What Caused The Early Millenium Slowdown? Evidenece Based on Vector Autoregressions

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Abstract

Abstract to be written here. The abstract should not be too long and should provide the reader with a good understanding what you are writing about. Academic papers are not like novels where you keep the reader in suspense. To be effective in getting others to read your paper, be as open and concise about your findings here as possible. Ideally, upon reading your abstract, the reader should feel he / she must read your paper in entirety.

Keywords: Multivariate GARCH, Kalman Filter, Copula

JEL classification L250, L100

1. Test wether variables are stationary

Variables that are included in the dataset (same order): oil, output growth, consumer inflation and short-term nominal interest rate for EU and US.

Gideon suggested I only do the replication for the US, since this will be a lot of work.

In order to test whether a variable is stationary, you can use a unit root test such as the Dickey-Fuller (DF) test

Null hypothesis: There is a unit root Alternative hypothesis: Time series is stationary

If p-values is less than 0.05, it means we can reject the null hypothesis.

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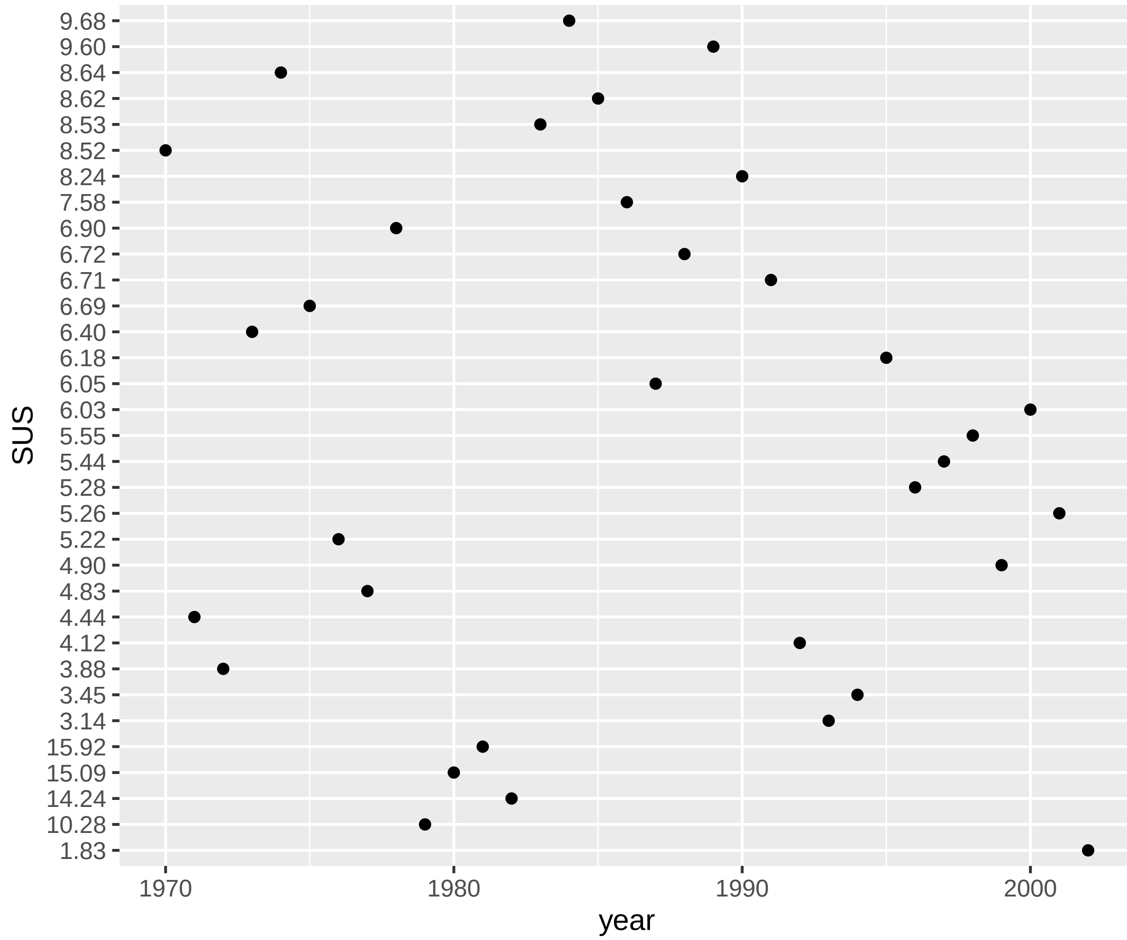



```
##
##  Augmented Dickey-Fuller Test
##
## data:  slowdown_dataset$OIL
## Dickey-Fuller = -2.0358, Lag order = 5, p-value = 0.5616
## alternative hypothesis: stationary
```

```
##
##  Augmented Dickey-Fuller Test
##
## data:  slowdown_dataset$YUS
## Dickey-Fuller = -1.3894, Lag order = 5, p-value = 0.8304
## alternative hypothesis: stationary
```

```
##
##  Augmented Dickey-Fuller Test
##
## data:  slowdown_dataset$SUS
## Dickey-Fuller = -3.4394, Lag order = 5, p-value = 0.05113
## alternative hypothesis: stationary
```

```
##
##  Augmented Dickey-Fuller Test
##
## data:  slowdown_dataset$CPUS
## Dickey-Fuller = -1.5413, Lag order = 5, p-value = 0.7672
## alternative hypothesis: stationary
```

```
##
##  Phillips-Perron Unit Root Test
##
## data:  slowdown_dataset$OIL
## Dickey-Fuller Z(alpha) = -8.7804, Truncation lag parameter = 4, p-value
## = 0.6091
## alternative hypothesis: stationary
```

```
##
##  Phillips-Perron Unit Root Test
##
## data:  slowdown_dataset$YUS
## Dickey-Fuller Z(alpha) = -3.501, Truncation lag parameter = 4, p-value
## = 0.9108
## alternative hypothesis: stationary
```

```
##
##  Phillips-Perron Unit Root Test
##
## data:  slowdown_dataset$SUS
## Dickey-Fuller Z(alpha) = -11.903, Truncation lag parameter = 4, p-value
## = 0.4288
## alternative hypothesis: stationary
```

```
##
##  Phillips-Perron Unit Root Test
##
## data:  slowdown_dataset$CPUS
## Dickey-Fuller Z(alpha) = -1.0566, Truncation lag parameter = 4, p-value
## = 0.9855
## alternative hypothesis: stationary
```

2. Optimal lag length

I now determine the optimal lag length for an unrestricted VAR with a maximum lag length of 10.

According to the AIC and the FPE, the optimal lag length is 4. However, the SC and HQ criterion indicates an optimal lag length of 1. The data estimates a VAR including a constant and a trend as deterministic regressor.

I will use a VAR with lag length eual to one as specified by the paper.

```
## $selection
## AIC(n)  HQ(n)  SC(n) FPE(n)
##      4      1      1      4
##
## $criteria
##                  1           2           3           4           5
## AIC(n)     9.388028    9.276473    9.256966    9.110758     9.33497
## HQ(n)      9.614431    9.653811    9.785239    9.789965    10.16511
## SC(n)      9.945526   10.205637   10.557796   10.783253    11.37913
## FPE(n) 11948.510504 10700.252306 10522.129466 9135.114589 11518.86905
##                  6           7           8           9          10
## AIC(n)     9.47171     9.679419    9.682826    9.802003    9.872561
## HQ(n)     10.45279    10.811433   10.965774   11.235887   11.457380
## SC(n)     11.88754    12.466911   12.841983   13.332826   13.775050
## FPE(n) 13354.70319 16692.619524 17095.671652 19774.982422 21940.976772
```

3. VAR

Diagram of fit and residuals for OIL

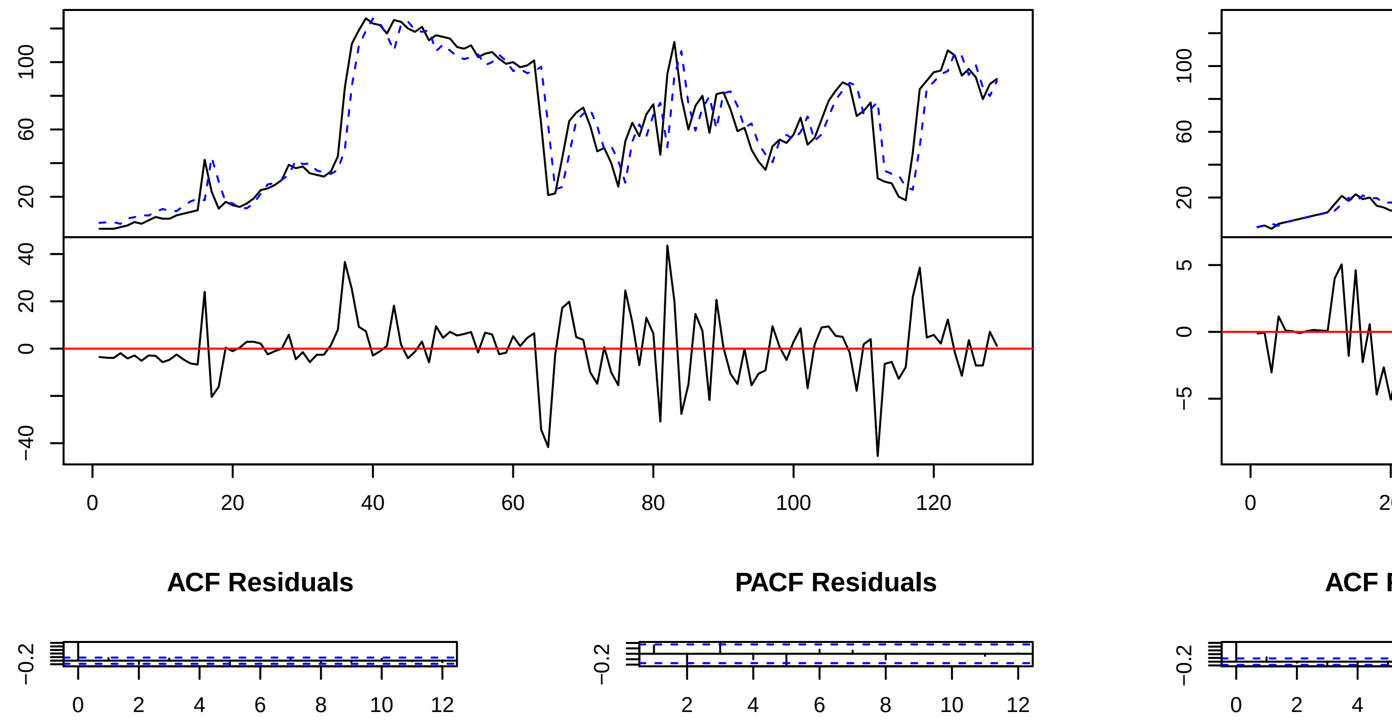
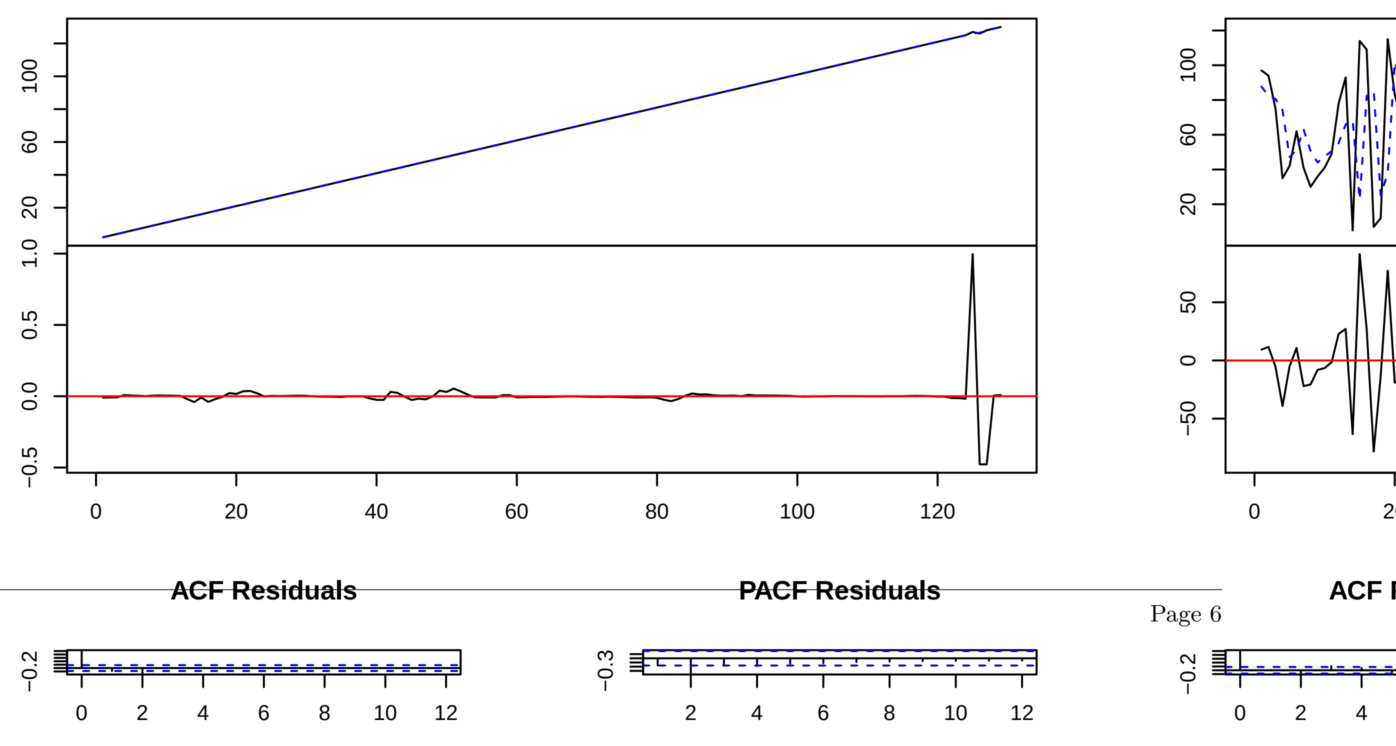


Diagram of fit and residuals for CPUS



4. Diagnostic tests and Test statistics

The results for diagnostic test for VAR(1), VAR(2) and VAR(3) are provided in the table below.

Here you look and interpret all the test to determine whether VAR(1) is too restrictive. ARGUE this as part of your robustness test for the paper.

```
##
##  Portmanteau Test (asymptotic)
##
## data:  Residuals of VAR object VAR(ts_us, p = 1, type = "both")
## Chi-squared = 212.62, df = 240, p-value = 0.898
```

```
## $JB
##
##  JB-Test (multivariate)
##
## data:  Residuals of VAR object VAR(ts_us, p = 1, type = "both")
## Chi-squared = 18850, df = 8, p-value < 2.2e-16
##
##
## $Skewness
##
##  Skewness only (multivariate)
##
## data:  Residuals of VAR object VAR(ts_us, p = 1, type = "both")
## Chi-squared = 472.22, df = 4, p-value < 2.2e-16
##
##
## $Kurtosis
##
##  Kurtosis only (multivariate)
##
## data:  Residuals of VAR object VAR(ts_us, p = 1, type = "both")
## Chi-squared = 18377, df = 4, p-value < 2.2e-16
```

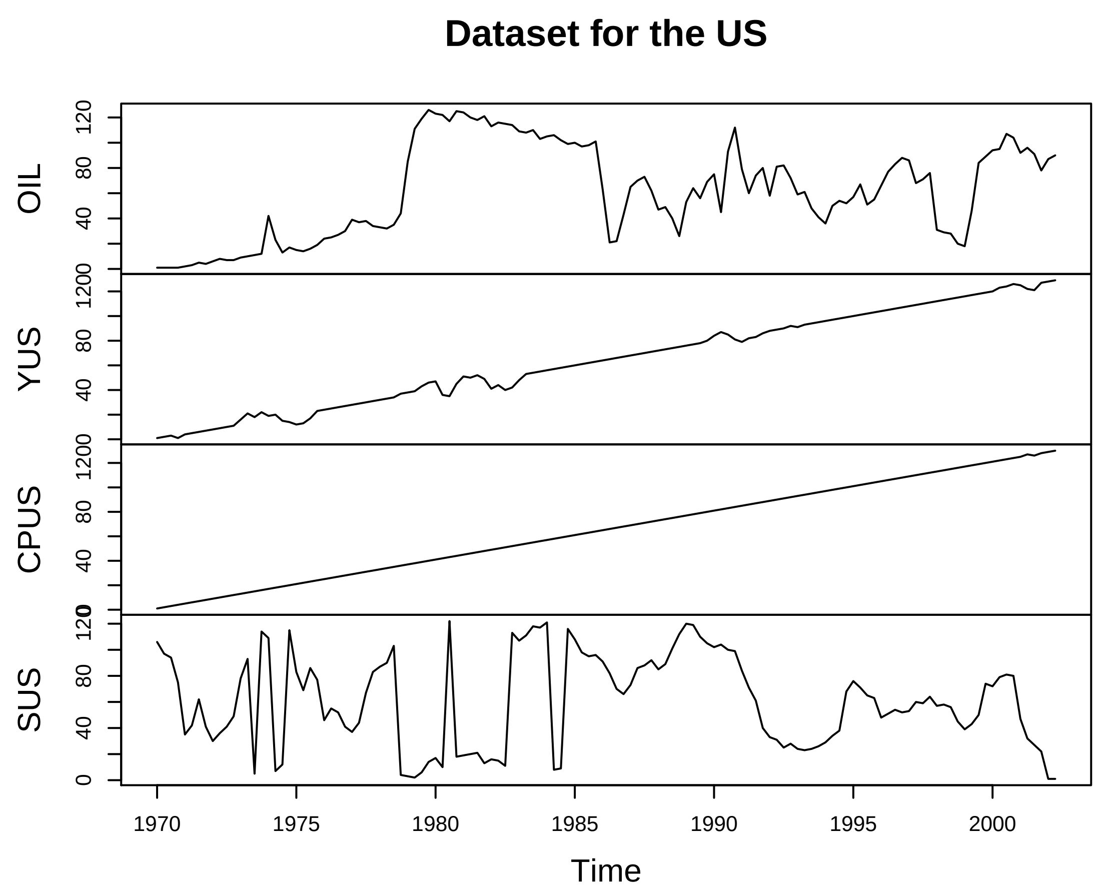
```
##
```

```
##  ARCH (multivariate)
##
## data:  Residuals of VAR object VAR(ts_us, p = 1, type = "both")
## Chi-squared = 786.65, df = 500, p-value = 3.886e-15
```

5. Impulse response function

First thing I need to do is convert the data to a time series object in R. And to do this I need to create a date column.

The graph below, just shows you the dataset for the US. This is nice because you can see the pattern all the vaaraibles follow. This is not in the paper but might be nice to put in under 'descriptive statistics'.



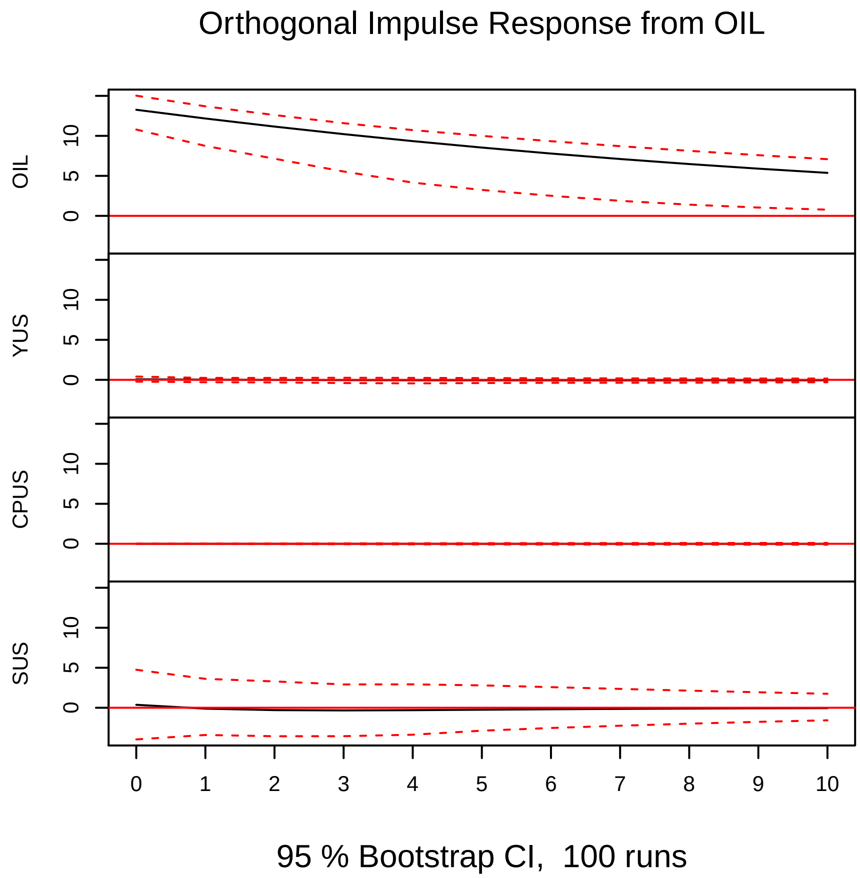

```
## NULL
```

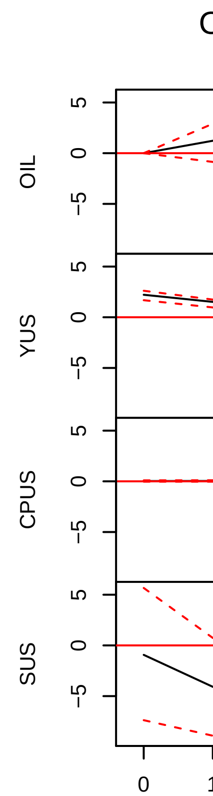
Now that I have a nice little graph, I can continue by creating my VAR. WE first look at a simple four variable VAR. These variables are OIL, CPUS, YUS and SUS. This VAR will then be used for my impulse response functions.

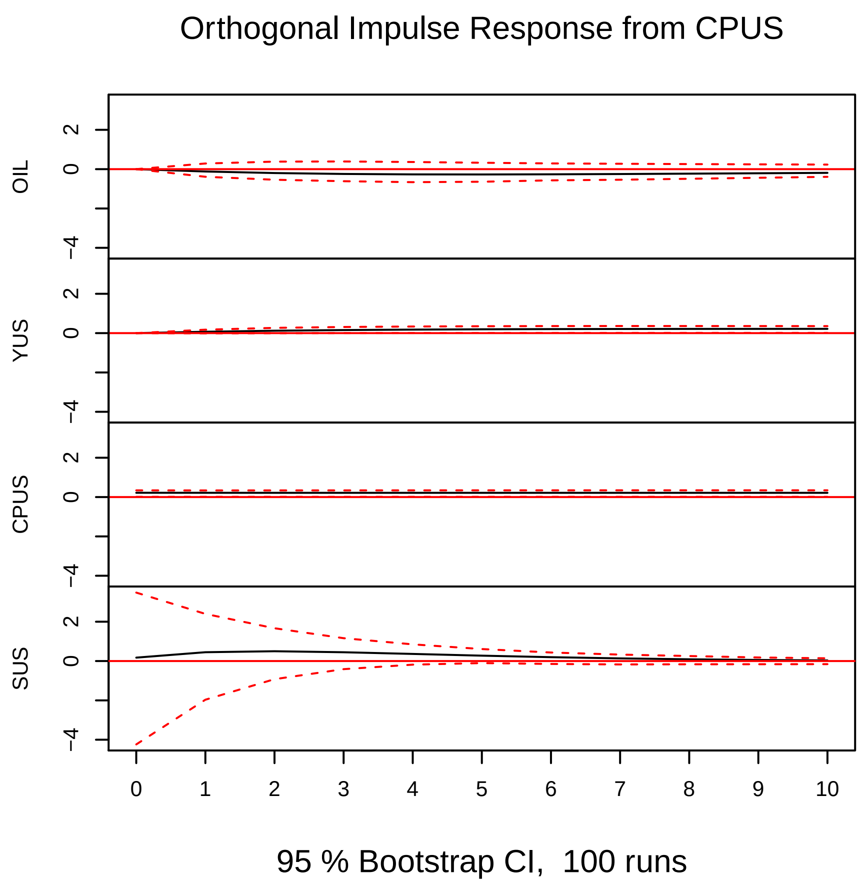
```
##
## VAR Estimation Results:
## =========================
## Endogenous variables: OIL, YUS, CPUS, SUS
## Deterministic variables: const
## Sample size: 129
## Log Likelihood: -1390.997
## Roots of the characteristic polynomial:
##     1 0.9102 0.6452 0.6452
## Call:
## VAR(y = ts_us, p = 1, type = "const")
##
##
## Estimation results for equation OIL:
## ====================================
## OIL = OIL.l1 + YUS.l1 + CPUS.l1 + SUS.l1 + const
##
##         Estimate Std. Error t value Pr(>|t|)
## OIL.l1   0.91555    0.03417  26.790   <2e-16 ***
## YUS.l1   0.54651    0.39879   1.370    0.173
## CPUS.l1 -0.52412    0.39871  -1.315    0.191
## SUS.l1  -0.03032    0.03407  -0.890    0.375
## const    6.81916    3.50527   1.945    0.054 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Residual standard error: 13.26 on 124 degrees of freedom
## Multiple R-Squared: 0.8771,  Adjusted R-squared: 0.8731
## F-statistic: 221.2 on 4 and 124 DF,  p-value: < 2.2e-16
##
##
## Estimation results for equation YUS:
## ====================================
```

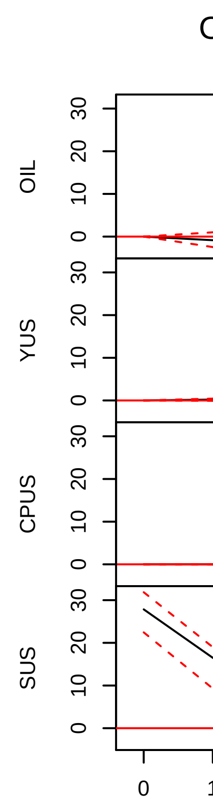
```
## YUS = OIL.l1 + YUS.l1 + CPUS.l1 + SUS.l1 + const
##
##          Estimate Std. Error t value Pr(>|t|)
## OIL.l1  -0.002347   0.005720  -0.410    0.682
## YUS.l1   0.682845   0.066743  10.231  < 2e-16 ***
## CPUS.l1  0.317619   0.066729   4.760  5.3e-06 ***
## SUS.l1   0.007525   0.005701   1.320    0.189
## const    0.330629   0.586645   0.564    0.574
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Residual standard error: 2.219 on 124 degrees of freedom
## Multiple R-Squared: 0.9966,  Adjusted R-squared: 0.9965
## F-statistic:  9047 on 4 and 124 DF,  p-value: < 2.2e-16
##
##
## Estimation results for equation CPUS:
## =====================================
## CPUS = OIL.l1 + YUS.l1 + CPUS.l1 + SUS.l1 + const
##
##           Estimate Std. Error t value Pr(>|t|)
## OIL.l1  -4.596e-05  5.657e-04  -0.081    0.935
## YUS.l1   4.581e-03  6.601e-03   0.694    0.489
## CPUS.l1  9.954e-01  6.600e-03 150.823   <2e-16 ***
## SUS.l1   9.405e-05  5.639e-04   0.167    0.868
## const    1.000e+00  5.802e-02  17.238   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Residual standard error: 0.2195 on 124 degrees of freedom
## Multiple R-Squared:     1,   Adjusted R-squared:     1
## F-statistic: 9.279e+05 on 4 and 124 DF,  p-value: < 2.2e-16
##
##
## Estimation results for equation SUS:
## ====================================
## SUS = OIL.l1 + YUS.l1 + CPUS.l1 + SUS.l1 + const
```

```
##
##         Estimate Std. Error t value Pr(>|t|)
## OIL.l1  -0.01602    0.07181  -0.223 0.823796
## YUS.l1  -1.60957    0.83798  -1.921 0.057057 .
## CPUS.l1  1.58774    0.83780   1.895 0.060404 .
## SUS.l1   0.59208    0.07158   8.272 1.74e-13 ***
## const   24.97556    7.36556   3.391 0.000935 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Residual standard error: 27.87 on 124 degrees of freedom
## Multiple R-Squared: 0.3841,  Adjusted R-squared: 0.3642
## F-statistic: 19.33 on 4 and 124 DF,  p-value: 2.216e-12
##
##
##
## Covariance matrix of residuals:
##            OIL      YUS     CPUS       SUS
## OIL  175.87030  0.96627 -0.01711   4.93399
## YUS    0.96627  4.92607  0.05235  -2.04011
## CPUS  -0.01711  0.05235  0.04819   0.01546
## SUS    4.93399 -2.04011  0.01546 776.53784
##
## Correlation matrix of residuals:
##            OIL      YUS      CPUS       SUS
## OIL   1.000000  0.03283 -0.005879  0.013351
## YUS   0.032829  1.00000  0.107433 -0.032985
## CPUS -0.005879  0.10743  1.000000  0.002528
## SUS   0.013351 -0.03299  0.002528  1.000000
```


Orthogonal Impulse Response from OIL
OIL
YUS
CPUS
SUS
0 5 10
0 1 2 3 4 5 6 7 8 9 10
95 % Bootstrap CI, 100 runs


OIL
YUS
CPUS
SUS
−5 0 5
0





6. Conclusion

References

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Appendix

Appendix A

Some appendix information here

Appendix B