Online Appendix for: "Complementary Bidding Mechanisms and Startup Costs in Electricity Markets"

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This appendix contains complementary material for the paper "Complementary Bidding Mechanisms and Startup Costs in Electricity Markets." It contains a description of the market mechanism and the data sources used. It also contains a discussion of the model main assumptions. It includes a description of the methods used to compute the optimal strategy of a strategic firm. Finally, it contains additional tables and graphs that complement the main text.

A The ISO algorithm

I explain the details of the pseudo-algorithm that I use to replicate the independent system operator (ISO) algorithm. First, I discuss the actual algorithm used by the ISO and explain how the algorithm is approximated in my application. Then, I compare predicted and actual market outcomes for a set of 120 days in the sample.

A.1 Details of the actual algorithm

The official algorithm used by the ISO to compute the market outcomes of the day-ahead market is explained in the "Appendix on the Functioning of the Wholesale Electricity Day-Ahead and Intra-day Markets."[1] I outline the major steps that are taken to solve for the optimal dispatch.

After receiving and verifying the supply and demand offers made by the market participants, the ISO solves for the optimal dispatch using the following order:

1. Construct aggregate supply and demand curves from simple bids taking into account merit order rules and interconnection constraints.

2. Solve for the optimal dispatch using these aggregate curves (uniform auction rule). Use established rules to deal with indivisible steps and ties.

3. Check ramping constraints at the unit level and change quantities to satisfy them (only check once for ramping up and once for ramping down).

[1] Boletín Oficial del Estado num. 128, 05/30/2006, pp. 20157-20192 (in Spanish).

4. Order the units with complex bids whose minimum revenue constraints are not satisfied according to the difference between their average required price and the average price they receive.

5. Discard the unit whose deviation is largest.

6. Repeat 1 to 5 until no complex bid binds. This is the provisional solution.

7. Order units with complex bids that have been discarded according to the difference between their average required price and the average price they would receive at *current* prices. Note that some units that have been discarded might be willing to produce at current prices.

8. Use the resulting merit order from step 7 in step 4 when repeating 1 to 5, again until no complex bid binds, to obtain a new provisional solution.

9. Repeat 7 to 8 until no discarded units would be willing to produce at current prices or stop if time exceeds 30 minutes or number of iteration is larger than 3,000, taking the provisional solution that minimizes the foregone rents of discarded units that would be willing to produce at current prices. This is the final solution.

Mimicking the ISO algorithm poses some challenges. In particular, the ISO algorithm can take up to 30 minutes to complete, which is computationally not feasible in my application, in which I need to simulate hundreds of market outcomes for each firm and each day. Furthermore, the treatment of the interconnections requires some information that I do not have available. For this reasons, it is important to approximate the ISO in an heuristic manner.

A.2 Details of the pseudo-algorithm

Implementing the ISO algorithm exactly is not possible for two main reasons. On the one hand, I do not have the information necessary to account for congestion at the interconnections. On the other hand, the procedure is computationally very costly. The ISO allows the algorithm to do up to 3,000 iterations during up to 30 minutes. However, for estimation purposes, I need to simulate market outcomes thousands of times. Therefore, there is a need to trade-off the trustworthiness of the pseudo-algorithm with its computational efficiency, but trying to preserve the actual outcomes of the algorithm as much as possible.

I follow Garcia et al. (1999) to implement an heuristic ISO algorithm as a mixed integer linear programming problem.[2] This problems takes into account the ramping constraints submitted by

[2]García, Javier, Jaime Román, Julián Barquín, and Avelino González. 1999. Modelo de Casación de Ofertas para el Mercado Diario mediante Programación Lineal Entera-Mixta (in Spanish). 6a Jornadas Hispano-Lusas de Ingeniera Elctrica, 4: 605616.

the units, as well as the indivisibility conditions of the steps as a single maximization problem. The minimum revenue requirements are dealt in a similar fashion than the actual ISO algorithm, although I only allow for one iteration. I check that this does not produce very different outcomes using additional methods that iterate more than once.

The pseudo-algorithm is programmed as follows:

1. Solve a mixed-integer linear program that includes indivisibility and ramping constraints.

2. Order the units with complex bids whose minimum revenue requirements are not satisfied according to the difference between their average required price and the average price they receive.

3. Discard the unit whose deviation is largest.

4. Repeat 1 to 3 until no complex bid binds.

The pseudo-algorithm is implemented in Java and the mixed-integer linear program is solved using the solver CPLEX 12.0, which is very efficient for this type of problems.[3]

A.3 Simulations to assess the performance of the pseudo-algorithm

I present a comparison of actual and predicted prices by the pseudo-algorithm in Table A.1. The algorithm predicts the prices accurately and the difference between the two is not significant for any hour of the day. The overall error is small, with a mean close to zero. The predicted prices also present the same standard deviation as actual prices.

I also implement different version of the algorithm, some of which relax the integer constraints. Some other algorithms allow for a certain degree of iteration, following the minimization criteria used by the ISO. Overall, I find that the pseudo-algorithms replicate very accurately the patterns across the different hours of the day. Results are presented in Table A.1.

[3]This solver is available for free to the academic community through IBM.

Table A.1: Price predicted and simulation error at the hourly level

Hour	MgPrice	Alg 1	Alg 2	Alg 3	Alg 4	Δ1	Δ2	Δ3	Δ4
1	33.20	33.11	33.23	33.16	33.21	-0.09	0.03	-0.04	0.01
	(6.98)	(6.91)	(6.96)	(7.04)	(7.06)	(0.83)	(1.19)	(0.95)	(0.97)
2	29.77	29.98	30.07	29.97	29.98	0.20	0.30	0.19	0.21
	(5.40)	(5.39)	(5.36)	(5.46)	(5.45)	(1.03)	(0.96)	(0.88)	(0.86)
3	26.57	26.90	26.90	26.81	26.88	0.33	0.33	0.24	0.30
	(4.24)	(4.39)	(4.33)	(4.44)	(4.33)	(0.75)	(0.64)	(0.71)	(0.70)
4	25.45	25.63	25.67	25.64	25.71	0.18	0.22	0.19	0.26
	(3.86)	(3.99)	(4.02)	(3.97)	(3.81)	(0.70)	(0.76)	(0.68)	(0.67)
5	24.47	24.66	24.66	24.66	24.75	0.19	0.19	0.19	0.28
	(3.98)	(3.98)	(3.99)	(3.98)	(3.91)	(0.59)	(0.61)	(0.59)	(0.52)
6	24.47	24.72	24.71	24.61	24.71	0.25	0.24	0.14	0.24
	(3.53)	(3.49)	(3.49)	(3.50)	(3.35)	(0.56)	(0.58)	(0.47)	(0.50)
7	26.82	27.03	27.00	26.95	27.03	0.21	0.18	0.13	0.21
	(3.76)	(3.57)	(3.56)	(3.62)	(3.41)	(0.89)	(0.88)	(0.72)	(0.70)
8	30.39	30.73	30.70	30.74	30.81	0.33	0.31	0.35	0.42
	(6.28)	(6.25)	(6.29)	(6.28)	(6.23)	(1.09)	(1.34)	(1.07)	(1.12)
9	33.87	34.00	33.83	34.02	34.08	0.13	-0.04	0.15	0.21
	(7.71)	(7.50)	(7.47)	(7.52)	(7.47)	(1.09)	(1.23)	(1.11)	(1.14)
10	36.51	36.69	36.43	36.68	36.73	0.18	-0.07	0.18	0.22
	(7.84)	(7.87)	(7.80)	(7.89)	(7.93)	(1.17)	(1.33)	(1.16)	(1.20)
11	39.93	39.84	39.49	39.86	39.93	-0.10	-0.44	-0.07	-0.00
	(8.08)	(8.23)	(8.17)	(8.23)	(8.25)	(1.26)	(1.27)	(1.25)	(1.24)
12	41.44	41.44	40.99	41.46	41.51	-0.00	-0.44	0.02	0.07
	(8.81)	(8.97)	(8.90)	(8.95)	(8.90)	(1.30)	(1.60)	(1.18)	(1.17)
13	41.97	42.04	41.56	42.05	42.06	0.07	-0.41	0.08	0.09
	(9.40)	(9.50)	(9.42)	(9.49)	(9.47)	(1.28)	(1.64)	(1.20)	(1.19)
14	40.23	40.29	39.91	40.30	40.34	0.06	-0.32	0.07	0.11
	(8.73)	(8.74)	(8.76)	(8.73)	(8.78)	(1.19)	(1.48)	(1.11)	(1.14)
15	37.34	37.41	37.10	37.45	37.47	0.08	-0.23	0.11	0.13
	(8.12)	(8.03)	(8.09)	(8.03)	(8.07)	(1.12)	(1.26)	(1.06)	(1.04)
16	36.12	36.06	35.72	36.07	36.09	-0.06	-0.40	-0.05	-0.03
	(8.59)	(8.60)	(8.57)	(8.61)	(8.62)	(1.14)	(1.22)	(1.11)	(1.07)
17	35.96	35.84	35.44	35.82	35.85	-0.12	-0.52	-0.15	-0.11
	(9.30)	(9.18)	(9.21)	(9.16)	(9.14)	(1.01)	(1.37)	(0.93)	(0.89)
18	36.21	36.02	35.65	36.00	36.01	-0.19	-0.56	-0.21	-0.21
	(9.78)	(9.56)	(9.52)	(9.57)	(9.61)	(1.00)	(1.13)	(0.98)	(0.87)
19	35.00	35.07	34.69	35.08	35.14	0.07	-0.31	0.08	0.14
	(8.87)	(8.63)	(8.65)	(8.63)	(8.61)	(0.96)	(1.21)	(0.93)	(0.92)
20	34.30	34.33	33.97	34.30	34.32	0.03	-0.33	0.00	0.02
	(6.63)	(6.46)	(6.39)	(6.50)	(6.47)	(1.22)	(1.49)	(1.21)	(1.20)
21	35.93	35.33	34.79	35.40	35.51	-0.60	-1.14	-0.53	-0.42
	(6.31)	(6.29)	(6.04)	(6.32)	(6.30)	(1.92)	(2.24)	(1.64)	(1.61)
22	42.35	41.73	41.10	41.78	41.72	-0.62	-1.24	-0.57	-0.63
	(9.12)	(9.40)	(8.91)	(9.31)	(9.19)	(1.90)	(2.25)	(1.70)	(1.90)
23	38.82	38.53	38.11	38.54	38.57	-0.30	-0.72	-0.29	-0.26
	(7.37)	(7.50)	(7.25)	(7.51)	(7.47)	(1.35)	(1.61)	(1.37)	(1.20)
24	32.72	32.82	32.37	32.80	32.81	0.10	-0.34	0.09	0.10
	(5.32)	(5.61)	(5.34)	(5.65)	(5.58)	(1.20)	(1.30)	(1.19)	(1.17)
Total	34.16	34.17	33.92	34.17	34.22	0.01	-0.24	0.01	0.06
	(9.07)	(8.99)	(8.83)	(9.01)	(8.98)	(1.17)	(1.40)	(1.11)	(1.11)

Notes: Monte Carlo simulation covers the period of March-June of 2007. Prices are in €/MWh.

B Data sources

The major part of the data is obtained from the Market Operator website, http://www.omel.es. I obtain the bidding data from the bidding files DET and CAB. Physical bilateral contracts are obtained from the PDBF files. Congestion restrictions are obtained from the PDVD files as well as from the System Operator I90 form, http://www.esios.ree.es. Similarly, unavailability of units as well as the reason of the unavailability are obtained from the INDIP files and the I90 form. Outcomes of sequential markets as well as final dispatch data are obtained from the PHF files.

Plant characteristics are obtained from the annual statistic reports of the System Operator as well as from the structural data in their website. These include maximum capacity, vintage and main type of fuel. I complement the data set with fuel mix obtained from the Ministry of Industry registrar as well as emission rates obtained from the EPER registrar. I also obtain engineering thermal rates for previously regulated plants from the National Energy Commission and the Ministry of Industry.

I complement the data set with other information available at the System Operator's website. I acquire demand and wind production forecasts, which are made available before the auction is run to reduce balancing needs in real-time. The files are DEMAND_AUX and PREVEOL. I also get commodity price data to include it in the cost estimation. I use NBP day ahead prices for natural gas (UK), API coal indexes, and European ARA prices for low sulfur fuel-oil and gas oil.

C Model assumptions

C.1 Assumption regarding threshold for complex bids

In the bidding model, I assume that a unit is accepted whenever its minimum revenue requirement is satisfied, and rejected otherwise. However, in practice, not all units that have their minimum revenue requirement satisfied are turned on. The reason behind this mismatch is due to the discrete and lumpy nature of the bidding mechanism. When a unit is taken out from the market, prices can jump up. Thus, the new prices could satisfy the revenue requirement of the unit just taken out, and there would be no equilibrium possible. Similarly, units can be taken out in different order and achieve a different equilibrium. In this section, I examine the relevance of such deviations.

The ISO minimizes the revenue of units that are taken out from the market but would have been willing to produce at final prices. As a result, in practice deviations from this rule of thumb are not important. In particular, only in 2 to 3% of the cases a unit is taken out from the supply curve, but it could have covered its minimum revenue requirement. Furthermore, the revenue obtained in such cases is not far from zero. On average, these units could have received 3,800€ in net revenue, compared to the average 41,406€ *net* revenue of the average accepted units and the average 220,005€ *gross* revenue requirement.

Overall, this evidence suggests that the stylized rule of thumb, which accepts a unit if the minimum revenue requirement is satisfied and discards it otherwise, characterizes well the underlying data generation process.

C.2 Discussion regarding marginal effects of simple bids

This section provides an empirical verification that the term assumed to be negligible in Assumption 1 is indeed small. In other words, I show that the effect of marginal changes of simple hourly bids on expected profits due to the changes on the probability of a complex bid being binding is negligible. In addition, I show that ignoring this effect does not seem to be a potential source of bias in the estimation.

First, I calculate the probability of a bid being binding and the revenue requirement being just satisfied. Then, I show that for plausible (estimated) parameter values, the contribution to the total derivative coming from changes in the probability of a bid being binding (holding profits constant) is small compared to the contribution coming from changes in profits (holding probabilities constant). Finally, I show that the omitted term coming is not particularly correlated with the elements included in the main empirical specification, which could be a potential source of bias.

The probability. I first compute the empirical probabilities $Pr(R_{ik} = 0|b_{ijk} = p_h)$, $Pr(R_{jk} = 0)$ and $Pr(b_{ijk} = p_h)$ using data from the market. Empirically, the probability that the minimum revenue requirement is just satisfied is zero, and thus, $Pr(R_{ik} = 0|b_{ijk} = p_h) = 0$ and $Pr(R_{jk} = 0) = 0$. The probability of a given bid setting the price is $Pr(b_{ijk} = p_h) = 0.35\%$ (note that I disregard extreme bids, as those are not valid for the first order condition and not used in the estimation, using the full sample $Pr(b_{ijk} = p_h) = 0.24\%$). As one can see, the probability of setting the price is still relatively small.

If I take a broader definition of satisfying this equalities, rounding prices to e terms and rounding the minimum revenue requirement to average price terms (R_{ij}/Q_j), I find that $Pr(||b_{ijk}|| = ||p_h||) = 3.92\%$ and, conditional on submitting a complex bid, $Pr(||R_{jk}/Q_j|| = 0) = 3.71\%$. The joint probability is much smaller relative to the probability of setting the price, with $Pr(||R_{jk}/Q_j|| = 0 \;\&\; ||b_{ijk}|| = ||p_h||) = 0.16\%$.

Assessing relative magnitudes. I now show that the relative contribution of marginal effects due to probability changes are very small when compared to the marginal effects of bids on profits.

$$\frac{\sum_{s\in S}\frac{\partial Pr(s)}{\partial b_{jkh}}\mathbb{E}[\Pi_i(\sigma_i,\sigma_{-i})|s]}{\sum_{s\in S}Pr(s)\frac{\partial\mathbb{E}[\Pi_i(\sigma_i,\sigma_{-i})|s]}{\partial b_{jkh}}},$$

which is the ratio of the contributions to the FOC due to the changes in the probabilities relative to changes on profits. Note that the numerator can be computed as

$$Pr(b_{jkh}=p_h)\sum_l Pr(\rho(R_{il})=0|b_{jkh}=p_h)E[\Pi_i^{lin}-\Pi_i^{lout}|\rho(R_{il})=0,b_{jkh}=p_h].$$

This ratio is no greater than 10.55% on average, with an interquartile range with value of zero and median value 0. Trimming the outliers from the simulated outcomes (top and bottom 0.5%), this average ratio is reduced to 1.98%.

Assumption 1 and omitted variable bias. Finally, I check that the term

$$\sum_{s\in S}\frac{\partial Pr(s)}{\partial b_{jkh}}\mathbb{E}[\Pi_i(\sigma_i,\sigma_{-i})|s]$$

does not systematically correlate with either simple bids, the markup variable in the simple bids and the main term in the FOC, which are included in the main regression. The raw correlations between these terms and the omitted term is small (0.02-0.05) and not significant, both on average across units and conditional on a given unit.

D Computational model

In this section, I describe how the best response of the firm is computed in the presence of startup costs as a linear mixed integer program. Both the strategic firm problem and the competitive experiment are defined.

Strategic firm The problem of the firm is to maximize profits given the shape of the residual demand. In the computational model, one can solve the optimal strategy choosing the quantity produced by each unit at each hour of the day, taking into account the cost structure of the units and taking the strategies of other firms as given (best response).

As shown in equation (1) below, the firm maximizes gross revenue minus production costs. The gross revenue depends on the total quantity produced by the firm, which in equilibrium equals the residual demand. The costs depend on the hourly production at the unit level. Units have both a minimum and a maximum capacity. Units incur a startup cost β_j whenever they turn on, and therefore production involves discrete decisions. The startup cost is set to zero in the experiments without dynamic costs. To account for linkages across several days, the model considers a finite horizon problem, in which firms look at five days ahead. For each day, the optimal strategy is optimized with firms considering expected market outcomes in the following days.

Solving for the global optimum of the problem of the firm can be time consuming, as there are many combinations of on/off patterns that are available.[4] To reduce the dimensionality of problem, I approximate the many steps of the residual demand with a piece-wise linear function in increments of 160MWh. To preserve the linearity of the problem, I approximate the gross revenue of the firm using a piece-wise linear approximation as well. Similarly, in order to represent the quadratic costs at the unit level, the quantity levels at the unit level are discretized into different steps. As the number of steps increases, the solution approximates one in which no linear approximation is being made.

The linearity of the program is preserved to ensure that the global optimum is found and that computational time is fast. In the actual calculations, the number of linear pieces for both the gross revenue and residual demand is set to 35. To solve the model, I use CPLEX, a mixed-integer solver that is available for free to the academic community through IBM. Note that the optimal solution depends on the estimated parameters, $\{\alpha, \beta, \gamma\}$.

Omitting the firm i subscript for clarity, the mathematical program is described as follows:

$$\max_{\{\mathbf{q}_t, \mathbf{u}_t, \mathbf{y}_t\}} \quad \sum_{t=\tau}^{\tau+5} \sum_{h=1}^{24} \Big(GR_{th}(DR_{th}, \gamma) - \sum_{j=1}^{J} (\sum_{k=1}^{K} \alpha_{jk} q_{jkth} + \beta_j y_{jth}) \Big) \tag{1}$$

$s.t.$

[Market Clearing]	$DR_{th} = \sum_{j=1}^{J} q_{jth}, \ \forall t, h,$
[Capacity Constraint]	$u_{jth} \underline{K}_j \leq \sum_{k=1}^{K} q_{jkth} \leq u_{jth} \overline{K}_j, \ \forall j, t, h,$
[Startup Constraint]	$y_{jth} = \mathbf{1}(u_{jt,h} > u_{jt,h-1}), \ \forall j, t, h > 1,$
	$y_{jth} = \mathbf{1}(u_{jt,1} > u_{jt-1,24}), \ \forall j, t, h = 1,$
[Positive Quantities]	$q_{jkth} \geq 0, \ \forall j, k, t, h,$
[Integer Constraint]	$u_{jth} \in \{0, 1\}, y_{jth} \in \{0, 1\}, \ \forall j, t, h.$

[4] For example, for a problem with 5 days, 24 hours and 8 power plants, there are 2^{2080} combinations of on/off patterns.

where

t	day index,
h	hours of the day, $h = 1, ..., 24$,
j	unit index, $j = 1, ..., J$,
k	quantity steps at the unit level, $k = 1, ..., K$,
q_{jkth}	quantity produced by unit j at step k, day t and hour h,
u_{jth}	run indicator, takes value of one if unit is on in day t and hour h,
y_{jth}	startup indicator, takes value of one if unit starts up in day t and hour h,
DR_{th}	residual demand function (piecewise linear approximation, uses auxiliary integer variables),
GR_{th}	gross revenue function (piecewise linear approximation, uses auxiliary integer variables),
C_{jt}	daily costs of production.

Cost minimization The competitive counterfactual is defined as the outcome that minimizes production costs, instead of maximizing profits. Because the experiments consider unilateral market power, the strategies of other firms are also held constant, as in the strategic case.

Production costs for the firm at consideration are taken from the structural cost function, as in the strategic model (see equation (2) below). One still needs to define the costs of producing with other units. For the other firms, their offers at the day-ahead market are used. Therefore, the program solves for the cost-minimizing strategy of the firm, given other firms market strategies. This would be the competitive solution if other firms were bidding truthfully, but in general it should be interpreted as the competitive strategy of the firm, holding market offers from other firms constant.

As in the strategic case, to solve the model, I use CPLEX, a mixed-integer solver that is available for free to the academic community through IBM. Note that the optimal solution depends on the estimated cost parameters, $\{\alpha, \beta\}$, but not on the forward position γ. This is because the optimal social planner solution is not affected by the strategic position of the firm, which is determined by this parameter.

Omitting the firm i subscript for clarity, the mathematical program is described as follows:

$$\min_{\{\mathbf{q}_t, \mathbf{u}_t, \mathbf{y}_t\}} \quad \sum_{t=\tau}^{\tau+5} \sum_{h=1}^{24} \Big(OC_{th}(DR_{th}) + \sum_{j=1}^{J} (\sum_{k=1}^{K} \alpha_{jk} q_{jkth} + \beta_j y_{jth}) \Big)$$

$$s.t.$$

$$\begin{array}{ll}
\text{[Market Clearing]} & DR_{th} = \sum_{j=1}^{J} q_{jth}, \ \forall t, h, \\
\text{[Capacity Constraint]} & u_{jth} \underline{K}_j \leq \sum_{k=1}^{K} q_{jkth} \leq u_{jth} \overline{K}_j, \ \forall j, t, h, \\
\text{[Startup Constraint]} & y_{jth} = \mathbf{1}(u_{jt,h} > u_{jt,h-1}), \ \forall j, t, h > 1, \\
 & y_{jth} = \mathbf{1}(u_{jt,1} > u_{jt-1,24}), \ \forall j, t, h = 1, \\
\text{[Positive Quantities]} & q_{jkth} \geq 0, \ \forall j, k, t, h, \\
\text{[Integer Constraint]} & u_{jth} \in \{0, 1\}, y_{jth} \in \{0, 1\}, \ \forall j, t, h.
\end{array}$$

where

t	day index,
h	hours of the day, $h = 1, ..., 24$,
j	unit index, $j = 1, ..., J$,
k	quantity steps at the unit level, $k = 1, ..., K$,
q_{jkth}	quantity produced by unit j at step k, day t and hour h,
u_{jth}	run indicator, takes value of one if unit is on in day t and hour h,
y_{jth}	startup indicator, takes value of one if unit starts up in day t and hour h,
OC_{th}	cost from other firms production (piecewise linear approximation, uses auxiliary integer variables),
DR_{th}	residual demand function (piecewise linear approximation, uses auxiliary integer variables),
C_{jt}	daily costs of production.

E Additional Tables and Figures

Table E.1: Marginal Cost Estimates at the Unit Level

Plant	Type	Size MW	α_1 €/MWh	α_2 €/MWh^2
CTJON2	CCGT	380	32.83	8.89e-03
			(3.72)	(5.88e-03)
ESC6	CCGT	804	32.83	8.89e-03
			(3.72)	(5.88e-03)
GUA1	CO	148	23.79	1.19e-01
			(2.66)	(3.13e-02)
GUA2	CO	350	27.32	5.36e-03
			(1.78)	(1.15e-02)
LAD3	CO	155	23.81	8.63e-02
			(1.99)	(2.08e-02)
LAD4	CO	350	26.61	4.35e-03
			(0.92)	(9.23e-03)
PAS1	CO	214	26.08	8.97e-03
			(1.43)	(1.57e-02)
STC4	CCGT	396	32.83	8.89e-03
			(3.72)	(5.88e-03)

Notes: Sample from March to June 2007.Estimates computed using a GMM estimator with 210 moments. Bandwidth parameter set to 3€.

Table E.2: Agreggate Marginal Cost Estimates for Firm 2

	(1)	(2)	(3)	(4)
Coal (€/MWh)	23.10	22.96	10.31	23.15
	(0.74)	(0.74)	(NaN)	(1.16)
Coal X q (€/MWh^2)			3.97e-02	
			(NaN)	
Forward Position (%)	89.84	88.39	79.36	90.04
	(6.67)	(6.67)	(NaN)	(10.19)
Time Periods	120	120	120	120
Moments	321	321	321	321

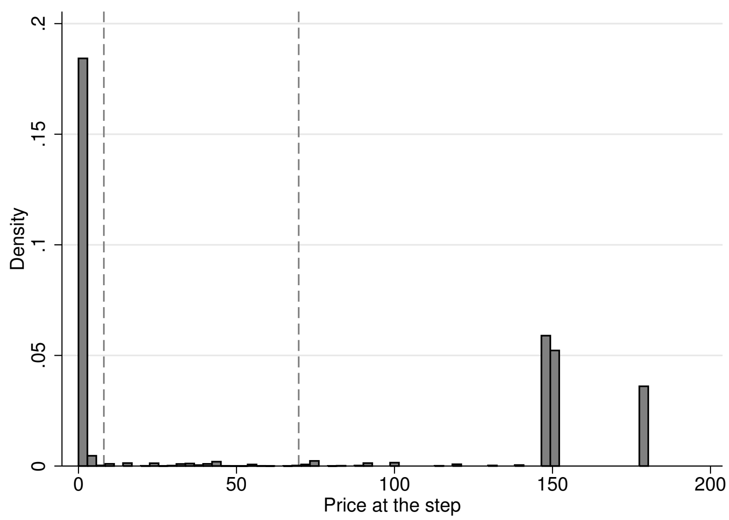
Notes: Sample from March to June 2007. Input variable constructed with European fuel prices of coal, natural gas and oil. Heat rates as provided in reports by the Spanish Ministry of Industry. Estimates computed using a GMM estimator. Bandwidth parameter set to 3€.

Table E.3: Startup Cost Estimates for Firm 2

	(1)	(2)	(3)	(4)	(5)	(6)
Coal (€)						
150.0MW	21,290	17,007	19,363	20,565	20,557	21,979
	(2,884)	(723,987)	(3,537)	(3,125)	(3,003)	(3,640)
350.0MW	50,887	46,150	50,155	51,653	51,673	54,561
	(4,030)	(1,020,844)	(4,865)	(3,861)	(3,563)	(4,900)
Input Controls	N	N	Y	N	N	N
Weekday Controls	Y	N	Y	Y	Y	Y
Congested Excluded	Y	Y	Y	N	N	N
Unavailable Excluded	Y	Y	Y	Y	N	N
Already On Excluded	Y	Y	Y	Y	Y	N

Notes: Sample from March to June 2007. Dependent variable is the difference in profits of getting one plant in or out from the market. Estimates computed using a locally linear regression around observations for which the minimum revenue requirement is just satisfied. Regression performed by fuel groups controlling different plant sizes.

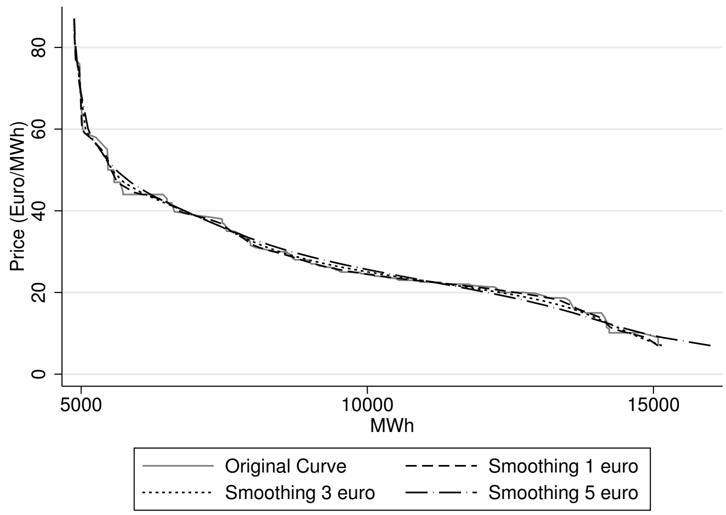
Figure E.1: Bidders in the market appear to choose commitment ex-ante



The distribution of first-step bids for units with no bilateral contract and no complex bid shows that firms ensure ex-ante whether a unit will be turned on or not during that day. Dashed lines represent minimum and maximum price observed in the whole sample. Firms submit either very low or very high first step bids. Sample from March to June 2007.

Figure E.2: Example of Residual Demand for Different Smoothing Parameters

(a) Residual demand fit for different values in the relevant range of observed bids and prices.



(b) The smoothing technique should also approximate the residual demand slope, which is a key statistic in the construction of the first order conditions. One can see that a low smoothing parameter might produce jagged slope estimates. A large smoothing parameter might flatten out the slope. Note that the original slope is approximated as the slope between the 10 closest bids at each point.