An experimental analysis of Irish electricity auctions

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Abstract

This paper examines the recently deregulated Irish electricity market. We ask: given this newly imposed institutional structure, does the availability of true marginal prices for electricity products affect the price/quantity bids submitted by market participants? First, we analyse the price movements within this market since 2007 to produce a model which best describes the data. Second, we test the auction design of the electricity markets experimentally. The current auction design is a static bidding framework. We find that if the auction were to operate under a sequential bidding auction, all market participants would benefit, as lower clearing prices would result.

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1. Introduction

In Ireland there has been a recent move to separate electricity transmission from generation, resulting in increased competition in the marketplace (All Island Project, 2009).

This paper describes and analyzes the electricity market since the opening up of competition in 2007. We first focus on the newly available marginal price data. After analyzing more than two years of data on electricity prices and quantities, we develop an ARMA(1,1)/GARCH(3,1) model to examine the degree to which the availability of past price data effects current pricing decisions in electricity auctions. We find that it doesn’t.

What really affects the current price and quantity bid in an auction is the set of rules that market participants must adhere to when choosing their bids. Using an experimental approach we ask: given this newly imposed institutional structure, does the availability of true marginal prices for electricity products affect the price/quantity \((P, Q)\) bids submitted by market participants?

We vary the type, extent, and quality of information available to participants, as well as changing the underlying market mechanism to answer this question.

The main result of the paper is that if the auction were to operate under a dynamic game (that is, conduct a sequential bidding auction), all market participants would benefit, as lower clearing prices would result. This is currently not the case. Future work will focus on implementing a more robust and complex experimental environment, as well as changing electricity pricing policy nationally to reflect our findings.

We describe the institutional background in Section 1.1. We describe the fitting procedures and pre and post estimation of the ARMA(1,1)/GARCH(3,1) model in Section 2. We describe the experimental design in Section 3. We discuss the results of the four treatments in Section 4. Our policy recommendations and a discussion concludes our paper in Section 5.

1.1. Institutional background

Since the opening up of electricity generation markets in November 2007, eligible suppliers have had the right to purchase power from various generators on a half
hourly electricity spot market managed by national regulatory bodies\(^1\). The spot clearing price at any time \(t\) is called the System Marginal Price (SMP). The SMP price for electricity during any half-hour period is made up of two components, a shadow price and an uplift price. The combination of these prices ensures all generators meet their costs.

Thus:

\[
\text{System Marginal Price} = \text{Shadow Price} + \text{Uplift Price}
\]

(1)

Generating entities submit their true marginal costs at each half hourly period. The role of the regulating bodies is to set a fair price, to ensure that the generation costs are covered. Marginal costs are determined by the varying and various input costs faced by the different types of generators in the market, (i.e., peat, wind, oil-fired, coal), which all have different efficiencies of production, and different associated costs. The variation in the cost of power generation is considerable, since they depend on which generators are required at each moment to meet demand. To provide the eligible suppliers a means to hedge against their unknown future costs, and to further mitigate market power, the regulators have created an electricity auction market, within which suppliers can bid the right to purchase electricity units in advance at a predetermined price.

The shadow price, \(SP_t\) is an individual generator’s half hourly true marginal cost of unit demand, which under the Bidding Code of Practice all of the 137 generators in the market must submit All Island Project (2009). We express the shadow price as \(P_t = \Delta \text{Production Cost/}\Delta \text{Demand}\).

In each half hour, the level of demand is what determines the shadow price and the market shadow price is set to the marginal generation unit, i.e. the highest generator marginal cost required to cover the demand in that half hour time period. The price is determined by solving a mixed integer program that decides which units (generators) to commit (turn on), to minimize the total system production costs, to meeting demand in each half hour, and considering the necessary technical constraints\(^2\).

\(^1\)The Commission for Energy Regulation in the Republic of Ireland, and in Northern Ireland, the Authority for Utility Regulation.

\(^2\)These include: maximum capacity of each generator, minimum stable generation rates, ramp
Since the shadow price is a true marginal cost, it does not take into account fixed costs such as the start-up or idling costs (no-load) of generators. Consequently if the total price paid for electricity was $SP_t$, some generators would not recover all of their running costs. This is undesirable. An additional price, known as the uplift, $UP_t$, is added to the market price. We can express the running costs ($CR_x$) faced by a generator, $x$, producing some quantity $Q_{xt}$ for any given period, $t$, (typically a half-hour) is expressed as:

$$CR_x = \sum_h [Q_{xt}C_x + NLC_x \prod_{(Q_{xt} > 0)}] + ST_x,$$

where $C_x$ is generator $x$’s variable cost per unit, $NLC_x$ is $x$’s no load cost, and $ST_x$ is the generator’s start up cost.

The power station operation must be scheduled. This is a complicated problem, which is determined by pricing and policy preference objectives related to peat and wind power. In this paper, we take the scheduling problem as solved. The next step is to calculate the uplift price when the day is done, given the schedule and costs. To ensure running costs are covered for a given day uplift should be calculated and expressed half-hourly such that:

$$\sum_t [SP_t + UP_t]Q_{xt} \geq CR_x,$$

and $UP_t \geq 0$ for all generators, and for each half hourly period 7 days a week. The constraints do not specify values for $UP_t$, however an objective in the form of a quadratic program is provided by the regulatory authorities that uplift is chosen such that:

$$\alpha \sum_t [(SP_t + UP_t)\left(\sum_t Q_{xt}\right)] + \beta \sum_t (UP_t)^2.$$

Equation 4 minimizes the uplift revenues (Cost objective) and minimizes the shadow price misrepresentation (Profile Objective) subject to the constraints. Here $\alpha$ determines the uplift cost objective and $\beta$ determines the uplift profile object rates, and minimum on-off times.
and are constrained such that $\alpha + \beta = 1^3$. Eligible suppliers submit their quantities required on Day$_{t-1}$ and prices are determined by the regulator via the formula above on Day$_{t_+4}$.

1.2. Auction mechanisms in the Irish electricity market

In addition to the spot clearing market described above, there are also three auction mechanisms by which suppliers can agree to purchase electricity in advance should they wish to hedge against future unknown market prices.

These are:

1. Direct Contract (DC)

2. Non-Direct Contract (NDC) and

3. Public Service Obligation (PSO) auctions.

In each of these auctions, contracts for difference (CfD) are sold by the generators$^4$. These CfD’s enable generators and suppliers to manage their price risk within the market. The auctions are also run by the regulatory authorities and exist to further mitigate market power in Ireland with the ultimate benefit of final customers.

The regulators set and allocate the volume of electricity the generators are required to sell to eligible suppliers in the form of a contract during specified ‘subscription windows’. The contract sold during the subscription window is a future agreement that the supplier has the right to purchase electricity from the generator at some predetermined time in the future at a price decided at the time of the issue of the contract.

In Ireland there are only a small number of eligible suppliers that meet the criteria set by the regulators. Consequently, the number of bidders in the market is always constant and small, roughly 5-6 competitors. Initially the subscription window was extended to 6 weeks with contracts beginning in October 1st and

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$^3$Values are set annually. Currently $\alpha = 0$ and $\beta = 1$

$^4$In the Republic of Ireland, generation is carried out by the Electricity Supply Board (ESB), and in Northern Ireland, Northern Irish Energy, (NIE)
can be drawn out until 30th September 2010. Within this subscription window is a series of auctions lasting between 6 and 28 days.

This type of auction is highly regulated since the price is set each day of the subscription period according to a specified formula applied to the various commodity inputs of electricity such as gas, carbon, low sulphur fuel oil and gas/oil.

The specific regression equation is determined by the regulators, where the dependent variable is the DC strike price, and the independent variables are the forward fuel(s) and carbon prices. Those suppliers who have elected to subscribe to the DC will be told on that day of the calculated strike price (All Island Project, 2009).

CfD’s are made with respect to various lasting terms such as one quarter, a season and a year and which include four standard products, Baseload, Peak Mid-Merit 1 and Mid-Merit 2 products. Prices are quoted per Megawatt hour (MWh) for specified quantities. For example, one might purchase 25 unites of Baseload for quarter 1 of 2010 in September 2009. Since the DC prices are constantly changing with respect to market conditions, it is considered to be a ‘fair price’.

Since the price is regarded as being fair, eligible suppliers will generally avail of their full volume allowed hence the only real decision they face is which days to decide to take advantage of the available supply. The DC process is subsequently followed by the auctioning of the remaining CfD’s by the serving generators and finally the auctioning of Irish supported Public service obligations (PSO). The latter two fall under the non-direct contract auction method, which is the focus of the remainder of the paper.

1.3. Non direct contracts auctions

Non-Direct Contracts (NDCs) can be described as a true auction, which are also regulated with respect to the quantity that must be put forward by the generating

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5 Baseload product is the simplest product which is sold for trading periods relating to 24 hours a day, 7 days a week. Mid-Merit 1 product is sold during trading periods at the full contract quantity during the hours from 7.00 to 23.00 on weekdays and 80% contract quantity on non-business days. The Mid-Merit 2 product runs from 7.00 to 19.00 on Monday to Friday whether Business days or not. Finally, peak product is sold which applies to power generated from 17.00 to 21.00 on all days during the winter months (October - March).
companies. NDC auctions are conducted on a staged basis over a series of dates roughly 4 or 5 times per year during the period from April to June and last for approximately 3 - 5 days. In this auction bidders are given the opportunity to submit a finite number of their price quantity pairs, \((P_n, Q_n)\) for the 4 types of products described above, which may be offered for various future quarters or on an annual basis.

Bidders complete an offer form which contains offered volumes available, and a reserve price \((p^*)\). The submitted/offered price has a floor level, the reserve price, so \(p_n \geq p^*\). The price and quantity bids submitted by the eligible suppliers are determined by the spark spread for the product in question (i.e. the difference in the selling value of the electricity and the cost of generation). The price is set at the level to clear the auction, such that

\[
Q_s = \sum_p Q_p \prod [p_n > p^*],
\]

where \(Q_s\) is the total quantity offered, \(p_n\) is the price that individual suppliers submit, \(p^*\) is the clearing price paid for \(Q_p\) quantities, which correspond to individual suppliers prices being above the clearing price \(p^*\).

All participants then pay the clearing price which will be equal to the reserve price for under-scribed volumes and equal to the lowest successful offer price. Within 2-3 business days a confirmation letter is issued to the successful supplier to be checked and return to the regulator.

The terms of settlement of these CfD’s sold by the auctions is similar to those of settling a stock call option and is best explained by the following example. Suppose that Company A buys from Company B a CfD for Q1’10 50 euro/MWh with a quantity of 25MW Baseload. Suppose that for each half hour in Q1’10 the SMP is 60euro/MWh Since, SMP - strike = 60 - 50 = 10MW/h, at settlement Company B must pay Company A: \(25 \times 24 \times 90 \times (60 - 50) = 540,000\) euro, where, the 25 is from the quantity (25MW), the 24 is the number of hours per day, there are 90 days in the quarter and 60 is SMP, 50 is strike price. In real life this is extended to half-hourly varying prices. Bidders will use the spark spreads of the various products to hedge against their positions for example if they are long
Baseload, they will short the input fuels\footnote{Spark spread is the difference between selling one unit of electricity and the cost incurred from producing that unit of electricity.}. Public service obligation auctions are similar to NDC’s, except that only the Baseload Product is up for auction.

\section{1.4. Related literature}

Recent experimental and theoretical studies have examined multi-unit unit auctions (Kagel and Levin, 2001; Goeree and Offerman, 2002; Neugebauer and Selten, 2006; Milgrom, 2004). Here much of the focus has been devoted to mechanism design issues (Kagel and Roth, 1997). To study auctions of this type, one implements the design of a combinatorial auction experimentally, where preferences are expressed for collections of homogeneous items (Ledyard et al., 2009; Day and Raghavan, 2007).

These auctioned bundles can also consist of complementary heterogeneous goods, whose value of their combination can be higher than the sum of their individual values (Jehiel and Moldovanu, 2003). Combinatorial auctions have been carried out for spectrum licenses by the Federal Communications Commission, advertising time slots, auctions for shipping-lanes and other such procurements in the private sector, pollution emissions allowances in Los Angeles, as well as the proposed auctioning of airport landing slots by the FAA in the public sector (Banks et al., 2003).

In each of these auction environments, the expression of aggregate information allows the bidders to ‘realize synergies’ or benefits such as economies-of-scale or owning complementary goods. This type of auction mechanism stimulates competition, assisting the seller of the good with achieving more competitive prices.

Most of the combinatorial auction literature is centered on the underlying issue of finding an efficient allocation—the winner-determination problem. Typically the winner-determination problem is \footnote{That is, the amount of information required to describe a bidder’s preferences for all combinations grows exponentially with the number of items (Papadimitriou, 1996; Velupillai, 2000).} NP-hard. Proposed solutions to winner-determination problems have been the description of classes of winner-determination instances which are tractable, and the development of ‘bidding
languages’, which can express preferences more efficiently (Day and Raghavan, 2007; Zhang, 2009).

Since theory has not provided any viable solution to the problem of the many permutations and combinations, experiments have been developed to give clues how to determine an optimal strategy. We follow this logic in our paper. Much of the current literature focuses on experimenters creating their own designs, which they believe a combinatorial auction will perform well in (Ledyard et al., 2009). This can often be subject to researcher bias, though various tentative conclusions can still be made from their findings. For instance, package bidding can improve efficiency and revenue, but the auction must exist in an environment where the ability of bidders to express their willingness to pay must not be hindered at the expense of efficiency and revenue.

Clearly environments can be selected which work in favor of one particular auction design. To overcome this, experimenters can perform stress tests on their results by examining boundary environments and collections of payoff parameters that give the specific auction the best or worst opportunity of achieving high revenue or efficiency. Other conclusions can be drawn such as, the length of time an auction is allowed to continue for significantly affects the marginal productivity of revenue. Diminishing marginal revenue is experienced the longer an auction is permitted to run (Kwasnica and Sherstyuk, 2007).

We now turn to the description of our data and the model attempting to fit this data.

2. Data and model fitting

On the 1st of November 2007 at 6.00am, the first system marginal price (SMP) for electricity became available to eligible suppliers. The regulator provides the price every half an hour for 24 hours a day. There are 30,432 data points available covering a period of 634 days from 1st of November, 2007 to the 26th of July, 2009.

In terms of the auction, we are focusing in this paper on the idea of how the availability of the SMP data can affect the price quantity pairs submitted by the suppliers for the NDC auctions, following Neugebauer and Selten (2006). To gain a sense of the type of pricing being done in the market, we performed an
econometric analysis of the half hourly raw data. The aim was to construct a pricing model which best describes the data available to the agents within the real life auction setting.

Our thinking was that the market participants could perhaps forecast what future prices might be, and thus decide whether or not to enter the auction. Given the highly volatile nature of the dataset, we employ a GARCH and ARMA-GARCH parameter estimation of the SMP data in the presence of conditional heteroscedasticity\(^8\).

After cleaning the data, we computed the daily average of the each of the 634 days. The data appears seasonal, as we can see in Figure 1.

A further examination of the data revealed that 91 of the half hourly prices reached over 300 euro, giving the data a substantially large range, with the maximum price being 696.85 euro on the 15th of October 2008 and the minimum value just 3.29 euro on the 22nd of October\(^9\).

Removing the 91 data points above 300 from the daily data, and replacing them with the average of 67.42, in Figure 2 one can see a more clear seasonal effect in the data displaying higher electricity prices in the winter months.

In order to remove this seasonal effect we converted the prices to a daily log returns. The presence of volatility clustering in both the daily averages and half hourly data is clear, as Figure 3 shows. Prices seems to continuously to fluctuate at certain times. We used a GARCH model set to account for this heteroskedasticity.

One can conclude from table 1 that the raw daily averaged data is less dis-

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\(^8\)Recall that conditional heteroscedasticity refers to the property of time-varying variance depending on past observations of variance thus model the serial dependence of volatility i.e. past variances can explain future variances (Greene, 2002).

\(^9\)The price jump to almost 700 euro was as result of un-recouped start-up costs for the scheduling of the generator ‘Tarbert 3’ on the previous day, the 14th. The Tarbert unit has a minimum running or up-time of 24 hours, and the unit was scheduled to run until 12.00pm on the 15th. However, all costs were allocated for the hour period from 6.00am -7.00am on the day of the 15th instead of being spread out over the 6 hour previously decided look-ahead period when the unit commitment was formulated on the 14th at 12.00pm. Thus, the spike in the Uplift resulted in this system marginal price spike at 6.00am and 6.30am on the 15th of October 2008. The minimum price experience on the 22nd of October 2008 was due to a zero uplift charge applied on that day. The a high amount of wind generation overnight resulted in a zero charge for uplift since the conventional generator units were not required and were reduced to their minimum stable generation levels. The shadow price during this time period was instead set by the hyrdo-plant with a short-run marginal cost of zero All Island Project (2009).
Figure 1: Daily Averaged SMP. Clearly, seasonal variation is present.

Figure 2: Modified SMP Less the extreme outliers over 300 euro.
Figure 3: Differenced half hourly SMP data.

<table>
<thead>
<tr>
<th>Statistic</th>
<th>Raw SMP data</th>
<th>Raw SMP data</th>
<th>Returns SMP Data</th>
<th>Returns SMP Data</th>
</tr>
</thead>
<tbody>
<tr>
<td>Statistic</td>
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<td>Half hourly (Euro)</td>
<td>Daily Averaged</td>
<td>Half hourly (Euro)</td>
</tr>
<tr>
<td></td>
<td>N=634</td>
<td>N=30,432</td>
<td>N=634</td>
<td>N=30,432</td>
</tr>
<tr>
<td>Mean</td>
<td>67.42</td>
<td>67.42</td>
<td>-0.0011</td>
<td>0.00001148</td>
</tr>
<tr>
<td>Median</td>
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<td>58.87</td>
<td>-0.0047</td>
<td>0</td>
</tr>
<tr>
<td>Min</td>
<td>28.69</td>
<td>3.29</td>
<td>-0.4420</td>
<td>-2.4282</td>
</tr>
<tr>
<td>Max</td>
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<td>696.85</td>
<td>0.6457</td>
<td>2.8137</td>
</tr>
<tr>
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<tr>
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<tr>
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<td>37.9988</td>
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<td>Std Dev</td>
<td>20.61</td>
<td>37.43</td>
<td>0.1442</td>
<td>0.1793</td>
</tr>
</tbody>
</table>

Table 1: Descriptive statistics.
persed and has a more ‘normal’ distribution than the raw half hourly data\textsuperscript{10}.

When both data series were convert into returns, the main change noted was that the skewness for the half hourly data became more normal since its value approached 0, however the half hourly data remained to have a large kurtosis (fat tailed). Empirically, this has been found to be a feature of high frequency returns data (McCulloch, 1997). A 95% confidence interval for the mean of the half hourly SMP data, hence 95% of the time the mean lies in the interval $[65.82, 69.03]$\textsuperscript{11}.

2.1. Identified model

Given the size of the half hourly data set, for computational efficiency with respect to model fitting it was decided to work with the daily averaged data set with the inclusion of the extreme outliers (greater than 300) so as to capture the real volatility effects of the market data. The various diagnostic tests performed much more efficiently and accurately when using the daily averaged data set, which is smaller by a factor of 48. The first step in the model fitting process was to perform a pre-estimation analysis to select the simplest model that describes the data. By computing the graphic plots of the autocorrelation function (ACF) and the partial-autocorrelation (PACF) we quantitatively checked for a visual of correlation of the return series. These preliminary identification tools reveal that it is appropriate that a correlation structure in the conditional mean should be used to describe the averaged daily return series since the ACF and the PACF exponentially decline over 500 lags, as we see in Figure 4.

Two types of formal hypothesis tests were then carried out in order to quantify the correlation, the Ljung-Box-Pierce Q-test and Engle’s ARCH test. Both indicated a rejection of the null hypothesis, concluding that significant correla-

\textsuperscript{10}In fact, the half hourly data is almost twice as volatile than the daily average data as it is more prone to the effects of the outliers than the daily averaged data. (Consequently, the kurtosis for the half hourly data, 35.16, is much greater than the kurtosis of the normal distribution of 3).

\textsuperscript{11}One can construct a frequency plot of the differenced half hourly data. Taking the absolute value of the differences and plotting their frequencies one can graphically infer what the most likely difference was, that is the absolute value of roughly 13,000 of the changes between each half hour was in-between 0 and 0.5. These frequency plots were used to inform experimental participants in subsequent treatments.
tion exists. GARCH effects were likely to be present.

Having tested positively for the presence of heteroscedasticity, the next step in the model selection process is to estimate the model parameters and examine the estimated GARCH model. We first fit a GARCH(1,1) of the form:

\[ p_t = C + \varepsilon_t \]  

\[ \sigma^2 = \kappa + G_1 \sigma^2_{t-1} + A_1 \varepsilon^2_{t-1}. \]  

Here the (returns) \( p_t \) consists of some constant, \( C \) and an uncorrelated white noise process, \( \varepsilon_t \). The conditional variance model also consists of constant plus a weighted average of the previous time period’s variance, \( G \), plus a weighted average of the previous white noise process, \( A \). The following constraints apply: \( \sum_{i=1}^{p} G_i + \sum_{j=1}^{q} A_j < 1, \forall A,G > 0 \). The appropriate log-likelihood objective function estimates the model parameters via maximum likelihood estimation. The GARCH(1,1) of the SMP data chosen was:

\[ p_t = -8.0802e^{0.05} + \varepsilon_t \]  

**Figure 4:** Exponential decay in autocorrelation function across 500 lags.
\sigma^2 = 0.00027 + 0.953\sigma^2_{t-1} + 0.0349\varepsilon^2_{t-1} \quad (9)

Note that the sum of the ARCH (A) and the GARCH (G) coefficients is 0.989, which is close to the integrated, non-stationary boundary given by the constraints associated with the conditional variance models, which specifies that the sum of the ARCH and GARCH coefficients be less than one.

Performing a post-estimation analysis on the fitted GARCH(1,1) model revealed that the model selected is not sufficient, since not all the correlation has been removed. The analysis involves comparing the model’s residuals, conditional standard deviations and returns and then uses plots and quantitative techniques to compare correlation of the standardized innovations.

Simple plotting revealed the innovations (residuals) and returns series appear to show little volatility clustering. It made sense to explicitly specify a particular structure of the conditional variance model required, that is the mean and variance model orders, and possibly the initial coefficient estimates.

A range of GARCH\((p,q)\) models were specified for the data and statistical comparisons were made in order to select the optimum model. Testing various combinations of \((p,q)\) the GARCH\((3,1)\) model proved to be the most sufficient since the model accepted the null hypothesis that there is no correlation remaining in the data for 10 lags in the Q-test and each 10,15, and 20 lags for the ARCH test. A likelihood ratio tests also favoured the \((3,1)\) model over GARCH\((1,1)\). We specified an ARMA\((R,M)\) conditional mean structure over the selected GARCH\((3,1)\) model. The same statistical tests were applied to compare the ARMA\((1,1)\) GARCH\((3,1)\) to the GARCH\((3,1)\) process in order to see has the model become unnecessarily complicated. The post-estimation analysis revealed that the preferred model is to be the more complicated ARMA\((1,1)\) GARCH\((3,1)\) model which is to be given by:

\begin{align*}
  p_t &= -0.000406 + 0.40p_{t-1} + \varepsilon_t \quad (10) \\
  \sigma^2 &= 0.00026 + 0.961\sigma^2_{t-1} + 0.0237\varepsilon^2_{t-1} \quad (11)
\end{align*}

It is interesting to note that while fitting an ARMA\((R,M)\) over the GARCH\((3,1)\) the resulting optimum model selected resulted in being ARMA\((1,1)/\text{GARCH}(1,1)\). Hence one can conclude by adding in the ARMA property to the GARCH model,
that $P = (2, 3)$ became redundant and the conditional mean model ($R = 1, M = 1$) became more statistically significant than the $P = (2, 3)$ coefficients were.

### 2.2. The non-direct contract auction data

The eligible suppliers enter into the NDC auctions to purchase electricity sale contracts in advance of the effective date with the hope of hedging the future unknown system marginal prices for their known future demand profile. Baseload (BL) and Mid-Merit 2 (MM2) are the closest the SMP data, since BL correspond to 24 hours a day, 7 days a week. And Mid-Merit 2 is from 7.00am to 7.00pm on Monday to Friday. Accordingly, it was decided to see do the half hourly prices (SMP) around the time period in the lead up to the auction

1. influence the reserve price set by the regulators?

2. influence the premium that is to be paid by all suppliers. i.e. the amount over and above the reserve price which clears the market, (corresponding to the lowest price bided that clears the market)?

Figure 5 shows there is no evidence of a strong relationship between past and current auction prices. Our empirical findings are at odds with previous electricity auction studies in this regard, for example Rothkopf (1999), which was a purely theoretical study of auction design in electricity markets. Our findings square with the simulation study of UK and Welsh electricity markets performed by Bower and Bunn (2001), but the institutional details they studied were quite different.

Given our findings, we feel it is reasonable to assume that each auction is independent from earlier auctions. The clustering effect displayed in Figure 5 expresses the fact that there is a central tendency for the suppliers to submit their true value for the contracts, irrespective of increases or decreases in the SMP on the previous day(s). Based on the above results, one can deduce that the rules of the auction have the most influence on the results. This makes simulating an auction experimentally an interesting problem to study experimentally. It is to this question we now turn.
Figure 5: Fitting a polynomial around the relationship $\Delta SMP_{t-1} = SMP_{t-1} - SMP_{t-2}$ revealed that a 4th degree polynomial fitted the best. Clearly the relationship is extremely complicated.

3. Experimental design

Laboratory experiments were conducted to examine how varying informational and situational circumstances affect pricing decisions in simulated electricity auctions. The optimization problem of what bids qualify to purchase the product will also be solved in this laboratory setting.

3.1. NDC auction model

Each bidder must submit their price quantity pairs $(P, Q)$ simultaneously to be considered for the auction. For the purposes of this auction design experiment we hold $Q$ constant. Only information surrounding the price (with a given quantity demanded) is varied in the auction experiment. The structure of the experimental auction will closely mirror the actual NDC auction mechanism. For example, the price that successful subjects will theoretically have to pay is given under the follow conditions:
\[ p = \begin{cases} 
  p^* \quad \text{if} \quad Q_d > Q_s \\
  p^* \quad \text{if} \quad Q_d = Q_s \\
  p^0 \quad \text{if} \quad Q_d < Q_s .
\end{cases} \]

Here \( p \) is the price that is paid by all successful subjects in the auction, \( Q_s \) is total quantity offered, \( Q_d \) is the total quantity demanded. \( p^* \) is the clearing price, \( p^0 \) is the reserve price set by the regulator. \( p_n \) is the price that individual suppliers submit, \( Q_p \) are quantities that correspond to individual suppliers prices being above the clearing price, \( p^* \). (Recall that \( Q_s \) is satisfied such that \( Q_s = \sum_p Q_p \prod[p_n > p^*] \)).

Like the NDC auction the initial design experiment auction will take the form of a sealed-bid one-shot auction, where each bidder has a common value for the good. All subjects will be given the same information. In some of the auction experiments a reserve price (like the real NDC auction) will be given, which the bids must not go below. Making the same set of subjects face decisions under different the conditions or treatments results in the reduction of the effect of subject heterogeneity and sampling variability (Dechenaux and Kovenock, 2007).

All subjects were a selection of undergraduate and post-graduate students of varying levels education across a mix of courses. The instructions we gave are given in the appendix. Instructions included basic information about the Irish electricity market and were phrased in a way such that all participants will be homogenous irrespective of age, gender and level of education. Market conventions were slightly simplified to ensure subjects’ maximum understanding. The experimental environment examines the subject’s willingness to pay for a specified quantity of electricity as the information and situation varies.

Altering the auction rules changes the circumstances the subjects face. Since the experiment is based on the real life NDC auction, scarcity has to be created which is done by setting up the auction in a limit order only interrupted market (LOOIM) as described by Osborne (1965) and Osborne (1977). The experimenter will act as the auctioneer or market maker and sets the ‘limit sell order’ determines the supply function. In some cases a reserve price will be set, which the
auctioneer will not accept a bid below. Bidders who are assumed to have been
given the same information will not find out if they were successful until the auc-
tion is completed. Subjects were provided with a monetary incentive in order to
encourage honest participation while submitting their bids. The winner of the
auctions receives a monetary prize, and is the bidder who determines the clear-
ing price, similar to the market convention, the bidder who has bid the lowest
successful bid to clear the auction. (i.e. satisfy the quantity supplied).

4. Experimental results

The auction design experiment was conducted over 8 sessions in September 2009.
A total of 84 subjects participated in the experiment over the three days, 46 of
which were males and 38 females. At the beginning of the 30-minute long ses-
sion each of the subjects were handed out a sign-up sheet to complete. The sub-
jects were a combination of undergraduate (38), post-graduate students (42) and
some members of university staff (4). The mean age of participants was 22. Each
session had a varying number of subjects varying from 6 to the maximum lab
capacity of 14 participants thus the sell limit order of each session was adjusted
accordingly approximately the same ratio between the number of bidders in the
market and the number of units up for auction.

<table>
<thead>
<tr>
<th>No. of subjects</th>
<th>No. of Units</th>
<th>Ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td>14</td>
<td>10</td>
<td>0.714</td>
</tr>
<tr>
<td>12</td>
<td>9</td>
<td>0.75</td>
</tr>
<tr>
<td>10</td>
<td>7</td>
<td>0.7</td>
</tr>
<tr>
<td>8</td>
<td>6</td>
<td>0.75</td>
</tr>
<tr>
<td>6</td>
<td>4</td>
<td>0.666</td>
</tr>
</tbody>
</table>

*Table 2: Subject number adjustments.*
4.1. Treatment 1

In this treatment subjects played a static game bidding on behalf of companies supplying to specific types of customers. As set out earlier, the winner of the auction was the bidder to determine the clearing price (i.e. the last successful bidder to secure the right to purchase the good). Since subjects were bidding in triplicate, the amounts over which bidders place over the reserve prices was summed across the three bids and from these summed values the winner was determined. For example, imagine there were the maximum number subjects participating in the auction (14), and there were 10 units of electricity up for auction, the winner would be the bidder who ‘snapped up’ the last of those 10 units, i.e. the 10th highest bidder or in this case the 10th highest summed value. The average bids made by the 84 subjects on behalf of the three consumer profiles are laid out in table 3.

<table>
<thead>
<tr>
<th>Consumer Profile</th>
<th>Mean Prices</th>
<th>Reserve price set</th>
<th>Average bid</th>
<th>Average Premium willing to be paid</th>
<th>Number of subjects that bid above the Reserve price</th>
</tr>
</thead>
<tbody>
<tr>
<td>Winter residential</td>
<td>73</td>
<td>74.5</td>
<td>72.23</td>
<td>0</td>
<td>17</td>
</tr>
<tr>
<td>Summer Residential</td>
<td>64.82</td>
<td>60</td>
<td>64.79</td>
<td>4.79</td>
<td>81</td>
</tr>
<tr>
<td>Industrial</td>
<td>67.42</td>
<td>66.49</td>
<td>66.25</td>
<td>0</td>
<td>61</td>
</tr>
</tbody>
</table>

Table 3: Treatment 1 results

The reserve prices were set so as to reflect volatility sentiment, which the researcher hoped would have been expressed to the subject through descriptive statistics provided to the subjects. However, only 17 subjects thought the winter prices were volatile enough to bid substantially above the reserve price. The summer recommended strategy was followed by many, with 38 placing bids under the mean but with three outliers bidding under the reserve price. Although the mean for the annual prices was 67.42 euro the average bid was below. Two
occasions of subjects not bidding rationally were discovered (outliers), for example bidder 1 in session 7 bid just 2 euro for industrial electricity. Figure 6 contains the plots of each of the bidders on the three occasions. The two outliers have been removed from the plot as indicated by the broken lines.

Figure 6: Plot of each Consumer Profile Bids excluding outliers. The average premium of the 8 winners of Treatment 1 was 5.24 euro, that is to say the average clearing price was on average 5.24 greater than the reserve across the three consumer profiles.

4.2. Treatment 2

In this auction the subjects were bidding a price they considered fair for the purchase of annual electricity (based on the SMP information given whose historical mean was found to be 67.42 euros). First they were asked to all bid simultaneously. Some subjects placed bids below the mean, indicating that they didn’t think the SMP was so volatile to warrant paying a higher price than the mean for the year ahead, while others bid above the mean– suggesting that those bidders considered that data so volatile so as they were willing to pay a higher price than the historical mean in order secure a constant price for the coming year. The
winner was determined from the simultaneous bids. Since no reserve price was specified in this treatment, those that deviate from the SMP mean the greatest will be classified as having the highest bids. The winner bidding to receive the prize was determined from the sum of the deviations of all four bidding simultaneously prices.

For example, consider the 14 subject case bidding for 10 electricity units, the 10 highest deviations were classified as being the 10 highest bids, therefore the 10th lowest of them was the winner since he/she was the last bidding in to claim the last remaining unit of electricity.\(^{12}\)

On average, simultaneous bids put place before each round selection (i.e. Bids 1 and 3) were on average 74 cent higher than simultaneous bids placed after the round selection sub-treatment (i.e. Bids 2 and 4). This finding is important, because the current market structure demands simultaneous bids. This was to be expected, since subjects were continuously attempting to undercut each in order to be the lowest successful bid whilst also not reducing their bids substantially so that they would under bid for the commodity on auction. Similarly, on average the value of the first simultaneous bid over the second simultaneous bid was 1.48 euros. The third simultaneous bid was on average 23 cent higher than the fourth as bidders continued to attempt to undercut each other. Considering all subjects, the first simultaneous bid was 2.17 euro higher than the fourth simultaneous bid. The average standard deviation from the mean of the historical SMP data was 2.32 euros.

All bidders were given the opportunity to bid both first and second on two different occasions. This was done by dividing the subjects into two groups. Group 1 was the odd numbered computers and selected to bid first. Group 2 was the even numbers computers, these were subjects who selected round 2 and bid second. Table 4 outlines the average results of the strategies taken by Group 1 and 2. For example, the data in position (1, 1) are the averages of both groups when

\(^{12}\)Three extreme outliers believed to be causing bias when analysing the data, had to be removed, one occurred in session 4, where a value of 5 euro was bid for electricity in the first simultaneous bid and 51.25 euro in the 4th simultaneous bid. Another one involved a person in the same session bidding a value of 99.99 in their 4th simultaneous bid. A final outlier was in session 7, where a person was bidding 2 euro for the electricity. For consistency the same 3 bidders were deleted across the rounds bids also since they continued to not ask rationally and bid extremely low or high values.
they both bid simultaneously before round selection. Conversely the information in the position (2,1), that is 65.78 is the average bid places by even numbered computers when they bid second after learning that the average bid of the odd numbered computers was 66.02.

One considers a (round 1 round 1) bid to be the first simultaneous bid submitted by the two groups just before round selection i.e. the sum of the simultaneous bids 1 and 3 and the (round 2 round 2) Figures to be the fourth simultaneously bid submitted by the group after round chooses have been made i.e. simultaneous bid 1 and 4. In both the dynamic situations, on average the round 2 bidders bid below the round 1 subjects. This is a pleasing result and is consistent with other papers that study simultaneous bids Alsemgeest et al. (1998); Kwasnica and Sherstyuk (2007).

Baring in mind the objective is that all the successful bidders pay the same clearing price, considering the average of the both the simultaneous outcomes and comparing these to the matrix outcomes for the sequential cases is revealing. Both the averages of simultaneous bids (66.75 and 66.21) are higher then what could be achieved when round selection is allowed whose lowest values are 61.62, and 63.84.
When Bayesian-Nash equilibrium\(^\text{13}\) is played, both equilibria are more optimal than playing the static game. When both groups seek to achieve a dominant strategy in the static game, both groups are worse off as they would have to pay a higher market clearing price. The overall optimum strategy for all if the even numbered computers bid first and the odd bid second since a lower clearing price would be secured. We believe that strategy (Round 1 Round 2) is lower than the other dynamic game because (Round 1 Round 2) was the second game played (odd computers select to bid second), so a clear first-mover advantage is present.

4.3. \textbf{Treatment 3}

The structure of this treatment is the same as treatment 2, except that a reserve price is specified throughout. As before the bidders have placed 4 bids simultaneously and 2 sequentially, taking turns who bids first like above. The winner will be determined, as before, from the four simultaneous bids submitted.

This time a reserve price was set at 69 euro. We calculated how much subjects had to bid above this price. In terms of the maximum capacity subject group of 14 with 10 units up for auction it was the 10 highest bidders above the reserve price were then identified as being successful.

The winner was the 10th highest successful bidder to just qualify or clear the limit supplier order. In this treatment all subjects appear to have acted rationally since no extreme outliers could be identified for exclusion.

Providing a reserve price resulted in a less dispersion of bids. There was no

\(^{13}\)Recall that a strategy profile \(S = (s_1, \ldots, s_i)\) is in Bayesian-Nash equilibrium if, for every agent \(i\) and for all preferences \(\theta_i \in \Theta_i\), \(u_i(s_i, s_{-i}, \theta_i) \geq u_i(s_i^1, s_{-i}, \theta_i)\), for all \(s_i^1 \neq s_i\). In this instance \(u_i\) denotes the expected utility over the distribution \(N(\theta)\).
noticeable difference on average between the simultaneous bids submitted before the round selection, and the simultaneous bids placed after round selection sub-treatment. Subjects became more cautious in changing the values of their bids. The four individual bids revealed differences. This time on average the value of the first simultaneous bid was less than the second simultaneous bid by 28 cent.

The third simultaneous bid was on average 41 cent higher than the fourth as bidders continued to attempt to undercut each other. On average, the first simultaneous bid was 32 cent higher than the fourth simultaneous bid. Subjects continued to undercut each other to try and be the lowest successful bidder (the bidder who determines the clearing price).

Since the subjects could not submit bids below the reserve price, and no outliers had to be removed, the average deviation from the reserve price across the 4 submitted bids was 8.78. (This is the average of the four summed differences) Divided by 4 gives an average deviation per bid of 2.19 euro, which is slightly less than Treatment 2. Figure 8 displays all of the simultaneous bids in Treatment 3.

![Figure 8: Results of all of the simultaneous bids in Treatment 3.](image)

Interestingly, the round 1 and round 2 sub-treatment was less successful in this treatment. This time there was a 40% success rate with the matching of the
Round 1 and Round 2 subjects as only 53 times the program worked successfully. 67% of those who bid second in the rounds sub-treatment decided to bid below their competitor. A comparison of the over all round 1 versus round 2 prices revealed that Round 2 bidders on average bid prices less than 54cent than their round 1 competitors. This is in line with earlier results with showed bidders trying to undercut each other. The same computational steps were followed as in treatment 2 in the creation of table 5.

<table>
<thead>
<tr>
<th>Group 1 - odd numbers</th>
<th>Group 2 - even numbers</th>
</tr>
</thead>
<tbody>
<tr>
<td>Round 1</td>
<td>(70.41, 70.33)</td>
</tr>
<tr>
<td>Round 2</td>
<td>(70.43, 70.58)</td>
</tr>
<tr>
<td>Round 1</td>
<td>(69.87, 69.36)</td>
</tr>
<tr>
<td>Round 2</td>
<td>(70.39, 70.41)</td>
</tr>
</tbody>
</table>

Table 5: Treatment 3 Round outcomes

In both the dynamic games, the round 2 bidder attempts to undercut the round 1 bidder, again this is consistent with the theory that the subjects are attempting to win the auction. Considering the averages of the both the simultaneous outcomes and comparing these to the matrix outcomes for the dynamic games. Both the averages of simultaneous bids (70.37 and 70.40) are higher then what could be achieved when Nash equilibrium is played, however only in the case when the odd numbers bid second.

Figure 9 displays the round 1 bids and the round 2, one can see that round 2 closely mirrors round one’s bidding pattern. From data points 22-50 it is particularly evident that round 2 bidders are attempting to undercut the bids so as to improve their chance of winning the treatment auction.

4.4. Treatment 4

In this treatment subjects were asked to bid on four occasions for the four different electricity products on offer. Subjects were provided with reserve prices, which were taken to be the average reserve prices in this years NDC auction. The difference between the subjects bid and the reserve price, (known as the premiums subjects were willing to offer) were summed across the four bids, it was from
Figure 9: Plot of Round 1 versus Round 2. A comparison between Treatment 2 and 3 bids revealed that on average as was expected: Treatment 3 bids simultaneous bids were approximately 6% higher.

this Figure that the winner was determined. As usual the winner was determined as being the last highest bidder to clear the auction. Two outliers were noted in the Baseload and MM1 bids but their effect was thought to be only marginal. Figure 10 displays all the bids for each of the four products with the inclusion of these outliers.

By separating out the bids made for each product and determining a winner or clearing price for each product, one can formulate a comparison between the clearing prices of the simulated auction and clearing prices of this years real NDC auction with the hope that there will be some similarities between the two.

From table 6, one can see that the clearing prices from the simulated auction and the average bids were consistently under the actually NDC auction prices. This is due to the fact that the subjects have no real understanding of the potential value of these products where as the eligible suppliers in the real NDC auction situation have more technical knowledge of the worth of these products. (for example how valuable it is to secure a fixed price for the peak product due to the high demand experienced during those times and the volatile nature of the
Figure 10: Bids placed for each of the 4 electricity products

<table>
<thead>
<tr>
<th>Product</th>
<th>NDC Auction Average Clearing Price</th>
<th>Premiums</th>
<th>Simulated Auction Clearing Price</th>
<th>Premiums</th>
<th>Simulated Auction Average of Bids</th>
<th>Premiums willing to be paid</th>
</tr>
</thead>
<tbody>
<tr>
<td>Baseload</td>
<td>60.99</td>
<td>0.87</td>
<td>60.62</td>
<td>0.50</td>
<td>60.93</td>
<td>0.92</td>
</tr>
<tr>
<td>Peak</td>
<td>103</td>
<td>6.34</td>
<td>98.44</td>
<td>1.78</td>
<td>99.32</td>
<td>2.66</td>
</tr>
<tr>
<td>MM1</td>
<td>69.74</td>
<td>3.12</td>
<td>67.09</td>
<td>0.27</td>
<td>67.62</td>
<td>0.78</td>
</tr>
<tr>
<td>MM2</td>
<td>70.41</td>
<td>1.08</td>
<td>69.59</td>
<td>0.26</td>
<td>69.91</td>
<td>0.58</td>
</tr>
</tbody>
</table>

Table 6: Treatment 4 Results
winter prices). Also, the experimenter believe that subjects were keeping their bids on average lower since they were biased towards attempting to be the lowest successful bidder in order to win the monetary incentive.

5. Conclusion and further work

This paper empirically and experimentally examined the existing market design of auctions in the Irish electricity market, which has recently opened up to competition.

Combining econometric and experimental approaches, we found that daily market prices could not be well explained by simple pricing models used in the literature.

We studied 2 years of pricing data with over 30,000 observations. There appeared to be no relationship between the half hourly marginal price data and the outcome of the auction. We aver that the rules of the auction and the rational bids placed by the participants that determines the outcome (Milgrom, 2004). We studied these rules experimentally.

In particular, we asked if the availability of true marginal prices for electricity products affect the price/quantity \((P, Q)\) bids submitted by market participants.

We varied the type, extent, and quality of information available to participants, as well as changing the underlying market mechanism to answer this question. We employed a homogeneous good-auction bidding model, where all subjects were provided with the same information from which prices were selected.

Data from the experiment continuously showed that the value of bids within the same treatment decreased the more often the bids were submitted. This result was satisfactory since it was consistent with theory–that subjects would continue to undercut each other within the same treatment, since the subjects were attempting to be the lowest successful bidder (the bidder who determines the clearing price). Our findings are in contrast to previous studies of electricity auctions like Bower and Bunn (2001) and Rothkopf (1999), though our study is empirically driven, while these studies were theoretical and simulation-based. Also, the institutional structure we examine is different from previous studies.
In two of the treatments (Treatment 2 and 3) a dynamic game was played. From the dynamic games a ‘pay-off’ or strategy matrix could be constructed for Treatment 2 and 3, which revealed that when bidders adopt to play a Bayesian-Nash equilibrium in each of games, a lower average bid was realised. This lower bid would be beneficial to all market participants since all pay the lowest successful clearing price.

The main result of the paper is that if the auction were to operate under a dynamic game (that is, conduct a sequential bidding auction), all market participants would benefit, as lower clearing prices would result. This is currently not the case. Future work will focus on implementing a more robust and complex experimental environment, as well as changing electricity pricing policy nationally to reflect our findings.

However, if the non-direct contract auction were to operate under a dynamic game, that is an auction of sequential bidding, all market participants would benefit since lower clearing prices would result, as demonstrated by the simulated auction.

**References**


