# Time Series Research Assignment

Jacques Rossouw - 21159793[a]

[a]*Stellenbosch, Western Cape, South Africa*

**Abstract**

Abstract to be written here.

*Email address:* `gerardrossouw@gmail.com` (Jacques Rossouw - 21159793)

Table of Contents

## 1. Part I

## 2. Introduction

The aim of this paper is to replicate the work by MacDonald & Ricci (2004). They analyse the determinants of the Real Effective Exchange Rate (REER) based on a collection of variables as determinants, using a Vector Error Correction Model. The purpose of their study was to use the most current research to investigate a set of variables with explanatory power in determining the long term behaviour of the REER in South Africa. They used the period starting from the first quarter of 1970 until the first quarter of the year 2002. Towards this end, they made use of the Maximum Likelihood method of estimating the VECM, developed in Johansen (1995). Their choice of variables is based on the most recent research at the time, of the determinants of the real exchange rate in developing economies such as South Africa. This paper serves to replicate the steps taken by MacDonald & Ricci (2004) and reach a conclusion independently, and thus will critically evaluate the logical flow towards estimating the final model. Therefore, additional tests and evaluations are made to reassess the robustness of the final mode.

The choice of the model vector introduced later, is based on several developments prior to 2004. Briefly, the variables have been found to serve as feasible explanatory variables for the REER includes: productivity, real interest rates relative to mostly traded with, the relative openness of the selected economy to trade, and the magnitude of the fiscal balance and net foreign assets (MacDonald & Ricci, 2004).

The Purchasing Power Parity (PPP) points to the equality between the price levels between two countries if they were quoted in the same currencies. When the PPP holds, the real exchange rate must not vary (Sarno & Taylor, 2002). The VECM for the REER is thus an attempt to elucidate the nature of deviations from the PPP. A comprehensive and accurate model for the deviations from the PPP that is explainable by real factors would provide an appropriate framework for policy-makers to respond with ideal policy (Sarno & Taylor, 2002). In light of this, MacDonald & Ricci (2004) attempt to bring various explanatory variables together in a broad model that can appropriately explain these deviations.

## Part II: Replication

### 3. Importing and Cleaning the Data

### 4. Plotting the Model Variables (STEP 0.)

Figures 4.1 & 4.2 displays each variable as they as they were before their natural logarithm transformation.

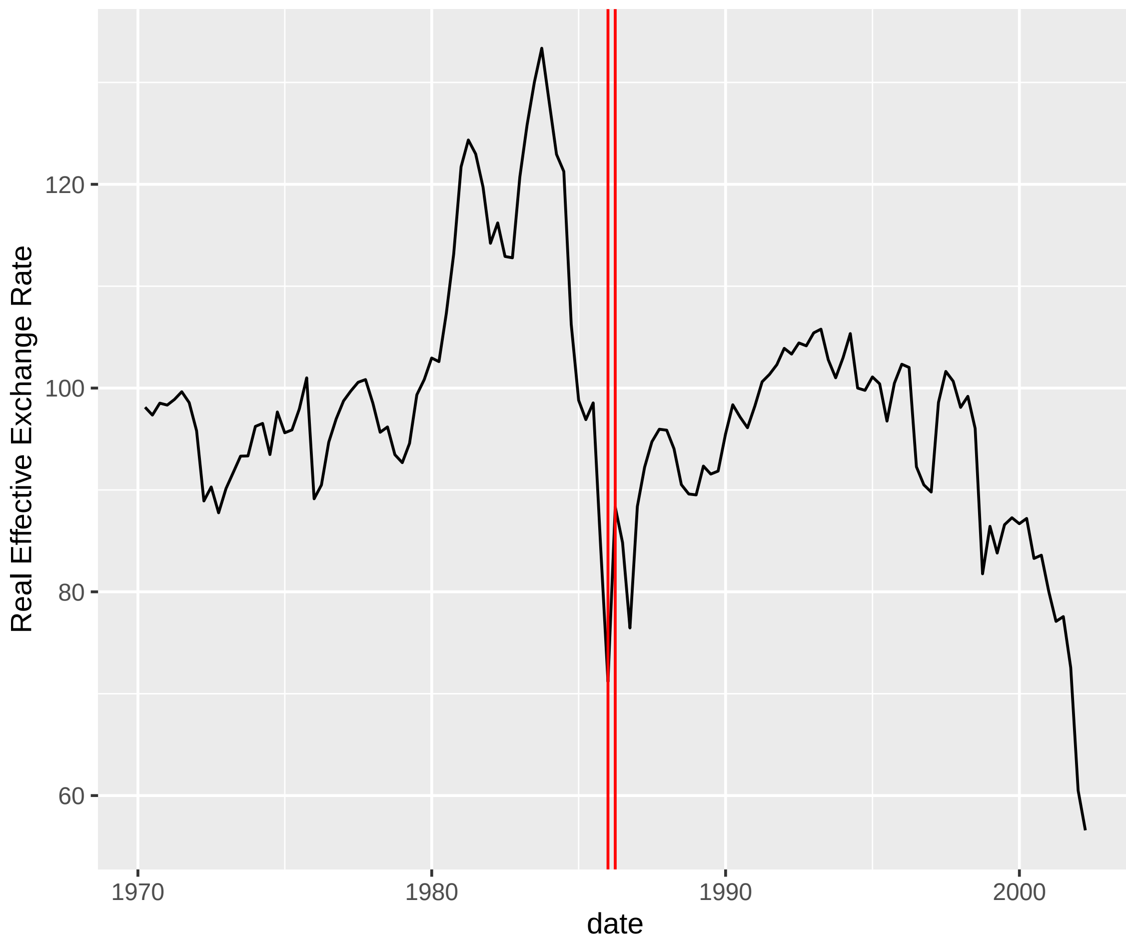



Figure 4.1: The South Africa Real Exchange Rate

*might have to rethink this: The regime changes might be accounted for/proxied by including the openness, real commodity prices and net foreign assets??*

The red lines indicate the dates at which dummy variables for possible outliers will be included as an alternative model specification. This alternative specification aims to account for the large changes in the real exchange rate regime over the period. There was little consistency in the manner in which the real exchange rate was determined over the period from 1970 to 2002. Most significantly, intermittent changes in the degree and nature of intervention from the South African Reserve Bank (SARB) suggests that the explanatory factors determining the REER will necessary be inconsistent over this period (Aron, Elbadawi & Kahn, 1998). The period from 1979 to 1988 from figure 4.1 for example, is visually unique from the rest of the time series. The coincidence seems unlikely with some research suggesting that intervention during this period was based on maintaining the real price of gold in rand (Aron *et al.*, 1998). This suggests that a model that can account for some structural deviations might be more appropriate. The VECM developed by MacDonald & Ricci (2004) to explain the equilibrium deviations of the REER might achieve more preciseness by accounting for these periods of deviation from free market behaviour.

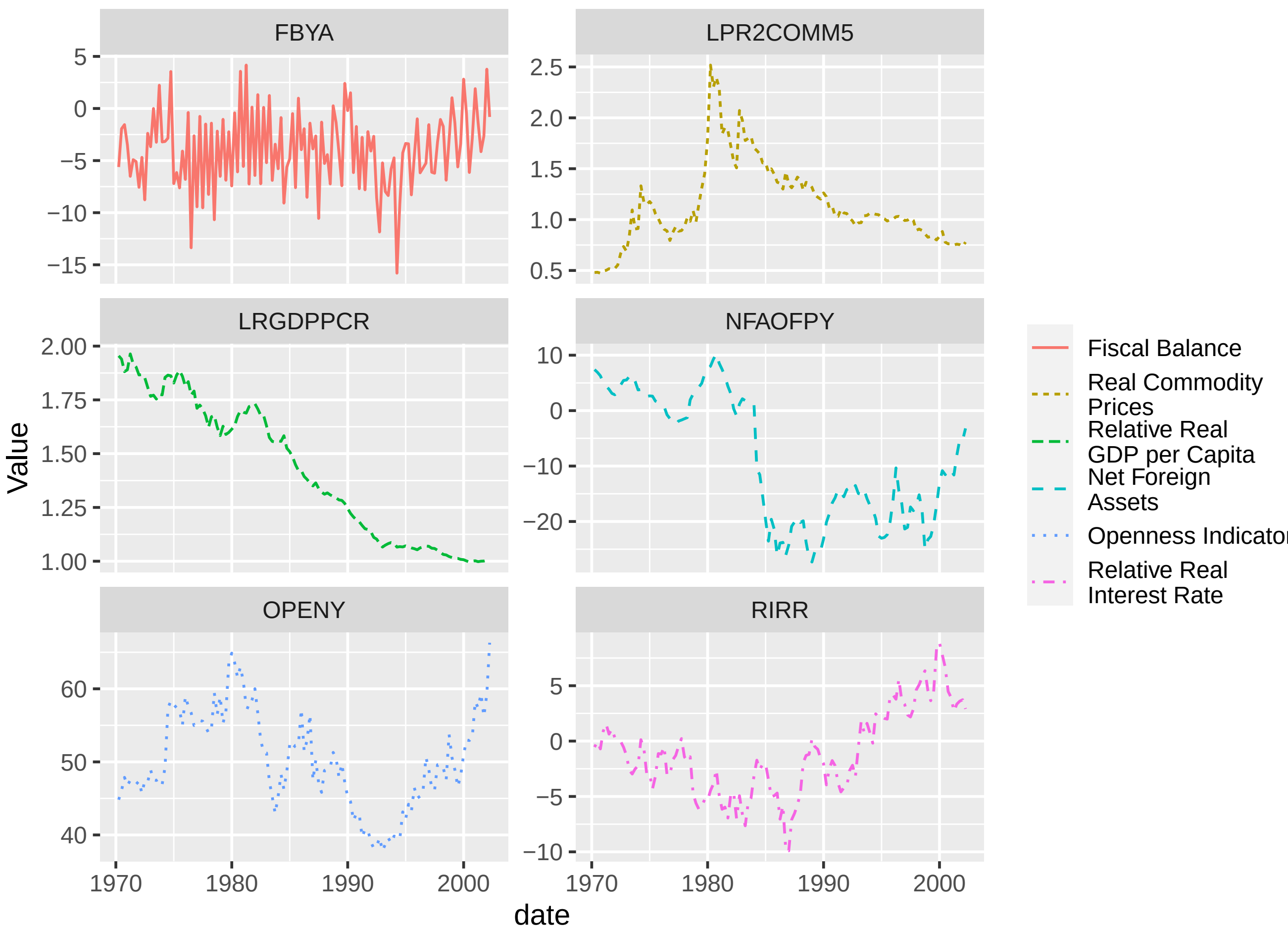



Figure 4.2: Determinants of the Real Exchange Rate for South Africa

Figure 4.2 above might also suggest that there is a possible structural break in the time series around the year 1985. This is mostly evident in the behaviour of the variable `NFAOFPY`, the Net Foreign Assets proxy. The openness indicator, Relative Real Interest Rate, Relative Real GDP, and Real Commodity prices slightly correspond to this theory as well. A test for this is therefore necessary.

To illustrate the co-movement of the system, figure **??** below plots them jointly. Note that the Openness Indicator has also been logged to make the visual comparison easier.

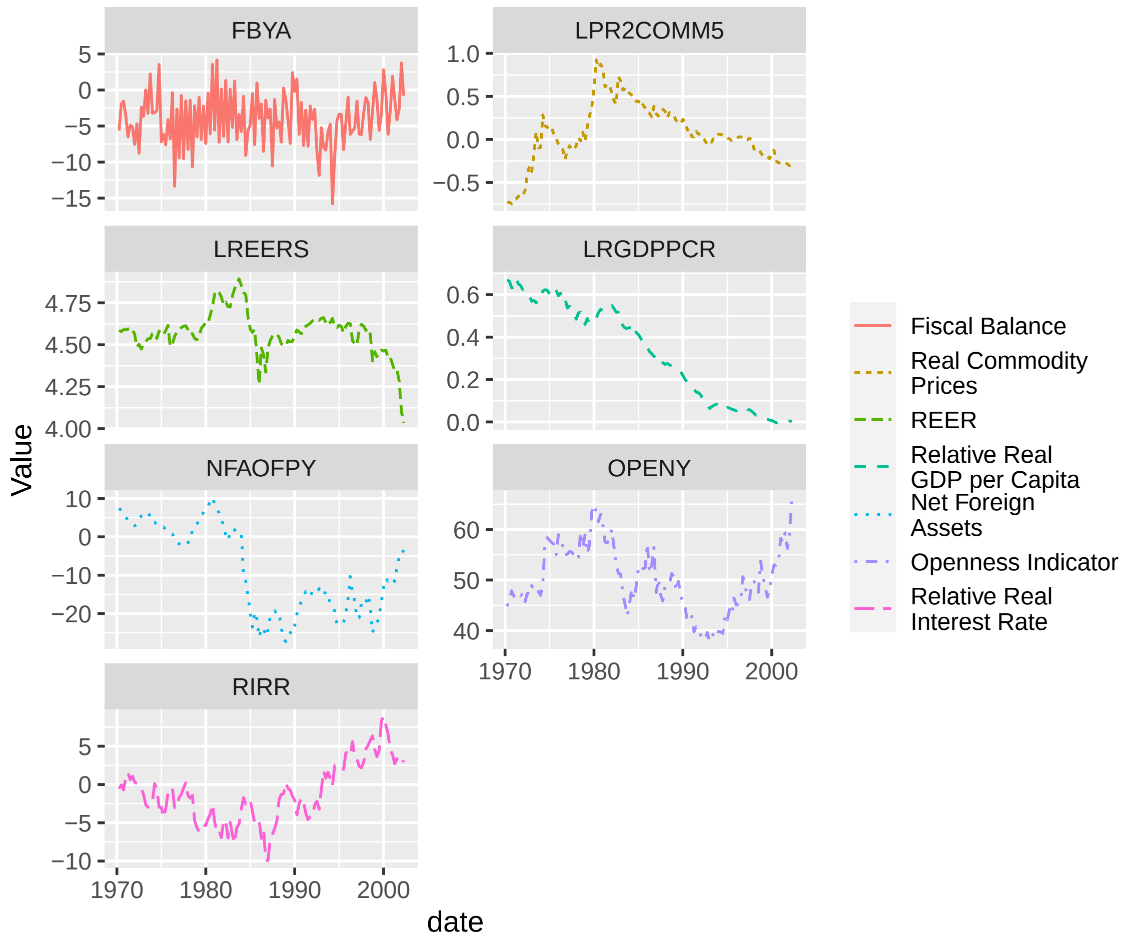



Figure 4.3: The Joint plot of the Model Varibales (Logged where necessary)

A relative degree of co-movement is noticeable in each of these time series altogether. The Log of Real GDP, however, requires one to take into account the declining trend, after which the co-movement seems more evident. Also worth noting, is that none of these series seem to be stationary.

## 5. The Johansen Method in Theory

*explain johansen method*

The Johansen (1995) method requires six steps in the estimation process, which follows as:

1. Choosing a specification for the deterministic parts of the model
2. Pre-testing the variables in the system to ensure that they are likely integrated of order one (i.e. $x_t \sim I(1)$$)
3. Estimating the unrestricted Vector Autoregressive model in levels and checking this models adequacy
4. Estimating the VECM form and determining the cointegration rank (i.e. 'r')
5. etc.

### 6. 1. Plotting the Diffirenced Variables

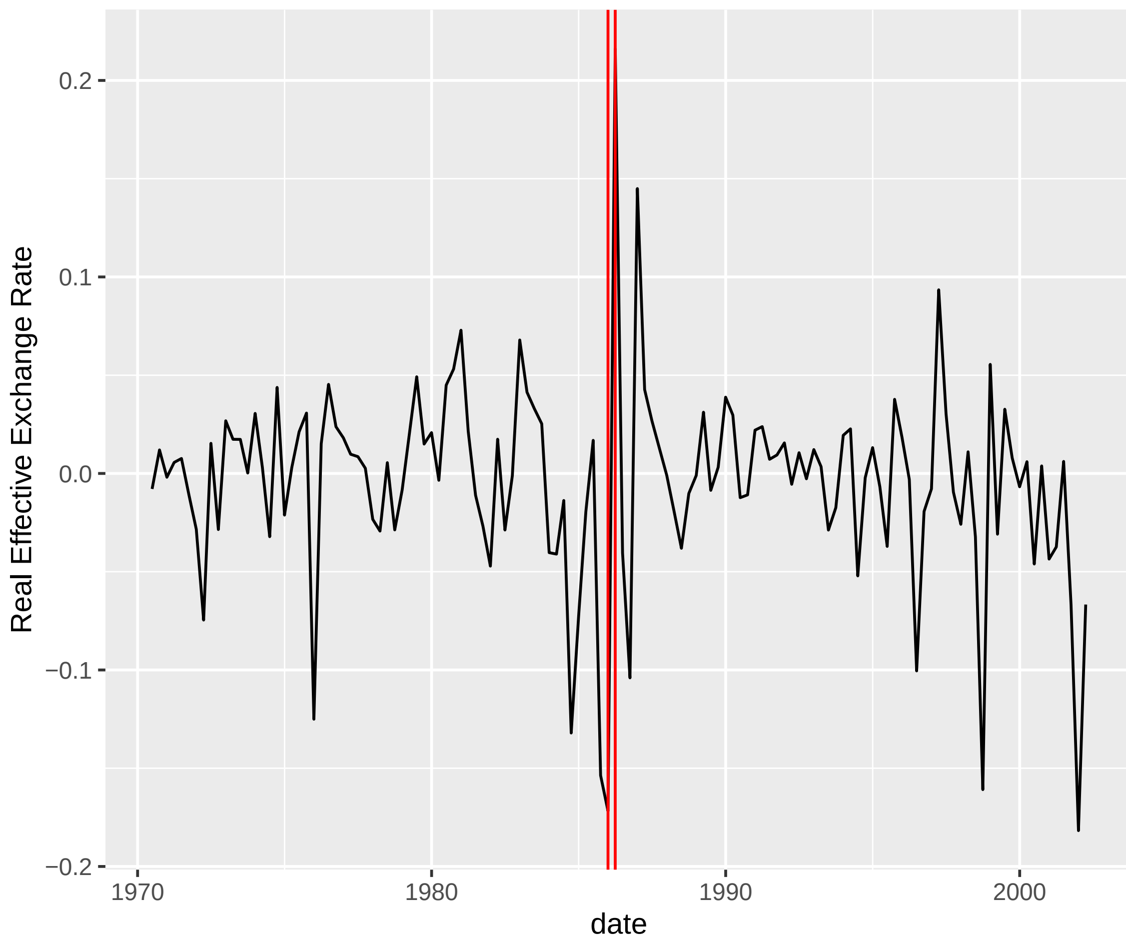



Figure 6.1: The First Difference of the LREERS

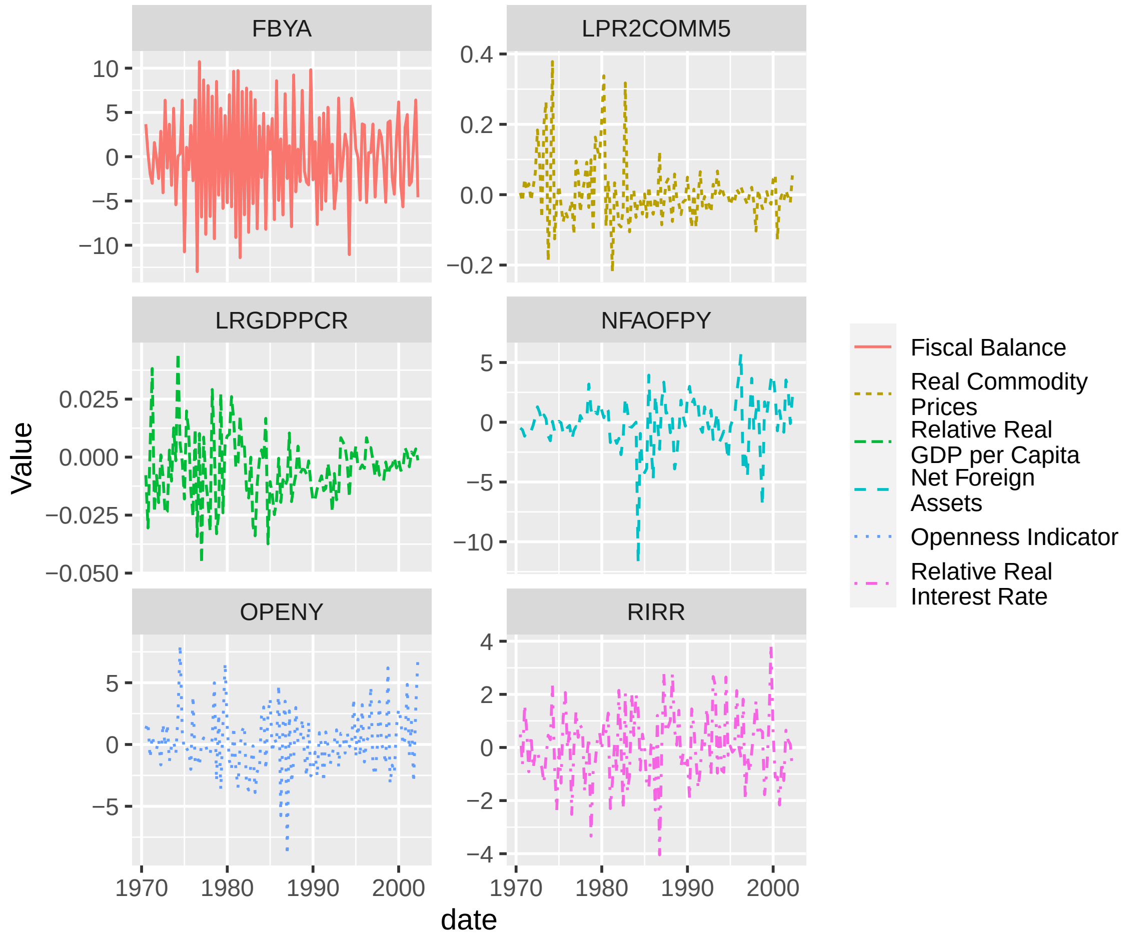



Figure 6.2: The First Difference of the Determinants of the Real Exchange Rate

figures 6.2 and 6.1 above suggest that the REER time series and its candidate explanatory variables are possibly integrated of the first order (i.e. $REER \sim I(1)$). The deterministic component is most likely a constant term. Each of these variables seem somewhat stationary after their first difference is been determined.

The Augmented Dicky-Fuller tests for the differenced time series values of all the variables in the system are displayed in figure **??** below.

Table 6.1: ADF Test on the Model Time Series Variables

| | Statistic | Lags | Null_Hypothesis | p_value |
|---|---|---|---|---|
| RIRR | −2.385 | 5 | stationary | 0.417 |
| OPENY | −1.415 | 5 | stationary | 0.820 |
| FBYA | −2.785 | 5 | stationary | 0.250 |
| NFAOFPY | −0.727 | 5 | stationary | 0.966 |
| LREERS | −1.160 | 5 | stationary | 0.910 |
| LRGDPPCR | −2.140 | 5 | stationary | 0.518 |
| LPR2COMM5 | −2.755 | 5 | stationary | 0.263 |

Table 6.2: ADF Test on the Model Time Series Variables

| | Statistic | Lags | Null_Hypothesis | p_value |
|---|---|---|---|---|
| D_RIRR | −5.101 | 5 | stationary | 0.010 |
| D_OPENY | −3.767 | 5 | stationary | 0.023 |
| D_FBYA | −6.184 | 5 | stationary | 0.010 |
| D_NFAOFPY | −4.901 | 5 | stationary | 0.010 |
| D_LREERS | −4.718 | 5 | stationary | 0.010 |
| D_LRGDPPCR | −3.857 | 5 | stationary | 0.018 |
| D_LPR2COMM5 | −4.491 | 5 | stationary | 0.010 |

To test this hypothesis, that each of these series are only stationary after the first difference, the Augmented Dickey Fuller test is employed. The Augmented Dicky-Fuller tests for the differenced time series values of all the variables in the system, as well as the first difference of each of these series are displayed in figures **??** and **??** above. The figures confirm that none of the variables are stationary, and that all but `NFAOFPY` i.e. the net foreign assets are stationary after the first difference. For those that are stationary, the null hypothesis was rejected at the 1% significance level, barring the openness indicator for which the p-value is less than 0.05. This might be due to the large deviations created by the apartheid era sanctions (MacDonald & Ricci, 2004). The problem with only using the Dicky-Fuller test in this case is that this test has a lower size when there exists structural breaks in the data. To mitigate this problem the ADF-GLS test is implemented to confirm whether the series are non-stationary before the first difference.

### 7. 2.A: Estimating the Unrestricted VAR in Levels

```
options(scipen=999)

var_sel <- endog_df %>% dplyr::select(2:8) %>%
    VARselect(., type = "both", lag.max = 8, season = 4)
var_sel$selection
```

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

```
var_sel2 <- endog_df %>% dplyr::select(2:8) %>%
    VARselect(., type = "both", lag.max = 8, season = 4,
          exogen = exog_df[,5:8])
var_sel2$selection
```

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

```
endog_alt <- endog_df %>% mutate(OPENY = log(OPENY))
VARselect(endog_alt[,c(2:8)], type = "both", lag.max = 8, season = 4)$selection
```

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

```
VARselect(endog_alt[,c(2:8)], type = "both", lag.max = 8, season = 4,
          exogen = exog_df[,5:8])$selection
```

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

The model selection based on the Akaike Information Criteria (AIC) suggests that two lags be included in the model. The AIC and Schwartz Criterion (SC) tends to select over-paramterised models however, but the Schwartz Criterion tends to yield asymptotically consistent results compared to the AIC. For the purpose of the replication the AIC will be used. It is worth noting that this might yield more inconsistent results. Based on the all of information criterion displayed above, there seems to be no reason to choose a model with higher lag order than 2. Therefore, using the suggested lag length from MacDonald & Ricci (2004), 4, is in disagreement with the replication above. Many of the variables have already been scaled to span over similar smaller ranges. The only variable that remains relatively large is the openness indicator (`OPENY`). This paper thus continues with an additional variable specification compared to that of MacDonald & Ricci (2004). This alternative includes a natural log standardised value for `OPENY` (i.e. `LOPENY`) instead, and compares this specification with the model obtained from data used in the original paper. The suggested number of lags with this alternative specification results in a choice of two lags to be included in the VECM, according to the AIC. The same problem still exists in terms of the conflict between the AIC and SC.

Adding additional lags is usually an alternative option for when the residuals display serial correlation (Johansen, 1995). However, MacDonald & Ricci (2004) do not explicitly mention this concession and its reasoning. It is important to note that adding additional lags when it is not explicitly suggested so by the information criterion is not recommended in the multivariate case (Johansen, 1995). The tests for serial correlation that follows in the next section provide a likely reason for the decision to include four lags.

*Using the results as they are displayed above leads to a series of VAR model with serial correlation exisiting for each of these mentioned above.*

Table 7.1: VAR Estimation Results

| | *Dependent variable:* | |
|---|---|---|
| | y | |
| | (1) | (2) |
| LREERS.l1 | 1.116*** | 1.163*** |
| RIRR.l1 | −0.003 | −0.004 |
| LRGDPPCR.l1 | −0.131 | 0.245 |
| OPENY.l1 | 0.002 | 0.001 |
| FBYA.l1 | 0.003** | 0.001 |
| NFAOFPY.l1 | −0.004* | −0.008*** |
| LPR2COMM5.l1 | 0.023 | 0.075 |
| LREERS.l2 | −0.149 | −0.262 |
| RIRR.l2 | 0.001 | −0.002 |
| LRGDPPCR.l2 | −0.227 | 0.045 |
| OPENY.l2 | −0.001 | −0.005* |
| FBYA.l2 | −0.001 | −0.001 |
| NFAOFPY.l2 | 0.004* | 0.006 |
| LPR2COMM5.l2 | 0.006 | 0.020 |
| LREERS.l3 | | 0.231 |
| RIRR.l3 | | 0.004 |
| LRGDPPCR.l3 | | −0.496 |
| OPENY.l3 | | 0.002 |
| FBYA.l3 | | −0.0005 |
| NFAOFPY.l3 | | 0.004 |
| LPR2COMM5.l3 | | 0.048 |
| LREERS.l4 | | −0.174 |
| RIRR.l4 | | 0.002 |
| LRGDPPCR.l4 | | 0.249 |
| OPENY.l4 | | 0.003 |
| FBYA.l4 | | −0.0004 |
| NFAOFPY.l4 | | −0.004 |
| LPR2COMM5.l4 | | −0.138** |
| const | 0.380 | 0.133 |
| trend | −0.002** | |
| sd1 | 0.015 | 0.033* |
| sd2 | 0.002 | 0.018 |
| sd3 | 0.008 | 0.002 |
| DUMRER1 | 0.176*** | |
| DUMRER2 | 0.196*** | |
| DUMFBYA | 0.003 | |
| DUMNFAOFPY | −0.020 | |
| Observations | 127 | 125 |
| $R^2$ | 0.905 | 0.894 |
| Adjusted $R^2$ | 0.885 | 0.859 |

*Tests to perform: 1. Structural break 2. White noise residuals 3. autocorr resid's 4. time-varying params 5. heteroskedasticity 6. test (or check?) for Weak Exog*

## 8. 2.B: Tests on VAR

### 8.1. I. White Noise Residuals

#### 8.1.1. Plot Residuals

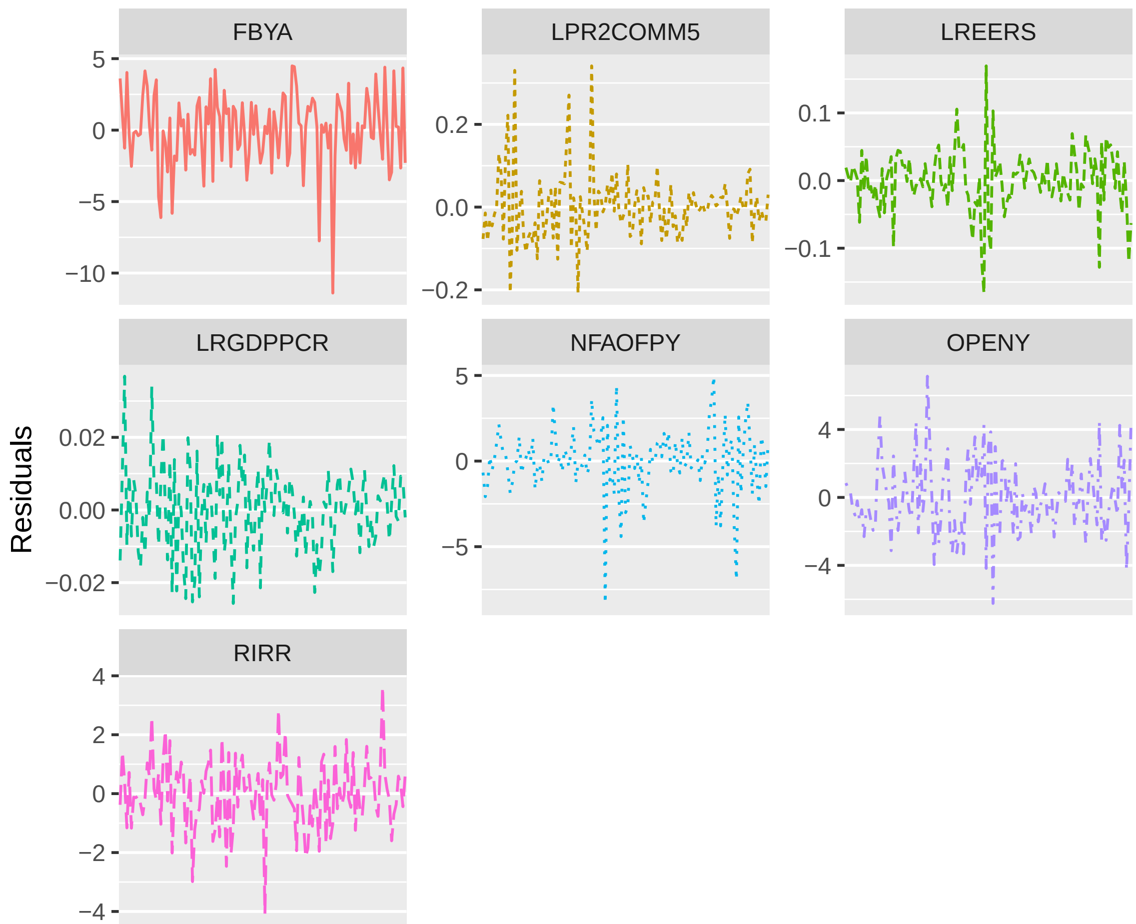



Figure 8.1: VAR Residuals plot - Model 1

The plot of the residuals from the first VAR model in figure 8.1 seems very close to a white noise process, however, there do appear to be deviations from the zero mean that could imply otherwise. The clusters of larger residuals appear to be concentrated around the timeline that corresponds with the outliers identified by MacDonald & Ricci (2004). Alternatively, this could add an additional illustration of the underlying effect of a structural change in the data. The nature of the Johansen (1995) method, however, allows for some non-normality in the errors as MacDonald & Ricci (2004) point out. The asymptotic nature of their method allows for this, however, the assumption of serial correlation is not allowed to be violated (Johansen, 1995).

*8.1.2. Serial Correlation Tests:*

```
stargazer(rbind(pmt_test, es_tests), header = FALSE, summary = F, title = "Serial Correlation Te
    notes = c("Null-hypotheses: The Residuals Display No Serial Corrrelation", "Note: Both tests
```

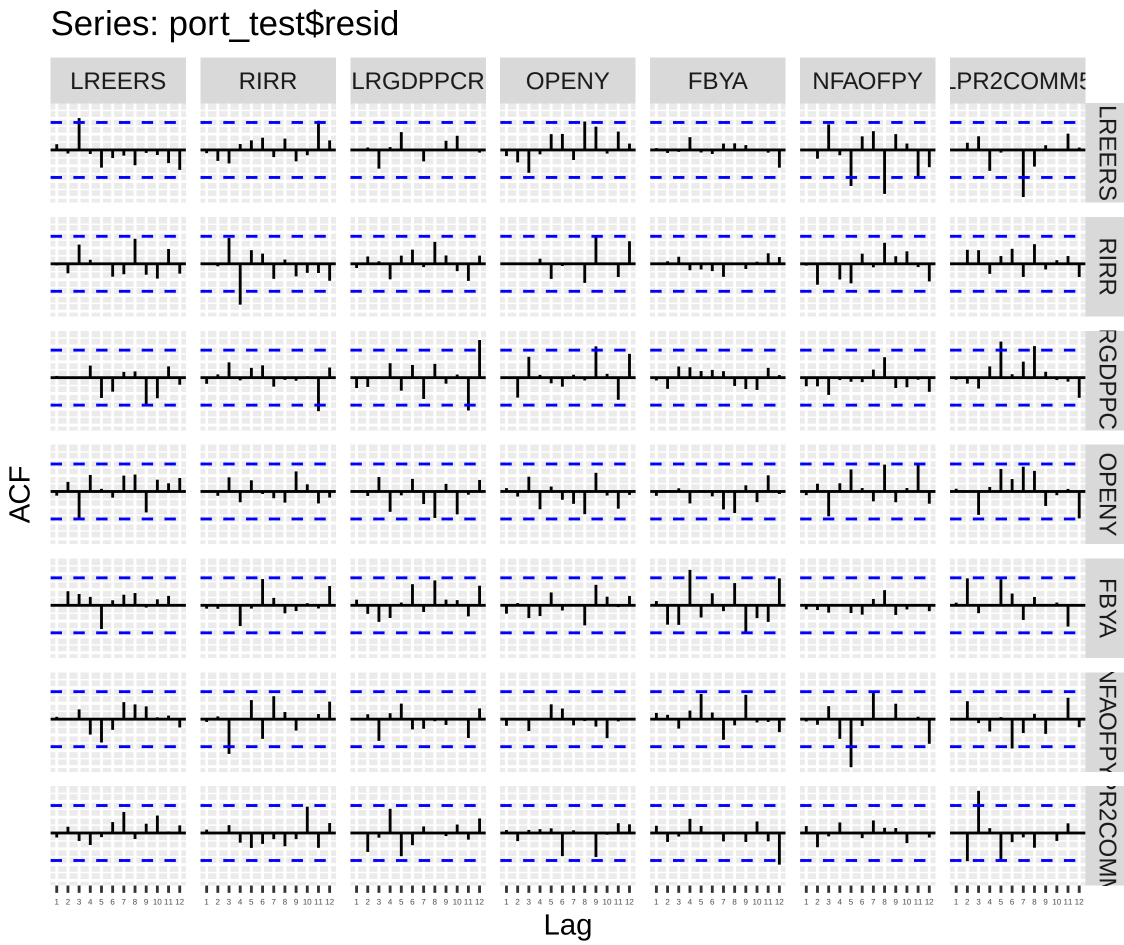
Table 8.1: Serial Correlation Tests on VAR Models' Residuals

| | Model | DoF1 | DoF2 | p_value | Statistic | Test |
|---|---|---|---|---|---|---|
| 1 | VAR_Residuals_Auto | 686 | N_A | 0.0177 | 766.2365 | Portmanteau_(adj) |
| 2 | VAR_Residuals_Auto_Outliers | 686 | N_A | 0.0584 | 745.0479 | Portmanteau_(adj) |
| 3 | VAR_Residuals_Forced | 588 | N_A | 0.0149 | 665.0041 | Portmanteau_(adj) |
| 4 | VAR_Residuals_Forced_Outliers | 588 | N_A | 0.0149 | 665.0041 | Portmanteau_(adj) |
| 5 | VAR_Residuals_Auto | 245 | 473 | 0.0307 | 1.2274 | Edgerton-Shukur_F |
| 6 | VAR_Residuals_Auto_Outliers | 245 | 445 | 0.1795 | 1.1069 | Edgerton-Shukur_F |
| 7 | VAR_Residuals_Forced | 245 | 370 | 0.0986 | 1.1603 | Edgerton-Shukur_F |
| 8 | VAR_Residuals_Forced_Outliers | 245 | 370 | 0.0986 | 1.1603 | Edgerton-Shukur_F |

Null-hypotheses: The Residuals Display No Serial Corrrelation
Note: Both tests adjust for small sample bias

As pointed out in section 7, the inclusion of additional lags up to 4, is most likely to solve the problem of serial correlation. From table 8.1, the Models with the suffix `Forced` or `Forced_Outliers` are the VAR models with four lags. The latter being those with added dummies for the outlier observations. The table above displays the results from the 'Adjusted Portmanteau Test' and the 'Edgerton-Shukur F-test' [REFERENCE]. Both of these tests incorporate for small sample corrections that are necessary in the case of this dataset. The Portmanteau Test

*8.1.3. ACF of Residuals Plot*




*8.2. II Check for the presence of Structural Break*

## 9. 3. Determining the order of CI

```
jo <- endog_alt %>% dplyr::select(2:8) %>% ca.jo(., type = "trace",
                                                  ecdet = "const",
                                                  spec = "longrun",
             K = 2, season = 4)

jo2 <- endog_alt %>% dplyr::select(2:8) %>% ca.jo(., type = "trace",
                                                  ecdet = "const",
                                                  spec = "longrun", K = 2,
```

```
                                              season = 4,
                                              dumvar = exog_df[,5:8])

jo_forced <- ca.jo(full_df[,2:8], type = "trace", ecdet = "const",
                   spec = "longrun",
                    K = 4, season = 4)

jo2_forced <- full_df %>% dplyr::select(2:8) %>% ca.jo(., type = "trace",
                                              # ecdet = "const",
                                              spec = "longrun",
                                              K = 4,
                                              season = 4,
                                              dumvar = exog_df[,5:8])
summary(jo_forced)
```

```
##
## ######################
## # Johansen-Procedure #
## ######################
##
## Test type: trace statistic , without linear trend and constant in cointegration
##
## Eigenvalues (lambda):
## [1] 2.741384e-01 2.056177e-01 1.997777e-01 1.202430e-01 1.111450e-01
## [6] 6.313826e-02 4.743264e-02 8.789624e-17
##
## Values of teststatistic and critical values of test:
##
##            test  10pct   5pct   1pct
## r <= 6 |   6.07   7.52   9.24  12.97
## r <= 5 |  14.23  17.85  19.96  24.60
## r <= 4 |  28.95  32.00  34.91  41.07
## r <= 3 |  44.97  49.65  53.12  60.16
## r <= 2 |  72.83  71.86  76.07  84.45
## r <= 1 | 101.60  97.18 102.14 111.01
## r = 0  | 141.65 126.58 131.70 143.09
##
## Eigenvectors, normalised to first column:
```

```
## (These are the cointegration relations)
##
##                  LREERS.l4      RIRR.l4  LRGDPPCR.l4    OPENY.l4       FBYA.l4
## LREERS.l4      1.000000000  1.000000000  1.000000000  1.00000000  1.0000000000
## RIRR.l4       -0.034477285 -0.063811357 -0.009346723  0.13402907  0.0005436228
## LRGDPPCR.l4   -0.230930452 -1.979972815  0.220425455  1.21783849  0.1933115316
## OPENY.l4       0.008764965  0.058750655  0.034174450 -0.01896788  0.0092309447
## FBYA.l4        0.018668473  0.038031301 -0.063011996  0.50306497  0.0190210726
## NFAOFPY.l4    -0.005434018 -0.004171023 -0.036568269 -0.03361502 -0.0127952636
## LPR2COMM5.l4 -0.479741162 -1.216902985 -0.584758148 -0.99438252 -0.0630707443
## constant      -4.888234747 -6.999166718 -6.698582220 -1.81614163 -5.1579047707
##                NFAOFPY.l4 LPR2COMM5.l4     constant
## LREERS.l4      1.00000000  1.000000000  1.000000000
## RIRR.l4        0.02712490  0.006444232  0.023024728
## LRGDPPCR.l4    0.93836513 -0.448950307  0.576574119
## OPENY.l4       0.03025468  0.012413433 -0.007913675
## FBYA.l4       -0.01188010 -0.007032678 -0.013589504
## NFAOFPY.l4    -0.01613723  0.002262130 -0.011528765
## LPR2COMM5.l4 -0.30291162 -0.127398851 -0.183636782
## constant      -6.53786889 -5.026297709 -4.525355672
##
## Weights W:
## (This is the loading matrix)
##
##                 LREERS.l4      RIRR.l4 LRGDPPCR.l4      OPENY.l4      FBYA.l4
## LREERS.d      -0.03905540  0.009542747  0.02039254 -3.016394e-03  0.056264052
## RIRR.d         2.85186904  0.672316964  0.55505618 -9.518194e-02 -0.620548723
## LRGDPPCR.d    -0.03738182  0.012467654 -0.01100385  4.345389e-05 -0.008292489
## OPENY.d       -4.11197066 -0.971890116 -0.27421153  2.471038e-01 -6.750016203
## FBYA.d       -14.32992479  0.677115272  1.52182656 -3.805992e-01 -1.127317608
## NFAOFPY.d      0.50573233  1.705655623  1.46584329  3.250713e-01 -0.405973425
## LPR2COMM5.d    0.16445725  0.039012790 -0.02156001 -8.125198e-03 -0.241502261
##                NFAOFPY.l4 LPR2COMM5.l4      constant
## LREERS.d      0.001401803 -0.087318974 -8.897356e-15
## RIRR.d       -1.192751656  0.720502337  9.019749e-14
## LRGDPPCR.d   -0.006841840  0.001697689 -6.117938e-15
## OPENY.d      -1.236150400  0.836600047 -6.321306e-13
## FBYA.d        0.690078812  1.881228636 -5.040780e-13
## NFAOFPY.d     0.560346240 -1.969193524  8.207158e-13
```

```
## LPR2COMM5.d  0.036485387 -0.033810781  7.318486e-14
```

```
summary(jo2_forced)
```

```
##
## ######################
## # Johansen-Procedure #
## ######################
##
## Test type: trace statistic , with linear trend
##
## Eigenvalues (lambda):
## [1] 0.32468129 0.19269627 0.13718841 0.11916971 0.06378205 0.05025718 0.01424256
##
## Values of teststatistic and critical values of test:
##
##            test  10pct   5pct   1pct
## r <= 6 |   1.79   6.50   8.18  11.65
## r <= 5 |   8.24  15.66  17.95  23.52
## r <= 4 |  16.48  28.71  31.52  37.22
## r <= 3 |  32.34  45.23  48.28  55.43
## r <= 2 |  50.78  66.49  70.60  78.87
## r <= 1 |  77.54  85.18  90.39 104.20
## r = 0  | 126.61 118.99 124.25 136.06
##
## Eigenvectors, normalised to first column:
## (These are the cointegration relations)
##
##                  LREERS.l4     RIRR.l4 LRGDPPCR.l4     OPENY.l4      FBYA.l4
## LREERS.l4     1.000000000  1.00000000  1.00000000  1.000000000  1.000000000
## RIRR.l4      -0.036943960 -0.02765677  0.01983759  0.010245323 -0.011379819
## LRGDPPCR.l4  -0.258662096 -0.33328999  0.07658100  0.854705771 -0.897317715
## OPENY.l4      0.008597203  0.02052903  0.01427627  0.002836793  0.012359118
## FBYA.l4       0.033448445 -0.01155898  0.08357627 -0.006046150 -0.004646072
## NFAOFPY.l4   -0.003274714 -0.01307187 -0.01580912 -0.017978981  0.009234609
## LPR2COMM5.l4 -0.501952611 -0.49731276 -0.19512950  0.053283492  0.083191331
##                NFAOFPY.l4 LPR2COMM5.l4
## LREERS.l4     1.000000000  1.000000000
```

```
## RIRR.l4       0.032491970  0.014669113
## LRGDPPCR.l4   0.281352862  0.088955137
## OPENY.l4      0.050148878 -0.001033585
## FBYA.l4      -0.026806210 -0.004332704
## NFAOFPY.l4   -0.008084834 -0.003704163
## LPR2COMM5.l4 -0.396716791 -0.195174888
##
## Weights W:
## (This is the loading matrix)
##
##                 LREERS.l4      RIRR.l4  LRGDPPCR.l4    OPENY.l4      FBYA.l4
## LREERS.d     -0.04567174  0.041245989  0.006234502  0.03530007 -0.019830700
## RIRR.d        0.99794193  3.918799924 -0.360842062 -1.77070506  0.467132713
## LRGDPPCR.d   -0.01512369 -0.007715683  0.005129479 -0.03190737  0.007535987
## OPENY.d      -3.41373709 -3.784173912 -0.887802559 -3.77494715 -1.483963384
## FBYA.d      -14.34433404  3.725125011 -1.323057573 -0.21317788  0.674519186
## NFAOFPY.d     0.57335652  3.667558501  2.185334200 -1.36544762 -1.546477656
## LPR2COMM5.d   0.16251321  0.021594235 -0.094864672 -0.12928396 -0.039099515
##                 NFAOFPY.l4 LPR2COMM5.l4
## LREERS.d    -0.0065474234 -0.042984636
## RIRR.d      -0.5699629397  0.178392044
## LRGDPPCR.d  -0.0008776753 -0.004761522
## OPENY.d     -0.6199357969  1.286714597
## FBYA.d       0.8037268670  0.377154487
## NFAOFPY.d    0.3041793134 -0.696864535
## LPR2COMM5.d  0.0372947508 -0.021999861
```

```r
# stargazer(summ, header = FALSE, summary = F)
```

### 10. 4. Estimating VECM with Restriction

The authors specify that the model they are estimating is for the long-run cointegration relationship, and so, the specification parameter chose is "long-run".

Table 10.1: Normalised Cointegration Relation Vector

| | ect1 | ect1.1 | ect1.2 | ect1.3 | ect1.4 |
|---|---|---|---|---|---|
| LREERS.l2 | 1 | 1 | 1 | 1 | 1 |
| RIRR.l2 | -0.029 | -0.024 | -0.025 | -0.036 | -0.026 |
| LRGDPPCR.l2 | 0.037 | -0.142 | -0.100 | 0.108 | -0.143 |
| OPENY.l2 | 0.007 | 0.011 | 0.011 | 0.013 | 0.011 |
| FBYA.l2 | 0.005 | 0.040 | 0.039 | -0.011 | 0.040 |
| NFAOFPY.l2 | -0.010 | -0.008 | -0.009 | -0.014 | -0.009 |
| LPR2COMM5.l2 | -0.433 | -0.450 | -0.454 | -0.497 | -0.417 |
| constant | -4.938 | -4.961 | -4.986 | -5.366 | -4.431 |

% Table created by stargazer v.5.2.3 by Marek Hlavac, Social Policy Institute. E-mail: marek.hlavac at gmail.com % Date and time: Wed, Jun 29, 2022 - 19:40:18

Table 10.2: Estimate of the Normalised Cointegration Relation Vector

| | ect1 | ect1.1 |
|---|---|---|
| LREERS.l2 | 1 | 1 |
| RIRR.l2 | -0.037 | -0.035 |
| LRGDPPCR.l2 | 0.051 | 0.094 |
| OPENY.l2 | 0.014 | 0.013 |
| FBYA.l2 | -0.010 | -0.012 |
| NFAOFPY.l2 | -0.013 | -0.013 |
| LPRGOLD.l2 | -0.458 | -0.487 |
| constant | -4.739 | -5.355 |

```
# blrtest(ca.jo_custom(df = full_df, i = "8"))
```

## 11. 5. Norm, Eval/interpret content/forecasts, test further restrictions

```
#alrtest()
```

## 12. Directly from (MacDonald & Ricci, 2004)

### *12.1. Section 3 Data and Methodology*

- Plotting the exp(LREER) and the rest of the variables
- Showcase the vector of interest
- Investigate LR CI Rel's amongst var's in vector
  - Method: MLE of Johansen (1995)
  - Why? Corrects for Autocorr and ednog parametrically using VECM specif.
  - Key Advantage: the estimated coefficient - the $\beta$ vector - can be used to provide a measure of the equilibrium real exchange rate and therefore a quantification of the gap between the prevailing real exchange rate and its equilibrium level. The methodology also derives estimates of the speed at which the real exchange rates converges to the equilibrium level.

## 13. Old Stuff

## 14. References

10 Aron, J., Elbadawi, I. & Kahn, B. 1998. Determinants of the real exchange rate in South Africa. (1997-16). [Online], Available: https://ideas.repec.org/p/csa/wpaper/1997-16.html [2022, June 28].

Johansen, S. 1995. *Likelihood-based inference in cointegrated vector autoregressive models*. Oxford University Press. [Online], Available: https://EconPapers.repec.org/RePEc:oxp:obooks:9780198774501.

MacDonald, R. & Ricci, L.A. 2004. Estimation of the equilibrium real exchange rate for south africa 1. *South African Journal of Economics*. 72(2):282–304.

Sarno, L. & Taylor, M.P. 2002. Purchasing Power Parity and the Real Exchange Rate. *IMF Staff Papers*. 49(1):65–105. [Online], Available: https://www.jstor.org/stable/3872492 [2022, June 27].

## Appendix

## 15. Introduction

- What did I do?
- why did I do this?

## 16. Literature Review

### *16.1. What did the Authors do?*

### *16.2. Motivation*

- Importance
- Methods
- Novel Contribution(s)

### *16.3. Critical Evaluation*

- Robustness checks/extensions

### *16.4. Variable Names (SECTION TO BE DELETED)*

### *16.5. VECM Model Estimation in Theory:*

*paper table 1 col's:*

*1. Var's + Seasonal(4) + lags(4) 2. $^{Above}$ + outlier_dummies -> Trace test $\implies$ two CI vectors*

*Multiple ways to estimate VEC models:*

*First approach: ordinary least squares (yields accurate result) but does not allow to estimate the cointegrating relations among the variables. The estimated generalised least squares (EGLS) approach would be an alternative.*

*Most popular estimator: MLE of Johansen (1995) [In R: ca.jo function of the urca package of Pfaff (2008a)] Alternatively, `VECM` of tsDyn package of Di Narzo et al. (2020)*

*Before VECM: 1. Determine lag order p -> Det. rank of CI matrix r 2. deterministic terms have to be specified. 3. Choose lag order: est. the VAR in levels 4. Choose lag specification that minimises an Information criterion*