How Risk Appetite in U.S Banks Change with Fluctuations in Profitability and Economic Conditions

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1. Introduction

The focus of my research is to identify the risk appetite of banks in the United States when they face tougher economic conditions and uncertainty, does their risk appetite increase to keep shareholders happy at the risk of hurting depositors?

The financial system of the United States is critical for the functioning of markets throughout the world . Banks play a key role in ensuring this system functions properly ,they provide finances which allow business environments to flourish and have a responsibility to ensure that funds of depositors are not put at risk.

As can be seen in the recent past in 2023 , there were significant bank failures which occurred due to banks inability to manage risk, to prevent a failure of the banking system the federal government had to intervene and provide funds/ assist in selling the failing banks to larger banks. Banks have come under scrutiny as most banks are “Too Large to Fail” hence should banks take on risk as when their risk is managed well, they can capitalize on profits however if they fail to manage the risks the losses are socialized as the government must intervene to stabilize the financial markets.

2. Literature Review

Itai Agur and Maria Demertzis (2012) focused their paper on the implications of monetary policy and banks taking excessive risk. The paper further tries to identify how a bank regulator can counteract banks’ risk-taking incentives using a risk-based capital requirement. I found this paper provided great insights on how the cost of borrowing for banks could help to determine how the risk appetite could change when faced with increased costs and pressure to improve profitability.

Kiridaran Kanagaretnam, Gerald J. Lobo, Chong Wang, and Dennis J. Whalen (2019), looked at how banking industries risk taking behavior is affected by the societal trust placed on them, the paper indicated that as people place more trust and faith in banks ,banks do not actively take excessive risks and focus on pro- social behavior. Surveys indicate that americans place a high level of trust on US banks in general , should this indicate that banks in response are more conservative or are there other factors which drives risk appetites as well.

Lamont Black and Lieu Hazelwood (2012) presented in their paper how big banks were willing to take on more risk after the Troubled Asset Relief Program (TARP) was used during the 2008 financial crisis as it indicated the support of the government for failing banks. This paper provided me insights as how risk appetites might have changed after the 2008 crisis and hence gave me the inspiration to identify if I can compare results from the pre and post 2008 recession to see if there was a significant change visible in behavior.

3. Data

The data for this analysis is collected from the Federal Reserve Bank of St Louis(FRED), all the data is quarterly reported and is not seasonally adjusted. The period which will be covered in this paper would be from the year 1988 to 2020.

The key variables of interest in my analysis are as follows :

- Loan Loss Reserve Ratio – This ratio is the key dependent variable which will be used to capture the risk appetite of banks. The Loan Loss Reserve Ratio reflects the level of loan provisions set aside by banks to cover potential losses from loan defaults , a bank with an increasing ratio would indicate a conservative nature with risk appetite who wants to protect themselves against losses.

- Net Interest Margin (NIM) – The Net Interest Margin captures the difference between the interest income earned and the interest expenses which are paid to depositors and other funding sources. The NIM would help understand the profitability of banks with an increasing NIM indicating increased returns.

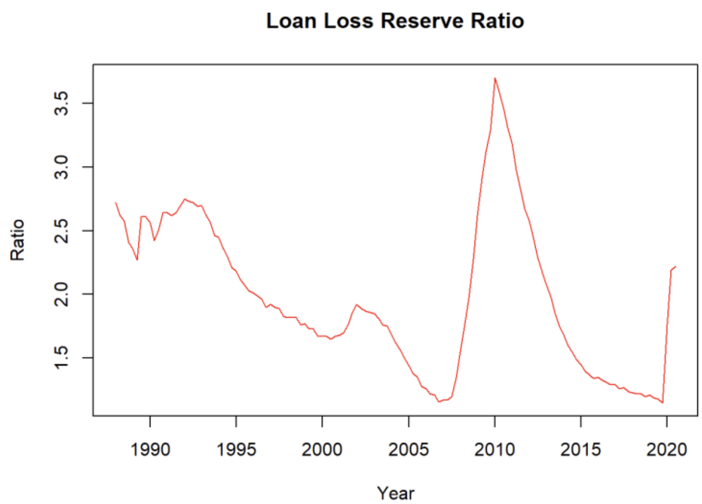
- NASDAQ Composite Index – The NASDAQ is used as another one of the indicators which could help to see how the US economy is performing , it is an index that represents the performance of all the common stocks listed on the NASDAQ, with a variety of companies across various sectors with a focus on technology.

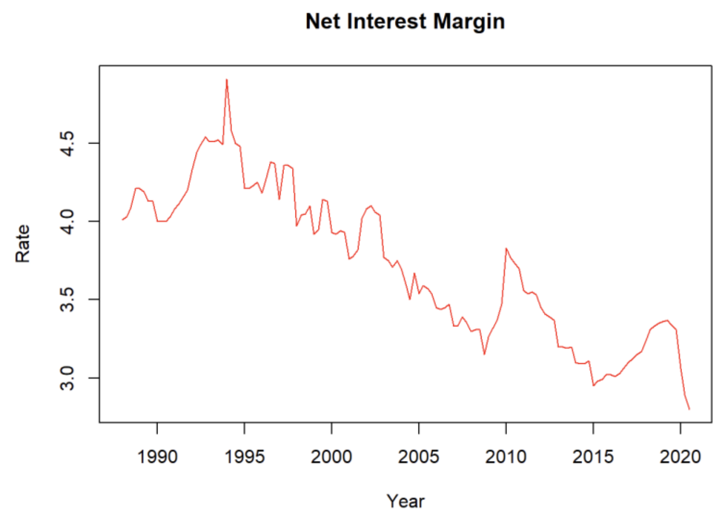
- Consumer Confidence – We look at consumer confidence through a monthly survey from the University of Michigan, it measures the level of confidence or optimism that consumers have regarding the overall state of the US economy and their personal finance situations.

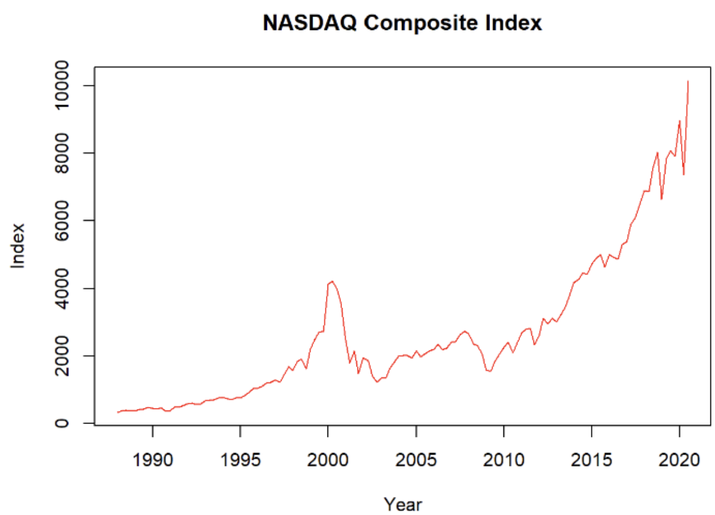
- Federal Funds Effective Rate (FED) – This measures the interest rate at which depository institutions lend and borrow funds from each other on an overnight basis in the federal funds market. This is a good indicator of the monetary policy in effect and is a cost for banks, hence as the rate increases the cost of borrowing for banks increases, which could have an impact on their profitability and cause changes in behavior of banks.

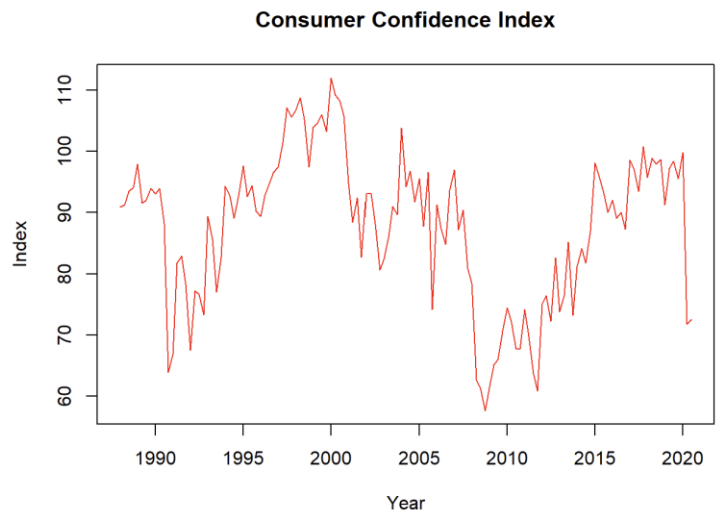
Summary Statistics

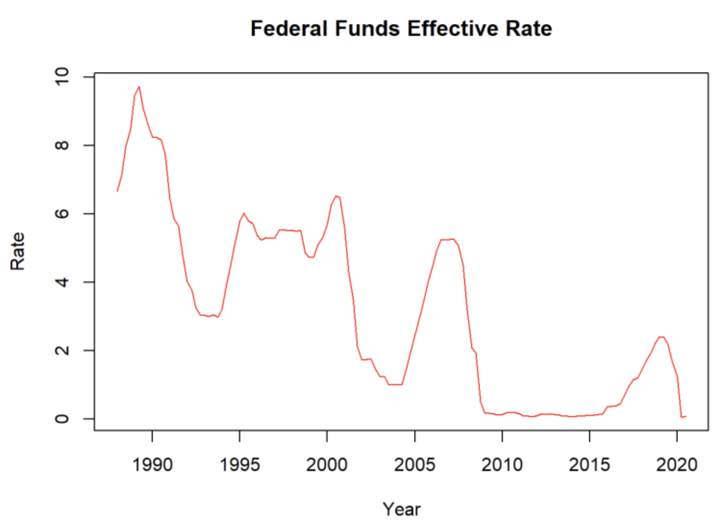
Variable	N	Mean	Std. Dev.	Min	Pctl. 25	Pctl. 75	Max
Loan_loss_reserve_ratio	131	1.982	0.603	1.15	1.495	2.455	3.7
NIM	131	3.727	0.481	2.8	3.33	4.12	4.91
Nasdaq	131	2641.335	2137.496	330.47	1079.35	3336.83	10154.629
Consumer_confidence	131	87.789	12.286	57.6	79.5	96.2	112
FED_Funds	131	3.184	2.669	0.059	0.422	5.292	9.726


Loan Loss Reserve Ratio
Ratio
1.5
2.0
2.5
3.0
3.5
1990
1995
2000
2005
2010
2015
2020
Year


Net Interest Margin
Rate
3.0
3.5
4.0
4.5
1990
1995
2000
2005
2010
2015
2020
Year


NASDAQ Composite Index
Index
0
2000
4000
6000
8000
10000
1990
1995
2000
2005
2010
2015
2020
Year


Consumer Confidence Index
Index
60
70
80
90
100
110
1990
1995
2000
2005
2010
2015
2020
Year


Federal Funds Effective Rate
Rate
0
2
4
6
8
10
1990
1995
2000
2005
2010
2015
2020
Year

4. Empirical Methodology

The empirical methodology my paper will use is as follows. The key techniques used in the analysis will be a time series analysis which will be used to help prove how certain key variables which capture the state of the economy, and the cost of operations could have an impact on banks risk taking behavior.

The analysis will first consist of determining the order of integration of the variables and identifying if there are any concerns with regards to seasonality as well. The focus on this research would not be to forecast the variables of interest but to instead identify the causal relationship between them.

Hence the key focus of my analysis would be done using a Vector Error Correction Model (VECM). I will use impulse response functions to shock other key variables of interest to determine the impact they have on the Loan Loss Reserve Ratio (which acts as a proxy for banks risk appetite). Next, I use a variance decomposition matrix to see how the influence of these variables changes over time. Finally, to further determine any causal relationships which might exist I will check to see if the variables granger cause each other.

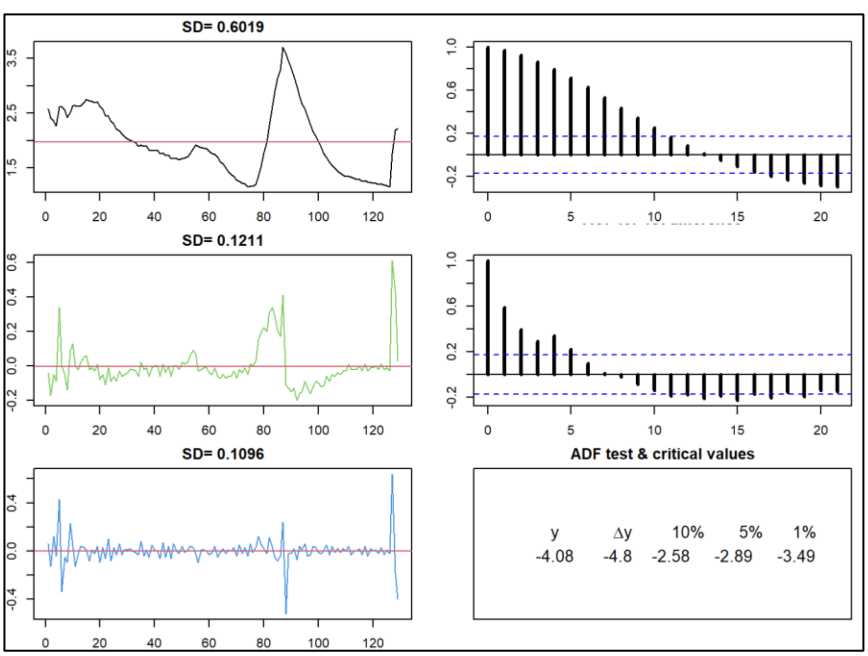
$$Loan\ loss\ Reserve\ Ratio_t \;\; = \alpha + \beta_1 Net\ Interest\ Margin_t + \beta_2 NASDAQ_t + \beta_3 Federal\ Funds\ Rate_t + \beta_4 Consumer\ Confidence_t + \varepsilon_t$$

5. Results

The preliminary results from the analysis of my data are used to show the order or integration of key variables of interest . Modeling has been carried out to prove causality through a VECM model, Impulse response functions & variance decompositions.

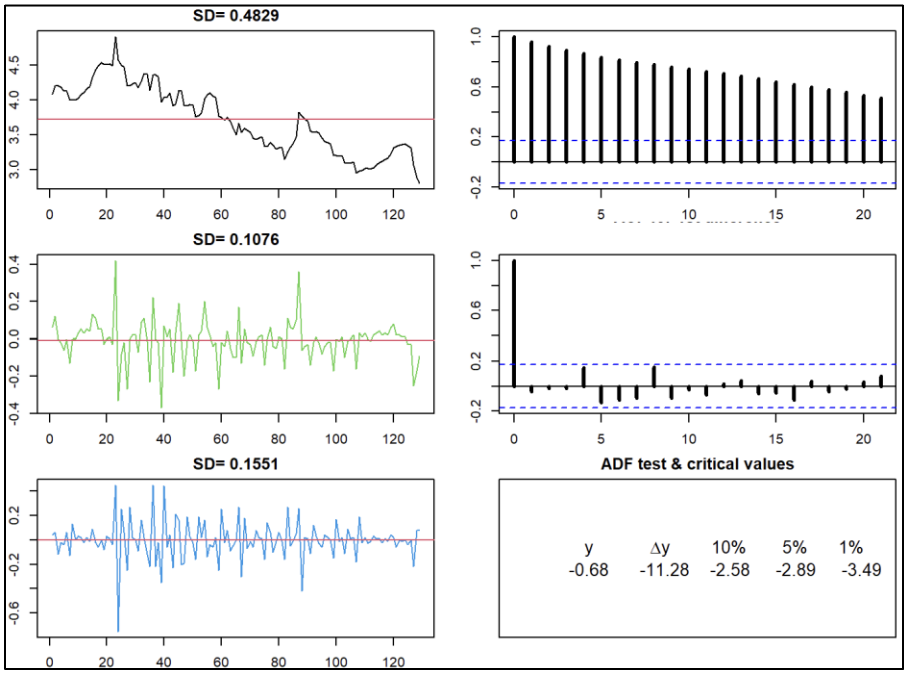
I. Order of Integration

As can be seen from the below ACF, PACF and the Augmented Dickey-Fuller (ADF) test , the Loan Loss Reserve Ratio has a unit root problem. This can be observed from the ACF and the significant drop in standard deviation coupled with the results from the ADF test. The variable has an order of integration of 1 and needs to be first differenced to become stationary.



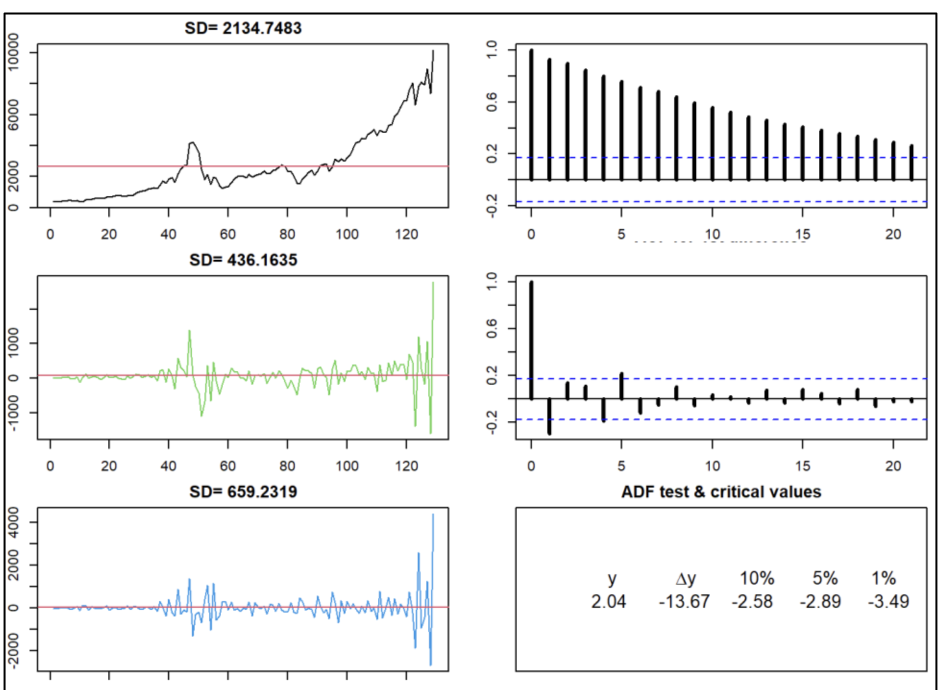

```
###############################################
# Augmented Dickey-Fuller Test Unit Root Test #
###############################################

Test regression trend


Call:
lm(formula = z.diff ~ z.lag.1 + 1 + tt + z.diff.lag)

Residuals:
    Min      1Q  Median      3Q     Max
-0.2924 -0.0421 -0.0116  0.0167  0.6073

Coefficients:
             Estimate Std. Error t value          Pr(>|t|)
(Intercept)  0.080781   0.042323    1.91             0.059 .
z.lag.1     -0.036560   0.015772   -2.32             0.022 *
tt          -0.000139   0.000256   -0.54             0.587
z.diff.lag   0.607933   0.071428    8.51 0.000000000000045 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.0967 on 125 degrees of freedom
Multiple R-squared:  0.378,     Adjusted R-squared:  0.363
F-statistic: 25.3 on 3 and 125 DF,  p-value: 0.000000000000742


Value of test-statistic is: -2.32 1.88 2.82

Critical values for test statistics:
      1pct  5pct 10pct
tau3 -3.99 -3.43 -3.13
phi2  6.22  4.75  4.07
phi3  8.43  6.49  5.47
```

The Net Interest Margin has a unit root problem. This can be observed from the ACF which has an extremely slow decay and the significant drop in standard deviation coupled with the results from the ADF test. The variable has an order of integration of 1 and needs to be first differenced to become stationary.



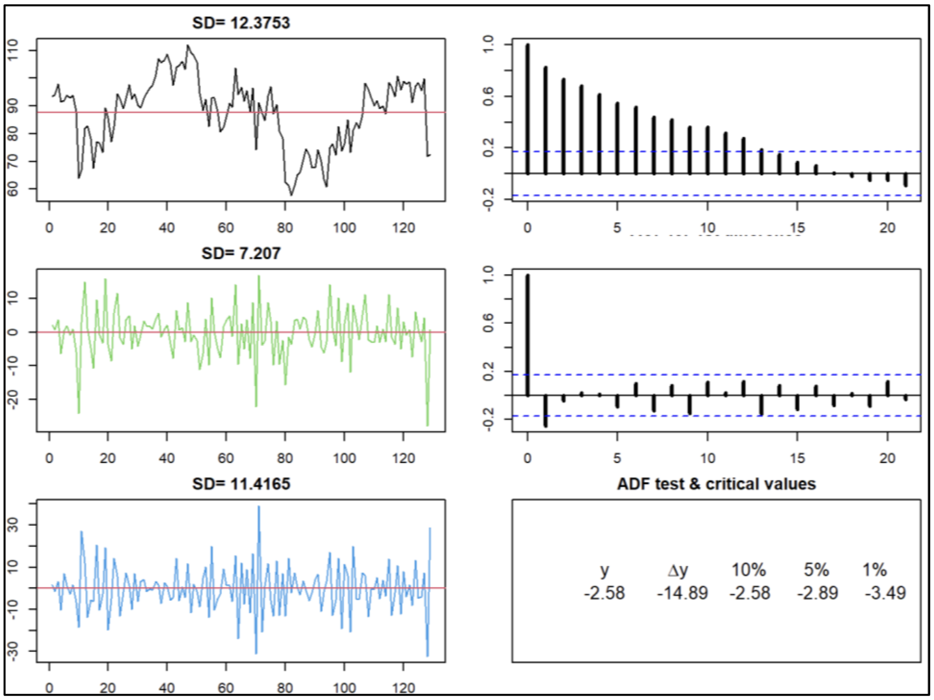

```
###############################################
# Augmented Dickey-Fuller Test Unit Root Test #
###############################################

Test regression trend


Call:
lm(formula = z.diff ~ z.lag.1 + 1 + tt + z.diff.lag)

Residuals:
    Min      1Q  Median      3Q     Max
-0.3235 -0.0366  0.0111  0.0404  0.4588

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept)  0.614693   0.195635    3.14   0.0021 **
z.lag.1     -0.136015   0.043482   -3.13   0.0022 **
tt          -0.001766   0.000549   -3.22   0.0016 **
z.diff.lag   0.013345   0.088227    0.15   0.8800
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.104 on 125 degrees of freedom
Multiple R-squared:  0.0802,	Adjusted R-squared:  0.0581
F-statistic: 3.63 on 3 and 125 DF,  p-value: 0.0148


Value of test-statistic is: -3.13 3.94 5.34

Critical values for test statistics:
      1pct  5pct 10pct
tau3 -3.99 -3.43 -3.13
phi2  6.22  4.75  4.07
phi3  8.43  6.49  5.47
```

The NASDAQ variable also has a unit root problem. This can be observed from the ACF which has a slow decay and the drop in standard deviation coupled with the results from the ADF test. The variable has an order of integration of 1 and needs to be first differenced to become stationary.



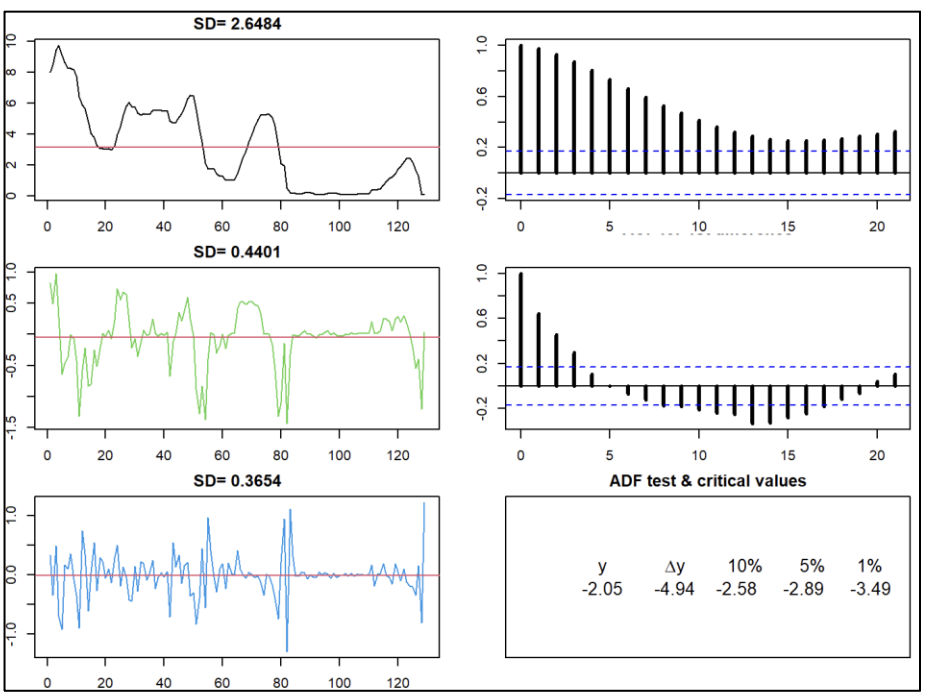

```
###############################################
# Augmented Dickey-Fuller Test Unit Root Test #
###############################################

Test regression trend


Call:
lm(formula = z.diff ~ z.lag.1 + 1 + tt + z.diff.lag)

Residuals:
    Min      1Q  Median      3Q     Max
-1463.0   -86.1    41.3   127.1  1784.0

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept) -44.6560    74.2019   -0.60     0.55
z.lag.1       0.0148     0.0348    0.43     0.67
tt            1.6171     1.8742    0.86     0.39
z.diff.lag   -0.4561     0.1006   -4.54 0.000013 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 403 on 125 degrees of freedom
Multiple R-squared:  0.165,	Adjusted R-squared:  0.145
F-statistic: 8.25 on 3 and 125 DF,  p-value: 0.0000472


Value of test-statistic is: 0.426 4.52 2.98

Critical values for test statistics:
      1pct  5pct 10pct
tau3 -3.99 -3.43 -3.13
phi2  6.22  4.75  4.07
phi3  8.43  6.49  5.47
```

The Consumer Confidence variable also has a unit root problem. This can be observed from the ACF which has a slow decay and the drop in standard deviation after first differencing coupled with the results from the ADF test. The variable has an order of integration of 1 and needs to be first differenced to become stationary.




```
###############################################
# Augmented Dickey-Fuller Test Unit Root Test #
###############################################

Test regression trend


Call:
lm(formula = z.diff ~ z.lag.1 + 1 + tt + z.diff.lag)

Residuals:
   Min     1Q Median     3Q    Max
-25.77  -4.12   1.28   4.04  14.35

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  12.6763     4.8973    2.59   0.0108 *
z.lag.1      -0.1376     0.0522   -2.64   0.0095 **
tt           -0.0114     0.0164   -0.70   0.4876
z.diff.lag   -0.1847     0.0883   -2.09   0.0385 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 6.86 on 125 degrees of freedom
Multiple R-squared:  0.115,     Adjusted R-squared:  0.0936
F-statistic: 5.41 on 3 and 125 DF,  p-value: 0.00157


Value of test-statistic is: -2.64 2.38 3.53

Critical values for test statistics:
      1pct  5pct 10pct
tau3 -3.99 -3.43 -3.13
phi2  6.22  4.75  4.07
phi3  8.43  6.49  5.47
```

The Federal Funds Effective Rate has a unit root problem. This can be observed from the ACF which has a slow decay and the drop in standard deviation after first differencing coupled with the results from the ADF test. The variable has an order of integration of 1 and needs to be first differenced to become stationary.

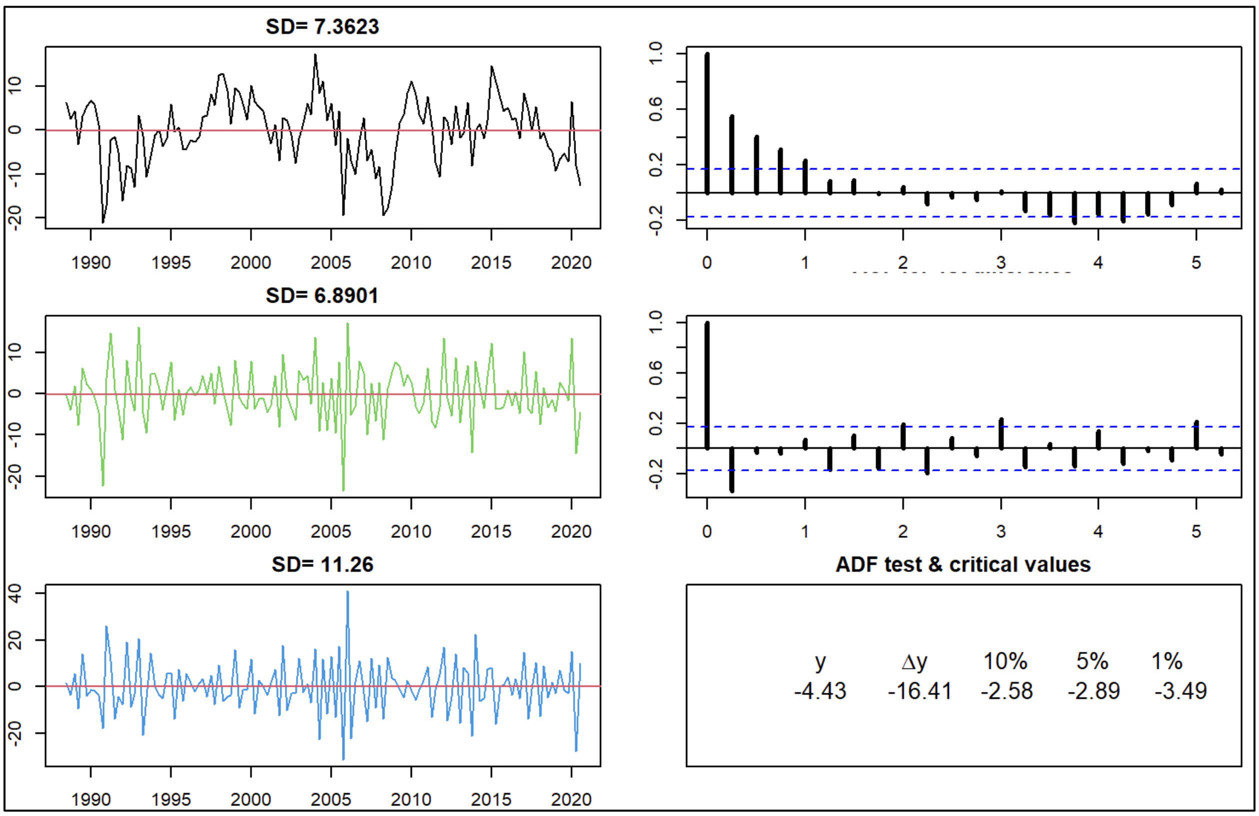



```
###############################################
# Augmented Dickey-Fuller Test Unit Root Test #
###############################################

Test regression trend


Call:
lm(formula = z.diff ~ z.lag.1 + 1 + tt + z.diff.lag)

Residuals:
    Min      1Q  Median      3Q     Max
-1.3390 -0.1064  0.0017  0.1674  0.8872

Coefficients:
            Estimate Std. Error t value             Pr(>|t|)
(Intercept)  0.39736    0.13545    2.93              0.00399 **
z.lag.1     -0.06285    0.01768   -3.56              0.00053 ***
tt          -0.00329    0.00125   -2.62              0.00977 **
z.diff.lag   0.68506    0.06446   10.63 < 0.0000000000000002 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.32 on 125 degrees of freedom
Multiple R-squared:  0.485,     Adjusted R-squared:  0.472
F-statistic: 39.2 on 3 and 125 DF,  p-value: <0.0000000000000002


Value of test-statistic is: -3.56 4.44 6.38

Critical values for test statistics:
      1pct  5pct 10pct
tau3 -3.99 -3.43 -3.13
phi2  6.22  4.75  4.07
phi3  8.43  6.49  5.47
```

I. Cointegration , Seasonality and Vector Error Correction Model(VECM)

Now that we have determined the order of integration of our key variables, I look at using the Engle-Granger approach which indicates that there is a long run equilibrium which is reached through the error correction term. This would ensure that a linear combination of the variables will have an order of integration of zero(I 0) even though the variables by themselves are of the order of integration of 1 (I 1).

After identifying a linear combination of variables which are cointegrated , I check to ensure that the residuals of the Engle- Granger are I0 which can be seen from the below ACF and the Augmented Dickey Fuller test.



```
VAR Estimation Results:
=========================
Endogenous variables: dCC, dLLR, dNIM, dNASDAQ, dFED
Deterministic variables: const
Sample size: 128
Log Likelihood: -1108.501
Roots of the characteristic polynomial:
0.702 0.556 0.465 0.465 0.402 0.354 0.354 0.215 0.215 0.093
Call:
VAR(y = dy, p = 2, type = "cons", season = 4L, exogen = ecm1)


Estimation results for equation dCC:
====================================
dCC = dCC.l1 + dLLR.l1 + dNIM.l1 + dNASDAQ.l1 + dFED.l1 + dCC.l2 + dLLR.l2 + dNIM.l2
+ dNASDAQ.l2 + dFED.l2 + const + sd1 + sd2 + sd3 + exo1

             Estimate Std. Error t value Pr(>|t|)
dCC.l1      -0.127606   0.121320   -1.05  0.29513
dLLR.l1    -22.880238   6.597753   -3.47  0.00074 ***
dNIM.l1      9.550186   5.728229    1.67  0.09824 .
dNASDAQ.l1  -0.000101   0.001860   -0.05  0.95677
dFED.l1      1.727698   2.043091    0.85  0.39955
dCC.l2      -0.072604   0.108273   -0.67  0.50387
dLLR.l2     13.429164   7.377924    1.82  0.07138 .
dNIM.l2     -9.160867   5.965585   -1.54  0.12743
dNASDAQ.l2   0.000860   0.001895    0.45  0.65073
dFED.l2     -0.518166   1.963658   -0.26  0.79235
const       -0.121822   0.596639   -0.20  0.83858
sd1         -1.325514   1.845981   -0.72  0.47421
sd2         -4.064073   1.769893   -2.30  0.02351 *
sd3         -4.785538   1.630103   -2.94  0.00403 **
exo1        -0.288329   0.103838   -2.78  0.00643 **
```

```
Estimation results for equation dLLR:
=====================================
dLLR = dCC.l1 + dLLR.l1 + dNIM.l1 + dNASDAQ.l1 + dFED.l1 +
dCC.l2 + dLLR.l2 + dNIM.l2 + dNASDAQ.l2 + dFED.l2 + const +
sd1 + sd2 + sd3 + exo1

               Estimate  Std. Error t value     Pr(>|t|)
dCC.l1       0.00302348  0.00183366    1.65      0.10195
dLLR.l1      0.59181280  0.09971993    5.93 0.000000033 ***
dNIM.l1     -0.15431188  0.08657774   -1.78      0.07738 .
dNASDAQ.l1   0.00000593  0.00002811    0.21      0.83317
dFED.l1     -0.02196190  0.03087974   -0.71      0.47842
dCC.l2       0.00095442  0.00163647    0.58      0.56091
dLLR.l2      0.03959713  0.11151160    0.36      0.72318
dNIM.l2     -0.03528952  0.09016520   -0.39      0.69625
dNASDAQ.l2  -0.00001918  0.00002863   -0.67      0.50434
dFED.l2      0.00333638  0.02967916    0.11      0.91069
const       -0.00195035  0.00901773   -0.22      0.82916
sd1         -0.09590881  0.02790058   -3.44      0.00082 ***
sd2         -0.03587419  0.02675057   -1.34      0.18259
sd3         -0.05774232  0.02463775   -2.34      0.02084 *
exo1        -0.00318405  0.00156944   -2.03      0.04483 *
```

```
Estimation results for equation dNIM:
=====================================
dNIM = dCC.l1 + dLLR.l1 + dNIM.l1 + dNASDAQ.l1 + dFED.l1 +
dCC.l2 + dLLR.l2 + dNIM.l2 + dNASDAQ.l2 + dFED.l2 + const +
sd1 + sd2 + sd3 + exo1

              Estimate Std. Error t value Pr(>|t|)
dCC.l1      -0.0001989  0.0020793   -0.10   0.9240
dLLR.l1     -0.0414502  0.1130784   -0.37   0.7146
dNIM.l1     -0.0191730  0.0981757   -0.20   0.8455
dNASDAQ.l1   0.0000319  0.0000319    1.00   0.3184
dFED.l1     -0.0358211  0.0350164   -1.02   0.3085
dCC.l2      -0.0014299  0.0018557   -0.77   0.4426
dLLR.l2      0.0810998  0.1264497    0.64   0.5226
dNIM.l2      0.0079796  0.1022437    0.08   0.9379
dNASDAQ.l2   0.0000296  0.0000325    0.91   0.3647
dFED.l2     -0.0045183  0.0336550   -0.13   0.8934
const       -0.0155550  0.0102257   -1.52   0.1310
sd1          0.0628126  0.0316381    1.99   0.0495 *
sd2          0.0728431  0.0303341    2.40   0.0180 *
sd3          0.0844238  0.0279382    3.02   0.0031 **
exo1         0.0004877  0.0017797    0.27   0.7846
```

```
Estimation results for equation dNASDAQ:
========================================
dNASDAQ = dCC.l1 + dLLR.l1 + dNIM.l1 + dNASDAQ.l1 + dFED.l1
+ dCC.l2 + dLLR.l2 + dNIM.l2 + dNASDAQ.l2 + dFED.l2 + const
+ sd1 + sd2 + sd3 + exo1

            Estimate Std. Error t value Pr(>|t|)
dCC.l1         1.083      8.044    0.13    0.893
dLLR.l1     -817.070    437.438   -1.87    0.064 .
dNIM.l1      205.413    379.787    0.54    0.590
dNASDAQ.l1    -0.323      0.123   -2.62    0.010 *
dFED.l1      -72.948    135.459   -0.54    0.591
dCC.l2        -1.103      7.179   -0.15    0.878
dLLR.l2     1148.124    489.164    2.35    0.021 *
dNIM.l2     -357.308    395.524   -0.90    0.368
dNASDAQ.l2     0.116      0.126    0.92    0.358
dFED.l2      166.776    130.192    1.28    0.203
const         94.347     39.558    2.39    0.019 *
sd1           55.288    122.390    0.45    0.652
sd2            8.883    117.346    0.08    0.940
sd3          -27.533    108.078   -0.25    0.799
exo1           0.816      6.885    0.12    0.906
```

When looking at the seasonal dummies in the error correction model we can see that there is a concern with regards to **seasonality**, which highlights a seasonal impact on our variables of interest.

Also, we can see from the above estimation outputs that there is no concern with regards to our **error correction term** from the **Engle-Granger** as in none of the outputs is the error correction term positive and statistically significant thus indicating that it will reach a long run equilibrium.

II. Testing for serial correlation

Next using the **Box-Ljung test** , we test to ensure that there is no serial correlation present in the variables of interest. Once this has been confirmed I look at the impulse response functions to determine any causal relationships which may exist.

```
        Box-Ljung test

data:  resi
X-squared = 14, df = 20, p-value = 0.8

> blt = rep(0,20)
> for (i in 1:20){
+   b = Box.test(resi,lag = i, type="Ljung-Box")
+   blt[i]=b$p.value
+ }
> blt
 [1] 0.953 0.945 0.829 0.635 0.541 0.516 0.552 0.620 0.626 0.592 0.643 0.707 0.755 0.816
0.653 0.628 0.695 0.723
[19] 0.776 0.811
```

Consumer Confidence has no serial correlation.

```
        Box-Ljung test

data:  resi
X-squared = 15, df = 20, p-value = 0.8

> blt = rep(0,20)
> for (i in 1:20){
+   b = Box.test(resi,lag = i, type="Ljung-Box")
+   blt[i]=b$p.value
+ }
> blt
 [1] 0.923 0.326 0.523 0.212 0.151 0.231 0.285 0.344 0.436 0.501 0.591 0.574 0.617
[14] 0.682 0.713 0.771 0.745 0.799 0.810 0.790
```

Loan Loss Reserve Ratio has no serial correlation.

```
        Box-Ljung test

data:  resi
X-squared = 17, df = 20, p-value = 0.7

> blt = rep(0,20)
> for (i in 1:20){
+   b = Box.test(resi,lag = i, type="Ljung-Box")
+   blt[i]=b$p.value
+ }
> blt
 [1] 0.937 0.997 1.000 0.988 0.905 0.729 0.684 0.636 0.680 0.763 0.796 0.821 0.743
[14] 0.798 0.845 0.530 0.524 0.588 0.629 0.658
```

Net Interest Margin has no serial correlation.

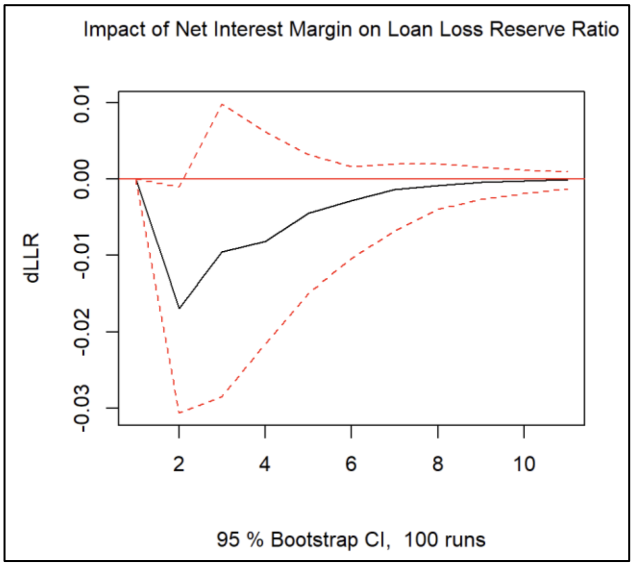
```
        Box-Ljung test

data:  resi
X-squared = 9, df = 20, p-value = 1

> blt = rep(0,20)
> for (i in 1:20){
+   b = Box.test(resi,lag = i, type="Ljung-Box")
+   blt[i]=b$p.value
+ }
> blt
 [1] 0.849 0.769 0.682 0.531 0.559 0.575 0.686 0.733 0.812 0.863 0.910 0.941 0.952
[14] 0.969 0.934 0.939 0.960 0.968 0.977 0.980
```

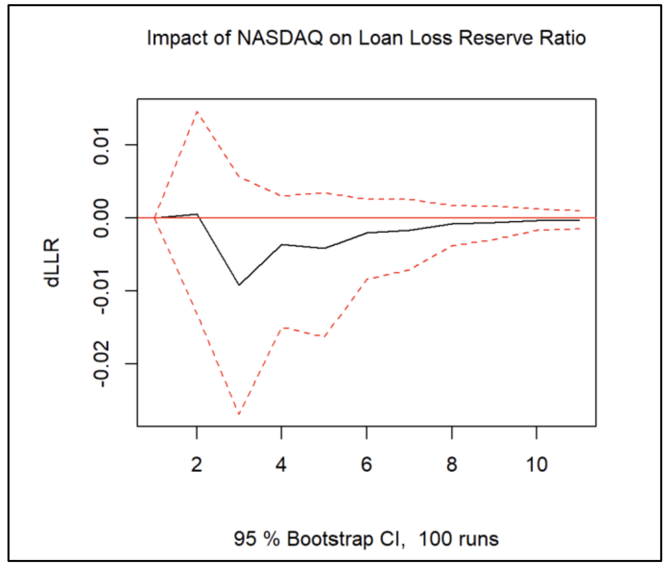
NASDAQ has no serial correlation.

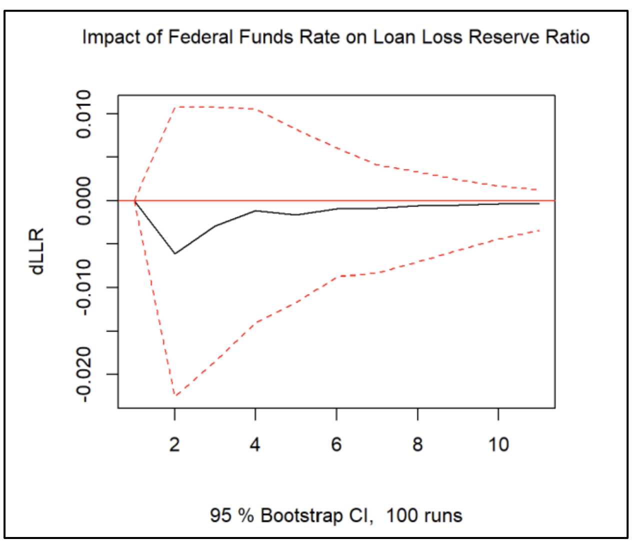
```
        Box-Ljung test

data:  resi
X-squared = 19, df = 20, p-value = 0.5

> blt = rep(0,20)
> for (i in 1:20){
+   b = Box.test(resi,lag = i, type="Ljung-Box")
+   blt[i]=b$p.value
+ }
> blt
 [1] 0.758 0.775 0.431 0.458 0.311 0.351 0.458 0.269 0.355 0.280 0.296 0.371 0.389
[14] 0.373 0.444 0.355 0.380 0.447 0.438 0.503
```

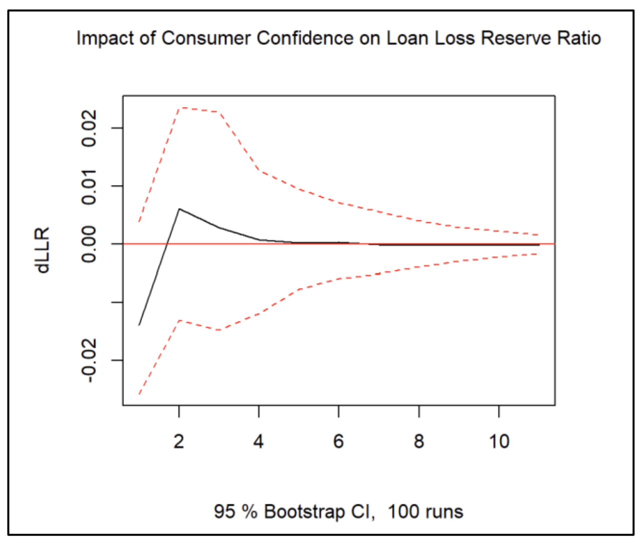
Federal Funds has no serial correlation.

III. **Using impulse response functions to determine causal relationships.**



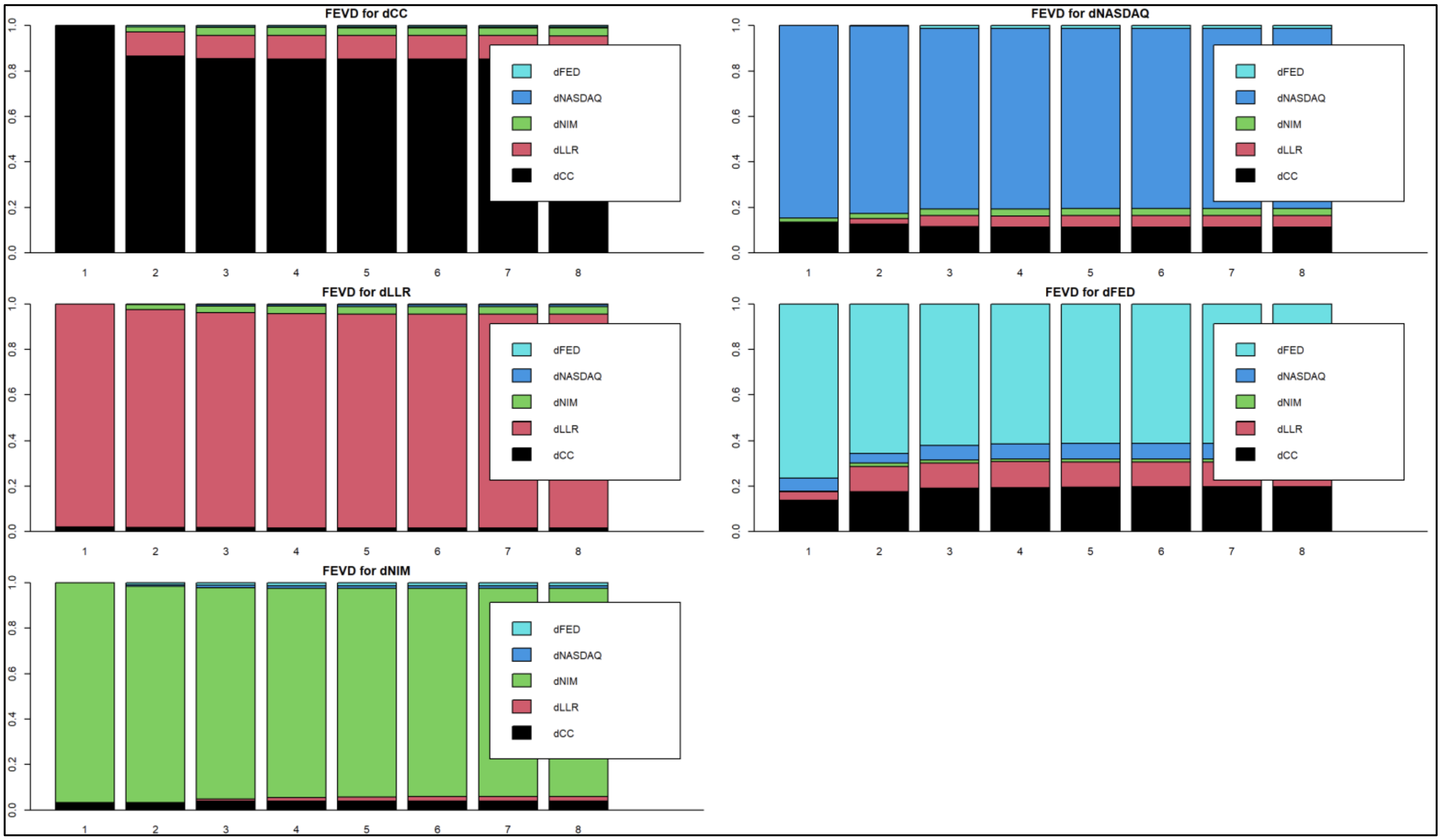






As can be seen from the above impulse response functions we can see that when we shock Net Interest Margin it has a statistically significant impact on the Loan Loss Reserve Ratio in future periods. This indicates that as there is a change in Net Interest Margins which acts as an indicator of the profitability of banks , they reduce the Loan Loss Reserve Ratio indicating a change in risk appetite to be more aggressive risk takers. The other variables of interest do not have a statistically significant impact.

IV. **Variance Decomposition Matrix**



Looking at the above variance decomposition matrix, we can see that the impact of net interest margin on the loan loss reserve ratio increases significantly as we go into the future.

We also see that the stock market which is reflected through the NASDAQ has an impact on the loan loss reserve ratio as well which could indicate that as stock markets perform well there is a direct impact on the banks risk appetite.

Consumer confidence also has a slightly increasing impact on the loan loss reserve ratio as times goes on. As consumer confidence acts as a proxy for the health of the economy, we can assume that the state of the economy can play a role in how banks determine their risk appetite.

V. Granger Causality

```
        Granger causality H0: dCC do not Granger-cause dLLR dNIM dNASDAQ dFED

data:  VAR object var5
F-Test = 0.7, df1 = 8, df2 = 565, p-value = 0.7
```

```
        Granger causality H0: dNIM do not Granger-cause dCC dLLR dNASDAQ dFED

data:  VAR object var5
F-Test = 1, df1 = 8, df2 = 565, p-value = 0.3
```

```
        Granger causality H0: dNASDAQ do not Granger-cause dCC dLLR dNIM dFED

data:  VAR object var5
F-Test = 0.4, df1 = 8, df2 = 565, p-value = 0.9
```

```
        Granger causality H0: dFED do not Granger-cause dCC dLLR dNIM dNASDAQ

data:  VAR object var5
F-Test = 0.7, df1 = 8, df2 = 565, p-value = 0.7
```

As can be seen from the above **Granger causality** outputs, none of the variables had a high enough p-value to reject the null hypothesis. Hence there is no **Granger causality** present between the key variables of interest.

6. Conclusion and future research

As can be seen from the various tests that have been carried out above, we can see that there is a clear impact of net interest margins(NIM) on risk appetite. As visible from the impulse response function when there is a shock to the NIM which captures the ability of banks to generate profits, there is a response of reducing the loan loss reserve ratio(LLR). As this ratio captures how much reserves are left to absorb loan losses, the indication that this reserve ratio drops from shocks to NIM indicates that banks are willing to take on more risks to generate higher returns.

I expected other factors such as the stock market and other economic indicators to have a statistically significant impact on the LLR as well however the impulse response functions did not seem to show any impact from these variables, however when we looked at the variance decomposition matrix, we could see that these variables had an increasing impact on LLR as time went on.

Future research could focus on how risk appetite in banks changes at the micro level through an in-depth comparison of top banks in the USA to see if certain banks are willing to take on more risk than others.

Furthermore, the analysis carried out uses the Loan Loss Reserve Ratio as a proxy on how banks determine their risk appetite, my research assumes that based upon this ratio we can determine whether banks are conservative or aggressive risk takers, a possible caveat of my assumption is that banks with low/high reserve ratios might be doing a good job of managing their risk. Hence if there is a way to link the profits/losses incurred from their risk management into the analysis we could have a better understanding of their risk appetite.

7. References

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