Understanding Consumer Sentiment with implications on the labor market and Inflationary pressures

A time-series approach

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I. INTRODUCTION

Consumer sentiment plays a crucial role in shaping economic conditions and decision-making processes. It reflects consumers' confidence and expectations regarding their financial situation and the broader economic environment. Understanding consumer sentiment is vital as it is a leading indicator of consumer spending and economic activity.

This project aims to investigate the dynamics of consumer sentiment and its relationship with two key economic variables: the unemployment rate and the consumer price index (CPI). The unemployment rate and the CPI are expected to impact consumer sentiment significantly. Higher unemployment rates may lead to decreased consumer confidence due to concerns about job security and future income prospects. Similarly, higher inflation rates, as reflected by rising CPI, can erode purchasing power and dampen consumer sentiment, particularly if wage growth fails to keep pace with rising prices.

Through this analysis, the paper aims to provide valuable insights into the determinants of consumer sentiment and its forecasting, which can inform policy decisions, business strategies, and economic forecasting efforts.

II. DATA DESCRIPTION

For this analysis, three related time series variables were chosen. They are the Consumer Sentiment Index, the focus variable, the Unemployment rate, and the Consumer Price Index. The Michigan Consumer Sentiment Index (MCSI) is a monthly survey of consumer confidence levels in the United States conducted by the University of Michigan. The unemployment rate represents the unemployed as a percentage of the labor force. Consumer Price Index is a price index of a basket of goods and services paid by urban consumers. Percent changes in the price index measure the inflation rate between two time periods.

The data for all three variables were collected from the Federal Reserve Bank of St. Louis (FRED). The data was monthly, not seasonally adjusted, and for all the variables, the data was collected from January 1992 to December 2023. There are 384 observations in the dataset for all the three variables.

III. EXPLORATORY DATA ANALYSIS

The time series plots for all the variables are given below:

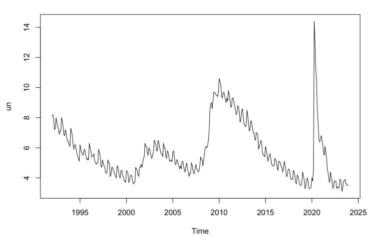


Figure 1: Plot of Unemployment Rate.

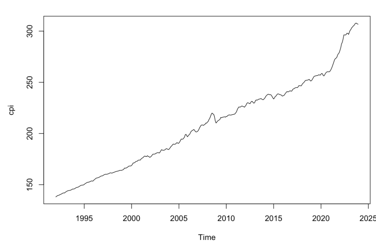


Figure 2: Plot of Consumer Price Index

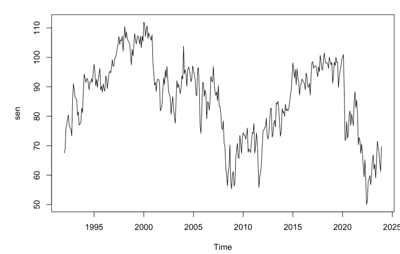


Figure 3: Plot of Consumer Sentiment

From the time series plots, there are different trends for all the variables that can be seen. There was a sharp rise in unemployment in 2020, explained by the COVID-19 pandemic. There's also a rise near 2010, indicated by the 2008 financial housing crisis. The decline in the consumer sentiment index can also be seen in 2010 and 2020, which are explained by the same reasons as unemployment. From the trends in the variables, it is understood that the three variables are not stationary in level. After running the Intord function for all three variables, it was determined that they were I (1).

After the visual interpretation, it can be said that the variable unemployment is stationary after the first differencing since the SD is less than half of the original SD. Looking at the ADF statistic, since Δy ADF value is less than the critical value of -3.45 at the 1% significance level. Therefore, the variable is I1 stationary.

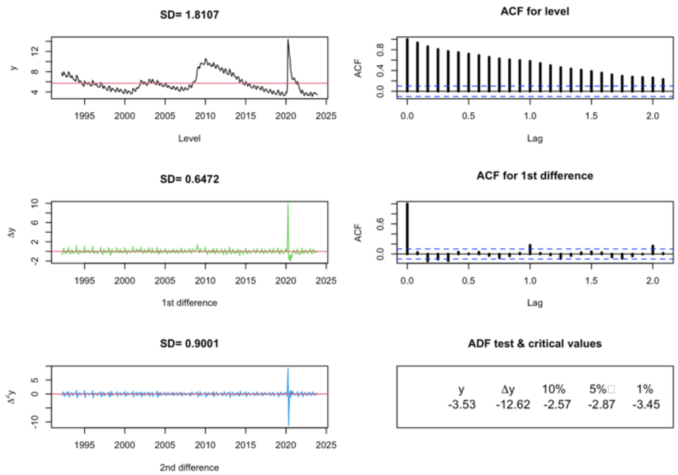


Figure 4: Intord for the unemployment rate

After the visual interpretation, it can be said that the variable CPI is stationary after the first differencing since the SD is less than half of the original SD. Looking at the ADF statistic, since Δy ADF value is less than the critical value of -3.45 at the 1% significance level. Therefore, the variable is I1 stationary.

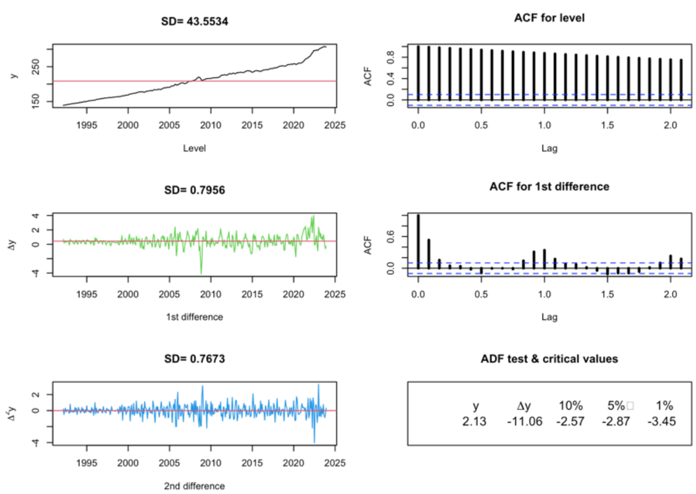
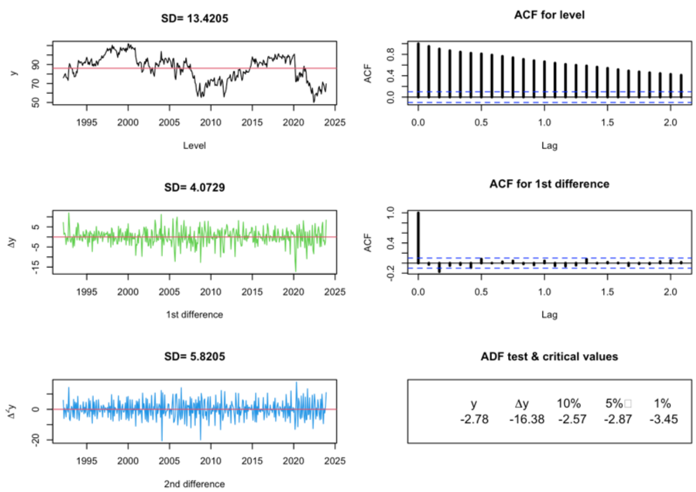


Figure 5: Intord for CPI

After the visual interpretation, it can be said that the variable Consumer Sentiment Index is stationary after the first differencing since the SD is less than half of the original SD. Looking at the ADF statistic, since Δy ADF value is less than the critical value of -3.45 at the 1% significance level. Therefore, the variable is I1 stationary.



Since all the variables are stationary after the first differencing, the VECM/VAR model can be estimated, and the best model can be selected.

IV. MODEL ESTIMATION

The model was estimated using both Johansen and Engle-Granger methods. The lag selection criteria were based on the results given from the VARselect command. The lag was selected according to the BIC (SC(n)), which showed 1. Since a minimum of 2 lags is required, the lag selected was 2.

The Johansen procedure test was carried out, and the results are below. For the first test, we can see that r=0 we reject the null hypothesis, but when r=1, we fail to reject the null hypothesis. Therefore, there is at least one linear combination. For the second test, we can see that when r=0, we reject the null hypothesis. When r=1, we reject the null hypothesis, but when r=2, we fail to reject the null hypothesis. Therefore, there are at least two linear combinations.

```
> jc <- ca.jo(ly, type="eigen", ecdet="const",K=2)
> summary(jc)

######################
# Johansen-Procedure #
######################

Test type: maximal eigenvalue statistic (lambda max) , without linear trend and constant i
n cointegration

Eigenvalues (lambda):
[1] 1.099261e-01 4.718046e-02 3.209516e-02 3.885781e-16

Values of teststatistic and critical values of test:

          test 10pct  5pct  1pct
r <= 2 | 12.46  7.52  9.24 12.97
r <= 1 | 18.46 13.75 15.67 20.20
r = 0  | 44.48 19.77 22.00 26.81

Eigenvectors, normalised to first column:
(These are the cointegration relations)

               un.l2       cpi.l2      sen.l2     constant
un.l2      1.000000000   1.00000000  1.00000000    1.0000000
cpi.l2     0.009305076   0.03073449 -0.04182991    1.0432224
sen.l2     0.145349893   0.13096655 -0.21635652   -0.6239477
constant -22.835689968 -22.25857710 21.52814599 -181.4948425

Weights W:
(This is the loading matrix)

            un.l2       cpi.l2       sen.l2      constant
un.d  -0.04366884 -0.03556481 -0.018930650 -1.486701e-17
cpi.d -0.04844862  0.06402645 -0.002100499  1.162002e-17
sen.d -0.19915201 -0.13110256  0.159322096 -1.345742e-16
```

Figure 6: Johansen Procedure first test

```
> jct <- ca.jo(ly, type="trace", ecdet="const",K=2)
> summary(jct)

######################
# Johansen-Procedure #
######################

Test type: trace statistic , without linear trend and constant in cointegration

Eigenvalues (lambda):
[1] 1.099261e-01 4.718046e-02 3.209516e-02 3.885781e-16

Values of teststatistic and critical values of test:

          test 10pct  5pct  1pct
r <= 2 | 12.46  7.52  9.24 12.97
r <= 1 | 30.92 17.85 19.96 24.60
r = 0  | 75.41 32.00 34.91 41.07

Eigenvectors, normalised to first column:
(These are the cointegration relations)

               un.l2       cpi.l2      sen.l2     constant
un.l2      1.000000000   1.00000000  1.00000000    1.0000000
cpi.l2     0.009305076   0.03073449 -0.04182991    1.0432224
sen.l2     0.145349893   0.13096655 -0.21635652   -0.6239477
constant -22.835689968 -22.25857710 21.52814599 -181.4948425

Weights W:
(This is the loading matrix)

            un.l2       cpi.l2       sen.l2      constant
un.d  -0.04366884 -0.03556481 -0.018930650 -1.486701e-17
cpi.d -0.04844862  0.06402645 -0.002100499  1.162002e-17
sen.d -0.19915201 -0.13110256  0.159322096 -1.345742e-16
```

Figure 7: Johansen Procedure second test

The Johansen and Engle-Granger model was estimated, and the stationarity of the errors needs to be tested.

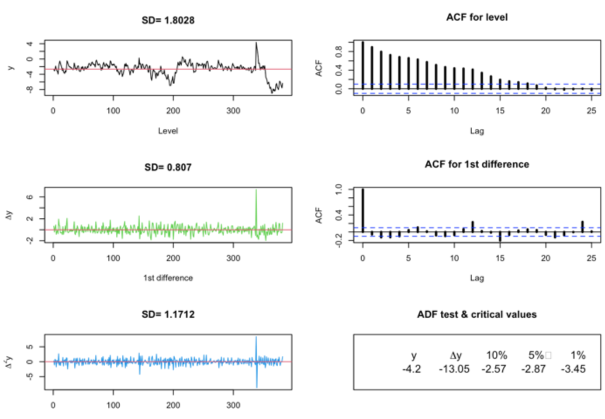


Figure 8: Intord of error for Johansen

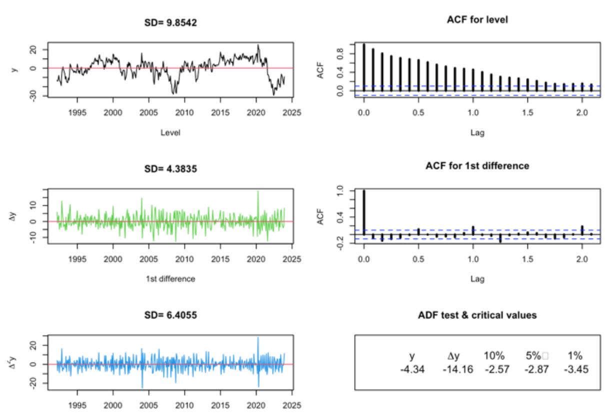


Figure 9: Intord of error for Engle-Granger

We can see that the ADF test statistic (-4.2), from Figure 8, is smaller than the critical value of -3.45. Therefore, the error term is stationary in level for Johansen. We can see that the ADF test statistic (-4.34), from Figure 9, is smaller than the critical value of -3.45. Therefore, the error term is stationary in level for Engle-Granger.

VECM model

A VECM model was estimated for both the Johansen and Engle-Granger model. For both the models, the exo1 component was negative and significant, which is necessary. Among the two models, the Johansen model showed a more significant result than the Engle-Granger. Therefore, the best model was chosen as the Johansen model.

```
VAR Estimation Results:
=========================
Endogenous variables: dun, dcpi, dsen
Deterministic variables: const
Sample size: 381
Log Likelihood: -1663.947
Roots of the characteristic polynomial:
0.4255 0.4255 0.3774 0.3774 0.2737 0.2737
Call:
VAR(y = dy, p = 2, type = "cons", season = 12L, exogen = ecmj1)


Estimation results for equation dun:
====================================
dun = dun.l1 + dcpi.l1 + dsen.l1 + dun.l2 + dcpi.l2 + dsen.l2 + cons
t + sd1 + sd2 + sd3 + sd4 + sd5 + sd6 + sd7 + sd8 + sd9 + sd10 + sd1
1 + exo1

         Estimate Std. Error t value Pr(>|t|)
dun.l1  -0.028658   0.054410  -0.527 0.598722
dcpi.l1 -0.206437   0.052324  -3.945 9.57e-05 ***
dsen.l1 -0.016645   0.007874  -2.114 0.035205 *
dun.l2  -0.109154   0.053834  -2.028 0.043335 *
dcpi.l2  0.026037   0.054041   0.482 0.630236
dsen.l2  0.007491   0.007880   0.951 0.342438
const   -0.096984   0.055312  -1.753 0.080382 .
sd1     -0.618447   0.165337  -3.741 0.000213 ***
sd2     -0.669661   0.167920  -3.988 8.06e-05 ***
sd3     -0.714443   0.161071  -4.436 1.22e-05 ***
sd4     -0.651494   0.158382  -4.113 4.83e-05 ***
sd5     -0.261354   0.153044  -1.708 0.088548 .
sd6     -0.583625   0.155366  -3.756 0.000201 ***
sd7     -0.932183   0.153876  -6.058 3.46e-09 ***
sd8     -0.986034   0.149700  -6.587 1.59e-10 ***
sd9     -0.854396   0.150283  -5.685 2.69e-08 ***
sd10    -0.790338   0.148025  -5.339 1.65e-07 ***
sd11    -0.804059   0.144990  -5.546 5.66e-08 ***
exo1    -0.062319   0.018573  -3.355 0.000877 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1


Residual standard error: 0.5669 on 362 degrees of freedom
Multiple R-Squared: 0.2702,     Adjusted R-squared: 0.2339
F-statistic: 7.445 on 18 and 362 DF,  p-value: < 2.2e-16
```

```
Estimation results for equation dcpi:
=====================================
dcpi = dun.l1 + dcpi.l1 + dsen.l1 + dun.l2 + dcpi.l2 + dsen.l2 + con
st + sd1 + sd2 + sd3 + sd4 + sd5 + sd6 + sd7 + sd8 + sd9 + sd10 + sd
11 + exo1

         Estimate Std. Error t value Pr(>|t|)
dun.l1   0.035404   0.055536   0.637 0.524204
dcpi.l1  0.592139   0.053407  11.087  < 2e-16 ***
dsen.l1  0.012723   0.008037   1.583 0.114295
dun.l2   0.039802   0.054949   0.724 0.469324
dcpi.l2 -0.135450   0.055160  -2.456 0.014535 *
dsen.l2 -0.003733   0.008043  -0.464 0.642831
const    0.151264   0.056457   2.679 0.007715 **
sd1     -0.602472   0.168759  -3.570 0.000405 ***
sd2     -0.290229   0.171396  -1.693 0.091254 .
sd3     -0.711333   0.164405  -4.327 1.96e-05 ***
sd4     -0.601288   0.161661  -3.719 0.000231 ***
sd5     -0.574948   0.156212  -3.681 0.000268 ***
sd6     -1.026897   0.158582  -6.475 3.08e-10 ***
sd7     -0.661598   0.157062  -4.212 3.19e-05 ***
sd8     -0.642119   0.152799  -4.202 3.33e-05 ***
sd9     -1.022050   0.153393  -6.663 1.00e-10 ***
sd10    -1.265249   0.151089  -8.374 1.24e-15 ***
sd11    -1.101528   0.147992  -7.443 7.24e-13 ***
exo1    -0.034340   0.018958  -1.811 0.070909 .
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1


Residual standard error: 0.5787 on 362 degrees of freedom
Multiple R-Squared: 0.4972,     Adjusted R-squared: 0.4722
F-statistic: 19.89 on 18 and 362 DF,  p-value: < 2.2e-16
```

```
Estimation results for equation dsen:
=====================================
dsen = dun.l1 + dcpi.l1 + dsen.l1 + dun.l2 + dcpi.l2 + dsen.l2 + const + sd1
+ sd2 + sd3 + sd4 + sd5 + sd6 + sd7 + sd8 + sd9 + sd10 + sd11 + exo1

        Estimate Std. Error t value Pr(>|t|)
dun.l1  -0.64805    0.37705  -1.719  0.08652 .
dcpi.l1 -0.84881    0.36259  -2.341  0.01978 *
dsen.l1 -0.07901    0.05457  -1.448  0.14851
dun.l2   0.30892    0.37306   0.828  0.40818
dcpi.l2  0.49905    0.37449   1.333  0.18350
dsen.l2 -0.15718    0.05461  -2.878  0.00423 **
const   -0.18839    0.38330  -0.491  0.62338
sd1     -0.70751    1.14575  -0.618  0.53729
sd2     -2.13614    1.16365  -1.836  0.06722 .
sd3     -1.36559    1.11619  -1.223  0.22196
sd4     -1.56535    1.09756  -1.426  0.15467
sd5     -0.85382    1.06056  -0.805  0.42131
sd6     -1.68897    1.07666  -1.569  0.11759
sd7     -2.91163    1.06633  -2.731  0.00663 **
sd8     -1.72271    1.03739  -1.661  0.09766 .
sd9     -1.99034    1.04143  -1.911  0.05677 .
sd10    -0.70970    1.02579  -0.692  0.48947
sd11     0.25997    1.00476   0.259  0.79598
exo1    -0.12076    0.12871  -0.938  0.34876
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1


Residual standard error: 3.929 on 362 degrees of freedom
Multiple R-Squared: 0.1087,     Adjusted R-squared: 0.06434
F-statistic: 2.452 on 18 and 362 DF,  p-value: 0.0009271



Covariance matrix of residuals:
          dun     dcpi    dsen
dun   0.32140 -0.06011 -0.6302
dcpi -0.06011  0.33485 -0.1473
dsen -0.63017 -0.14731 15.4346

Correlation matrix of residuals:
         dun    dcpi    dsen
dun   1.0000 -0.1832 -0.2829
dcpi -0.1832  1.0000 -0.0648
dsen -0.2829 -0.0648  1.0000
```

Figure 10: VECM estimation table for Johansen model.

Serial Correlation

Since the best model selection was made, a serial correlation test must be done to check if the variables have a serial correlation. After conducting the Ljung-Box test, it was seen that there was a serial correlation in the Consumer Price Index. For the unemployment rate, the Box-Ljung test's p-value was 0.9437, which is greater than 0.05 at the 5% significance level. Hence, there is no serial correlation. For the consumer sentiment index, the Box-Ljung test's p-value was 0.3324, which is greater than 0.05 at the 5% significance level. Hence, there is no serial correlation.

```
        Box-Ljung test

data:  resi
X-squared = 11.094, df = 20, p-value = 0.9437
```

Figure 11: Box-Ljung for the unemployment rate

```
        Box-Ljung test

data:  resi
X-squared = 22.151, df = 20, p-value = 0.3324
```

Figure 12: Box-Ljung for the consumer sentiment index.

Granger Causality

Firstly, we check if consumer sentiment granger causes the unemployment rate.

```
> anova(ve1, ve1r, test="F")
Analysis of Variance Table

Model 1: z@Z0[, reg.number] ~ constant + sd1 + sd2 + sd3 + sd4 + sd5 +
    sd6 + sd7 + sd8 + sd9 + sd10 + sd11 + un.dl1 + cpi.dl1 +
    sen.dl1 + un.l2 + cpi.l2 + sen.l2 + trend.l2 - 1
Model 2: z@Z0[, reg.number] ~ sd1 + sd2 + sd3 + sd4 + sd5 + sd6 + sd7 +
    sd8 + sd9 + sd10 + sd11 + un.dl1 + cpi.dl1 + un.l2 + cpi.l2 +
    constant - 1
  Res.Df    RSS Df Sum of Sq      F   Pr(>F)
1    363 116.34
2    366 120.82 -3   -4.4754 4.6546 0.003311 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Figure 13: Granger Causality

From Figure 13, the p-value is 0.003311. At the 5% significance level, since the p-value is less than 0.05, we reject the null hypothesis. Hence, the Consumer Sentiment Index Granger Causes the Unemployment rate. Next, we check if consumer sentiment granger causes the CPI.

```
> anova(ve1, ve1r, test="F")
Analysis of Variance Table

Model 1: z@Z0[, reg.number] ~ constant + sd1 + sd2 + sd3 + sd4 + sd5 +
    sd6 + sd7 + sd8 + sd9 + sd10 + sd11 + un.dl1 + cpi.dl1 +
    sen.dl1 + un.l2 + cpi.l2 + sen.l2 + trend.l2 - 1
Model 2: z@Z0[, reg.number] ~ sd1 + sd2 + sd3 + sd4 + sd5 + sd6 + sd7 +
    sd8 + sd9 + sd10 + sd11 + un.dl1 + cpi.dl1 + un.l2 + cpi.l2 +
    constant - 1
  Res.Df   RSS Df Sum of Sq      F Pr(>F)
1    363 122.5
2    366 123.4 -3  -0.90369 0.8927  0.445
```

Figure 14: Granger Causality

From Figure 14, the p-value is 0.445. At the 5% significance level, since the p-value is greater than 0.05, we fail to reject the null hypothesis. Hence, the Consumer Sentiment Index does not Granger Causes Consumer Price Index.

Impulse Response Function

We are particularly interested in examining the response of consumer sentiment to shocks in the unemployment rate and the consumer price index (CPI). When a shock is given to unemployment, the variable Consumer Sentiment and CPI can predict for one period; then it becomes insignificant. For its own prediction, the shock can predict for almost two periods ahead.

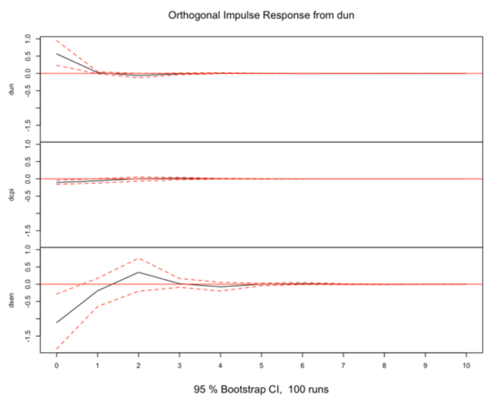


Figure 15: Impulse Response function from the unemployment rate.

When a shock is given to CPI for its own prediction, it can predict for almost three periods ahead, and Consumer Sentiment isn't significant. The shock can predict up to 3 periods ahead for the variable unemployment.

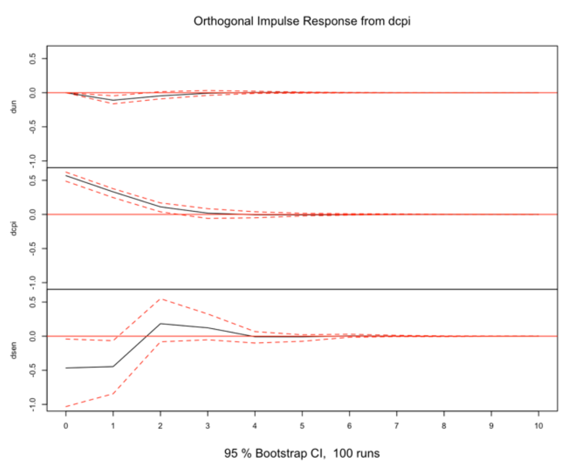


Figure 16: Impulse response function from CPI.

When a shock is given to the consumer sentiment index for the variable unemployment, it can predict almost three periods. For CPI, it isn't significant. But for its own prediction, it can predict almost three periods.

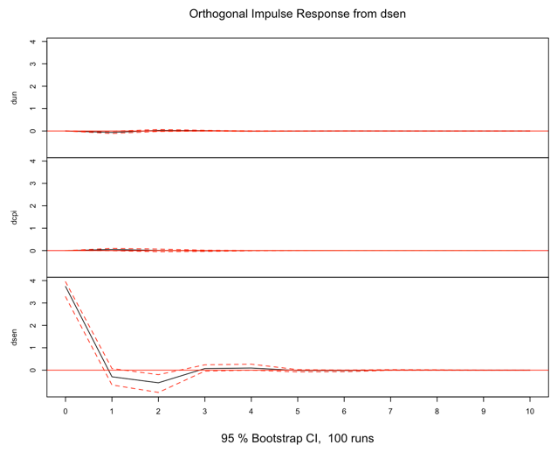


Figure 17: Impulse Response function from Consumer Sentiment Index

Variance Decomposition

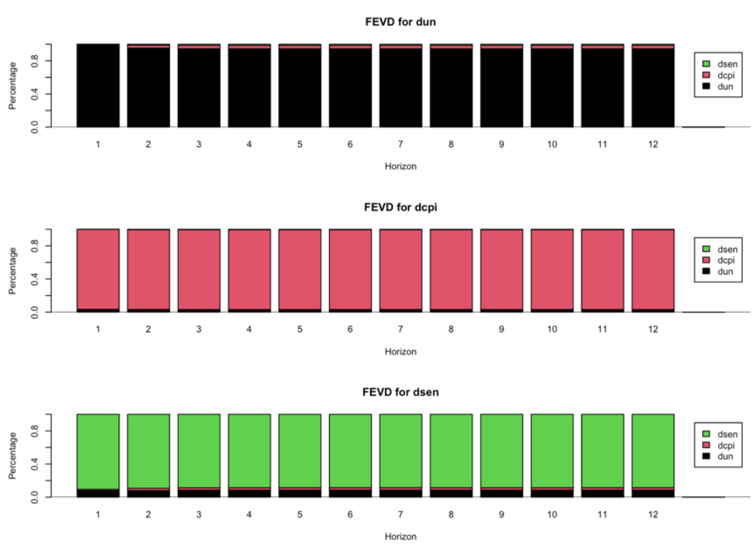


Figure 18: Variance Decomposition

The variance decomposition plot shows that the variables don't influence each other for future values. We can see that the variable dcpi is slightly influencing desen.

Forecasting

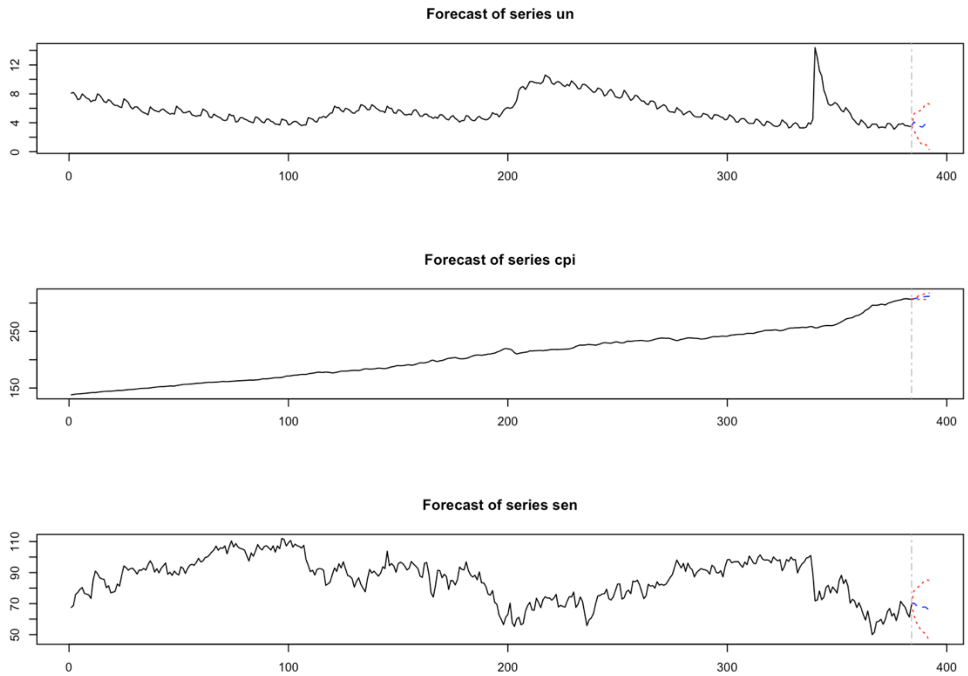


Figure 19: Forecasting.

The forecasting was done for all three variables for eight periods ahead. For CPI, the forecasting is good since the gap between the confidence interval is not wide. However, the gap is wide for the other two, so we can conclude that forecasting is unsuitable for unemployment and the Consumer Sentiment Index.

V. CONCLUSION

This project aimed to investigate the dynamics of consumer sentiment and its relationship with the unemployment rate and the consumer price index (CPI). By employing VAR/VECM time series techniques, we found insights into the relationship between the Consumer Sentiment Index and CPI and the unemployment rate. Further research could be done by adding more variables to understand the relationship between them and the consumer sentiment index, such as Median Household income. In conclusion, this project contributes to understanding consumer sentiment dynamics and highlights the importance of considering labor market conditions and inflationary pressures in forecasting and policy analysis. The findings can inform decision-making processes for policymakers, businesses, and economists, ultimately contributing to better economic planning and resource allocation.

VI. REFERENCES

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