BUNN, D.W. and OLIVEIRA, F.S. 2016. Dynamic capacity planning using strategic slack valuation. *European journal of operational research* [online], 253(1), pages 40-50. Available from: https://doi.org/10.1016/j.ejor.2016.02.013

Dynamic capacity planning using strategic slack valuation.

BUNN, D.W. and OLIVEIRA, F.S.

2016

Dynamic capacity planning using strategic slack valuation

Derk W. Bunn
London Business School, UK, dbunn@london.edu

Fernando S. Oliveira
ESSEC Business School, oliveira@essec.edu

In this paper we analyze a particular aspect of capacity planning that is concerned with the active trading of production facilities. For a homogenous product market we provide a theoretical rationale for the valuation and trading of these assets based on a metric of strategic slack. We show that trading production assets with non-additive portfolio profitability involves complex coordination with multiple equilibria and that these equilibria depend on the foresight in the planning horizon. Using the concept of strategic slack we have analyzed the dynamics of market structure, the impact of asset trading on the level of production of the industry, and to derive boundaries on the value of the traded assets. Moreover, through computational learning, the formulation is applied to a large oligopolistic electricity market, showing that plant trading tends to lead to increased market concentration, high prices, lower production and a decrease in consumer surplus.

Key words: Strategic planning; Investment; Energy; Real options; Simulation.

1. Introduction

The capacity planning problem has been analyzed from many different perspectives. Whereas the dominant theme of analysis has been concerned with optimal facilities expansion, following cost minimization under uncertainty (e.g. Van Mieghem, 2003 and Julka, Baines, Tjahjono, Lendermann, & Vitanov, 2007), the implications of capacity decisions on market price formation is an important consideration in profit maximizing plans. Thus, Bish and Wang (2004) have examined the capacity expansion problem with endogenous prices for a monopoly with demand uncertainty, whilst Goyal and Netessine (2007) looked at strategic capacity investment in a competitive product market as a game of technology choice. In this article we also analyze the capacity planning problem from a strategic aspect, but in the context of competitive, profit-maximizing companies trading production facilities amongst themselves, as distinct from investing in new capacity.

Our motivation for this formulation is primarily taken from events in the electricity industry. Until the 1990s, capacity planning in the electricity sector was undertaken by long-term, least cost optimization modeling (Bloom, 1983). With the prospect of steady growth in demand and regulated returns on assets, risks were low and the planning issues were mainly about optimizing the operational mix of technologies. New capacity would be built in time to meet rising demand at least cost and old capacity would be retired at obsolescence. But, with the advent of deregulation and competitive markets in many regions since the 1990s, capacity planning became more focused upon optimizing a portfolio of production facilities, and companies often traded assets amongst themselves to increase profits, manage risks and perhaps influence market prices. Thus, Bunn (2004) documents 22 trades of power stations between companies in the British market from 1995-2004, and observes that their declining asset values followed, as expected, the declining wholesale electricity prices. Similarly, Downward, Young, & Zakeri, (2011) assert that the ”swapping of assets is relatively common in power markets” and proceed to discuss how asset rearrangements (either divestures to a new firm or swaps between existing firms) in electricity markets may benefit the producers. By 2014, with some developed countries facing flat, or declining long-term projections for electricity demand (Eurelectric, 2013), and with many governments incentivizing energy sustainability, conventional capacity planning in the power sector had, in these situations, become less about expansion and more about divestment and adjusting the existing asset portfolios. Thus, Ernst and Young (2014) report 70 asset trades globally in power generation in 2012, up from 60 in 2011.

In general, there are many factors that may help in understanding the process of plant trading as a capacity planning strategy. For instance by acquiring a plant a firm may enter a market niche only available to that technology and offer different operational options to the owner (as with intermittent renewable energy, e.g., Wu & Kapuscinski, 2013). In a more general context, the prospects of operational synergies or product variety, scale economics, opportunistic accounting, strategic positioning, different attitudes to risk, can all motivate plant trading (e.g., Aydemir & Schmutzler, 2008; Banal-Estanol & Ottaviani, 2006), as well as asset divestures imposed by regulation (e.g., Bunn, 2004; Bunn & Oliveira, 2007, 2008; Downward et al. 2011). However, theoretical results upon whether acquisitions increase or decrease profits are still mixed (e.g., Daughety, 1990; Farrell & Shapiro, 1990; Nilsson, 2005; Salant, Switzer, & Reynolds, 1983), and furthermore, market complexities may create substantial scope for interaction, experimentation, learning and co-evolution in asset ownerships. Thus, pathdependency may be an emergent property of asset-trading dynamics through the influence of initial and distinctive resource-bases (e.g., Nelson & Winter, 1982).

Thus, the emergence of heterogeneity in the ownership of production facilities, in markets where resources are readily transferred between competitors, has motivated several avenues of research, including asymmetric market structure (Reynolds & Wilson, 2000), out-of-equilibrium rents (Klepper & Graddy, 1990) as well as real-option valuations in the presence of development opportunities and search costs (Williams, 1993, 1995) and with alternative technologies (Siddiqui & Fleten, 2010). Setting aside the usual framing of this problem in the context of market entry and innovation, we address the apparently simpler question of why, in the absence of any financial distress, the same real asset, in the same product market, should apparently be worth more to one company than another and thereby motivate a trade. In our analysis of the emergence of market heterogeneity through asset trading, we draw upon two main concepts, namely, complexity in the decision to trade an asset and the strategic slack associated with the tradable asset, the value of which varies by firm.

Complexity is manifest as the size of the asset trading problem grows exponentially with the number of assets and firms in the market, with the consequence that decisions are likely to be made under bounded rationality. Thus, an approach based upon search methods (e.g., Williams, 1995) and computational learning is appealing (following, e.g., Chari & Agrawal, 2007; Sutton & Barto, 1998; Gosavi, 2009; Powel, 2010). Computational learning has become increasingly useful for examining the strategic behavior of competing agents interacting in markets for products or financial assets. A key ingredient in these applications of the methodology has been the stylization reflecting the market microstructure of the repeated instances of interaction, e.g. pricing and quantity decisions, from which the computational agents in the model can learn (e.g., Banal-Estanol & Micola, 2009; Bunn & Oliveira, 2008; Micola, Banal-Estanol, & Bunn, 2008; Sutton & Barto, 1998). But in the setting of market structure evolution, where agents may be acquiring, disposing or trading real assets, such as production facilities, these instances do not occur frequently, and the extensive repetitions required for learning from experience are not realistic. Furthermore, as the uncertainty in market structure evolution, due to the process of coupled search for viable asset trades, becomes unforeseeable, adaptive co-evolution will be prone to path dependency (e.g., Foray, 1997; Nelson & Winter, 1982). Modeling market structure evolution where real assets are substantially, but not frequently, traded amongst market participants, therefore, represents a challenging but relevant problem in understanding market dynamics, and in explaining the value of the traded assets.

Strategic slack is a concept that has many interpretations and functions in describing the underutilization of resources by a company, including deliberate policies for flexibility, optionality and competitive behavior (e.g., Piccolo, D'Amato, & Martina, 2008; von der Fehr & Mørch, 1992), and has an impact on the way that organizations learn to manage resources (e.g., Moreno, Fernandez, & Montes, 2009; Voss, Sirdeshmukh, & Voss, 2008) and on the real options available to the firm. We use strategic slack in the specific sense of companies choosing to underutilize real assets in order to maintain higher prices. We prove, by using this concept, that, in the context of our model: the buyers tend to be the larger firms who aim to protect their portfolios from lower prices; real asset trading increases market concentration, as firms seek to grow within their market niche; a seller may optimally sell an asset at a price below its operational profit; and the sequence of trading influences the prices of the traded assets.

A crucial aspect is the determination of the value of the assets. The value of an asset depends on its profits in the current and subsequent market states and on the implied real options that trading presents (e.g., Majd & Pindyck, 1987; Williams, 1993, 1995; Meier, Christofides, & Salkin, 2001; Smit, 2001; Smit & Ankum, 1993; Tseng & Barz, 2002; Secomandi, 2010; Shackelton, Tsekrekos, & Wojakowski, 2004; Siddiqui & Fleten, 2010; Siddiqui & Takashima, 2012). Insofar as the trading of facilities occurs, in the absence of any financial distress, the same asset must be worth more to the buyer than to the seller, yet with rational expectations, the classic "no-trade" results (following Milgrom & Stokey, 1982; Tirole, 1982) indicate that it is necessary to look beyond private information to understand the different valuations and therefore why this trading occurs.

With physical assets, the scope for externalities induced by portfolio effects, which may be transparent to all agents in the market, can induce different valuations, but this must depend upon the ability of the buyer to operate the asset more profitably than the seller, in the same product market. To the extent that the real assets are used to produce a commodity, such as electricity, and the input factors of production do not change by ownership, heterogeneous valuations and the consequent plant trading raise subtle questions on the links between asset ownership, operations and market structure in revenue formation. For example, if the asset traded is part of a portfolio, the way the tradable asset is operated to produce may depend on the other assets in the firm's portfolio. To envision the equilibrium value of an asset, therefore, requires an evaluation of all possible portfolios within which it could operate. Because of this complexity we, generally, cannot compute the exante value of such a tradable asset. Nonetheless, in practice, companies will attempt a reduced-form analysis of this calculation. We have, therefore, linked computational learning to the strategic slack valuation.

Furthermore, the learning formulation needs to take into account multi-stage, forward looking behavior in the context of realoption games (e.g., Shackelton et al., 2004; Siddiqui & Takashima, 2012; Smit, 2001; Smit & Ankum, 1993; Williams, 1993, 1995) and it is associated with the models of search in which buyers and sellers need to find the best trading partners, as analyzed in Williams (1995). We show that foresight needs to extend several periods into the planning horizon to reflect the intricate nature of emergent strategic opportunities. This means that the buyer may buy assets that temporarily decrease the value of its portfolio, yet this trade is rational in the context of anticipating the subsequent evolution of the market.

Amongst the many manufacturing and service sectors that exhibit ownership changes in their assets, electricity is an appealing example because of the range of technologies available to produce a homogeneous product and the widespread use of a wholesale market at an intermediate stage in the supply chain. Electricity markets have been researched extensively regarding the relationship between market structure and price formation mechanisms. For example, the relationship between forward and spot energy markets relates to the ability of firms to profit from market power (e.g., Anderson & Hu, 2008a and Gulpinar & Oliveira, 2012), having substantial implications related to vertical arrangements (e.g., Aid, Chemla, Porchet, & Touzi, 2011) and on investment strategies (e.g., Murphy & Smeers, 2005). Market design, including the type of auction mechanism, such as supply function offers (e.g., Anderson & Hu, 2008b), mandatory pools or bilateral trading (e.g., Bower et al., 2000), and the relationship between day-ahead and real time energy market (e.g., Borenstein, Bushnell, Knittel, & Wolfram, 2008) are crucial in determining the ability of firms to achieve prices above the competitive levels.

In summary, this paper examines why firms trade real assets in oligopolistic industries among themselves and investigates how this trading may lead to heterogeneous market structure in a homogenous product market. This analysis provides insights both for firms who may be aiming to adjust capacity in the short-term and for regulators to determine when such trades should be allowed.

2. Real asset trading as a repeated game with dynamic planning

The model proposed for the trading of real assets is a discreteevent repeated game in which only the change in market structure affects the prices and, therefore, the value of the different assets. The dynamic nature of the process arises as the optimal trade in an earlier stage depends on the ability of the firm to buy (sell) other assets in the future. Trading can therefore be formulated as a dynamic program in which the different events correspond to a transition from one state to another. The profit generated by the acquisition of assets is non-linear and non-convex; i.e., the acquisition of a substantial amount of capacity may be necessary so that prices can be increased sufficiently to give the buying firm a profit from the trade.

2.1. The real assets trading game

Let the set Ω_t represent the state of the world at time t, a vector that identifies the owner of each asset. Let N stand for the number of firms in the industry and M for the number of assets, then, at each state, a firm can choose $M+1$ different actions (one per asset plus doing nothing) and, therefore, there are $(M+1)^N$ possible transitions between states and N^M possible states of the industry. Over a finite, sequentially dependent time horizon S, this is indeed a very large coordination problem: at any moment every potential seller needs to find the best buyer for his plant and every potential buyer needs to find the cheapest seller for the type of plant he wants to acquire. Given the complex structure of this very large coordination game with incomplete information, each firm learns by interacting with others in the market for assets, learning the probabilities that other firms will trade assets with them. We therefore need to model the conjecture formation, as these conjectures allow an easier coordination between the buyers and the sellers.

We now describe how these conjectures may be computed. Let ξ_{ijt} stand for the probability of success of a trade action a_{ijt} (buy or sell j) by firm i regarding asset j, at time t. A firm infers a model of the others' behavior by keeping in memory the results of the interactions with each one of them, i.e., if the trade was possible or not. ξ_{ijt} can be computed as the simple average of the number of iterations, since the last time j was traded, in which a trade was possible, i.e., the seller (buyer) was willing to sell (buy) at a price lower (higher) than the reservation price of firm i. The assets selected for possible trading are such that $\xi_{ijt} \geq \theta$, in which and θ is a cut-off parameter. Let Φ_{it} be the set of assets for which the firm conjectures that a future trade is possible, at time t. Then, from the actions in Φ_{it}, each firm i uses dynamic programming (e.g., Bertsekas, 2000) to maximize its expected value at time t, V_{it}^*, computing the optimal asset trading strategy, as represented by Eq. (1), in which S is the planning horizon, $0 < \rho < 1$ is the discount factor, and $\pi_{it}\left(\Omega_t, \Theta_{it}^*, P_t^*\right)$ is the profit received by firm i, at time t. This profit depends on the vector of equilibrium productions, Θ_{it}^*, and vector of prices P_t^*, of the Nash Cournot game played at each node of the tree, the computation of which we describe in Section 2.2.

$$\forall t = 0, \ldots, S-1:$$
$$V_{it}^*\left(\Omega_t, \Phi_{it}\right) = \max_{a_{ijt} \in \Phi_{it}} E\left[\pi_{it}\left(\Omega_t, \Theta_{it}^*, P_t^*\right) + \rho V_{i(t+1)}^*\left(\Omega_{t+1}, \Phi_{i(t+1)}\right)\right] \quad (1)$$

In Eq. (1) the a_{ijt} are equal to one if the firm i decided to trade (buy or sell) asset j, at time t, and zero, otherwise; given the recursive nature of the problem, the firm computes a plan for S optimal trades. Ω_{t+1} stands for the state of the industry after the optimal trade at stage t occurs, and $\Phi_{i(t+1)}$ represent the remaining set of actions available to firm i, at time $t+1$. Then, after computing the optimal plan for trading, the firms attempt to buy (sell) the assets required by the optimal plan. An asset is sold to the buyer that values it the most if the price offered by the buyers is higher than the seller's bid.

After testing with different criteria, we chose to trade the asset with the largest difference between offer and bid prices. The major reason is its intuitiveness: these are the trades that create more value, per MWh of capacity, for the buyer and for the seller. Some of the other criteria tested were to trade the assets a) with the smallest different between offer and bid prices, b) the largest assets get traded first; c) the smallest assets get traded first. Option a) seems to have the advantage of a closer consensus between the seller's and the buyer's valuations but it leads more often than not to buyer's regret with the consequence that at a later stage the buyer would sell the same asset for a lower price (clear evidence that this method leads to overvaluations). Options b) and c) are based on the main idea that the size of the trades has an impact on the evolution of the market structure. In favor of option b), we would argue that the largest assets are more important to define the market structure and, for this reason, should be allowed to trade first; whereas option c) has the main advantage of allowing the trades that have a smaller impact on price to occur first, allowing, in principle, smaller jumps in the valuation after trading and, therefore, a smoother evolution in the market structure and of the price discovery process. However, both b) and c) options suffer from the buyer's regret issue as very often the buyer would re-sell the asset he bought at a lower price. Moreover, even though it would be possible to allow multiple assets to be traded at any given time, for reasons related to convergence properties, and to avoid wide jumps between successive states of the industry, with the associated evaluation errors (which would cause buyer's regret), in this model we allow the trade of at the most one asset at any given time, as it leads to a smoother adjustment trajectory, better valuations, and better decisions by buyers and sellers. Nonetheless, in reality, this does not preclude a buyer, after evaluating the assets, to acquire them all at the same time, as discussed in Proposition 8.

The repeated game in which the different firms trade assets eventually converges on an equilibrium in which no trading occurs. In equilibrium the ownership structure of the industry is such that no potential buyer values the asset more than its current owner. An important innovation in our formulation is the use of endogenous prices in the decision trees, which are computed using a Cournot model, as described below.

2.2. Modeling endogenous prices

As we are modeling the trading of real assets we need to model the endogenous product market price which, given the oligopolistic nature of the electricity market, needs to be done using game theoretical models. There is a plethora of possible models that can be used ranging from the Bertrand model (in which players set a price assuming that a small price difference is enough to capture the entire market) to the Cournot model (in which the players compute the optimal quantity to be produced at any given time, assuming that the others will behave likewise). From a theoretical perspective, Kreps and Scheinkman (1983) proved that the Cournot equilibrium is the outcome of games where there is a capacity pre-commitment followed by Bertrand competition and Daughety (1985), in analyzing conjectural variations, has shown that a rational oligopoly equilibrium is, in general, a Cournot equilibrium, and vice versa. Given the nature of the game in the electricity industry, which includes both capacity and price decisions, it seems that the Cournot model is a good approximation to represent the decision making process of the players in the market. In the Cournot model with capacity constraints represented in (2), for each time in the planning horizon, all the players compute the optimal level of production, solving model (2), assuming the Cournot conjectural variation, and the price that clears the market, at time t, is then computed as an endogenous result of the player's behavior.

We consider the existence of multiple niches in the product market which give rise to asset specificities insofar as some technologies can only reach some niches. This could, in general, be caused by locational separations, or reflect consumer restrictions and (or) operational constraints. In the context of electricity generation we capture this specificity as an operations feature, by allowing firms to sell their production to serve different periods of time, such as continuous baseload operation, or, subject to technical constraints, for short peak periods of time, thereby receiving different clearing prices in each niche (as suggested by Borenstein, Bushnell, & Knittel, 1999).

Therefore, in the system of Eq. (2) each firm i maximizes the profit $\pi_{it}\left(\Omega_t, \Theta_{it}, P_t\right)$ by choosing the outputs, Q_{ijlt}, from each production asset j, to serve each demand in niche l, at time t, each one of them in the vector $\Theta_{it}.P_{lt} = a_{lt} - b_{lt}\sum_i Q_{ilt}$ is the inverse demand function in market l, at time t, P_{lt} represents the price in market l, each P_{lt} belongs to the set P_t, and $Q_{ilt} = \sum_j Q_{ijlt}$. The a_{lt}, and b_{lt} are the intercept and slope of the inverse demand function and d_{lt} is the time duration of niche l, i.e., the number of time periods during which the firm sells to market $l.c_{ijt}$ is the marginal cost of asset j at time t. Furthermore, k_{ijlt} represents, for firm i, asset j ' available capacity to be offered in niche market l, at time t. This game is a quadratic programming problem which is solved, after each trade of generation assets, using Lemke's algorithm (e.g., Oliveira, 2008). The Nash equilibrium of the problem represented in (2) is solved at every node of the planning problem (1), at time t; in (2) we do not consider the fixed costs as they are sunk.

$$
\begin{aligned}
&\max \pi_{it} = \sum_j \sum_l \left(P_{lt} - c_{ijt}\right) Q_{ijlt} d_{lt} \\
&\text{st.} \\
&\quad P_{lt} = a_{lt} - b_{lt} \sum_i Q_{ilt} \quad \forall l \\
&Q_{ijlt} \leq k_{ijlt} \quad \forall i, j, l \\
&Q_{ijlt} \geq 0 \quad \forall i, j, l
\end{aligned}
\tag{2}
$$

3. From local incentives to global dynamics

In this section we explain how the industry structure is expected to evolve given the way firms value the different assets.

3.1. Real asset valuation and the strategic slack

In this subsection we introduce the concept of strategic slack as it facilitates the valuation of a real asset by taking into account its contribution to the total operations of the firm. A similar concept to the strategic slack value, in the context of realoptions, has been referred to as the "expected value of synergies", e.g., Smit (2001), and as "managerial discretion" by Siddiqui and Takashima (2012). The main innovation of the strategic slack concept is to capture how the value of an asset is affected by the interactions between the options of the different players in real option games (e.g., Shackelton et al., 2004; Siddiqui & Takashima, 2012; Smit, 2001; Smit & Ankum, 1993) and, in particular, to analyze how portfolios of assets affect the optimal production of an individual asset. It is, therefore, misleading to accept the common intuition that the value of an asset is a function only of its cash flows, an extra source of value is its strategic slack (e.g., Moreno et al., 2009; von der Fehr & Mørch, 1992; Voss et al., 2008): it results from not allowing others to use the capacity of the asset differently from the owner's optimal operation (which might otherwise lead to lower prices). In an extreme situation, an asset that is having losses may still have a positive slack value and, therefore, a firm may pay to acquire it.

We now formalize this concept. For simplicity of presentation we assume that all the revenues and the costs have already been discounted to the valuation date. π^*_{ijt} denotes the operational profit of for asset j owned by i, at time t (Definition 1); $Q_{i(-j)lt}$ represents the production of i 's assets sold in market l, excluding the production from asset j, at time t, and $Q_{(-i)lt}$ stands for the production of all the assets in the industry, not owned by i, sold in market $l; f_{jt}$ is the fixed operational cost of asset j, at time t, and k_j is the total capacity of asset j. The operational profit represents, therefore, the present value of the sum of all cash flows associated with the asset's production activities during a year.

Definition 1 (Operational Profit). For a firm i and asset j:

$$\begin{aligned}\pi^*_{ijt} = &\sum_l d_{lt}\left(a_{lt} - b_{lt}Q^*_{(-i)lt} - b_{lt}Q^*_{i(-j)lt} - b_{lt}Q^*_{ijlt}\right)Q^*_{ijlt}\\ &- \sum_l d_{lt}c_{ijt}Q^*_{ijlt} - f_{jt}k_j\end{aligned}$$

Additionally, let ϕ^*_{ijt} stand for the optimal slack value of asset j, owned by i, and P_{ijlt} represent the market price in l when an asset j, owned by i, offers its full capacity in l, at time t. Then, as the current price in market niche l equals $P_{lt} = a_{lt} - b_{lt}Q_{(-i)lt} - b_{lt}Q_{(-i)jlt} - b_{lt}Q_{ijlt}$ the price resulting from offering the remaining capacity of asset j in l is equal to $P_{ijlt} = a_{lt} - b_{lt}Q_{(-i)lt} - b_{lt}Q_{i(-j)lt} - b_{lt}Q_{ijlt} - b_{lt}\left(k_{ijlt} - Q_{ijlt}\right)$. We can now define the optimal strategic slack value of an asset (Definition 2) as the profit variation due to a reduction of the output of this asset when compared to its full capacity, in which k_{ijlt} is the capacity of asset j available for selling at market l, at time t. The strategic slack value considers the contribution of the asset to the value of the firm as a whole and goes beyond the value of its own production.

Definition 2 (Optimal Strategic Slack Value). $\phi^*_{ijt} = \sum_l d_{lt} \left(P_{lt} - \ P_{ijlt}\right) Q^*_{i(-j)lt}$ and, therefore, $\phi^*_{ijt} = \sum_l b_{lt} \left(k_{ijlt} - Q^*_{ijlt}\right) Q^*_{i(-j)lt} d_{lt}$.

For a seller, the optimal strategic slack value of an asset is equal to the worst possible loss arising from selling the asset. The strategic slack ensures that the seller does not thereby undercharge, given the way the asset may operate with a new owner. We can now compute the optimal value of asset j owned by a firm i, at time t, V^*_{ijt}, Definition 3: it is the sum of the operational profit and the slack value. This valuation takes into consideration not only the expected operational profit of asset j but also the way it contributes to the profits of the other assets in the portfolio. This contribution is the core issue at the center of the strategic value of each asset in the portfolio.

Definition 3. $V^*_{ijt} = \pi^*_{ijt} + \phi^*_{ijt}$.

On the other hand, the buyer, even though having a higher valuation of the asset, is not willing to pay the full value for it, as he already benefits from some of its strategic value in the market clearing-price. Instead, the buyer is only willing to pay up to the value created by the asset trade. Let λ^{sb}_{jt}, Definition 4 , stand for a seller s's strategic slack valuation of the trade of asset j with buyer b, and μ^{bs}_{jt}, Definition 5 , represent a buyer b's strategic slack valuation of the trade of asset j with the seller s : in both definitions the strategic value is a function of the difference between the production of the asset before and after the trade, taking into account the specific buyer bidding for the asset.

Definition 4. The seller's marginal strategic slack valuation is $\lambda^{sb}_{jt} = \sum_l b_{lt} \left(Q^*_{sjlt} - Q^*_{bjlt}\right) Q^*_{s(-j)lt} d_{lt}$.

Definition 5. The buyer's marginal strategic slack valuation is $\mu^{bs}_{j} = \sum_l b_{lt} \left(Q^*_{sjlt} - Q^*_{bjlt}\right) Q^*_{b(-j)lt} d_{lt}$.

Moreover, let v^{sb}_{jt} (Definition 6) represent the minimum the seller is willing to receive from b for asset j, at time t, and ϑ^{bs}_{jt} (Definition 7) stand for the maximum the buyer is willing to pay to s for asset j, at time t. We can now describe the valuation functions used by the seller and by the buyer. The seller s's valuation function (Definition 6) states that the minimum at which s is willing to sell j, to buyer b, needs to compensate s for the loss in operational profit deduced by an eventual increase of the seller's portfolio profit due to j 's new management. As the possible increase in value due to asset trading depends on who the buyer is, the seller has a valuation function that is buyer dependent. Moreover, this valuation is a function of the total quantity that would be optimally produced by the asset j after trading.

Definition 6. The lower bound of seller s on the value of asset j is $v^{sb}_{jt} = \pi^*_{sjt} - \lambda^{sb}_{jt}$.

Definition 7. The buyer's upper bound valuation is $\vartheta^{bs}_{jt} = \pi^*_{bjt} + \ \mu^{bs}_{jt}$.

The buyer b 's valuation function (Definition 7), on the other hand, states that the buyer is willing to pay, at the most, the asset's operational profit after trade (which will not be larger than its operational profit before trading) plus the strategic value of the asset, after trading, for the buyer. As this strategic value (for a buyer that reduces the asset's output) is positive, the buyer actually is willing to pay a price over the asset's operational profit. The buyer's valuation function depends on who the seller is, as this trade is a function of the production level of the asset before the trade: the larger the production before the transaction, the higher the strategic value of j to the buyer.

Then, given the lower and upper bound valuations by the seller and potential buyers, respectively, we calculate the transaction price of asset j, at time $t, \gamma_{jt} = \max\left(\frac{\vartheta_{jt}^{b_1 s} + v_{jt}^{s b_1}}{2}, \vartheta_{jt}^{b_2 s}\right)$, in which $\vartheta_{jt}^{b_1 s}$ and $\vartheta_{jt}^{b_2 s}$ represent, respectively, the highest and second highest valuations for asset j, from buyers b_1 and b_2. This assumption sets the transaction price between the valuation of the traders, but postulating that this price would not be less than the second highest valuation by potential buyers. Next, we discuss how we can analyze the dynamics of the market structure of the industry by using the concept of strategic slack valuation.

3.2. The dynamics of asset trading with strategic slack valuation

We are now in position to derive the first results, based on the concept of strategic slack valuation. The major goal of this section is to better explain the dynamics underlying the trading of assets, and its implications on market structure, levels of production, and asset trading prices, by analyzing the properties of the slack value. We start from Propositions 1 and 2 by attempting to understand how the slack value of an asset depends on its the portfolio membership. Then in Propositions 3-5 we analyze how the slack value influences the trading dynamics and the evolution of market structure. We continue by analyzing the impact of asset trading on the production of the industry in Proposition 6. Finally, in Propositions 7 and 8 we analyze analytically the bounds for the actual asset trading prices.

In Proposition 1 a) we state that, when a firm i uses asset j at full capacity, the operational profit of this asset is an upper bound on its value. Furthermore, in Proposition 1 b) we prove that, when a firm i withholds some of the capacity of an asset j, the slack value of this asset is positive only in markets where the clearing price is higher than this asset's marginal cost (c_{ijt}). Moreover, Proposition 2 shows that an asset has different valuations in different types of portfolio. Particularly, a marginal asset is more valuable in larger portfolios. As $P_{lt} > P_{ijlt}$, for assets not producing at full capacity, the strategic slack increases with the size of the firm (i.e., the production from the other assets it owns) and with the market duration.

Proposition 1. (a) Let for all ijlt, $Q_{ijlt}^* = k_{ijlt}$, then $\phi_{ijt}^* = 0$. (b) $\phi_{ijt}^* > 0$ only if, for at least one market l, at time t, such that $Q_{ijlt}^* < k_{ijlt}$ we have $c_{ijt} < P_{lt}$.

[Proof in the Online Appendix.]

Proposition 2. Let $c_{ijt} < P_{lt}$ in all markets l. If a firm i has a larger total production in every market than player i, then the slack value of an asset j is larger for i than for i '.

[Proof in the Online Appendix.]

Next we analyze how the strategic slack value influences the trading dynamics. On the one hand a firm buys an asset that has a positive value due to its operational profit and, or, due to its slack value. On the other, a firm sells an asset only to a potential buyer that values the asset more than it does. We analyze when these conditions are, simultaneously, met. Proposition 3 states that, for any asset j traded among s and b, the buyer's strategic slack valuation, after the trade of asset j, is larger than the seller's.

Proposition 3. For any asset j, given the optimal level of production by the buyer, $Q_{bjt}^{*}, V_{bjt}^{*} > V_{sjt}^{*}$ if and only if $\phi_{bjt}^{*}\left(Q_{bjt}^{*}\right) > \phi_{sjt}^{*}\left(Q_{bjt}^{*}\right)$.

[Proof in the Online Appendix.]

In Proposition 4 we prove that the buyer always has a larger average production (weighed by the strategic slack valuation) than the seller. It is obvious that any potential buyer that has no current sales cannot buy asset j, and that any seller that only owns asset j, for the same reason, would sell to a buyer that owns some capacity sold in the same markets targeted by j, as proved in Proposition 3. Moreover, it also follows from Proposition 4 that a potential buyer with current production less than the current owner's production from all his assets except j, cannot buy asset j. Additionally, in Proposition 5 we prove that in portfolios with large total production in every market where j sells, the production of a marginal asset is lower than in portfolios with small outputs.

Proposition 4. For any asset j, $V_{bjt}^{*} > V_{sjt}^{*}$ if and only if $\frac{\sum_{l} d_{lt}\left(P_{lt}-P_{bjlt}\right) Q_{b(-j)lt}^{*}}{\sum_{l} d_{lt}\left(P_{lt}-P_{bjlt}\right)} > \frac{\sum_{l} d_{lt}\left(P_{lt}-P_{bjlt}\right) Q_{s(-j)lt}^{*}}{\sum_{l} d_{lt}\left(P_{lt}-P_{bjlt}\right)}$.

[Proof in the Online Appendix.]

Proposition 5. For any asset j such that for at least in a market l, at time $t, c_{ijt} < P_{lt}$ if, for all lt, we have $Q_{b(-j)lt}^{*} > Q_{s(-j)lt}^{*}$ then $V_{bjt}^{*} > V_{sjt}^{*}$.

[Proof in the Online Appendix.]

Furthermore, given the expectations regarding the other firms' behavior, the only possible asset trades are the ones in which the buyer expects to reduce the production of the acquired asset. This means that asset trading tends to decrease the total output from the industry. In Proposition 6 we state that, for any marginal asset j, the buyer's valuation is larger than the seller's if and only if the total production from asset j after trade is less than before trade.

Proposition 6. For any asset j such that for at least in a market l, at time $t, c_{ijt} < P_{lt}$ if, for all lt we have $Q_{b(-j)lt}^{*} > Q_{s(-j)lt}^{*}$ then $Q_{bjlt}^{*} < Q_{\mathrm{sjlt}}^{*}$.

[Proof in the Online Appendix.]

These results prove that asset trading in oligopolistic industries tends to increase concentration, decrease total production and, from the definition of demand, increase prices and decrease social welfare. Consequently, the strategic slack valuation allows the seller to restrict the considered trades to the ones with firms that give a higher value to the asset (including the strategic slack) than the seller.

Furthermore, given the type of buyer that can afford to buy j, the strategic value for the seller tends to be positive, as the buyer reduces j 's output, increasing the value of seller's portfolio. For this reason, as proved in Proposition 7, the seller may accept to sell a production facility at a price below its operational profit. The actual trading price would be the result of a bargaining process and it would be between $v_{jt}^{sb} = \pi_{sjt}^{*} - \lambda_{jt}^{sb}$ and $\vartheta_{jt}^{bs} = \pi_{sjt}^{*} + \mu_{jt}^{bs}$, but if the buyer's valuation is not much higher than the seller's, indeed, the asset may be traded at a value below its operational profit.

Proposition 7. A seller s optimally accepts to sell an asset j at a price below its operational profit if $\lambda_{jt}^{sb} > 0$.

[Proof in the Online Appendix.]

From Propositions 4 and 6 it follows that the output of the traded assets tends to decrease after trading and that real asset trading increases market concentration. This implies that the value of the assets in the industry tends to increase with trading. Therefore, in the markets in which the traded assets sell, if the buyer is larger than the seller (in total sales), a buyer (seller) that buys one asset to meet the optimal policy computed by using (1), tends to pay (receive) more for the assets bought (sold) at later stages than they are worth at the earlier stage. For this reason, the buyer would benefit from acquiring all the assets at the same time (Proposition 8a) and the seller would profit from selling them one at the time (Proposition 8 b). From Proposition 8 we conclude that new entry via asset trading in oligopolistic markets may be possible if the buyer is able to acquire several assets simultaneously; this was the strategy of TXU in the British electricity market. Note that there is no contradiction between this conclusion, which is about the way trading actions are performed, and the evaluation of the assets performed one trade at the time, as this evaluation process allows a better assessment of the value set of trades required by the capacity management project. Proposition 8. Let the buyer be larger than the seller in sales in the markets where the traded assets sell. In order to fulfill the optimal policy computed using (1): a) the buyer is willing to pay more if he buys all the desired assets sequentially; b) the seller demands a higher price if he sells the assets in sequence.

[Proof in the Online Appendix.]

So, do these upper and lower valuations truly reflect the value of the assets traded? Do they reflect the post-trade value of the assets? From Eqs. (1) and (2), for player i, at time zero, the added value by the trading plan over the S scenarios is $V_{i0}^{*}(\Omega_0, \Phi_{i0})\ \pi_{i0}^{*}(\Omega_0, \Theta_{i0}, P_0)$, reflecting the contribution of the new assets to the value of i 's portfolio. This means that the total spent in the project cannot be more than the value created by the project (including the total paid for the acquisitions minus the total received by the sale of assets.) The actual price to be paid (charged) for a given asset depends on the transaction sequence (Proposition 8) and on the specific trading partners (Definitions 6 and 7). The concept of strategic slack, nonetheless, helps in explaining the range within which the transaction prices may vary and the different sources of value of a given asset.

Table 1 summarizes this algorithm. In step one each firm calculates, from previous instances interacting with others, a set of possible trades. Then in step 2 the optimal trades are computed for each firm, conditioned on the possible set. In step 3 the price of the traded plant is calculated. And, finally, in step 4, the asset is traded; the Cournot model is solved and the operational profits are computed for the new market structure.

Table 1 The repeated game with a dynamic planning algorithm.

For each iteration t, while the last iteration is not reached, for each firm in the market:

Step 1. Each firm i identifies the possible trades at time t, Φ_{it}.

(1.a) $\xi_{ijt} = \frac{\sum_{t'=g+1}^{t} a_{ijt'}}{t-g}$.

g is the iteration in which j was last traded.

$a_{ijt'} = 1$ if firm i has attempted to sell (buy) j.

$a_{ijt'} = 0$, otherwise.

(1.b) An asset $j \in \Phi_{it}$ if and only if $\xi_{ijt} \geq \theta$, in which $0 \leq \theta < 1$.

Step 2. Compute the optimal policy:

$\forall t = 0, \ldots, S-1$

$V_{it}^{*}(\Omega_t, \Phi_{it}) = \max_{a_{ijt} \in \Phi_{it}} E\left[\pi_{it}(\Omega_t, \Theta_{it}^{*}, P_t^{*}) + \rho V_{i(t+1)}^{*}\left(\Omega_{t+1}, \Phi_{i(t+1)}\right)\right]$

Step 3. Plant trading - compute the price of the traded plant: $\gamma_{jt} = \max\left(\frac{\vartheta_{jt}^{b_1 s} + v_{jt}^{s b_1}}{2}, \vartheta_{jt}^{b_2 s}\right)$

Step 4. Industry dynamics stage:

(a) Update the state of word: Ω_{t+1};

(b) Solve the Cournot game using Eq. (2);

(c) Compute the operational profits $\pi_{it}(\Omega_t, \Theta_{it}^{*}, P_t^{*})$.

4. Simulating the trading of electricity generation plants

We now extend the theoretical propositions into a series of large scale experiments using agent-based computational learning. Our simulations start from a detailed specification of the England & Wales electricity market including all generating assets, with operating costs and demand profile as it was in 2000 (Electricity Association, 1999, 2000a,b,c). This facilitates a comparison with how the industry actually emerged over the subsequent decade. The initial ownership structure in the market is shown in Table 2. The experiments simulated trading at the electricity asset level (137 assets) distributed among 24 different firms. In Table 3 we depict the marginal and operational fixed costs per technology.

Table 2 Market structure at the initial stage (2000).

Capacity (GW)	AES	BE	EDF	Edison	Magnox	NP	PG	TXU	Others	Total
CCGT	0.25		0.80	0.23		3.90	2.55	0.79	10.30	18.82
Coal	4.28	1.98		3.89		2.75	5.46	4.89		23.24
Nuclear		6.20	2.00		2.30				1.00	11.50
OCGT	0.08			0.07		0.41	0.40	0.09	0.03	1.08
Petroleum						1.27	1.35			2.62
Pumped storage				2.10					2.10	
Total	4.61	8.18	2.80	6.29	2.30	8.33	9.76	5.77	11.33	59.36

Table 3 Marginal and fixed costs per technology.

	CCGT	Coal	Nuclear	OCGT	Petroleum	Pumped storage
Marginal cost (£/MWh)	10	14	3	50	40	20
Fixed cost (£/kW)	13	20	76	10	18	30

The demand functions were parameterized by taking into account demand elasticity, price, and traded quantities in the three market niches (baseload, mid-merit and peak), and the respective durations in number of hours of load per year. The demand elasticities used were $0.5, 0.35$ and 0.25 , respectively, for baseload (nuclear), mid-merit (large coal and Combined Cycle Gas Turbine, CCGT) and peak markets (small coal, oil, small hydro, and Open Cycle Gas Turbine, OCGT), which are similar to those used

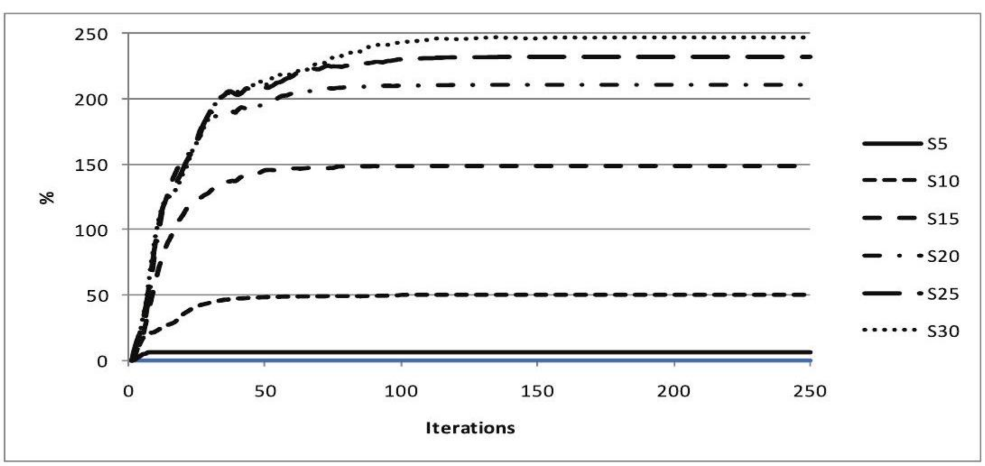

Figure 1 Increase (%) in the industry's profit, as a function of the planning horizon, S.

elsewhere, e.g., Ramos, Ventosa, and Rivier (1998), with durations for the baseload, mid-merit and peak markets of 8760,5500 and 500 hours/per year, respectively. Note that these elasticities are used for the initial conditions in the market, but they change with the evolution of the market equilibrium, as we use linear demand functions. We do not explicitly take into account the asset startup costs and dynamic operating constraints (e.g., Ramos et al., 1998; Borenstein et al., 1999), instead, since these technical constraints define the capability of an asset to access a given market niche, our model exogenously defines, for each asset, the market niche(s) that it can access (Li & Tirupati, 1994).

Following the trading principles described in previous sections, we simulated 250 iterations of trading to create market structure trajectories. Since these trajectories involved stochastic adaptive learning by the agents, these were re-created 100 times to produce averages and standard errors. Fig. 1 presents the average percentage change in the industry's profit from the base case, at each iteration point, as a function of the planning horizon envisaged by each firm in making each trading decision, denoted S5, S10, ... S30, for horizons of $5, 10, 30$ periods, etc.

All simulations reported in Fig. 1 converged to equilibrium within the 250 iterations, but what is surprising is that they converge to different equilibria. It is not at all the case, as might have been expected from the simulations, that agents using more foresight (longer planning horizons) in their decisions will simply converge more quickly to the same market equilibrium. We see that the longer the planning horizon, the slower the convergence process. In contrast, and most importantly, the percentage gained in the industry's profit increases with the length of this planning horizon. There is no profit gain with planning horizons of 1 to 4 periods as no trades occurred with myopic foresight. In contrast, the gains ranged from 6% for 5 periods to 250% for the 30 period planning horizons. These results show that asset trading evidently facilitates profitable self-evolution in the industry only if agents envisage a long-enough planning period. It implies that, given the asset and demand specificities in an electricity market, with its different market niches, the value of a given asset does not have a simple additive value to a firm's asset portfolio, and that strategic slack, as well as operational valuations, will need to be assessed. Implicitly, there is an implication that a firm may need to buy subsequent assets before a purchased asset becomes profitable.

Evidently, to the extent that the equilibria attained in Fig. 1 depend upon the planning horizons presumed for the firms, there is only a single rational equilibrium when the planning horizon tends to infinity. However, there are good reasons to take the multiple equilibria under a finite horizon seriously from a behavioral perspective. Clearly decision-making limitations, in the bounded rationality sense, would apply in practice, as would a pragmatic consideration of the extent to which firms will value strategic slack, even if they are able to compute it extensively over a long horizon. Whilst operational profit is a balance sheet item, the valuation of strategic slack will only be evident in longer term growth performance. It may well be that smaller, less well-capitalized companies cannot afford the financial reporting consequences of reducing operational profits in favor of the more long term strategic slack valuations.

Table 4 shows the equilibrium market shares for the eight largest firms in the industry. It is interesting to see that BE, being the largest player, increases its market share to 29.5% in the 30 period planning horizons. This is in keeping with the earlier propositions concerning size, but it may be surprising that the market does not converge steadily to a BE monopoly: instead, because the marginal value received from the different market niches is not the same, BE's marginal cost of investing in the mid-merit and peak niches outweigh the marginal benefit it might receive from such investments (as these are limited by its relatively small size in these niches) making the monopoly strategy not a profitable option. Also, amongst the smaller players, only Magnox and EdF increased their market shares, from about 3.9% before trade to $5.2-6.0\%$ after trade, and from 4.7% before trade to $6.3-7.6\%$ after trade, respectively, again reflecting their initial resources. It appears, therefore, that a resource endowment of baseload technology, as well as size, favor strategic slack valuations, which over time, leads to market share dominance. The standard errors (S.E.) are very small, ensuring the significance of the results.

Table 4 **Market shares (by production) per firm as a function of the planning horizon,** S.

Marketshare		BE	Magnox	EdF	AES	TXU	NP	PG	Edison
$S \leq 4$	Average	18.3	5.2	6.3	5.9	6.8	10.6	10.8	10.3
	S.E.	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
$S = 5$	Average	18.3	5.2	6.4	5.9	6.8	10.8	10.7	10.1
	S.E.	0.01	0.00	0.00	0.00	0.00	0.02	0.04	0.05
$S = 10$	Average	19.1	5.4	6.5	6.3	5.1	13.1	11.7	6.3
	S.E.	0.05	0.01	0.01	0.04	0.16	0.09	0.15	0.20
$S = 15$	Average	21.4	5.7	7.6	6.5	5.7	12.1	11.2	6.2
	S.E.	0.21	0.03	0.10	0.13	0.17	0.23	0.26	0.14
$S = 20$	Average	26.0	5.9	7.5	7.0	5.6	8.6	6.6	6.4
	S.E.	0.28	0.01	0.07	0.20	0.14	0.24	0.22	0.14
$S = 25$	Average	28.4	6.0	7.4	6.2	5.8	7.7	6.0	6.8
	S.E.	0.24	0.02	0.07	0.19	0.17	0.17	0.18	0.17
$S = 30$	Average	29.5	6.1	7.3	5.7	4.5	7.4	7.0	6.5
	S.E.	0.24	0.02	0.06	0.19	0.20	0.18	0.19	0.16

As well as the strategic slack considerations driving growth, operational profit is important for financial performance. In Table 5 we present each firm's average relative operational profit, expressed as a percentage of the average operational profit of the industry in each equilibrium solution. It is evident that the relative operational profits of the three baseload generators BE, Magnox and EdF were initially the highest in the market but, because they pursued growth in our simulations, their relative operational profits decreased monotonically with the planning horizon.

This means that BE, Magnox and EdF were successful in increasing market shares at the cost of a decrease in their operational profit shares, this is justified by the purchase of capacity that it is withhold from the market, increasing the prices and profits, but, as the other firms in the industry act as free-riders, their profit increases more and hence the share of profit by the largest firms decreases.

Table 5 Operational profit per firm as % of the industry's operational profit.

Profit proportion	BE	Magnox	EdF	AES	TXU	NP	PG	Edison	
$S \leq 4$	Average	41.3	13.2	14.4	-0.9	-2.9	1.4	-6.2	-3.5
	S.E.	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
$S = 5$	Average	39.7	13.1	14.3	-0.7	-2.6	2.0	-5.3	-3.0
	S.E.	1.11	0.08	0.06	0.16	0.17	0.46	0.58	0.30
$S = 10$	Average	36.8	12.2	13.6	0.7	2.4	3.3	-7.6	0.8
	S.E.	0.15	0.34	0.34	0.40	1.85	0.14	1.93	1.30
$S = 15$	Average	29.8	10.5	12.0	3.5	4.5	10.9	-4.4	4.3
	S.E.	0.58	0.09	0.14	0.11	0.81	0.83	1.02	1.28
$S = 20$	Average	27.1	9.2	10.7	7.5	3.1	10.2	0.8	2.5
	S.E.	0.70	0.42	0.49	0.66	0.12	0.23	1.08	0.92
$S = 25$	Average	26.0	9.1	10.5	6.0	4.2	5.7	4.2	4.2
	S.E.	2.36	0.33	0.33	1.57	0.54	0.56	1.25	0.03
$S = 30$	Average	22.7	8.0	9.3	9.0	2.9	8.0	1.3	5.8
	S.E.	2.09	0.15	0.18	0.71	0.10	0.18	2.85	1.83

Nonetheless, given the increase in total industry profits presented in Fig. 1, all of them increased their actual profits. Interestingly, in the base case, the simulations showed AES, TXU, PG and Edison initially making losses, but through trading with longer horizons, they all improved to give positive performance. These results show that even in an industry with a homogeneous product, such as electricity, the interaction between technological differences and strategic moves leads to intra-industry differences in performance.

In Table 6 we analyze the average number of trades, by technology and firm, to reach the equilibrium solution at iteration 250 , for S equal to 30. The largest firm, BE, as expected, is by far the most active buyer. Surprisingly, PG, which was initially the most loss-making, is the second most active buyer as it seeks to bring its portfolio into profit (in practice this may be limited by capital restrictions, which this model does not consider), by specializing in the market niches in which it has a larger market share (mid-merit and peak markets) gaining from price increases in these niches.

Most interestingly, the acquisitions tend to follow resource patterns, reflecting a restructuring of the firms' resource structure through acquisitions and divestments. There is almost no trading of baseload assets, and the dominant baseload generator extends mainly into the mid-merit niche. AES started with mainly midmerit assets and mainly buys more of the same. TXU was initially

Table 6 **Average number of trades by technology and buyer, for planning horizon S equal to 30.**

Technology	BE	Magnox	EdF	AES	TXU	NP	PG	Edison
Nuclear	0.0	0.0	0.0	0.03	0.0	0.0	0.02	0.02
Large coal	23.3	0.1	0.1	1.7	0.0	0.0	1.3	0.1
CCGT	14.4	0.0	0.0	2.4	0.7	0.2	4.6	2.0
OCGT	2.1	0.0	0.0	0.3	0.2	0.2	2.9	0.4
Oil	0.7	0.0	0.0	0.0	0.1	0.0	0.7	0.1
Hydro	1.8	0.0	0.0	0.2	0.1	0.2	1.4	0.0
Small coal	3.0	0.0	0.2	0.6	0.4	0.9	3.2	0.2
Total	45.4	0.1	0.3	5.2	1.5	1.4	14.2	2.8

almost equally spread between mid-merit and peaking, and bought more in that way. NP was initially mainly peaking, and bought mostly peaking. PG also reflected its initial endowment ratio of mid-merit to peaking in its buying pattern. These results support the idea that firms tend to specialize and move between niche markets, as firms abandon some niches to specialize in their most profitable technology. Evidently, this is a reflection in our model of the combination of Cournot pricing and players tending to consolidate in their niches rather than diversifying across all niches.

Fig. 2. The evolution of the HHI as a function of the iteration, the average production as a function of the HHI, and the average prices as a function of average production, for planning horizon S equal to 30 .

Moreover, this evolutionary pattern results both from internal selection (arising from the firm's initial position in a given technology) and from external pressures (the other firms' technological profiles).

Although these results have a basis in the real situation in 2000 they are simply stylized evolutions following the economic rationale of asset trading based upon operational profit and strategic slack. Substantial asset trading did actually take place in the British market in the decade following 2000 but these were influenced by externalities such as vertical integration, capitalization, fuel commodity cycles, government interventions and multinational strategies. However, BE did remain the largest player until 2009 when there was further consolidation of the nuclear sector following a merger with (the more highly capitalized) EdF. The other initially weak companies were all taken over. AES and TXU went into financial distress and their assets dispersed. NP and PG were acquired by the large German utilities, RWE and EON, and consolidated their mid-merit and peaking niches through further acquisitions. Edison was acquired by International Power, who acquired further midmerit assets. So, in general, despite the corporate takeovers, the portfolio pattern of asset trading was broadly consistent with our simulated principles. Towards the end of the decade the profitability of the market attracted several new entrants. Thereafter, the combination of an economic recession and government interventions to decarbonize the sector created awkward circumstances for the incumbent generating companies.

Finally, in Fig. 2 we depict the evolution of the average Herfindahl-Hirschman Index (HHI), along the 250 iterations, over the 100 repetitions, for the planning horizon of S equal to 30 . It shows that the concentration in the industry increases with the number of trades. Moreover, by analyzing the relationship between the HHI and the total production in the industry it is evident that the increase in concentration leads, on average, to a decrease in average production which, in turn increases the average price. Therefore, the final cumulative effect of plant trading is a decrease of consumer surplus due both to an increase in prices and a decrease in production.

5. Conclusions

Developing a theoretical explanation for capacity planning via the trading of real assets among oligopolistic market participants, with its consequent implications for the evolution of marketstructure and price formation, is an open and challenging research question. When operational factors lead to asset specificities, which in turn creates non-additive portfolio profit performance, the valuation of marginal assets can be complex. Furthermore due to this complexity and the size of the asset trading problem (which is exponential in the number of production units and firms in the market) the analysis of the trading of real assets requires a computationally intensive approach with heuristic elements.

In this research we formulate a computational learning model, based upon the heuristic of strategic slack valuation, to explain why real assets may have different values to different participants and, thereby, motivate mutually beneficial trades. This formulates the valuations of productive assets by the firms in the market in the context of real option games (e.g., Shackelton et al., 2004; Siddiqui & Takashima, 2012; Smit, 2001; Smit & Ankum, 1993; Williams, 1993, 1995), allowing the derivation of analytical results on the long-term market dynamics from the operational, short term properties of the assets. The optionality in our analysis is, however, distinct from conventional real options formulations where underlying stochastic processes are critical; we do not consider uncertainty in the factors of production, or risk aversion, but rather focus upon the imperfect nature of the market context and the option to influence the market price by operating assets differently. In particular, we show how the same production facilities embed the option to be operated selectively, and therefore valued differently, according to the emergent resource bases of each company.

Moreover, in analyzing the properties of the asset-trading decisions, we demonstrate that foresight in the planning horizon is essential for optimal trading, and that equilibria may depend upon the length of horizon envisaged by the decision-making firms. Thus, in real asset trading, the buyers may be willing to discount an immediate trade in order to get to a better future market position. This motivated our evaluation of strategic slack, alongside operational profit, as the two economic determinants of asset valuations. It should be noted that the importance of the planning horizon arises from the fact that the valuation of an asset is dependent on the portfolio of assets in which it is based, hence, by dynamically assessing the planned evolutionary policy for the portfolio of assets a firm is better equipped to calculate the contribution of a given asset to the value of the firm as a whole.

The particular market context we addressed in this paper is the valuation of electricity assets in their specific trading environment. Here asset specificities in wholesale electricity markets imply that the profitability of asset portfolios is not additive in their asset composition. We demonstrate the absence of single market equilibrium in ownership and instead derive a number of behavioral properties which determine market evolution. These include: (a) Marginal assets are more valuable to larger portfolios. (b) Asset trading increases market concentration. (c) Firms will first seek to grow within their market niche(s) rather than diversify widely, increasing intra-industry differences in the firms' performance. (d) The real asset trading prices are buyer dependent. (e) The seller may sell a real asset for less than its current operational profit. (f) Whereas buyers would benefit from acquiring all their target assets simultaneously, sellers prefer to sell one asset at the time. (g) New entry in an oligopolistic market via real asset trading is profitable if the buyer is able to acquire simultaneously a large portfolio. (h) A baseload resource endowment facilitates more growth in market share and it is clear that, in a realistic setting, the ability to value strategic slack in asset acquisitions will be resource dependent and this, in turn, will influence heterogeneity in market structure evolution.

In the context of this research, we have modeled risk-neutral firms that aim to maximize the value of a portfolio of assets, given the current industry structure, in terms of costs, capacity installed per technology, and demand behavior. These results are useful to firms that are seeking to understand how market structure and prices may emerge and who may be planning to expand production facilities via acquisition rather than new build. The analysis is also important to regulators and competition authorities who may have to approve mergers, as the results show that even a firm that does not have a large market share can have a strong impact on market prices by strategically choosing the assets to add to its production portfolio. Finally, in this study we have focused only upon the effects of operational asset specificities, and we have not considered many other factors that may influence the agents trading decision, such as cost uncertainty, economies of scale, regulatory responses, financing and risk aversion. All of these, and more, are likely to have an impact on the firms' decisions regarding the type of technology they want to include in their portfolio.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.ejor.2016.02.013.

References

Aid, R., Chemla, G., Porchet, A., & Touzi, N. (2011). Hedging and vertical integration in electricity markets. Management Science, 57(8), 1438-1452.

Anderson, E. J., & Hu, X. (2008a). Forward contracts and market power in an electricity market. International Journal of Industrial Organization, 26, 679-694.

Anderson, E. J., & Hu, X. (2008b). Finding supply function equilibria with asymmetric firms. Operations Research, 56, 697-711.

Aydemir, Z., & Schmutzler, A. (2008). Small scale entry versus acquisitions of small firms: Is concentration self-reinforcing? Journal of Economic Behavior E Organization, 65(1), 133-146.

Banal-Estanol, A., & Ottaviani, M. (2006). Mergers with product market risk. Journal of Economics & Management Strategy, 15(3), 577-608.

Banal-Estanol, A., & Micola, A. R. (2009). Composition of electricity generation portfolios, pivotal dynamics and market prices. Management Science, 55(11), 18131831 .

Bish, E. K., & Wang, Q. (2004). Optimal investment strategies for flexible resources, considering pricing and correlated demands. Operations Research, 52(6), 954964.

Bertsekas, D. P. (2000). Dynamic programming and optimal control: I and II ((2nd ed.)). Belmont, Massachusetts: Athena Scientific.

Bloom, J. A. (1983). Solving an electricity generating capacity expansion planning problem by generalized benders' decomposition. Operations Research, 31(1), 84100. Borenstein, S., Bushnell, J., & Knittel, C. R. (1999). Market power in electricity markets: Beyond concentration measures. The Energy Journal, 20(4), 65-88.

Borenstein, S., Bushnell, J., Knittel, C. R., & Wolfram, C. (2008). Inefficiencies and market power in financial arbitrage: a study of California's electricity markets. Journal of Industrial Economics, 56(2), 347-378.

Bower, J., & Bunn, D. W. (2000). A model-based comparison of pool and bilateral market mechanisms for electricity trading. The Energy Journal, 21(3), 1-29.

Bunn, D. W. (2004). Modelling prices in competitive electricity markets. Wiley.

Bunn, D. W., & Oliveira, F. S. (2007). Agent-based analysis of technological diversification and specialization in electricity markets. European Journal of Operational Research, 181(3), 1265-1278,

Bunn, D. W., & Oliveira, F. S. (2008). Modeling the impact of market interventions on the strategic evolution of electricity markets. Operations Research, 56(5), 11161130.

Chari, K., & Agrawal, M. (2007). Multi-issue automated negotiations using agents. Informs Journal on Computing, 19(4), 588-595.

Daughety, A. F. (1990). Beneficial concentration. American Economic Review, 80(5), $1231-1237$.

Daughety, A. F. (1985), reconsidering cournot: The cournot equilibrium is consistent. The RAND Journal of Economics, 16(3), 368-379.

Downward, A., Young, D., & Zakeri, G. (2011). Swapping generators' assets: Market salvation or wishful thinking? The Energy Journal, 32(2), 31-58.

Electricity Association (1999). The UK electricity system. http://www.electricity.org.ukwww.electricity.org.uk.

Electricity Association (2000a). Electricity companies in the United Kingdom. www. http://electricity.org.ukelectricity.org.uk.

Association, Electricity (2000b). List of power stations. http://www.electricity.org.ukwww.electricity.org.uk.

Association, Electricity (2000c). Who owns whom in the UK electricity industry? http://www.electricity.org.ukwww.electricity.org.uk.

Ernst and Young (2014). Power transactions and trends. http://www.ey.comwww.ey.com.

Eurelectric (2013). Power statistics and trends. http://www.eurelectric.org/http://www.eurelectric.org/powerstats2013

Farrell, J., & Shapiro, C. (1990). Horizontal mergers. American Economic Review, 80(1), 107 – 126.

Foray, D. (1997). The dynamic implications of increasing returns: Technological change and path dependent inefficiency. International Journal of Industrial Organization, 15, 733-752.

Goyal, M., & Netessine, S. (2007). Strategic technology choice and capacity investment under demand uncertainty. Management Science, 53(2), 192-207.

Gosavi, A. (2009). Reinforcement learning: A tutorial survey and recent advances. Informs Journal on Computing, 21(2), 178-192.

Gulpinar, N., & Oliveira, F. S. (2012). Robust trading in sport and forward oligopolistic markets. International Journal of Production Economics, 138(1), 35-45.

Julka, N., Baines, T., Tjahjono, B., Lendermann, P., & Vitanov, V. (2007). A review of multi-factor capacity expansion models for manufacturing plants: Searching for a holistic decision aid. International Journal of Production Economics, 106(2), 607-621.

Klepper, S., & Graddy, E. (1990). The evolution of new industries and the determinants of market structure. RAND Journal, 21(1), 27-44.

Kreps, D. M., & Scheinkman, J. A. (1983). Quantitative precommitment and bertrand competition yield cournot outcomes. The Bell Journal of Economics, 14(2), 326337.

Li, S., & Tirupati, D. (1994). Dynamic capacity expansion problem with multiple products: Technology selection and timing of capacity additions. Operations *Re* search, 42(5), 958-976

Majd, S., & Pindyck, R. (1987). Time to build, option value, and investment decisions. Journal of Financial Economics, 18, 7-27.

Meier, H., Christofides, N., & Salkin, G. (2001). Capital budgeting under uncertainty An integrated approach using contingent claims analysis and integer programming. Operations Research, 49(2), 196-206.

Micola, A. R., Banal-Estanol, A., & Bunn, D. W. (2008). Incentives and coordination in vertically coordinated energy markets. Journal of Economic Behavior E Organization, 67, 381-393.

Milgrom, P., & Stokey, N. (1982). Information, trade and common knowledge. Journal of Economic Theory, 26, 17-27.

Moreno, A. R., Fernandez, L. M. M., & Montes, F. J. L. (2009). The moderating effect of slack resources on the relation between quality management and organizational learning. International Journal of Production Research, 47(19), 5501-5523.

Murphy, F., & Smeers, Y. (2005). Generation capacity expansion in imperfectly competitive restructured electricity markets. Operations Research, 53(4), 646-661.

Nelson, R. R., & Winter, S. (1982). An evolutionary theory of economic change. Harvard University Press

Nilsson, M. (2005). Electric power oligopoly and suspicious minds - A critique of a recent approved merger. Energy Policy, 33, 2023-2036.

Oliveira, F. S. (2008). A constraint logic programming algorithm for modeling dynamic pricing. Informs Journal on Computing, 20(1), 69-77.

Piccolo, S., D'Amato, M., & Martina, R. (2008). Product market competition and organizational slack under profit-target contracts. International Journal of Industrial Organization, 26(6), 1389-1406.

Powel, W. B. (2010). Merging AI and OR to solve high-dimensional stochastic optimization problems using approximate dynamic programming. Informs Journal on Computing, 22(1), 2-17.

Ramos, A., Ventosa, M., & Rivier, M. (1998). Modelling competition in electric energy markets by equilibrium constraints. Utilities Policy, 7, 233-242.

Reynolds, S., & Wilson, B. (2000). Bertrand-edgeworth competition, demand uncertainty, and asymmetric outcomes. Journal of Economic Theory, 92, 122-141

Secomandi, N. (2010). On the pricing of natural gas pipeline capacity. Manufacturing & Service Operations Management, 12 (3), 393–408.

Shackelton, M. B. , Tsekrekos, A. E. , & Wojakowski, R. (2004). Strategic entry and market leadership in a two-player real options game. Journal of Banking & Finance, 28, 179–201.

Salant, S., Switzer, S., & Reynolds, R. (1983). Losses from horizontal merger: The effects of an exogenous change in industry structure on Cournot–Nash equilibrium. Quarterly Journal of Economics, 98, 185–199.

Smit, H. , & Ankum, L. A. (1993). A real options and game-theoretic approach to corporate investment strategy under competition. Financial Management, 22 (3), 241–250.

Smit, H. (2001). Acquisition strategies as option games. Journal of Applied Corporate Finance, 14 (2), 79–89.

Siddiqui, A., & Fleten, S.-E. (2010). How to proceed with competing alterna- tive energy technologies: A real options analysis. Energy Economics, 32, 817–830.

Siddiqui, A., & Takashima, R. (2012). Capacity switching options under rivalry and uncertainty. European Journal of Operational Research, 222, 583– 595.

Sutton, R. S., & Barto, A. G. (1998). Reinforcement learning: An introduction. MIT Press.

Tirole, J. (1982). On the possibility of speculation under rational expectations. Econometrica, 50 (5), 1163–1182.

Tseng, C.-L. , & Barz, G. (2002). Short-term generation asset valuation: A real options approach. Operations Research, 50 (2), 297–310.

Van Mieghem, J. A. (2003). capacity management, investment, and hedging: Review and recent developments. Manufacturing & Service Operations Management, 5 (4), 269–302.

von der, Fehr, & Mørch, N.-H. (1992). How entry induces slack. International Journal of Industrial Organization, 10 (2), 231–249.

Voss, G., Sirdeshmukh, D., & Voss, Z. (2008). The effects of slack resources and environmental threat on product exploration and exploitation. Academy of Management Journal, 51 (1), 147–164.

Williams, J. T. (1993). Equilibrium and options on real assets. The Review of Financial Studies, 6 (4), 825–850.

Williams, J. T. (1995). Pricing real assets with costly search. The Review of Financial Studies, 8 (1), 55–90.

Wu, O. Q. , & Kapuscinksi, R. (2013). Curtailing intermittent generation in electrical systems. Manufacturing and Service Operations Management, 15 (4), 578–595.