
AN EMPIRICAL ANALYSIS OF SPECULATOR UNITS IN A SHORT TERM ELECTRICITY MARKET

A PREPRINT

Joseph Collins, Andreas Amann, Kieran Mulchrone

Department of Applied Mathematics, School of Mathematical Sciences, University College Cork

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ABSTRACT

TODO

Keywords **TODO · TODO · TODO**

Glossary

B	Balancing, a market where the TSO dispatches on/off generation to ensure supply matches demand
BETTA	British Electricity Trading & Transmission Arrangements (British Electricity Market)
BidAskCurve	A data source containing anonymised demand and supply curve information
DA	Day-Ahead, the electricity auction that occurs on day D-1 for each delivery hour in day D
EPF	Electricity Price Forecasting
ETS Bid File	A data source containing granular participant order information
EUPHEMIA	Pan-European DA algorithm
IC	Intraday Continuous, a market allows participants to balance their exposures closer to delivery time
ID	Intraday, auctions or markets that occur after the DA auction
IDA1/2/3	In the Irish electricity market there are three intraday auctions
I-SEM	Integrated Single Electricity Market (Irish Electricity Market)
Marginal Pricing	Uniform pricing whereby all buyers/sellers pay the same market price
Matched Quantity	The amount that was bought or sold
NIV	Overall system imbalance
Order Quantity	The quantity in the bid or offer
Real-Time	Short-term electricity market in the United States, has parallels to Balancing markets in a European setting
SEMO	Single Electricity Market Operator (I-SEM)
SEMOpX	Designated Nominated Electricity Market Operator (I-SEM)
Simulated DA	A small perturbation to either of the DA supply or demand curves
Speculator	A market participant that does not consume or generate electricity
TSO	Transmission System Operator
Virtual-Bidding	A mechanism in the United States which enables speculators to participate in short term electricity markets

1 Introduction

Electricity markets have undergone significant change in recent decades. Factors influencing the change include electricity market liberalisation [1][2] and the build out of renewable generation to meet climate change targets [3][4]. These influences are evident in short-term electricity markets [5], in particular *Day-Ahead* markets (section 2.1) which are a cornerstone of electricity markets in Europe and the USA. The prices which result from these markets impact retail electricity prices, can act as a signal for the building (or indeed closure) of electricity generation assets etc. In recent times the mechanism by which short-term electricity prices are determined, *marginal pricing*, has received increasing public attention [6][7][8]. This has largely been driven by the European energy crisis which over the course of 2021 and 2022 saw sustained periods of high and volatile electricity (and gas) market prices.

Short-term electricity market prices feature in literature relating to

- *Electricity Price Forecasting (EPF)*: papers such as Ziel and Steinert [9] and Lago et al [10] which use statistical, machine learning and deep learning modelling techniques to forecast short-term electricity market prices.
- Electricity market pricing mechanisms: papers such as Bower and Bunn [11] and Van der Veen et al. [12] which investigate the impact of pricing mechanisms (e.g. marginal pricing) on short-term electricity market prices.
- Publications such as [13][14][15] which consider the impact of financial traders on short-term electricity markets.

While it is well understood that short-term electricity market prices exhibit sharp price spikes, what has received less attention in the literature is a treatment and discussion of the complexities associated with short-term electricity market price formation. When considering the design of current/future electricity markets and systems it is our view that policy makers, modellers and market participants would benefit from a deeper and more nuanced understanding of this aspect of short-term electricity markets.

We bridge the gap by performing an analysis of the Irish electricity market. The setting has the advantage of (a) being reflective of short-term European electricity market structures (b) having a high wind generation penetration (c) a liquid Day-Ahead market and (d) a number of financial traders. To highlight the complexity and sensitivity in the short-term electricity market price formation process we perform minute perturbations to supply and demand curves and estimate the impact on the Day-Ahead market price. It is observed that post a structural market change there is a dampening in the sensitivity of Day-Ahead market prices to such perturbations and that this is most likely attributable to the cohort of financial traders, henceforth called *speculators*. It will be seen that these speculators exhibit changing commercial behaviours and that they constitute an increasing share (and overall importance from a price setting perspective) of the Day-Ahead market. The data used in the study has the benefit of coinciding with a diverse and volatile set of commodity price regimes including the Covid-19 pandemic¹ and the previously referenced European energy crisis.

1.1 Problem Setting and Related Work

The analysis takes place in a *multi-settlement market* setting, this is where the bidding and dispatch of electricity for a specific trading period is managed in successive runs. In these settings speculators do not consume or generate electricity, they receive (or pay) a financial payoff related to the spread between the price at which they buy & sell electricity in the different markets. Examples include *Virtual Bidding* in the USA (the payoff relates to the spread between Day-Ahead & *Real-Time* electricity market price) and *Net Imbalance Volume (NIV) Chasing* strategies [18] [19] in the electricity market in Great Britain².

In modelling supply and demand curves for a Day-Ahead market Ziel and Steinert [9] touch upon the short-term electricity market price formation process. As motivation to their approach they present an example where the "*equilibrium price is very sensitive to external shocks*" and another that is more reflective of the "*typical behavior of price curves when the market is not very prone to extreme events*". He et al. [20], which also deals with electricity price forecasting, note that after applying the 0-1 chaos test [21] to an electricity price time series the results "*provide the indications of chaotic data characteristics for price movements*".

Non-academic references that document the dynamicism in the commercial behaviours of subsets of market participants, thereby hinting at the complexities in the short-term electricity market price formation process, include [22] and [23]. Report [22], from the Australian Renewable Agency (ARENA), "*tracks the trend towards more dynamic bidding*

¹Which resulted in a low price commodity environment at the outset of the pandemic [16][17].

²*British Electricity Trading and Transmission Arrangements, BETTA*

strategies" and observes an increasing utilisation of automated bidding software in the Australian National Electricity Market. Article [23], from *Bloomberg*, considers the impact that a small group of physical market players have on a specific segment of the British electricity market.

In relation to speculators, papers [13], [14] and [15] analyse the impact of Virtual Bidding in short-term electricity markets in the USA. Parsons et al. [13] brings to the fore the complexity of the short-term electricity market pricing algorithms, in addition they provide specific examples in which Virtual Bidding would result in a narrowing of the Day-Ahead versus Real-Time spread without any corresponding system benefits. Akshaya and Wolak [14] suggest that a potential motivation for Virtual Bidding in short-term electricity markets is that they have the potential to enhance market liquidity resulting in improvements in future spot price transparency and real-time market performance. They find strong evidence that (a) Day-Ahead versus Real-Time price spreads fell (b) volatility of Day-Ahead versus Real-Time price spreads fell and (c) no discernible deterioration in system performance, after the introduction of speculators in the California wholesale electricity market. In Mercadal [15] the author investigates the Midwest electricity market, MISO, in the USA in which a change in transaction costs resulted in increased speculator activity. The author stresses the *"importance of considering dynamics when investigating the role of financial traders"* in addition to presenting other empirical observations.

In this paper, we combine some of the aforementioned narratives in a single setting/study. In perturbing the supply and demand curves we underscore the complex and at times sensitive nature of short-term electricity market price formation process. In subsequently focusing on speculators we develop an understanding as to some of dynamic factors in short-term electricity markets.

1.2 Paper Structure

The structure of the remainder of the paper as follows: in section 2 we present both an overview of the short-term electricity market of interest and the related pricing algorithms, we also provide a hypothetical example of a speculator in this setting. In section 3 we detail the data sources and methodology. Section 4 presents the empirical analysis whilst in section 5 we discuss the main findings. In section 6 we conclude. Supplementary details & materials are available in the accompanying appendices.

2 Market Structure

2.1 Route To Market

The *Integrated Single Electricity Market (I-SEM)*, is the electricity market in Ireland. Albeit it is small in overall size (net electricity consumption in Ireland in 2021 was 30TWh, the equivalent figure for Great Britain was 305TWh [24]) it typifies spot European wholesale electricity market structures. Some of the routes to market (i.e. how to buy and sell electrical energy) include

- *Day-Ahead, DA, market*: at 11am on day D participants submit orders to buy or sell electricity for hourly delivery periods in the [11pm D, 10pm D+1] interval. The *market coupling* algorithm, *EUPHEMIA*, takes these inputs, in conjunction with interconnector transmission capacities (and other factors), and determines hourly prices and the direction of energy flow on the interconnectors. If the network is congested then nodal prices will diverge.
- *Intraday, ID, market*: after the DA auction has cleared additional auctions are held; these auctions, *IDA1*, *IDA2* and *IDA3* are similar in nature to the DA with the main differences being that they are held closer to the delivery time & the delivery periods are 30 minute intervals³.
- *Intraday Continuous, IC, trading*: this is an important market in other European jurisdictions, but in an I-SEM context it comprises less than half a percent of traded energy volumes and hence is out of scope.
- *Balancing, B, market*: one hour prior to delivery the *ex-ante*⁴ trading opportunities cease and the *Transmission System Operator, TSO*, takes over. The TSO compares forecast demand versus forecast generation (including what volumes have been traded in the *ex-ante* markets) and dispatches on/off units to ensure that demand meets supply. The prices that result from these dispatch decisions are called *settlement imbalance prices* (or *Balancing market prices*).

³IDA1/IDA2/IDA3 auctions cover the [11pm D, 10:30pm D+1]/[11am D+1, 10:30pm D+1]/[7pm D+1, 10:30pm D+1] time horizons respectively.

⁴*ex-ante* in this context means occurring before the delivery period, *ex-post* means that it occurs after the delivery period.

In the I-SEM a physical position is only possible by participating in one the aforementioned markets, this is in contrast to other European electricity markets where self-dispatch is also a route to market. The I-SEM is connected to the electricity market in Great Britain via two interconnectors. **Prior to Great Britain exiting the European Union, I-SEM and BETTA were coupled in DA and IDA1 auctions; as of 1st January 2021 market coupling between I-SEM & BETTA takes place at the IDA1 and IDA2 auctions [25][26].**

2.2 Pricing Algorithms

As outlined in section 2.1 EUPHEMIA (the *Pan-European Hybrid Electricity Market Integration Algorithm*), is the algorithm used to calculate hourly Day-Ahead market prices in a number of European markets. As per the EUPHEMIA Public Description [27]:

- "The algorithm can handle a large variety of order types at the same time"; these include *Aggregated Hourly Orders, Complex Orders (including Minimum Income Condition, MIC, and/or Load Gradient constraints), Scalable Complex Orders & Block Orders*.
- The algorithm solves a *Welfare Maximization Problem (Master Problem)* & three interdependent sub-problems one of which is the *Price Determination Sub-Problem*. In the Master Problem "EUPHEMIA searches among the set of solutions for a good selection of block and MIC orders that maximises the social welfare. Once an integer solution has been found for this problem, EUPHEMIA moves on to determine the market clearing prices." i.e. the Price Determination Sub-Problem.

From the above it is clear that viewing the algorithm solely in a supply and demand curve intersection context, while intuitive, is an oversimplification of the underlying mechanics. It is also worth noting that as per [28][29] the algorithm has undergone (and continues to undergo) incremental change.

The approach taken in the Balancing markets in Ireland and Great Britain is that it is the set of energy only actions taken by the TSO to keep supply and demand in balance that are used to calculate the Balancing market price. These energy only actions are identified using a *flagging and tagging* process. The I-SEM Balancing market algorithm is fully described by Bharatwaj and Downey [30]⁵ (this is in contrast to EUPHEMIA for which to the best of our knowledge only the aforementioned high-level public description is available). Only a subset of physical market participants (i.e. physical market participants that deviate from their *final physical notification* positions upon instruction from the TSO) are used to determine the Balancing market price.

2.3 Speculator Units

We explain the concept of speculators in the I-SEM by way of a simple example. Consider a single speculator and delivery period in the I-SEM. For this trading period the speculator unit forecasts prices of $\text{€}X/\text{MWh}$ in the DA/IDA1/IDA2/IDA3 markets, they forecast a price of $\text{€}(X+20)/\text{MWh}$ in the Balancing market. Based on these forecasts the speculator's strategy is to buy in the cheaper ex-ante markets and sell implicitly⁶ in the more expensive balancing market. They buy 50MW/25MW/0MW/0MW in the DA/IDA1/IDA2/IDA3 markets. Given these ex-ante market positions, it immediately follows that their balancing market position will be a sell of 75MW. If the participant's forecasts turn out to be correct they stand to make a profit of $\text{€}750$ as the cost of the buys, $\text{€}\frac{(50X+25X+0X+0X)}{2}$, would be less than the income from the sell, $\text{€}\frac{75(X+20)}{2}$. In this example, the $\frac{1}{2}$ factor is used to reflect the quantity of energy bought or sold in a 30 minute interval.

3 Datasets and Methodology

3.1 Datasets

SEMOpx and SEMO are two of the bodies involved in the operation of the I-SEM⁷. Some of the datasets they publish which are utilised in the empirical analysis are as follows:

- **Granular Order Data:** For each of the four ex-ante markets referenced in section 2.1 SEMOpx publishes a distinct file called the *ETS Bid File* [34]. These files "contain all the orders submitted during the auction...for

⁵For BETTA, Elexon have a similar imbalance pricing guidance note available in [31]

⁶The speculator units balancing position must equate to the negative of the net of its ex-ante positions given it does not consume or generate electricity.

⁷A high level overview of their roles and responsibilities is given in [32] and [33].

a given Area Set and Auction Day.". We use these files to interrogate the order data at a participant and trading period level of granularity. The sign convention inherent in each ETS Bid File is that positive (negative) quantities represent purchase (sell) orders⁸.

- **Bid Ask Curve Data:** For each ex-ante auction SEMOpx publish a *BidAskCurve* file containing a monotonic increasing (decreasing) and anonymised view of the sell (buy) orders for each trading period in the auction⁹.
- **Other Data:** Other datasets include
 - *PUB_MnlyRegisteredCapacity* files which provide participant registration data such as registered plant capacity and *FuelType* (if applicable).
 - *PUB_30MinImbalCost & MarketResult* files which contain the *ex-post* Balancing Market and ex-ante DAM/IDA1/IDA2/IDA3 prices respectively.

In appendix F we describe an exercise in which we reconcile the granular order data in the ETS Bid File with the anonymised order data in the BidAskCurve file.

3.2 Methodology

In subsections 3.2.1 and 3.2.2 we describe the approach to the I-SEM DA perturbation analysis. Subsections 3.2.3 to 3.2.6 detail the I-SEM speculator empirical analysis.

3.2.1 Parallel Shift

For trading period i , to simulate the impact of a **small** perturbation in the DA ask curve on the DA market price:

1. Retrieve the bid and ask curve for trading period i from the relevant DA BidAskCurve File.
2. For every (*quantity, price*) point in the ask curve add X MW to each of the quantity values.
3. Determine where this horizontally shifted ask curve intersects the bid curve. We call the resulting price the *Simulated DA* market price for trading period i . It is denoted by P_i^{SDA} .
4. Next, take the DA market prices for the corresponding hour over the previous 20 days and calculate the standard deviation of these observations. Denote the value by SD_i .
5. Define and calculate the *Price Difference* and *Custom Metric* values as

$$Price\ Difference_i = P_i^{SDA} - P_i^{DA} \quad (1)$$

$$Custom\ Metric_i = \frac{|Price\ Difference_i|}{SD_i} \quad (2)$$

where P_i^{DA} denotes the DA market price in trading period i .

We choose values of X equal to $+1MW$ & $+10MW$. The intuition behind the $1MW$ value is that it equates to the minimal incremental quantity in any order; similarly given that the average I-SEM forecast DA demand by trading period over the November 2018 to December 2022 time period is circa 4300MW a $10MW$ horizontal shift can be viewed as being a small perturbation. The approach outlined above can be amended to analyse the impact of small parallel shifts in the bid curve; for conciseness purposes in section 4.1.1 (Figures 1, 2 and 3) we restrict ourselves to presenting the results of the ask curve perturbations.

3.2.2 Speculator Unit Impact

In the I-SEM, participants may register one or more *Supply, Generator, Assetless, Trading* or other unit types. There is flexibility in how these units behave, hence we use the sequence of steps outlined in appendix B to identify speculators in the I-SEM.

Having identified the population of speculators, to estimate the impact of a single speculator, j , on the DA price for trading period i , we execute the sequence of steps outlined in appendix E. The first portion of the algorithm (i.e. Steps 1

⁸The DA ETS Bid file for example is published on a day+1 basis relative to the trading day and typically it consists of in excess of circa twenty thousand rows with an average of three hundred plus participants per auction.

⁹As of July 2021 SEMOpx have simplified matters somewhat by publishing a single BidAskCurve file for each ex-ante auction with the supply and demand information per trading presented in €/MWh. Prior to that date, SEMOpx would publish two BidAskCurve files for each ex-auction auction, one containing information in £/MWh relating to the Northern Ireland (NI) marketarea and the other containing information in €/MWh relating to the Republic of Ireland (ROI) marketarea.

to 4) is akin to a validation step in that granular order data from the ETS Bid File is used to reproduce the published BidAskCurve data. In the remaining step we again reconstruct the BidAskCurve but this time we exclude the speculator unit's order data and calculate the simulated DA market price. With this approach, the assumption of a small or local perturbation in the bid or ask curve may not always be justified. Results are presented in Figures 4 and 5 in section 4.1.2.

3.2.3 Day Ahead Market Quantities

The DA market in the I-SEM accounts for approximately 85% of traded volumes [35][36][37], hence we are interested in seeing how the volumes have evolved over time both for the overall market & for the population of speculators. Using information in the DA market ETS Bid Files (section 3.1) we derive a per trading period time series that shows

- The quantities of energy that participants were willing to buy or sell, we refer to this as the *order quantities*.
- The quantities of energy bought or sold which we term the *matched quantities*.

See Figures 6 & 7 in section 4.2.1.

3.2.4 Speculator Unit DA Order Evolution

For the population of speculator units how have their DA market order's evolved over time? Start by considering a single trading period, i . Split the price domain into three distinct intervals (or buckets)

- Interval 1: $[-500, P_i^{DA} - SD_i]$
- Interval 2: $[P_i^{DA} - SD_i, P_i^{DA} + SD_i]$
- Interval 3: $[P_i^{DA} + SD_i, 3000]$

The P_i^{DA} and SD_i variables are described in section 3.2.1 and the -500 and 3000 values correspond to the minimum and maximum permissible DA market prices¹⁰. For trading period i sum the buy (sell) speculator order quantities that are associated with that price interval. The process is then repeated for all trading periods in the November 2018 to December 2022 timeframe. In section 4.2.2 Figure 11 we plot the resulting time series.

3.2.5 DA Marginal Units

Marginal pricing is the principle by under which the DA market operates (for a high level overview see [7] and [8]). We undertake the sequence of steps described in appendix C to identify which participants are *marginal* in the DA market and whether or not this pattern has changed over time. The high level approach is that for each trading period

- We retrieve the corresponding bid (i.e. demand) and ask (i.e. supply) curves from the BidAskCurve file and determine how they intersect.
- The intersection point(s) are then cross-referenced against the participant order data in the relevant ETS Bid File to determine which unit, or units, are marginal.

When examining the bid and ask curve intersections, it can be seen that they are either perpendicular, horizontal or vertical intersections. In section 4.2.3, Figure 12, we plot both the marginal unit (grouping by FuelType) and the bid and ask curve intersection type.

3.2.6 Estimating Speculator Unit Profitability

Ignoring trading or transaction costs (which in the I-SEM are minimal), the approach to estimating speculator unit profitability mimics the hypothetical example in section 2.3. With E denoting the set of ex-ante markets¹¹, for Speculator unit j in trading period i its balancing market quantity, $Q_{i,j}^B$, is given by:

$$Q_{i,j}^B = - \sum_{m \in E} Q_{i,j}^m \quad (3)$$

¹⁰As per [38] and [39] the maximum DA price has increased in stages from €3000/MWh to €5000/MWh. We take this into account in our empirical analysis by assuming all orders are capped at the €3000/MWh level.

¹¹ $E = \{DA, IDA1, IDA2, IDA3\}$

$Q_{i,j}^m$ in equation (3) represents the quantity of power bought or sold in trading period i by speculator j in market m . Speculator unit j 's profit and loss in trading period i is then estimated by

$$-\frac{1}{2} \sum_{m \in A} P_i^m Q_{i,j}^m \quad (4)$$

where P_i^m denotes the market price for trading period i in market m and A represents the set of all markets (i.e. $\{DA, IDA1, IDA2, IDA3, B\}$). As is clear from equation (4) a portion of profit and loss could relate to opposing ex-ante market positions (see appendix D for additional details). In section 4.2.4 we report on the estimated profitability for the population of speculator units in the I-SEM over the November 2018 to December 2022 timeframe.

4 Results

4.1 DA Perturbation Analysis

4.1.1 Parallel Shift

Figure 1 presents time series plots showing the impact of a +1MW horizontal shift in the DA ask curve. The top & bottom plots present the Price Difference and Custom Metric time series values respectively (section 3.2.1). The latter time series is of particular interest as it incorporates the price level¹². The Custom Metric plot shows a visible reduction in values from 2021 onwards. Examining the underlying data it is the case that in approximately 6.3% (3.6%) of all trading periods pre (post) 1st January 2021 if we apply a +1MW horizontal shift to the ask curve it would result in a change to the market price. For those trading periods in which a +1MW perturbation results in a price change, on average it would yield a reduction of 3.8% (0.8%) in the DA price pre (post) 1st January 2021.

Similar to Figure 1, in Figure 2 we show the impact of a +10MW horizontal shift in the DA ask curve. We observe that in approximately 42% (30%) of all trading periods in which we apply a +10MW horizontal shift in the ask curve it would result in a price change¹³ pre (post) 1st January 2021. Finally, if we take the Price Difference and Custom Metric time series values but instead plot them against the corresponding DA price then we arrive at Figure 3. In the scatter plots we distinguish between pre and post 1st January 2021 trading periods. The difference in distributions is clear¹⁴.

4.1.2 Speculator Unit Impact

The 50 participants which have been identified using the approach described in section [UPDATE REF](#) are listed in Appendix G.

Of the 50 participants, 47 of the units are registered with AU (*assetless units*) identifiers and the remaining 3 are registered with SU (*supplier units*) identifiers. A small minority of the above ResourceNames are no longer active participants in the I-SEM. For context, since the inception of the I-SEM there have been 472 distinct participants/ResourceNames which have been active in the DA market.

Following the methodology described in section 3.2.2, in Figures 4 and 5 we simulate the impact that a single speculator unit has on the DA bid & ask curve intersection. Figure 4 shows the bid & ask curves for two separate trading periods on 10th January 2019; the blue lines exclude the speculator unit whereas the red lines include the speculator unit. For these trading periods, the speculator unit only submitted sell orders and hence the red and blue **bid** curves are identical. For the 4am-5am trading period the speculator unit submitted sell orders of 4MW at €40/MWh and an additional sell of 4MW at €50/MWh; for the 5am-6am trading period the speculator unit submitted similar sell quantities but at price points of €44/MWh & €54/MWh respectively. The DA price for 4am-5am was €59.16/MWh and for 5am-6am the price was €64.09/MWh. For the 4am-5am trading period, it can be seen that without the speculator unit the ask curve is effectively shifted to the left, which results in a higher intersection price (€61.77/MWh). In contrast, for the 5am-6am trading period while the ask curve without the speculator unit is again shifted to the left, the intersection price remains unchanged.

For the same speculator unit, if we calculate the Price Difference time series values (calculated as DA price without the speculator unit minus DA price with the speculator unit) and plot it against the speculator's corresponding DA matched quantities then we arrive at Figure 5. From this plot it is clear that if a speculator unit is selling (buying), then the impact of removing the speculator from the ask (bid) curve is to push up (down) the price.

¹²For reference, time series plots of DA and Balancing market prices are available in Figure 14 in Appendix J.

¹³When a +10MW ask curve perturbation results in a DA price change, pre and post 1st January 2021 it leads to an average reduction in price of circa 4.6% and 1.1% respectively.

¹⁴The newly formed I-SEM came into inception in Q4 2018, the difference in distributions is still clear whether we include/exclude the data associated with the first six months operation of the newly formed market.

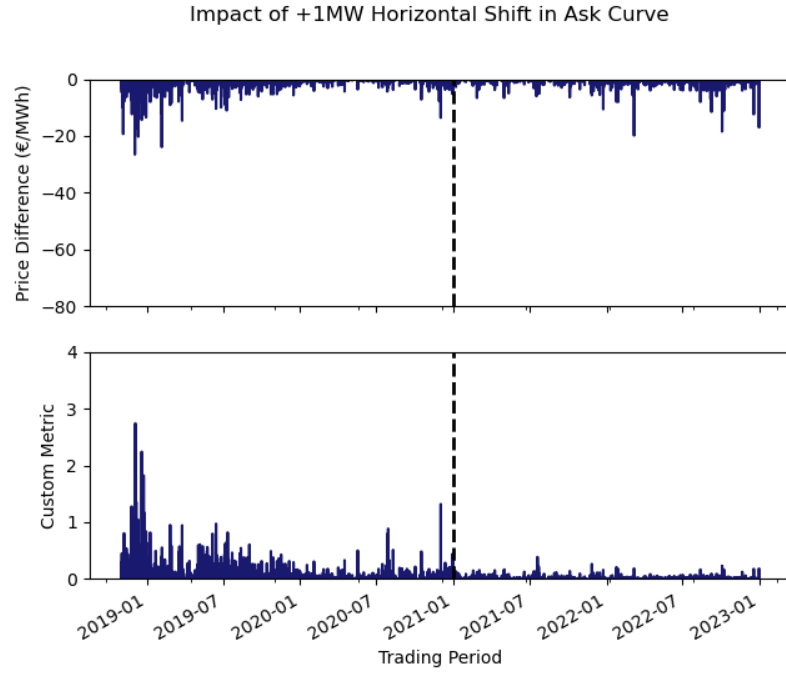


Figure 1: Impact, per trading period, of a +1MW horizontal shift in the ask curve. Top plot shows the Price Difference values in €/MWh, bottom plot shows the Custom Metric values.

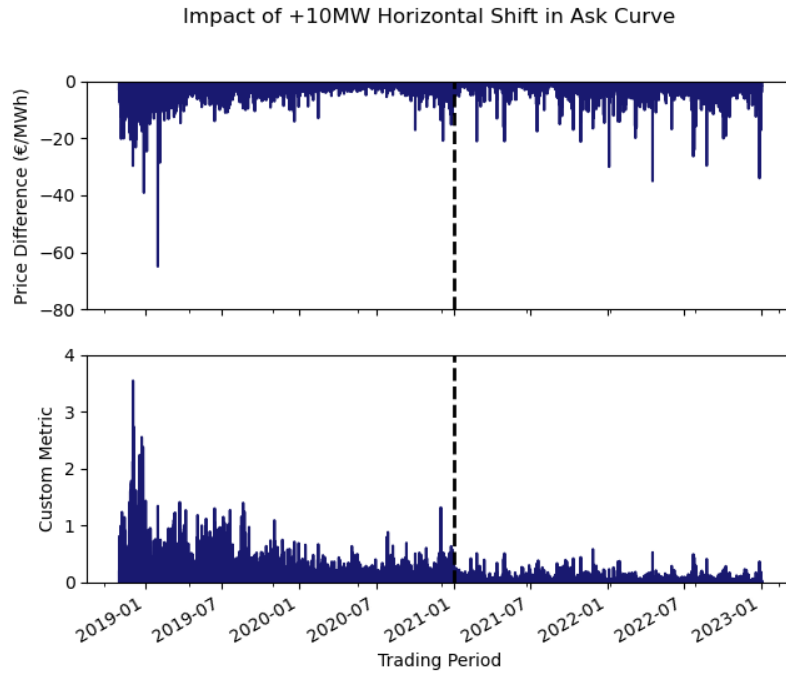


Figure 2: Impact, per trading period, of a +10MW horizontal shift in the ask curve. Top plot shows the Price Difference values in €/MWh, bottom plot shows the Custom Metric values.

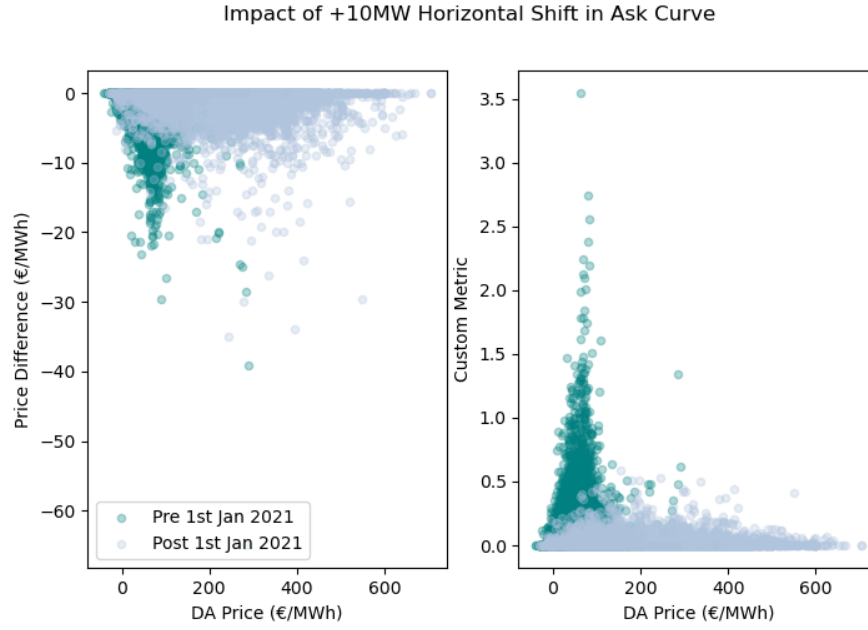


Figure 3: Scatter plot showing the impact, per trading period, of a +10MW horizontal shift in the ask curve distinguishing between observations pre and post 1st January 2021.

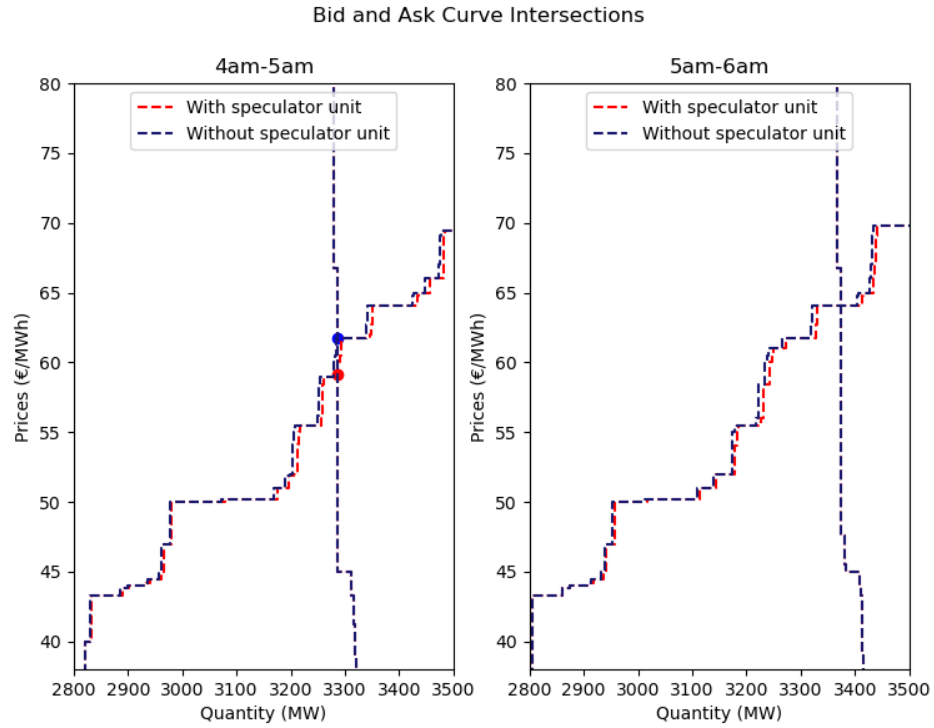


Figure 4: DA bid and ask curve intersections, with and without, a single speculator unit, 10th January 2019.

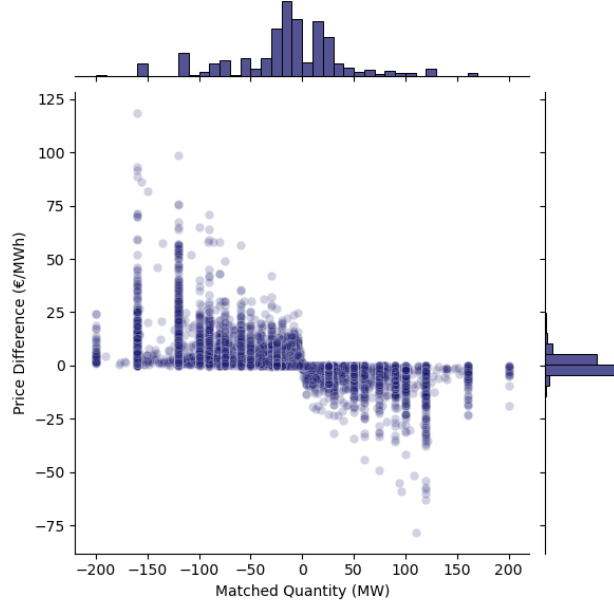


Figure 5: Impact of a single speculator on DA bid and ask curve intersection; negative (positive) x-axis values indicate sell (buy) matched quantities; y-axis equals the intersection price without the speculator minus the intersection price with the speculator.

4.2 Empirical Analysis

4.2.1 Day Ahead Market Quantities

To provide some insight into the typical composition of the I-SEM DA market Figure 6 presents stacked area charts showing the sell order and sell matched quantities (section 3.2.3) in TWh, grouped by FuelType¹⁵ and month. In this and subsequent plots negative (positive) power/energy quantities represent sells (buys) aligning with the sign convention referenced in section 3.1. It can be seen that approximately 52% of the sell order quantities will on average be matched (the corresponding figure for buys is circa 83%). The presence of the (a) Coal and (b) Oil & Distillate categories in the sell order quantities plot and their absence for significant periods of time in the sell matched quantities plot is indicative of the I-SEM DA merit order¹⁶.

Given our focus on speculator units, in Figure 7 we present stacked area charts showing how speculator DA order and matched quantities, grouped by month and whether they are buys or sells, evolve over time. From the plots it is clear from January 2021 onwards, when I-SEM & BETTA were no longer market coupled in the DA, there was a step change in the buy/sell order and matched quantities for the speculators.

The monthly grouped data has the potential to mask volatility inherent in the data, hence in the top plot in Figure 8 we present speculator matched quantity time series data at a trading period level of granularity (i.e. underlying data for bottom plot in Figure 7 and top plot in Figure 8 are the same). Both the volatility and the step change from January 2021 onwards is again evident. In the bottom plot in Figure 8 we present the net of speculator balancing market quantities; given the step change in speculator DA matched quantity values one might have anticipated a similar step change post January 2021, but this is not the case. This is best understood by considering Figures 9 and 10 in appendix I which indicate that post January 2021 there is evidence of a negative correlation between speculator DA and IDA1 matched quantities (e.g. speculator DA positions are partially unwound in IDA1), this results in a less obvious correlation between speculator DA matched quantities and speculator Balancing market quantities pre and post January 2021.

As to what proportion of the DA markets do speculator units comprise, bearing in mind the caveat about monthly versus trading period granularity, on average pre (post) January 2021, speculator units accounted for circa 10% (20%) of DA order quantities and approximately 2% (6%) of DA matched quantities. Interestingly, for the IDA1 market (which

¹⁵For details on the FuelType notation used in Figure 6 see appendix H.

¹⁶Loosely speaking, the merit order is an ordering of generation sources/types in terms of production cost from the least expensive to the most expensive [8].

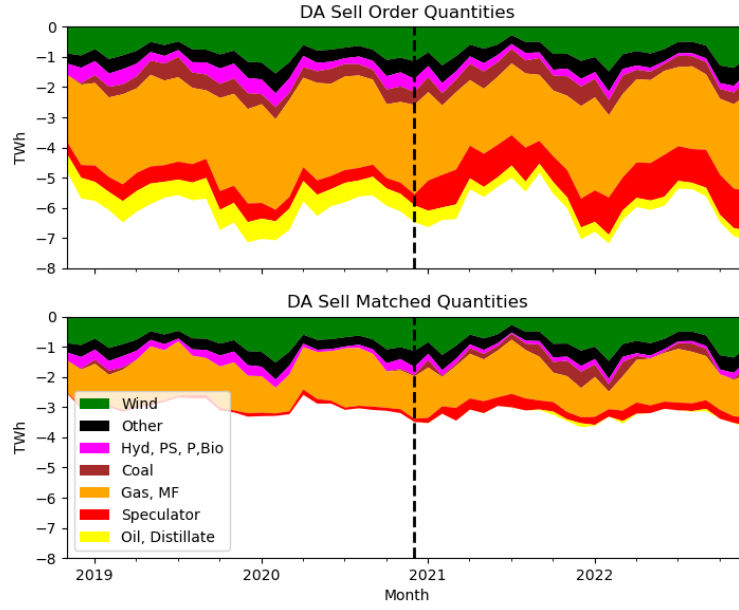


Figure 6: The top plot presents I-SEM DA Sell Order Quantities, the bottom plot presents I-SEM DA Sell Matched Quantities. Values are in TWh and the data has been grouped by FuelType and month.

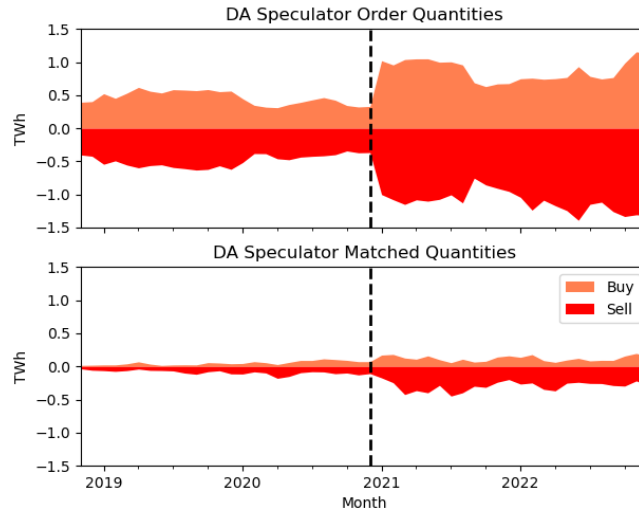


Figure 7: Summing over the population of speculators, the top (bottom) plot displays I-SEM DA Speculator Order (Matched) Quantities, buys and sells, grouped by month. The info is in TWh.

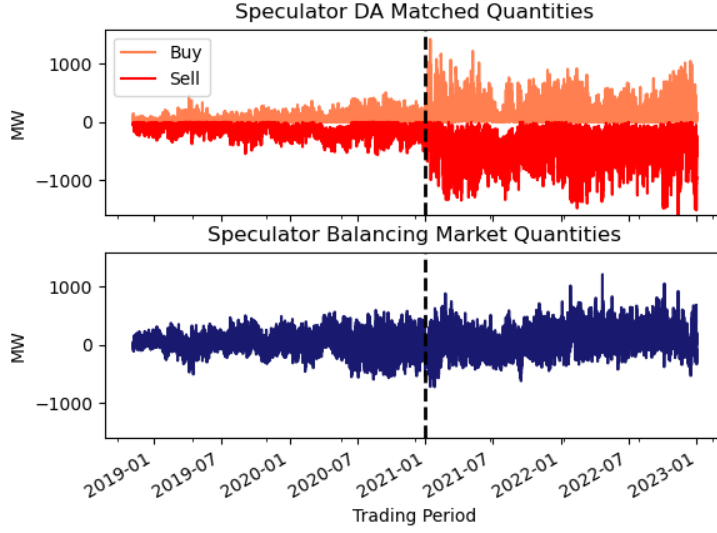


Figure 8: The top plot shows I-SEM DA buy and sell matched quantities (summed over all speculators). The bottom plot shows the net of speculator balancing market quantities. The time series is per trading period and the units are MW.

accounts for approximately 10% of traded volumes), speculator units have a significantly larger market share. On average speculator units account for 54% (42%) of buy (sell) IDA1 order volumes and 46% (33%) of buy (sell) IDA1 matched volumes.

In Figure 9 we plot Speculator IDA1 Matched Quantity against Speculator DA Matched Quantity, distinguishing between pre and post January 2021 observations. In a similar manner in Figure 10 we plot the Speculator Balancing Market Quantity against the Speculator DA Matched Quantity, again distinguishing between pre/post January 2021 observations.

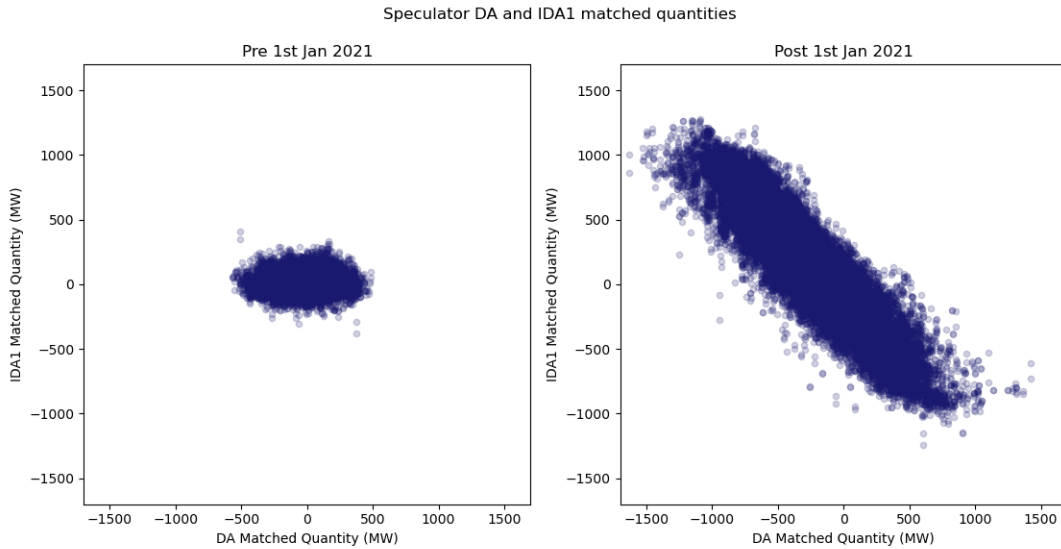


Figure 9: Scatter plot of speculator DA and IDA1 matched quantities which are defined by equations (5) and (6). Values are in MW.

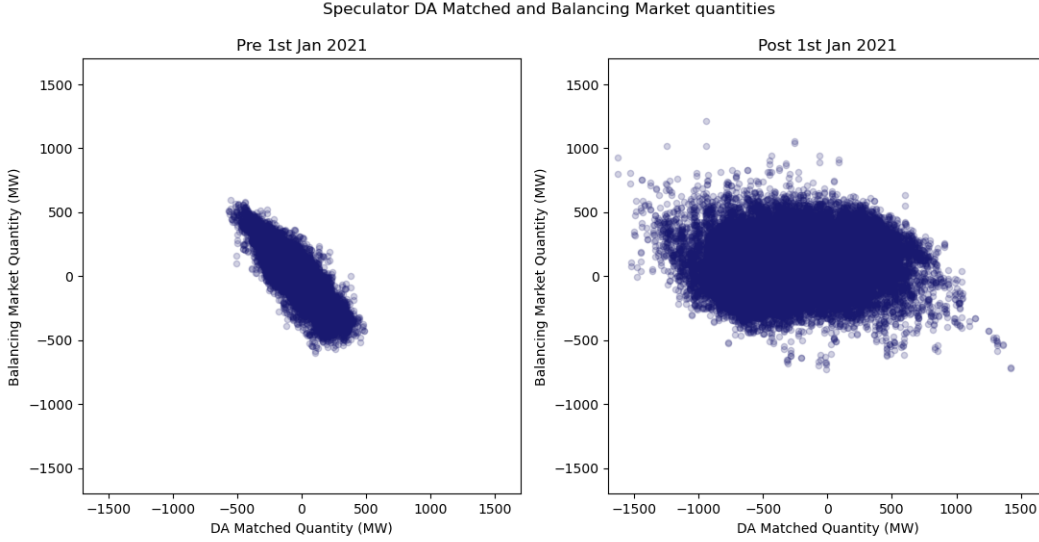


Figure 10: Scatter plot of speculator DA matched and Balancing Market quantities which are defined by equations (5) and (7). Values are in MW.

4.2.2 Speculator Unit DA Market Order Evolution

Taking the top plot from Figure 7, but splitting by price interval (section 3.2.4) we arrive at the top plot in Figure 11. It presents a stacked area chart showing speculator DA buy and sell order quantities grouped by price interval (section 3.2.4) and month, the y-axis range is -1.5TWh to +1.5TWh. In this plot the *All* category represents speculator orders in the price interval where all orders get matched; for sells and buys it corresponds to the $[-500, P_i^{DA} - SD_i]$ and $[3000, P_i^{DA} + SD_i]$ price intervals respectively. Similarly, the *Proportion* and *None* categories indicate the price intervals where a proportion and none of speculator orders will get matched. For comparison purposes the bottom plot in Figure 11 presents similar information but for the population of non-speculators; note the y-axis range is -7.5TWh to 7.5TWh¹⁷.

What is apparent from the top plot in Figure 11 is that a lot of the increase in speculator buy and sell orders from January 2021 onwards is associated with the *Proportion* category which corresponds to the $[P_i^{DA} - SD_i, P_i^{DA} + SD_i]$ price interval. Examining the non-speculator plots there is no obvious step change in the *All* or *Proportion* categories pre and post 1st January 2021. It is also interesting to note that on average 97% of non speculator buy order volumes occur in the *All* category which is an indication of the inelasticity of non-speculator demand.

Separately, it is worth highlighting that when we examined the underlying data we observed that prior to 1st January 2021 on average 16 (14) speculator units would submit sell (buy) orders to the DA. Post 1st January 2021 the corresponding number is 30 (24) speculator units i.e. almost a doubling in the number of active speculator units.

4.2.3 DA Marginal Units

Using the marginal unit identification methodology (section 3.2.5) the top plot in Figure 12 presents a stacked area chart showing the percentage of marginal observations grouped by FuelType and month. It is clear that Gas and Multi-Fuel units have seen a decreasing tendency to act as the marginal unit. While speculator units on average make up somewhere between 10% to 20% of the DA order quantities and between 2% to 6% of the DA matched quantities (section 4.2.1), on average they are marginal in approximately 60% of trading periods. Separately, if we count the number of instances where a speculator unit is marginal, over half of these instances are attributable to six specific speculator units.

The bottom plot in in Figure 12 presents a stacked area chart showing how the DA bid and ask curve intersections (i.e. vertical/horizontal/perpendicular) have evolved since the I-SEM inception. A noticeable change occurs from January 2021 onwards¹⁸.

¹⁷The interpretation of the *All* category for non speculators is less clear cut in that orders may exist in this price interval that do not get matched, such instances may occur for Complex Orders types.

¹⁸Given our lack of insight into the inner workings of the DA algorithm, EUPHEMIA, in the discussion section we can only conjecture as to reasons for the step change.

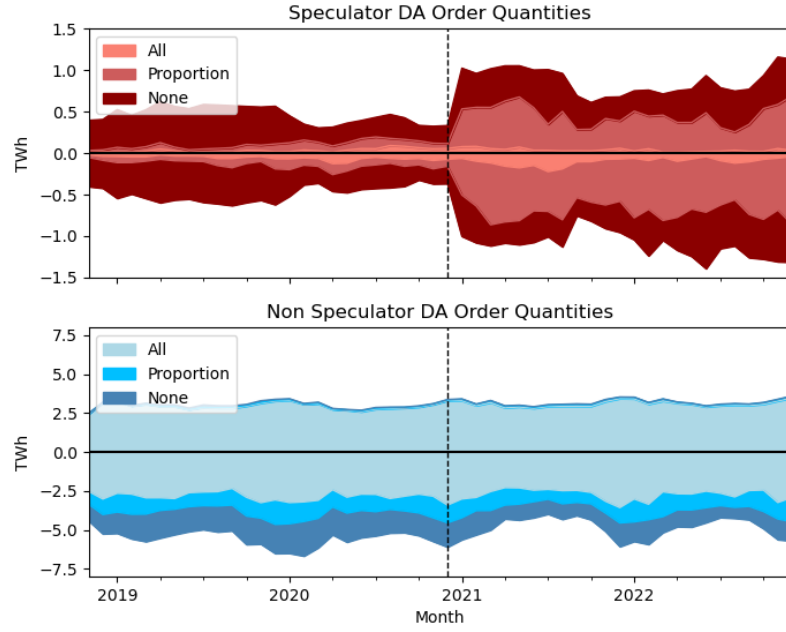


Figure 11: The top plot presents speculator buy and sell order quantities grouped by price interval & month. The bottom plot presents corresponding data for non-speculator units. Values are in TWh.

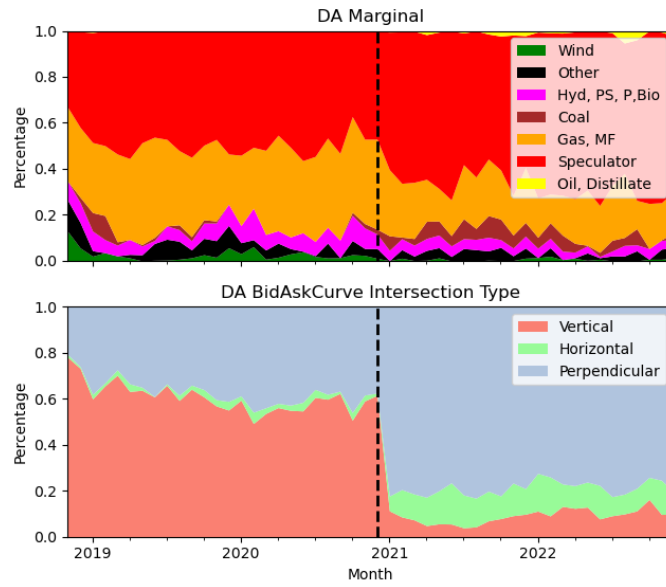


Figure 12: Top plot shows the the percentage of marginal observations in the DA grouped by FuelType & month. Bottom plot shows the percentage of DA bid and ask curve intersection types by month.

4.2.4 Estimating Speculator Unit Profitability

Using the approach described in section 3.2.6, if we sum over the population of speculator units, the estimated profit and loss, P&L, from November 2018 to December 2022 is €76.8 million¹⁹. Of the total amount €66.2 million is attributable to calendar years 2021 and 2022. The six speculator units referenced in section 4.2.3 account for €32.4 million (i.e. 42% of estimated speculator unit profitability). Of the €76.8 million total, the amount that relates to speculator units taking opposing positions in ex-ante markets is estimated at €29.9 million.

If we look at the granular P&L data (i.e. by speculator unit and trading period) then it can be seen that in circa 54% (46%) of observations in which there was a cash-flow it was positive (negative). This could perhaps be interpreted as being indicative of the challenge speculator units face in pursuing profitable trading strategies i.e. speculation in short-term electricity markets is not a risk-free activity.

5 Discussion

The empirical analysis of speculator units in the Irish electricity market presented in section 4 showed distinct changes pre and post the structural market change. In the DA market the number of active daily speculators almost doubled, their order/matched quantities also showed significant increases (in particular order quantities close to the price setting regions). Speculators also appeared to be marginal in a higher percentage of trading periods post the structural market change. While some aggregate speculator trading behaviours were noticeable post Brexit (Figures 9, 10 and 13 in appendix I), the full richness and diversity in the commercial behaviours of speculators becomes apparent on examination of individual speculator granular trading period data.

The perturbation analysis in section 4.1.1 and 4.1.2 was perhaps unsurprising in that, *ceteris paribus*, increases in supply (demand) decreases (increases) the DA market price. It was however interesting to observe that minute changes in supply or demand had the potential to impact price; intuitively this aligns with previous findings of the chaotic characteristics of electricity market price time series [20]. A dampening in the sensitivity to small perturbations in DA supply or demand was evident post the structural market change.

It would seem plausible that the change in speculator behaviour pre and post Brexit is the common thread linking the preceding two paragraphs. That is, the increased order quantities that speculators submitted close to the price setting region acted as a dampener to the supply and demand curve sensitivities. The increased order quantities that speculators submitted close to the price setting region could also potentially explain the change in bid and ask curve intersection types post Brexit (bottom plot Figure 12). We would however suggest a degree of caution based on the following:

- **Dynamics:** as noted in Mercadal [15] system dynamics are an important consideration when analysing short-term electricity markets. The I-SEM DA auction has a reasonably large number of participants, subtle changes in the commercial behaviours of non speculator units, at either an individual or aggregate level, could be a contributing factor (albeit from our exploratory analysis we view this as being less likely).
- **Pricing Algorithms:** an important consideration is the lack of access to the market pricing algorithms (in particular the DA algorithm). There is the possibility, however small, that some of the changes could be algorithm related. Parsons et al. [13] makes similar points (in addition to highlighting that the DA pricing algorithm is more complex than simply intersecting supply and demand curves).

It is our considered opinion that short-term electricity markets are complex non stationary environments with a number of moving parts. As a result it can oftentimes be difficult to arrive at conclusions regarding cause and effect relationships on market price formation/outcomes.

6 Conclusion

In this paper we presented empirical observations relating to a dynamic cohort of market participants, speculators, in a short-term electricity market. The Irish electricity market setting aligned with the short-term European electricity market template, it also had the benefit of having a liquid DA market. It was observed that viewing speculators order and matched quantities in aggregate their trading behaviours displayed differences pre and post structural market changes related to Brexit. In all likelihood, this was a significant contributory factor to the dampening effect in the sensitivity of the DA bid and ask curves to small perturbations in demand and supply.

¹⁹For reference, as outlined in [37], [36] and [35] close to €21.76 billion worth of energy has been traded in I-SEM ex-ante over the same timeframe.

From this paper, and the referenced literature, the reader should have a deeper understanding as to the dynamicism and complexity of short-term electricity markets. Motivated in part by the perturbation/sensitivity analysis findings, potential future areas of research include

- Investigating how *Fundamental* [40] (or what we term bottom-up) DA price forecasting techniques perform relative to other DA price forecasting approaches.
- Scenario analyses of future electricity markets with and without the deployment of significant levels of energy storage solutions.

For such research a key component will be in ensuring to capture the range and dynamicism in the commercial behaviours of short-term electricity market participants. Such research may indicate that in the absence of sufficient levels of energy storage solutions, the complex and volatile nature of electricity market price formation is likely to remain.

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A Appendix: Simplifications and Other Considerations

In this appendix we list some of the simplifications, considerations and caveats that accompany the empirical analysis. These include

- The perturbation analysis described in subsections 4.1.1 and 4.1.2 assumes that small changes in supply or demand would not necessitate a full rerunning of the EUPHEMIA algorithm. We do not have access to the algorithm and hence cannot validate whether or not this assumption is correct in an I-SEM setting.
- We classify I-SEM market participants as being speculator units utilising the criteria outlined in appendix B. Alternative interpretations and rulesets as to what constitutes a speculator are possible.
- Given the quantum of data that is available and the limited size of the paper we mainly present a high level aggregated view of the data. Presenting the data at an aggregated level allows the reader to observe high level patterns but this is often at the expense of developing an understanding as to the volatility and complexity inherent in the underlying datasets.
- The data pipelines we constructed do not have access to the following datasets
 - DA order data for the first 5 days of the I-SEM market.
 - IDA1/IDA2/IDA3 order data for the first 3 months of the I-SEM market.

The implication are that our estimates of speculator unit profitability might be under/over stated for the first 3 months of the I-SEM market. Given that speculator order/matched quantities were small in the immediately following months, we believe it is reasonable to assume that the under/over estimation would not have a material impact on the profit and loss estimates.

B Appendix: Identifying Speculator Units

The following steps, developed through trial & error, are used to identify the population of speculators in the I-SEM:

- The PUB_MnlyRegisteredCapacity file referenced in section 3.1 contains a list of registered market participants with *ResourceName*, *RegisteredCapacity* & *FuelType*²⁰ information. Select ResourceNames where the FuelType is not specified.
- Using the ResourceNames from the previous step, in conjunction with DA order information from the ETS Bid Files, drop or ignore ResourceNames which are
 - Always buying in the DA market or
 - Always selling in the DA market

The former are likely to correspond to supplier units while the latter are likely to correspond to generator units.

- Cognisant that some ResourceNames might have commenced commercial operations as demand units and over time switched strategy to that of a supply unit (or vice versa), we endeavour to filter out such units. That is, drop ResourceNames that are *predominantly* either buying or selling²¹.
- The final step is to drop ResourceNames which have both a demand and variable renewable generation. For such units, given that the order quantity is the net of demand plus variable renewable generation, it can be expected that their order quantities in contiguous trading periods would exhibit jumps/discontinuities. The approach is to keep track of the number of trading periods in a day which have a similar order quantity, and if over the horizon of interest the proportion of such trading periods is less than some arbitrary threshold (e.g. 7.5%) we drop the ResourceName.

To add to the overall robustness of the approach once the population of speculators have been identified we perform a cursory manual inspection of each unit (i.e. their positions in the ex-ante markets) removing any units from consideration that do not subscribe to speculator unit type behaviour.

²⁰ResourceName is an identifier that is unique to each market participant; FuelType categories include wind, multi_fuel, gas, hdyro, peat, coal, pump_storage, biomass, oil, distillate, solar.

²¹Picking an arbitrary threshold, if a ResourceName is buying (selling) > 92.5% of trading periods it is active in the DA, then we treat it as a demand (supply) unit and exclude it.

C Appendix: DA Marginal Units

Consider a single trading period in the I-SEM DA market. To identify the marginal unit(s) in that trading period:

1. From the MarketResult file (section 3.1), determine the market price for the trading period.
2. Using the ETS Bid File, select the rows where market participants have an active order in that trading period.
3. Iterating through each row in the previous step
 - if the market price equals any of the price points in the participant's order, we flag the participant
 - else do nothing

If one or more participants have been flagged, then we have identified the marginal unit(s) and the process ends. If no units have been flagged, continue to the next step.

4. Utilising the BidAskCurve file, for that trading period, ascertain how the bid and ask curves intersect. If the curves intersect vertically, determine the two points at which the curves overlap. Denote the prices associated with the overlap as *lower_price* and *upper_price*.
5. Iterate through each of the rows selected in step 2. If either the *lower_price* or the *upper_price* identified in step 4 equals any of the price points in the participant's order, we flag the participant as being marginal.

D Appendix: Speculator Unit Ex-Ante Trading

Consider the following hypothetical scenarios for speculator j in trading period i :

- **Scenario 1:** the speculator unit buys 100MW in DA and sells 100MW in IDA1; in this situation the profit and loss equals $\frac{1}{2} (100P_i^{IDA1} - 100P_i^{DA})$.
- **Scenario 2:** the speculator buys 50MW in DA and sell 150MW in IDA1; using equations (3) and (4) from section 3.2.6 the profit & loss is given by $\frac{1}{2} (150P_i^{IDA1} - 50P_i^{DA} - 100P_i^B)$. Rearranging, this is equivalent to $\frac{1}{2} (50P_i^{IDA1} - 50P_i^{DA}) - \frac{1}{2} (100P_i^{IDA1} - 100P_i^B)$.

That is, in both scenarios a proportion of the profit & loss is attributable to the loss or gain associated with taking opposing positions in ex-ante markets.

E Appendix: Simulating Speculator Unit DA Price Impact

To estimate the impact of a single speculator, j , on the DA price for trading period i , the process is as follows

1. Retrieve all participant orders for trading period i from the relevant DA ETS Bid File. Convert each of the orders into price and quantity pairs.
2. Take the buy price and quantity pairs from step 1 and combine them to produce an aggregated stepwise bid curve. Similarly, take the sell price quantity pairs and combine them to produce an aggregated stepwise ask curve.
3. Adjust the stepwise bid and ask curves from step 2 as described in Appendix F.
4. Use the bid and ask curves from step 3 to determine the intersection point/price.
5. Repeat steps 1 to 4 but this time exclude the order data for speculator j .

F Appendix: Reconciling ETS Bid File & BidAskCurve

Following a significant amount of experimentation, using hourly I-SEM data from November 2018 to end of December 2022, it has been possible to reconstruct the BidAskCurve data using the ETS Bid File once the following adjustments are made for each trading period

1. *Complex Orders*²² are not part of the ask curve, unless the Complex Order is matched. If a Complex Order is matched then the matched quantity is included in the ask curve at the minimum price point.

²²Defined as "a Simple Sell Order or a set of Simple Sell Orders submitted by an Exchange Member in respect of a Unit, covering one or more Trading Periods on a specified Trading Day, and which is subject to: (a) a Minimum Income Condition (with or without a Scheduled Stop Condition) and/or (b) a Load Gradient Condition".

2. Using the ETS Bid File, filter on orders which have settlement currency of €. Calculate the difference between the matched buy quantities and matched sell quantities; depending on the sign, the difference needs to be added to either the bid or ask curve at the maximum or minimum price point. Repeat, but for orders which have settlement currency of £.

It is our assumption that step 2 is a result of EUPHEMIA scheduling flows on the interconnectors joining Great Britain and Ireland. For example, if EUPHEMIA schedules electricity to flow from Great Britain to Ireland then the ETS Bid File will show greater matched purchase quantities than matched sell quantities. In the BidAskCurve file this will correspond to a greater quantity at the minimum price point in the ask curve than is evident from individual participant sell orders in the corresponding ETS Bid File.

In addition, we have found that as of July 2021 onwards, when SEMOpx commenced publishing a single combined ETSBidAskCurve (footnote 9 on page 5) the adjustments described in step 2 are no longer required when reconciling the ETS Bid File and BidAskCurve files.

G Appendix: Speculator Units

AU_400137, AU_400139, AU_400143, AU_500104, AU_400140, SU_400314, AU_500101, AU_500126, AU_500012, AU_400118, AU_400100, AU_400122, AU_400002, AU_400128, AU_500110, SU_400136, AU_500114, AU_400103, AU_400138, AU_500109, AU_400003, AU_400006, AU_400101, AU_400135, SU_500082, AU_400105, AU_500001, AU_400005, AU_400010, AU_400141, AU_400111, AU_400125, AU_400106, AU_500115, AU_400114, AU_500121, AU_400112, AU_400132, AU_400119, AU_400116, AU_400113, AU_500122, AU_400134, AU_400117, AU_500105, AU_400011, AU_400009, AU_500113, AU_500111, AU_400136

H Appendix: FuelType Notation

Categories for the FuelType field in the PUB_MnlyRegisteredCapacity file (section 3.1) include wind, multi_fuel, gas, hdyro, peat, coal, pump_storage, biomass, oil, distillate & solar (this field can also be unpopulated). When presenting stacked area chart plots in section 4, we combine some of the FuelType categories and utilise the following notation:

- **Wind** category represents those ResourceNames (i.e. units or participants) where the FuelType is wind.
- **Other** category represents the units which don't have a FuelType (and from their commercial behaviours appear in the main to be either demand or wind participants).
- **Gas, MF** category corresponds to gas and multi-fuel thermal generation units.
- **Hyd, PS, P, Bio** denote hydro, pumped storage, peat and biomass units.
- **Speculator** represents those units specified in appendix G.

I Appendix: Speculator Matched Quantities

Letting *Speculator* denote the set of speculators and $Q_{i,j}^m$ denote what speculator j bought or sold in trading period i in market m (section 3.2.6), we define

$$\text{Speculator DA Matched Quantity}_i = \sum_{j \in \text{Speculator}} Q_{i,j}^{DA} \quad (5)$$

$$\text{Speculator IDA1 Matched Quantity}_i = \sum_{j \in \text{Speculator}} Q_{i,j}^{IDA1} \quad (6)$$

$$\text{Speculator Balancing Market Quantity}_i = \sum_{j \in \text{Speculator}} Q_{i,j}^B \quad (7)$$

Finally, the top plot in Figure 8 (section 4.2.1) presented a time series plot, at trading period level of granularity, of speculator DA buy and sell matched quantities. In Figure 13 we present the same time series data except we present it in a scatter plot format.

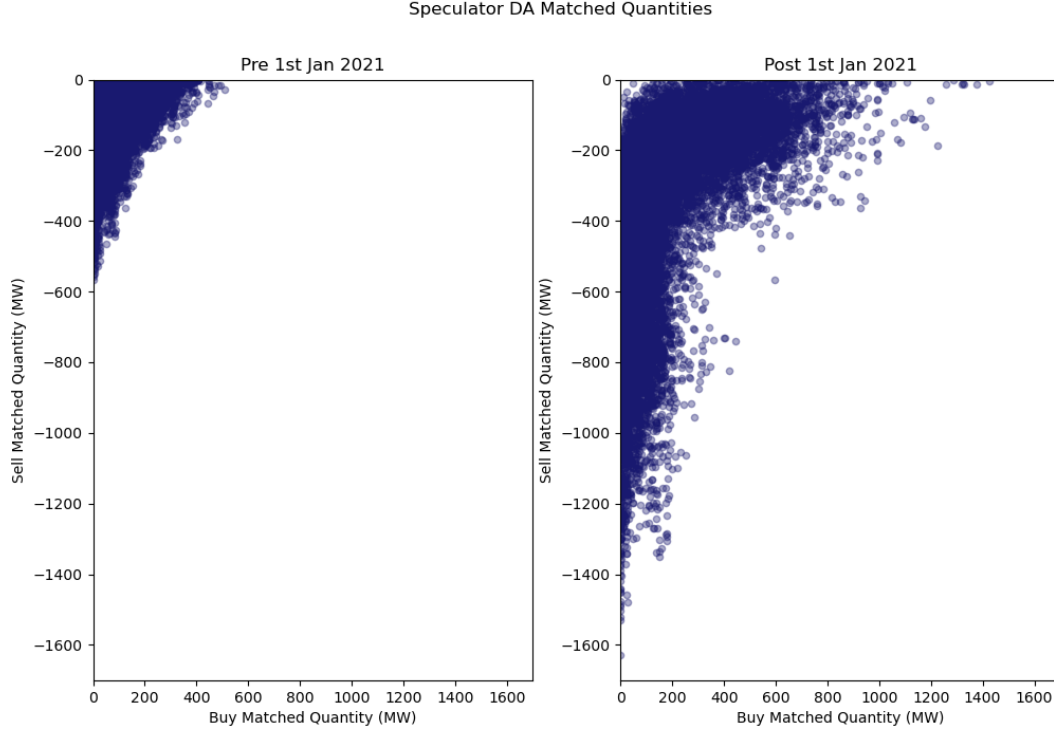


Figure 13: Scatter plot of DA speculator buy versus DA speculator sell matched quantities, in MW by trading period summed over all speculators, pre and post 1st Jan 2021.

J Appendix: Market Prices

Figure 14 presents a time series plot of the DA and Balancing market prices from November 2018 to end of December 2022. Analogous to equations (1) and (2) we define the *Spread*, W and *DA - BM Metric* in trading period i as follows:

$$Spread_i = P_i^{DA} - P_i^B \quad (8)$$

$$W_i = \frac{|Spread_i|}{|P_i^{DA}| + |P_i^B|} \quad (9)$$

$$DA - BM Metric_i = \begin{cases} 0, & \text{if } W_i \text{ undefined} \\ W_i, & \text{otherwise} \end{cases} \quad (10)$$

In Figure 15 we plot the empirical cumulative distribution function (ECDF) for the *DA - BM Metric* time series distinguishing between observations before & after 1st January 2021. There is a visible difference between the ECDF's i.e. pre 1st January 2021 observations tend to be more widely dispersed. For both ECDF's there is also a noticeable jump at the *DA - BM metric* value of 1²³.

²³Values of 1 occur when (a) the DA & BM prices are of opposite sign or (b) one of the DA or BM price is 0.

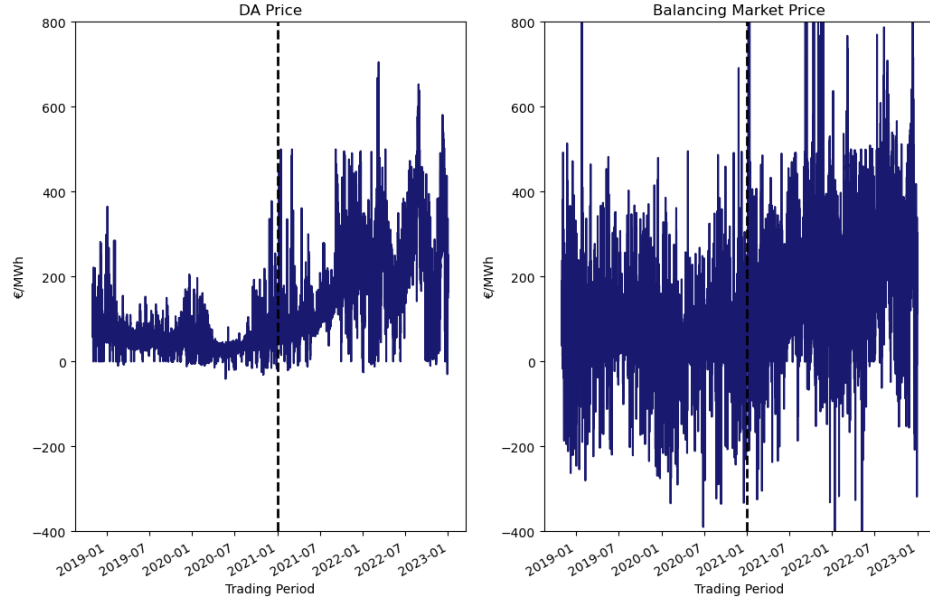


Figure 14: Time series plots of I-SEM DA and Balancing Market prices (y-axis has been cropped to cover the $[-400, 800]$ €/MWh range). From November 2018 to end December 2022, the BM had 56 settlement periods where the price exceeds €800/MWh (maximum BM price over the period was €4,800/MWh).

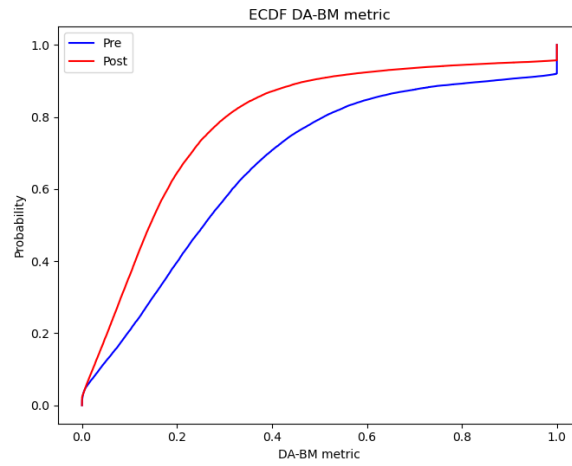


Figure 15: Empirical cumulative distribution function for the $DA - BM Metric_i$ time series. We distinguish between observations pre & post 1st January 2021.