

Lab 2

Stationarity and Cointegration

Case study of biodiesel fuel and soybean oil

Roadmap

- Stationarity Tests - Levels
 - Dickey Fuller test
 - Augmented Dickey Fuller test
 - Lags
 - Flow chart of testing specification
- Stationarity Tests – First differences
- Cointegration
 - Engle Granger 2 step test
 - Engle Granger function to retrieve correct critical values
 - Johansen Procedure

Packages

- Load the following packages

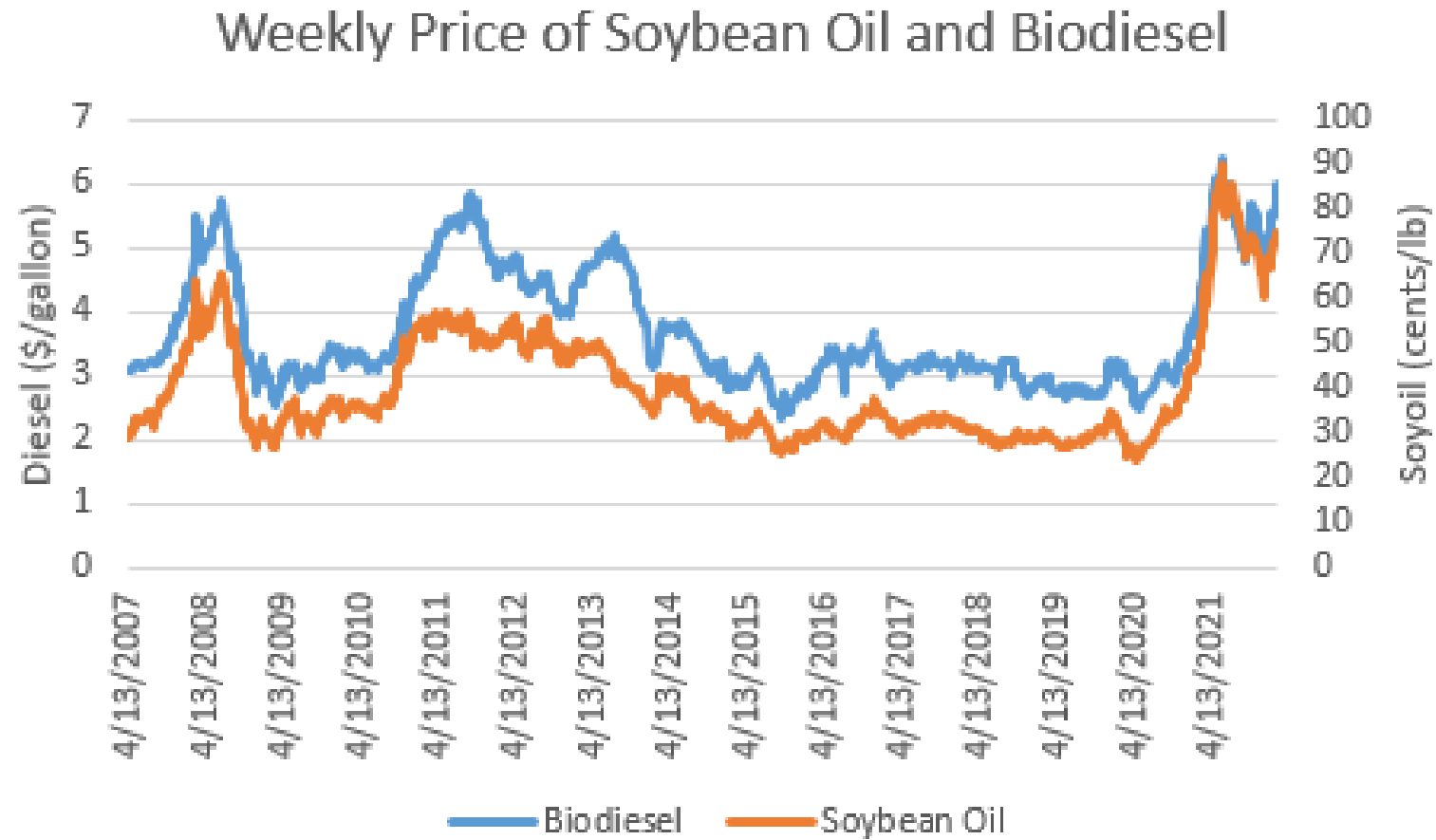
`pacman::p_load(here, readxl, dplyr, janitor, Quandl, xts, lubridate, urca, forecast, tidyverse, vars)`

Data

- Data sources
 - Biodiesel and soybean oil – [Iowa State University](#)
 - Diesel – [U.S. EIA](#)
 - Crude – [U.S. EIA](#)
- Load `data_lecture2.csv` posted on Canvas

```
> head(data)
# A tibble: 6 x 5
  date      biodiesel soyoil  diesel  crude
<chr>      <dbl>   <dbl>   <dbl> <dbl>
1 4/13/2007    3.1    29.9    2.88  62.6
2 4/20/2007    3.1    29.3    2.85  63.1
3 4/27/2007    3.08   30.2    2.81  65.3
4 5/4/2007     3.14   31.1    2.79  63.8
5 5/11/2007    3.14   31.1    2.77  61.9
6 5/18/2007    3.18   32.9    2.80  63.6
```

Data



Data Cleaning

```
data <- data %>%
```

```
  mutate(date = mdy(date),
```

```
    lnbio = log(biodiesel),
```

```
    lnsoy = log(soyoil),
```

```
    lndiesel = log(diesel),
```

```
    ln crude = log(crude))
```

```
soydiesel <- xts(data[,c("biodiesel", "soyoil", "diesel", "lnbio", "lnsoy", "lndiesel", "ln crude")], order.by = data$date)
```

```
> head(soydiesel)
```

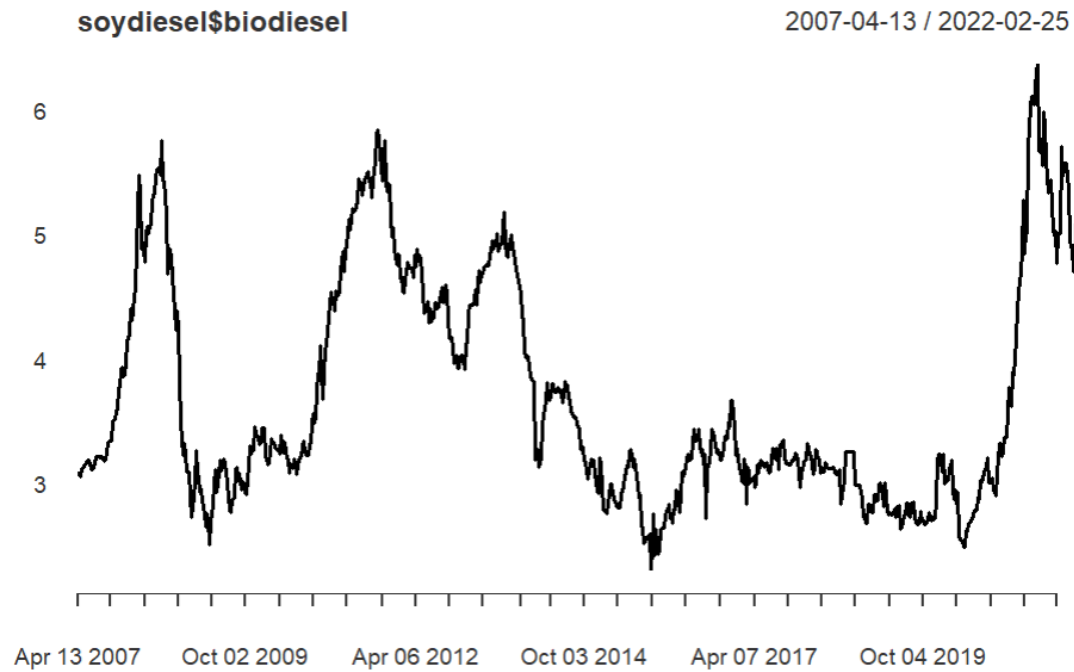
	biodiesel	soyoil	diesel	lnbio	lnsoy	lndiesel	ln crude
2007-04-13	3.100	29.900	2.877	1.131402	3.397858	1.056748	4.136446
2007-04-20	3.100	29.310	2.851	1.131402	3.377929	1.047670	4.144087
2007-04-27	3.075	30.190	2.811	1.123305	3.407511	1.033540	4.178379
2007-05-04	3.140	31.130	2.792	1.144223	3.438172	1.026758	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

Dickey-Fuller Test

- General model: $y_t = \alpha + \delta t + \rho y_{t-1} + u_t$
- We wish to test the null hypothesis that S_t is a random walk, which is equivalent to testing that y_t has a unit root $\rightarrow \rho = 1$
- The unit root test is known as the Dickey-Fuller test
- We will use the `ur.df()` function of the `{urca}` package

`ur.df(y, type = c("none"), lags = 0)`

Dickey-Fuller Test



R – Dickey Fuller Test

```
df_biodiesel <- ur.df(soydiesel$biodiesel, type = c("none"), lags = 0)
```

```
summary(df_biodiesel)
```

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

```
Test regression none
```

```
Call:  
lm(formula = z.diff ~ z.lag.1 - 1)
```

```
Residuals:  
    Min       1Q   Median       3Q      Max   
-0.68384 -0.05700 -0.00171  0.06738  0.69698
```

```
Coefficients:  
             Estimate Std. Error t value Pr(>|t|)      
z.lag.1  0.0006016   0.0012122   0.496   0.62
```

```
Residual standard error: 0.1287 on 771 degrees of freedom  
Multiple R-squared:  0.0003194, Adjusted R-squared:  -0.0009772  
F-statistic: 0.2463 on 1 and 771 DF,  p-value: 0.6198
```

```
Value of test-statistic is: 0.4963
```

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

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

Interpretation

- Absolute value of τ_1 t-statistic is smaller than the absolute value of the critical values
- Fail to reject the null hypothesis of a unit root
- Biodiesel price is not stationray

Augmented Dickey-Fuller (ADF) test

$$y_t = \alpha + \delta t + \rho y_{t-1} + u_t$$

- In recent years an Augmented Dickey Fuller (ADF) test has been developed to account for potential autocorrelation in the residuals

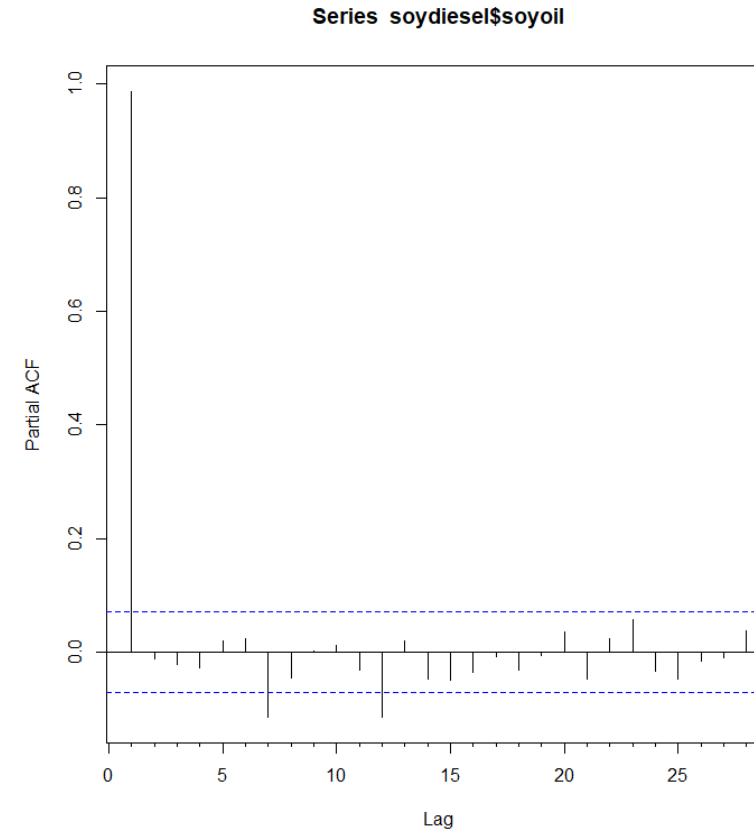
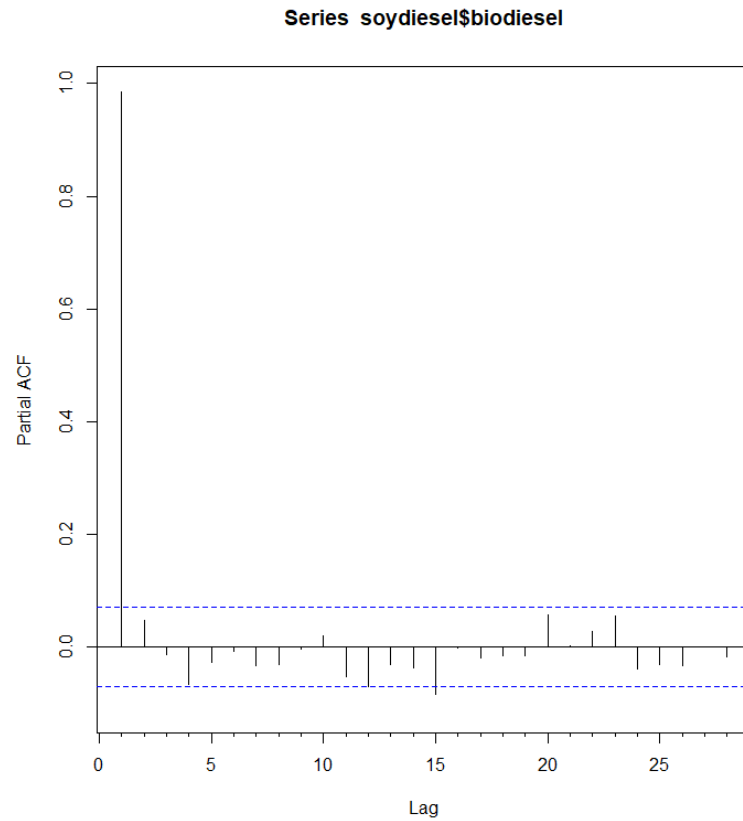
$$\Delta y_t = \alpha + \delta t + \beta y_{t-1} + \sum_{i=1}^k \tau_i \Delta y_{t-i} + \varepsilon_t$$

- We will use the `ur.df()` function of the {urca} package

`ur.df(y, type = c("trend", "drift"), lags = 5, selectlags = c("AIC"))`

Lag length selection

- Partial autocorrelation function – **Pacf()**



Lag length selection

- `{urca}`'s automatic lag selection functionality
- `summary(ur.df(soydiesel$biodiesel, type = c("none"), lags = 4, selectlags = c("AIC")))`

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

Residuals:
    Min       1Q   Median       3Q      Max
-0.69096 -0.05993  0.00111  0.06862  0.72149

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
z.lag.1      0.0004404  0.0012178   0.362   0.7178
z.diff.lag1 -0.0268090  0.0362382  -0.740   0.4596
z.diff.lag2  0.0530633  0.0362628   1.463   0.1438
z.diff.lag3  0.0767265  0.0363048   2.113   0.0349 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.1287 on 764 degrees of freedom
Multiple R-squared:  0.009252, Adjusted R-squared:  0.004065
F-statistic: 1.784 on 4 and 764 DF, p-value: 0.1302

Value of test-statistic is: 0.3616

Critical values for test statistics:
      1pct  5pct 10pct
tau1 -2.58 -1.95 -1.62
```

Lag length selection

- [`VARselect\(\)`](#) function of the `{var}` package
 - Select lag length with lowest AIC
- **`VARselect(soydiesel$biodiesel, lag.max = 5)`**

```
$criteria
      1      2      3      4      5
AIC(n) -4.09451821 -4.09233331 -4.09269044 -4.09662299 -4.09465117
HQ(n)   -4.08986361 -4.08535141 -4.08338124 -4.08498650 -4.08068738
SC(n)   -4.08242501 -4.07419350 -4.06850403 -4.06638998 -4.05837156
FPE(n)  0.01666377 0.01670022 0.01669426 0.01662874 0.01666156
```

- **`VARselect(soydiesel$soyoil, lag.max = 5)`**

```
$criteria
      1      2      3      4      5
AIC(n) 0.9274930 0.9295556 0.9277867 0.9293476 0.9318206
HQ(n)  0.9321476 0.9365375 0.9370959 0.9409841 0.9457843
SC(n)  0.9395862 0.9476954 0.9519731 0.9595806 0.9681002
FPE(n) 2.5281630 2.5333832 2.5289060 2.5328567 2.5391284
```

1. Test $\beta = 0$ in full model with intercept and time trend →
(use “trend” option and τ_3 test in R)

$$\Delta y_t = \alpha + \delta t + \beta y_{t-1} + \sum_{i=1}^k \tau_i \Delta y_{t-i} + \varepsilon_t$$

Reject
(no unit
root)

No Reject

2. Test significance of time trend ($\delta = 0$) in full model. → Use “trend” option and Φ_3 test in R.

Reject
(no unit
root)

No Reject
(remove and
re-estimate)

→ Use the “drift” option to re-estimate without a trend.

3. Test $\beta = 0$ in model with intercept and not trend. → Use the τ_2 test in R.

Reject
(no unit
root)

No Reject

4. Test significance of constant ($\alpha = 0$) → Use “drift” option and Φ_1 test in R.

Reject
(no unit
root)

No Reject (remove
and re-estimate)

→ Use the “no constant” option to re-estimate without an intercept.

5. Test $\beta = 0$ Use τ_1 test in R.

Reject: no unit root

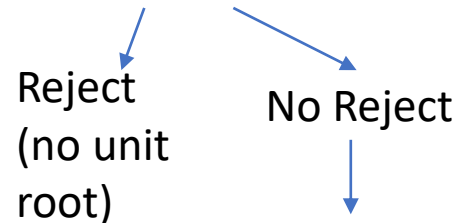
No Reject: unit root

ADF test – Step 1

$$\Delta y_t = \alpha + \delta t + \beta y_{t-1} + \sum_{i=1}^k \tau_i \Delta y_{t-i} + \varepsilon_t$$

1. Test $\beta = 0$ in full model with intercept and time trend

(use “trend” option and τ_3 test in R)



2. Test significance of time trend ($\delta = 0$) in full model.

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

```
Value of test-statistic is: -1.419 1.0367 1.2969
```

```
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

Interpretation

- Absolute value of τ_3 t-statistic is smaller than the absolute value of the critical values
- Fail to reject $\beta = 0$ null hypothesis
- Proceed with Step 2

ADF test – Step 2

$$\Delta y_t = \alpha + \delta t + \beta y_{t-1} + \sum_{i=1}^k \tau_i \Delta y_{t-i} + \varepsilon_t$$

2. Test significance of time trend ($\delta = 0$) in full model. → Use “trend” option and Φ_3 test in R.

Reject
(no unit
root)

No Reject
(remove and
re-estimate)

→ Use the “drift” option to re-estimate without a trend.

3. Test $\beta = 0$ in model with intercept and not trend.

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

```
Value of test-statistic is: -1.419 1.0367 1.2969
```

```
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

Interpretation

- Absolute value of the Φ_3 t-statistic is smaller than the critical values
- Fail to reject the null hypothesis that time trend is not significant
- Proceed with Step 3

ADF test – Step 3

$$\Delta y_t = \alpha + \delta t + \beta y_{t-1} + \sum_{i=1}^k \tau_i \Delta y_{t-i} + \varepsilon_t$$

Use the “drift” option to re-estimate without a trend.

3. Test $\beta = 0$ in model with intercept and not trend.

→ Use the τ_2 test in R.

Reject
(no unit
root)

No Reject

4. Test significance of constant ($\alpha = 0$)

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

Value of test-statistic is: **-1.5242** 1.4199

Critical values for test statistics:

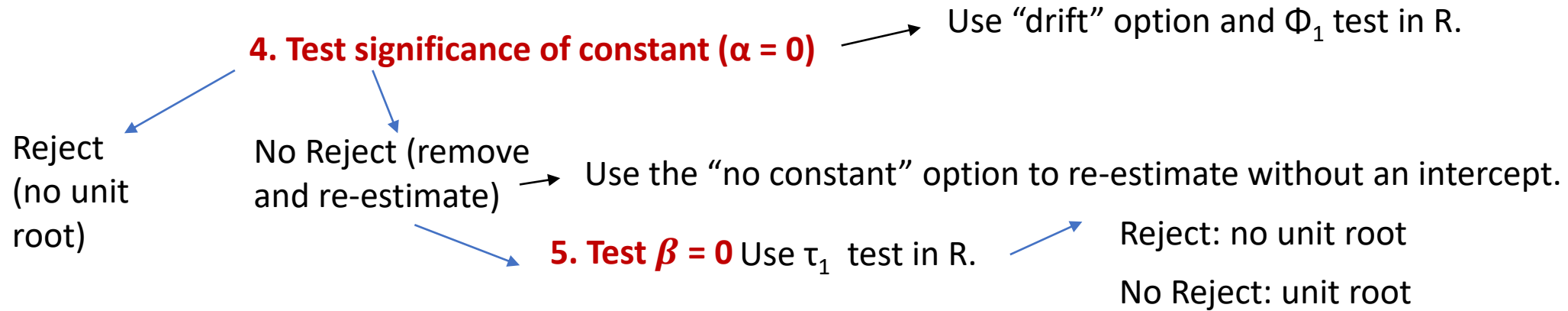
	1pct	5pct	10pct
tau2	-3.43	-2.86	-2.57
phi1	6.43	4.59	3.78

Interpretation

- We removed the time trend and retest the $\beta = 0$ null hypothesis.
- Absolute value of the τ_2 t-statistic is smaller than the critical values
- Fail to reject the $\beta = 0$ null hypothesis
- Proceed with Step 4

ADF test – Step 4

$$\Delta y_t = \alpha + \delta t + \beta y_{t-1} + \sum_{i=1}^k \tau_i \Delta y_{t-i} + \varepsilon_t$$



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

```
Value of test-statistic is: -1.5242 1.4199
```

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

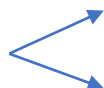
	1pct	5pct	10pct
tau2	-3.43	-2.86	-2.57
phi1	6.43	4.59	3.78

Interpretation

- Absolute value of the Φ_2 t-statistic is smaller than the critical values
- Fail to reject the null hypothesis that the intercept term is not significant
- Proceed with Step 5

ADF test – Step 5

Use the “no constant” option to re-estimate without an intercept.

5. Test $\beta = 0$ Use τ_1 test in R. 
Reject: no unit root
No Reject: unit root

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

```
Value of test-statistic is: 0.3367  
  
Critical values for test statistics:  
      1pct   5pct  10pct  
tau1 -2.58 -1.95 -1.62
```

Interpretation

- We removed the intercept and retest the $\beta = 0$ null hypothesis
- Absolute value of the τ_1 t-statistic is smaller than the critical values
- We fail to reject the null hypothesis
- We conclude that biodiesel has a unit root and is therefore non-stationary

ADF test – output in lecture notes

Pbiodiesel_t

Test Type	Test Statistic	1% Critical	5% Critical	10% Critical
No Constant	0.337	-2.580	-1.950	-1.620
Drift	-1.524	-3.430	-2.860	-2.570
Trend	-1.419	-3.960	-3.410	-3.120

Fail to reject unit root with all testing types and all three levels of significance.

PSoyoil_t

Test Type	Test Statistic	1% Critical	5% Critical	10% Critical
No Constant	0.722	-2.580	-1.950	-1.620
Drift	-0.815	-3.430	-2.860	-2.570
Trend	-0.783	-3.960	-3.410	-3.120

Fail to reject unit root with all testing types and all three levels of significance.

Roadmap

- Stationarity Tests - Levels
 - Dickey Fuller test
 - Augmented Dickey Fuller test
 - Lags
 - Flow chart of testing specification
- Stationarity Tests – First differences
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 - Engle Granger function to retrieve correct critical values
 - Johansen Procedure

First difference

- To take the difference, we use **diff.xts()**

biodiesel	d_biodiesel
<dbl>	<dbl>
3.1	NA
3.1	0
3.08	-0.02
3.14	0.06
3.14	0
3.18	0.03

ADF test – Step 1 (biodiesel)

```
VARselect(diff.xts(soydiesel$biodiesel, na.pad = F), lag.max = 5)
```

```
summary(ur.df(diff.xts(soydiesel$biodiesel, na.pad = F), type = c("trend"), lags = 3))
```

```
Value of test-statistic is: -12.4258 51.488 77.2258
```

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

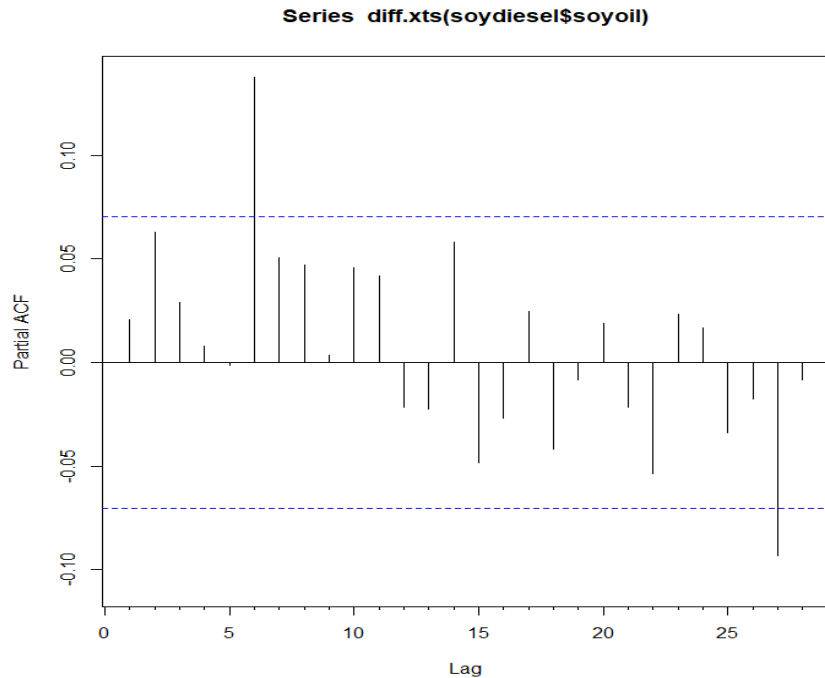
	1pct	5pct	10pct
tau3	-3.96	-3.41	-3.12
phi2	6.09	4.68	4.03
phi3	8.27	6.25	5.34

Interpretation

- Absolute value of τ_3 t-statistic is bigger than the absolute value of the critical values
- Reject the unit root null hypothesis
- Differenced price series is $I(0)$ stationary
- Not necessary to proceed with next steps
- If you do, you will still arrive at the same conclusion

ADF test – Step 1 (soybean oil)

- R's VARselect() function does not allow for lags = 0. Output suggests lags = 2
- Stata's varsoc function does, and the output suggests lags = 0
- Partial autocorrelation function suggests lags = 0



Value of test-statistic is: -27.1734 246.1313 369.1964

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

Interpretation

- Differenced price series is $I(0)$ stationary

Roadmap

- Stationarity Tests - Levels
 - Dickey Fuller test
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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_biodieselsoy <- lm(biodiesel ~ soyoil, data = soydiesel)
```

```
summary(reg_biodieselsoy)
```

```
Residuals:
    Min       1Q   Median       3Q      Max
-1.05258 -0.18850 -0.06624  0.14424  1.30709

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept)  1.0332423   0.0400385   25.81  <2e-16 ***
soyoil       0.0664150   0.0009456   70.23  <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_soydiesel <- resid(reg_biodieselsoy)
```

```
resid_ts <- xts(resid_soydiesel, order.by = index(soydiesel))
```

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

	biodiesel	soyoil	diesel	lnbio	lnsoy	Indiesel	lncrude	resid_ts
2007-04-13	3.100	29.900	2.877	1.131402	3.397858	1.056748	4.136446	0.08094869
2007-04-20	3.100	29.310	2.851	1.131402	3.377929	1.047670	4.144087	0.12013355
2007-04-27	3.075	30.190	2.811	1.123305	3.407511	1.033540	4.178379	0.03668834
2007-05-04	3.140	31.130	2.792	1.144223	3.438172	1.026758	4.156067	0.03925822
2007-05-11	3.140	31.060	2.773	1.144223	3.435921	1.019930	4.125520	0.04390728
2007-05-18	3.175	32.865	2.803	1.155308	3.492408	1.030690	4.152771	-0.04097183

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$resid_ts)`

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

```
Value of test-statistic is: -3.0262

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

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

$crit5
[1] -3.345434

$crit10
[1] -3.051473
```

Engle Granger Method

- We must compare the t-statistic of -3.0262 with the critical values of -3.91 (1%), -3.34 (5%), -3.05 (10%). The absolute value of the test statistic is smaller than the absolute values of the critical values, so we fail to reject the null hypothesis of a unit root.
- We find no evidence that biodiesel fuel and soybean oil prices are cointegrated

```
Value of test-statistic is: -3.0262
```

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

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

```
> englegranger(2, 0, 773)
```

```
$crit1  
[1] -3.913778
```

```
$crit5  
[1] -3.345434
```

```
$crit10  
[1] -3.051473
```

Retest for cointegration using log prices

- We will now work with log of prices – address skewed nature of price data
- Step 1
 - `reg_Inbiodieselsoy <- lm(lnbio ~ lnsoy, data = soydiesel)`
 - `summary(reg_Inbiodieselsoy)`
 - `resid_Insoydiesel <- resid(reg_Inbiodieselsoy)`
 - `lnresid_ts <- xts(resid_Insoydiesel, order.by = index(soydiesel))`
 - `soydieselr <- merge.xts(soydiesel, lnresid_ts)`

Retest for cointegration using log prices

- Step 2
 - `VARselect(soydieselr$lnresid_ts)`
 - `summary(ur.df(soydieselr$lnresid_ts, type = c("none"), lags = 3))`
 - `englegranger(2, 0, 773)`
- We can reject the null hypothesis of a unit root at the 95% confidence level. We have evidence that the pair of prices are cointegrated.

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

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

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

```
> englegranger(2, 0, 773)
```

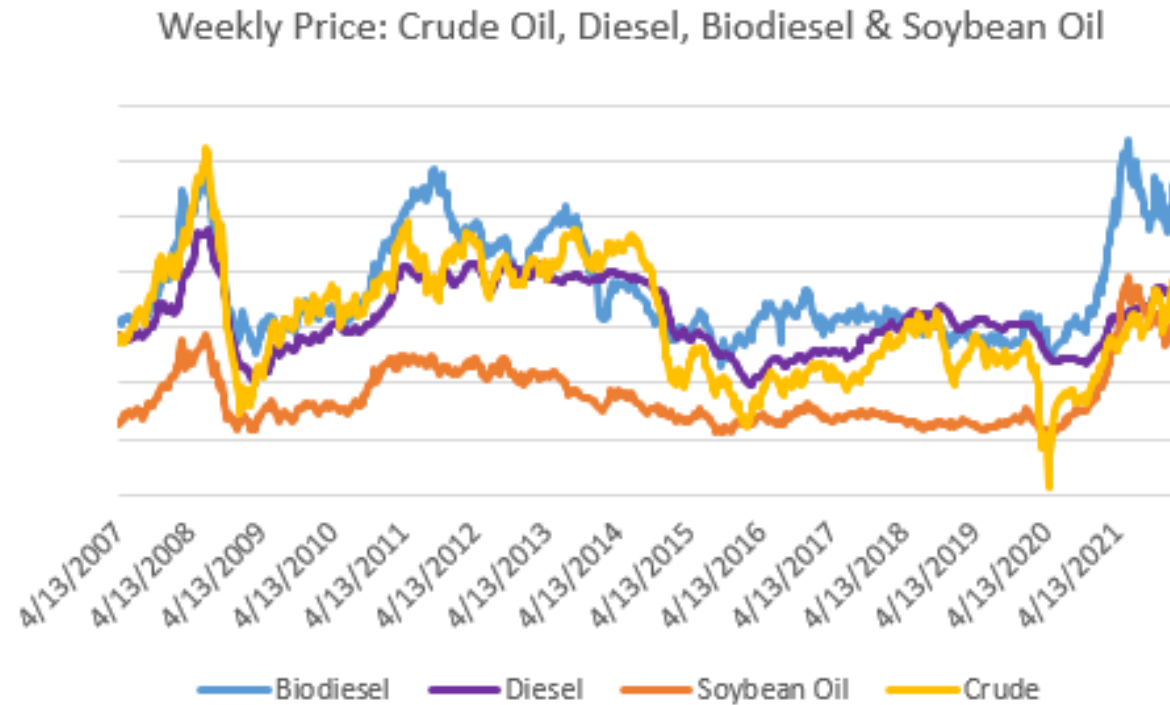
```
$crit1  
[1] -3.913778
```

```
$crit5  
[1] -3.345434
```

```
$crit10  
[1] -3.051473
```

Testing for cointegration with multiple prices

- Let's say we want to test for the cointegration of crude oil, diesel, biodiesel, and soybean oil
- We use the Johansen Procedure to test the cointegration of more than two data series.



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          Number of obs = 770
Sample: 4 - 773          Lags = 3
```

maximum				trace	5%
rank	parms	LL	eigenvalue	statistic	critical
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

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Summary

- Stationarity Tests – DF and ADF tests in R
 - `VARselect(y, lag.max = n)`
 - `ur.df(y, type = c("none", "trend", "drift"), lags = n)`
 - `ur.df(diff.xts(y, na.pad = F), type = c("none", "trend", "drift"), lags = n)`
- Cointegration
 - Step 1 – estimate the long run relationship between prices
 - Collect the residuals
 - Step 2 – conduct an ADF test on residuals and use correct critical values
 - Johansen Procedure
 - Tests for cointegration of more than 2 data series