Effects of Economic Factors on Rates of Violence in Nigeria; Final STAT 5000

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Nigerian-Inflation-Project

Introduction

Background

I chose this topic because I saw a graph of the violence in Nigeria presented by The Economist, which made me realize that the violence might be connected to rising inflation and general food prices.

Inflation is a serious challenge that affects everyone. It may also contribute to the unrest and violence that we witness in some countries, such as Nigeria. Climate change is another urgent issue that cannot be overlooked, especially since it will have disproportionate impacts on the working class of the global south, with global repercussions on the economies of the world, due to globalization. For example, in Nigeria, people spend 97.4% of their income on food. Inflation also has differential effects on various segments of the population, which affects their employment and access to basic needs.

Purpose of Analysis

I want to see if violence in Nigeria is in any way correlated with the rise in inflation and food prices, as well as the FX rate changes. I also wanted to see if these variables can be used to predict violence in the future.

Data Description

This data is from the Nigerian government. I cleaned the data in Excel and saved it as a .csv file to then import into RStudio.

I began by checking the data and removing the months, years, and dates to replace them with a time series formula. To avoid dealing with null values, I began the time series in 2004 and ended it in October 2024.

```
head(nigeria)
```

```
##   Year Month     Date All.Items Food  USDFX violence
## 1 2004   Jan 1/1/2004      22.4 11.9 136.08       18
## 2 2004   Feb 2/1/2004      24.8 14.5 135.16       13
## 3 2004   Mar 3/1/2004      22.5 15.6 134.47       30
## 4 2004   Apr 4/1/2004      17.5 14.4 133.51       32
## 5 2004   May 5/1/2004      19.8 18.1 133.01       17
## 6 2004   Jun 6/1/2004      14.1 14.5 132.75       11
```

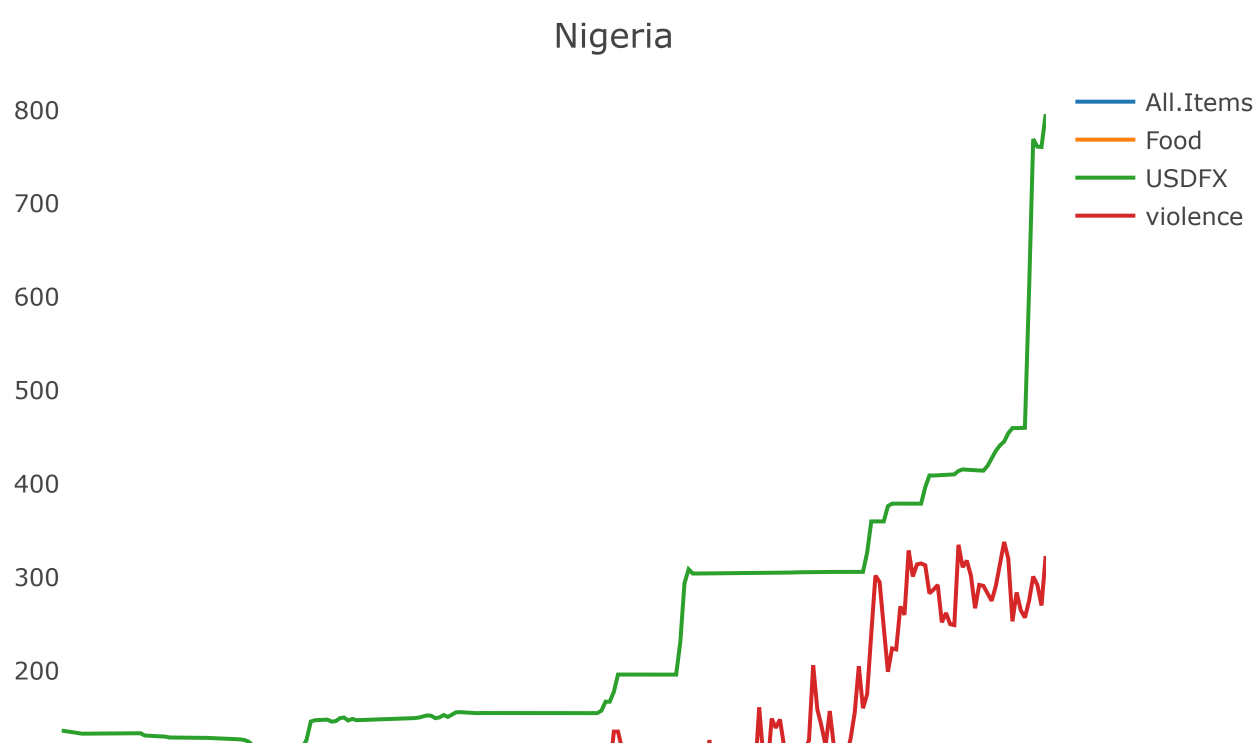
```
# checking variable type
str(nigeria)
```

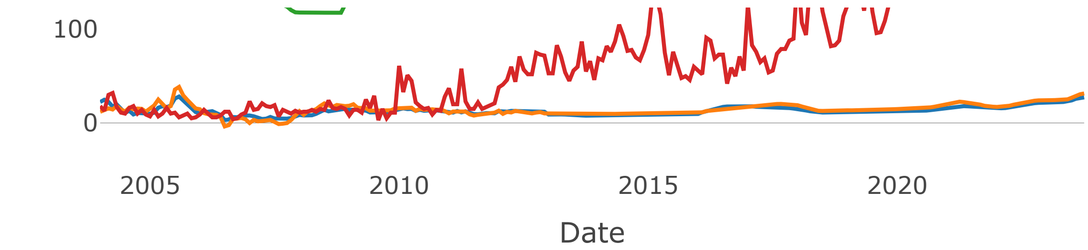
```
## 'data.frame':    238 obs. of  7 variables:
##  $ Year     : int  2004 2004 2004 2004 2004 2004 2004 2004 2004 2004 ...
##  $ Month    : chr  "Jan" "Feb" "Mar" "Apr" ...
##  $ Date     : chr  "1/1/2004" "2/1/2004" "3/1/2004" "4/1/2004" ...
##  $ All.Items: num  22.4 24.8 22.5 17.5 19.8 14.1 10.7 13 9.1 10.7 ...
##  $ Food     : num  11.9 14.5 15.6 14.4 18.1 14.5 12.2 16.3 14.6 15.4 ...
##  $ USDFX    : num  136 135 134 134 133 ...
##  $ violence : int  18 13 30 32 17 11 10 16 18 10 ...
```

```
ts.nigeria <- nigeria
ts.nigeria$Year <-NULL
ts.nigeria$Date <- NULL
ts.nigeria$Month <-NULL
tseries <- ts(ts.nigeria, start = c(2004,1),frequency = 12)
summary(tseries)
```

```
##    All.Items          Food           USDFX          violence
##  Min.   : 3.000   Min.   :-3.70   Min.   :117.7   Min.   :  3.00
##  1st Qu.: 9.425   1st Qu.:10.03   1st Qu.:138.5   1st Qu.: 15.00
##  Median :12.230   Median :13.89   Median :154.8   Median : 57.50
##  Mean   :13.009   Mean   :14.32   Mean   :231.3   Mean   : 93.54
##  3rd Qu.:15.908   3rd Qu.:18.00   3rd Qu.:305.8   3rd Qu.:124.50
##  Max.   :28.200   Max.   :38.50   Max.   :795.9   Max.   :338.00
```

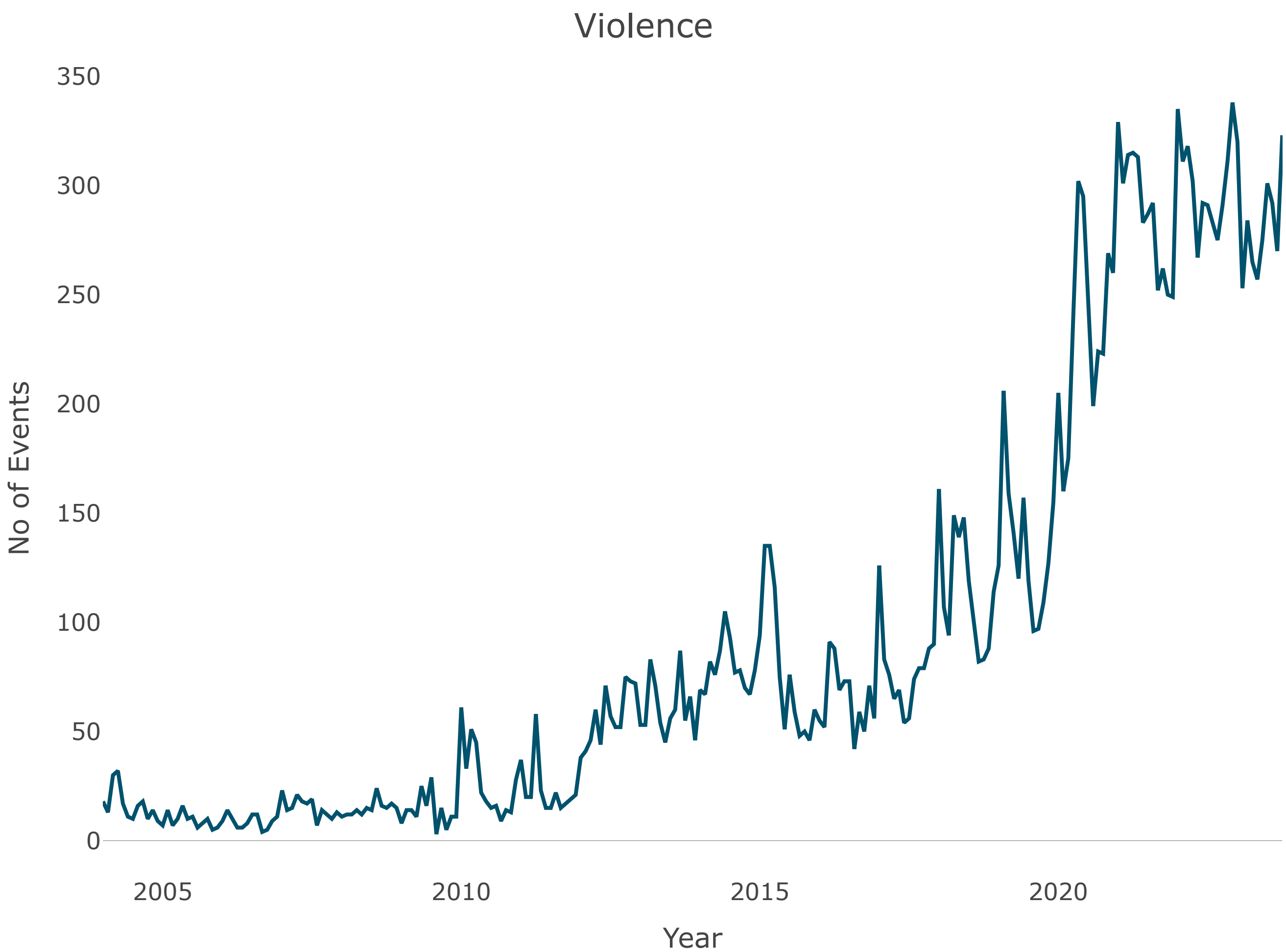
I then plotted the variables on a single graph. The variables I looked at were the dollar’s value against the Naira, food inflation and general inflation, which are the small lines, and the total number of acts of political violence each month.





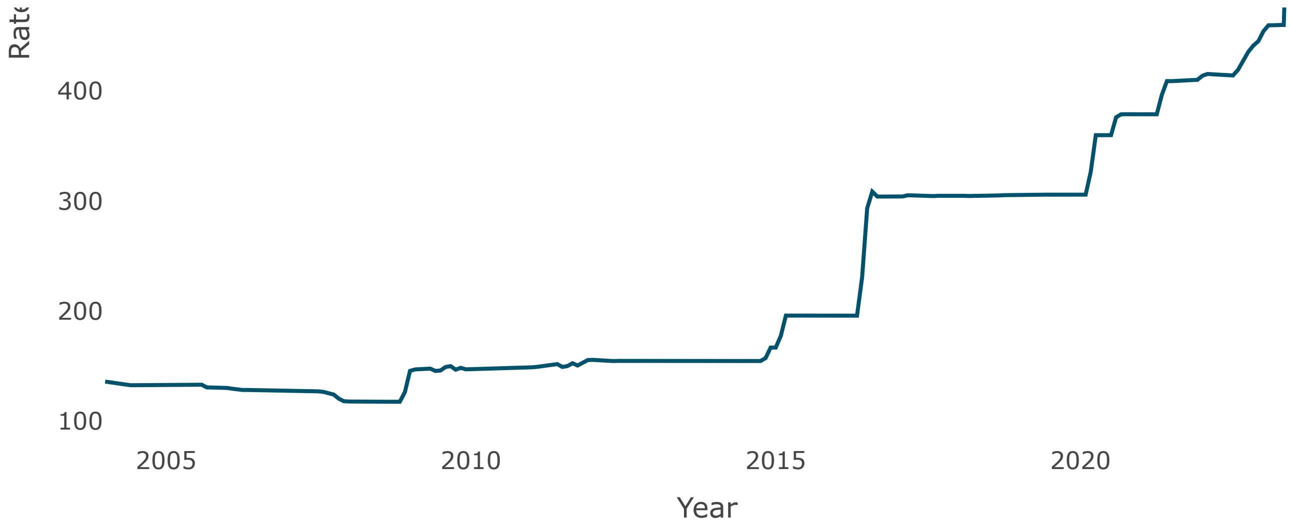
I also plotted each variable separately to better understand the series' patterns. I saw that there was generally an increase in each category.

The value of dollar has had the most steady increase with a very sharp increase corresponding with the recent election and decision to let the currency "float" and be determined soley by market activity.



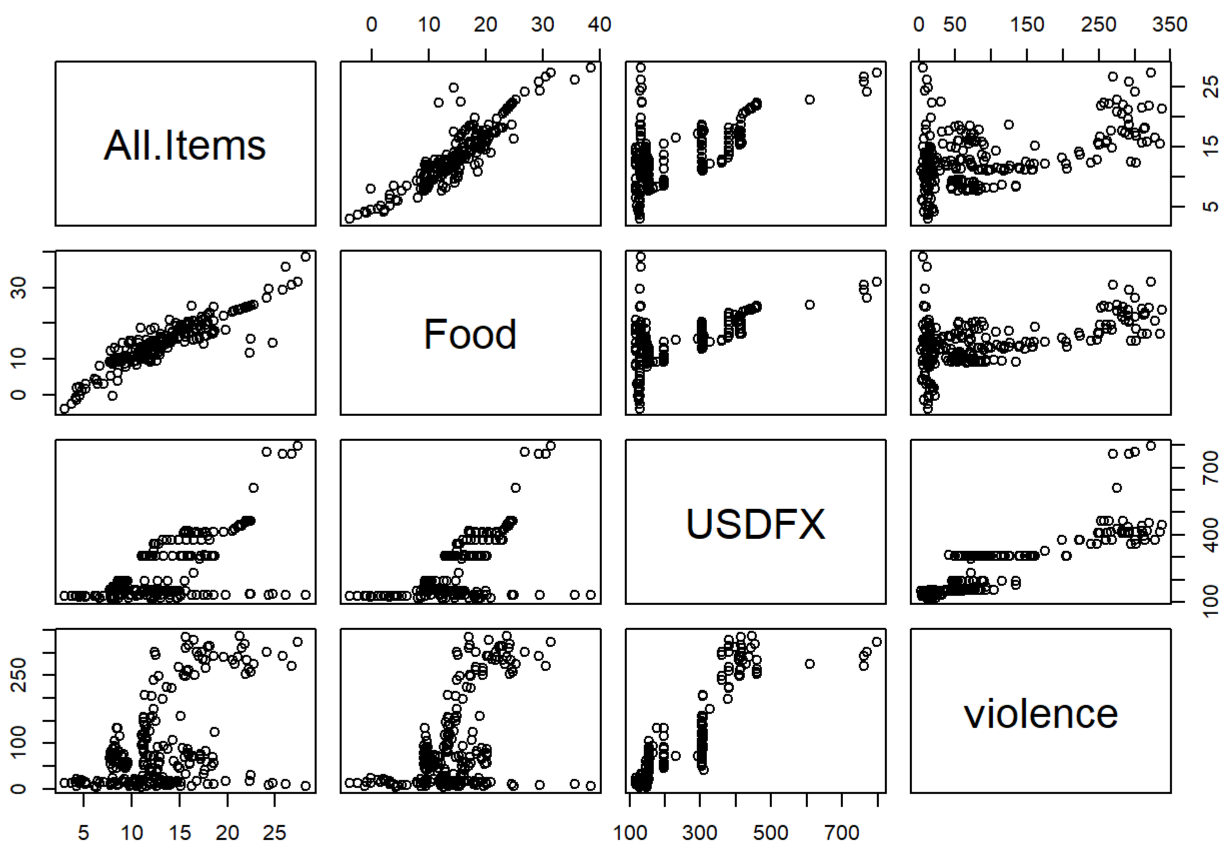
Gen. Inflation

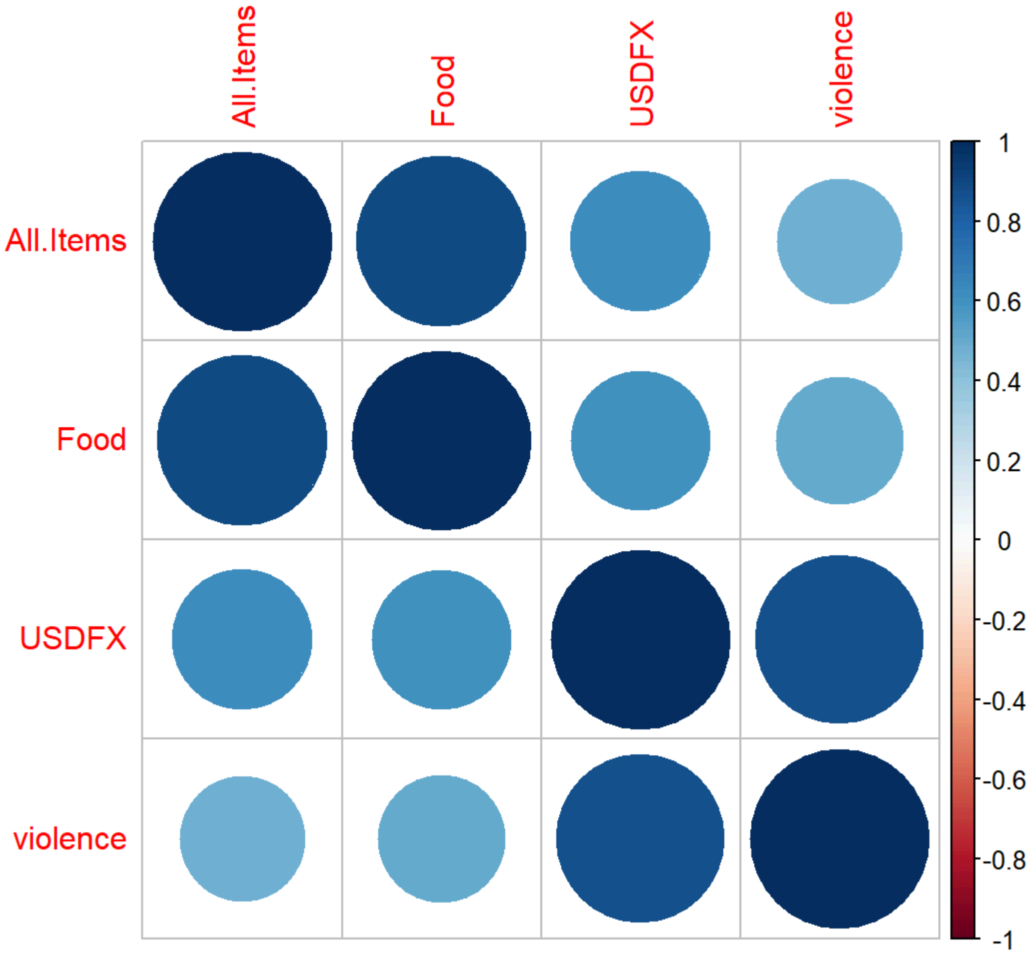
Value of Dollor Against Naira



I then visualized the relationships using `pairs()` and plotted a correlation matrix. From this plot, I can see that there is a strong relationship between food and general inflation which I will ignore since food inflation is a factor of general inflation. After that, USDFX and violence have a strong relationship. From the correlation plot, violence, and food inflation seem to be the least correlated.

```
pairs(tseries)
```





Methods and Analysis

Linear Regression

I then decided to use a linear regression model to see if inflation, food inflation, USD rates had any effect on the rate of violence that occurred. The overall model had an r^{2} of 77% and a small p-value, which is decent but not the best. From the model, I gathered the by p-value, t-value, and standard error, USD increases had a positive effect on the rate of violence, which is bad, and I hope something changes with the way they are handling the currency and the other variables that are affecting the rate of violence in the country. It was, however, somewhat of a surprise that the model showed a negative relationship with inflation. This is surprising the me since it has been reported that Nigerians spend 96% of their income on food supplies. I don't know how to explain that, but I do know that the value of the dollar is followed closely by merchants and sellers of various items.

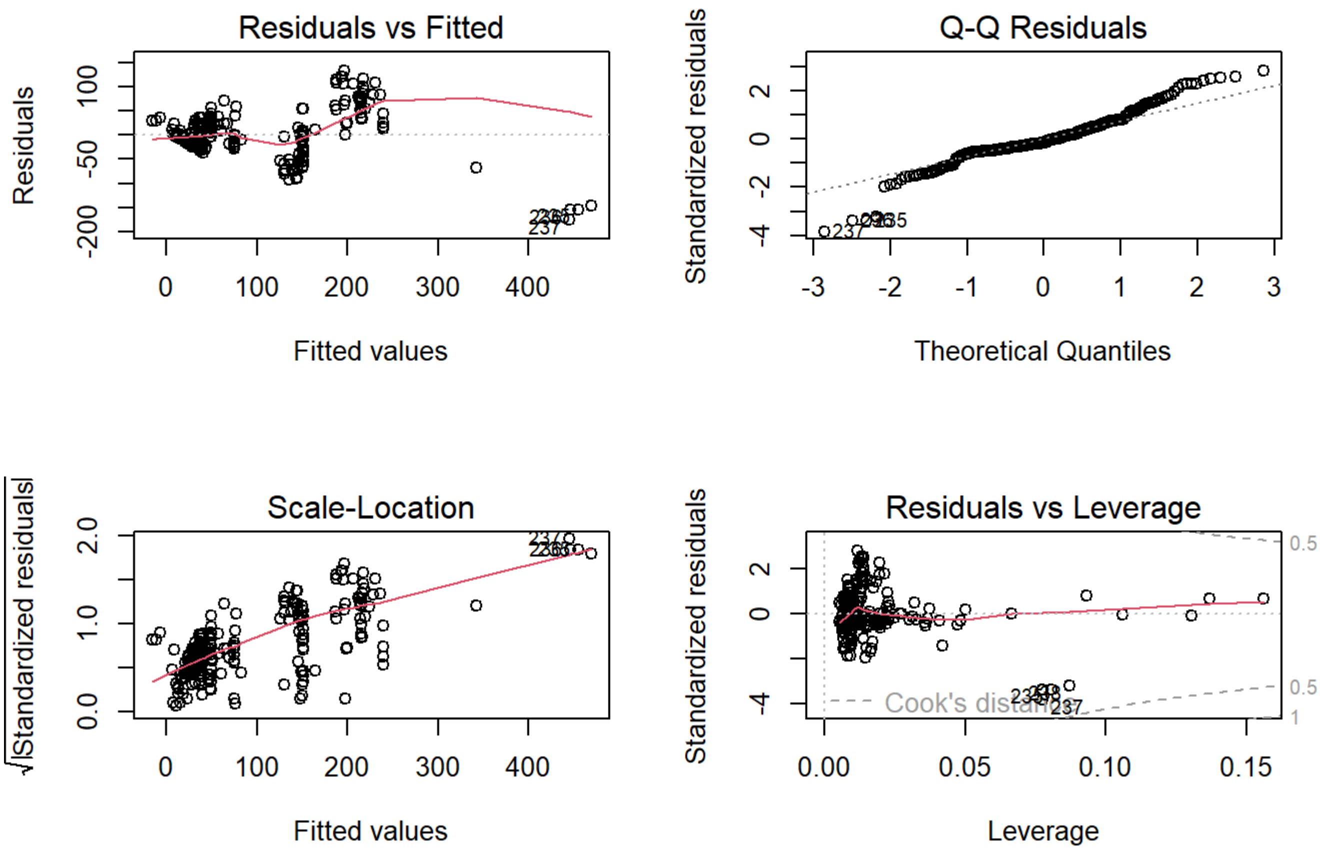
```
lm.violence <- lm(violence~., data=tseries)
lm.violence
```

```
##
## Call:
## lm(formula = violence ~ ., data = tseries)
##
## Coefficients:
## (Intercept)    All.Items         Food        USDFX
##    -47.1353      -3.5806       1.6735       0.7059
```

```
summary(lm.violence)
```

```
##
## Call:
## lm(formula = violence ~ ., data = tseries)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -175.57  -22.76   -7.55   24.35  133.13
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) -47.13528    9.04677  -5.210 4.14e-07 ***
## All.Items    -3.58062    1.51226  -2.368   0.0187 *
## Food          1.67349    1.14246   1.465   0.1443
## USDFX         0.70595    0.03078  22.938  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 47.52 on 234 degrees of freedom
## Multiple R-squared:  0.7711, Adjusted R-squared:  0.7682
## F-statistic: 262.8 on 3 and 234 DF,  p-value: < 2.2e-16
```

I then plotted the linear regression. The residual v fitted is curved with a significant number of outliers and appears to signify a nonlinear relationship of the predictors. This model doesn’t seem to be that good when looking at the q-q plot as it indicates a lack of normality. Therefore, I don’t think linear regression is good for modeling. I will now use methods specifically for time series.

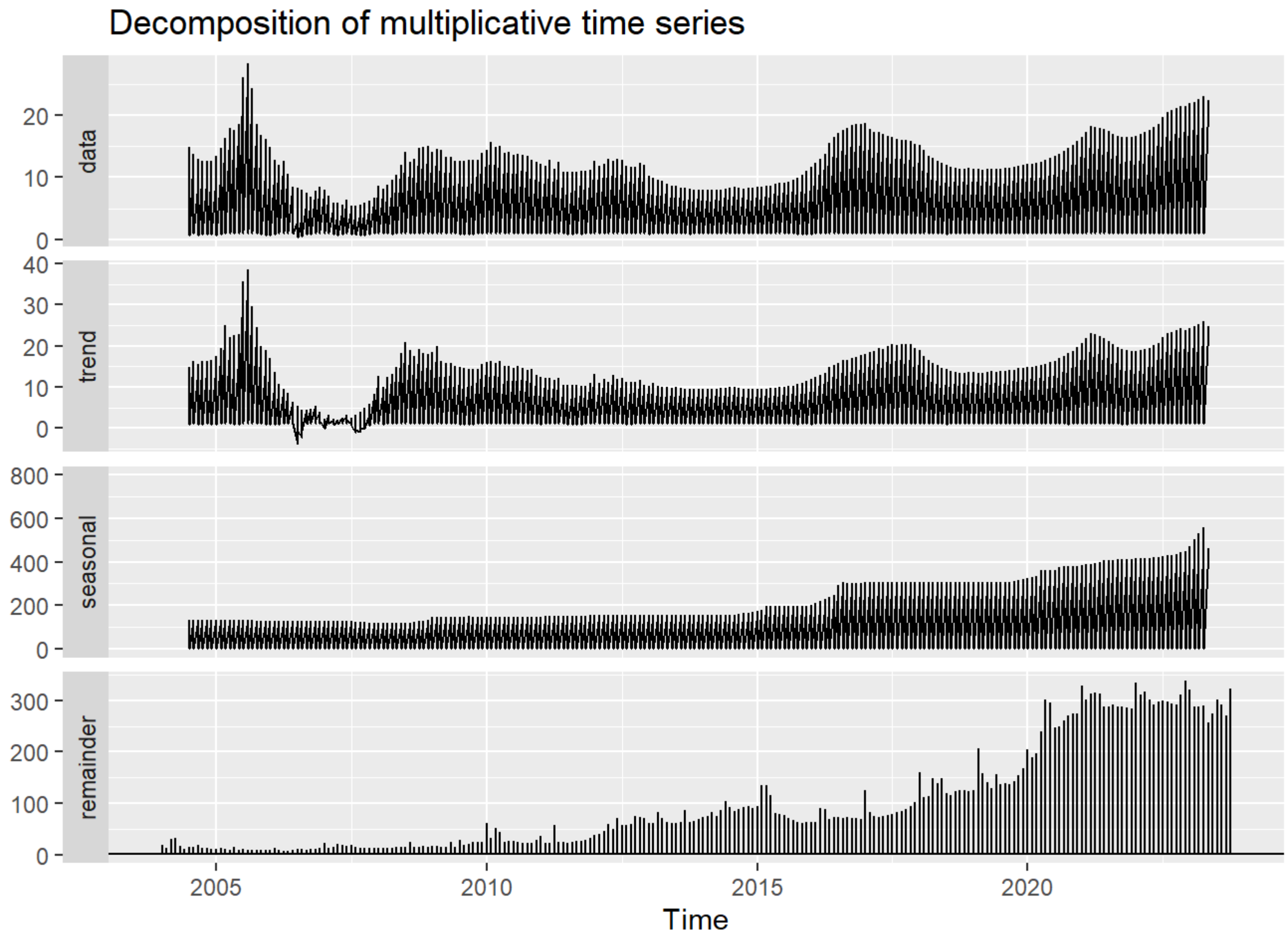


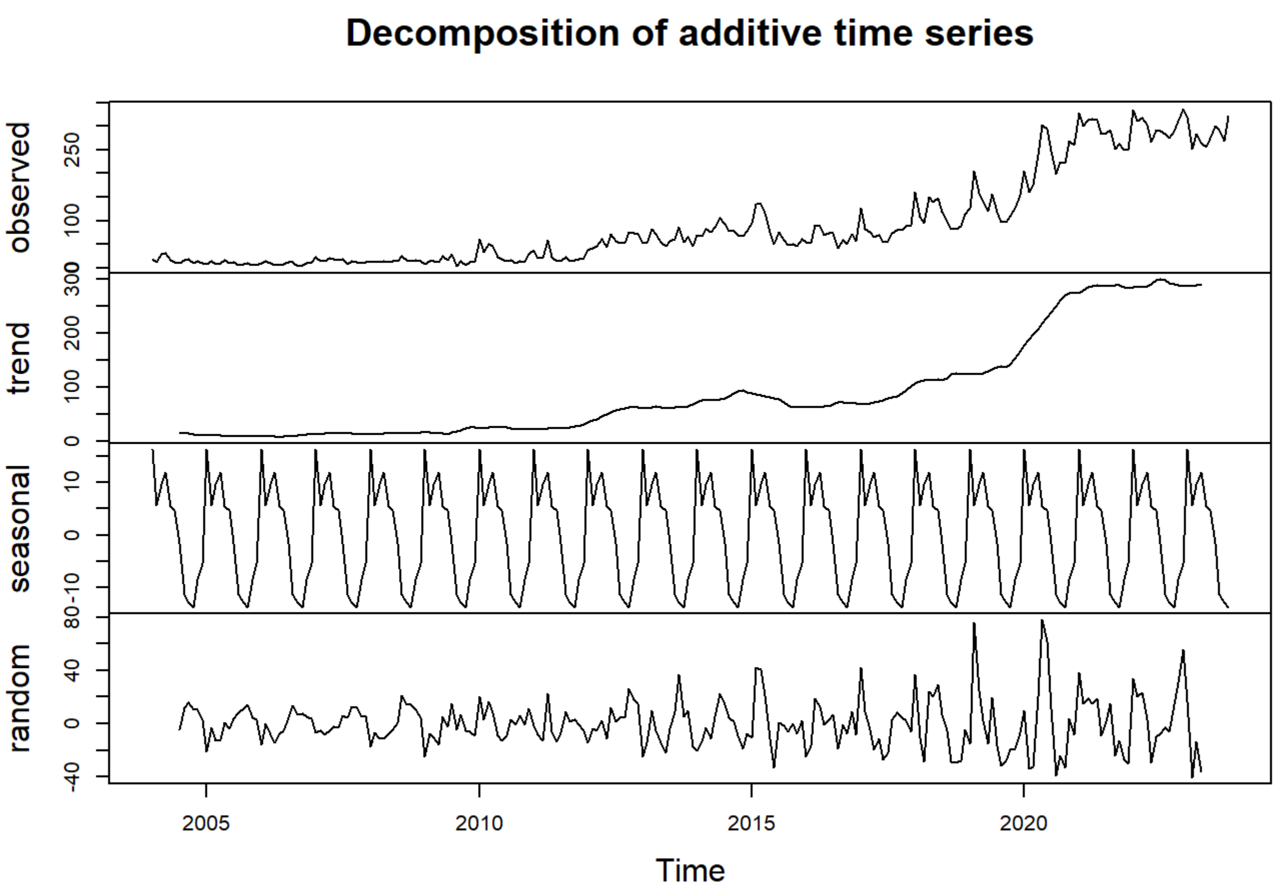

```
##                    2.5 %      97.5 %
## (Intercept) -64.9588091 -29.3117440
## All.Items    -6.5600192  -0.6012305
## Food         -0.5773275   3.9243025
## USDFX         0.6453115   0.7665798
```

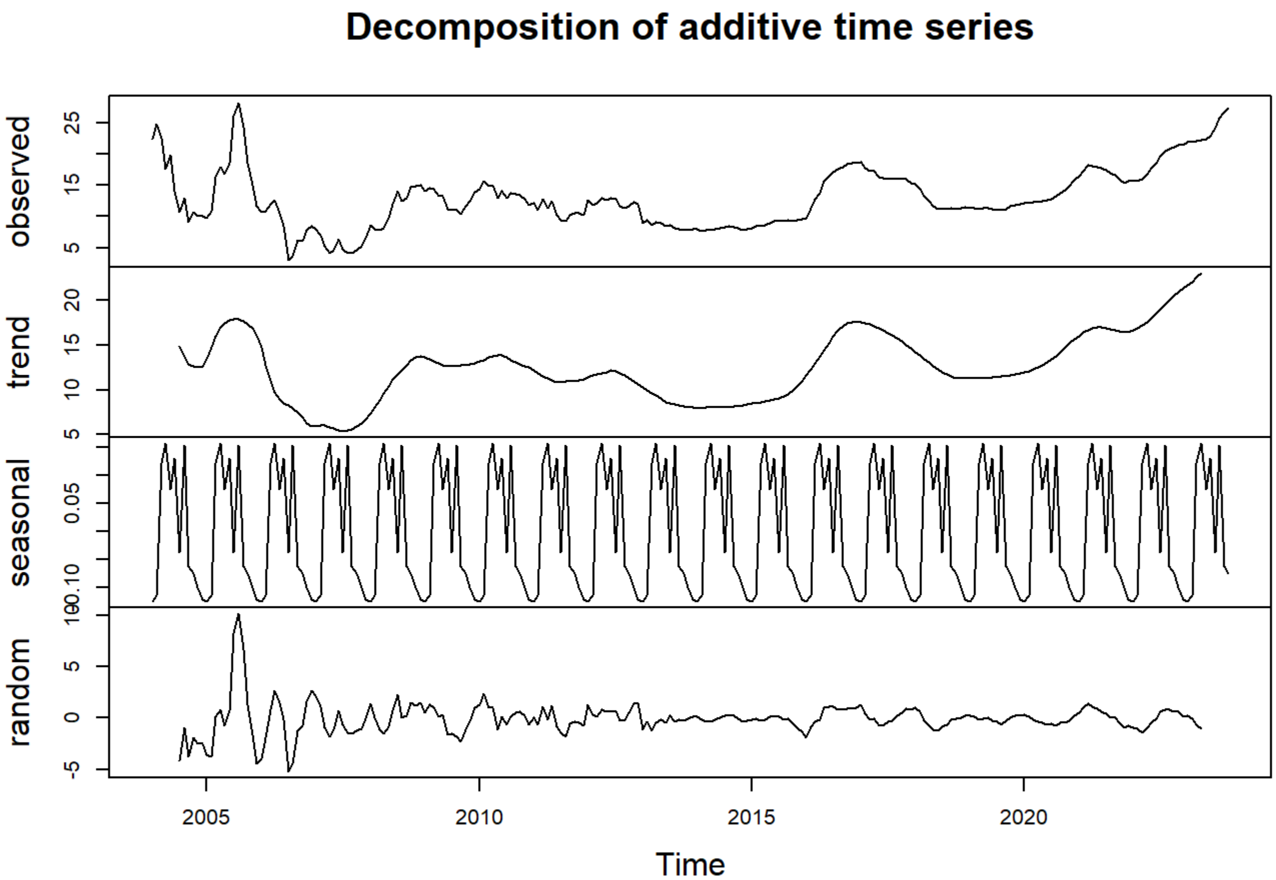
Set Up for ARIMA and VAR

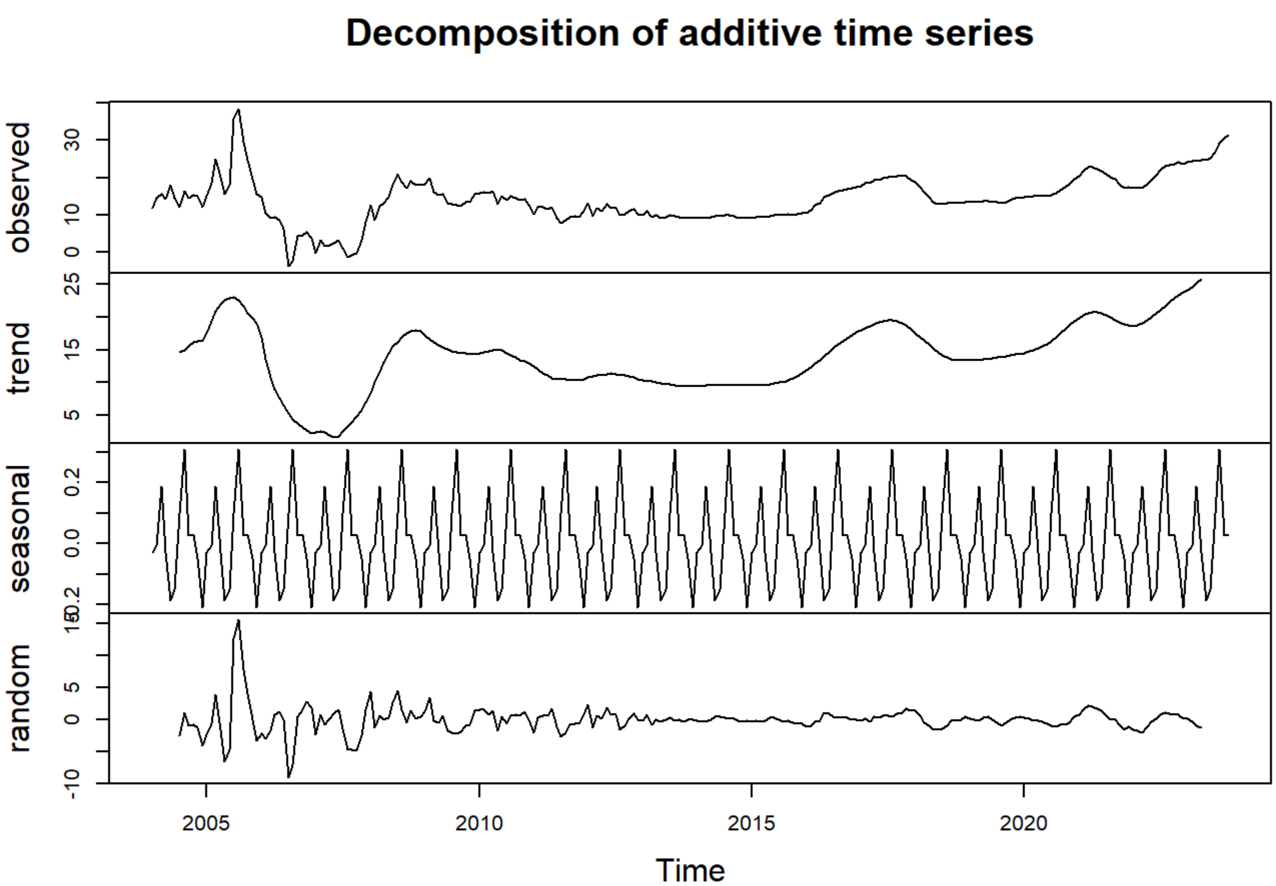
I first decomposed the variables together and seperately.

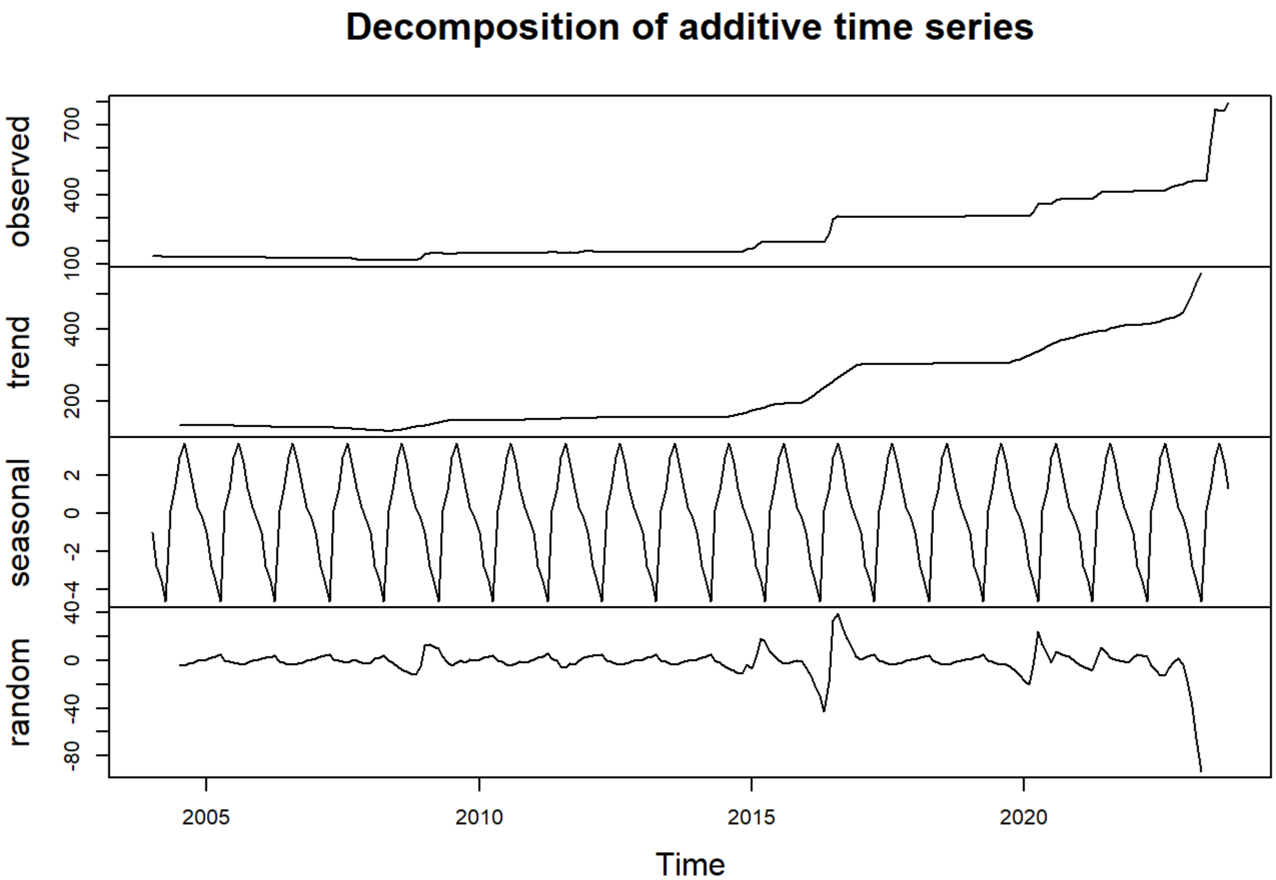
```
decom <- decompose(tseries, type = "mult")
```


Decomposition of multiplicative time series
data
trend
seasonal
remainder
0
10
20
30
40
200
400
600
800
100
300
2005
2010
2015
2020
Time

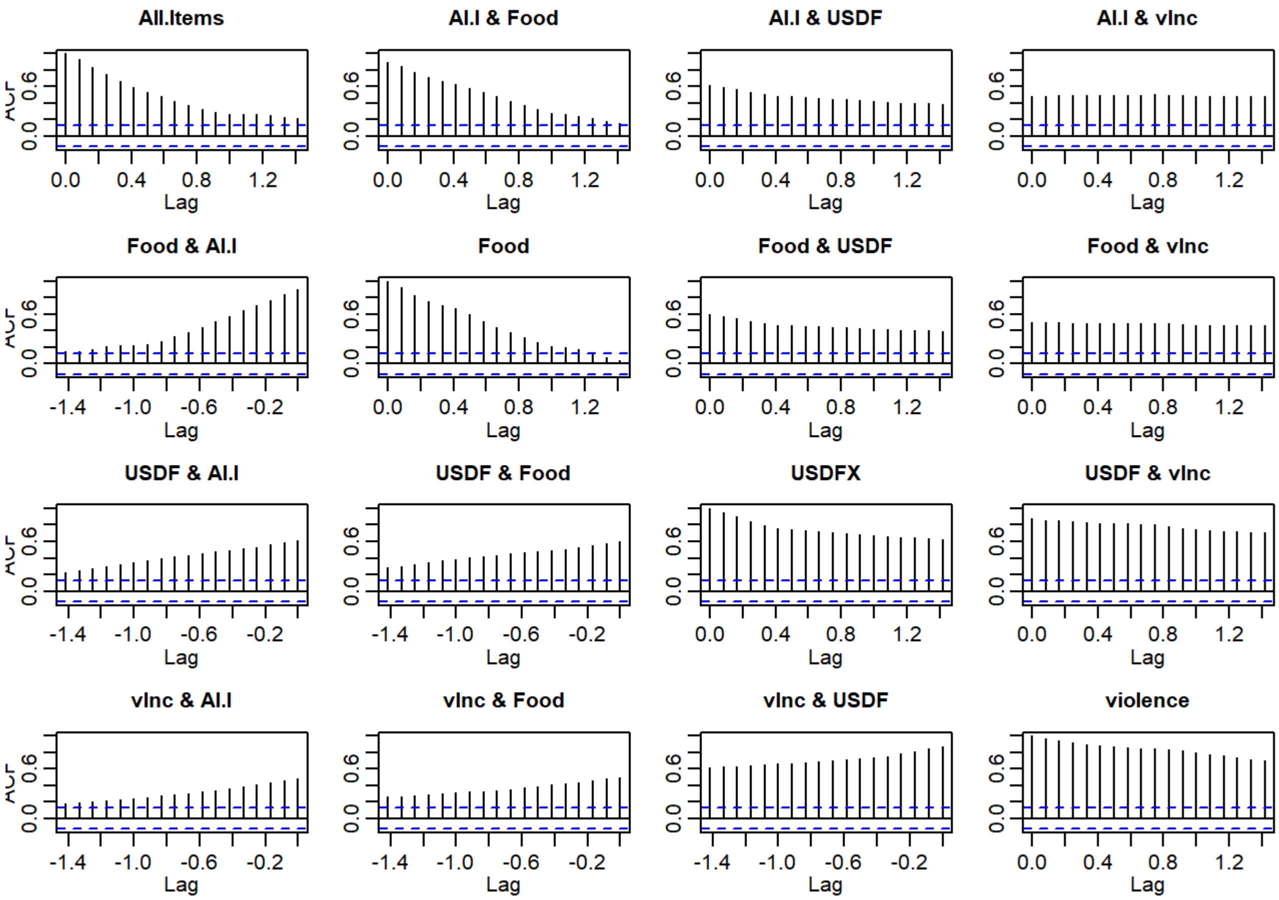

Decomposition of additive time series
observed
trend
seasonal
random
0
100
250
200
300
10
-10
80
40
-40
2005
2010
2015
2020
Time

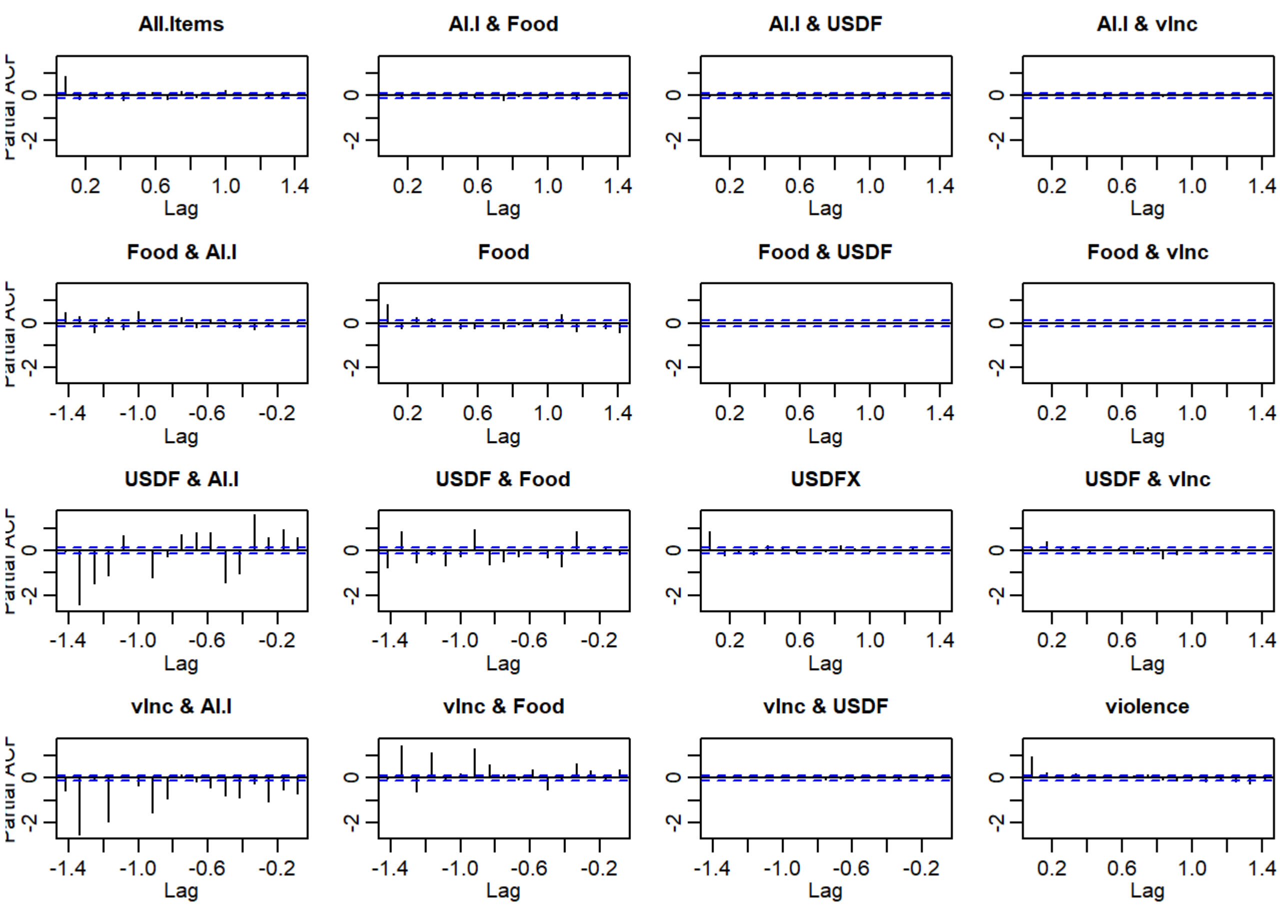

Decomposition of additive time series
observed
trend
seasonal
random
Time
2005
2010
2015
2020


Decomposition of additive time series
observed
trend
seasonal
random
Time
2005
2010
2015
2020



Then, I viewed the auto correlation present in the data. From the above graphs of the individual data, the variables seem to be nonstationary, so they depend on time. I also performed the box test, and the p-values were very small, so I can conclude that the data is nonstationary. But I don't think there is much seasonality outside of the inflations.


All.Items
Al.I & Food
Al.I & USDF
Al.I & vInc
Food & Al.I
Food
Food & USDF
Food & vInc
USDF & Al.I
USDF & Food
USDFX
USDF & vInc
vInc & Al.I
vInc & Food
vInc & USDF
violence
Lag


All.Items
Al.I & Food
Al.I & USDF
Al.I & vInc
Food & Al.I
Food
Food & USDF
Food & vInc
USDF & Al.I
USDF & Food
USDFX
USDF & vInc
vInc & Al.I
vInc & Food
vInc & USDF
violence
Lag

I also performed the Box-Pierce test and Augmented Dickey-Fuller test to test the stationarity of the variables. They were not stationary.

```
# box test
Box.test(tseries[,"All.Items"])
```

```
##
##  Box-Pierce test
##
## data:  tseries[, "All.Items"]
## X-squared = 206.09, df = 1, p-value < 2.2e-16
```

```
Box.test(tseries[,"violence"])
```

```
##
##  Box-Pierce test
##
## data:  tseries[, "violence"]
## X-squared = 220.43, df = 1, p-value < 2.2e-16
```

```
Box.test(tseries[,"Food"])
```

```
##
##  Box-Pierce test
##
## data:  tseries[, "Food"]
## X-squared = 202.26, df = 1, p-value < 2.2e-16
```

```
Box.test(tseries[,"USDFX"]) #none are stationary
```

```
##
##  Box-Pierce test
##
## data:  tseries[, "USDFX"]
## X-squared = 214.99, df = 1, p-value < 2.2e-16
```

```
#adf test to see if it is stationary
adf.test(tseries[,"All.Items"])
```

```
##
##  Augmented Dickey-Fuller Test
##
## data:  tseries[, "All.Items"]
## Dickey-Fuller = -2.1882, Lag order = 6, p-value = 0.4967
## alternative hypothesis: stationary
```

```
adf.test(tseries[,"violence"])
```

```
##
##  Augmented Dickey-Fuller Test
##
## data:  tseries[, "violence"]
## Dickey-Fuller = -1.8235, Lag order = 6, p-value = 0.6501
## alternative hypothesis: stationary
```

```
adf.test(tseries[,"Food"])
```

```
##
##  Augmented Dickey-Fuller Test
##
## data:  tseries[, "Food"]
## Dickey-Fuller = -3.1911, Lag order = 6, p-value = 0.09011
## alternative hypothesis: stationary
```

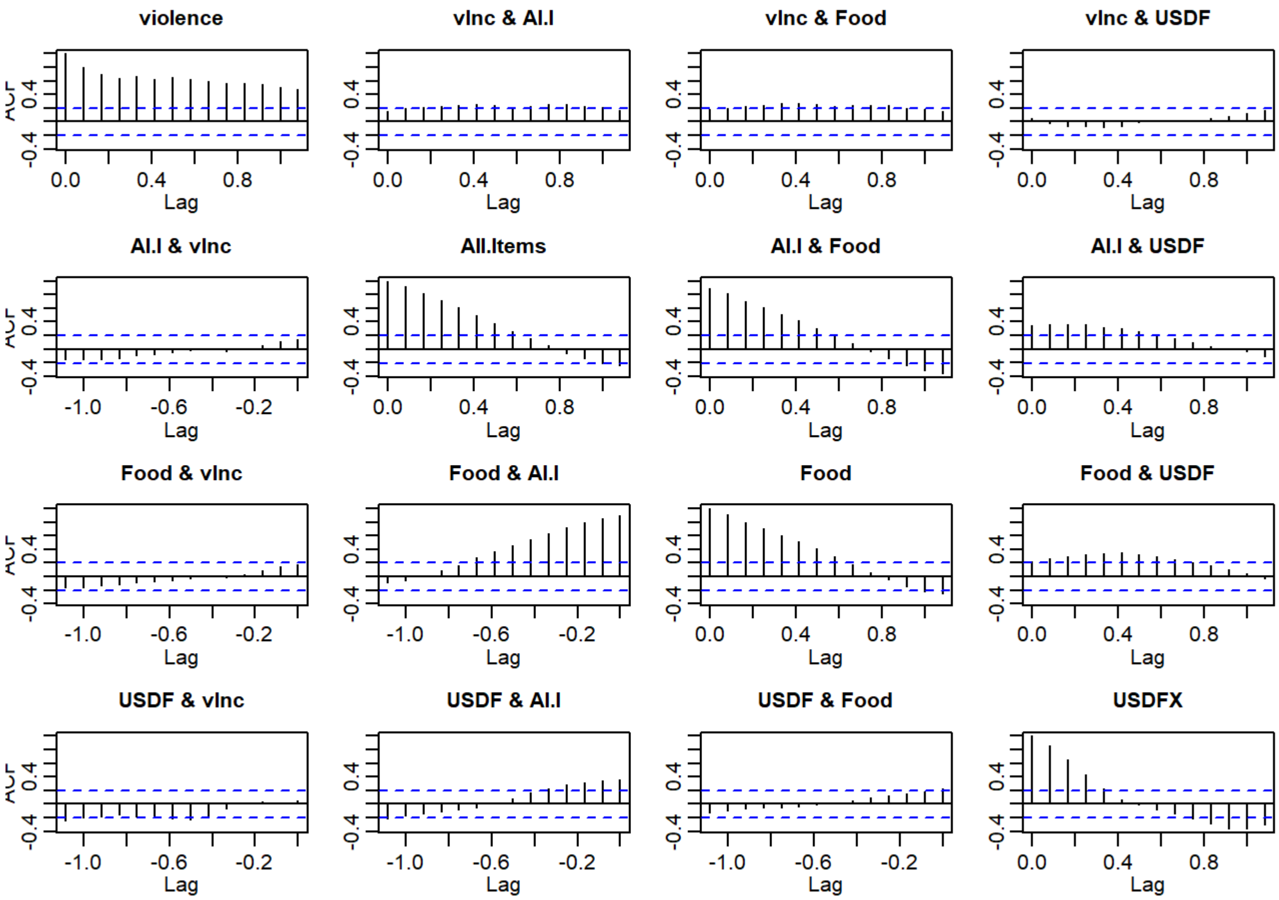
```
adf.test(tseries[,"USDFX"]) # none are stationary
```

```
## Warning in adf.test(tseries[, "USDFX"]): p-value greater than printed p-value
```

```
##
##  Augmented Dickey-Fuller Test
##
## data:  tseries[, "USDFX"]
## Dickey-Fuller = 1.1484, Lag order = 6, p-value = 0.99
## alternative hypothesis: stationary
```

So, I second order differenced all the variables for a new acf plot that looks more stationary and lagged them by a few years. The diagonal ones are the ones to look at.

```
dUSDFX<-diff(tseries[,"USDFX"], differences =2.4, lag = 72) #lagging to 2016
dFood<-diff(tseries[,"Food"], differences =2.4, lag = 72)
dviolence<-diff(tseries[,"violence"], differences =2.4, lag=72)
dInflation<-diff(tseries[,"All.Items"], differences =2.4, lag = 72) #diffed everything twice to
make mroe stationary and made new TS
difftseries <- cbind("violence" = dviolence, "All.Items" = dInflation,
      "Food" = dFood, "USDFX" = dUSDFX)
```



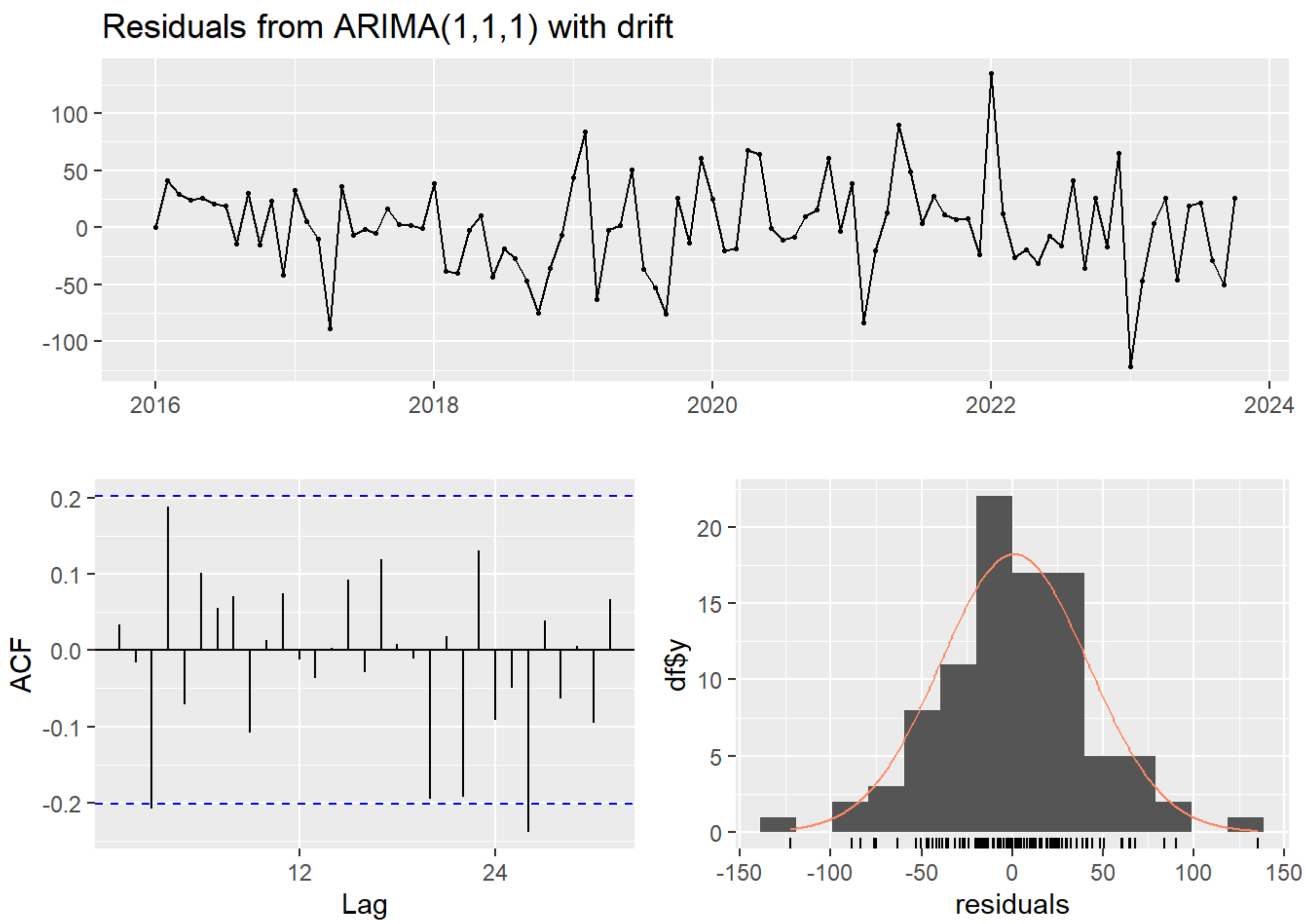
After differencing and lagging, the models I made passed the Ljung-Box test.

ARIMA Models

I then modeled the variables.

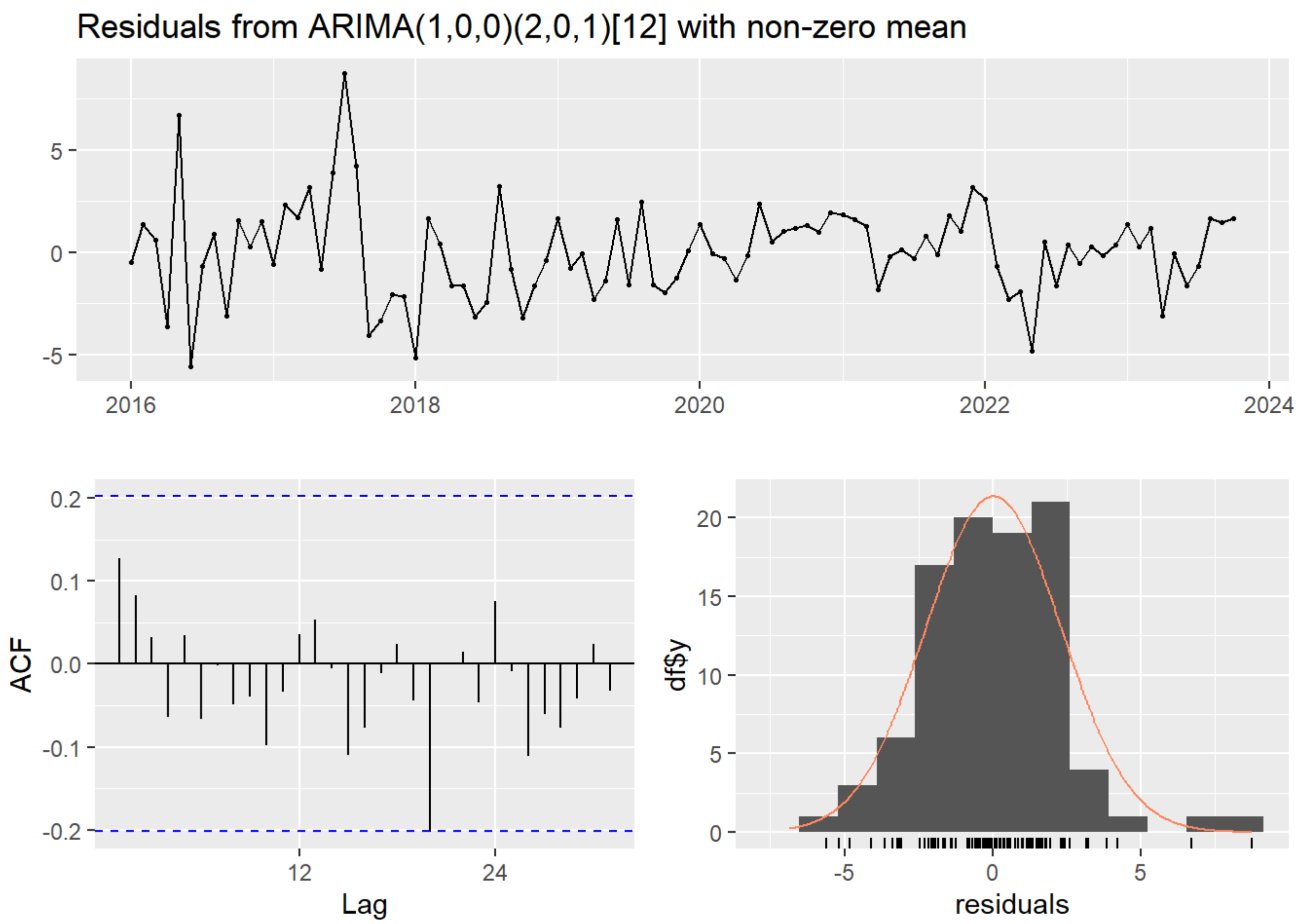
```
mymodel <-auto.arima(difftseries[,"violence"])
mymodel2 <-auto.arima(difftseries[,"All.Items"])
mymodel3 <-auto.arima(difftseries[,"USDFX"])
mymodel4 <-auto.arima(difftseries[,"Food"])
```

```
checkresiduals(mymodel)
```



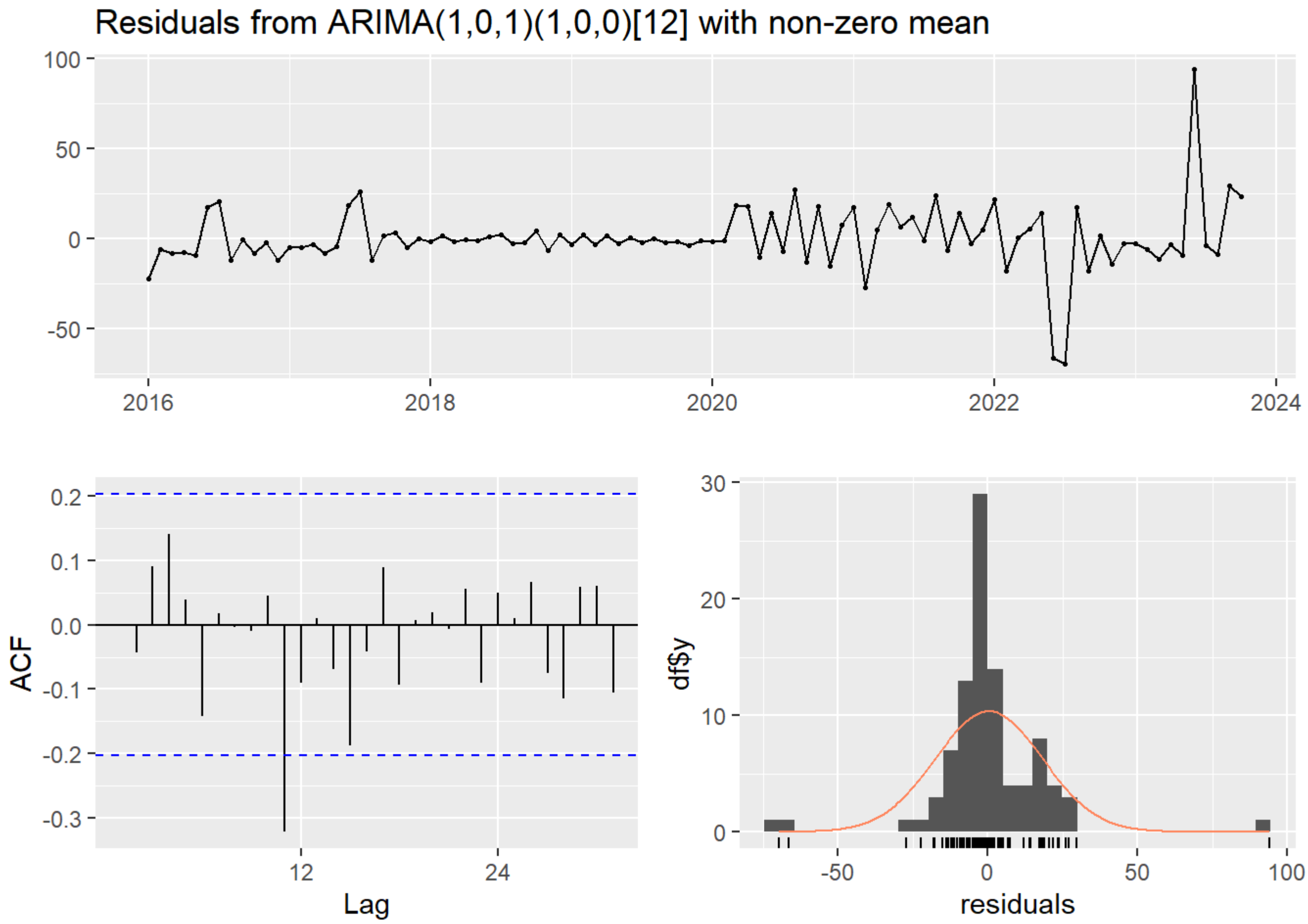

```
##
##  Ljung-Box test
##
## data:  Residuals from ARIMA(1,1,1) with drift
## Q* = 15.254, df = 17, p-value = 0.5772
##
## Model df: 2.   Total lags used: 19
```

```
checkresiduals(mymodel2)
```



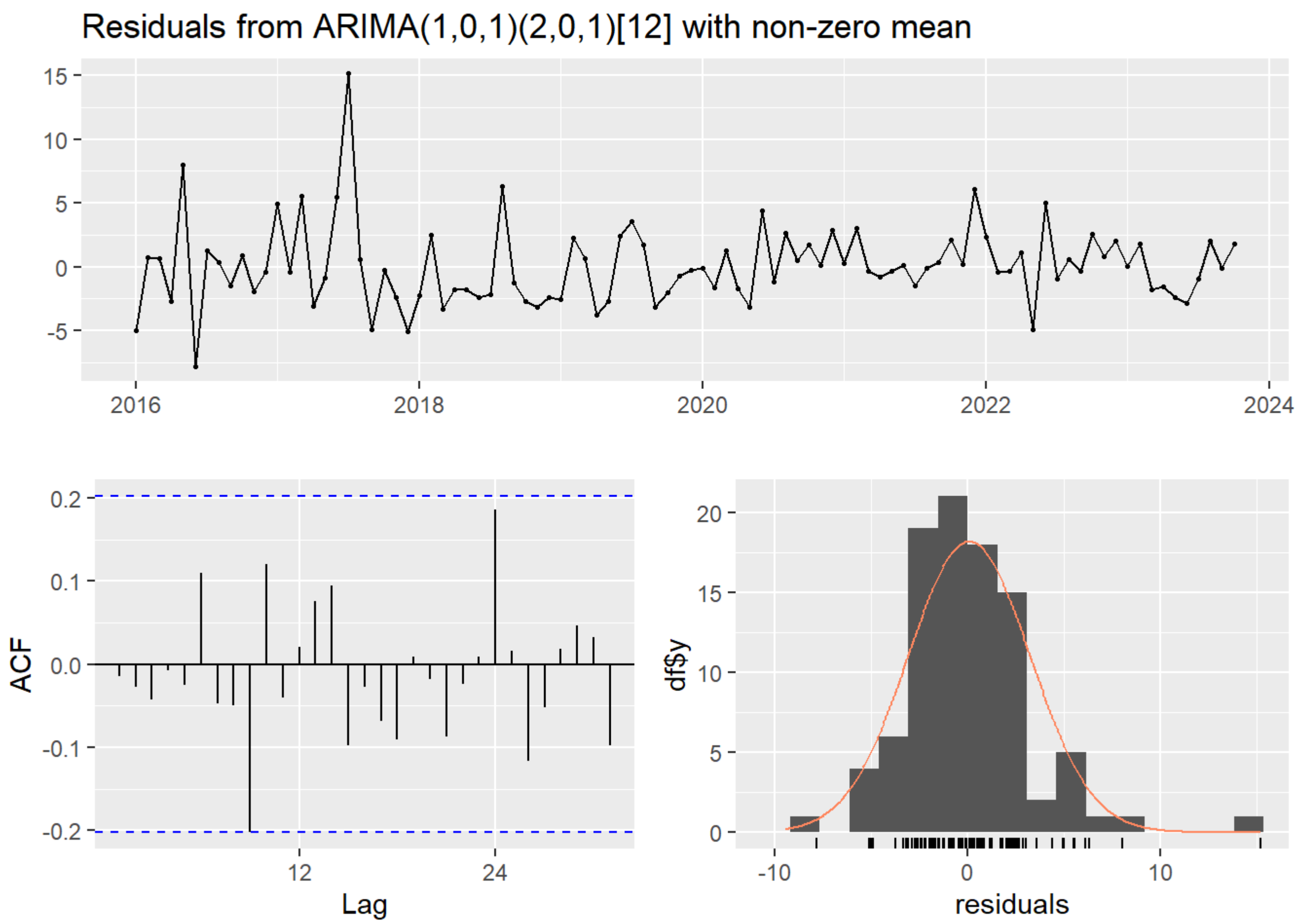

```
##
##  Ljung-Box test
##
## data:  Residuals from ARIMA(1,0,0)(2,0,1)[12] with non-zero mean
## Q* = 7.7666, df = 15, p-value = 0.9328
##
## Model df: 4.   Total lags used: 19
```

```
checkresiduals(mymodel3)
```




```
##
##  Ljung-Box test
##
## data:  Residuals from ARIMA(1,0,1)(1,0,0)[12] with non-zero mean
## Q* = 24.299, df = 16, p-value = 0.08317
##
## Model df: 3.   Total lags used: 19
```

```
checkresiduals(mymodel4)
```




```
##
##  Ljung-Box test
##
## data:  Residuals from ARIMA(1,0,1)(2,0,1)[12] with non-zero mean
## Q* = 12.541, df = 14, p-value = 0.5629
##
## Model df: 5.   Total lags used: 19
```

I then forecasted each variable and plotted them.

```
forecast(mymodel)
```

```
##          Point Forecast    Lo 80    Hi 80     Lo 95    Hi 95
## Nov 2023       182.0566 128.8663 235.2468 100.70907 263.4041
## Dec 2023       183.2571 123.0390 243.4752  91.16150 275.3527
## Jan 2024       184.8932 121.8297 247.9567  88.44592 281.3405
## Feb 2024       186.6951 121.8463 251.5439  87.51743 285.8727
## Mar 2024       188.5601 122.2729 254.8473  87.18252 289.9377
## Apr 2024       190.4491 122.8584 258.0398  87.07810 293.8202
## May 2024       192.3473 123.5159 261.1788  87.07868 297.6160
## Jun 2024       194.2490 124.2128 264.2852  87.13788 301.3601
## Jul 2024       196.1520 124.9367 267.3673  87.23759 305.0664
## Aug 2024       198.0555 125.6823 270.4288  87.37019 308.7409
## Sep 2024       199.9592 126.4470 273.4714  87.53200 312.3865
## Oct 2024       201.8630 127.2295 276.4965  87.72088 316.0051
## Nov 2024       203.7668 128.0287 279.5049  87.93533 319.5983
## Dec 2024       205.6706 128.8438 282.4974  88.17414 323.1671
## Jan 2025       207.5744 129.6742 285.4747  88.43624 326.7126
## Feb 2025       209.4783 130.5191 288.4374  88.72067 330.2359
## Mar 2025       211.3821 131.3781 291.3861  89.02654 333.7376
## Apr 2025       213.2859 132.2505 294.3213  89.35301 337.2188
## May 2025       215.1897 133.1359 297.2435  89.69930 340.6802
## Jun 2025       217.0935 134.0338 300.1533  90.06469 344.1224
## Jul 2025       218.9974 134.9438 303.0510  90.44849 347.5462
## Aug 2025       220.9012 135.8653 305.9371  90.85006 350.9523
## Sep 2025       222.8050 136.7981 308.8119  91.26878 354.3412
## Oct 2025       224.7088 137.7417 311.6760  91.70408 357.7136
```

```
forecast(mymodel2)
```

```
##          Point Forecast      Lo 80     Hi 80     Lo 95    Hi 95
## Nov 2023       5.687796  2.6801481  8.695443  1.087996 10.28760
## Dec 2023       4.650617  0.6156997  8.685535 -1.520257 10.82149
## Jan 2024       3.385081 -1.3120197  8.082182 -3.798515 10.56868
## Feb 2024       3.612021 -1.5542530  8.778296 -4.289113 11.51316
## Mar 2024       3.679486 -1.8336890  9.192661 -4.752187 12.11116
## Apr 2024       5.907101  0.1312310 11.682970 -2.926330 14.74053
## May 2024       7.108951  1.1311397 13.086763 -2.033323 16.25122
## Jun 2024       7.808551  1.6739340 13.943169 -1.573536 17.19064
## Jul 2024       8.320298  2.0630785 14.577518 -1.249293 17.88989
## Aug 2024       6.906945  0.5534109 13.260480 -2.809947 16.62384
## Sep 2024       6.002336 -0.4270963 12.431768 -3.830632 15.83530
## Oct 2024       5.048848 -1.4404912 11.538187 -4.875740 14.97344
## Nov 2024       5.178889 -1.3827299 11.740507 -4.856241 15.21402
## Dec 2024       5.329523 -1.2893865 11.948432 -4.793225 15.45227
## Jan 2025       5.129199 -1.5352103 11.793609 -5.063136 15.32153
## Feb 2025       5.047631 -1.6531104 11.748373 -5.200269 15.29553
## Mar 2025       4.592558 -2.1371324 11.322248 -5.699615 14.88473
## Apr 2025       5.202899 -1.5498798 11.955677 -5.124585 15.53038
## May 2025       4.833252 -1.9379543 11.604459 -5.522415 15.18892
## Jun 2025       5.250476 -1.5354482 12.036400 -5.127699 15.62865
## Jul 2025       5.254282 -1.5434005 12.051965 -5.141876 15.65044
## Aug 2025       4.767900 -2.0391802 11.574981 -5.642631 15.17843
## Sep 2025       4.303202 -2.5113896 11.117794 -6.118817 14.72522
## Oct 2025       4.014556 -2.8060397 10.835151 -6.416645 14.44576
```

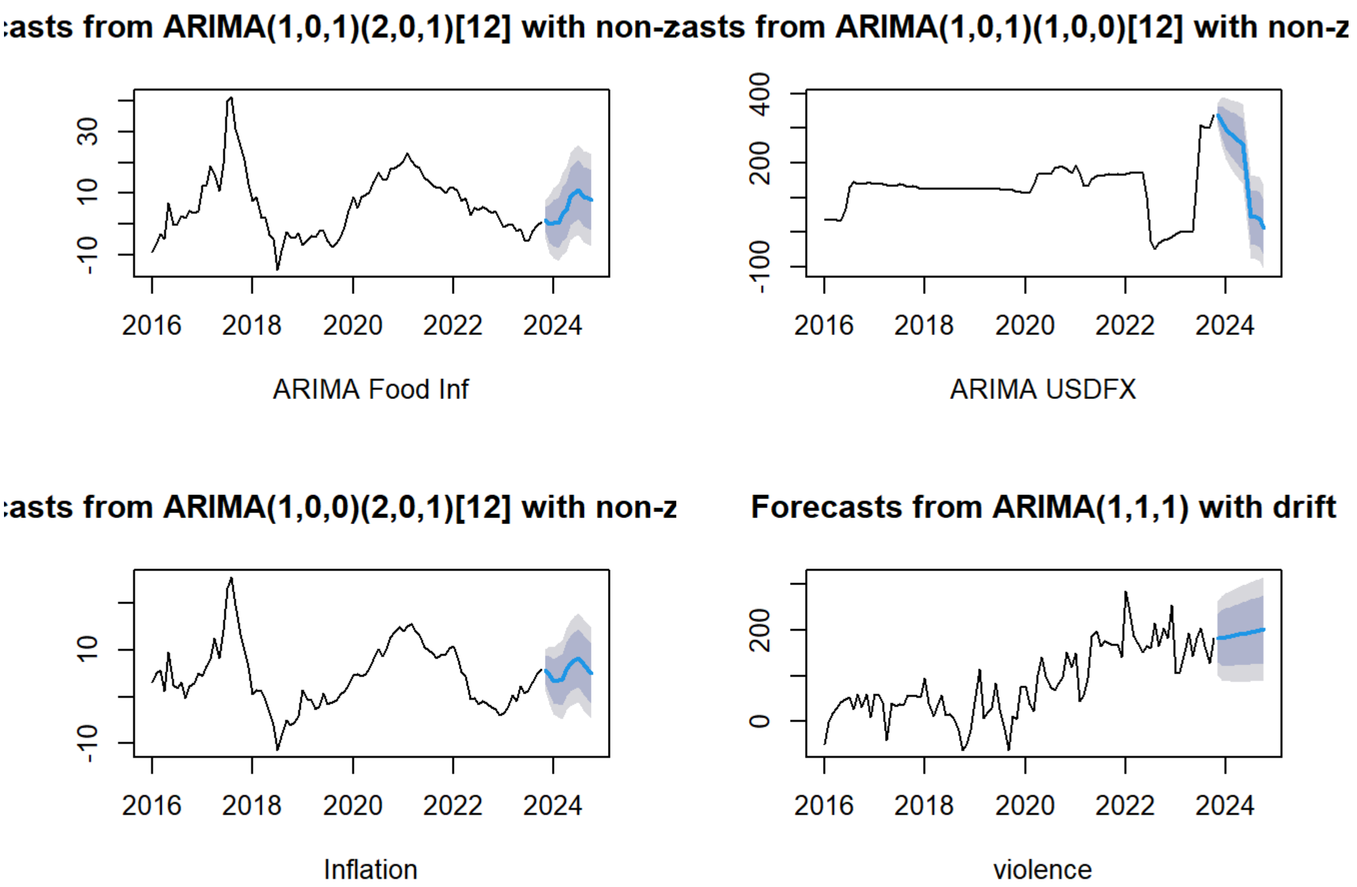
```
forecast(mymodel3)
```

```
##          Point Forecast     Lo 80     Hi 80      Lo 95    Hi 95
## Nov 2023     338.535955 315.09155 361.98036  302.68083 374.3911
## Dec 2023     319.475869 273.10495 365.84679  248.55766 390.3941
## Jan 2024     299.025857 241.40876 356.64296  210.90811 387.1436
## Feb 2024     283.480999 218.87309 348.08891  184.67173 382.2903
## Mar 2024     274.407718 205.13671 343.67873  168.46685 380.3486
## Apr 2024     264.378932 191.89031 336.86755  153.51715 375.2407
## May 2024     255.547254 180.79525 330.29926  141.22393 369.8706
## Jun 2024     152.737574  76.37427 229.10088   35.94998 269.5252
## Jul 2024      42.436069 -35.08333 119.95547  -76.11963 160.9918
## Aug 2024      42.418133 -35.93517 120.77144  -77.41290 162.2492
## Sep 2024      37.271038 -41.68597 116.22805  -83.48329 158.0254
## Oct 2024      11.758399 -67.63680  91.15359 -109.66607 133.1829
## Nov 2024       8.118897 -71.71224  87.95003 -113.97229 130.2101
## Dec 2024      18.215589 -64.15171 100.58289 -107.75432 144.1855
## Jan 2025      29.586389 -54.58561 113.75839  -99.14358 158.3164
## Feb 2025      38.030363 -47.43613 123.49685  -92.67936 168.7401
## Mar 2025      42.470672 -43.92935 128.87070  -89.66677 174.6081
## Apr 2025      47.764337 -39.31143 134.84011  -85.40656 180.9352
## May 2025      52.460149 -35.10605 140.02634  -81.46079 186.3811
## Jun 2025     119.257989  31.33520 207.18077  -15.20831 253.7243
## Jul 2025     191.133159 102.95075 279.31557   56.26980 325.9965
## Aug 2025     190.442431 102.07081 278.81405   55.28970 325.5952
## Sep 2025     193.234239 104.72463 281.74384   57.87048 328.5980
## Oct 2025     209.535704 120.92542 298.14599   74.01796 345.0534
```

```
forecast(mymodel4)
```

```
##          Point Forecast      Lo 80     Hi 80      Lo 95     Hi 95
## Nov 2023     1.36877149 -2.8030837  5.540627  -5.011530  7.749073
## Dec 2023    -0.04566775 -6.3209860  6.229650  -9.642939  9.551603
## Jan 2024     0.38219455 -7.0652371  7.829626 -11.007669 11.772058
## Feb 2024     0.37945776 -7.8203973  8.579313 -12.161138 12.920054
## Mar 2024     3.19446026 -5.5150847 11.904005 -10.125639 16.514560
## Apr 2024     4.55677399 -4.5077302 13.621278  -9.306189 18.419737
## May 2024     8.99338483 -0.3223883 18.309158  -5.253861 23.240630
## Jun 2024    10.12075013  0.6252592 19.616241  -4.401350 24.642850
## Jul 2024    11.09009453  1.4651798 20.715009  -3.629942 25.810131
## Aug 2024     8.87593351 -0.8426190 18.594486  -5.987310 23.739177
## Sep 2024     8.51835455 -1.2681588 18.304868  -6.448826 23.485535
## Oct 2024     7.79018444 -2.0457569 17.626126  -7.252590 22.832959
## Nov 2024     7.19641618 -2.8235823 17.216415  -8.127849 22.520682
## Dec 2024     8.62059648 -1.6768590 18.918052  -7.128003 24.369196
## Jan 2025     9.95956884 -0.5363438 20.455482  -6.092544 26.011682
## Feb 2025     9.73685326 -0.9019817 20.375688  -6.533841 26.007547
## Mar 2025     9.34325889 -1.3989956 20.085513  -7.085602 25.772119
## Apr 2025    10.31015836 -0.5071767 21.127493  -6.233528 26.853845
## May 2025     9.45254142 -1.4194270 20.324510  -7.174699 26.079782
## Jun 2025    11.28125261  0.3694638 22.193041  -5.406888 27.969393
## Jul 2025    11.35406317  0.4132162 22.294910  -5.378518 28.086645
## Aug 2025     9.97828204 -0.9837878 20.940352  -6.786757 26.743321
## Sep 2025     9.04511659 -1.9324631 20.022696  -7.743643 25.833876
## Oct 2025     8.57719803 -2.4117214 19.566117  -8.228904 25.383300
```

Afterwards, I plotted them one year forward. This is the final model. It seems like violence will still be on the increase. However, dollar hopefully seems to be coming down a well as some disinflation in the overall food inflation.



VAR Models

I chose a lag of 2

```
lagselect <- VARselect(difftseries, lag.max = 15, type = "const")
lagselect$selection # I CHOSE 2
```

```
## AIC(n)  HQ(n)  SC(n) FPE(n)
##     15      2      1     15
```

I then created the VAR model with a lag of 2. The R^{2} and the p-values of each are significant, showing that the model is good.

```
varmod1 <- VAR(difftseries, p=2, type = "const", season = NULL)
summary(varmod1)
```

```
##
## VAR Estimation Results:
## =========================
## Endogenous variables: violence, All.Items, Food, USDFX
## Deterministic variables: const
## Sample size: 92
## Log Likelihood: -1324.496
## Roots of the characteristic polynomial:
## 0.8721 0.8721 0.8498 0.7182 0.7182 0.1651 0.1651 0.08503
## Call:
## VAR(y = difftseries, p = 2, type = "const")
##
##
## Estimation results for equation violence:
## =========================================
## violence = violence.l1 + All.Items.l1 + Food.l1 + USDFX.l1 + violence.l2 + All.Items.l2 + Foo
d.l2 + USDFX.l2 + const
##
##              Estimate Std. Error t value Pr(>|t|)
## violence.l1   0.66721    0.10831   6.160 2.49e-08 ***
## All.Items.l1  6.51138    2.66041   2.448   0.0165 *
## Food.l1      -3.44275    1.77448  -1.940   0.0558 .
## USDFX.l1     -0.14963    0.16649  -0.899   0.3714
## violence.l2   0.17585    0.10502   1.674   0.0978 .
## All.Items.l2 -3.66605    2.66302  -1.377   0.1723
## Food.l2       2.25981    1.67970   1.345   0.1822
## USDFX.l2      0.05867    0.17105   0.343   0.7325
## const        22.44916   11.43777   1.963   0.0530 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Residual standard error: 43.25 on 83 degrees of freedom
## Multiple R-Squared: 0.7057,  Adjusted R-squared: 0.6774
## F-statistic: 24.88 on 8 and 83 DF,  p-value: < 2.2e-16
##
##
## Estimation results for equation All.Items:
## ==========================================
## All.Items = violence.l1 + All.Items.l1 + Food.l1 + USDFX.l1 + violence.l2 + All.Items.l2 + Fo
od.l2 + USDFX.l2 + const
##
##               Estimate Std. Error t value Pr(>|t|)
## violence.l1   0.006252   0.006762   0.925   0.3578
## All.Items.l1  0.703358   0.166084   4.235 5.88e-05 ***
## Food.l1       0.251417   0.110777   2.270   0.0258 *
## USDFX.l1      0.009119   0.010393   0.877   0.3828
## violence.l2  -0.008079   0.006556  -1.232   0.2213
## All.Items.l2  0.180516   0.166247   1.086   0.2807
## Food.l2      -0.253914   0.104860  -2.421   0.0176 *
## USDFX.l2     -0.002843   0.010678  -0.266   0.7907
## const        -0.124870   0.714035  -0.175   0.8616
```

```
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Residual standard error: 2.7 on 83 degrees of freedom
## Multiple R-Squared: 0.8609,  Adjusted R-squared: 0.8475
## F-statistic: 64.19 on 8 and 83 DF,  p-value: < 2.2e-16
##
##
## Estimation results for equation Food:
## =====================================
## Food = violence.l1 + All.Items.l1 + Food.l1 + USDFX.l1 + violence.l2 + All.Items.l2 + Food.l2
+ USDFX.l2 + const
##
##               Estimate Std. Error t value Pr(>|t|)
## violence.l1   0.008154   0.010550   0.773    0.442
## All.Items.l1  0.068955   0.259126   0.266    0.791
## Food.l1       0.966899   0.172835   5.594 2.77e-07 ***
## USDFX.l1     -0.001120   0.016216  -0.069    0.945
## violence.l2  -0.011587   0.010229  -1.133    0.261
## All.Items.l2  0.187779   0.259380   0.724    0.471
## Food.l2      -0.230027   0.163604  -1.406    0.163
## USDFX.l2      0.007302   0.016660   0.438    0.662
## const         0.160678   1.114045   0.144    0.886
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Residual standard error: 4.213 on 83 degrees of freedom
## Multiple R-Squared: 0.8531,  Adjusted R-squared: 0.8389
## F-statistic: 60.25 on 8 and 83 DF,  p-value: < 2.2e-16
##
##
## Estimation results for equation USDFX:
## ======================================
## USDFX = violence.l1 + All.Items.l1 + Food.l1 + USDFX.l1 + violence.l2 + All.Items.l2 + Food.l
2 + USDFX.l2 + const
##
##              Estimate Std. Error t value Pr(>|t|)
## violence.l1  -0.05054    0.06166  -0.820  0.41473
## All.Items.l1  3.20713    1.51444   2.118  0.03719 *
## Food.l1      -1.83326    1.01012  -1.815  0.07315 .
## USDFX.l1      1.37732    0.09477  14.533  < 2e-16 ***
## violence.l2   0.05474    0.05979   0.916  0.36249
## All.Items.l2 -0.72972    1.51593  -0.481  0.63152
## Food.l2       0.47400    0.95617   0.496  0.62139
## USDFX.l2     -0.54077    0.09737  -5.554 3.28e-07 ***
## const        19.55346    6.51097   3.003  0.00353 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
```

```
## Residual standard error: 24.62 on 83 degrees of freedom
## Multiple R-Squared: 0.8873,  Adjusted R-squared: 0.8764
## F-statistic: 81.65 on 8 and 83 DF,  p-value: < 2.2e-16
##
##
##
## Covariance matrix of residuals:
##          violence All.Items    Food    USDFX
## violence  1870.539   -1.4096  -1.486 111.3475
## All.Items   -1.410    7.2899   8.795  -0.9724
## Food        -1.486    8.7945  17.746 -11.9740
## USDFX      111.347   -0.9724 -11.974 606.1438
##
## Correlation matrix of residuals:
##           violence All.Items      Food    USDFX
## violence   1.000000  -0.01207 -0.008155  0.10457
## All.Items -0.012071   1.00000  0.773226 -0.01463
```

I performed the Portmanteau test and saw no autocorrelation. The ARCH test shows conditional heteroscedasticity. The normality test showed that the data is not normally distributed, and residuals aren't all in the confidence intervals.

The Granger test shows that violence does not cause the other variables.

```
serial <- serial.test(varmod1)
serial # pval seems high enough to have no autocorrelation i think
```

```
##
##  Portmanteau Test (asymptotic)
##
## data:  Residuals of VAR object varmod1
## Chi-squared = 217.58, df = 224, p-value = 0.6083
```

```
arch <- arch.test(varmod1)
arch # I think this shows heteroscedasticity
```

```
##
##  ARCH (multivariate)
##
## data:  Residuals of VAR object varmod1
## Chi-squared = 521.19, df = 500, p-value = 0.2476
```

```
normal <- normality.test(varmod1)
normal
```

```
## $JB
##
##  JB-Test (multivariate)
##
## data:  Residuals of VAR object varmod1
## Chi-squared = 259.27, df = 8, p-value < 2.2e-16
##
##
## $Skewness
##
##  Skewness only (multivariate)
##
## data:  Residuals of VAR object varmod1
## Chi-squared = 5.7866, df = 4, p-value = 0.2157
##
##
## $Kurtosis
##
##  Kurtosis only (multivariate)
##
## data:  Residuals of VAR object varmod1
## Chi-squared = 253.48, df = 4, p-value < 2.2e-16
```

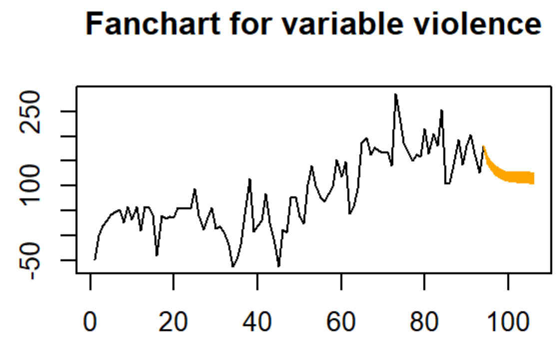
```
cause.v <- causality(varmod1, cause = "violence")
cause.v
```

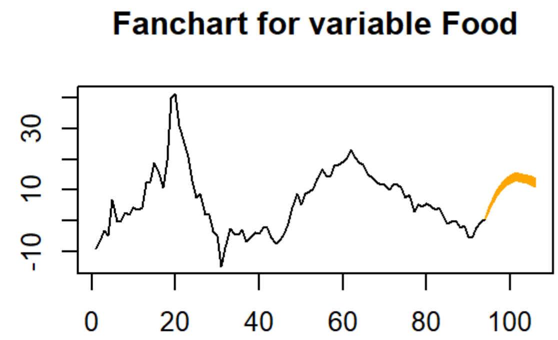
```
## $Granger
##
##  Granger causality H0: violence do not Granger-cause All.Items Food
##  USDFX
##
## data:  VAR object varmod1
## F-Test = 0.40869, df1 = 6, df2 = 332, p-value = 0.8732
##
##
## $Instant
##
##  H0: No instantaneous causality between: violence and All.Items Food
##  USDFX
##
## data:  VAR object varmod1
## Chi-squared = 1.0385, df = 3, p-value = 0.7919
```

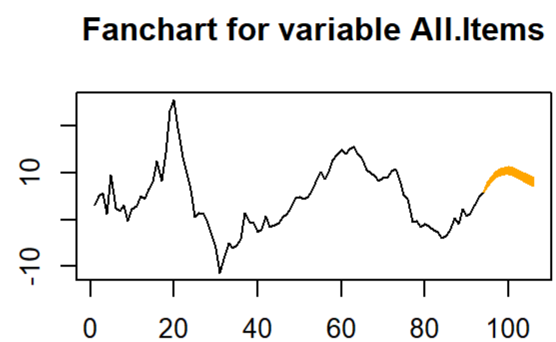
Afterward, I forecasted a year into the future. I tried the `predict()` and `forecast()` functions.

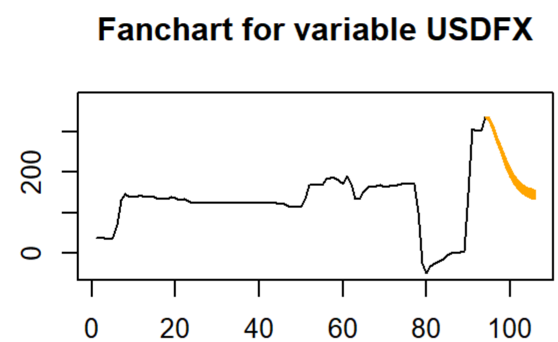
```
forecastv <- predict(varmod1, n.ahead = 12, ci=.95)
forecastm <- forecast(varmod1, h =12) #12 mo forecast
```

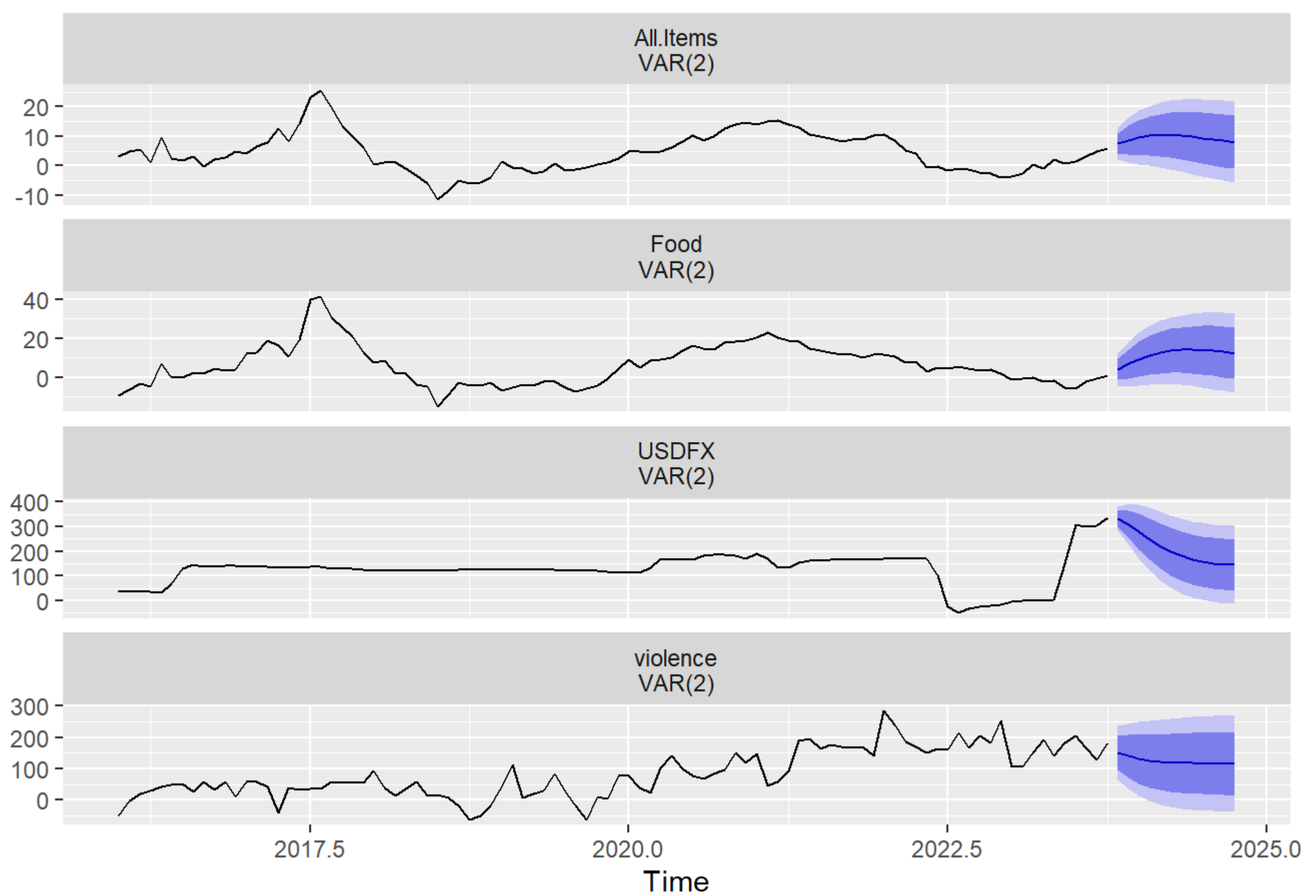
Below are the respective forecast plots.











Conclusion

After reviewing the plots of the ARIMA model, I see that violence will rise, but not very drastically. The value of the Dollar against Naira seems to drop dramatically in the next 12 months, which might help point to the new currency rules actually working. Both inflation variables show an overall constant growth that might be eased if the Dollar actually drops.

The VAR model shows a similar pattern but is not as dramatic and is smoother.

References

https://www.cbn.gov.ng/rates/inflrates.asp (https://www.cbn.gov.ng/rates/inflrates.asp)

https://www.cbn.gov.ng/rates/ExchRateByCurrency.asp (https://www.cbn.gov.ng/rates/ExchRateByCurrency.asp)

https://acleddata.com/africa/ (https://acleddata.com/africa/)

https://neusroom.com/the-struggle-to-eat-how-nigerians-are-spending-almost-all-their-income-on-food/ (https://neusroom.com/the-struggle-to-eat-how-nigerians-are-spending-almost-all-their-income-on-food/)