How Do Economic Indicators Impact the General Public's Interest in US Jobless Claims?

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Time Series and Forecasting

Summary

In this project, the main goal is to forecast future interest in US jobless claims using several major economic indicators. I selected the indicators that reflect the overall strength of the US economy, such as Jobless Claims (officially called Initial Claims (ICSA)), St. Louis Fed Financial Stress Index (STLFSI), S&P 500 Index and Russell 2000 Index.

For this project, I will be using an autoregressive–moving-average model with exogenous inputs (ARIMAX). This model contains the AR(*p*) and MA(*q*) models and a linear combination of the last *b* terms of known and external time series, denoted *d*.

$$X_t = \varepsilon_t + \sum_{i=1}^{p} \varphi_i X_{t-i} + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i} + \sum_{i=1}^{b} \eta_i d_{t-i}.$$

I constructed different models and compared the RMSE with baseline models. The baseline models, persistence and moving average, have RMSE of 10.62995 and 11.98249. I also tried Holt exponential smoothing which yields RMSE of 12.28643, as well as simple exponential smoothing which yields RMSE of 8.905084.

The hypothesis is that I could improve the forecasting by ARIMA and ARIMAX models so I fitted ARIMA(1,0,1); however the model has the RMSE of 10.3345, which is no better than a simple exponential smoothing model. After performing log differencing to all the explanatory variable indexes, I fitted ARIMAX(2,0,1), and that gives me the best RMSE of 8.186519.

Summary Statistics

Explanatory variables:

1) Percentage change in Initial Claims (ICSA)

> Jobless claims are a statistic reported weekly by the U.S. Department of Labor that counts people filing to receive unemployment insurance benefits. The purpose of reviewing jobless claims is to determine the direction of the unemployment rate and the overall health of the economy.

I decided to use percentage change rather than the raw ICSA values. By using the percent change transformation, it will make the time series stationary.

2) Logged-differenced St Louis Fed Financial Stress Index

> This index measures the degree of financial stress in U.S. markets on a weekly basis. The average of the index is zero. A value that is above zero indicates that there is an increase in the financial stress while a value below zero signals market conditions that are less stressful than average.

3 & 4) Logged-differenced S&P 500 and Logged-differenced Russell 2000

> Both S&P 500 and Russell 2000 are indexes that represent the stock market performances by widely quoted measure of the overall performance of capital stocks. Assumption: if the unemployment rate is higher, the general income will be limited; people have less cash in hand and therefore spend less money (demand for products decreases). This can mean that stock prices may go down in many areas because there isn't as much of a demand for certain goods.

For the St Louis Fed Financial Stress Index, Standard & Poor's 500, and Russell 2000, I decided to apply log difference transformations on each of the variables. By performing log difference transformations, the data will make highly skewed distributions less skewed. This allows the use of making patterns in the data more interpretable and to meet the assumptions of inferential statistics. Also, the log difference transformation allows it to make non-stationary data into stationary data.

Dependent variable:

Google Search Volume Index (SVI)

I used Google Search Volume Index (SVI) as an indicator for interest in US jobless claims. This index has a range of 0 to 100, and provides daily and weekly reports on the volume of queries for search terms used all around the globe.

I chose this index as the dependent variable because there is evidence that simple seasonal autoregressive models that incorporate relevant Google search trends as variables tend to outperform models that do not (Varian, 2009).

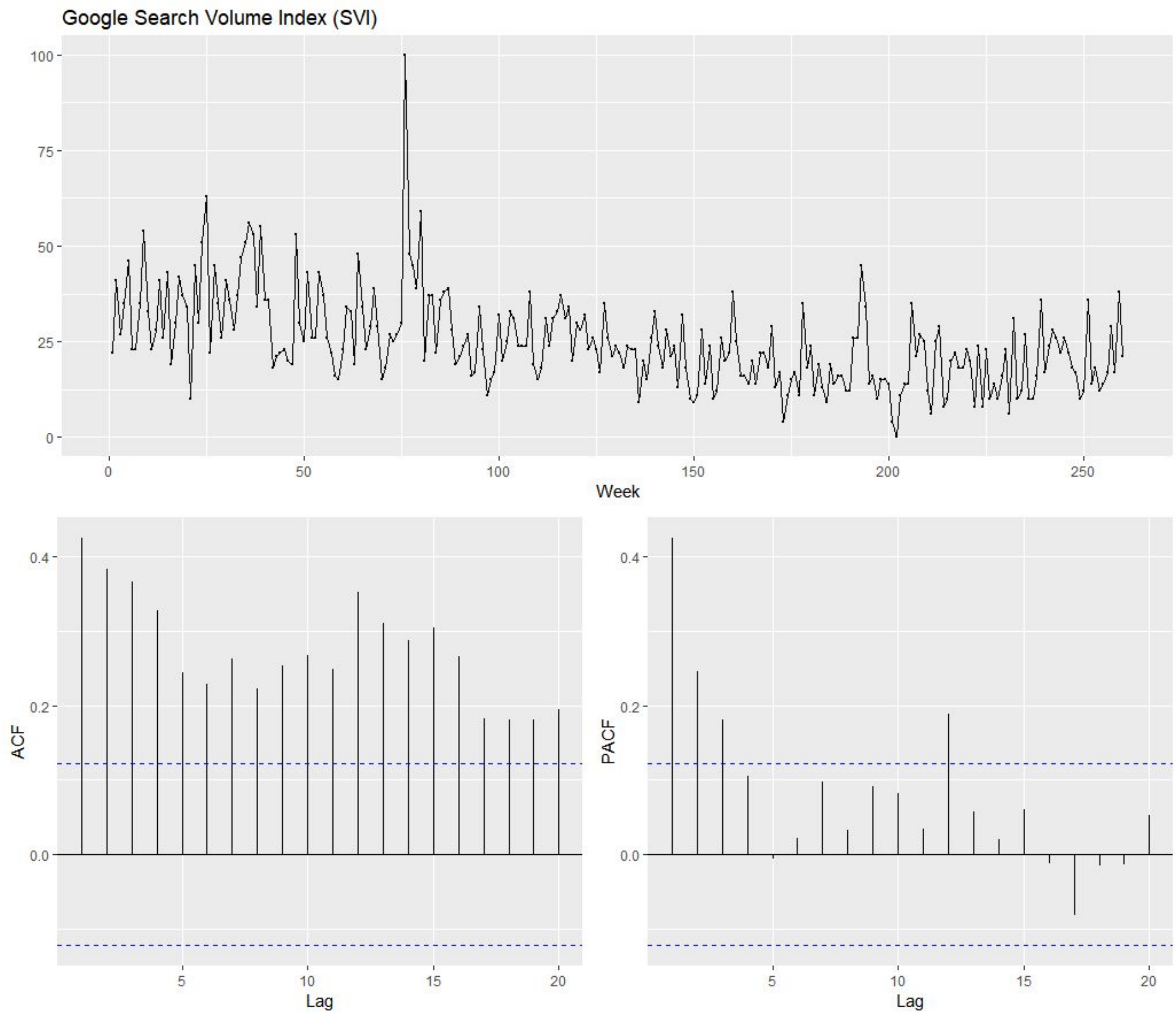
I focused on search queries that originated from the United States. For the analysis, I focus on data from the past 5 years.

Summary Statistics:

	Baseline models					
	Persistence (random walk)	Average of all previous observations	Holt Linear exponential smoothing	Simple smoothing	Arima(1,01)	Arimax(2,0,1)
RMSE	11.98249	10.62995	12.28643	8.905084	10.3345	8.186519

The table above shows the RMSE for each of the models tested. Arimax(2,0,1) performed the best with the lowest RMSE value of 8.186519.

<u>Time series and acf plots for each variable</u>:

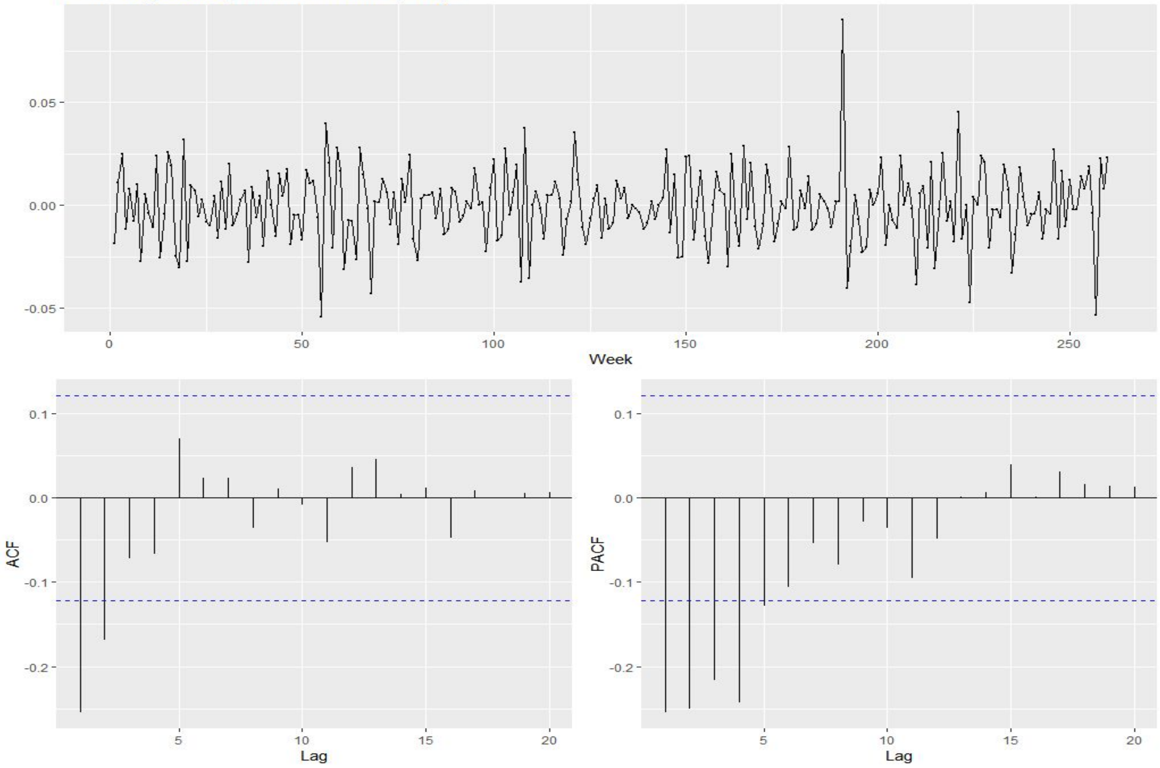


Based on the time series plot of Google Search Volume Index, it shows that it is stationary because there is no trend or seasonality.

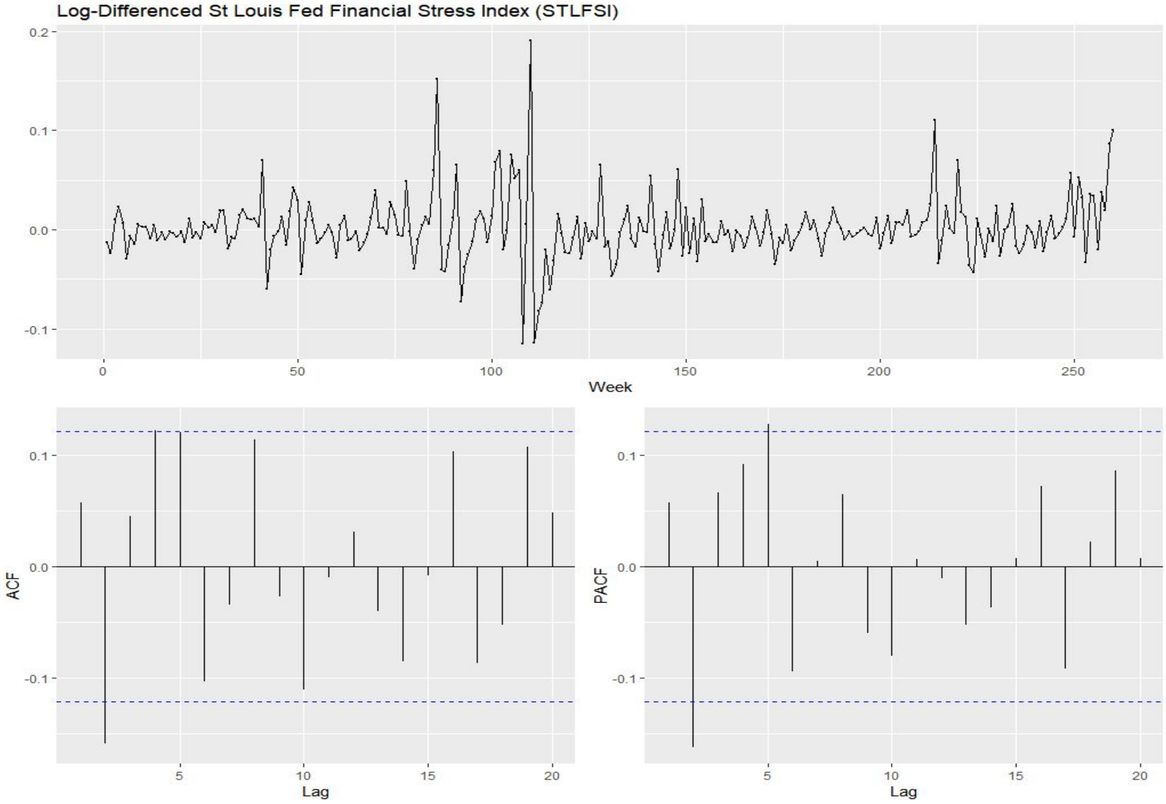
I tried a total of six models: two baseline models (persistence and moving average), holt exponential smoothing, simple smoothing, ARIMAX(1,0,1) and ARIMAX(2,0,1). Of the six models tested, I concluded that the results in an ARIMAX(2,0,1) model gives the smallest out-of-sample RMSE, when compared to the plain ARIMA model and the 2 baseline models.

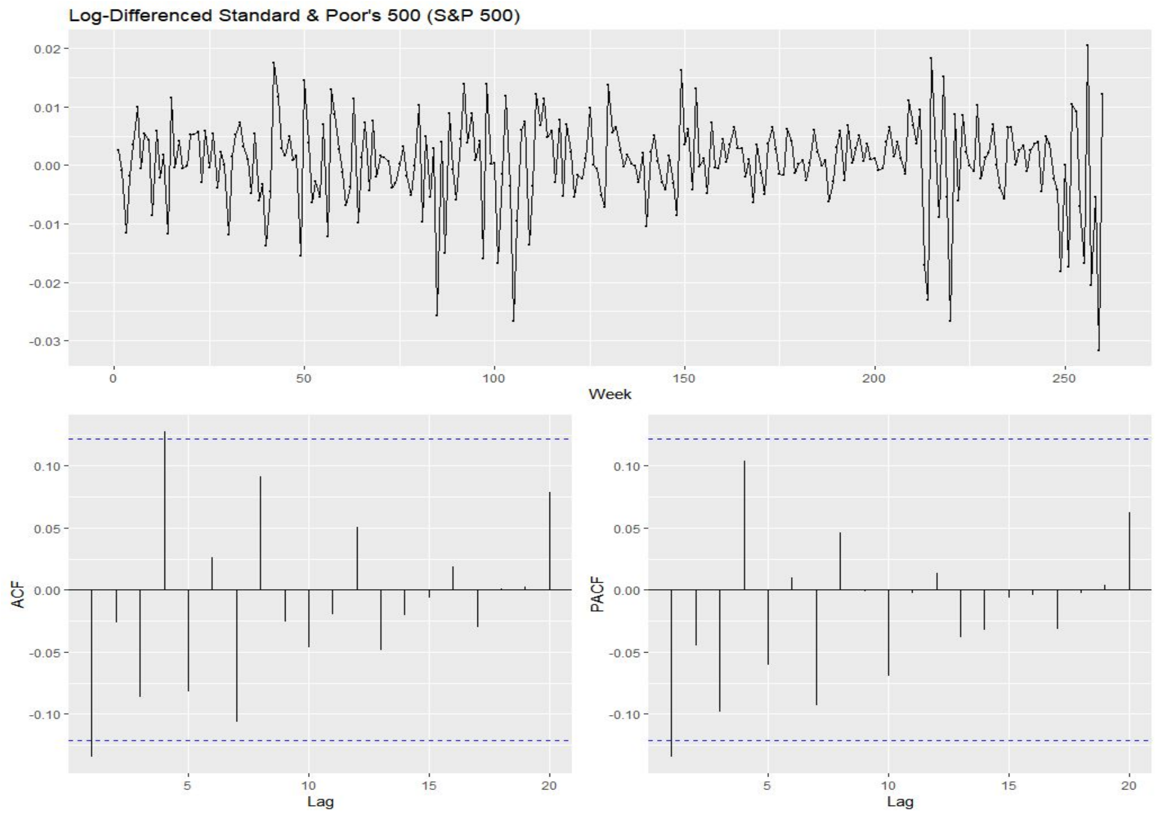
To make the data stationary, I applied a percentage change in Initial Claims and a logged difference in St Louis Fed Financial Stress Index (STLFSI). The graphs show stationarity after transformation. I also applied logged differencing in Standard & Poor's 500 (S&P 500) and Russell 2000 (RUT) as log differencing is a common practice to make stock data stationary.

Percentage Change in Initial Claims (ICSA)



Log-Differenced St Louis Fed Financial Stress Index (STLFSI)





Outline analysis

I decided to go with ARIMAX for the final model; I chose ARIMAX as it is the best model out of the six models I have built, it also allows me to use other explanatory variables for forecasting.

I did not do any transformation to the dependent variable -- SVI values, as it is stationary and it also has a fixed range of zero to 100, I am worried that applying any transformation may distort its value.

I decided to use percentage change in ICSA instead of raw ICSA values, so as to make it stationary. Initially I took the log-differences of the ICSA value, the approximations become a lot less accurate as they further apart from zero. For this reason, I opted for percentage changes in ICSA instead of log-differences, because ICSA values are pretty big (in the 100000s). For the remaining three explanatory variables, I applied log-differencing. I also lagged the explanatory variables by 2 so it captures the stickiness in the economy.

Appendix

R Code

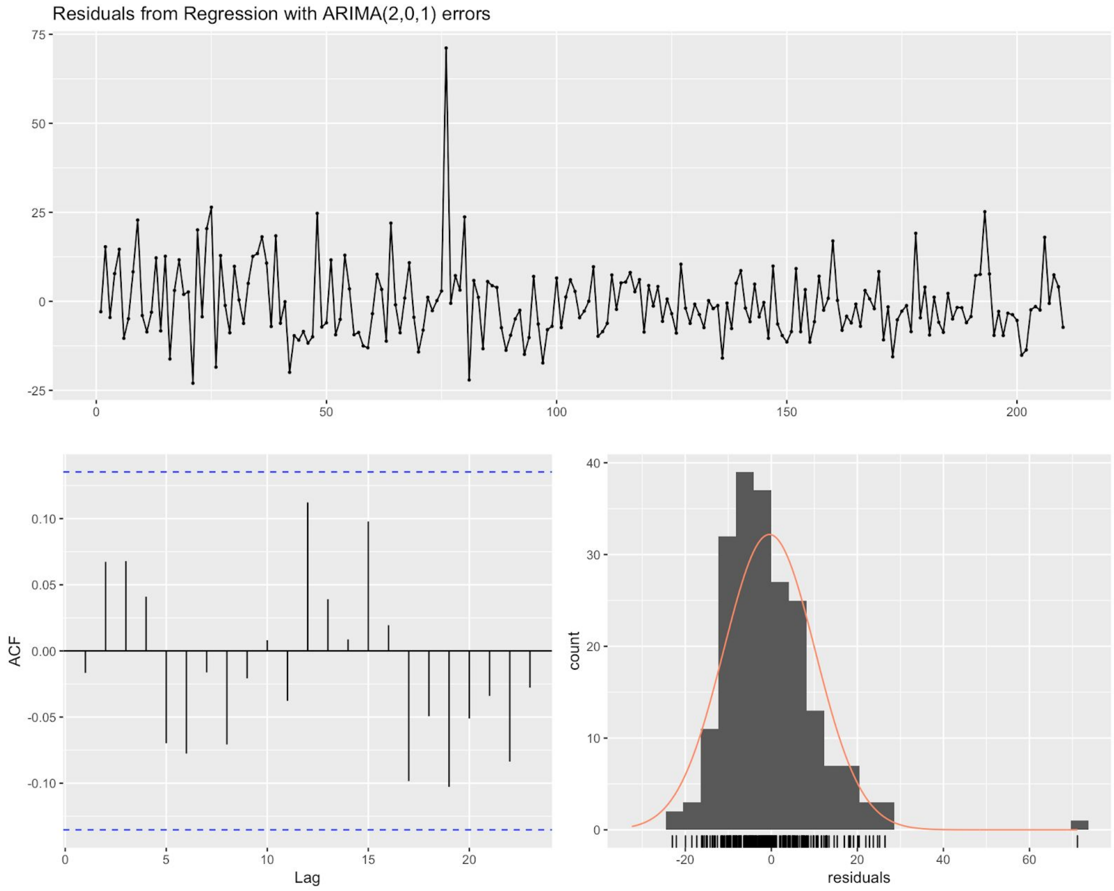
```
### ======================= STAT 443 Term Project =======================
###

# Project Title: How Do Economic Indicators Impact the General Public's Interest in US Jobless
Claims?
# Dependent variable: Google Search Volume Index (SVI)
# Explanatory variables: Initial Claims, St Louis Fed Financial Stress Index, Standard & Poor's
500, Russell 2000

# This results in an ARIMAX(2,0,1) model that gives the smallest out-of-sample RMSE, when
compared to the plain ARIMA model and the 2 baseline models.

# ============================ Beginning of Script ============================ #

# Clean workspace and set working directory
rm(list=ls())
setwd("E:/2018-19 W2/STAT 443/Term Project"); getwd()

# Load required packages
pacman::p_load(readxl, aTSA, xts, forecast, ggplot2, GGally, xtable)

# Import data
Data<-read_excel("Data.xlsx", sheet="Data", col_types=c("date", "numeric", "numeric",
"numeric", "numeric", "numeric"))

# Define time series data and set up matrix of explanatory variables
SVI<-ts(Data$`Google SVI`); ICSA<-ts(Data$ICSA); STLFSI<-ts(Data$STLFSI);
SP500<-ts(Data$`S&P 500`); RUT<-ts(Data$`Russell 2000`)
Data2<-Data; Data2$Week<-NULL; Data2$`Google SVI`<-NULL; Matrix<-data.matrix(Data2);
rm(Data2)

# Define training and holdout sets (Training set: 1st to 210th observations | Holdout set: 211th to
260th observations)
```

```
SVI_train<-SVI[1:210]; SVI_holdout<-SVI[211:260]
Matrix_train<-Matrix[1:210, 1:4]; Matrix_holdout<-Matrix[211:260, 1:4]

# ===================== Testing for stationarity in variables ======================
#

# Google Search Volume Index (SVI)
stationary.test(SVI, method="adf")# Stationary except if I don't allow for drift and trend at lags 2,
3 and 4

# Percentage Change in Initial Claims (ICSA)
stationary.test(ICSA, method="adf")# Stationary

# Log-differenced St Louis Fed Financial Stress Index (STLFSI)
stationary.test(STLFSI, method="adf")# Stationary

# Log-differenced Standard & Poor's 500 (S&P 500)
stationary.test(SP500, method="adf")# Stationary

# Log-differenced Russell 2000 (RUT)
stationary.test(RUT, method="adf")# Stationary

# =========================== Correlation plots =========================== #

# Simple plot of correlations between variables
Data2<-Data; Data2$Week<-NULL; Figure_1<-ggpairs(Data2, title="Correlations between
variables"); rm(Data2)

# Autocorrelation (ACF) & partial autocorrelation (PACF) plots for all variables
Figure_2<-ggtsdisplay(SVI, lag.max=20, main="Google Search Volume Index (SVI)",
xlab="Week")
Figure_3<-ggtsdisplay(ICSA, lag.max=20, main="Percentage Change in Initial Claims (ICSA)",
xlab="Week")
Figure_4<-ggtsdisplay(STLFSI, lag.max=20, main="Log-Differenced St Louis Fed Financial
Stress Index (STLFSI)", xlab="Week")
Figure_5<-ggtsdisplay(SP500, lag.max=20, main="Log-Differenced Standard & Poor's 500 (S&P
500)", xlab="Week")
```

```
Figure_6<-ggtsdisplay(RUT, lag.max=20, main="Log-Differenced Russell 2000 (RUT)",
xlab="Week")

# =================Out-of-sample RMSEs of baseline models =================== #

# Persistence (random walk) model
fc<-NULL; zt<-SVI_holdout; fcerror<-NULL; MSE<-NULL; fc[1]<-SVI_train[210]
for(i in 2:50){
  fc[i]<-SVI_holdout[i-1]
}
fcerror<-zt-fc; MSE<-sum(fcerror^2); RMSE_rwf<-sqrt(MSE/50); rm(fc); rm(zt); rm(fcerror);
rm(MSE); rm(i)

# Average of all previous observations
fc<-NULL; zt<-SVI_holdout; fcerror<-NULL; MSE<-NULL; cumsum<-sum(SVI_train);
fc[1]<-cumsum/210
for(i in 2:50){
  cumsum<-cumsum+SVI_holdout[i-1]
  fc[i]<-cumsum/(210+i-1)
}
fcerror<-zt-fc; MSE<-sum(fcerror^2); RMSE_avgpo<-sqrt(MSE/50); rm(fc); rm(zt); rm(fcerror);
rm(MSE); rm(cumsum); rm(i)

# Plotting forecasts with the "forecast" package
Figure_7<-autoplot(naive(ts(SVI[1:210]), h=50), main="Forecasts from Persistence (Random
Walk) Model on Google SVI", xlab="Week", ylab="")
Figure_8<-autoplot(meanf(ts(SVI[1:210]), h=50), main="Forecasts from Average of Past
Observations Model on Google SVI", xlab="Week", ylab="")
Figure_9<-autoplot(ts(SVI[1:210])) + autolayer(meanf(ts(SVI[1:210]), h=50), series="Avg. of
past", PI=FALSE) + autolayer(naive(ts(SVI[1:210]), h=50), series="Persistence", PI=FALSE) +
  ggtitle("Comparison of Baseline Forecasting Models on Google SVI") + xlab("Week") + ylab("")
+ guides(colour=guide_legend(title="Forecast"))

# ===================== Fitting ARIMA/ARIMAX models ===================== #
# ARIMA(1,0,1) model (without explanatory variables) # out-of-sample RMSE lower than
baseline models
```

```
Model1<-auto.arima(SVI_train, approximation=FALSE, test="adf"); print(Model1);
checkresiduals(Model1); Figure_10<-recordPlot()
Model1_fc<-forecast(Model1, h=50); fcerror<-SVI_holdout-Model1_fc$mean;
MSE<-sum(fcerror^2); RMSE_Model1<-sqrt(MSE/50); rm(fcerror); rm(MSE)
Figure_11<-autoplot(Model1_fc, main="Forecasts from ARIMA(1,0,1) on Google SVI",
xlab="Week", ylab="")

# ARIMAX(2,0,1) model (with explanatory variables) # lowest out-of-sample RMSE
Model2<-auto.arima(SVI_train, approximation=FALSE, xreg=Matrix_train, test="adf");
print(Model2); checkresiduals(Model2); Figure_12<-recordPlot()
Model2_fc<-forecast(Model2, h=50, xreg=Matrix_holdout);
fcerror<-SVI_holdout-Model2_fc$mean; MSE<-sum(fcerror^2); RMSE_Model2<-sqrt(MSE/50);
rm(fcerror); rm(MSE)
Figure_13<-autoplot(Model2_fc, main="Forecasts from ARIMAX(2,0,1) on Google SVI",
xlab="Week", ylab="")

# ===================== End of Script ===================== #
```

Secondary plots



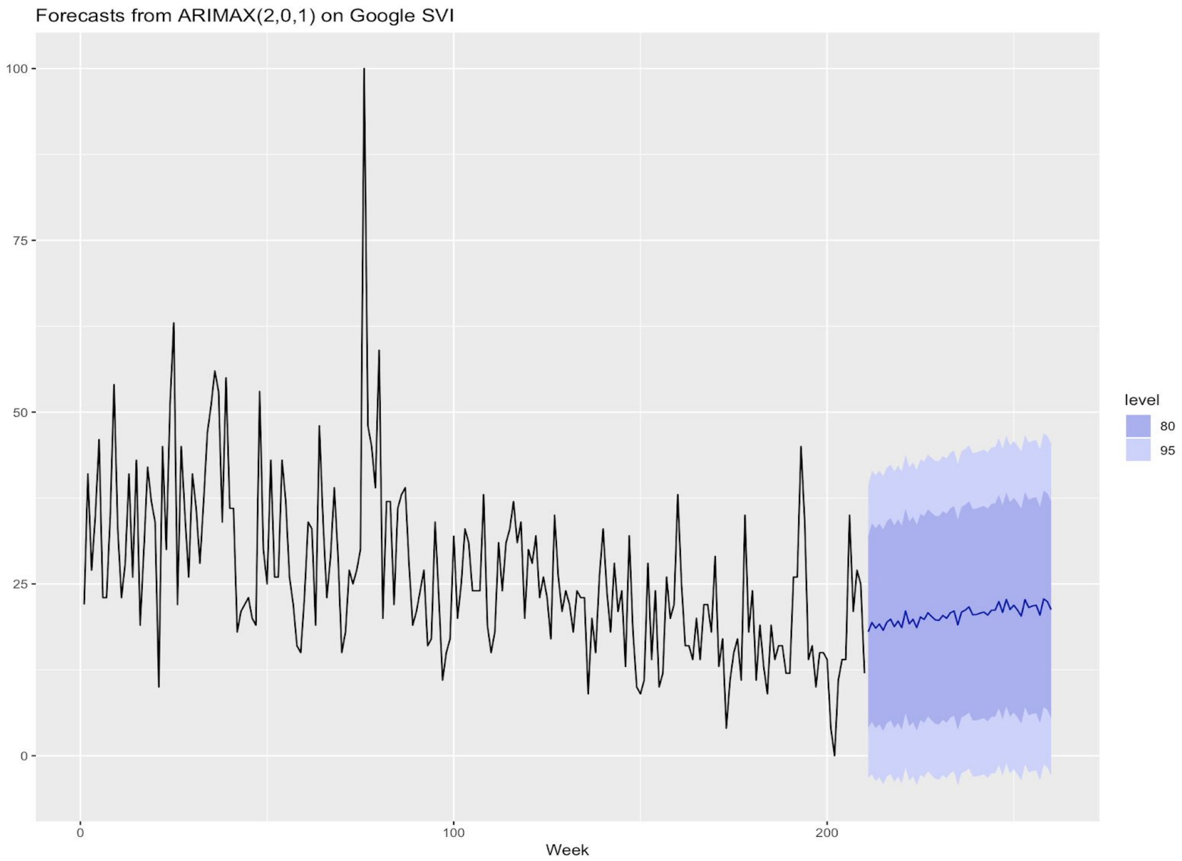


fig2: ARIMAX(2, 0, 1) forecast