eman ta zabal zazu

Universidad del País Vasco   Euskal Herriko Unibertsitatea

EAP MASTER

FACULTY OF ECONOMICS

Pedro Iraburu Muñoz

ENERGY MARKETS:

Time Series Analysis of the German Market

6th of April, 2020

Marbella

Understanding Temporal Series of Energy Markets in Germany

Pedro Iraburu Muñoz

06/04/2020

Abstract:

In this short project we analyze the prices of electricity of 2015 in Germany, by computing different measures and the VARs for those that are truly stationary, after doing normal distributions and uniroot tests, such as the Augmented Dickey Fuller one. A significance level of 1% is taken into account.

Keywords: Germany, Energy Markets, VAR.

1.0 Introduction of the German-Austrian Market

The German-Austrian Market was the largest cross border market in Europe (Clean Energy Wire, 2015), and was set up in 2002. This had been stated as a very important step to the total integration of all electricity markets across countries in Europe. In spite of this, the union had also carried negative effects: when Germany had an over-production, it sold very cheap energy to neighbor countries, such as Poland, Hungary and Slovakia, bringing ”unwelcome side effects”.

After complaints from Central Europe, like the Polish Operator URE (Politico, 2018), the Agency for the Co-operation of Energy Regulators (ACER), stated that ”German-Austrian interconnectors were not sufficient to accommodate all traded electricity” and thus, power often flooded to other countries. The electrical agencies from both countries, ”Bundesnetzagentur” from Germany, and ”E-control” from Austria, said that they would follow the request.

This split happened on the 30th of September of 2018, with Germany and Luxembourg on the one hand, and Austria on the other. As I stated before, this was made in order to protect the power markets of the Eastern European markets (Genscape, 2018). As the article states, this was necessary ”to circumvent German loop flows, and to ease bottlenecks in their region. In times of congestion, excess electricity could flow from northern Germany through east European grids into Austria or southern Germany, looping around the blockage.” ACER estimates that the loss in revenues for both Poland and the Czech Republic was around 25 million euros a year.

As the prices come from the year 2015, the split had not happened yet. Following the APG explanation of the model for electricity price zones, the deregulated energy market is essentially made up of two groups, the participants[1], and the system operators: the infrastructure (APG, 2020). Each country has its bidding zone, where no congestion can occur, that is, energy can be exchanged freely within its limits. Since the liberalization of the European electricity markets in 2001, almost all bidding zones were the national borders. What makes this specific distribution is that the cross-border interconnectors are only available to a limited extent.

The price formation in Germany, extracted from the European Comission, ”Overview of European Electricity Markets”, involves two power exchanges: EPEX SPOT for day-ahead and intraday markets, and EEX for forward products. The day-ahead market has uniform pricing, with 164 registered participants, where the auctions take place at 12pm each day in 24 hours intervals. Prices can be negative, ranging between -500 and 3000 euros per Megawatt per hour. In the intraday market, the price is also uniform, with 15 minute contracts. The auctions starts at 3 pm on the current day, where all the hours of the next day can be traded, and at 4pm to trade 15 minute periods. The prices range between -3000 and 3000 euros per Megawatt per hour.

[1] Involving the generation, the trading and the sales of electricity.

2.0 Descriptive Statistics

In order to properly understand the data I am analyzing (extracted from Egela, unknown source), we need first to take a look at the descriptive statistics. For this dataset, I will compute the mean, median, and the standard deviation, among others. These will be displayed in the table [1].

Table 1: Summary Statistics

	pt	*ln*(pt+pt^2+*1*)
Mean	31.6285	6.7583
Median	30.5400	6.8719
Std. Dev.	12.6643	1.0687
E. K.	5.7665	17.7993
C. A.	-0.3061	-2.9747
Min	-79.940	-0.2498
Max	99.770	9.2158
J-B (p.value)	0.0000	0.0000

Source: selfmade with R code.

Computing the logarithms of the prices can be useful to ease the analysis of the data. Before doing any further step, I check if there are any negative values[2]. As this is true (there are 126 negative prices), instead of calculating the logarithm of prices we calculate:

$$ln(pt + pt^2 + 1). \tag{1}$$

As seen in table [1], the mean of the prices is 31.68 E/kwh[3], and 6.75 E/kwh if we take the logarithm expression described above. Both medians are very close to the mean values. If we analyze the standard deviation, we can appreciate that is much bigger (relatively) at the first column, than in the second: the logarithmic expression has diminished considerably the volatility.

After these standard statistics comes the Excess of Kurtosis, and the Coefficient of Assymetry:

- Kurtosis is a measure of ”peakedness” (Stata Journal, 2020). More specifically, it measures how heavyly is the data distributed on the tails of the distribution. The so-called, Excess of Kurtosis, compares the value obtained with the statistic to 3, which is the one expected from a normal distribution. By taking the obtained value (5.766 and 17.799 respectively) and subtracting 3, we get the excess if we compared it to a normal distribution. In this case, both values are very far from the ones obtained from a normal distribution.

[2] If this is true, when computing the logs, we will get NAs, as logarithms of negative values cannot be calculated.

[3] Euros per kilowatt per hour.

- The Coefficient of Asymmetry, or coefficient of skewness, measures the assymetry of a distribution. If the obtained value is zero, it is completely symmetric to a normal distribution. Positive and negative values comes from positive and negative assymetries[4]. The first column shows that the prices are not very far from a normal distribution; and very, very far for the logarithmic distribution.

The min. and max. values are very far for each other, as negative prices are permitted in the German market. There are not many negative values (compared to the total number, more than eight thousands observations), so this is not a very good measure.

Finally, we have the result of the Jarque-Bera test, which mixes both the kurtosis and the skewness values to test the null hypothesis of the distribution being a normal one (Stata, 2020). Just by looking at the obtained values, we can predict that the result will reject the null hypothesis. As we can check in the output below, both null hypothesis are rejected.

Figure 1: Testing for Normality

```
Skewness/Kurtosis tests for Normality

Variable |     Obs  Pr(Skewness)  Pr(Kurtosis) adj chi2(2)   Prob>chi2
-------------+---------------------------------------------------------------
prices |      8,760     0.0000        0.0000           .         0.0000
```

Figure 2: Testing for Normality: logarithmic distribution

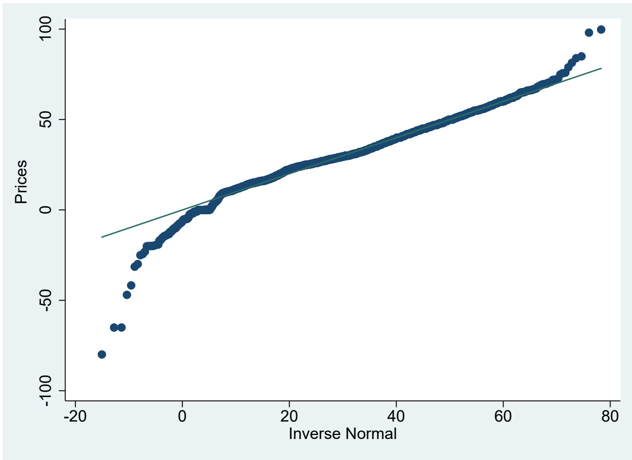
```
Skewness/Kurtosis tests for Normality

Variable |      Obs  Pr(Skewness)  Pr(Kurtosis) adj chi2(2)   Prob>chi2
-------------+---------------------------------------------------------------
lprices |      8,760     0.0000        0.0000           .              .
```

[4] Positive means more values are concentrated on the left side, and viceversa

The following figures show the results of the texts. I also computed the quantiles of the two variables (prices and its logarithm distribution), with those of a normal one. If the two are completely indistinguishable, the result should be a straight line of 45 degrees. As we can observe, this is not true, although if we do not take the negative prices into account, the distribution of the prices resembles a normal one.

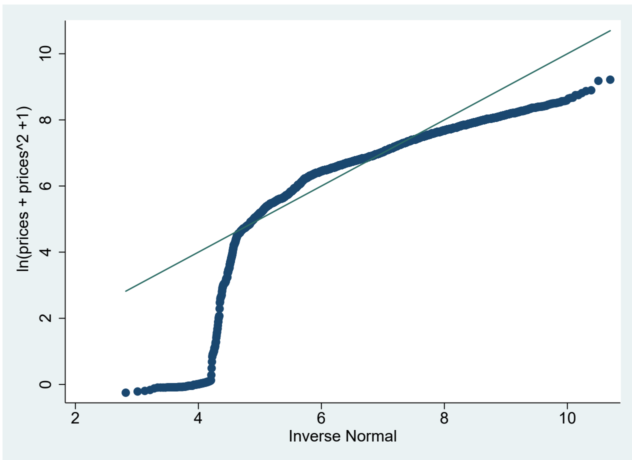
Figure 3: Quantiles of prices, against quantiles of normal distribution



Source: selfmade with Stata.

Figure 4: Quantiles of the logarithmic distribution of prices,

against quantiles of normal distribution



Source: selfmade with Stata.

3.0 Time Series Analysis

This part of the assignment can be split in two phases: first the testing of the unit roots to find which up to which lag is the estimation of the VAR the most optimal, and the estimation of those VAR models. In the first part of the assignment, I used all the observations (there is one for each hour for a whole year), whereas in the second, the average price per day is the variable I use.

3.1 Unit Root tests

I will be using two different tests, the ADF and the PP unit root tests.

- The Augmented Dick Fuller test checks if a variable follows a unit root process, with the null hypothesis being that the variable contains a unit root, and the alternative that it follows a stationary process (Stata, 2020).
- The Philips Perron tests exactly the same, with the same hypothesis. The difference with the ADF test is the methodology. The first one uses lags of the variable, and the second uses Newey-West standard errors to test if the variable has autocorrelation (Stata, 2020).

When using the first test, eight different instances will be computed: for each type of variables[5], with/without trend, and with/without logs. Below we can find an example of one of the tests. Taking differences is a very usual method for studying how the change rates evolve over time and, in that way, test if the variable is stationary or not. Before calculating the results of these tests, we need to obtain the optimal number of lags. In order to do this, we use the stata command $varsoc$, that computes several goodness of fit measures.

Figure 5: Testing for Stationarity of the variable: prices

```
Augmented Dickey-Fuller test for unit root
Number of obs   =       335

----------- Z(t) has t-distribution -----------
                 Test         1% Critical       5% Critical       10% Critical
               Statistic          Value             Value              Value
------------------------------------------------------------------------------
Z(t)             -2.227           -2.339            -1.650            -1.284
------------------------------------------------------------------------------
p-value for Z(t) = 0.0134
```

[5] Normal, and in differences.

Given that the observations are set to be measured in days, I calculated first the optimal number of lags within the (1-31) range. For the both the logarithmic expression and the prices, the optimal number is 29. I did not want to introduce more lags because I would loose too many observations. The optimal number of lags was obtained by the Akaike method.

We follow the same procedure when we consider the prices in differences. The optimal number of lags obtained for both are 28 (logically, as we are taking differences, one less lag is the optimum).

For the Phillips Perron test, we do not need to obtain the optimal number of lags, as the methodology does not need any. The results from all these tests are gathered in the following tables: the Z(t) statistic and p-values.

Table 2: Unit Root Test Results

	ADF				**PP**			
	Constant		Trend		Constant		Trend	
	Z(t)	**p-v**	**Z(t)**	**p-v**	**Z(t)**	**p-v**	**Z(t)**	**p-v**
P_t	-2.227	0.0134	-2.131	0.5289	-9.716	0.0000	-9.709	0.0000
$Ln(P_t)$	-2.037	0.0213	-1.881	0.6645	-10.567	0.0000	-10.551	0.0000
ΔP_t	-4.096	0.0000	-4.143	0.0055	-26.174	0.0000	-26.170	0.0000
$\Delta Ln(P_t)$	-4.420	0.0000	-4.532	0.0013	-28.565	0.0000	-28.563	0.0000

Source: selfmade with stata.

By looking at the ADF results, we can see that only the variables (normal and logarithmic) are stationary, if we take into account the level of significance as 1%. The PP results are very contradictory, as for all the test the null hypothesis is rejected at 1%, meaning that all variables are stationary. I will take here a conservative stance, by only acknowledging the ADF results. This way, the only stationary variables are the ones that are in differences.

3.2 Estimation of VAR models

After testing which model is best suited for VAR estimation in 3.1 (those that are stationary, the ones in differences), with the help of Stata, I compute the results for both regressions.

I will first analyze the first Vector Autoregression, the one without logarithms. Regarding the significance of the lags, the first 13 are very significant, and the same happens with the 19-21th and 28th. This shows that the correlation between the firsts and last lags are high. For a better interpretation, the plot of the impulse response function would be interesting to analyze. The goodness of fit of the first model is quite big: 55%, given that we are only using the lags of the independent variable.

Given the results of the second table, we can infer practically the same results. The relevant lag coefficients are, once again, the first 13, the 17-20th and the 28th. In spite of this, the goodness of fit descends to 51%, remaining still a very good result.

Table 3: VAR model of ΔP_t

VARIABLES	(1) davgp	VARIABLES	(1) davgp
L.davgp	-0.369***	L16.davgp	-0.0135
	(0.0532)		(0.0745)
L2.davgp	-0.387***	L17.davgp	-0.0994
	(0.0568)		(0.0734)
L3.davgp	-0.337***	L18.davgp	-0.119
	(0.0605)		(0.0727)
L4.davgp	-0.353***	L19.davgp	-0.162**
	(0.0630)		(0.0711)
L5.davgp	-0.367***	L20.davgp	-0.135*
	(0.0659)		(0.0707)
L6.davgp	-0.294***	L21.davgp	0.135*
	(0.0689)		(0.0700)
L7.davgp	-0.165**	L22.davgp	-0.0453
	(0.0708)		(0.0699)
L8.davgp	-0.227***	L23.davgp	-0.0444
	(0.0712)		(0.0675)
L9.davgp	-0.228***	L24.davgp	0.0211
	(0.0718)		(0.0644)
L10.davgp	-0.296***	L25.davgp	-0.0608
	(0.0729)		(0.0612)
L11.davgp	-0.0986	L26.davgp	-0.0360
	(0.0747)		(0.0590)
L12.davgp	-0.133*	L27.davgp	-0.0161
	(0.0755)		(0.0551)
L13.davgp	-0.157**	L28.davgp	0.215***
	(0.0757)		(0.0518)
L14.davgp	0.00819	Constant	-0.150
	(0.0754)		(0.302)
L15.davgp	-0.0429		
	(0.0751)	Observations	336

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

$R^2 = 0.5552$

Source: selfmade with stata.

Table 4: VAR model of $\Delta L(P_t)$

VARIABLES	(1) dlavgp	VARIABLES	(1) davgp
L.dlavgp	-0.442***	L16.dlavgp	-0.0725
	(0.0532)		(0.0818)
L2.dlavgp	-0.440***	L17.dlavgp	-0.151*
	(0.0584)		(0.0803)
L3.dlavgp	-0.409***	L18.dlavgp	-0.139*
	(0.0630)		(0.0791)
L4.dlavgp	-0.420***	L19.dlavgp	-0.217***
	(0.0666)		(0.0780)
L5.dlavgp	-0.384***	L20.dlavgp	-0.167**
	(0.0704)		(0.0777)
L6.dlavgp	-0.354***	L21.dlavgp	0.0391
	(0.0733)		(0.0770)
L7.dlavgp	-0.201***	L22.dlavgp	-0.0784
	(0.0764)		(0.0762)
L8.dlavgp	-0.275***	L23.dlavgp	-0.0861
	(0.0773)		(0.0728)
L9.dlavgp	-0.281***	L24.dlavgp	-0.0139
	(0.0790)		(0.0694)
L10.dlavgp	-0.307***	L25.dlavgp	-0.0827
	(0.0803)		(0.0641)
L11.dlavgp	-0.180**	L26.dlavgp	-0.0475
	(0.0829)		(0.0607)
L12.dlavgp	-0.184**	L27.dlavgp	-0.0371
	(0.0838)		(0.0563)
L13.dlavgp	-0.212**	L28.dlavgp	0.218***
	(0.0840)		(0.0515)
L14.dlavgp	-0.0542	Constant	-0.0145
	(0.0839)		(0.0274)
L15.dlavgp	-0.0715		
	(0.0832)	Observations	336

Standard errors in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

$R^2 = 0.5161$

Source: selfmade with stata.

4.0 Conclusion and potential improvements

From the analysis of the German-Austrian market, we can extract that the market power of other countries can be affected by a seemingly innocent act of integration. These are very complex systems, and sometimes the final result of a policy or a change, is unknown to everyone.

The prices of the German-Austrian market make a temporal series where its lags explains quite a lot of the changes in the variance. The distribution of the prices is stationary (at 1% level of significance) if we take differences. As seen in the previous VAR tables, many of these lags had highly significant coefficients. The relationships with this lags is negative for almost all of them, meaning that low values of prices today, will mean higher values of prices tomorrow. Strangely enough, this is not true for the 28th lag, where the relationship is positive, establishing a direct relationship between prices today, and prices at the end of the month. We have also tested that the distribution of this variable is not normal, for both logarithmic and non-logarithmic variables, although if we deleted the negative values, the functional form of the distribution of prices resembles much more a normal one, as we saw in fig. [3]. The results of the PP test needs further analysis, as they were contradictory to the ADF test ones. Finally, an improvement of this analysis can be made by computing the impulse response function, that can add more conclusions on top of the VAR estimations.

References

[1] Stata (2020): *"Augmented Dickey–Fuller unit-root test".*

[2] APG (2020): *"End of the German-Austrian electricity price zone – what does this mean?".*

[3] Clean Energy Wire (2015): *"Europe's largest electricity market set to split".*

[4] Politico (2018): *"Europe's power couple break up".*

[5] Genscape (2018): *"EPEX Splits Germany and Austria into two Separate Zones".*

[6] European Comission (2016): *"Overview of European Electricity Markets".*

[7] Stata (2020): *"Phillips–Perron unit-root test".*

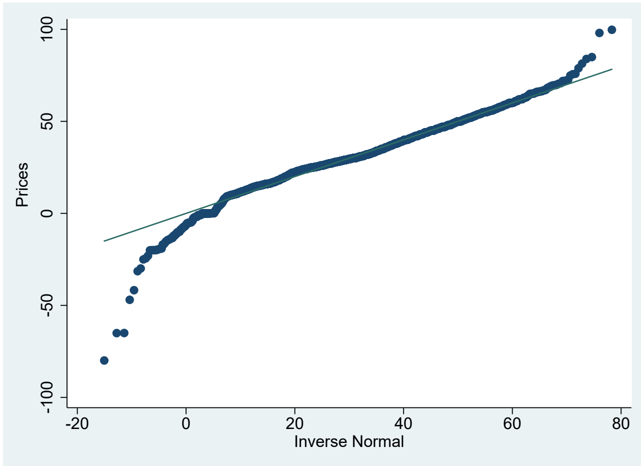
[8] Stata (2020): *"Skewness and kurtosis test for normality".*

[9] Stata Journal (2010): *"The limits of sample skewness and kurtosis".*

5.0 ANNEX

5.1 Figures

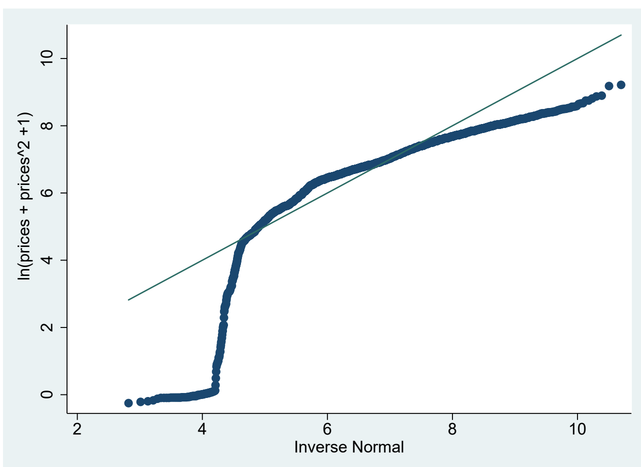
Quantiles of prices, against quantiles of normal distribution



Source: selfmade with Stata.

Quantiles of the logarithmic distribution of prices,

against quantiles of normal distribution



Source: selfmade with Stata.

5.2 Tests and Tables

Summary Statistics

	pt	*ln*($pt+pt^2+1$)
Mean	31.6285	6.7583
Median	30.5400	6.8719
Std. Dev.	12.6643	1.0687
E. K.	5.7665	17.7993
C. A.	-0.3061	-2.9747
Min	-79.940	-0.2498
Max	99.770	9.2158
J-B (p.value)	0.0000	0.0000

Source: selfmade with R code.

Testing for Normality

```
Skewness/Kurtosis tests for Normality

Variable |      Obs  Pr(Skewness)  Pr(Kurtosis) adj chi2(2)   Prob>chi2
-------------+-------------------------------------------------------------
prices |      8,760     0.0000        0.0000           .         0.0000
```

Testing for Normality: logarithmic distribution

```
Skewness/Kurtosis tests for Normality

Variable |      Obs  Pr(Skewness)  Pr(Kurtosis) adj chi2(2)   Prob>chi2
-------------+-------------------------------------------------------------
lprices |      8,760     0.0000        0.0000           .              .
```

Testing for Stationarity of the variable: prices

```
Augmented Dickey-Fuller test for unit root
Number of obs   =       335

----------- Z(t) has t-distribution -----------
Test          1% Critical       5% Critical       10% Critical
Statistic          Value             Value              Value
-------------------------------------------------------------------------------
Z(t)            -2.227           -2.339           -1.650           -1.284
-------------------------------------------------------------------------------
p-value for Z(t) = 0.0134
```

Unit Root Test Results

	ADF				**PP**			
	Constant		Trend		Constant		Trend	
	Z(t)	**p-v**	**Z(t)**	**p-v**	**Z(t)**	**p-v**	**Z(t)**	**p-v**
P_t	-2.227	0.0134	-2.131	0.5289	-9.716	0.0000	-9.709	0.0000
$Ln(P_t)$	-2.037	0.0213	-1.881	0.6645	-10.567	0.0000	-10.551	0.0000
ΔP_t	-4.096	0.0000	-4.143	0.0055	-26.174	0.0000	-26.170	0.0000
$\Delta Ln(P_t)$	-4.420	0.0000	-4.532	0.0013	-28.565	0.0000	-28.563	0.0000

Source: selfmade with stata.

VAR model of ΔP_t

	(1)		(1)
VARIABLES	davgp	VARIABLES	davgp
L.davgp	-0.369***	L16.davgp	-0.0135
	(0.0532)		(0.0745)
L2.davgp	-0.387***	L17.davgp	-0.0994
	(0.0568)		(0.0734)
L3.davgp	-0.337***	L18.davgp	-0.119
	(0.0605)		(0.0727)
L4.davgp	-0.353***	L19.davgp	-0.162**
	(0.0630)		(0.0711)
L5.davgp	-0.367***	L20.davgp	-0.135*
	(0.0659)		(0.0707)
L6.davgp	-0.294***	L21.davgp	0.135*
	(0.0689)		(0.0700)
L7.davgp	-0.165**	L22.davgp	-0.0453
	(0.0708)		(0.0699)
L8.davgp	-0.227***	L23.davgp	-0.0444
	(0.0712)		(0.0675)
L9.davgp	-0.228***	L24.davgp	0.0211
	(0.0718)		(0.0644)
L10.davgp	-0.296***	L25.davgp	-0.0608
	(0.0729)		(0.0612)
L11.davgp	-0.0986	L26.davgp	-0.0360
	(0.0747)		(0.0590)
L12.davgp	-0.133*	L27.davgp	-0.0161
	(0.0755)		(0.0551)
L13.davgp	-0.157**	L28.davgp	0.215***
	(0.0757)		(0.0518)
L14.davgp	0.00819	Constant	-0.150
	(0.0754)		(0.302)
L15.davgp	-0.0429		
	(0.0751)	Observations	336

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
$R^2 = 0.5552$

Source: selfmade with stata.

VAR model of $\Delta L(P_t)$

	(1)		(1)
VARIABLES	dlavgp	VARIABLES	davgp
L.dlavgp	-0.442***	L16.dlavgp	-0.0725
	(0.0532)		(0.0818)
L2.dlavgp	-0.440***	L17.dlavgp	-0.151*
	(0.0584)		(0.0803)
L3.dlavgp	-0.409***	L18.dlavgp	-0.139*
	(0.0630)		(0.0791)
L4.dlavgp	-0.420***	L19.dlavgp	-0.217***
	(0.0666)		(0.0780)
L5.dlavgp	-0.384***	L20.dlavgp	-0.167**
	(0.0704)		(0.0777)
L6.dlavgp	-0.354***	L21.dlavgp	0.0391
	(0.0733)		(0.0770)
L7.dlavgp	-0.201***	L22.dlavgp	-0.0784
	(0.0764)		(0.0762)
L8.dlavgp	-0.275***	L23.dlavgp	-0.0861
	(0.0773)		(0.0728)
L9.dlavgp	-0.281***	L24.dlavgp	-0.0139
	(0.0790)		(0.0694)
L10.dlavgp	-0.307***	L25.dlavgp	-0.0827
	(0.0803)		(0.0641)
L11.dlavgp	-0.180**	L26.dlavgp	-0.0475
	(0.0829)		(0.0607)
L12.dlavgp	-0.184**	L27.dlavgp	-0.0371
	(0.0838)		(0.0563)
L13.dlavgp	-0.212**	L28.dlavgp	0.218***
	(0.0840)		(0.0515)
L14.dlavgp	-0.0542	Constant	-0.0145
	(0.0839)		(0.0274)
L15.dlavgp	-0.0715		
	(0.0832)	Observations	336

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

$R^2 = 0.5161$

Source: selfmade with stata.

5.3 Stata code

```
clear all
set more off
import excel "C:\Users\pimpeter\Desktop\EM\EM HW3\5. Germany-Austria.xlsx", ///
sheet("Hoja1") firstrow

***** EXERCISE 1*****************************************************
* Converting from string to int
destring smpphelix, gen(prices)
tabstat prices, statistics(mean median sd skewness kurtosis min max)

* J-B test (sktest in stata) and qnorm to check if it has a normal dist.
sktest prices
qnorm prices

*J-B dice que asimetria=0, kurtsis=3, vemos que no, por el test
* por la distrib, y por los valores de asimetría y kurtosis.

* Checking for neg values
count if prices < 0


gen lprices = log(prices + (prices^2)+1)
tabstat lprices, statistics(mean median sd skewness kurtosis min max)

sktest lprices
qnorm lprices
```

```
***** EXERCISE 2****************************************************

* Preliminaries: setting the data
bysort year month day : egen avgp=mean(prices)
bysort year month day : egen lavgp=mean(lprices)

egen monthday = group(month day)

duplicates drop monthday, force

tsset monthday

******* ADF TEST:  *********************************
*
varsoc avgp, maxlag(31)
varsoc lavgp, maxlag(31)

* Opt for avginc is 43
* Opt for lavginc is 29
dfuller avgp, lags(29) drift regress
dfuller avgp, lags(29) trend regress
dfuller lavgp, lags(29) drift regress
dfuller lavgp, lags(29) trend regress



* Taking diffs.
gen davgp = d.avgp
gen dlavgp = d.lavgp
*
varsoc davgp, maxlag(31)
varsoc dlavgp, maxlag(31)
*
dfuller davgp, lags(28) drift regress
dfuller davgp, lags(28) trend regress
dfuller dlavgp, lags(28) drift regress
dfuller dlavgp, lags(28) trend regress
```

```
******* PP TEST:  **********************************
*
pperron avgp, regress
pperron avgp, trend regress
pperron lavgp, regress
pperron lavgp, trend regress

* In diffs.
pperron davgp, regress
pperron davgp, trend regress
pperron dlavgp, regress
pperron dlavgp, trend regress

******* VAR ESTIMATION:  ***************************
*
varsoc davgp, maxlag(31)
varsoc dlavgp, maxlag(31)
*
var davgp, lags(1/28)
outreg2 using var1, tex replace
var dlavgp, lags(1/28)
outreg2 using var2, tex replace
```