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# **ENERGY MARKETS:**

Second Homework, Supply Curves.

23th of March, 2020 Marbella

# Analysis of the supply curves: November 2011-2014

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#### **Abstract**

This short assignment will analyze the supply curves of the Spanish electricity market of the first Wednsesday of November from 2011 to 2014.

Keywords: Electricity market, Spain, Supply curves.

## 1 Introduction and Methodology

All of the data is extracted from the OMIE database (OMIE, 2020). OMIE is the nominated electricity market operator for the Iberian Peninsula (so for both Portugal and Spain). As it is said in its database, "OMIE manages the day-ahead and intraday markets based on the criteria of independence, transparency, and objectivity". OMIE has many functions, as receiving bids for the price of the electricity, proposing rules for the production market's operation, publishing aggregated supply and demand curves of both the day-ahead and intraday markets, etc.

In order to properly analyze the supply curves for the considered time period, I will make regressions for each of the two hours: at 6:00 AM and 21:00 PM for both supply curves (complex and simple bids) for each year. My assigned time period is the month of November from 2011 to 2014. All of the regressions follows the same model:

$$Price = \alpha + \beta * CUM + e, \tag{1}$$

where CUM is the cumulative quantity, and price is (logically) the price of the Mega Watts per hour (Mwh). The unit of the price is euros per Mwh. Table 1. contains an example of what these regressions look like. I did not include all of the regressions in the assingment to avoid adding excessive information, as the estimated coefficients and the goodness of fit of each regression is contained in a table that I will analyze in the next part of the homework. Why the cumulative quantity? This is how the supply curves in electricity markets are made. There are "blocks" of prices, that can be easily identified in the graphs at the annex. The maximum price for these blocks is 180.3, and the minimum is zero.

These regressions were made using R code, by a self-made programm that takes as input the database of a specific year, and gives as output the goodness of fit and the estimated coefficients of the regression, for each supply curve. This regressions only takes observations where its price its above zero. For all those observations where the price is exactly zero, I will include in that results table the cumulative quantity for each case.

In the annex you can also find the graphs of each supply curve for each data and type of bid. They were also made using a self-made programm that prints two curves for each year, one for the supply curve maded with the simple bids, and other supply curve for the complex bids. For the complex bids supply curve, I made a scatterplot because some of the first graphs it is better understood this way, as the curve is very flat, and the outliers made the line look strange.

As I said previously, I used one database for each year. In order to filter the data, I first eliminated all the data that was not for the supply curve (I deleted the demmand values), and I separated each file between complex and simple bids before working with them, sorted by the price.

Table 1: OLS regression

	Dependent variable:		
	Р		
CUM	0.017**		
	(0.003)		
Constant	-0.124		
	(0.089)		
Observations	5		
$R^2$	0.908		
Adjusted R <sup>2</sup>	0.878		
Residual Std. Error	0.093 (df = 3)		
F Statistic	29.662** (df = 1; 3)		
Note:	*p<0.1; **p<0.05; ***p<0.01		

An interpretation for this regression would be that, on average, the increase of one unit of the cumulative quantity (MWh), the price would rise by 0.017 units (euros per MWH).

# 2 Results from the Regressions

After computing all of the regressions and the cumulative quantities for those observations where its price was above zero, we get the following table:

Table 2: Results from the regressions

		Simple bids		Complex bids	
Date	Hour	MWh at	Slope	MWh at	Slope
		P=0	$(R^2)$	P=0	$(R^2)$
11/2011	06:00	17,084	5.437e-03	15,517	1.665e-02
			(0.9647)		(0.9081)
	21:00	23,481	4.210e-03	21,060	1.007e-02
	21.00	20,401	(0.8783)		(0.7170)
11/2012	06:00	25,118	3.767e-03	22,799	9.362e-03
			(0.9769)		(0.4820)
	21:00	22,881	4.044e-03	20,295	8.322e-03
	21100	22,001	(0.9327)	20,200	(0.9194)
11/2013	06:00	19,447	3.786e-03	17,147	1.332e-02
			(0.9766)		(0.9614)
	21:00	20,152	4.041e-03	16,717	5.466e-03
			(0.9024)		(0.8831)
11/2014	06:00	16,102	4.590e-03	15,022	5.860e-03
			(0.9803)		(0.8180)
	21:00	16,080	4.146e-03	14,831	5.388e-03
			(0.9137)		(0.9598)

As we can see, the table contains for each date, hour, and type of bid the Mwh at P=0, and the slope and the goodnes of fit for the regression (the model was shown at the introduction). Bids can be both either simplex or complex, the simple bids do not have any restrictions, they are plainly made of price and quantity offered. The complex do include restrictions: minimum revenue and load gradient. The goodnes of fit measure, the  $R^2$ , is included in the brackets.

## 3 Analysis of the results

The market operator collects all the bids, and the sypply offers are ordered from lowest to highest. For each hour, a System Marginal Price (SMP) is generated. In an uniform-price auction, all of the offers that are below that price will get that value, and those above will mantain its own price. That is why the supply offerers have bids at zero prize. This strategy will ensure that the quantity offered is sold (at the SMP price). I will start commenting the table, and then I will analyze the evolution of the graphs. Lets see how does the Mwh cumulative quantities evolves over time. Throughout the years, the MWh at P=0 seem to descend for both types of bids and for both hours. I assume that this tendency is due to the effect of the financial crisis, when the economy gets better, they try to obtain a better price for their supply offers by increasing their bids, as the economy is in a better place, and they can increase the risk of not selling their product. At 6:00 AM that amount is substantially smaller than the 9:00 PM quantity for the inital years, but that effect gradually disappears, maybe becasue of the previous explained reason. If we compare the quantities of MWh at zero price between the two bid types, we can appreciate that the simple bids has generally higher amounts for both times. I think this is because of the nature of the process behind them, as the simple bids has no restrictions, generally one would like to ensure the offer they want on them, more than in a restricted bid. For the regression analysis, we can see that the estimated coefficients for the slope within each year and type of bid, and between hours are, except for the complex bids of 2013, very close to each other. Analyzing these coefficients we cannot give a general conclusion, as for some years the simple bids slope is the highest, and for some it is not. I conclude that the time does not influence as much as I thought the price of electricity. If we compare between the two types of bids, we find that the estimated coefficients are higher for the complex slope. This means that the quantities has more influence over the price of the electricity, I assume this is because these bids are more regulated than the simpler ones and thus, the effect of an increase in the quantities is higer.

<sup>&</sup>lt;sup>1</sup>This two times are not randomly selected, as 6:00 AM is a time where the consumption of electricity is low, and 9:00 PM where the demand is very high.

If we compare between years, we can observe that the simple bid estimated coefficients do not change much, they hover around 4e-03. This is not the case for the complex bids, whose estimated coefficients start having higher values, and thus the quantity has a greater effect over the price than in the last years of the considered time period. This may be because in those years nearer to the start of the financial crisis, the market was more regulated than in the next years, and the price was higher. Towards the end of this period of time, the estimated coefficients, as seen in the year of 2014, are much more closely related in terms of absolute values. This may be because of the declinining of the financial crisis effects.

Regarding the graphs, we can appreciate the price blocks very easily for the simple bids, but not for the complex ones, who starts having a very flat curve. Towards the end of the time period, the complex bids supply curve almost follows the same trend as the simple bids supply curve. This could be appreciated too in the convergence of both estimated coefficients in the table. Throughout the years, the curve of both supply functions tend to be less flat at the beginning (so less bids at zero price, the companies risk more), and less steeper towards the higher end of the prices distribution, so they make a more equally distributed range of bids.

### 4 Conclusion

This analysis has shown that there is indeed differences between the time of the day regarding the supply side of this market. All of the regressions have a very high goodnes of fit, and further investigation would be interesting to see if there is any relationship between the dependent and the independent variables that makes the model unbiased. It has been also shown that the two type of bids have difference between them regarding the distribution of bids. Each fulfills their own function inside the market. For a further analysis of the electricity market in Spain, it would be interesting to also study the buyer side, to have doubly robust conclusions regarding the possible cause of variations in quantities, and for estimating the severity of the effects caused by the financial crisis of 2007.

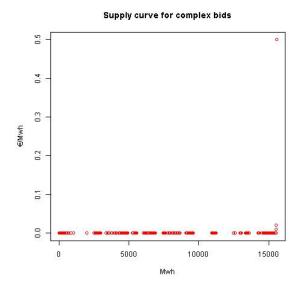
# References

[1] OMIE (2020): https://www.omie.es/en/market-results

### **5 ANNEX**

## 5.1 Graphs

Figure 1: November of 2011: Supply curve for complex bids at 6:00



Source: made with R and the OMIE database.

Figure 2: November of 2011: Supply curve for simple bids at 6:00

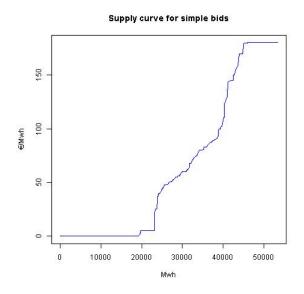


Figure 3: November of 2012: Supply curve for complex bids at 6:00

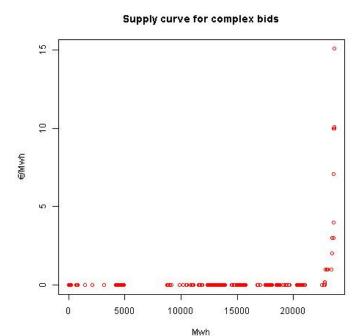


Figure 4: November of 2012: Supply curve for simple bids at 6:00

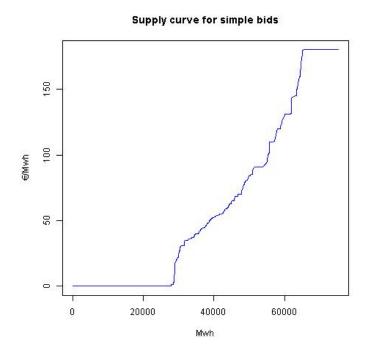
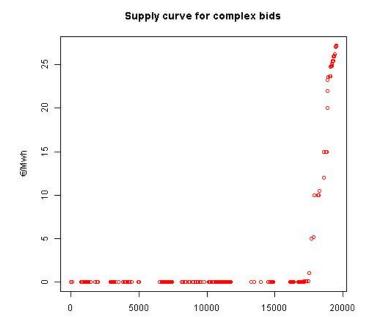


Figure 5: November of 2013: Supply curve for complex bids at 6:00



Mwh

Figure 6: November of 2013: Supply curve for simple bids at 6:00

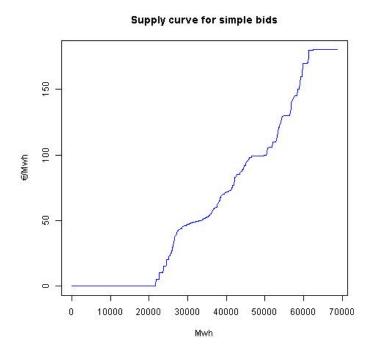
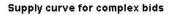


Figure 7: November of 2014: Supply curve for complex bids at 6:00



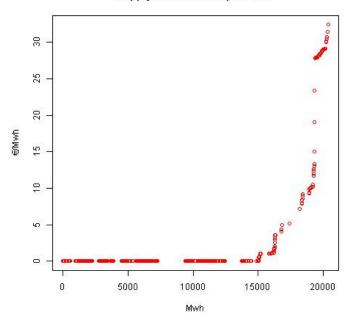


Figure 8: November of 2014: Supply curve for simple bids at 6:00

Supply curve for simple bids

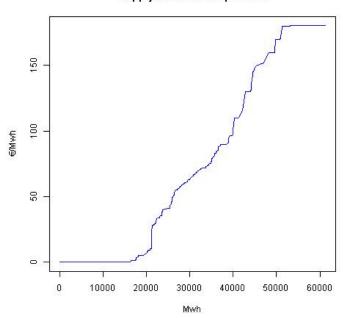


Figure 9: November of 2011: Supply curve for complex bids at 21:00

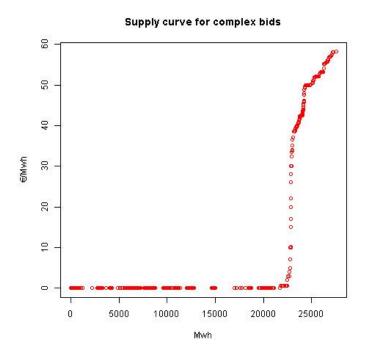


Figure 10: November of 2011: Supply curve for simple bids at 21:00

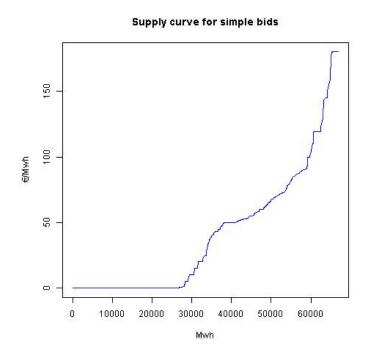
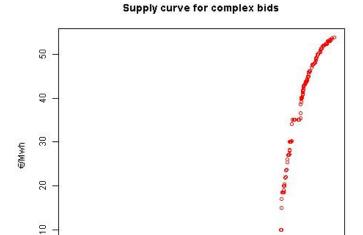


Figure 11: November of 2012: Supply curve for complex bids at 21:00



15000

Mwh

20000

25000

10000

5000

Figure 12: November of 2012: Supply curve for simple bids at 21:00

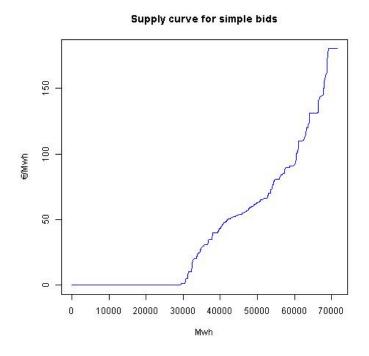


Figure 13: November of 2013: Supply curve for complex bids at 21:00

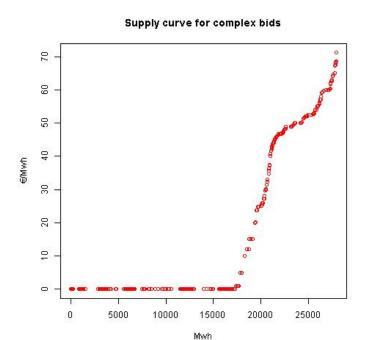


Figure 14: November of 2013: Supply curve for simple bids at 21:00

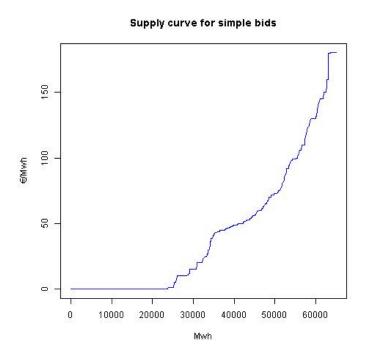
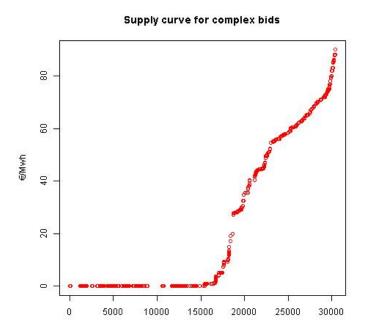
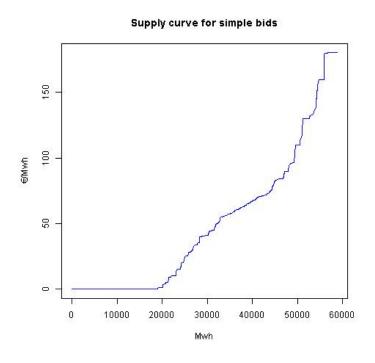


Figure 15: November of 2014: Supply curve for complex bids at 21:00



Mwh

Figure 16: November of 2014: Supply curve for simple bids at 21:00



#### 5.2 R code

```
#
# ENERGY MARKETS: Homework #2
#
# Author: Pedro Iraburu Muñoz
# 2020
#
# Master in Economics: Empirical Applications and Policies
# Energy Markets
# Clearing the Memory
rm(list = ls())
# Reading data
library(readxl)
data_2011_6 <- read_excel("6_2011.xls")</pre>
data_2012_6 <- read_excel("6_2012.xls")</pre>
data_2013_6 <- read_excel("6_2013.xls")</pre>
data_2014_6 <- read_excel("6_2014.xls")</pre>
data_2011_9 <- read_excel("9_2011.xls")</pre>
data_2012_9 <- read_excel("9_2012.xls")</pre>
data_2013_9 <- read_excel("9_2013.xls")</pre>
data_2014_9 <- read_excel("9_2014.xls")</pre>
# Function for printing graphs
grafic <- function(input){</pre>
input$Q <- as.numeric(input$...6)</pre>
input$P <- as.numeric(input$...7)</pre>
input$B <- input$...8</pre>
```

```
input <- subset(input,...5=="V")</pre>
input <- input[order(input$P),]</pre>
#### COMPLEX_BIDS -----
V_C <- subset(input, B=="C")</pre>
# Making the cum. quantities column
V_C$CUM <- V_C$Q
for (i in 1:length(V_C$Q)) {
if(i==1){
V_C$CUM[i] <- V_C$Q[i]</pre>
}
else{
V_C$CUM[i] <-V_C$CUM[i-1]+ V_C$Q[i]</pre>
}
}
#### SIMPLE BIDS -----
V_0 <- subset(input, B=="0")</pre>
# Making the cum. quantities column
V_O$CUM <- V_O$Q
for (i in 1:length(V_0$Q)) {
if(i==1){
V_0$CUM[i] <- V_0$Q[i]</pre>
}
else{
V_0$CUM[i] <-V_0$CUM[i-1]+ V_0$Q[i]</pre>
}
}
jpeg(file="simple.jpg")
plot(V_O$CUM, V_O$P, main="Supply curve for simple bids",
```

```
xlab='Mwh', ylab="e/Mwh",type="l", col="blue", lwd=1.3)
dev.off()
jpeg(file="complex.jpg")
plot(V_C$CUM, V_C$P, main="Supply curve for complex bids",
xlab='Mwh', ylab="e/Mwh", col="red")
dev.off()
}
# Function for getting the results for the table
# in the follwing order: sqr R, Tot Q, first for
# the complex bids, second for the simple bids
# I also added the slope (5th and 6th) first simple
# then complex
R <- function(input){</pre>
input$Q <- as.numeric(input$...6)</pre>
input$P <- as.numeric(input$...7)</pre>
input$B <- input$...8</pre>
input <- subset(input,...5=="V")</pre>
input <- input[order(input$P),]</pre>
#### COMPLEX_BIDS -----
V_C <- subset(input, B=="C")</pre>
# QUANTITY SUM WHEN P=0
V_C_q <- subset(V_C, P==0)</pre>
Q \leftarrow sum(V_C_q$Q)
# REGRESSION WHEN P!=0
V_C_r \leftarrow subset(V_C, P!=0)
# Making the cum. quantities column
V_C_r$CUM <- V_C_r$Q
```

```
for (i in 1:length(V_C_rQ)) {
if(i==1){
V_C_r$CUM[i] <- V_C_r$Q[i]</pre>
}
else{
V_C_r$CUM[i] <-V_C_r$CUM[i-1] + V_C_r$Q[i]
}
}
# regression
Reg <- lm(data = V_C_r, formula = P ~ CUM)</pre>
R <- summary(Reg) # regression summary</pre>
R$r.squared
results <-c(1,2,3,4,5,6)
results[1] <- R$r.squared</pre>
results[2] <- Q
results[6] <- R$coefficients[2,1]</pre>
#### SIMPLE BIDS -----
V_0 <- subset(input, B=="0")</pre>
# QUANTITY SUM WHEN P=0
V_0_q <- subset(V_0, P==0)</pre>
Q \leftarrow sum(V_0_q$Q)
# REGRESSION WHEN P!=0
V_0_r <- subset(V_0, P!=0)</pre>
# Making the cum. quantities column
V_O_r$CUM <- V_O_r$Q
for (i in 1:length(V_0_r$Q)) {
```

```
if(i==1){
V_0_r$CUM[i] <- V_0_r$Q[i]</pre>
}
else{
V_0_r$CUM[i] <-V_0_r$CUM[i-1]+ V_0_r$Q[i]</pre>
}
}
# regression
Reg <- lm(data = V_O_r, formula = P ~ CUM)</pre>
R <- summary(Reg) # regression summary</pre>
R$r.squared
results[3] <- R$r.squared</pre>
results[4] <- Q
results[5] <- R$coefficients[2,1]</pre>
return(results)
}
## TABLE RESULTS
R(input=data_2011_6)
R(input=data_2012_6)
R(input=data_2013_6)
R(input=data_2014_6)
R(input=data_2011_9)
R(input=data_2012_9)
R(input=data_2013_9)
R(input=data_2014_9)
```

#### ## GRAPHS

grafic(input=data\_2011\_6)

grafic(input=data\_2012\_6)

grafic(input=data\_2013\_6)

grafic(input=data\_2014\_6)

grafic(input=data\_2011\_9)

grafic(input=data\_2012\_9)

grafic(input=data\_2013\_9)

grafic(input=data\_2014\_9)