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Modeling the impact of market interventions on the strategic evolution of electricity markets.

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MODELING THE IMPACT OF MARKET INTERVENTIONS ON THE STRATEGIC EVOLUTION OF ELECTRICITY MARKETS

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This paper presents a large-scale computationally intensive model for understanding the dynamic strategic evolution of electricity generating asset portfolios in response to various market interventions, and the consequent longer term effects of such changes on market structure and prices. We formulate a multi-stage model involving a Cournot representation of the wholesale electricity market, the performance of which then determines plant trading between players and the co-evolution of market structure. An algorithm to model this game is presented. We apply this model to the full England and Wales system, as it was in 2000, and simulate the strategic responses to divestiture, capacity targets and the two market mechanism variants of pool and bilateral market clearing.

Subject classifications: Games/group decisions: non co-operative. Government: energy policies, regulations. Industries: electricity.

Area of Review: Natural Resources: Energy.

1. Introduction

After over a decade of various national experiments on introducing different forms of electricity restructuring around the world, it is apparent that the ideal of a fully liberalized deregulated market elusive in practice. Initial faith in the process of divestiture of assets to reduce market concentration has not generally been as effective as expected in reducing market power (see Borenstein et al., 1999), nor indeed sustainable in the face of subsequent market evolution through mergers and acquisitions (observe the re-concentration and vertical re-integration in the UK and Germany during 2000-2006). Attempts to implement price-caps have always been seen as transitional, and more fundamental measures such as institutionalized surveillance on the tactical withdrawal of capacity have been difficult to apply, because of the asymmetry of technical information between generators and regulators. In the case of the electricity market of England and Wales, one of the oldest fully competitive markets, all three of these regulatory interventions have been pursued, with mixed results, since 1990, together with a basic market mechanism change from a compulsory day-ahead uniform price auction to continuous, bilateral trading in 2001. Although this latter mechanism change was associated with a contemporaneous price fall, by 2004 prices were back to the previous levels, as companies re-organized themselves and adjusted their behavior. The research documented in this paper has, therefore, been motivated by the dynamic aspects of these kinds of regulatory interventions and the strategic market structure adaptations that the competing companies evolve as responses.

In contrast, almost all of the extensive modeling research relating market structure to market power in electricity has been analyzed from static perspectives, whilst the analysis of competitive company responses to market conditions has focused on the context of tactical daily bidding behavior rather than the longer-term strategic re-allocation of assets. Thus, several authors have addressed the analytical formulation of the supply function responses by generators in daily pool-based markets, e.g., Green and Newbery (1992), Day and Bunn (2001), Anderson and Philpott (2002a, 2002b, 2003), Neame et al. (2003). Other structural aspects such as spatial competition, e.g., Hobbs (2001), and technology mix, e.g., Bushnell (2003), create further modeling challenges to representing the imperfect competition of daily bidding in a realistic way. Furthermore, to the extent that returns in the wholesale markets for power determine the asset values of generating plant, e.g., Tseng and Barz (2002), and that such physical assets are now being repeatedly bought and sold, e.g., Ishii and Yan (2002)**,** there is a dynamic link between short-term performance in the daily markets and the longer-term evolution of market structure.

In this paper, we develop model-based insights into this multi-stage dynamic process linking market interventions (such as market share restrictions and targets for generation output) with individual company performance through strategic asset trading and structural change. Essentially, this is achieved with an evolutionary, agent-based, computational model that is capable of simulating how a Cournot player, by interacting with its opponents, can rationally adapt its generation portfolio in order to increase value.

Thus, we do not follow the real options approach to plant valuation, which assumes no market power, but price taking behavior by generation companies, e.g., Thompson et al. (2004). Under such assumptions, a particular plant would have the same value to any owner and therefore there would be no economic value in plant trading between existing generators. However, almost all power markets are imperfect to some extent, and the value of a plant differs according to the market power of the portfolio of ownership. The model developed here, therefore, seeks to capture the strategic value of plant as owners seek to improve the market power of their asset portfolios through plant trading.

Research into asset trading between Cournot players does not in general present clear expectations for market structure evolution. Farrel and Shapiro (1990) used a Cournot model with exogenous market structure to study the welfare effects of mergers in oligopolistic markets, showing that when there are no synergies (or economies of scale) between the firms, mergers lead to higher prices; whilst Salant et al. (1983) and Barros (1998) show that the combined profits would tend to decrease if the merging firms were very different. In terms of understanding the dynamics of plant trading, however, it is the perspective of increased value to the purchasing company that is crucial. In Appendix 1, we develop background insights into Cournot asset trading through some simple examples. These show, firstly that whether a productive asset is worth more to the buyer than the seller will depend upon market heterogeneity. We then explore the evolutionary tendency with a simple application of the computational learning approach developed in this paper. The general tendency is one of increasing concentration and market power reinforcement, but it is clear that for more realistic applications, because of evident market structure sensitivity and path dependencies, simple generalizations may not apply and a full computational simulation becomes valuable.

The functional capabilities of the computational approach therefore facilitate:

- The study of asset portfolio adaptation as a result of rational choice. This cannot be achieved with a static Cournot model that, by construction, does not take into account endogenously the adaptive selection of the installed capacities and technologies used by the players. Further, an evolutionary computational model can explore the path dependencies, resulting from the starting conditions, as one of the determinants of portfolio adaptation.
- The analysis of market structure and institutional intervention as an endogenous co-evolutionary process, enabling an adaptive view of the impact of regulatory policies on the evolution of the industry's market structure.

The model therefore incorporates two main components: a plant trading game and an electricity market game. The plant trading game simulates the interaction between electricity companies that trade generation plants. The electricity market game simulates the performance of portfolios of plant in price formation assuming Cournot players. From this multi-stage modeling platform, we analyze two sorts of anti-trust interventions: (a) the "structural changes" of enforced divestiture and (b) the "behavioral remedies" (*sic* Competition Commission[1]) of capacity availability requirements. In common with most studies on market power mitigation, we take the pragmatic perspective of the need to transfer welfare from producer to consumer, and compare market interventions to achieve this, without addressing the larger policy issue of how much welfare surplus to transfer. Furthermore, we test the sensitivity of these interventions to the current debate on market mechanisms. We do not address directly the merits of basic discriminatory *vs.* uniform pricing, as in Bower and Bunn (2000), Abbink et al. (2003), Rassenti et al.

(2003), but instead, we follow Borenstein et al. (1995) who suggested that there could effectively be different markets for baseload and peak plants, and also Elmaghraby and Oren (1999), who proposed a clearing mechanism that implied separate pricing by technology. We compare this technologically motivated multi-market pricing with a simple single clearing, uniform market mechanism.

2. The Electricity Market

In this paper, the endogenous wholesale market prices are computed by using the Cournot model in which the players' pricing tactics result from the use of quantities as instrumental variables. The Cournot model has become well-established in the electricity markets game theoretical literature: Allaz and Vila (1993) analyses Cournot competition in forward markets; Borenstein and Bushnell (1999) uses it to analyze market power and divestment in the California electricity market; whilst Wei and Smeers (1999) and Hobbs (2001) analyze spatial competition in restructured electricity markets assuming Cournot behavior. Hobbs and Pang (2007) analyze the electricity Cournot game with piecewise linear demand functions and joint constraints. In these contexts, the use of the Cournot model in electricity markets appears to be defensible for both theoretical and normative purposes.

There is empirical evidence from the California market, e.g., Puller (2002), that conduct has been "relatively consistent" with a Cournot pricing game. Theoretically, Kreps and Scheinkman (1983) show that the Cournot equilibrium is the outcome of games where there is a capacity pre-commitment followed by Bertrand competition, and this appears to be the *modus operandi* of electricity markets. Further, Daughety (1985) in analyzing conjectural variations for quantity setting firms (ranging from Bertrand to Cournot conjectures) shows that an oligopoly equilibrium in which the players hold consistent conjectures is, in general, a Cournot equilibrium, and *vice versa*. Nevertheless, other equilibrium models have been preferred by some researchers, most notably the supply function equilibrium for power pools where players effectively submit price-quantity profiles to the market (Green and Newbery, 1992), and some empirical research has doubted the extent to which generators actually do compete through quantity offering rather than price mark-up (Green, 2004). We are less concerned in this paper with the precise accuracy of the price-setting model, than in understanding its general influence on market structure evolution, and in that respect it seems most useful to formulate this problem in the context of the more generally applied, and better understood paradigm of Cournot. It is also analytically more tractable.

We develop two different variants of the electricity market game. The first is a single-clearing Cournot game in which there is a uniform clearing price for each hour of the day. This model simulates a game where each player defines how much to sell at each hour (for different levels of demand), given the portfolio of plant owned. This is typified by the day-ahead compulsory pool-based market, where all power is offered into a single auction for the next day. The second is a multi-clearing Cournot game in which there are different clearing prices for different markets (e.g., base, "shoulder" and peaking), and is inspired by the continuous voluntary forward trading markets where, for example inflexible plants are more likely to sell baseload power substantially forward, whereas peaking plant will be sold much closer to real-time. In the multi-clearing mechanism, each player decides how much to offer from each one of his plants in the different markets, given the durations, the different demand functions and the structure of his portfolio. Whilst the former captures a distinctive feature of the compulsory, uniform price pool-based markets, the latter is more descriptive of the continuous, bilateral, forward-trading power exchange based markets, where separate forward products for baseload and peak power are traded. We do not however, explicitly consider the influence of forward contracts on spot prices.

In general terms, each player *i* chooses his output $Q_{i,L}$ in a specific market *L*, which is characterized by a certain demand, where the definition of each market *L* will be adapted to the specific needs of the formulation to be analyzed, e.g., single or multi-clearing. Let $C_{i,L}$ stand for the marginal cost of player *i*, A_L, α_L represent the intercept and slope of the inverse demand function, and D_L stand for the duration of market *L*. [In practice, we will typically be looking at annual load duration curves, and three "markets" (L = 3), baseload, shoulder and peaking, with D_L being the durations in hours for each market]. Further, let $K_{i,L}$ stand for player *i*'s total available capacity in market *L*. In this case, $C_{i,L}$ is assumed locally constant for a given plant, but it may be different for the different plants owned by a player. Thus, $C_{i,L}$ will generally be a step-function, which makes the optimization problem computationally hard. In both models, the start-up costs and ramp rates are not explicitly taken into account. [This is a simplifying assumption that has also been used in several other studies of electricity markets (e.g., Ramos at al., 1998; Borenstein et al. 1999).] However, since these technical constraints effectively define the capability of a plant to access a particular market in the short-term, the model exogenously defines, for each plant, the market segment in which it can sell. This simplification does not change the economics of the model, but decreases its complexity as it allows its solution as a linear complementarity problem.

The Single-Clearing Cournot Game

This model assumes that there is only one clearing price at any given market time period of the day, and that a player receives the same price for the electricity generated by any plant selling at that time. So the market state *L* is defined by time of the day (e.g., peak or baseload) and each player receives the same clearing price P_L for the quantities sold in each of these markets. The capacity constraint for each market state *L* is the total capacity available for each player in that type of market (e.g., how much could be produced in peak or baseload market time periods).

Thus, for a player *i*, the profit (π_i) maximization problem is represented as:

$$\begin{aligned}
&\max \pi_i = \sum_L \left(P_L - C_{i,L}\right) Q_{i,L} D_L \\
&st. \\
&P_L = A_L - \alpha_L \sum_j Q_{j,L}, \forall L \qquad (2.1) \\
&Q_{i,L} \le K_{i,L}, \forall i, L \\
&Q_{i,L} \ge 0, \forall i, L
\end{aligned}$$

The Multi-Clearing Cournot Game

In the case of bilateral electricity markets, each generator has the possibility of selling the electricity of its various plants into different market segments. Based on the evidence from the England and Wales electricity forward markets, the baseload, shoulder, and peaking plants tend to sell electricity over different timescales with different prices. Thus, essentially, different technologies sell into different market segments. The multi-clearing price mechanism aims to capture this segmentation by allowing a player to sell the generation from specific plants into different segments for a given time, possibly receiving a different clearing price in each one of them. This procedure follows the model proposed by Elmaghraby and Oren (1999), also suggested by Borenstein et al. (1995), and aims to capture the interaction between different market segments and technologies in defining the value of a plant.

Thus, for a player *i*, the profit (π_i) maximization problem is similar to the one presented in problem (2.1), with the difference that the available capacity at any point in time is the sum of the available capacity in each market segment. Thus, the definition of market *L* is now not a state in time, as in the single clearing case, but a market segment that extends over a period of time. This implies that the definition of what type of plant can operate in each market segment *L* also changes. For example, in single clearing, the "peak" market would be a time state in which all technologies would generally operate, whereas in multi-clearing, the "peak" market would be a segment in which only the peaking technologies offered to operate. Thus, in problem (2.1) we need to replace the capacity constraint by a coupled capacity constraint $\sum_{L} Q_{i,L} \leq K_i$. Again, as in the previous model, the costs are a non-linear function of production. Furthermore, the shape of the annual load duration curve determines the duration of each market segment, as before but with, for example, the peak segment being just a few hundred hours, whilst the baseload segment, in this case, extends for the full year, i.e., 8760 hours.

The general feature of the multi-clearing mechanism is that for each trading period, it recognizes that the total energy may have been traded through several market segments, and the way these are defined depends on the objectives of the study under consideration. In the present case we were assuming that each market segment would be linked to the type of technology (as defined in Section 5 below), however it is useful to see the formulation as just one example of the general multi-clearing specification. The model can incorporate as many market segments as required to better represent the market.

3. Market Interventions

Institutional interventions have generally been either structural (e.g., divestiture) or behavioral (e.g., generation long-term adequacy requirements), and often both. Whilst the former is mainly a market share issue, and there has been extensive research on the relationship of market concentration to market power in electricity since the early days of restructuring, the latter has become more topical in the context of ensuring security of supply and mitigating the abuse of market power. Furthermore, whilst the structural remedies are often implemented *ex post* through a lengthy procedure involving competition authorities, behavioral incentives or regulations can be implemented *ex ante* by regulatory bodies and are therefore attractive for reasons of expediency.

Regulators do, of course, face a number of conflicting obligations and are generally obliged to promote both short-term market efficiency and long term market security. In this respect, whilst both structural and behavioral interventions can mitigate the abuse of market power and thereby increase short-term market efficiency, promoting longer term security via efficient market entry (and exit) essentially constitutes a behavioral requirement. This is being achieved in several ways including the creation of explicit adequacy requirements and capacity markets (as in some of the North-East markets of the US), or with obligations on the system operator (as in the UK), or through standard capacity payments (as in Spain and several S. America countries) or motivated by vague but statutory responsibilities for national intervention (as in the EU directive of 2004).

However, a forward market for capacity is just as vulnerable as an energy spot market to the abuse of a dominant generator, and markets for capacity do not preclude capacity withholding tactics that can lead to very high prices of capacity. Market power in the energy spot market can therefore re-appear in a compulsory forward capacity contracts market.

Thus it follows that any behavioral motivation for controlling capacity may need to control not only the required forward capacity contracts, for security reasons, but also, as a consequence, the actual generation quantity offered into the spot market, for market power mitigation. From a regulatory perspective, the control of capacity availability is also rather more attractive than price control, especially in bilateral markets, where the actual transaction prices are private information, but where the quantity generated by each plant in the system is known at least to the grid and regulator, if not to the whole industry.

Consequently, to the extent that the exercise of market-power often appears in practice through generation capacity withholding, the existence of a minimum generation requirement, explicitly or implicitly, can have strong implications for curtailing market abuse.[2] We see this kind of constraint being implemented, in a strict sense, through the various requirements that in some markets are directed to load serving entities to pre-contract for adequate generation through capacity markets. Explicit attempts are made by regulators to maintain capacity levels, as Green (2004) notes in his review of British regulatory practice, where he comments upon the license condition that required companies to provide an annual statement of their plans for making each unit available to the market, and to account *ex post* for deviations. Moreover, generators do not withdraw as much capacity as daily profit maximization would suggest. Rather more moderate price levels are maintained, perhaps in the belief that this would deter new entrants or avoid regulatory intervention (e.g., Wolfram, 1999).

To formalize these ideas, let $Q_{M,L}$ stand for the minimum generation requirement for market *L* and let *j* stand for the players in the industry (an exogenous parameter). In the presence of a minimum generation requirement for market *L*, the profit (π_i) maximization problem (in the single-clearing mechanism) for a player *i* is represented as:

$$
\begin{aligned}
&\max \pi_i = \sum_L \left(P_L - C_{i,L}\right) Q_{i,L} D_L \\
&st. \\
&P_L = A_L - \alpha_L \sum_j Q_{j,L}, \forall L \\
&Q_{i,L} \le K_{i,L}, \forall i, L \\
&Q_{i,L} \ge 0, \forall i, L \\
&\sum_j Q_{j,L} \ge Q_{M,L}, \forall L
\end{aligned}
\qquad (3.1)
$$

(In the multi-clearing mechanism the capacity constraint would be $\sum_{L} Q_{i,L} \le K_i$).

Further let $Q^{*}_{j,L}$ and $Q^{M}_{j,L}$ represent the optimal generation for player *j*, in market *L*, in a Nash-Cournot equilibrium of problems (2.1) and (3.1), respectively.[3] The constraint for the minimum generation requirement $\sum_{j} Q_{j,L} \ge Q_{M,L}$ imposes behavior on the market as a whole and not on any specific player, implying that any move (such as generation withholding by specific players) which violates this constraint cannot be a solution of the game. We state here a number of implications of this requirement (proofs in Appendix 2):

Lemma 3.1: *If* $\sum_{j} Q^{*}_{j,L} \le Q_{M,L}$ *then the solution* $Q^{M}_{j,L}$ *of the constrained Cournot game* (3.1) *satisfies* $\sum_{j} Q^{M}_{j,L} = Q_{M,L}$.

Lemma 3.2: *In the electricity market games described by problem* (2.1) *such that in equilibrium* $\sum_{j} Q^{M}_{j,L} = Q_{M,L}$, *the higher the minimum generation requirement the lower the prices.*

Therefore, because demand is relatively inelastic in electricity markets, the imposition of the minimum generation requirement is equivalent to imposing price cap in each market. However, whereas bilateral trading does not provide transparent transaction prices, let alone the possibility of enforcing a price cap in each market, information regarding generation output is easily available and therefore can be a crucial variable for market monitoring. It has also been a key issue in *ex ante* market power studies where potential individual and aggregated generation withholding from specific players has been under scrutiny (Bunn and Oliveira, 2003).

The implication of this is quite subtle and strong, reflecting the nature of Cournot players who may have market power. This shows that in Cournot industries price response to generation is the inverse of what happens in perfectly competitive industries.

Theorem 3.1: *In any electricity market with an inelastic demand, every minimum generation requirement such that* $\sum_j Q_{j,L}^M = Q_{M,L}$ *: a) reduces the value of each portfolio selling in the industry; b) reduces the value of the industry as a whole.*

Theorem 3.2: *Every minimum generation requirement such that* $\sum_j Q_{j,L}^M = Q_{M,L}$ *limits capacity withholding and the dynamics toward concentration.*

This is a useful result as it shows that a behavioral remedy is a viable alternative to restructuring (e.g., divestment) in order to regulate the performance of an electricity market.

4. Evolution, Equilibrium and the Plant Trading Game

In this section, we present the plant trading game, the main objective of which is to model how the market structure of a given electricity market evolves from the initial conditions to an evolutionary equilibrium.

Evolutionary Equilibrium

Definition 4.1: *An* ***evolutionary equilibrium*** *for plant trading is a state of the industry in which no plant trade occurs: the value of a plant for its owner is not less than its value for any other player in the industry*.

Thus, an evolutionary equilibrium represents a stationary state of the industry in which no rational player would propose a deal leading to a trade. More precisely, in this state of the industry, even if the value that each player gives to each asset is common knowledge, there is no asset such that its value is higher for any buyer than for its owner.

Thus, for each asset, there are an infinite number of offers and bids that do not result in a trade, as the buyers' valuation is always no more than the seller's valuation. Since, for a given market structure, any set of bids and offers by the firms in the industry represents a Nash equilibrium of the plant trading game if no player can profit from changing his current bids and offers, given the bids and offers of his opponents, then we can observe that any evolutionary equilibrium in this game includes an infinite number of Nash equilibria. In terms of defining equilibria, for the evolutionary equilibrium we need to look at the valuations of each one of the players, whereas to define a Nash equilibrium we need to look at actions in terms of bids or offers for each plant, i.e., the implications of these internal valuations.

To be more specific, let $Q_{(j,i),L}$ and $Q_{(-j,i),L}$ represent, respectively, the total output of plant *j*, and of the "rest of the plants owned by player *i*" in market L. Moreover, let *GM(j,i)* represent the gross margin of plant *j* for player *i*, and let $\Delta Q_{(j,B)_{,L}} \equiv Q_{(j,B),L} - Q_{(j,S),L}$ represent the change in generation from plant *j* introduced by its buyer *B*, when compared with the quantity the seller *S* was generating from the same plant. Theorem 4.1 defines conditions for the generation quantities of the owner of the plant (the seller) and each one of the potential buyers for which no trade is possible and therefore an evolutionary equilibrium, as defined in Definition 4.1, is reached.

Theorem 4.1: *Every state of the industry is an evolutionary equilibrium if for every possible transaction of plant j owned by a potential seller S, and for any buyer B, the optimal generation change* $\Delta Q_{(j,B)_{,L}}$ *is such that* $-\sum_{L} \alpha_L . \Delta Q_{(j,B),L} . \left(Q_{(-j,S),L} + Q_{(-j,B),L}\right) \leq GM\left(j,S\right) - GM\left(j,B\right)$. (Proof in Appendix 2.)

Theorem 4.1 shows that there is no trade if the increase in value of the rest of the seller's and buyer's portfolios is not higher than the loss in Gross Margin for asset *j* resulting from the trade, i.e., in order to have a trade the increase in the value of the portfolio of the buyer needs to be higher than the loss for the seller.

The Plant Trading Game

The plant trading game is a multi-stage game of incomplete information where each player chooses the amount of capacity he wants to hold from each different technology and he specifies the quantity of generation he wants to sell in the market from those technologies. Essentially the game progresses as repeated iterations of two component models: (a) the single stage Cournot model (either single or multi-clearing) that determines the market prices and hence values of each plant and (b) a trading algorithm that finds the most desirable trade of capacity between players who may value the same plant differently. There are five main stages in the plant trading game: *Initialization, Identification, Adaptation, Trading and Updating*. The interaction between these stages is summarized in Figure 1. We first present an overview, and then describe each of these stages in more detail.

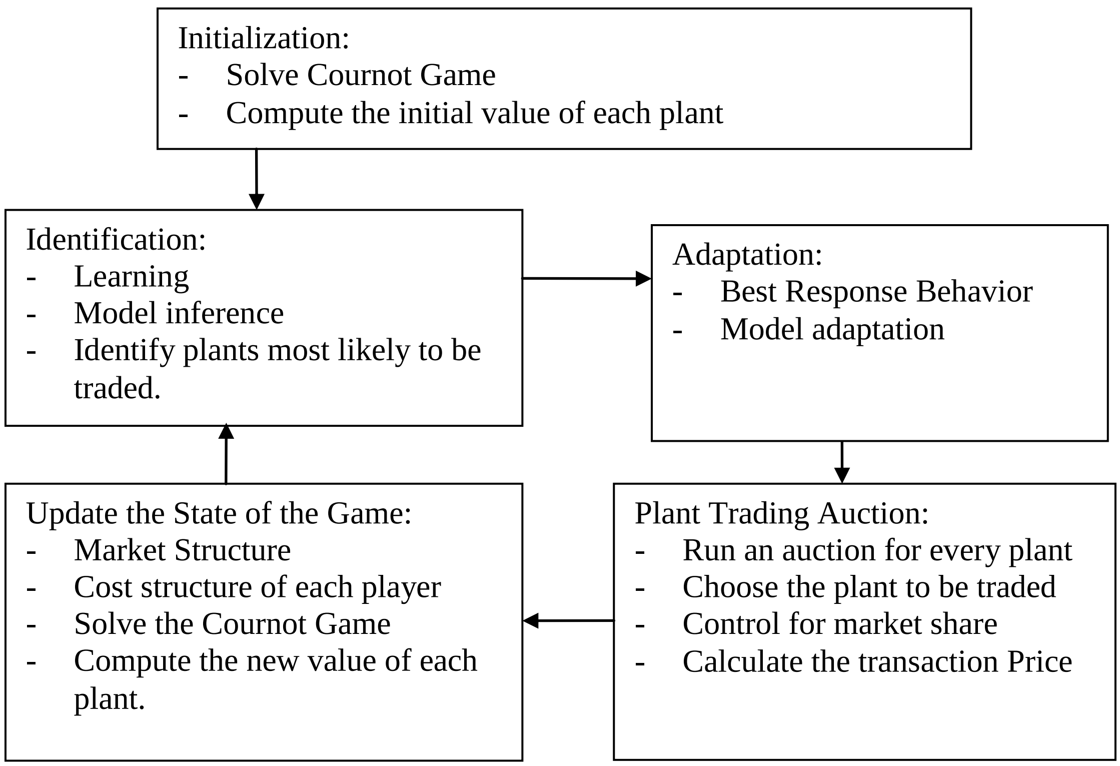

Figure 1. Plant Trading Game.

During Initialization, the Cournot model is solved for the initial market structure and the value of each plant is computed. The Identification and Adaptation stages model the internal processes of the players, attempting to capture how they interact with the market by modeling, separately, the processes of learning and adaptation. These two stages have as their main objective the identification of the list of plants that are likely to be traded during the next stage of the algorithm and, given this list, the player defines which plants it will attempt to buy or sell during the auction. After having collected all the bids and offers for every plant in the industry, an auction starts, aiming to compute the transaction price for each plant and to determine which one will be traded at any given time**.**

Subsequent to any plant transaction, the internal states of the buyer and seller change as their capacities and cost structures will be different. Moreover, this transaction also implies that the market structure will evolve. Therefore, the algorithm proceeds by updating the cost structures and capacities of the players, and recalculating the new solution of the Cournot game (under the new conditions) with capacity constraints. Thus, the computational burden is heavy, as we need to compute this solution every time there is a transaction. As a plant transaction implies a different solution of the Cournot game, a new value for each generating plant in the industry needs to be recalculated. Finally, given the new state of the industry, the players go to stage one, Identification, and the process restarts. We now describe the stages of the algorithm in more detail.

Table 1 presents the Identification algorithm, which proceeds as follows. During *Identification*, each player infers a model of how the system behaves by keeping in memory the results of each one of his actions, A_t^i (to sell, to buy or do nothing) in the last *K* periods. Further, a player is able to infer the results of actions that he did not take, $\Sigma^i \setminus \mathrm{A}_t^i$**,** by analyzing if-then-else scenarios, i.e., by deciding for each one of these actions, if a trade would have been possible if it had been chosen. The difference between the latter and the former is that actions actually submitted to an auction, A_t^i, influence the perception the other players hold on the system's behavior, while actions not submitted do not.

Table 1. Identification Algorithm.

D^i: Perceived outcomes of the player's actions in the path of his automaton, $D^i \equiv \{0,1\}$.

Σ^i: Set of actions a^i available to player *i*.

A_t^i Set of *W* actions actually bid by player *i*, in state *t; such that* $A_t^i \subseteq \Sigma^i$.

T_t^i, Plausibility table: a vector of size *M (number of plants)* representing the likelihood of each plant being traded in the next iteration.

θ: Plausibility cut-off parameter, $0 \le \theta \le 1$.

$S \equiv$ All prefixes (string with the perceived past outcomes) of D^i with a length less than or equal to *K*, such that *K*> *W;* $s\left(a^i\right) \in S$.

Update operator (ϕ). $s_t^i = \phi\left(s_{t-1}^i, D_t^i\left(a_t^i\right)\right)$, in which $D_t^i\left(a_t^i\right)$ represents the expected outcome of action a_t^i, $s_{t-1}^i = [d_1, d_2, ..., d_K]$ represents the vector of the past outcomes of action a^i, and $s_t^i = \left[d_2, ..., d_K, D_t^i\left(a_t^i\right)\right]$.

The forecast operator: $\Phi(p,\theta) = \begin{cases} 1 & if \quad p \ge \theta \\ 0 & if \quad p < \theta \end{cases}$

At stage zero initialize $\left(S, T_0^i\right)$: $\forall a^i \in \Sigma^i, s\left(a^i\right) = [1,1,...,1], T_0^i\left(s\left(a^i\right), \theta\right) = 1$.

Step 1. At any given stage *t* and for each player *i*:

Step 1.a) For each possible action, update the string of perceived outcomes

$$D_t^i\left(a_t^i\right) = \begin{cases} 0 & if \quad Trade\_not\_possible \\ 1 & if \quad Trade\_possible \end{cases}$$

$$\forall a_t^i \in \Sigma^i, s_t^i = \phi\left(s_{t-1}^i, D_t^i\left(a_t^i\right)\right)$$

Step 1.b) Compute $p_{i,t}^a$ the percentage of time each action is expected to be successful

Let $d_j \in s_t^i$ represent a perceived outcome in string s_t^i, such that $d_j \in \{0,1\}$.

$$\forall a_t^i \in \Sigma^i, p_{i,t}^a = \frac{\sum_{j=1}^{K} d_j}{K}$$

Step 1.c) Let $\tau_{a,t}$ represent the perceived outcome of action *a*, such that $\tau_{a,t} \in \{0,1\}$:

$\forall \tau_{a,t} \in T_t^i, \tau_{a,t} = \Phi^i\left(p_{i,t}^a, \theta\right)$.

Step 1.a) For each possible action, update the perceived outcomes. The perceived outcomes, D^i, are trade-possible (1) or not trade-possible (0). A trade is possible if the player wants to sell (buy) plant a^i and there were buyers (seller) in the market for plant a^i. The player iteratively updates the string of perceived outcomes (s_t^i), for each one of his actions, using an update operator (ϕ, a moving window) such that every new string s_t^i is computed by removing the first element of s_{t-1}^i and inserting a new perceived outcome D^i: $s_t^i = \left[d_2, ..., d_K, D_t^i\left(a_t^i\right)\right]$ (see the definition of update operator in Table 1).

Step 1.b) Compute the percentage of time each action would be successful, i.e., the average number of times the perceived outcome of an action is one and a trade is possible.

Step 1.c) A one dimensional table T^i summarizes the perceived model of player *i*, in which each cell represents a plant in the system. Each element $\tau_{j,t}$ of T^i is binary and represents the perceived outcome of action *j* at time *t*, which is 1 if and only if the action *j* produced a possible trade in sufficiently many recent time intervals. Thus, given the *K*-string of possible-events associated with each action, a player computes the percentage of time it would be possible for a trade to have happened, $p_{i,t}^a$, and, if $p_{i,t}^a \geq \theta$ this action is considered to be a plausible trade. The plausibility parameter θ is not important. It only helps to speed up the best-response algorithm, and the plant trading game, as it enables the players to concentrate the best-response algorithm on the set of actions that is more likely to lead to a trade, instead of insisting on using actions that will not lead to any transaction. In the experiments presented in Section 5 the value of θ is *0.1*. This algorithm used a simple moving average of the number of times a given action would have been successful if taken. This simple statistic tells the player how likely is that this action will be accepted, given all the other possible trading opportunities available. Since the probability of trading is computed for every single plant, and by every player, this simple statistic helps the players to select the actions that may lead to a trade.

Table 2 presents the *Adaptation* algorithm which models how players adapt in the evolutionary market structure. A player computes the actions to take (which plants to buy or sell) in order to maximize his long-term profit.

Step 1.a) Given the set of plausibly successful actions $\left(T_t^i\right)$ a player *i* computes the set of actions $\left(Z_t^i\right)$ that would improve the value of his portfolio using a best-response algorithm. However, as we are modeling an evolutionary game with simultaneous moves, the player applies the *Inertia principle* in order to decide if he should follow the policy recommended by best response or if he should keep the same automaton. Most importantly we would like to restrict the possibility of cyclical strategies, to which simple best response algorithms are prone, and facilitate a convergence towards an evolutionary equilibrium. In real markets players do not repeatedly buy or sell the same plant, i.e., a player needs to wait enough time before inferring the true value of an asset.

More subtle evolution can also appear. By choosing from among the proposed trades the one in which he is interested, he is able, particularly in the case where he owns the plant in discussion, to influence the plausibility of other players' actions (as computed in Table 1), as by not offering to sell a plant he leads others to believe that he is not interested to sell. Further, by choosing to propose some new actions and persisting with them, a player increases the plausibility of these trades. To the extent that the other players consider best response strategies, they adapt to plausible trades and are therefore, in a sense, influenced by the first player.

Step 1.b) A player *i* computes the best response policy given his perceptions of the other players' behavior. This policy is a dynamic programming algorithm that enables the player to compute the optimal set of actions, given the constraints of the possible trades, and taking into account the short-term evolution of the market structure implied by each trade. The utility $u\left(\Omega_t, a_t^i\right)$, in this case, is the Gross Margin *GM(i)* described in Table 4, Step 4. Then, function δ^i updates the plausibility table T_{t+1}^i, setting to zero the probability of the traded asset being traded in iteration *t+1*.

Table 2. Adaptation Algorithm.

Σ^i: Set of actions available to player *i*. a_t^i : action of player *i* at time *t*.

A_t^i Set of *W* actions actually bid by player *i*, in state *t; such that* $\mathrm{A}_t^i \subseteq \Sigma^i$.

Z_t^i: Set of optimal actions by player *i*, in stage t. $\left|Z_t^i\right|$: number of elements in the set Z_t^i.

T_t^i : Plausibility Table, vector of dimension *M (number of plants).*

Ω_t = {(*j*,*i*): player *i* owns plant *j*}: State of the industry at time *t*.

V_t^i : Value of *i*'s portfolio at time *t*.

$u(\Omega_t, a_t^i)$: utility (profit or reward) of player *i* at time *t*, for a given action a_t^i in state Ω_t.

ρ_i : Discount factor for agent *i*, $0 \le \rho_i \le 1$.

r: random generated number from a uniform distribution, such that $r \in [0,1]$.

w_t^i : inertia variable such that $w_t^i \in [0,1]$, at time *t*.

h: number of steps of look-ahead.

Step 1. Each player *i* decides to adapt

Step 1.a) Inertia principle, for a given w_t^i: $\begin{cases} Z_t^i = BR(\Omega_t, T_t^i, \rho_i) & if \quad r \ge w_t^i \\ Z_t^i = A_{t-1}^i & if \quad r < w_t^i \end{cases}$

Step 1.b) Algorithm Best-Response $Z_t^i = BR(\Omega_t, T_t^i, \rho_i)$:

Compute the optimal policy, Z_t^i:

$$\forall t = 1, \ldots, h$$

$$Z_t^i = \arg\max_{a_t^i} \left[u(\Omega_t, a_t^i) + \rho_i V_{t+1}^i (\Omega_{t+1}, T_{t+1}^i) \right]$$

$$s.t.$$

$$T_1^i = T_0^i, \Omega_1 = \Omega_0$$

$$\forall \tau_{j,t+1} \in T_{t+1}^i, \tau_{j,t+1} = \delta^i (\tau_{j,t}, a_t^i)$$

$$\Omega_{t+1} = \{\Omega_t \setminus (a,i)\} \bigcup \{(a,j)\}$$

$$\delta^i(\tau_{j,t}, a_t^i) = \begin{cases} \tau_{j,t} & if \quad j \ne a_t^i \\ 0 & if \quad j = a_t^i \end{cases}$$

Step 2. Complete Adaptation Model

If $\left|Z_t^i\right| < W$

Let $\Lambda_t^i = \{a_t^i : \tau_{j,t} \in T_t^i, \tau_{j,t} = 0\}$, $\overline{Z_t^i} = BR(\Omega_t, \Lambda_t^i, \rho_i)$

else $\overline{Z_t^i} = \{\ \}$

Step 3. Define the set of actions to bid into the auction

$A_t^i = Z_t^i \cup \overline{Z_t^i}$

Step 2) If the number of these actions, $\left|Z_t^i\right|$, is less than the maximum number a player can submit to the auction, he may bid some additional trading proposals $\left(\overline{Z_t^i}\right)$ that he perceives to be the most profitable, albeit having a low plausibility. Note that when a player adapts his behavior, first he is constrained by the behavior of the others but, at the same time, he is able to influence their behavior as this is another facet of the *Inertia Principle*.

The Plant Trading Auction is organized as a single-call auction (Cason and Friedman, 1997), in which all the players bid for the assets being auctioned only once and the auctioneer sells the asset to the highest bidder. This auction was chosen due to its efficiency. Therefore, as in any single-call auction, there is a separate auction for each plant. The algorithm also calculates the transaction price for the plant traded. Table 3 describes the trading auction algorithm.

Step 1) Compute the set of possible trades. A trade is possible only if simultaneously there are one or more buyers and a seller, and the price offered by the buyers is higher than the seller's bid. It is assumed that any player bidding or offering into an auction reveals his true valuation of the plant he wishes to buy or sell. For a buyer (seller) the value of a plant represents the increase (absolute value of the decrease) of the value of his portfolio by acquiring (selling) that plant.

Step 2) Find the set of all winning trades. For every plant compute the winning trade by choosing the buyer with the highest bid price.

Step 3) Find the asset to be traded among all possible trades. So far in Steps 1) and 2) we have implemented a standard single-call auction. Moreover, in this step the regulator controls for market share, not allowing trades that violate this constraint. However, in Step 3) the plant-trading auction needs to be adapted to the specific task of modeling the evolution of market structure in an electricity market.

It is possible to have more than one trade per iteration, as happens in a standard auction, and indeed this would not affect any of the theoretical properties of the model, and could easily be implemented within this simulation platform. However, this would imply that the jumps between successive states of the industry would be wider and the evaluation error for each plant would be higher. The most dramatic adverse implication of such errors, which we observed in several simulations, was the “winners curse” in which players would systematically overbid for the plants (due to the assumption of a market structure evolution that would not occur). Thus, for this reason, we use a one-trade-at-a-time algorithm, since the “winners curse”, which often occurs in practice, would, in our formulation be a systematic mistake in plant valuation and lead to a theoretically flawed market trajectory.

Table 3. The Trading Auction.

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a: Asset being auctioned
i, *j*: players offering (attempting to sell) or bidding (attempting to buy) assets in an auction
$P_{a,t}$: Transaction price of asset *a* at time *t*
$B_{a,i}$: Price bid by player *i* attempting to buy asset *a*
$B^{+}_{a,i}$: Winning bid by player *i* attempting to buy asset *a*
$B^{*}_{a,i}$: Bid by player *i* leading to a trade of asset *a* (bought by player *i*)
$O_{a,i}$: Price offered by player *i* attempting to sell asset *a*
$O^{+}_{a,i}$: Winning offer by player *i* attempting to sell asset *a*
$O^{*}_{a,i}$: Offer by player *i* leading to a trade of asset *a* (sold by player *i*)
T_a: Set of all possible trades for asset *a*
B_a: Set of all acceptable bids for asset *a*
T: Set of the all winning trades (at the most one per asset)

Step 1. For every asset *a* find T_a

$$T_a = \left\{ \left(B_{a,i}, O_{a,j} \right) : i \neq j, B_{a,i} > O_{a,j} \right\}$$

$$B_a = \left\{ B_{a,i} : \left(B_{a,i}, O_{a,j} \right) \in T_a \right\}$$

Step 2. For every asset find the winning trade $\left(B^{+}_{a,i}, O^{+}_{a,j} \right)$:

$$O^{+}_{a,j} = O_{a,j} \text{ and } B^{+}_{a,i} = \sup B_a$$

Find the set of all winning trades:

$$T = \bigcup_a \left(B^{+}_{a,i}, O^{+}_{a,j} \right)$$

Step 3. Find the asset to be traded, a^{*}, and the respective pair of bid and offer prices $\left(B^{*}_{a,i}, O^{*}_{a,j} \right)$. This asset a^{*} is such that player *i* passes the market share control, and with the largest difference between offer and bid price, that is, for every asset *a*

$$B^{+}_{a*,i} - O_{a*,j} \geq B^{+}_{a,i} - O_{a,j} \,,$$

Step 4. Compute the transaction price

Let $B^{++}_{a,z}$ represent the second highest bid for asset *a:*

$$B^{++}_{a,z} = \sup \left\{ B_a \setminus B^{*}_{a,i} \right\} \qquad\qquad P_{a,t} = \max \left(\frac{B^{*}_{a,i} + O^{*}_{a,j}}{2}, B^{++}_{a,z} \right)$$

However, if we decide that only one trade is to take place at a time, then a criterion needs to be specified to choose a given trade. After testing for several different criteria, we trade the one with the largest difference between offer and bid prices $B^{+}_{a*,i} - O_{a*,j} \geq B^{+}_{a,i} - O_{a,j}$. There are two main reasons for this choice:

- It implies that trading of bigger plants, which have the highest impact on the evolution of market structure, occurs earlier.
- It assumes that the trades in which the players have the highest expected profits occur first (and therefore maximizes the players' surplus).

Step 4) Computing the transaction price: For the traded plant *a*, the algorithm computes the transaction price $P_{a,t}$ by using the following standard procedure of the single-call auction:

- Compute the simple average of the seller's bid price and the buyers' highest offered price.
- $P_{a,t}$ equals the maximum of this simple average and the second highest bid price.

Finally, note that admissible trades are only those in which the transaction price is positive, as the seller would never pay to sell (due to the implicit option of closing-down a plant). Moreover, any transaction price $P_{a,t}$ above the bid of the second highest bid price (and the seller's offer price) and below the buyer's bid price (the average used here is just one of the possible solutions) will be valid but will not change any of the conclusions nor the market trajectory during the game.

After any successful trade, the algorithm computes a new state of the game, since the portfolios of traders, the equilibrium price and the output of the Cournot game have changed. Moreover, even if there is no trade, the probabilities associated with the inertia principle still need to be updated. Table 4 describes the algorithm for updating the state of the game.

Step 1) The algorithm starts by identifying the new owner of the plant traded (player *i* sells plant *a* to player *j*).

Step 2) Each player updates the capacities and marginal costs iteratively, taking into account the past performance of each plant. A player may offer in a given market the generation of every plant with a marginal cost lower than this player's marginal plant in this market during the previous iterations of the algorithm. Please note that the marginal cost of a given player is the highest one among all the plants he submits to a given market (Ramos at al., 1998; Borenstein et al. 1999).[4]

Table 4. Update State of the Game.

---

a: Any given plant that may be auctioned;
(a,i,t)**: Plant *a* is owned by player *i;*** $not(a,i,t)$ **: Plant *a* is not owned by player *i,* at time *t***
i, *j*: player *i* sells plant *a* to player *j* in an auction
$P_{L,t}$: Electricity price in market *L*, at time *t;* Ω_t : State of the industry at time *t*
$C_{i,,L}$: marginal cost of player *i* in market *L*
$C_{(a,i),L}$: marginal cost of plant *a*, owned by player *i*, for market *L*
$K_{(a,i)}$: available capacity of asset *a*, owned by player *i*
$K_{(a,i),L}$: capacity of asset *a* offered in market *L* in the previous iteration
$K_{i,L}$: capacity of player *i* assigned to market *L*
w^i: inertia variable such that $w^i \in [0,1]$; $\sigma \in (0,1)$ is the parameter for inertia updating
GM(*a*,*i*), *GM*(*i*): Gross Margin of plant *a* and player *i*, respectively
D_L : duration of market *L;* $Q_{(a,i),L}$: total generation of plant *i* sold in market *L*

Step 1. Update state of the industry Ω_t

$$\Omega_{t+1} = \{\Omega_t \setminus (a,i)\} \bigcup \{(a,j)\} \; ; \; w_{t+1}^z = \begin{cases} 1 & if \quad z = i, j \\ \sigma . w_t^z & if \quad otherwise \end{cases}$$

Step 2. Order the markets by ascendant order of peak typical demand
Update the cost structure and capacities bid into each auction (start from the lowest *L*)

$$\forall L, \forall i : K_{i,L} := 0 \, , \; \forall a \, , K_{(a,i),L} := 0$$

Step 2.1 For all available assets *a*

$$if \; C_{(a,i),L} \le C_{i,L}$$
$$K_{i,L} := K_{i,L} + K_{(a,i)} \; , \; K_{(a,i),L} := K_{(a,i)} \, , \;\; C_{i,L} := C_{i,L}$$
$$Otherwise \;\; if \;\;\; not(a,i,t) \, , \; C_{(a,i),L} \le C_{i,L+1}$$
$$K_{i,L} := K_{i,L} + K_{(a,i)} \; , \; K_{(a,i),L} := K_{(a,i)} \, , \;\; C_{i,L} := C_{(a,i),L}$$
$$Otherwise$$
$$K_{i,L} := K_{i,L} \; , \; K_{(a,i),L} := 0 \, , \;\; C_{i,L} := C_{i,L}$$

Step 2.2 Under multi-clearing if $K_{(a,i),L} > 0$ then $K_{(a,i)} := 0$

Step 3. Solve Cournot game
Step 4. Compute value of plant

$$\forall i,a : \;\; GM(a,i) = \sum_L \left[\left(P_{L,t} - C_{(a,i),L} \right) Q_{(a,i),L} D_L \right], \qquad GM(i) = \sum_{(a,i)} GM(a,i) \, .$$

Moreover, a player may offer the generation of a plant in a certain market even when its marginal cost is higher than this player's marginal cost. However, this is only possible if in the previous iteration, the player did not own this plant and, additionally, if the marginal cost of this plant is lower than the player's marginal cost in the subsequent markets (assuming that the markets are organized in increasing order by the typical peak demand).

Additionally, in the case of the multi-clearing mechanism (Step 2.2), the capacity of a plant offered in a market is not available for the subsequent auctions, and therefore the available capacity is set to zero.

Step 3) The Cournot game with capacity constraints is solved. The system with the Karush-Kuhn-Tucker conditions is solved using constraint logic programming by extending Lemke's algorithm[5] (Lemke, 1965). Alternatively the solver MILES, Rutherford (2006), can be used to implement a generalized Newton method based on the Lemke algorithm.

Step 4) After having computed the solution of the Cournot game the Gross Margin is calculated for each plant, and the sum of the Gross Margins of a player constitutes the value of his portfolio.

5. Computational Experiments

For a large scale application of the above algorithm, we applied it to the full England and Wales electricity market, as it was in 2000. This was partly a test of model efficacy in a realistic experimental setting. We were not, however, suggesting that the plant trading game is a forecast of how capacity trading may actually occur step-by-step, as in practice plants are not traded so frequently. Rather we are seeking to understand the attractor states in the evolution of market structure, where plant value is determined within a portfolio of assets performing on a spot market. From an evolutionary perspective, this study aims to clarify how the market mechanisms interact with regulatory behavior in influencing the players' behavior.

The generation capacity owned by each player was split into three categories (Table 5), taking into account the degree of flexibility, economics and hence load factors of each technology: Nuclear plants were the baseload technology running continuously. Large coal and Combined Cycle Gas Turbine

(CCGT) were the shoulder technologies. Small Coal, Open Cycle Gas Turbine (OCGT), Oil and Pumped storage provided the peaking plants. Thus BE had 54% of the Nuclear generation capacity installed in England and Wales (and 4.9% of the shoulder capacity), while AES owned both shoulder (10.1% of shoulder capacity) and peak plant (6.8% of peak capacity). These experiments simulated trading at a genset level (137 gensets) distributed among 24 different players. This leads to approximately 1.22E+189 possible states of the industry and 2.27E+51 total number of transitions between states of the industry, at every stage of the game. Such complexity makes a computational learning algorithm necessary.

Table 5. England and Wales Generating Capacity[6] in 2000.

Capacity of each Company (% of Total, 59 GW) in 2000				
	Total	Nuclear	Large Coal+CCGT	Small Coal +OCGT + OIL + Pump. Storage
PG	16.5		19.7	24.9
NP	13.9		16.3	22.5
BE	12.4	54.0	4.9	
Edison	10.6		10.1	30.7
TXU	9.7		11.6	14.7
AES	7.8		10.1	6.8
EDF	4.7	17.3	2.0	
Magnox	3.9	19.9		
Others	20.5	8.8	25.3	0.4
Total GW	59.1	11.4	40.7	7.0

Furthermore, in these experiments the demand functions were parameterized by defining the same elasticity, prices, and traded quantities in each one of the two clearing mechanisms, in each of the three simulated markets, baseload (bs), shoulder (sh) and peak (pk). In the multi-clearing case, baseload defines capital intensive and often inflexible plant that intends to runs for the whole year, and will be mostly traded forward if possible. Shoulder plant will often be seasonal in their usage and perhaps cycle within the day, running in total perhaps for about 60% of the time, and will be partially traded forward, if possible. Peaking plant will be flexible, with low start up costs and only come in for perhaps a few hours per day during the peak seasons, and will either be traded as spot or as call options, if possible. Thus, in the multi-clearing case the durations for the baseload, shoulder and peak markets were specified as 8760, 5500 and 500 hours; these durations in the single-clearing specification were equivalently represented as 3260, 5000 and 500 hours. All the experiments presented in this section simulate 400 iterations in each simulated scenario (and we may have several "runs" of each scenario).

The computational time of the plant trading game depends crucially on two major components, the Cournot game and the adaptation algorithm. Therefore, the smaller the number of players and plants, and the closer the initial state is to the evolutionary equilibrium, the faster a run of the experiments will be. In the case of the experiments presented in this paper, which were run in an Intel Pentium M with 1.6GHz processor and 1.00 GB of RAM, the computation time for the experiments of the non regulated market (worst case) was about 20 minutes for one run of the model with 400 iterations.

In the multi-clearing case we have used the following assignment of plants to markets. Nuclear: baseload only. CCGT: all. Big Coal: baseload and shoulder. Small Coal: shoulder and peak. Pumped Storage: shoulder and peak. OCGT: shoulder and peak. OIL: shoulder and peak.

The first experiments, presented in Table 6, analyze the impact of the minimum generation requirement (MGR) and market share control (which is defined by the regulatory policy and remains fixed in a given scenario), under the multi-clearing mechanism, assuming elasticities of 0.5, 0.35 and 0.25 for baseload, shoulder and peak, respectively. Moreover, the demand function is defined as a linear function and therefore the elasticities change as a function of the quantities effectively generated. Following a similar process to the one in Wei and Smeers (1999) we defined the elasticity for the typical demand at any given time.[7] Therefore, for each market the elasticity of demand is defined for the typical demand.

Firstly, Table 6 shows that the existence of a minimum generation requirement reduces prices and increases generation (in a multi-clearing mechanism). Further, it shows that the existence of market share constraints also decreases prices and the concentration levels. Secondly, from the comparison of experiments B and D, in Table 6, it is clear that together with a minimum generation requirement, the introduction of a market share control does not significantly change (in the economic sense) the generation and prices in these two experiments.

Table 6. Mininum Generation Requirement, Market Share and Performance.

Experiment	Mk Share	Min. Gen. Req. (MWh)			Quantities (MWh)			Prices (£/MWh)		
		Bs	Sh	Pk	Bs	Sh	Pk	Bs	Sh	Pk
A	100	0.0	0.0	0.0	20.7	13.7	3.0	19.1	28.4	119.0
B	100	24.0	20.0	4.0	24.0	20.0	4.0	15.0	20.0	60.0
C	10	0.0	0.0	0.0	22.7	16.0	4.1	16.5	19.9	51.7
D	10	24.0	20.0	4.0	24.0	20.0	4.0	15.0	19.9	60.0

In the second and third set of experiments (in a multi-clearing mechanism), which are presented in Table 7 and Table 8, respectively, we analyze how demand elasticity interacts with the minimum generation requirement and market share control.

Table 7. Mininum Generation Requirement, Elasticities and Performance.

Experiment	Min. Gen. Req. (MWh)			Elasticity			Quantities (MWh)			Prices (£/MWh)		
	Bs	Sh	Pk	Bs	Sh	Pk	Bs	Sh	Pk	Bs	Sh	Pk
A	0	0	0	0.1	0.05	0.01	17.5	13.1	3.3	55.8	91.8	1078.6
B	0	0	0	1.25	1.0	0.75	21.7	13.7	4.8	16.1	22.8	44.5
C	24	20	4	0.1	0.05	0.01	24.0	20.0	4.0	15.0	20.0	60.0
D	24	20	4	1.25	1.0	0.75	24.0	20.0	4.9	15.0	20.0	41.8

In Table 7, the comparison of experiments A and C shows that, in the presence of very low elasticity in the short-run, the minimum generation requirement significantly decreases prices and increases generation. However, the comparison of experiments A-C and B-D shows that the impact of minimum generation requirement is less strong in the presence of a higher elasticity of demand.

Next, in Table 8 a minimum generation requirement of zero in each market is assumed. The comparison of experiments A and C, and B and D, respectively, clearly shows that the existence of market share control increases generation and decreases prices. Altogether, in the presence of these market interventions, the results in Table 7 and 8 show that the elasticity of demand is a much less important factor in determining prices and generation. However, in the absence of regulatory intervention the lower the elasticities the higher the prices, as one would expect in a Cournot game.

Table 8. Market Share, Elasticities and Market Performance.

Experiment	Mk Share (%)	Elasticity			Quantities (MWh)			Prices (£/MWh)		
		Bs	Sh	Pk	Bs	Sh	Pk	Bs	Sh	Pk
A	100	0.1	0.05	0.01	17.5	13.1	3.3	55.8	91.8	1078.6
B	100	1.2	1.0	0.75	21.7	13.7	4.8	16.1	22.8	44.5
C	10	0.1	0.05	0.01	21.2	14.5	3.4	32.0	55.9	814.0
D	10	1.2	1.0	0.75	26.2	17.9	5.2	13.8	17.6	34.9

So far, the results in Tables 6 to 8 only show a static picture of the final state of each experiment. In order to provide a better understanding of the adaptive process underlying these experiments, Figure 2 presents the same experiments A, B, C, and D as in Table 6 and represents the evolution of the Herfindahl-Hirschman index during the 400 iterations of each experiment. These experiments represent the outcome of one run of the algorithm for the given parameters. This again shows that the existence of market-share control has a stronger implication for market concentration than the minimum generation requirement. Moreover, the minimum generation requirement only has an impact if the market share control is not a constraint.

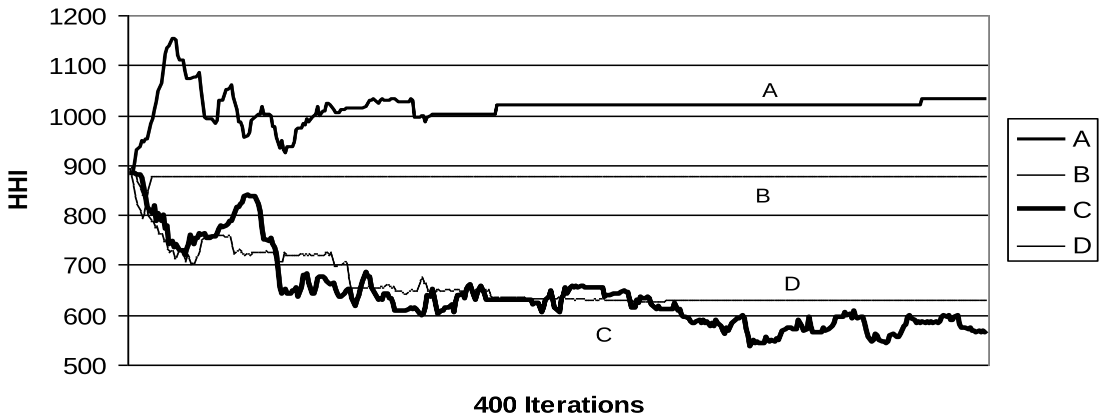


Figure 2. Herfindahl-Hirschman Index – multi-clearing mechanism.

It is also interesting to note that the experiments A, B and D converged to a flat line (and experiment C is also converging to an evolutionary equilibrium). This is the expected behavior of these experiments. This represents a steady state, an equilibrium, as in Definition 4.1, in which the value of any plant in the system is higher for its owner than for any of his competitors. These experiments show that the market structure can converge towards an evolutionary equilibrium.

Next, in Table 9, we present a fourth set of experiments in the single-clearing market in which, at each time, all the electricity sold receives the same price. These experiments assume an elasticity of 0.5, 0.35 and 0.25.

The results in Table 9 are very similar to the ones under the multi-clearing mechanism. Again the minimum generation requirement and the presence of market share control imply lower prices and higher generation.

Table 9. Single-Clearing, Mininum Generation Requirement, Market Share and Performance.

Experiment	Mk Share	Min. Gen. Req. (MWh)			Quantities (MWh)			Prices (£/MWh)		
		Bs	Sh	Pk	Bs	Sh	Pk	Bs	Sh	Pk
A	100	0.0	0.0	0.0	21.2	30.4	33.9	18.5	33.7	114.6
B	100	24.0	44.0	48.0	24.0	44.0	48.0	15.0	20.0	60.0
C	10	0.0	0.0	0.0	25.6	40.7	47.9	13.0	18.9	38.7
D	10	24.0	44.0	48.0	25.3	45.4	52.4	13.3	18.1	38.0

Figure 3 represents the evolution of the Herfindahl-Hirschman index (HHI)[8] during the 400 iterations of each experiment, during the set of experiments (A, B, C, and D) presented in Table 9. Once again, these experiments represent the outcome of one run of the algorithm for the given parameters.

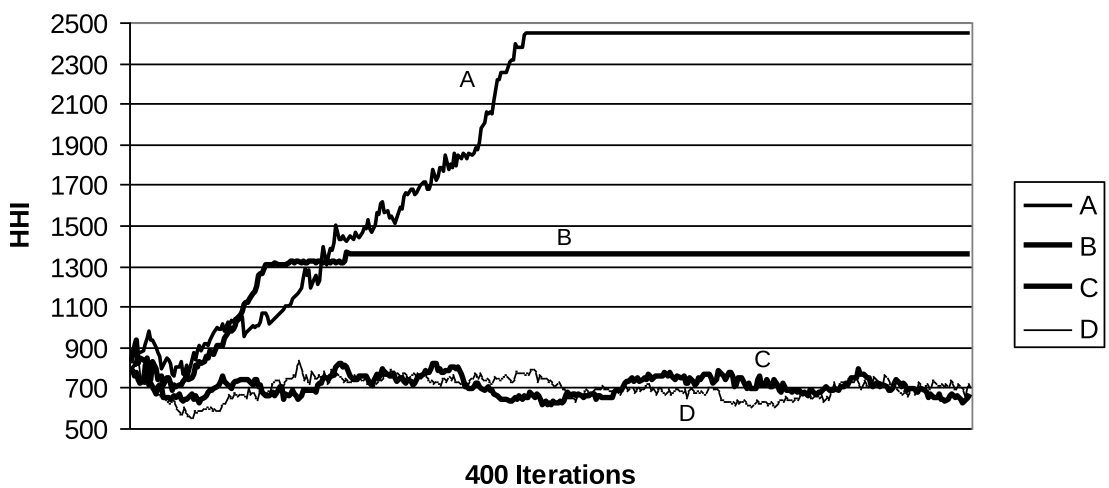


Figure 3. Herfindahl-Hirschman Index – single-clearing mechanism.

The main conclusions are similar to the multi-clearing ones. Figure 3 shows that the existence of market-share control has a stronger impact on market concentration than the minimum generation requirement. It is also interesting to note that the experiments A, B converged to a flat line (and experiments C and D are also converging to the evolutionary equilibrium). Again, this is the expected behavior of the structural evolution. Moreover, in Figures 2 and 3 the following pattern emerged:

- In the absence of market interventions the market structure converges to a steady state with the highest HHI.
- The minimum generation requirement imposes a faster convergence towards an evolutionary equilibrium.
- Initial conditions affect the speed of adjustment toward an evolutionary equilibrium.
- The presence of market share constraints makes it harder for the algorithm to converge to a steady state (even though it always converges to a market structure around which the system evolves). This is due to the fact that the control for market share is imposed in the auction but not in problem (3.1), and therefore every time a firm produces above the allowed market share a divestment is ordered (i.e., a sell of a small generation set).

Hence, in Table 10, we can now compare the average prices and total quantities traded in the multi-clearing and single-clearing mechanisms using the data presented in Table 6 (multi-clearing) and Table 9 (single-clearing).

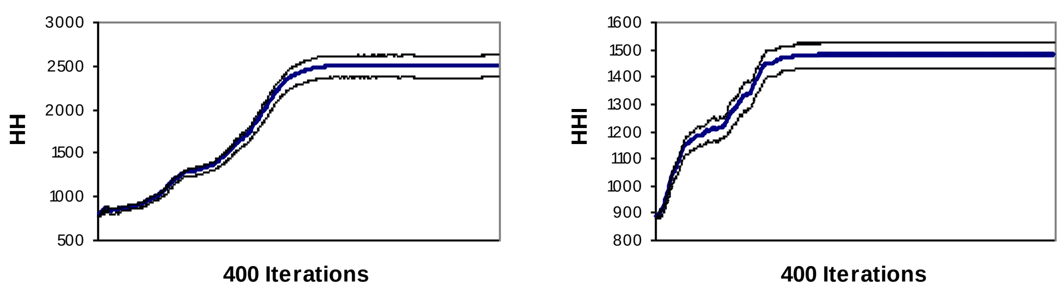
Table 10. Multi-Clearing vs Single-Clearing.

Experiment	Multi-Clearing		Single-Clearing	
	Quantity (TW/year)	Average Price (£/MWh)	Quantity (TW/year)	Average Price (£/MWh)
A	258	22.4	238	35.0
B	322	16.9	322	21.8
C	289	17.8	311	18.8
D	322	16.9	336	18.5

A first conclusion of the analysis of Table 10 is that the average prices in the single-clearing case are higher than in the multi-clearing case, independently of the experiment. Second, from the analysis of the experiments A (no interventions), in the single-clearing case, the average price is significantly higher than in the multi-clearing case, mainly due to the change in the quantities traded in each market. A third conclusion, arising from the comparison of scenarios C and D with A and B, is that the existence of market share control has a stronger impact on the prices and quantities of the single-clearing mechanism than on the multi-clearing mechanism. This conclusion can also be reached by comparing experiments A and B in Figures 2 and 3. Under single-clearing there is a stronger trend toward concentration, showing that the minimum generation requirement is non-binding; but with multi-clearing there is no trend towards concentration, showing that the minimum generation requirement by itself can prevent the evolutionary movement toward concentration.

These three observations imply that, in non-regulated “mandatory Pool” markets average prices could be higher than in non-regulated “continuous bilateral” markets. However, and most importantly, they also imply that regulatory interventions may be more effective in pool markets.

Finally, in Figure 4 we look at all the experiments and consider the sensitivity of these results to the inertia principle (the only stochastic variable in the model) and the possible existence of multiple equilibria. We repeat experiment *A* of the multi-clearing and single-clearing mechanisms (in Figures 2 and 3), and compute the 95% confidence intervals for the average HHI in experiment *A*, in the single and multi clearing mechanisms.



(a) Single-Clearing (b) Multi-clearing

Figure 4. Herfindahl-Hirschman Index: Confidence Intervals.

Figures 4.a and 4.b represent the behavior of the HHI in the forty experiments with the single-clearing and multi-clearing mechanisms, respectively. These results were computed from the simulation of 40 independent repetitions of experiment A under single and multi clearing (80 repetitions in total).

At iteration 400, in the single-clearing mechanism, the average HHI was 2499 and the 95% confidence interval was [2374, 2623]; moreover, in the multi-clearing mechanism, the average HHI was 1478 and the confidence interval was [1432, 1524]. Hence, the narrow confidence intervals in these sensitivity experiments corroborate the results in Figures 2 and 3, showing that the single-clearing mechanism, on average, leads to greater concentration levels (these results are statistically significant).

These sensitivity analyses also give general confidence to the overall pattern of results and conclusions. Furthermore, several other more extreme stylized experiments validated this model by testing its results under different market structures. For example, when all players behaved as price takers, no trading occurred as the players generate the market clearing quantities (which is a stable equilibrium). Similarly, in a simulation of the monopoly situation with potential new entrants, there was no entry, and the prices were always the ones of the monopoly market structure. In Appendix 1 we discuss the issue of capacity trading in the context of a simple stylized oligopoly.

6. Conclusions

This paper has presented a large-scale, computationally intensive model for understanding the dynamic strategic evolution of electricity generation asset portfolios in response to various market interventions, and the consequent longer term effects of such changes on market structure and prices. Such insights are elusive to conventional static equilibrium analyses of the effects of market structure on market performance. We have compared the traditional structural intervention of market share control with the behavioral remedy of generation adequacy.

Whilst both controls can lead to lower prices, it was interesting to observe that:

1. The minimum generation requirement imposes a constraint that limits the ability of incumbents to use capacity withholding as an instrument to increase the value of their portfolios, and hence, it limits the dynamics towards industry concentration by making it less attractive for them to buy plant from smaller players.

2. With the existence of a minimum generation requirement, the additional introduction of structural (i.e., market share) control does not significantly change (in the economic sense) the level of generation and prices.
3. The elasticity of demand has a comparatively smaller impact on the solution of the game, in the presence of other regulatory controls.
4. Still, even with market share control and minimum generation requirements in place, capacity withholding by the pivotal players remains a concern (even though with reduced implications on prices and generation).

Further, we have also compared the effectiveness of market interventions under the two variants of market clearing. The results of our experiments suggest that an "interventionist" regulator might prefer a mandatory Pool market where quantities and prices are public knowledge and where regulation appears to be more effective. However, a more liberal regulatory body, i.e., that wishes all incentives to come from the market, might prefer a multi-clearing mechanism, which leads to higher consumer welfare (under the non-interventionist scenario.

Finally, apart from validating the use of a large scale, computationally intensive multi-stage gaming model involving a mixture of Cournot market behavior and plant trading to capture the dynamics of market structure, a further observation from this work relates to the topic of modeling electricity markets using Cournot models. In such specifications, demand elasticity is crucial and is often done in an ad hoc way to achieve realistic prices. In the daily market place, demand is actually inelastic, except for conditions of extreme scarcity, but because oligopolies of generators in practice have not generally chosen to exercise their market power to the fullest extent (e.g., for political or repeated game reasons), higher values for elasticities have generally been specified in market models as surrogates for longer term considerations.[7] In contrast, with the kinds of regulatory intervention explicitly represented in this study, rather lower, more realistic elasticities can be used to model the behavior of electricity consumers.

In summary, the contributions of this paper can be positioned in three main directions:

- *Computational modeling*: through the presentation of an innovative evolutionary model to simulate the evolution of a market structure in response to market microstructure and interventions.
- *Policy and regulation*: through the analysis of how structural and behavioral regulatory policies could affect not only prices and conduct in the short term, but also longer term strategic evolution .
- *Electricity markets design*: through providing further model based evidence on the price effects of market rule changes, and new insights into their market structure incentives as well.

In this paper we aimed to explain how market structure, the clearing mechanism and regulatory behavior interact in order to shape the evolution of an electricity market. However, we have not argued that we are predicting how the industry will evolve in the future, as any model, even a complex one, is always a simplification in order to provide conditional insights only on specific features of reality. Moreover, even though the main drivers of the system are mostly determined by the market structure and rules, the introduction of stochastic shocks in the model may change the evolutionary equilibrium, given the apparent path dependency of the results. Hence, whilst we believe that the model and platform presented in this paper can be used both by policy makers and companies to better understand the evolutionary implications of their actions; more specific questions would require the introduction of additional details into the basic model.

Endnotes

1. The UK Competition Commission (www.competition-commission.org.uk) indicated in 2004 that it would be seeking to implement more "behavioral remedies" than "structural changes" to deal with dominance and potential market power abuse. Initial attempts during the 1990s to reduce market concentration by enforced divestiture had clearly not gone far enough, and were difficult to achieve in the face of corporate resistance. Nevertheless, wholesale market concentration did reduce substantially through further new entry so that by 2003, prices became very competitive.
2. It should also be noted that because, in the medium and long-terms, there is some demand elasticity, then through increasing prices, demand decreases and effectively some capacity is not

called. Thus, the minimum generation requirement would indirectly impose a constraint on price rises. Moreover, these market interventions are such that the market price is always higher than marginal cost, for obvious efficiency reasons.

3. In the general case of the Cournot game with a constraint for minimum output, there can be multiple equilibria. A solution is however possible by assuming that the constraint has the same shadow price for every player, and this ensures that with symmetrical players, they would have the same level of generation. Hobbs and Pang (2007) have also used equal shadow prices for maximum sales in order for Lemke's (1965) algorithm to perform correctly and the same assumption has been used in Harker (1991) as well as in Wei and Smeers (1999).

4. This step represents a simplification of the more general procedure that would be to concatenate together the first order conditions for every plant in the system. However, although we adopted that approach at first, it did not work well, as Lemke's (1965) algorithm failed to converge in many instances of the problem. This is due to the linear relationship between the dual variables associated with maximum capacity constraint of these plants. Even though results could be obtained eventually, through the use of a backtracking procedure (that looked for a feasible solution when Lemke's procedure failed), this was extremely time consuming, especially as we needed to solve the Cournot model very often whilst simulating market structure evolution. See also endnote 5 below.

5. The solution of the game with the minimum generation constraint can be characterized as a generalized Nash game, e.g., Harker (1991) and Oren (1997). It is well known that Lemke's algorithm can fail under certain conditions, see Oliveira (2008) and Hobbs and Pang (2007). Hobbs and Pang (2007) show that in the case of joint capacity constraints by assuming the same shadow price the Lemke's algorithm converges to a solution. Further, Oliveira (2007) proposes a constraint logic programming extension for Lemke's algorithm which incorporates an iterative procedure to look for a feasible solution when the basic algorithm fails to converge. In the approach used in this paper, after modifying the algorithm using constraint logic programming to proceed in this way, Lemke's algorithm worked well.

6. For sources, refer to the UK Electricity Association (1999, 2000a,b,c)

7. For example, Wei and Smeers (1999) use 0.4 and 0.53 for residential and industrial clients respectively, in simulating the Belgium, France, Germany and Italy markets, whilst Ramos et al. (1998) use an elasticity of 0.6 in simulating the Spanish market.

8. The Herfindahl-Hirschman index (HHI) is a measure of the size of the firms' market share in comparison to the industry as a whole. It is an indicator of market-power. It is calculated as the

sum of the squares of the market shares (as a percentage) of each individual firm, ranging from 0, if there are infinitely many firms to 10000 for the monopoly. A possible reference, among many others, is Rhoades (1995).

Appendix 1: Analysis of Cournot Asset Trading [1]

In order to explore a basic perspective on the interaction of plant trading and market structure, we consider a simple Cournot model where an agent *i* aims to maximize his profit (π_i), equation (A.1), taking into account the demand function, equation (A.2), and the existence of capacity constraints, as in equation (A.3), in which K_i represents the available capacity for agent *i*.

$$\max \pi_i = (P - C_i)Q_i \tag{A.1}$$

$$P = a - \alpha \sum_j Q_j \tag{A.2}$$

$$0 \le Q_i \le K_i \tag{A.3}$$

We consider the duopoly with two agents A and B. We analyze three different cases, taking into account the number of plants and capacity available for each agent.

First Case: In this case, with no excess capacity, the loss of the seller due to capacity trading is equal to the gain of the buyer, therefore no trade is possible.

For this example, firm A owns 1000 units of capacity with a total of 100 plants and the marginal cost is zero, whereas firm B owns 990 units of capacity with a total of 99 plants and the marginal cost is equal to 10 monetary units. The inverse demand function is P =100 - 0.02Q.

Under these conditions the solution for the Cournot model is Q_A =1000, Q_B=990 and P=60.2. The profits earned by the two firms are Profit_A= 60200 and Profit_B= 49698 monetary units and there is no spare capacity.

If there were a trade of a plant from firm A to Firm B (the plausible direction), the new structure of the market would be Firm A owning 990 units of capacity with a total of 99 plants (marginal cost zero) and

[1] Online Appendix

firm B owning 1000 units of capacity with a total of 99 plants (marginal cost 10) and one plant with a marginal cost equal to zero. The inverse demand function remains the same.

Under these new conditions the solution for the Cournot model is Q_A =990, Q_B=1000 and P=60.2. The profits earned by the two firms are $Profit_A$= 59598 and $Profit_B$= 50300. In this case there is no spare capacity and the profit of agent A decreases by 602 and the profit of player B increases by 602 monetary units. Therefore there is no incentive for capacity trading.

Second Case. In this case, with A having excess capacity, no trade is possible because the loss of the seller due to plant trading is higher than the gain of the buyer.

In this second example, firm A owns 2500 units of capacity with a total of 250 plants and the marginal cost is zero, whereas firm B owns 990 units of capacity with a total of 99 plants and the marginal cost is equal to 10 monetary units. The inverse demand function is P =100 - 0.02Q. Under these initial conditions the solution for the Cournot model is Q_A =2005, Q_B=990 and P=40.1. The profits earned by the two firms are $Profit_A$= 80400.5 and $Profit_B$= 29799 monetary units. Here, firm A has some excess capacity and firm B is using its full capacity. Therefore, intuitively it would seem that firm B would profit from buying a more efficient plant from firm A, and that a trade would be possible.

However, after a trade of a plant from firm A to Firm B the new structure of the market is the following. Firm A owns 2490 units of capacity with a total of 249 plants (marginal cost zero), whereas firm B owns 1000 units consisting of 99 plants with marginal cost equal to 10 and one plant with a marginal cost equal to zero. The inverse demand function remains the same.

Under these new conditions the solution for the Cournot model is Q_A =2000, Q_B=1000 and P=40.0. The profits earned by the two firms are $Profit_A$= 80000 and $Profit_B$= 30100. In this case there is no spare capacity. The profit of agent A decreases by 400.5 units and the profit of player B increases by 301 units. Surprisingly, there is no incentive for capacity trading. In this case capacity trading leads to lower prices and to higher losses for the selling agent. Therefore, there is no trade as the dominant player would prefer to withhold capacity.

Third Case. In this case both players have excess capacity and the lower unit cost agent can profit from selling its plant to the other firm with more expensive technology.

In this third example, firm A owns 2500 units of capacity with a total of 250 plants and the marginal cost is zero, whereas firm B owns 2490 units of capacity with a total of 249 plants and the marginal cost is equal to 10 monetary units. The inverse demand function is P =100 - 0.02Q.

Under these initial conditions the solution for the Cournot model is Q_A =1833.3, Q_B=1333.3 and P=36.7. The profits earned by the two firms are Profit_A= 67282.1 and Profit_B= 35599.1. In this case both firms have excess capacity.

After the trade of a plant from firm A to Firm B the new structure of the market is the following. Firm A owns 2490 units of capacity with a total of 249 plants and the marginal cost is zero, whereas firm B owns 2500 units of capacity with a total of 249 plants, with marginal cost equal to 10, and one plant with a marginal cost equal to zero. The inverse demand function remains the same.

Under these new conditions the solution for the Cournot model is Q_A =1833.3, Q_B=1333.3 and P=36.7. The profits earned by the two firms are Profit_A= 67282.1 and Profit_B= 35699.1; i.e., the profit of agent A is the same and the profit of player B increased by 100 units. In this case, the intuition holds: the player with the expensive technologies buys the cheaper plant that replaces its more expensive plant at the margin. However this Cournot equilibrium is not sustainable. The continuous trade of plants would lead to a market structure in which firm A owns 1833.3 units of capacity and firm B owns 3156.6 units of capacity. The total production in equilibrium would not change, as it remains Q_A=1833.3 and Q_B= 1333.3, but we observe that not only is the market structure suggested by the static Cournot model not sustainable in the long run but also, in the end, it is the larger player, eventually, B, that withholds capacity, and that is the one holding the inefficient plants.

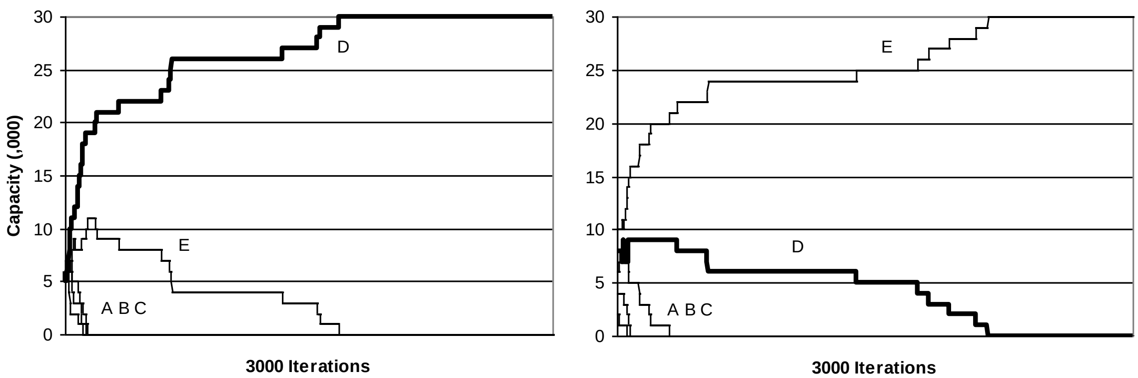
These simple examples raise several questions on the sustainability of a given market structure, on the direction of plant trade and evolution of the market structure, and on the way to compute the value of a plant (as player A in case two refuses to sell any of the plant that he is actually not using). Clearly, the mutual trading incentives are dependent upon the market structure and excess capacity, and this suggests that more detailed market specific, evolutionary modeling is needed, especially for a particular market such as electricity, which is typically an oligopoly with substantial technological cost disparities and moderate, time-varying, excess capacity.

Next, we use a very simplified version of the computational learning model to explore the evolution of asset trading and its relationship with the value of firms. We again model a simple market characterized by a inverse demand function $P = 90 - 0.003\sum_{i=1}^{N} Q_i$, in which N is the total number of players. Each firm behaves as a Cournot player. There is no regulation. There is only one type of plant with a marginal cost equal to zero and a production capacity of 1000. There are 30 plants (so the total capacity is 30,000) and five players in the industry. We model two different experiments for market structure, as presented in Table 11.

Table 11. Market Structure.

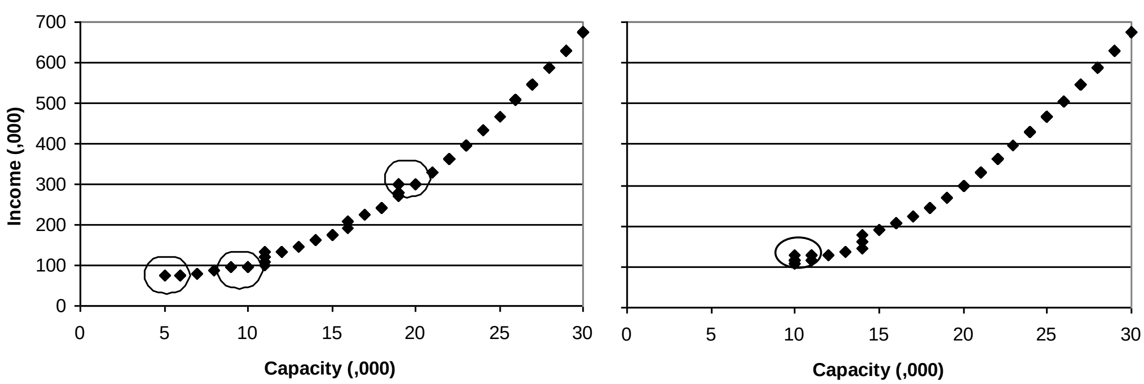
	Number of plants Owned	
Player	Experiment 1	Experiment 2
A	6	2
B	6	4
C	6	6
D	6	8
E	6	10

In Experiment 1 all the firms are equal and owned the same quantity of capacity. In Experiment 2 the firms have very different installed capacity, with firm E being the biggest. These are two extreme scenarios for asset ownership. We simulate plant trading between the firms in the industry, using the model in section 4. The results are presented in Figures 5 and 6.



(a) (b)

Figure 5. Evolution of Capacity Ownership per Player. (a) Experiment 1, (b) Experiment 2.



(a) (b)

Figure 6. Evolution of Capacity Ownership and Income for the Dominant Player. (a) Experiment 1, (b) Experiment 2.

Figure 5 shows that in both experiments the market structure converged towards a monopoly. Figure 6 shows that the income of the dominant player in both cases increases by almost 700% from the initial market structure to the monopoly market structure. Moreover, as under a Cournot oligopoly the sum of the players' incomes is always less than the monopolist's income, it follows that possible for a firm to buy out its rivals paying them more than their current value and still retaining some extra-value resulting from its future dominant position. Therefore, these results are similar to Farrel and Shapiro's (1990) with plant trading leads to higher prices. However, there are situations in which the profits of the buying firm may not increase after buying an asset. In Figure 6 we have signaled four different situations in which plant trading failed to change income. Since we have not incorporated the purchase price of the assets in these figures, in such situations, buying a new asset could temporarily decrease the value of the firm. This example shows that a mere static analysis of a Cournot model is not sufficient to get a full perspective over the impacts of asset trading and a model in which market structure is endogenous can provide a better insight into the dynamics of asset trading.

Appendix 2: Proofs [2]

Lemma 3.1: *If* $\sum_j Q^*_{j,L} \le Q_{M,L}$ *then the solution* $Q^M_{j,L}$ *of the constrained Cournot game* (3.1) *satisfies* $\sum_j Q^M_{j,L} = Q_{M,L}$.

Proof: First, by definition of minimum generation requirement $\sum_j Q^M_{j,L} \ge Q_{M,L}$ and therefore any solution such that $\sum_j Q^M_{j,L} < Q_{M,L}$ is not possible. Second, we need to prove that $\sum_j Q^M_{j,L} > Q_{M,L}$ is not a solution. For any player *i* not generating at its full capacity $\left(K_{i,L} > Q^M_{i,L} > Q^*_{i,L}\right)$ we have the following optimization conditions $A_L - \alpha_L \sum_{j \ne i} Q^*_{j,L} - 2\alpha_L Q^*_{i,L} - C_{i,L} = 0$ and

$A_L - \alpha_L \sum_{j \neq i} Q_{j,L}^M - 2\alpha_L Q_{i,L}^M - C_{i,L} + \lambda = 0$, where $\lambda > 0$. Hence, as $\lambda > 0$ and by the complementarity condition of the minimum generation requirement it follows that $\lambda\left(\sum_j Q_{j,L}^M - Q_{M,L}\right) = 0$, and thus $\sum_j Q_{j,L}^M = Q_{M,L}$, contradicting $\sum_j Q_{j,L}^M > Q_{M,L}$. If all the players are generating at full capacity when the minimum generation requirement is imposed, i.e., if $Q_{j,L}^* = K_{j,L}$, then, as $\sum_j Q_{j,L}^* = \sum_j K_{j,L}$ and $\sum_j Q_{j,L}^* \leq Q_{M,L}$ it follows that $\sum_j K_{j,L} \leq Q_{M,L}$. As by definition of generation capacity $\sum_j K_{j,L} \geq Q_{M,L}$ if all the players, at the optimum solution, are generating on full capacity, the minimum generation requirement can only be such that $Q_{j,L}^M = K_{j,L}$ and $\sum_j Q_{j,L}^M = Q_{M,L}$, as it represents the maximum capacity available. Q.E.D.

Lemma 3.2: *In the electricity market games described by problem (2.1) such that in equilibrium* $\sum_j Q_{j,L}^M = Q_{M,L}$, *the higher the minimum generation requirement the lower the prices.*

Proof For any market *L* the market price is $P_L = A_L - \alpha_L \sum_i Q_{i,L}$. Let $Q_{M,L}$ stand for the minimum generation requirement for market *L*, and $\sum_i Q_{i,L}^*$ represent the total generation for market *L* in the unconstrained solution. Further let $Q_{M,L}^{'}$ and $Q_{M,L}^{''}$ represent two minimum generation requirements such that $Q_{M,L}^{''} > Q_{M,L}^{'} > \sum_i Q_{i,L}^*$. By definition of price, and Lemma 3.1 it follows that $P_L^{'} = A_L - \alpha_L \sum_i Q_{i,L}^{'}$ and $P_L^{''} = A_L - \alpha_L \sum_i Q_{i,L}^{''}$, and hence $P_L^{''} < P_L^{'}$. Q.E.D.

[2] Online Appendix

Theorem 3.1: *In any electricity market with an inelastic demand, every minimum generation requirement such that* $\sum_j Q_{j,L}^M = Q_{M,L}$ *: a) reduces the value of each portfolio selling in the industry; b) reduces the value of the industry as a whole.*

Proof1: Let $\sum_i Q_{i,L}^*$ represent the total generation for market *L*, and let $Q_{M,L}$ represent the minimum generation requirement. a) We need to look at three scenarios. In the first scenario, every player *j* keeps the same generation $Q_{j,L}^M = Q_{j,L}^*$ and player *i* generates $Q_{i,L}^M$, such that $Q_{i,L}^M > Q_{i,L}^*$. As by definition of optimality $\pi\left(Q_{i,L}^M\right) < \pi\left(Q_{i,L}^*\right)$ the value of player *i*´s portfolio decreases. In the second scenario player *i* maintains his generation, i.e., $Q_{i,L}^M = Q_{i,L}^*$, and at least one of his competitors *j* increases generation, i.e., $Q_{j,L}^M > Q_{j,L}^*$. In such a case the value of player *i*´s portfolio decreases as by definition of market price, i.e., $P_L = A_L - \alpha_L \sum_i Q_{i,L}$, *i* sells the same quantity at a lower price. Finally, in a third scenario both *i* and some of his competitors increase their generation. From scenario one, it is known that $\pi\left(Q_{i,L}^M \mid \sum_{j \neq i} Q_{j,L}^*\right) < \pi\left(Q_{i,L}^* \mid \sum_{j \neq i} Q_{j,L}^*\right)$. Further, from scenario two, and as $\sum_{j \neq i} Q_{j,L}^* < \sum_{j \neq i} Q_{j,L}^M$ then $\pi\left(Q_{i,L}^M \mid \sum_{j \neq i} Q_{j,L}^M\right) < \pi\left(Q_{i,L}^M \mid \sum_{j \neq i} Q_{j,L}^*\right)$, this relationship implies that $\pi\left(Q_{i,L}^M \mid \sum_{j \neq i} Q_{j,L}^M\right) < \pi\left(Q_{i,L}^* \mid \sum_{j \neq i} Q_{j,L}^*\right)$. This implies that the value of player *i*'s portfolio decreased with the introduction of the minimum generation requirement. b) As $Q_{M,L} > \sum_i Q_{i,L}^*$, and since in equilibrium the total generation equals $Q_{M,L}$ (from Lemma 3.1), the market price for any market *L*, $P_L = A_L - \alpha_L \sum_i Q_{i,L}$, decreases. As the demand is inelastic, this leads to a loss of revenue, which together with increased costs, imply lower profits. Q.E.D.

Theorem 3.2: *Every minimum generation requirement such that* $\sum_j Q_{j,L}^M = Q_{M,L}$ *limits capacity withholding and the dynamics toward concentration.*

Proof: Let $Q_{i,L}$ and $Q_{-i,L}$ represent, respectively, the total generation of player *i* and of the "rest of the industry" for market *L*. Further, let $Q_{(j,i),L}$ and $Q_{(-j,i),L}$ represent, respectively, the total output of plant *j*, and of the "rest of the plants owned by player *i*" to market *L*. Moreover, let $C_{(j,i),L}$ and $C_{(-j,i),L}$ stand, respectively, for the marginal cost of plant *j* and of the "rest of player *i*'s plants" (i.e., player *i*'s marginal plant at market *L*, after removing plant *j*) selling in market *L*. Finally, let $K_{(j,i),L}$ represent the capacity available of plant *j* for market *L*.

At any given time, the gross margin of a given player *i* is a function of market price and of the output of each one of his plants, i.e.,

$$GM(i) = \sum_L \left(A_L - \alpha_L Q_{-i,L} - \alpha_L Q_{(-j,i),L} - \alpha_L Q_{(j,i),L}\right)\left(Q_{(j,i),L} + Q_{(-j,i),L}\right) - \sum_L \left(C_{(j,i),L} + C_{(-j,i),L}\right).$$

Therefore,

$$GM(i) = GM(j,i) + \sum_L \left(A_L - \alpha_L Q_{-i,L} - \alpha_L Q_{(-j,i),L} - \alpha_L Q_{(j,i),L}\right)Q_{(-j,i),L} - \sum_L C_{(-j,i),L} .$$

Thus, the value of a plant *j* for the player *i* is not only a function of its output $Q_{(j,i),L}$, but also of the capacity withheld, ($K_{(j,i),L}$- $Q_{(j,i),L}$), as by withholding capacity the player increases the value of the other plants by increasing the price received by those plants, this conclusion follows from the term $A_L - \alpha_L Q_{-i,L} - \alpha_L Q_{(-j,i),L} - \alpha_L Q_{(j,i),L}$.

Therefore, a player buys a plant *j* only if $Q_{(-j,buyer),L} > Q_{(-j,seller),L}$ since it is more profitable for the buyer to withhold capacity and therefore increase the price received by the generation of his larger portfolio. However, if the market is generating at the minimum generation requirement level no extra capacity withholding is possible. Hence, the value of the rest of the buyer's portfolio remains unchanged, as the price $A_L - \alpha_L Q_{-i,L} - \alpha_L Q_{(-j,i),L} - \alpha_L Q_{(j,i),L}$ is the same, and the quantities do not change. Thus, the buyer does not have extra-profit to pay for the plant, and therefore trade cannot happen. Conclusion, the existence of minimum generation requirements limits capacity withholding and the dynamics toward concentration. Q.E.D.

Theorem 4.1: *Every state of the industry is an evolutionary equilibrium if for every possible transaction of plant j owned by a potential seller S, and for any buyer B, the optimal generation change* $\Delta Q_{(j,B),L}$ *is such that* $-\sum_L \alpha_L.\Delta Q_{(j,B),L}.\left(Q_{(-j,S),L}+Q_{(-j,B),L}\right)\leq GM(j,S)-GM(j,B)$.

Proof: At any given time, the gross margin of a given player *i* is a function of market price and of the output of each one of his plants, i.e.,

$$GM(i)=\sum_L\left(A_L-\alpha_L Q_{-i,L}-\alpha_L Q_{(-j,i),L}-\alpha_L Q_{(j,i),L}\right).\left(Q_{(j,i),L}+Q_{(-j,i),L}\right)-\sum_L\left(C_{(j,i),L}+C_{(-j,i),L}\right)$$ therefore,

$$\begin{aligned}GM(i)=&\sum_L\left(A_L-\alpha_L Q_{-i,L}-\alpha_L Q_{(-j,i),L}-\alpha_L Q_{(j,i),L}\right).Q_{(j,i),L}-\sum_L C_{(j,i),L}+\\&+\sum_L\left(A_L-\alpha_L Q_{-i,L}-\alpha_L Q_{(-j,i),L}-\alpha_L Q_{(j,i),L}\right).Q_{(-j,i),L}-\sum_L C_{(-j,i),L}\end{aligned}.$$

And equivalently,

$$GM(i)=GM(j,i)+\sum_L\left(A_L-\alpha_L Q_{-i,L}-\alpha_L Q_{(-j,i),L}-\alpha_L Q_{(j,i),L}\right).Q_{(-j,i),L}-\sum_L C_{(-j,i),L}\ .$$

So we can write a gross margin for the seller (*S*) and another one for the buyer (*B*), in order to analyze how they evaluate a plant *j*:

$$GM(S)=GM(j,S)+\sum_L\left(A_L-\alpha_L Q_{-S,L}-\alpha_L Q_{(-j,S),L}-\alpha_L Q_{(j,S),L}\right).Q_{(-j,S),L}-\sum_L C_{(-j,S),L}$$

$$GM(B)=GM(j,B)+\sum_L\left(A_L-\alpha_L Q_{-B,L}-\alpha_L Q_{(-j,B),L}-\alpha_L Q_{(j,B),L}\right).Q_{(-j,B),L}-\sum_L C_{(-j,B),L}\ .$$

From these profit equations it follows that a player *cannot* extracts value from a given plant if it does not change its generation output: if the generation level of a plant bought does not change the buyer's profits in the rest of his portfolio will not change and therefore the transaction is not profitable. Moreover, a player cannot extract extra value from a plant by increasing its generation as bigger buyers will lose more from price reductions, and smaller buyers are not able to generate extra-profit to compensate the seller from the effects of lower prices (if this strategy was profitable the seller would implement it himself). Therefore, the only possible strategy to extract extra value from a plant is to decrease its generation, i.e., $\sum_L \Delta Q_{(j,B),L} \equiv \sum_L \left(Q_{(j,B),L} - Q_{(j,S),L}\right) < 0$.

Thus, as $\sum_L \Delta Q_{(j,B),L} < 0$ we have *no* transaction, and therefore an evolutionary equilibrium, if and only if the gross margin forfeit by the seller of asset *S* is higher than the extra total profit gain by the buyer: $GM(j,S) + \sum_L \alpha_L.\Delta Q_{(j,B),L}.Q_{(-j,S),L} \geq GM(j,B) - \sum_L \alpha_L.\Delta Q_{(j,B),L}.Q_{(-j,B),L}$. Hence, by simple manipulation of this formula we see that there is no trade if the increase in value of the rest of the seller and buyer's portfolio is not higher than the loss in value for asset *j*: $-\sum_L \alpha_L.\Delta Q_{(j,B),L}.\left(Q_{(-j,S),L} + Q_{(-j,B),L}\right) \leq GM(j,S) - GM(j,B)$. Q.E.D.

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