1$ . Several models were considered by making adjustments to variations resulting in the models found in Table 2.

### 4.2 Model Fit

This will need to be adjusted to make reflect our current decision on the models.

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Table 2: Model Summaries

Model #	Order	Seasonal Order	AIC	BIC
1	0,2,1	1,1,0	-2.27	-3.23
2	0,2,1	3,1,0	-2.44	-3.37
3	4,2,1	3,1,0	-2.44	-3.32
4	0,2,1	1,0,0	-2.61	-3.58
5	1,2,1		-2.63	-3.60
6	1,0,1		-2.617	-3.578
7	1,0,1		-2.672	-3.565

Based on the AIC values, the two models that show the most promise are models 5 and 7. Model 5 includes only the time series data whereas model 7 also includes some of the predictors of interest. The diagnostic plots are shown in Figures ?? and ??. Both models show a great deal of promise. The standardized residuals show no apparent pattern. The ACF of the residuals show no departure from normality. Although the Normal Q-Q plot of the standardized residuals shows some slight departure from normality in the tails, there is no strong evidence of lack of normality in the residuals. The p-values for the Ljung-Box statistic are high enough at all plotted lags, so there is no indication of lack of fit in the models. Therefore, we will continue to refine these models further as we explore the nature of US Unemployment rate patterns.

### 4.3 Predictor Variables

Hello, here is some text without a meaning. This text should show what a printed text will look like at this place. If you read this text, you will get no information. Really? Is there no information? Is there a difference between this text and some nonsense like “Huardest gef-burn”? Kjift – not at all! A blind text like this gives you information about the selected font, how the letters are written and an impression of the look. This text should contain all letters of the alphabet and it should be written in of the original language. There is no need for special content, but the length of words should match the language.

## 5 Forecasting

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## 6 Discussion and Implications

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