

Lab 3

Cointegration & Error Correction Model

Case study of biodiesel fuel and soybean oil

Roadmap

- Review - ADF Tests
- Cointegration
 - Engle Granger 2 step test
 - Engle Granger function to retrieve correct critical values
 - Johansen Procedure
- Error Correction Model

Packages

- Load the following packages

`pacman::p_load(here, readxl, dplyr, janitor, Quandl, xts, lubridate, urca, forecast, tidyverse, vars, modelsummary)`

Data

- Load *data_lecture2.csv* and do the data cleaning steps – same data as last week
- Last week, we used price levels. Today, we will focus on log prices

```
> head(soydiesel)
```

	biodiesel	soyoil	diesel	lnbio	lnsoy	ln diesel	ln crude
2007-04-13	3.100	29.900	2.877	1.131402	3.397858	1.056748	4.136446
2007-04-20	3.100	29.310	2.851	1.131402	3.377929	1.047670	4.144087
2007-04-27	3.075	30.190	2.811	1.123305	3.407511	1.033540	4.178379
2007-05-04	3.140	31.130	2.792	1.144223	3.438172	1.026758	4.156067
2007-05-11	3.140	31.060	2.773	1.144223	3.435921	1.019930	4.125520
2007-05-18	3.175	32.865	2.803	1.155308	3.492408	1.030690	4.152771

ADF Tests

- General to specific
- Type = c("trend") $\Delta y_t = \alpha + \delta t + \tau y_{t-1} + \varepsilon_t$
 - Tau3 ($\tau = 0$) – If fail to reject, then unit root is present (not stationary)
 - Phi3 ($\tau = \delta = 0$) – If fail to reject, then there is a unit root AND there is no trend term.
 - Phi2 ($\alpha = \tau = \delta = 0$) – If fail to reject, then there is a unit root AND there is no trend term AND there is no drift term.
- Type = c("drift") $\Delta y_t = \alpha + \tau y_{t-1} + \varepsilon_t$
 - α is the constant or drift term
 - Tau2 ($\tau = 0$) – If fail to reject, then unit root is present (not stationary)
 - Phi1 ($\alpha = \tau = 0$) – If fail to reject, then there is a unit root AND there is no drift term.
- Type = c("none") $\Delta y_t = \tau y_{t-1} + \varepsilon_t$
 - Tau1 ($\tau = 0$) – If fail to reject, then unit root is present (not stationary)

ADF Tests – Lag Length

- VARselect(soydiesel\$lnbio, lag.max = 5)\$select

```
> VARselect(soydiesel$lnbio, lag.max = 5)$select
AIC(n)  HQ(n)  SC(n)  FPE(n)
    4      1      1      4
> VARselect(soydiesel$lnbio, lag.max = 5)
$selection
AIC(n)  HQ(n)  SC(n) Value of test-statistic is: 0.3569
    4      1
Critical values for test statistics:
      1pct  5pct 10pct
$criteria tau1 -2.58 -1.95 -1.62
    1      4      5
AIC(n) -6.761081153 -6.761597249 -6.760340277 -6.765082550 -6.762501692
HQ(n)  -6.756426556 -6.754615354 -6.751031084 -6.753446059 -6.748537902
SC(n)  -6.748987950 -6.743457445 -6.736153872 -6.734849544 -6.726222085
FPE(n)  0.001157977  0.001157379  0.001158835  0.001153352  0.001156333
```

ADF Tests – Log Prices

```
summary(ur.df(soydiesel$lnbio, type = c("trend"), lags = 4))
```

```
summary(ur.df(soydiesel$lnbio, type = c("drift"), lags = 4))
```

```
summary(ur.df(soydiesel$lnbio, type = c("none"), lags = 4))
```

```
Value of test-statistic is: -1.5295 1.0646 1.3833
```

```
Critical values for test statistics:
```

	1pct	5pct	10pct
tau3	-3.96	-3.41	-3.12
phi2	6.09	4.68	4.03
phi3	8.27	6.25	5.34

```
Value of test-statistic is: -1.6272 1.5378
```

```
Critical values for test statistics:
```

	1pct	5pct	10pct
tau2	-3.43	-2.86	-2.57
phi1	6.43	4.59	3.78

```
Value of test-statistic is: 0.3569
```

```
Critical values for test statistics:
```

	1pct	5pct	10pct
tau1	-2.58	-1.95	-1.62

ADF Tests – First Difference

```
VARselect(diff.xts(soydiesel$lnbio, na.pad = F), lag.max = 5)$select  
summary(ur.df(diff.xts(soydiesel$lnbio, na.pad = F), type = c("trend"), lags = 3))
```

```
Value of test-statistic is: -12.9334 55.7676 83.6491
```

```
Critical values for test statistics:
```

	1pct	5pct	10pct
tau3	-3.96	-3.41	-3.12
phi2	6.09	4.68	4.03
phi3	8.27	6.25	5.34

Roadmap

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Engle Granger Method

- We meet the necessary condition that prices in levels are $I(1)$ and prices in first differences are $I(0)$
- Step 1 – estimate the longrun relationship between biodiesel and soybean oil
- Collect the residuals
- Step 2 – run an ADF test on the residuals

Engle Granger Method

- Step 1 – estimate the longrun relationship between biodiesel and soybean oil

$$PBioDiesel_t = \alpha + \beta PSoyoil_t + \varepsilon_t$$

```
reg_Inbiodieselsoy <- lm(lnbio ~ lnsoy, data = soydiesel)
```

```
summary(reg_Inbiodieselsoy)
```

```
Call:
lm(formula = lnbio ~ lnsoy, data = soydiesel)

Residuals:
    Min       1Q   Median       3Q      Max
-0.17870 -0.04941 -0.01361  0.03892  0.26583

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept) -1.542059   0.035108  -43.92  <2e-16 ***
lnsoy         0.773298   0.009579   80.72  <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.07578 on 771 degrees of freedom
Multiple R-squared:  0.8942,    Adjusted R-squared:  0.8941
F-statistic: 6517 on 1 and 771 DF,  p-value: < 2.2e-16
```

Engle Granger Method

- Collect the residuals from the previous regression
- In R, (1) save the residuals, (2) convert residuals to ts object, (3) merge to soydiesel

```
resid_Insoydiesel <- resid(reg_Inbiodieselsoy)
```

```
Inresid_ts <- xts(resid_Insoydiesel, order.by = index(soydiesel))
```

Will use this term later in ECM

```
soydieselr <- merge.xts(soydiesel, Inresid_ts)
```

```
> head(soydieselr)
```

	biodiesel	soyoil	diesel	lnbio	lnsoy	Indiesel	lncrude	lnresid_ts
2007-04-13	3.100	29.900	2.877	1.131402	3.397858	1.056748	4.136446	0.045904189
2007-04-20	3.100	29.310	2.851	1.131402	3.377929	1.047670	4.144087	0.061315803
2007-04-27	3.075	30.190	2.811	1.123305	3.407511	1.033540	4.178379	0.030342904
2007-05-04	3.140	31.130	2.792	1.144223	3.438172	1.026758	4.156067	0.027550531
2007-05-11	3.140	31.060	2.773	1.144223	3.435921	1.019930	4.125520	0.029291353
2007-05-18	3.175	32.865	2.803	1.155308	3.492408	1.030690	4.152771	-0.003305434

Format regression output

```
models <- list(  
  "Biodiesel-Soy (Log)" = lm(lnbio ~ lnsoy, data = soydiesel)  
)  
modelsummary(models, estimate = "{estimate}{stars}")
```

Biodiesel-Soy (Log)	
(Intercept)	-1.542***
	(0.035)
lnsoy	0.773***
	(0.010)
Num.Obs.	773
R2	0.894
R2 Adj.	0.894
AIC	-1790.9
BIC	-1776.9
Log.Lik.	898.437
F	6516.511

Engle Granger Method

- Step 2 – run an ADF test for a unit root on the residuals
 - No need to use time trend or intercept because, by construction, the residuals will have a zero mean
 - If we reject the null hypothesis of a unit root, then we conclude that the two price series are cointegrated

```
VARselect(soydieselr$lnresid_ts)$select
```

```
summary(ur.df(soydieselr$lnresid_ts, type = c("none"), lags = 3))@teststat
```

```
Value of test-statistic is: -3.6603
```

```
Critical values for test statistics:
```

```
      1pct   5pct  10pct  
tau1 -2.58 -1.95 -1.62
```

Interpretation

- It **appears** that we can reject the unit root null hypothesis
- But this is **not correct** because we must use different critical values

Engle Granger Method

- Stata gives the correct critical values as part of the **egranger** test, but R does not
- We wrote an R function that will give you the correct critical values

englegranger(var, trend, n)

- var = # of variables, in our case **2** (biodiesel and soybean oil)
- trend = **0** if no trend in step 1 regression, 1 if we included a trend in step 1 regression
- n = number of observations = **773**

```
> englegranger(2, 0, 773)
$crit1
[1] -3.913778

$crit5
[1] -3.345434

$crit10
[1] -3.051473
```

Engle Granger Method

- `summary(ur.df(soydieselr$lnresid_ts, type = c("none"), lags = 3))@teststat`
- We must compare the t-statistic of -3.6603 with the critical values of -3.91 (1%), -3.34 (5%), -3.05 (10%). We can reject the null hypothesis of a unit root at the 5% level.
- We have evidence that the biodiesel and soybean oil prices are cointegrated

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Testing for cointegration with multiple prices

```
jotest <- soydiesel[,c("Incrude", "Indiesel", "Inbio", "Insoy")]
```

```
VARselect(jotest, lag.max = 10)
```

```
summary(ca.jo(jotest, type = c("trace"), ecdet = c("none"), K = 3, spec = c("transitory")))
```

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

```
Test type: trace statistic , with linear trend
```

```
Eigenvalues (lambda):
```

```
[1] 0.041681178 0.031194654 0.014892591 0.006756065
```

```
Values of teststatistic and critical values of test:
```

	test	10pct	5pct	1pct
r ≤ 3	5.22	6.50	8.18	11.65
r ≤ 2	16.77	15.66	17.95	23.52
r ≤ 1	41.18	28.71	31.52	37.22
r = 0	73.96	45.23	48.28	55.43

Interpretation

- We work from the bottom row to top, and stop only when it is no longer possible to reject the null
- $r = 0$ -> reject null of rank 0
- $r \leq 1$ -> reject null of rank ≤ 1
- $r \leq 2$ -> reject null at 90% confidence

Testing for cointegration with multiple prices

- Note that there is a difference in critical values across programs (read [here](#) and [here](#) for more info); trace statistic is the same though.
- But the important thing is that we reject the null that there is no cointegrating relationship.

```
. vecrank lncrude lndiesel lnbio lnsoy, lags(3)
```

Johansen tests for cointegration

Trend: constant

Sample: 4 - 773

Number of obs = 770

Lags = 3

					5%
maximum				trace	critical
rank	parms	LL	eigenvalue	statistic	value
0	36	6397.9106	.	73.9584	47.21
1	43	6414.3019	0.04168	41.1759	29.68
2	48	6426.5032	0.03119	16.7734	15.41
3	51	6432.2799	0.01489	5.2198	3.76
4	52	6434.8899	0.00676		

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

Test type: trace statistic , with linear trend

Eigenvalues (lambda):

[1] 0.041681178 0.031194654 0.014892591 0.006756065

Values of teststatistic and critical values of test:

	test	10pct	5pct	1pct
r <= 3	5.22	6.50	8.18	11.65
r <= 2	16.77	15.66	17.95	23.52
r <= 1	41.18	28.71	31.52	37.22
r = 0	73.96	45.23	48.28	55.43

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Error Correction Model

- So far we have established that
 - Biodiesel and soybean are non-stationary
 - First difference of biodiesel and soybean oil are stationary, i.e. $I(1)$
 - Estimated $\mathbf{PBioDiesel_t = \alpha + \beta PSoyoil_t + \varepsilon_t}$
 - Collected the residuals and did an ADF test -> reject null hypothesis of a unit root
 - Biodiesel and soybean are cointegrated
- We now want to investigate how quickly prices return to the long run equilibrium if one or both variables experience a shock – error correction model

Error Correction Model

- $Pbiodiesel_t = \alpha + \beta Psoy oil_t + \varepsilon_t$
 - $\varepsilon_t = resid_t = Pbiodiesel_t - \alpha - \beta Psoy oil_t$
- Enhanced ECM
 - $\Delta Pbiodiesel_t = \alpha + \sum_{i=1}^k \beta_i \Delta Pbiodiesel_{t-i} + \sum_{j=0}^l \gamma_j \Delta soy oil_{t-j} + \lambda * resid_{t-1} + \epsilon_t$
- In the lecture, you will learn that λ is the deviation from the LR equilibrium
 - Negative sign
 - Has a value between -1 and 0

Error Correction Model

- Step Pre: Determine the optimal number of lags (i.e., k).
- Step One: Regress y_{t-1} on x_{t-1} to estimate the long run relationship and then collect the residuals.
 - Or regress y_t on x_t , save the residuals, and lag the residuals
- Step Two: Estimate the general ECM with the appropriate number of lags.

Error Correction Model

- Step Pre: Determine the optimal number of lags
 - `VARselect(soydieselr$lnbio, lag.max = 5)` -> 4 lags
 - `VARselect(soydieselr$lnsoy, lag.max = 5)` -> 1 lag
- Step 1: regress y_t on x_t , save the residuals, and lag the residuals
 - `lag.xts(lnresid_ts)`

Error Correction Model

- Step Two: Estimate the general ECM with the appropriate number of lags.

```
ecm <- lm(diff.xts(lnbio, na.pad = T) ~
```

```
  lag.xts(diff.xts(lnbio, na.pad = T)) +
```

```
  lag.xts(lag.xts(diff.xts(lnbio, na.pad = T))) +
```

```
  lag.xts(lag.xts(lag.xts(diff.xts(lnbio, na.pad = T)))) +
```

```
  lag.xts(lag.xts(lag.xts(lag.xts(diff.xts(lnbio, na.pad = T))))) +
```

```
  diff.xts(lnsoy, na.pad = T) +
```

→ Include Δx_t -- see notes for discussion

```
  lag.xts(diff.xts(lnsoy, na.pad = T)) +
```

→ 1 lag for biodiesel

```
  lag.xts(lnresid_ts), data = soydieselsr)
```

→ error correction term / speed of adjustment

} 4 lags for biodiesel

Error Correction Model

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)	
(Intercept)	0.000178	0.001011	0.176	0.8603	
lag.xts(diff.xts(lnbio, na.pad = T))	-0.212774	0.035473	-5.998	3.09e-09	***
lag.xts(lag.xts(diff.xts(lnbio, na.pad = T)))	-0.025750	0.030394	-0.847	0.3971	
lag.xts(lag.xts(lag.xts(diff.xts(lnbio, na.pad = T))))	0.051046	0.029941	1.705	0.0886	.
lag.xts(lag.xts(lag.xts(lag.xts(diff.xts(lnbio, na.pad = T)))))	0.022265	0.029963	0.743	0.4577	
diff.xts(lnsoy, na.pad = T)	0.494722	0.029281	16.896	< 2e-16	***
lag.xts(diff.xts(lnsoy, na.pad = T))	0.186336	0.034879	5.342	1.21e-07	***
lag.xts(lnresid_ts)	-0.071474	0.013759	-5.195	2.64e-07	***

Summary

- Review - ADF Tests
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