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 iof 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-reovery 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 seasonaly 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, 2016). 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".

Unemployment tends to follow a countercyclical pattern, increasing quickly during times of economic slowdowns and decreasing slowly in times of growth (Montgomery et al., 1998). To address this we have chosen to include a recession indicator as a possible predictor of

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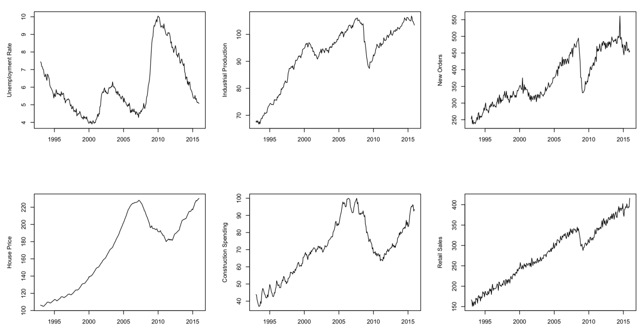
unemployment. Resession dates were obtained from the National Bureau of Economic Research (NBER) (The National Bureau of Economic Research, 2016). The NBER identifies recessions and US business cycles based upon a variety of economic indicators. These include Gross Domestic Product (GDP), Gross Domestic Income (GDI), and a variety of less well known indicators such as Aggregate hours of work in the total economy.

Figure 1: Timeplots of included variables



We also explored several 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 Semicondutor 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). Each of these predictors shows an overall increasing trend over time, see Figure 1.

2 Exploratory Analysis

As a first step, the data was plotted over time to identify any obvious patterns visually, considering the seasonlly adjusted version of the unemployment rate, see Figure 2. 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).

Figure 2: Plot of the original data

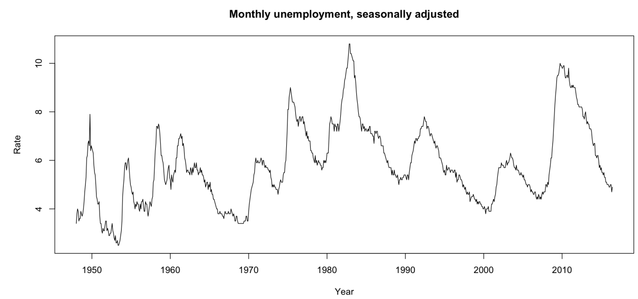
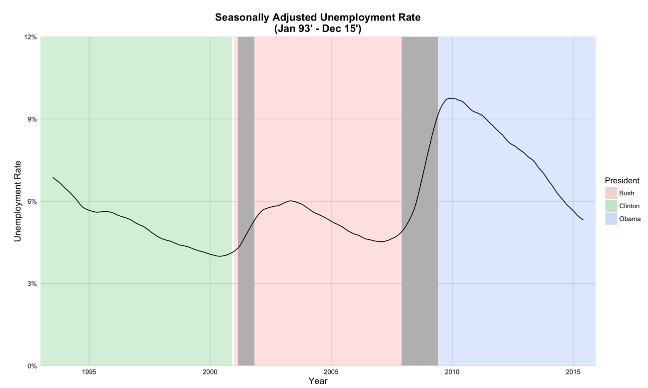


Figure 3: Smoothed unemployment for the study time period

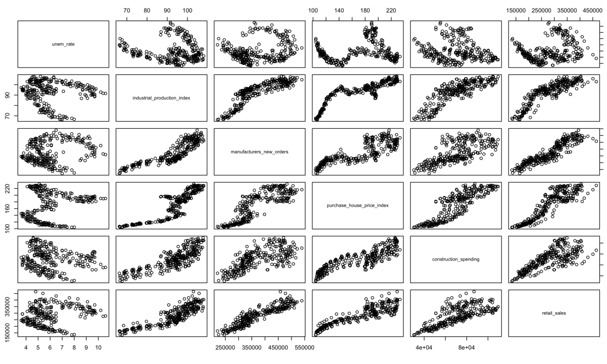


Due to marked potential differences in the trend surrounding times of economic downturn, such as those that occured after World War II and in the 70s and the 80s, we have chosen to limit our analysis on a more recent set of unemployment data. Ultimately, we decided to focus the time preceeding and following the Great Recession of 2007. We limited our inital analysis to 1992 to 2015, which encompases 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 begining of each president's term and fell gradually over the time he was in office, see Figure 3. There are also two noticeable spikes the represent that 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 matrix of these predictors can be seen in Figure 4.

3 Achieving Stationarity

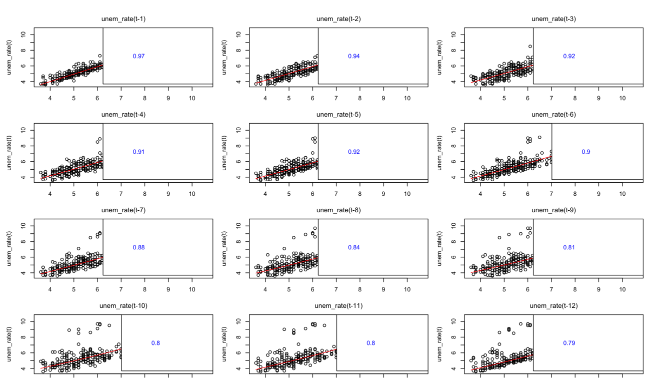
In analyzing the inital plots, it appears that the series could benefit from detrending. A graph of vari-

Figure 4: Scatterplot matrix of unemployment and potential predictors



ous potential lagged values for unemployment can be seen in Figure 5. The high values of the correlation coffecients, particularly through lag 6 further suggest a high degree of autocorrelation within the unemployment dataset. 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). The Dickey-Fuller test statistic for the unemployment data is -2.1377, 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.

Figure 5: Autocorrelation of unemployment data



The first, second, and third differences of the unemployment data were plotted for seasonally adjusted unemployment data, see Figure 6. All three sets of differencing, bring the data closer to stationarity with a consistent mean and more constant variance. 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 differenced models. Visually, the second differences best approximate a white noise series. Futhermore, even though the ADF statistic is more negative for the 3^{rd} differences there appears to be more variability in the model that includes third differences. Therefore, the consensus in the group was to continue the model building process using second differences.

Figure 6: Timeplots with and without differencing

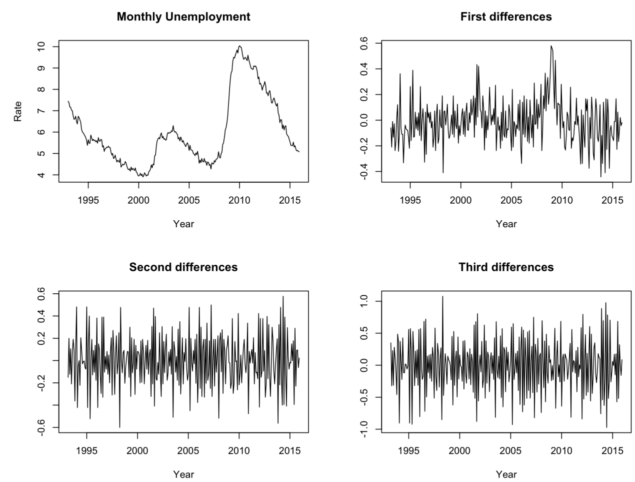


Table 1: ADF Test Results for unemployment

Model	Statistic	Lag order	p-value
1^{st} difference	-9.3595	6	< 0.01
2^{nd} difference	-9.3595	6	< 0.01
3^{rd} difference	-13.02	6	< 0.01

The predictor variables were also detrended using second differences. The timeplots of these second differences can be seen in Figure 7. Although the housing prices still retains some nonconstant variance, overall the differencing improves the stationarity of all the predictor variables. Futhermore, the ADF test of the differenced data provides evidence of stationarity for each of the variables, See table 2.

An attempt to stabalize the variance of the housing prices, utilizing a log transform, does not improve this stationarity much (ADF changes from -9.104 to -9.5211 and a scatterplot of the differenced logs still shows evidence of heteroscedasticity in the variance over time, see figure 8.

4 Model Building

We began our model building process by inspecting the correlogram (ACF plot) and partial correlogram (PACF plot) of tthe unemployment data, see Figure 9. The

Figure 7: Timeplots of differenced predictors

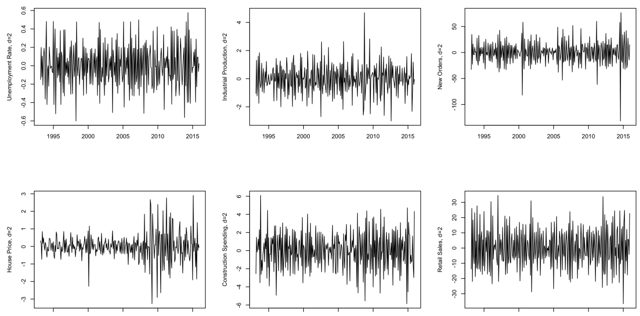
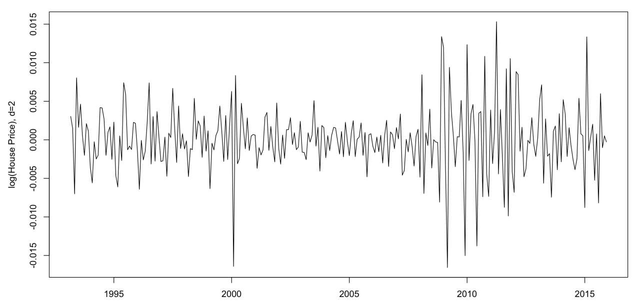


Figure 8: Timeplot of transformed housing prices, d=2



ACF seems to tail off and the PACF seems to cut off at either 1 or 3. A tailing ACF function with a PACF that cuts off at p suggests an AR(p) model (Box et al., 2008). Therefore, these inital plots suggest a possible AR(1) or AR(3) model. When looking at the ACF and PACF of the second differences, we have evidence of a possible mixture model with $d = 2$. For example, an ACF of difference d that decays exponentially after lag 1 with a PACF that is dominated by an exponential decay pattern after lag 1 would be evidence of an ARIMA(1,d,1) model . Therefore, it is worthwhile considering ARIMA models such as ARIMA(1,2,1). Of course predictor variables may help to improve the predictive strength of our models, therefore models with regressors and Vector Autogressive Models (VAR) were considered as well.

Table 2: ADF Test Results for Predictors, $d = 2$

Variable	**Statistic**	**p-value**
Industrial Production	-9.2333	< 0.01
New Orders	-8.391	< 0.01
House Prices	-9.104	< 0.01
Construction Spending	-10.447	< 0.01
Retail Sales	-10.72	< 0.01

Figure 9: ACF & PACF Plots

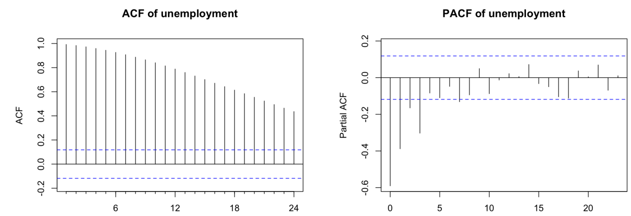
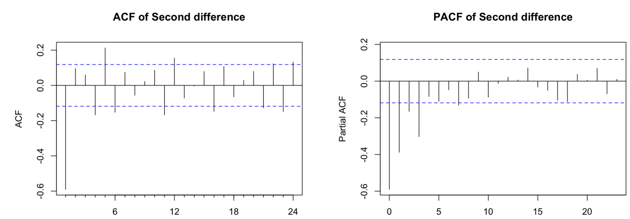


Figure 10: ACF & PACF Plots of Second Differences



4.1 Models Considered

4.1.1 ARIMA Models

Table 3: ARIMA models considered

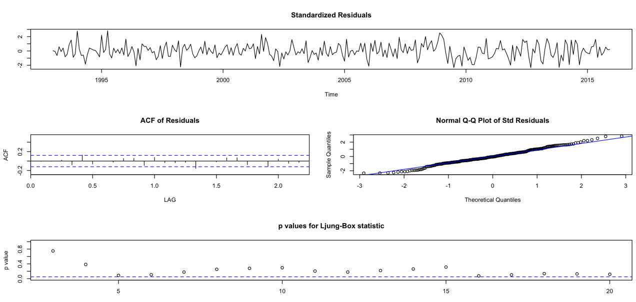
Model	Order	Reg	AIC	BIC	Best
1	1,2,1	NA	-212.30	-201.46	BIC
2	2,2,2	NA	-211.81	-193.74	
3	3,2,3	NA	-215.48	-190.19	
4	1,2,1	X	-211.56	-182.65	
5	2,2,2	X	-209.83	-177.32	
6	3,2,3	X	-215.10	-171.74	
7	1,2,1	LagX	-222.45	-193.69	AIC
8	2,2,2	LagX	-220.70	-188.35	
9	3,2,3	LagX	-217.89	-174.76	

Given the potenial of ARIMA models to represent the unemployment data we began by exploring three potential models without regressors, ARIMA(1,2,1), ARIMA(2,2,2), and ARIMA(3,2,3). Although model 3, ARIMA(3,2,3), has the lowest AIC of the three models, model 1, the ARIMA(1,2,1) model, has the lowest BIC. Model 1 is also the most parsimonious model of the three. So of the three intitial models, without regressors, we chose to retain model 1.

The univariate ARIMA models we began with seem to fit the data well and have the added strength of being relatively simple models. Nevertheless, in their simplicity univariate models are not equiped to accurately portray the asymmetric nature of unemployment data and have a tendency of underpredicting during economic slowdowns (Montgomery et al., 1998). Therefore, we repeaded the above analysis using multivariate ARIMA models. The variables Industrial Production, Value of Manufacturers' New Orders, Purchase Only House Price Index, Retailers Sales, and Total Construction Spending were includedpotential predictors of unemployment.

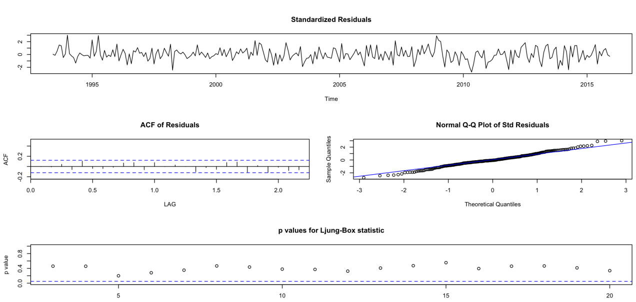
Models 4 through 6 were ARIMA(1,2,1), ARIMA(2,2,2), and ARIMA(3,2,3) respectively. These predictors had lower AIC and BIC values than their original counterparts without regressors, see Table 3. Since, these models were predicting a lagged response variable using data that was potentially nonstationary, we chose to repeat the process using lagged regressors. Models 7, 8, and 9 refer to the ARIMA(1,2,1), ARIMA(2,2,2), and ARIMA(3,2,3) models with lagged predictor variables. Of these three new models, model 7 has both the smallest AIC and the smallest BIC values. In fact of all 9 of our original models, model 7 has the lowest AIC overall, see Table 3.

Figure 11: Model 7: Residual Diagnostics



ARIMA(1,2,1) with no regressors

Figure 12: Model 7: Residual Diagnostics



ARIMA(1,2,1) with lagged regressors

Based on the AIC and BIC values, the two ARIMA models that show the most promise are models 1 and 7. Model 1 includes only the time series data whereas model 7 also includes some lagged versions of the predictors of interest. The diagnostic plots for these models are shown in Figures 11 and 12. 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, for both models, 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.

4.1.2 VAR Models

Table 4: VAR models considered

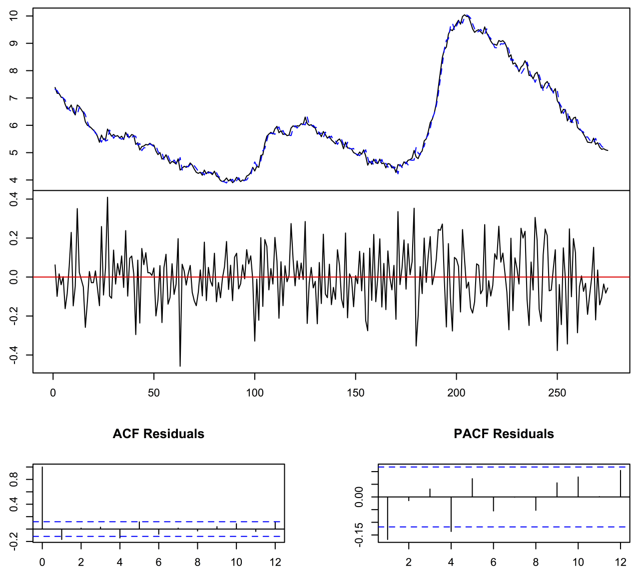
Model	P	Type	AIC	BIC	Best
1	1	NA	-223.67	-201.97	
2	2	NA	-217.83	-185.31	
3	1	Ind	-256.77	-231.45	BIC/AIC
4	1	LagX	-216.65	-195.06	
5	2	LagX	-212.53	-180.17	
6	1	Both	-245.72	-220.53	

Much of the recent literature on modeling unemployment trends has suggesting that vector autoregressive models (VAR) have the capacity to outperform ARIMA models and are widely used by professional forcasters (Meyer and Tasci, 2015; Tasci and Treanor, 2015; Barnichon and Garda, 2016). VAR models provide a mechanism for modeling complex, multivariate times series in the absense of a moving average term (Chatfield, 2001) . The ACF and PACF plots shown in Figures 9 and 10 do not conclusively demonstrate that the moving average term is necessary in this case, therefore we have decided to explore the potential in fitting VAR models to the unemployment data in order to improve the performance of our predictions.

We started 6 inital VAR models to compare. Models 1, 2, and 3 use the predictors of construction spending and retail sales, without differencing. Model 1 is a VAR(1), model 2 is a VAR(2), and model 3 is a VAR(1) with the regression indicator included as well. Models 4, 5, and 6 repeat the analysis using the differenced version of the predictors. Table 4 shows the AIC and BIC values for each of these models.

Model 3, the unlagged model with the regression indicator, has the lowest AIC and BIC values. The diagram of the fit and residuals for model 3 is provided in Figure 13. The blue line indicates that the actual and predicted values of unemployment are similar in this model. A timeplot of the residuals is consistent with a white noise series. The ACF and PACF of the residuals give no indication of lack of fit. Therefore, we have chosen to retain model 3 to compare with the ARIMA models developed earlier.

Figure 13: Model 3 fit and residuals for unemployment



4.2 Initial Model comparisons

Table 5: Comparison of ARIMA and VAR models

Model	Type	AIC	BIC
ARIMA #1	Univ ARIMA(1,2,1)	-212.29	-201.45
ARIMA #7	Mult ARIMA(1,2,1)	-222.45	-193.69
VAR #3	VAR(1)	-256.76	-231.45

In the previous model building process, we retained 3 models for further comparison. ARIMA model 1 is a univariate ARIMA(1,2,1) model without predictors, ARIMA model 7 is a multivariate ARIMA(1,2,1) model with lagged predictors, and

At first glance the VAR(1) model appears to be the best model. It has the lowest values of both AIC and BIC. Of the two ARIMA models the multivariate ARIMA(1,2,1) model has a lower AIC but a higher BIC. However, being a multivariate model, ARIMA #7 allows us to leverage the additional information provided by indicators of the nature of the economy to refine our predictions about future unemployment rates.

Since the rate of increasing unemployment is so different from the rate of decreasing unemployment, forcasing can be very difficult without some indicator of whether we are currently in a increasing or decreasing portion of the cycle (Montgomery et al., 1998). For this reason, we have chosen continue our model comparisons with only the two models that include predictors of economic strength. In the next section, we compare the forcasting performance of the best multivariate ARIMA model with best VAR model. These are the multivariate ARIMA(1,2,1) model and the VAR(1) with an indicator variable for recession among its predictors.

5 Forcasting

In the initial data setup, the 2016 values were initially excluded to provide a dataset with which to evaluate the performance of our predictions. Short-term predictions from the multivariate ARIMA(1,2,1) model and VAR(1) models were then compared compared with the actual unemployment rates for January 2016 through May 2016. These results were used to create our final model.

5.1 Multivariate ARIMA(1,2,1)

Figure 14: 5 month forcast with ARIMA(1,2,1)

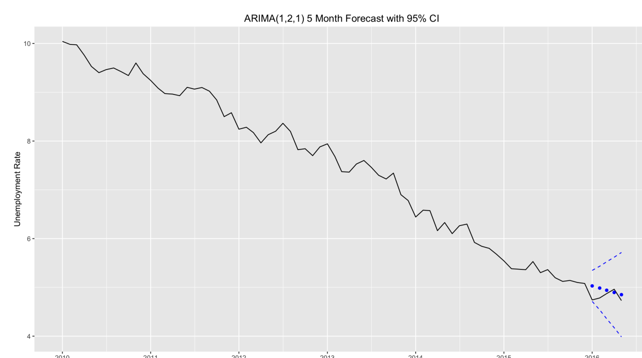


Table 6: 2016 Unemployment Rate Predictions from Multivariate ARIMA(1,2,1)

Month	Observed	Predicted	95% CI	Residual
Jan	4.74	5.03	(4.71 , 5.35)	-0.29
Feb	4.78	4.99	(4.54 , 5.43)	-0.20
Mar	4.87	4.94	(4.36 , 5.53)	-0.07
Apr	4.96	4.90	(4.17 , 5.62)	0.07
May	4.73	4.85	(3.99 , 5.72)	-0.12

The unemployment rates for January 2016 to May 2016 were forcast using the Multivariate ARIMA(1,2,1) model, see Table 6. This model did a good job overall, as all predicted values were within 0.3% of the actual unemployment rates and entirely inside the confidence bands. Figure 14 shows the predicted values graphed against the actual unemployment rates. The model predicts a steady decrease in the unemployment rate over the 5 month period. In general, the ARIMA model provided an overprediction of unemployment rate, except in April-16 when the rate spiked slightly. The confidence bands spread outward rapidly, suggesting an overall pattern of either falling or rising unemployment rate.

5.2 VAR(1)

Figure 15: 5 month forcast with VAR(1)

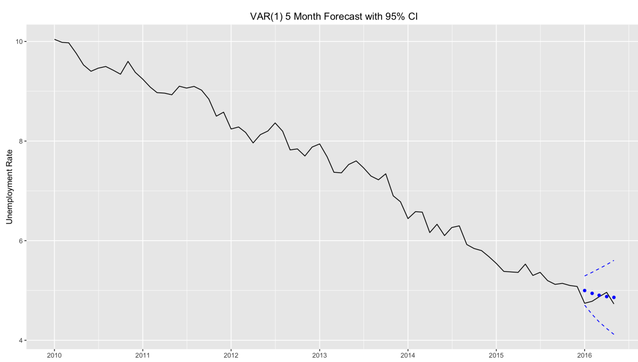


Table 7: 2016 Unemployment Rate Predictions from Multivariate VAR(1)

Month	Observed	Predicted	95% CI	Residual
Jan	4.74	5.00	(4.71 , 5.29)	-0.26
Feb	4.78	4.94	(4.52 , 5.36)	-0.16
Mar	4.87	4.90	(4.37 , 5.44)	-0.03
Apr	4.96	4.88	(4.24 , 5.52)	0.09
May	4.73	4.86	(4.12 , 5.60)	-0.13

The unemployment rates for January 2016 to May 2016 was also forcast using the Var(1) model, see Table 7. At first glance the results look very similar to the ARIMA(1,2,1) model. All predicted values were within 0.3% of the actual unemployment rates and entirely inside the confidence bands. Figure 15 shows the predicted values graphed against the actual unemployment rates. The model predicts a nonlinear decrease in the unemployment rate over the 5 month period, with the rate of decrease slowing over time. In general, the VAR model also provided an overprediction of unemployment rate, except in April-16.

5.3 Forcast comparisons

Figure 16: ARIMA and VAR Model comparison of 3 month forecast

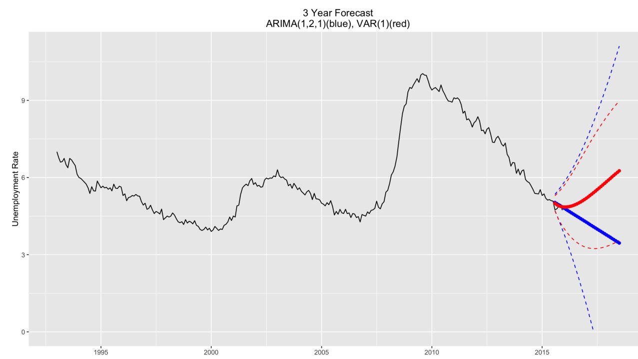


Figure 16 provides a graphical comparison of the two candidate models. The ARIMA(1, 2, 1) shows a steady, linear decrease of the unemployment rate over time, which is unrealistic in the long term. The Var model predicts a decrease in unemployment followed by an increase, which is more consistent with actual unemployment patterns. The mean square error from the VAR(1) model (0.0097) is much lower than the mean square error of the ARIMA(1,2,1) model(0.0151). The implication of this is that the confidence interval of the ARIMA model quickly explodes, suggesting that it may not a good choice for longer term forecasts.

6 Final model

6.1 Model estimates

6.2 Forcasts

7 Discussion and Implications

"Because of the evidence of fractional integration in the unemployment, stationarity and non-linearity issues (background noise) an multivariate singular spectrum model (MSSA) for modelling unemployment in Croatia is presented in this paper" (Skare and Buterin, 2015).

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