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. Introduction

In this research assignment, I replicate a research assignment by Gert Peersman (2005), a German economist, titled "What caused the early millennium slowdown? Evidence based on vector autoregressions". In this paper, Peersman (2005) uses a simple four-variable VAR (vector autogressive model) and an identification based scheme based on sign restrictions to examine the effects of a supply, demand, monetary policy and oil price shocks. Peersman (2005) uses data from the United States and Euro area. However, this assignment will only focus on analyzing shocks for the USA. Peersman (2005) concludes that the millennial slowdown is not the result of one particular shock, but a combination of them. The goal of this assignment is to replicate the results of Peersman (2005) as well as preform additional robustness test to ensure the validity of Peermans (2005) results.

- summarize what robustiness checks and analysis you did(including the ones that you replicate)

This paper is structured as follows: The first section will give an overview of the paper with respects to the economics, methodology and data that Peersman (2005) used. The second section will replicate

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the results for the US. The third section will perform robustness checks and the forth section will conclude.

2. Overview of the paper

2.1. Theory

2.2. Data

2.3. Methodology

3. Reconstructing data

4. Test wether variables are stationary

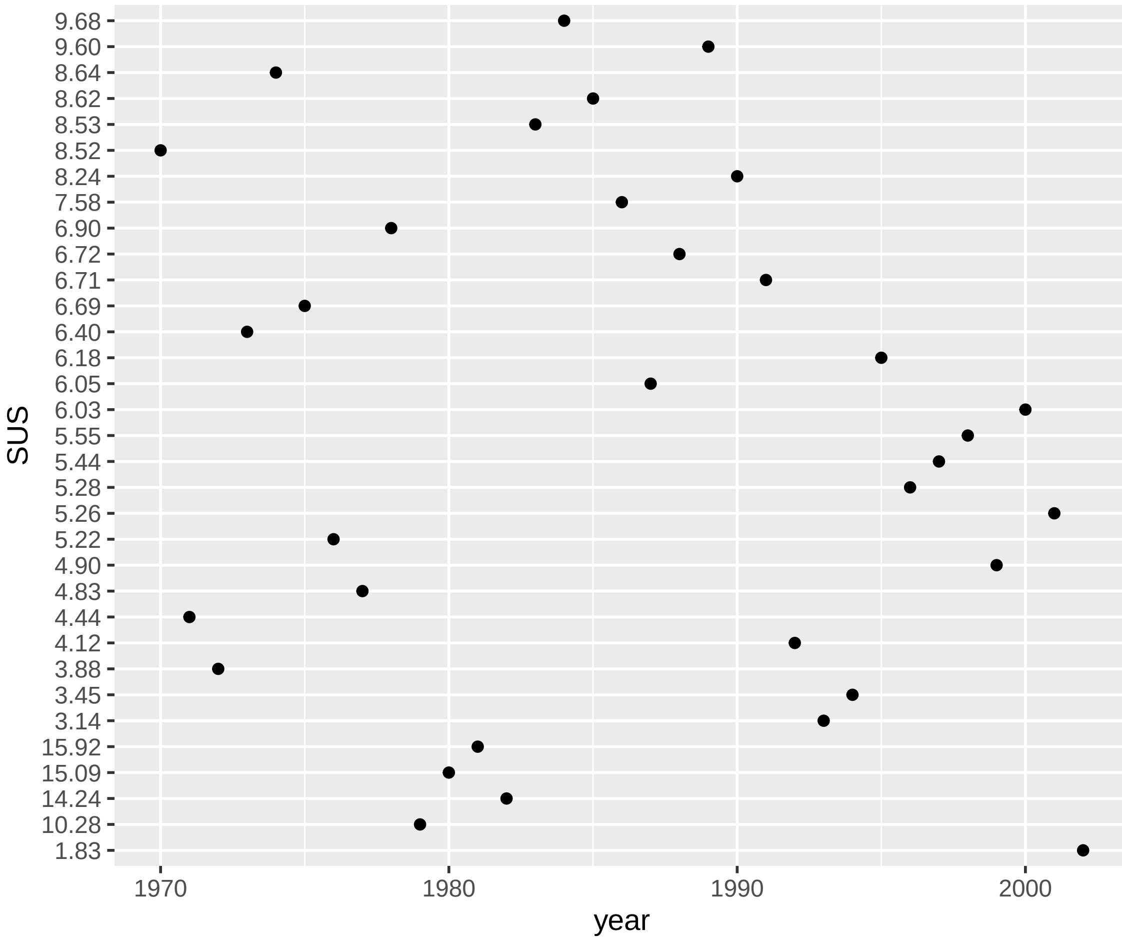
Variables that are included in the dataset (same order): oil, output growth, consumer inflation and short-term nominal interest rate for EU and US.

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.




```
##
##  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
```

5. 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
```

6. VAR

Diagram of fit and residuals for OIL

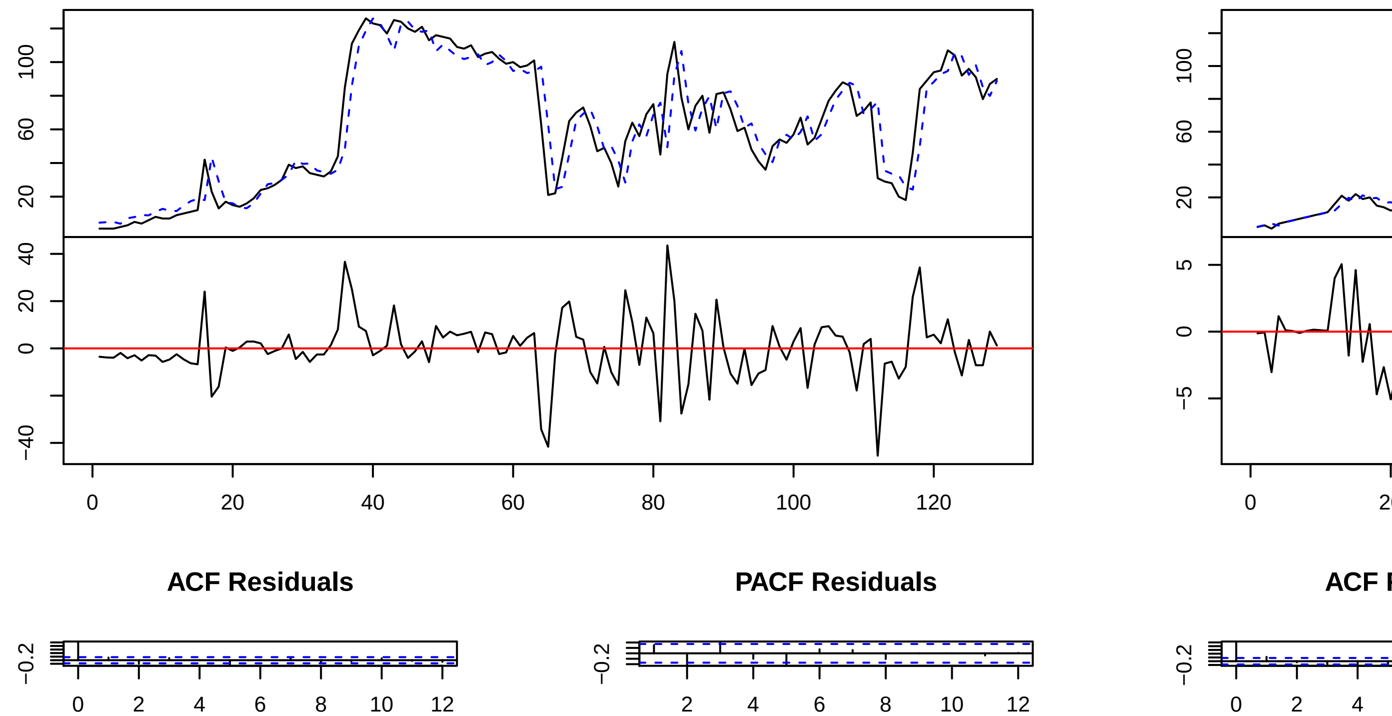
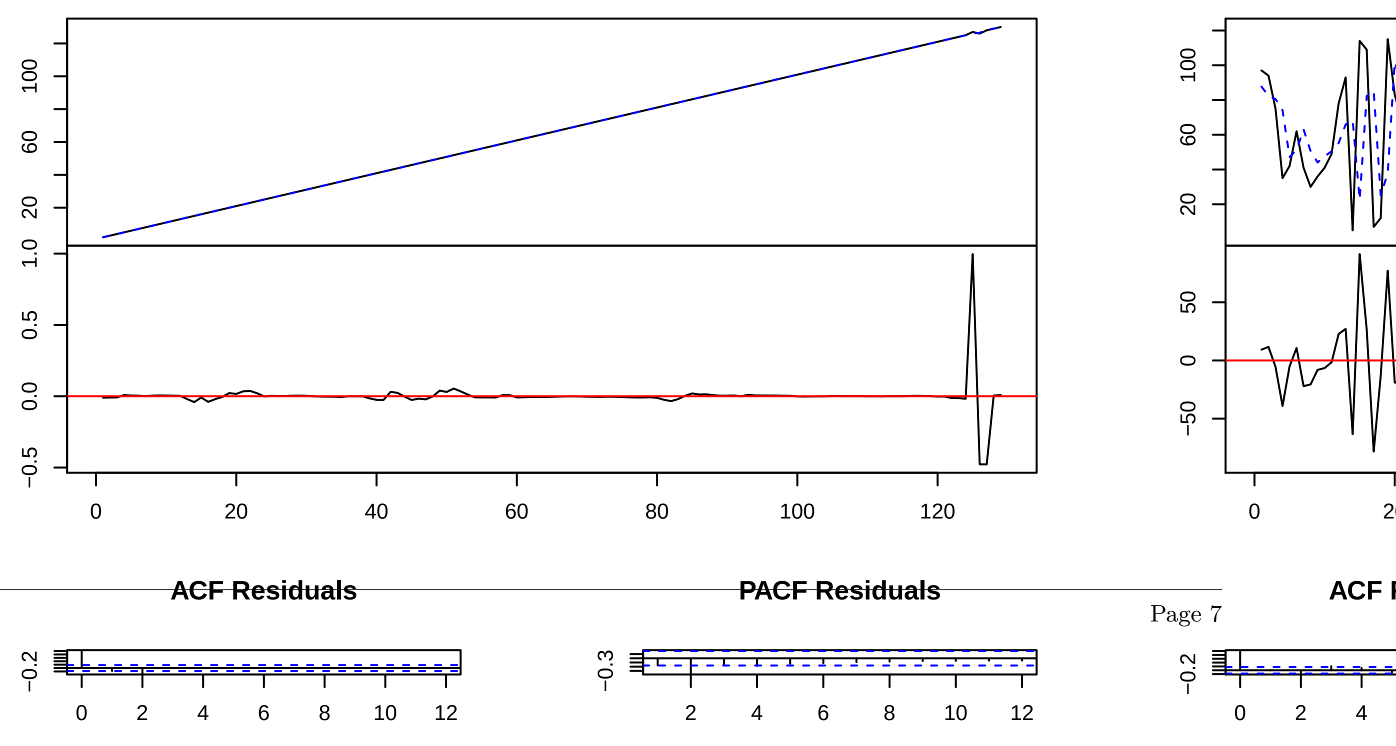


Diagram of fit and residuals for CPUS



7. 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
```

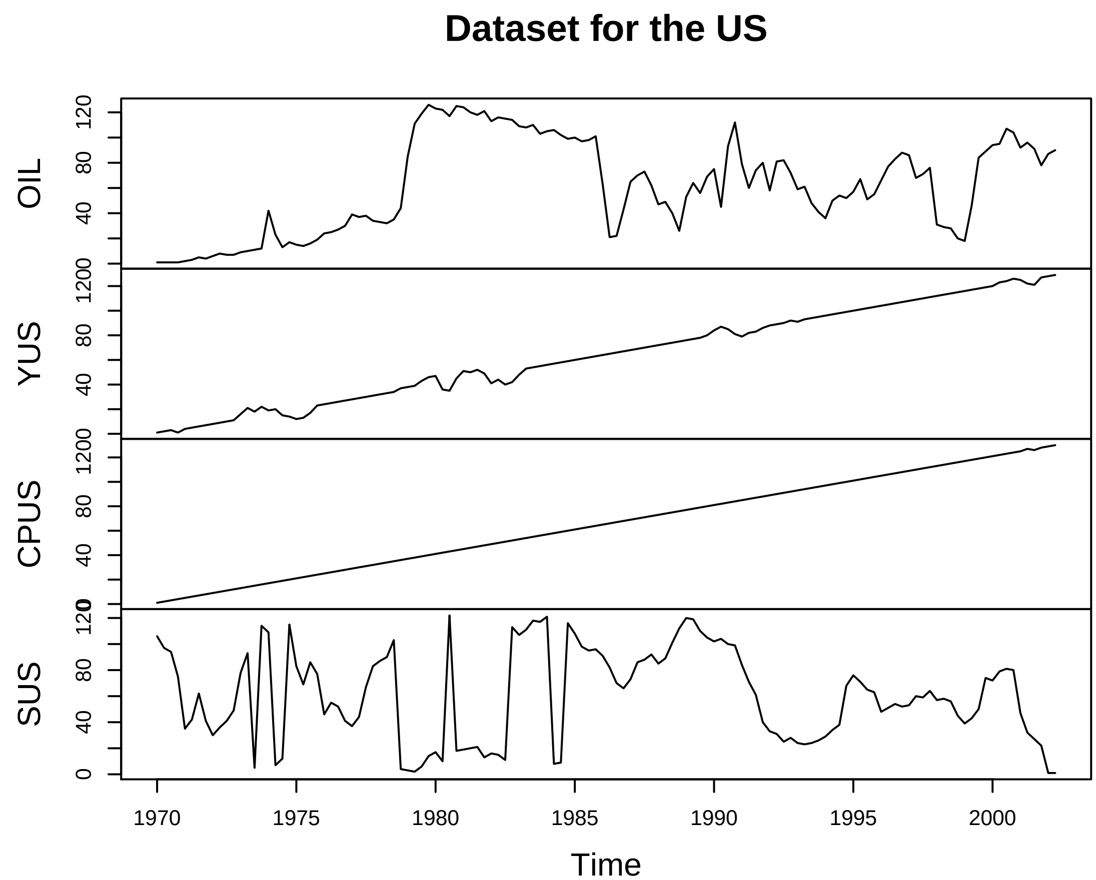
```
##
```

```
##  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
```

8. 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'.

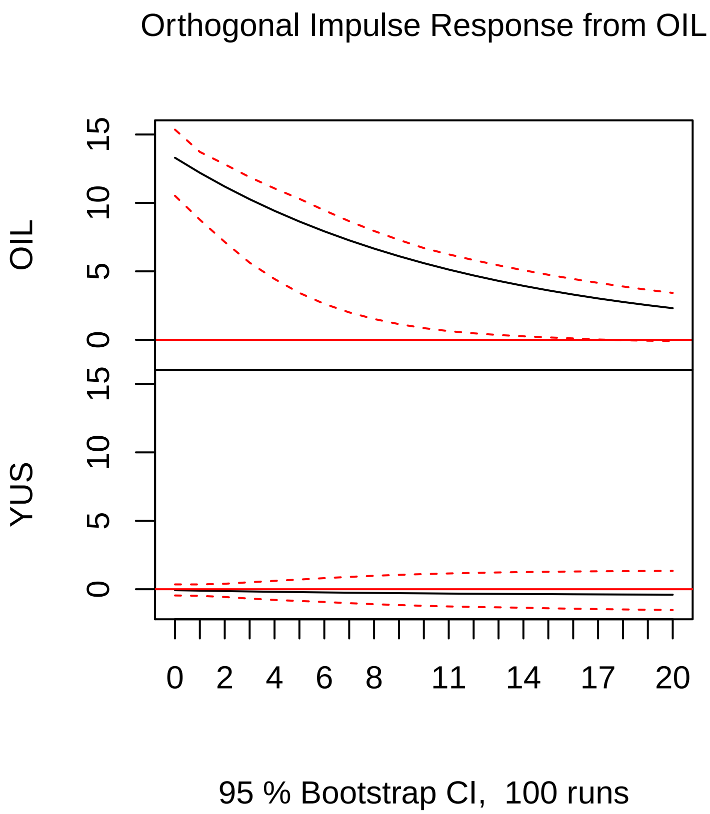


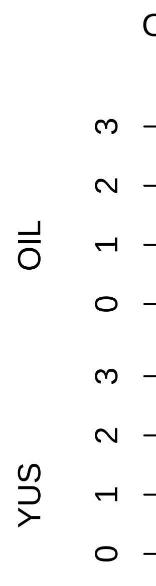

```
## NULL
```

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
## Deterministic variables: const
## Sample size: 129
## Log Likelihood: -810.799
## Roots of the characteristic polynomial:
## 0.9985 0.9184
## Call:
## VAR(y = ts_us, p = 1, type = "const")
##
##
## Estimation results for equation OIL:
## ====================================
## OIL = OIL.l1 + YUS.l1 + const
##
##        Estimate Std. Error t value Pr(>|t|)
## OIL.l1  0.91767    0.03408  26.927   <2e-16 ***
## YUS.l1  0.02448    0.03423   0.715    0.476
## const   4.17798    2.63385   1.586    0.115
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Residual standard error: 13.3 on 126 degrees of freedom
## Multiple R-Squared: 0.8744,  Adjusted R-squared: 0.8724
## F-statistic: 438.5 on 2 and 126 DF,  p-value: < 2.2e-16
##
##
## Estimation results for equation YUS:
## ====================================
## YUS = OIL.l1 + YUS.l1 + const
##
```

```
##         Estimate Std. Error t value Pr(>|t|)
## OIL.l1 -0.002518   0.006199  -0.406   0.6853
## YUS.l1  0.999285   0.006226 160.496   <2e-16 ***
## const   1.192616   0.479075   2.489   0.0141 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Residual standard error: 2.419 on 126 degrees of freedom
## Multiple R-Squared: 0.9959,  Adjusted R-squared: 0.9958
## F-statistic: 1.522e+04 on 2 and 126 DF,  p-value: < 2.2e-16
##
##
##
## Covariance matrix of residuals:
##          OIL     YUS
## OIL 176.9160 -0.9235
## YUS  -0.9235  5.8532
##
## Correlation matrix of residuals:
##         OIL     YUS
## OIL  1.0000 -0.0287
## YUS -0.0287  1.0000
```

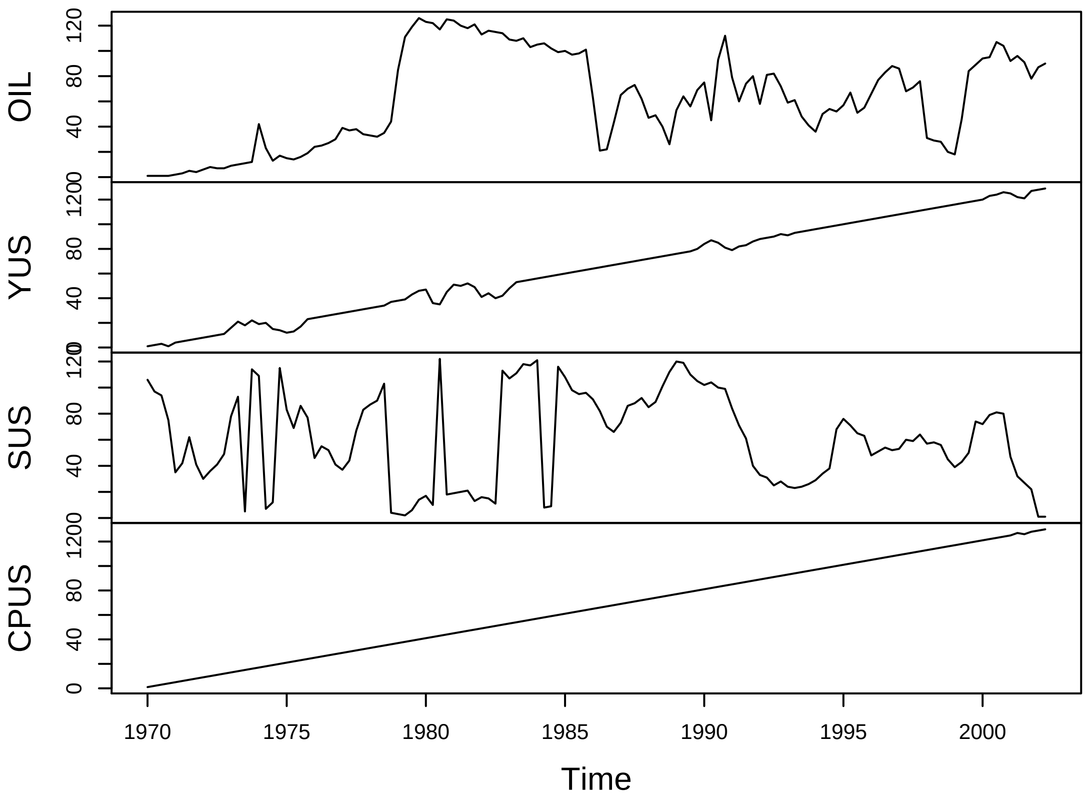




9. Structural VAR

Argue that authors do no make use of a simple VAR but rather a structural VAR.

First VAR analysis that Peersman does is based on conventional zero contemporaneous and long run restrictions. Peersman assumes that there is a contemporaneous impact of an oil shock on all other variables in the system, but no immediate impact of the other shocks on oil prices.




```
##
## VAR Estimation Results:
## =========================
## Endogenous variables: OIL, YUS, SUS, CPUS
## Deterministic variables: both
## Sample size: 129
## Log Likelihood: -1297.142
## Roots of the characteristic polynomial:
## 0.9102 0.6412 0.6412 0.4923
## Call:
## VAR(y = ts_us, p = 1, type = "both")
##
##
## Estimation results for equation OIL:
## ====================================
```

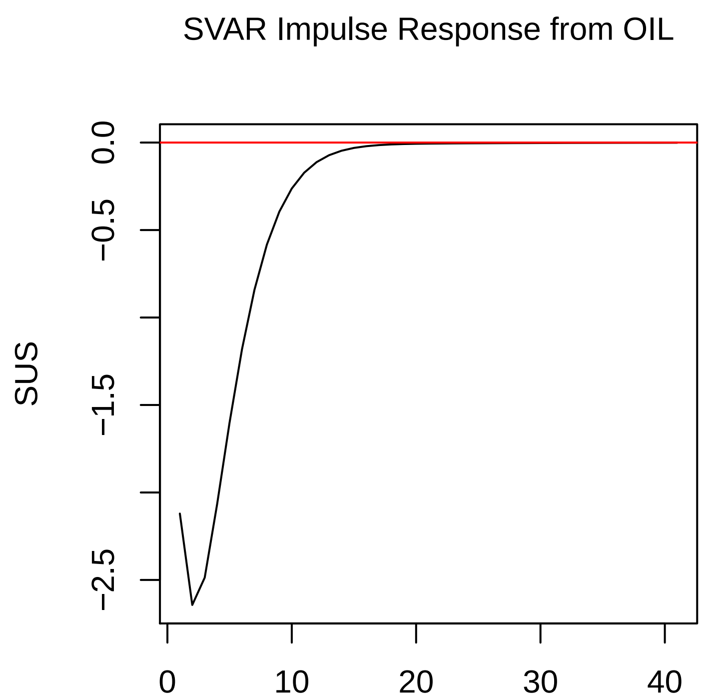
```
## OIL = OIL.l1 + YUS.l1 + SUS.l1 + CPUS.l1 + const + trend
##
##          Estimate Std. Error t value Pr(>|t|)
## OIL.l1   0.91540    0.03429  26.699   <2e-16 ***
## YUS.l1   0.54635    0.40008   1.366    0.175
## SUS.l1  -0.03048    0.03418  -0.892    0.374
## CPUS.l1  3.75254    9.41724   0.398    0.691
## const   11.11224   10.07828   1.103    0.272
## trend   -4.27647    9.40833  -0.455    0.650
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Residual standard error: 13.3 on 123 degrees of freedom
## Multiple R-Squared: 0.8773,  Adjusted R-squared: 0.8723
## F-statistic: 175.9 on 5 and 123 DF,  p-value: < 2.2e-16
##
##
## Estimation results for equation YUS:
## ====================================
## YUS = OIL.l1 + YUS.l1 + SUS.l1 + CPUS.l1 + const + trend
##
##           Estimate Std. Error t value Pr(>|t|)
## OIL.l1  -0.002228   0.005626  -0.396   0.6928
## YUS.l1   0.682975   0.065645  10.404   <2e-16 ***
## SUS.l1   0.007653   0.005608   1.365   0.1748
## CPUS.l1 -3.196317   1.545194  -2.069   0.0407 *
## const   -3.196802   1.653659  -1.933   0.0555 .
## trend    3.513784   1.543733   2.276   0.0246 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Residual standard error: 2.183 on 123 degrees of freedom
## Multiple R-Squared: 0.9967,  Adjusted R-squared: 0.9966
## F-statistic:  7483 on 5 and 123 DF,  p-value: < 2.2e-16
##
##
## Estimation results for equation SUS:
```

```
## ====================================
## SUS = OIL.l1 + YUS.l1 + SUS.l1 + CPUS.l1 + const + trend
##
##          Estimate Std. Error t value Pr(>|t|)
## OIL.l1  -0.01606    0.07210  -0.223   0.8241
## YUS.l1  -1.60960    0.84137  -1.913   0.0581 .
## SUS.l1   0.59204    0.07187   8.237 2.19e-13 ***
## CPUS.l1  2.65874   19.80468   0.134   0.8934
## const   26.05067   21.19487   1.229   0.2214
## trend   -1.07095   19.78596  -0.054   0.9569
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Residual standard error: 27.98 on 123 degrees of freedom
## Multiple R-Squared: 0.3841,  Adjusted R-squared: 0.359
## F-statistic: 15.34 on 5 and 123 DF,  p-value: 1.051e-11
##
##
## Estimation results for equation CPUS:
## =====================================
## CPUS = OIL.l1 + YUS.l1 + SUS.l1 + CPUS.l1 + const + trend
##
##            Estimate Std. Error t value Pr(>|t|)
## OIL.l1    5.145e-06  2.821e-04   0.018    0.985
## YUS.l1    4.637e-03  3.292e-03   1.408    0.162
## SUS.l1    1.488e-04  2.812e-04   0.529    0.598
## CPUS.l1 -5.050e-01  7.749e-02  -6.517 1.66e-09 ***
## const   -5.060e-01  8.293e-02  -6.101 1.26e-08 ***
## trend    1.500e+00  7.742e-02  19.380  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Residual standard error: 0.1095 on 123 degrees of freedom
## Multiple R-Squared:     1,   Adjusted R-squared:     1
## F-statistic: 2.985e+06 on 5 and 123 DF,  p-value: < 2.2e-16
##
##
```

```
##
## Covariance matrix of residuals:
##            OIL      YUS       SUS     CPUS
## OIL  177.00283  1.21842   4.89965  0.08706
## YUS    1.21842  4.76540  -1.99552 -0.03294
## SUS    4.89965 -1.99552 782.83251  0.04171
## CPUS   0.08706 -0.03294   0.04171  0.01199
##
## Correlation matrix of residuals:
##          OIL      YUS      SUS     CPUS
## OIL  1.00000  0.04195  0.01316  0.05977
## YUS  0.04195  1.00000 -0.03267 -0.13782
## SUS  0.01316 -0.03267  1.00000  0.01362
## CPUS 0.05977 -0.13782  0.01362  1.00000
```

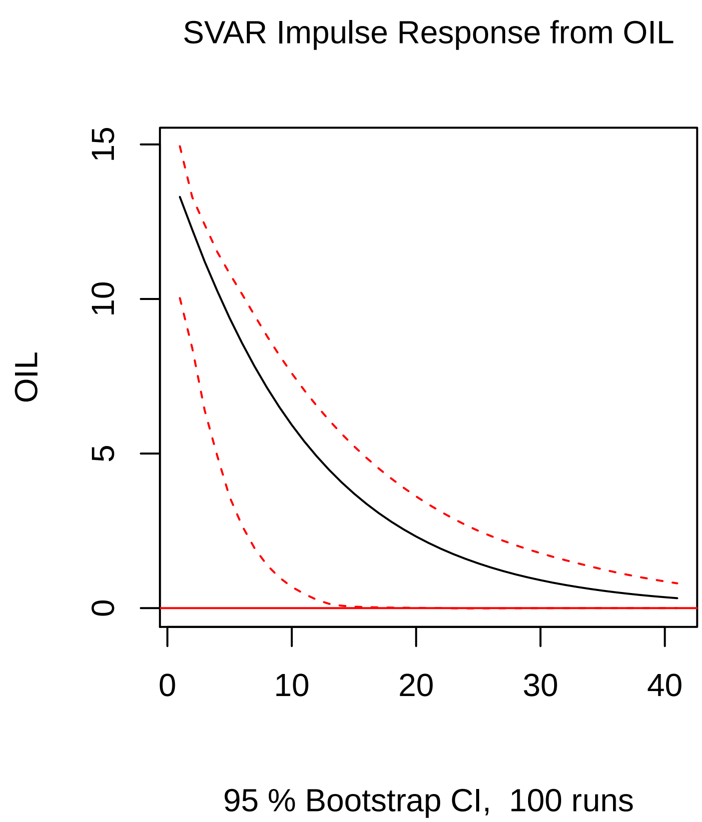
```
##
## SVAR Estimation Results:
## ========================
##
## Call:
## BQ(x = var1)
##
## Type: Blanchard-Quah
## Sample size: 129
## Log Likelihood: -1309.43
##
## Estimated contemporaneous impact matrix:
##             OIL      YUS      SUS    CPUS
## OIL  12.6575204 -3.57344  1.98768 -0.2639
## YUS   0.7361474  1.98758 -0.47169  0.2248
## SUS  -2.1204506  6.25470 27.18786 -0.1870
## CPUS  0.0002438 -0.02664  0.00841  0.1059
##
## Estimated identified long run impact matrix:
##             OIL        YUS      SUS    CPUS
## OIL  160.319298  0.0000000  0.00000 0.00000
## YUS    0.821661  6.0610476  0.00000 0.00000
## SUS  -14.739307 -8.5814350 66.72326 0.00000
```

```
## CPUS   0.001784  0.0001243  0.01218 0.07033
##
## Covariance matrix of reduced form residuals (*100):
##            OIL      YUS       SUS   CPUS
## OIL  17700.283  121.842   489.965  8.706
## YUS    121.842  476.540  -199.552 -3.294
## SUS    489.965 -199.552 78283.251  4.171
## CPUS     8.706   -3.294     4.171  1.199
```




```
##      [,1] [,2] [,3] [,4]
## [1,]   NA    0    0    0
## [2,]   NA   NA    0    0
## [3,]   NA   NA   NA    0
## [4,]   NA   NA   NA   NA
```

```
##       [,1] [,2] [,3] [,4]
## [1,]   NA    0    0    0
## [2,]    0   NA    0    0
## [3,]    0    0   NA    0
## [4,]    0    0    0   NA
```



10. Conclusion

References

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Appendix

Appendix A

Some appendix information here

Appendix B