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Network Industry Liberalization: The Case of the England and Wales Electricity Market

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Dissertation

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Abstract

The dissertation consists of a general introduction on network industries and three chapters. The first and second chapters analyze the behavior of electricity producers at a uniform price auction. In the first chapter I examine market power manifested in submitting price bids in excess of marginal production costs. The theoretical model allows identifying the incentive and disincentive to exercise market power. Then an empirical analysis is performed at the level of producer and production unit of various input types used in electricity production. I examine how the incentive and disincentive to exercise market power change during different regulatory regime periods and draw conclusions regarding the effectiveness of regulatory reforms to improve competition.

The second chapter, which is coauthored with Lubomír Lízal, investigates another possible means of increasing prices. In particular, we examine if producers apply a capacity cutting strategy to increase prices. This strategy may be feasible when a significantly large increase in demand is forecasted so that a market operator will have to use high-cost (and sometimes even less efficient), i.e., expensive, production facilities to satisfy demand. The major purpose of this research is to analyze whether the regulatory reforms decreased the extent of strategic capacity bidding.

Generally, strategic submission of price bids or capacity bids tend to make equilibrium prices in a market more volatile. Therefore, in the third chapter, I analyze and discuss the dynamics of price level and volatility. On the one hand, the analysis of a price level is important in determining the expected revenues for producers and, in the end, costs for consumers. On the other hand, the analysis of price volatility could be important for understanding uncertainty and new entry decisions. Also, high price and low volatility levels could be interpreted as a signal of possible tacit collusion. These issues and their policy evaluation are addressed in the last chapter.

Abstrakt

Disertační práce má tři kapitoly a je doplněna obecným úvodem do problematiky síťových odvětví, zejména elektroenergetiky. První a druhá kapitola se věnují chování výrobců elektřiny na aukcích s uniformní cenou. V první kapitole zkoumám, jak se tržní síla projevuje v navýšení cenových nabídek nad mezní výrobní náklady. Teoretický model umožňuje identifikovat motivace k uplatnění či neuplatnění tržní síly. Následně na základě tohoto teoretického modelu provádím empirickou analýzu na úrovni výrobců a výrobních jednotek, které používají různé typy vstupů při výrobě elektrické energie. Dále v této kapitole zkoumám, jak se motivace k uplatnění či neuplatnění tržní síly mění během různých regulatorních období a z toho vyvozuji závěry o účinnosti regulatorních reforem, které měly za cíl zlepšit hospodářskou soutěž.

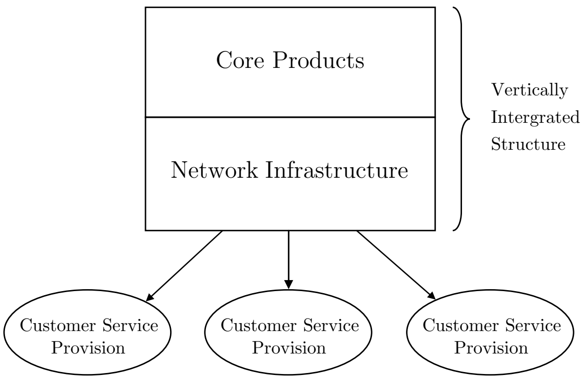
V druhé kapitole, jejímž spoluautorem je Lubomír Lízal, zkoumáme jiný možný způsob zvyšování aukčních cen. Zaměřujeme se na model, kdy výrobci strategicky snižují kapacity dodávek v uniformní aukci s cílem dosáhnout zvýšení aukční ceny. Teoreticky je tato strategie uskutečnitelná, pokud je očekáván dostatečně velký nárůst poptávky, takže operátor trhu bude muset zapojit vysokonákladové (někdy dokonce i méně efektivní), a tedy drahé, výrobní kapacity k uspokojení poptávky. Hlavní cíl tohoto výzkumu je pak následná analýza, zda regulatorní reformy snížily rozsah strategického krácení dostupných nabídek kapacit.

Obecně platí, že strategické modifikace aukčních nabídek cen a kapacit mají tendenci zvyšovat pozorovanou volatilitu aukčních cen. Proto ve třetí kapitole analyzuji a diskutuji dynamiku pozorované cenové hladiny a volatility na trhu elektrické energie. Na jedné straně je analýza cenové úrovně důležitá pro určení očekávaných příjmů výrobců a nákladů koncových spotřebitelů. Na druhé straně je analýza volatility cen také důležitá pro pochopení nejistoty a rozhodování dalších firem o vstupu na daný trh. Vysoká cena a nízká volatilita mohou být vykládány jako signál možné koluze. Poslední kapitola je tedy věnována právě zmíněným tématům a jejich ekonomickému posouzení a interpretaci.

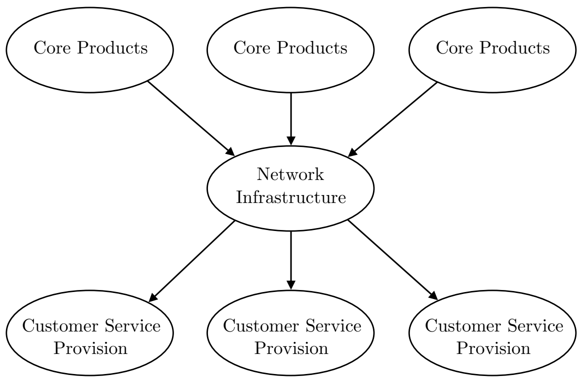
Introduction

Network industries like energy (for example, electricity and natural gas), postal services, telecommunications, and transport (for example, air, maritime, and rail) provide essential services of general economic interest. Promotion of competition at all possible levels of these network industries was the primary goal of the liberalization process started during the 1990s in many European countries (Bergman, Doyle, Gual, Hultkrantz, Neven, Röller, and Waverman, 1998).

In general, a network industry is one in which products are provided to customers via a network infrastructure. As described in Bergman et al. (1998), a network industry is represented by three key components: core products, network infrastructure, and customer service provision. These are schematically presented in Figure 1.



(a) Vertically integrated case



(b) Vertically separated case

Source: Bergman et al. (1998).

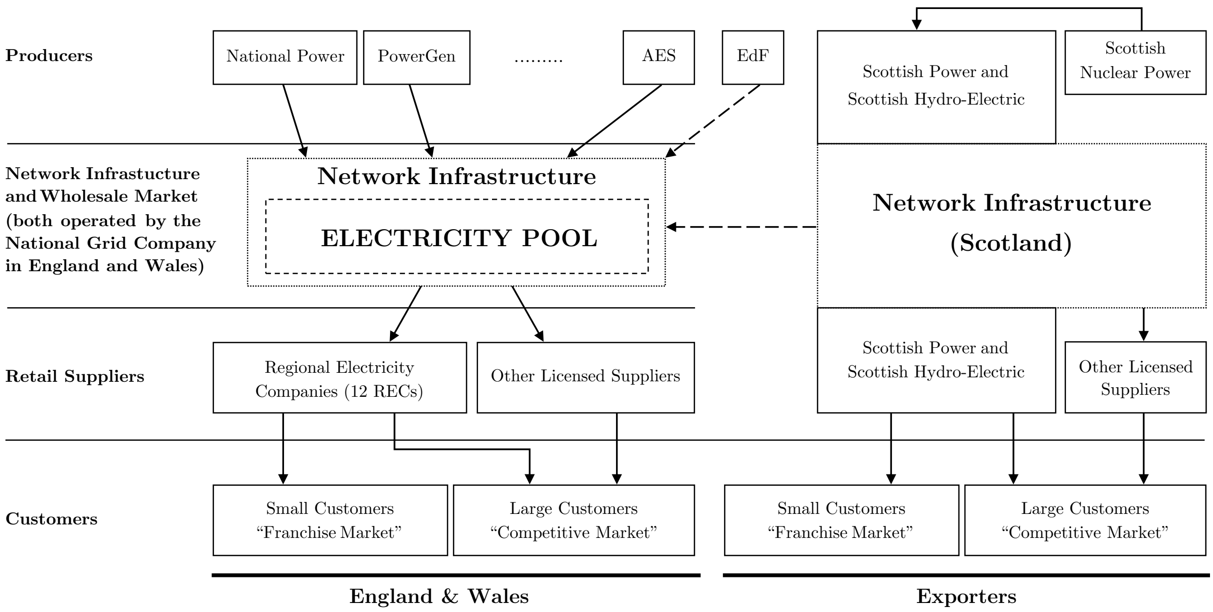
Figure 1: Structure of a network industry

Core products are delivered by producers in the upstream production level, and customer service provision is delivered by suppliers in the downstream supply level. The upstream production and downstream supply levels are coordinated via the network infrastructure.

Until the 1980s, the upstream production and network infrastructure levels were mostly vertically integrated and regulated as a single "natural monopoly" structure, which is described in Figure 1a. It was then widely believed that those vertically integrated organizations are better managed as regulated state or private natural monopolies, mainly due to the presence of economies of scale and large fixed costs (Geradin, 2006).

The liberalization in network industries included the splitting up of the previously vertically integrated monopoly structure, which is described in Figure 1b. The purpose of this restructuring was to introduce competition in the upstream production and downstream supply levels while still allowing for the network infrastructure to remain the only monopoly structure because its replication would not be economical.

For the case of an electricity supply industry (ESI), described in Figure 2, the upstream production level is represented by electricity producers, the network infrastructure by the network operator responsible for electricity transmission over a high-voltage net, and the downstream supply level by retail suppliers responsible for electricity distribution over a low-voltage net to consumers.



Source: Department of Trade and Industry (1997–2002). Modified for illustration purposes.

Figure 2: Description of the electricity supply industry in Great Britain in 1998

As described in Figure 2, in England and Wales, electricity producers sold electricity to retail suppliers through the wholesale market known as the Electricity Pool, which was managed by the network operator, the National Grid Company (NGC). The NGC was also responsible for transmitting electricity to retail suppliers, which then distribute electricity to final customers.

In Scotland, the South of Scotland Electricity Board and the North of Scotland Hydro-Electric Board were replaced by Scottish Power and Scottish Hydro-Electric, which are responsible for production, transmission, and retail supply. As illustrated in Figure 2, the production and transmission have been kept vertically integrated and were not unbundled as was done, for example, in England and Wales.

The liberalization process of the ESI during the 1990s included several institutional changes and regulatory reforms. Those changes and reforms, both in the production and distribution levels, shared heavy-handed features of regulation because specific rules and institutions were established to regulate the ESI in Great Britain. The dissertation focuses on the evaluation of regulatory reforms introduced in order to improve competition in the England and Wales wholesale electricity market.

The dissertation consists of three chapters. The first two chapters examine the bidding behavior of electricity producers on the wholesale market operated as a uniform price auction. In particular, we analyze the strategic bidding of price and capacity bids, respectively, which could affect the wholesale price. The third chapter investigates the dynamics of the wholesale price in terms of level and volatility. All three chapters examine the effect of reforms introduced during the liberalization process on market outcomes.

1. Analysis of Electricity Industry Liberalization in Great Britain: How Did the Bidding Behavior of Electricity Producers Change?*

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Abstract

Promoting competition among electricity producers is crucial for ensuring allocative efficiency and lower electricity prices. In this paper, I empirically examine the wholesale electricity market of England and Wales in order to analyze to what extent regulatory reforms were successful at promoting competition among electricity producers.

As a theoretical benchmark I consider a duopoly case, based on which a regression model is specified. The estimation of the regression model allows documenting new results about the impact of regulatory reforms on the incentive and disincentive to exercise market power by electricity producers during the liberalization process.

Keywords: liberalization; electricity markets; uniform price auction; market power; regulation

JEL Classification: D21; D44; L90; L94

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1.1 Introduction

Great Britain was the first among the OECD countries to liberalize its electricity supply industry. The liberalization included splitting up the previously vertically integrated utility into its production and infrastructure parts and creating a wholesale market to exchange electricity between producers and retail suppliers in England and Wales. Trading was organized as a uniform price auction, where electricity producers are asked to bid prices at which they are willing to produce electricity.

Producers, however, exercised market power by submitting price bids significantly exceeding marginal costs (see, for example, Crawford, Crespo, and Tauchen, 2007; Sweeting, 2007). An exercise of market power leads to higher uniform auction prices, i.e., the System Marginal Price (SMP), and, therefore, higher revenues for electricity producers. On the other hand, a higher SMP increases payments by retail suppliers, which are in the end reflected in higher prices paid by consumers. Another consequence of an exercise of market power are possible losses in the efficient allocation of production facilities. In other words, due to possible differences in setting bid markups, there need no longer be any guarantee that, based on ordered price bids, the least-cost production facilities are indeed scheduled to produce electricity.

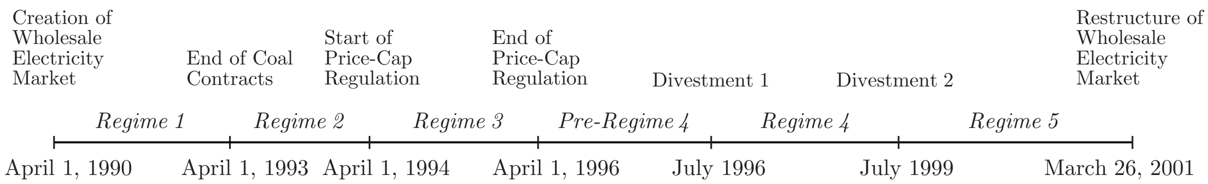
These issues related to the exercise of market power are also discussed in Bergman, Doyle, Gual, Hultkrantz, Neven, Röller, and Waverman (1998) in the analysis of the first form of benefits that electricity market reforms could bring to consumers: lower prices resulting from lower price-cost margins and more cost-efficient electricity production. The other forms of benefits that electricity market reforms could bring to consumers include a high degree of security of supply and an environmentally friendly electricity supply system, which in the long run would not critically depend on exhaustible natural resources.

During the liberalization process, in order to mitigate an exercise of market power by incumbent electricity producers, the regulatory authority, the Office of Electricity Regulation (Offer), introduced several reforms. A duopoly case allows determining the incentive and disincentive to exercise market power, which are then used in the regression model in order to quantify and document new empirical evidence about the changes in the bidding behavior of electricity producers during the liberalization process.

The measures designed to mitigate an exercise of market power and promote competition during the liberalization process were more extensive in Great Britain compared to Germany, France, Italy, or Sweden (Bergman et al., 1998). Joskow (2009) characterizes the privatization, restructuring, market design, and regulatory reforms pursued in the liberalization process of the electricity industry in England and Wales as the international gold standard for energy market liberalization. In this respect, the new findings documented in this research could be of interest to countries that have formed or are about to form their electricity markets similar to the original model of the electricity market in England and Wales.

1.2 Regulation in the electricity supply industry

The institutional changes and regulatory reforms that took place in the production level of the electricity supply industry (ESI) in Great Britain during 1990–2001 are summarized in Figure 1.1 and described in detail in the following paragraphs.



Sources: Department of Trade and Industry (1997–2002), National Grid Company (1994–2001), Newbery (1999), Robinson and Baniak (2002), Wolfram (1999); author's illustration.

Figure 1.1: Institutional changes and regulatory reforms during 1990–2001

The regulatory authority noted the growing discrepancy between rising wholesale electricity prices and falling fuel costs, and specifically the sharp increase in electricity prices in April 1993.[1] In the literature, this is also associated with the expiry of coal and other

[1]However, the regulatory authority rarely made comparisons between price bids and marginal costs (Green, 2011), which is the purpose of this research.

initial contracts imposed by the government. Hence, April 1, 1993 is considered as the *first structural break*.

Earlier research (see, for example, Green and Newbery, 1992) concluded that an exercise of market power enabled electricity producers to raise prices above competitive levels. Later, the regulatory authority advocated the introduction of price-cap regulation into the ESI, which would set an explicit ceiling on annual average prices charged for electricity production by the two incumbent electricity producers: National Power (the larger producer) and PowerGen (the smaller producer). Faced with the alternative of a referral to the Monopolies and Mergers Commission (MMC), these producers agreed to a price cap for two financial years: 1994/1995 and 1995/1996 (Wolfram, 1999; Robinson and Baniak, 2002). Therefore, April 1, 1994 and April 1, 1996 are considered as the *second* and *third structural breaks*, respectively.

In order to improve competition and decrease the influence of the incumbent electricity producers, the regulatory authority introduced horizontal restructuring through two series of divestments which took place in 1996 and 1999.

When defining regime periods for an ex-post regulation analysis, I consider the exact dates in which the reforms were introduced. This approach better corresponds to the nature of the divestment series introduced by the regulatory authority. For example, the introduction of the first series of divestments for PowerGen led to the transfer of all medium coal production facilities to Eastern Group (National Grid Company, 1994–2001). A separate analysis of the bidding behavior of PowerGen with respect to medium coal production facilities several days or weeks before the actual divestment took place may not be statistically reliable due to a small number of observations. For Eastern Group, it would not be possible because Eastern Group did not have coal production facilities before and therefore could not participate in the auction by submitting bids for coal production units. Hence, I assume that the structural breaks are exogenously given by the dates in which the reforms were introduced. It is also worth mentioning that the structural changes introduced through the divestment series differ because the first series of divestments included the lease[2] and the second series of divestments included the sale of production facilities (National Grid Company, 1994–2001). Therefore, the effect of the two divestment series, generally, need not be the same.

In March 2001, the wholesale electricity market was replaced by the New Electricity Trading Arrangements (NETA) in order to introduce bilateral trading arrangements.

1.3 Related literature

Seminal research in modeling electricity auctions is presented in Von der Fehr and Harbord (1993). The authors assume that N electricity producers serve the British electricity market operated as a uniform price auction. They also assume that marginal costs are common knowledge and differ only across electricity producers. The last assumption implies that all production units of a certain electricity producer have the same marginal costs, which can be partly supported by the fact that during the early 1990s approximately 70% of production capacity was based on coal (Department of Trade and Industry, 1997–2002). However, this assumption has a limitation because thermal efficiency rates of different coal production units belonging to a certain electricity producer generally need not be the same.

The authors show that no pure-strategy bidding equilibrium exists when electricity demand falls within a certain range. Their result is explained by an electricity producer's conflicting incentives to bid high in order to set a high price and to bid low in order to ensure that its production unit is scheduled to produce electricity.

Wolfram (1998) empirically examines the bidding behavior of electricity producers in the same electricity market. As a benchmark model she analyzes a duopoly case, where the first producer has several production units and the second producer has one production unit. The intuition and conclusions of the duopoly case are then used in the construction of a regression model.

The main finding of Wolfram (1998) is that electricity producers submit price bids

[2]Eastern Group was charged an earn-out payment per MWh output, which affects the calculation of marginal costs. Details of the earn-out payment are described in Evans and Green (2005).

reflecting higher markups for production units which are likely to be scheduled to produce electricity if that producer has a large infra-marginal production capacity. The author indicates that the incentive to submit a price bid reflecting a higher markup for a certain production unit is moderated by the presence of a threat that the production unit might not be scheduled to produce electricity. Wolfram (1998) also finds that larger producers submit higher price bids than smaller producers for comparable production units (i.e., production units using the same input to produce electricity and having almost the same marginal costs).

The findings of Wolfram (1998) are in line with the findings of Green and Newbery (1992), which is a seminal study using the framework of the supply function equilibrium (SFE) for the England and Wales electricity market. This framework assumes that each producer submits a continuously differentiable supply function, which may be applicable when producers' production units are small enough or when each producer has a sufficiently large number of production units as was the case with the incumbent producers during the early years of the wholesale electricity market. Green and Newbery (1992), using the concept of SFE for a duopoly case, show that a producer with a larger production capacity has more incentive to exercise market power by bidding in excess of marginal costs.

Crawford et al. (2007) extend the work of Von der Fehr and Harbord (1993) by allowing production units belonging to a particular electricity producer to have different marginal costs. Similar to Von der Fehr and Harbord (1993), Crawford et al. (2007) assume complete information about the marginal costs of electricity producers because it was possible to approximate them using data on the thermal efficiency rates of production units and input prices. The authors also assume no demand uncertainty and that no electricity producer is able to serve the whole demand.

Crawford et al. (2007) find the presence of asymmetries in the bidding behavior of marginal and infra-marginal electricity producers during 1993–1995. In particular, their results suggest that during peak-demand trading periods marginal producers behave strategically by submitting price bids higher than their marginal costs, whereas infra-marginal producers behave competitively by submitting price bids reflecting their marginal costs.

For the following period of 1995–2000, Sweeting (2007) analyzes the development of market power in the same electricity market. The author measures market power as the margin between observed wholesale market prices and estimates of competitive benchmark prices, where the latter is defined as the expected marginal cost of the highest-cost production unit required to meet electricity demand. Sweeting (2007) finds that electricity producers were exercising increased market power during 1995–2000. This finding, as the author indicates, is however in contradiction with oligopoly models, which, given that during this period market concentration was falling, would have predicted a reduction in market power. The author also finds that from the beginning of 1997 the National Power and PowerGen incumbent electricity producers could have increased their profits by submitting lower price bids and increasing output. From a short-term perspective, these findings are explained as tacit collusion.

As explained in Borenstein, Bushnell, and Wolak (2002), the application of competitive benchmark prices to analyze whether an electricity market, as a whole, is setting competitive prices has an advantage of being less vulnerable to the arguments of coincidence and bad luck. This approach also allows estimating the scope and severity of departures from competitive bidding over time.

However, the application of competitive benchmark prices does not allow for a more detailed analysis of specific manifestations of noncompetitive bidding behavior for different electricity producers. For this reason I follow an alternative approach similar to Wolfram (1998) and Crawford et al. (2007). More precisely, in order to analyze the development of an exercise of market power in relation to the regulatory reforms, I consider the bidding behavior of individual electricity producers with respect to marginal and extra-marginal production units during peak-demand trading periods.

Focusing on peak-demand trading periods is in line with the methodology adopted in Crawford et al. (2007). Moreover, the choice of peak-demand trading periods is also in agreement with the finding in Borenstein et al. (2002), where the authors, using the case of the wholesale electricity market in California, show that market power is most commonly exercised during peak-demand trading periods.

1.4 Methodology

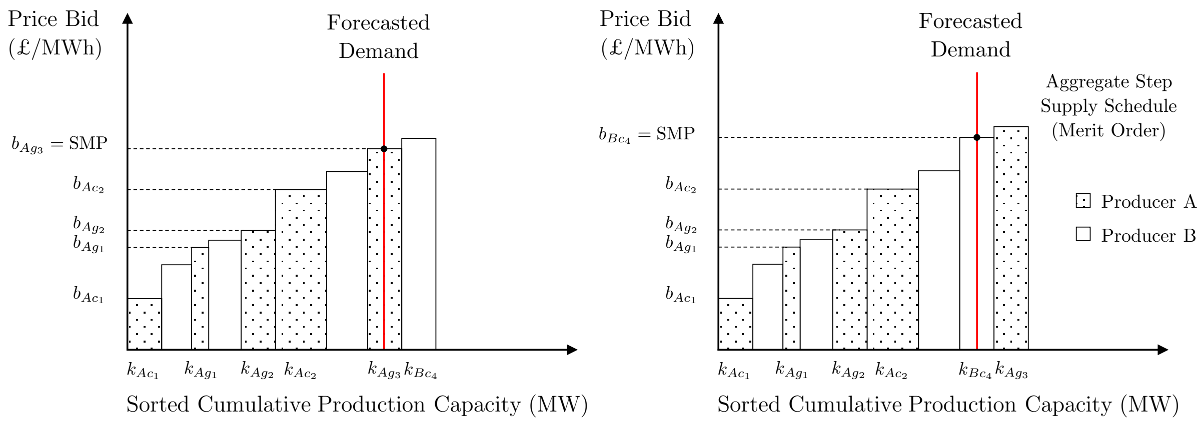
For the analysis of the bidding behavior of electricity producers, I assume no uncertainty in the forecasted demand for electricity and that the marginal costs of electricity production can be approximated. The first assumption is based on the fact that the methodology the market operator (i.e., the National Grid Company) applied to forecast electricity demand for each trading period of the following trading day was common knowledge (Wolak, 2000; Wolak and Patrick, 2001) and independent of producers' bidding behavior (Green, 2006). The second assumption is based on the availability of data describing the technical characteristics (i.e., the thermal efficiency rate and input type) of production units, which allows approximating the marginal costs.

In Section 1.4.1, I consider a duopoly case with an asymmetric technology structure. Based on the conclusions obtained from the duopoly case, a regression model is developed in Section 1.4.2 in order to analyze the bidding behavior of electricity producers with respect to marginal and extra-marginal production units. This analysis allows us to empirically evaluate the success of the reforms introduced by the regulatory authority in order to mitigate an exercise of market power by electricity producers during 1995–2000. The methodology how to approximate marginal costs is presented in Appendix 2.A.

1.4.1 Analysis of a duopoly case with an asymmetric technology structure

For the theoretical part, similarly to Wolfram (1998) and Crawford et al. (2007), I consider a duopoly case with the main distinction that I analyze at the level of the type of production unit. This modeling approach allows me to analyze the behavior of electricity producers with respect to marginal and extra-marginal production units of different types that are identified using the forecasted demand. This is needed for my ex-post evaluation of the impact of the reforms introduced by the regulatory authority to mitigate the exercise of market power by electricity producers. Namely marginal and extra-marginal production units of different input types located close to forecasted demand could likely be used for strategic bidding because of being potential candidates for setting a uniform auction price.

Assume that there are two risk-neutral electricity producers A and B, where producer A has several types of production unit and producer B has one type of production unit. For the explanation of the model I refer to the hypothetical example in Figure 1.2. More general cases demand complex notations, which may complicate the illustration of derivation results important for the construction of the regression model described in Section 1.4.2.



(a) Producer A sets the uniform price (b) Producer B sets the uniform price

Source: Author's illustration.

Figure 1.2: Determination of the SMP: a hypothetical example

Let $k_{A\tau}$ denote the production capacity of type τ belonging to producer A that is declared available to produce electricity. In other words, $k_{A\tau}$ is the overall capacity of production units of type τ from the supply schedule constructed by the market operator (i.e., the auctioneer). For the example described in Figure 1.2, it follows that $k_{Ac} = k_{Ac_1} + k_{Ac_2}$, $k_{Ag} = k_{Ag_1} + k_{Ag_2} + k_{Ag_3}$, $k_{Bc} = k_{Bc_1} + k_{Bc_2} + k_{Bc_3} + k_{Bc_4}$.

Let $c_{A\tau}$ denote the marginal cost of producer A's highest-cost production unit of type

τ. For the hypothetical example this would mean that $c_{Ac} = c_{Ac_2}$, $c_{Ag} = c_{Ag_3}$, and $c_{Bc} = c_{Bc_4}$. Setting the marginal costs of all production units of type τ by the marginal cost of the most expensive production unit in the calculation of expected profits is partly similar to the concept of competitive benchmark prices used in Sweeting (2007).

Let b_B denote producer B's price bid submitted for the highest-cost production unit. Because producer B is assumed to have one type of production unit, the subscript for the type is omitted. Assume that the probability distribution of b_B is defined according to a cumulative distribution function $F(b_B)$ and the respective probability density function $f(b_B)$ with support on the compact interval $[\underline{b}, \bar{b}]$, where $\underline{b}$, $\bar{b} \in \mathbb{R}^+$ and $\underline{b} < \bar{b}$. This is assumed to be common knowledge.

Similarly, let $b_{A\tau}$ denote producer A's price bid submitted for the highest-cost production unit of type τ. For the example described in Figure 1.2, it is the price bid of the third gas production unit that could be used for strategic bidding by producer A. In other words, $b_{Ag} \in [\underline{b}, \bar{b}]$ is producer A's strategic choice variable.

Submitted price and capacity bids[3] for individual production units represent private knowledge for each producer that owns those production units. This is a feature of a sealed-bid uniform price auction, where the bids of one producer are unknown to the other producers.

The payoff of a producer is represented by an expected profit, which is dependent on the outcome of the uniform price auction (i.e., who sets the uniform auction price), the amount of electricity a producer sells at the market, and production costs. More precisely, given the bid b_B of producer B, we define the expected profit maximization problem of producer A:

[3] More precisely, half-hourly price bids for every production unit are computed based on daily bids and half-hourly declared (submitted) capacity bids. Daily bids include incremental price-offer bids, elbow points, start-up and no-load costs. These rules are common knowledge and described in detail in the Electricity Pool (1990), which is a technical summary used by the market operator, the National Grid Company (NGC). A more intuitive description of trading rules, including the Generator Ordering and Loading (GOAL) algorithm, is also presented in Sweeting (2007).

$$E[\pi_A(b_{Ag}, b_B)] = E[\pi_A \mid \underbrace{b_B > b_{Ag}}_{\text{A sets}}] + E[\pi_A \mid \underbrace{b_B \leq b_{Ag}}_{\text{B sets}}] =$$

$$= \int_{b_{Ag}}^{\bar{b}} \left[(b_{Ag} - c_{Ac}) \cdot \frac{1}{2} k_{Ac} + (b_{Ag} - c_{Ag}) \cdot \frac{1}{2} k_{Ag} \right] \cdot f(b_B)\, db_B \; +$$

$$+ \int_{\underline{b}}^{b_{Ag}} \left[(b_B - c_{Ac}) \cdot \frac{1}{2} k_{Ac} + (b_B - c_{Ag}) \cdot \frac{1}{2} \alpha_{Ag} k_{Ag} \right] \cdot f(b_B)\, db_B \,. \quad (1)$$

In the calculation of the expected profit,[4] producer A considers two possible scenarios depending on who sets the uniform auction price as described in Figure 1.2. If producer A sets the price, then the uniform auction price is b_{Ag}. However, if producer B sets the price, then the uniform auction price is b_B and only α_{Ag} part of the submitted gas production capacity belonging to producer A will be scheduled to produce electricity.

Taking the first-order condition[5] with respect to b_{Ag}, rearranging, and applying logarithms to both sides leads to

$$\log(b_{Ag} - c_{Ag}) = \log(k_{Ac} + k_{Ag}) - \log(1 - \alpha_{Ag})k_{Ag} + \log\big(1 - F\big(b_{Ag}\big)\big) - \log\left(f(b_{Ag})\right) \,. \quad (2)$$

In equation (2), $b_{Ag} - c_{Ag}$ denotes the markup defined as the price bid minus the approximated marginal cost of the production unit of type g that belongs to producer A.

By $k_{A\tau}$ we denote the total capacity of production units of type τ belonging to producer A. Then, $k_{Ac}+k_{Ag}$ denotes the total capacity of production units located up to price bid b_{Ag} in the aggregate supply schedule. The optimality condition represented by equation (2), suggests that a larger total production capacity creates an incentive to submit a higher price bid because when that price bid sets the uniform auction price it is applied to

[4] I use a factor of $\frac{1}{2}$ to convert MW to MWh. This follows from the fact that the duration of a trading period is 30 minutes. A production capacity of, for example, 40 MW multiplied by this time gives the amount of electricity produced by a production unit during a half-hour period: $40\,\text{MW} \cdot \frac{1}{2}\,\text{h} = 20\,\text{MWh}$.

[5] For differentiation I use the Leibniz's formula provided in Sydsæter, Hammond, Seierstad, and Strøm (2008).

producer A's total (scheduled) production capacity.

However, the incentive to increase a price bid is moderated by the presence of a threat that a production unit at stake may not eventually be scheduled to produce electricity. The next term in equation (2), $(1-\alpha_{Ag})k_{Ag}$, denotes part of production capacity of type g belonging to producer A that might not be scheduled to produce electricity due to a significantly high price bid. A negative sign reflects the presence of a trade-off when increasing the price bid, which is associated with profit losses caused by the production unit at stake not being scheduled to produce electricity.

The term $f(b_{Ag})$ denotes the likelihood that a production unit of type g that belongs to producer A becomes marginal. As the optimality condition suggests, a higher price bid decreases the likelihood of setting the uniform auction price, which therefore negatively affects the producer's incentive to submit an excessively high price bid. Finally, $1-F\big(b_{Ag}\big)$ represents the probability that b_{Ag} sets the price. This probability is predicted to positively affect producer A's bid markup.

For an ex-ante analysis, it is necessary to accurately estimate these probability values. The accurate estimation of these time-variant probabilities is, however, a difficult task in the case of several producers. Besides the fact that these probabilities are generally different across producers, they are also expected to vary across the types of input an individual producer uses for electricity production. For an assessment of the regulatory reforms, an ex-post analysis of the bidding behavior of electricity producers with respect to marginal and extra-marginal production units could be more applicable. Given the market outcomes, I evaluate the success of regulatory reforms directed at mitigating the exercise of market power by electricity producers.

The presented theoretical model suggests considering a log-linear functional relationship in the specification of a regression model, which is presented in the next section.

1.4.2 Specification of a regression model

Based on derivation results from the duopoly case we can formulate the following regression model to empirically analyze the bidding behavior of electricity producers:

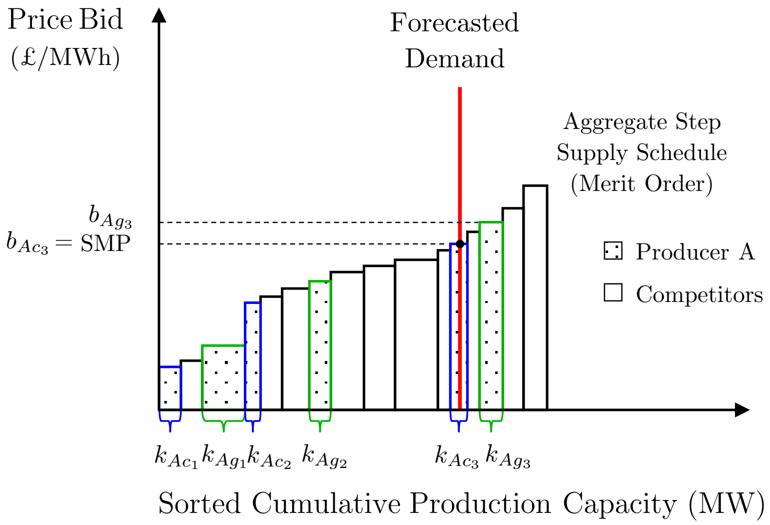
$$\log\left(\mathit{Markup}_{ijt}\right) = \beta_0 + \beta_{1i} \cdot \log\left(\mathit{Production\ Capacity\ below\ Bid}\ b_{ijt}\right) + \\ + \beta_{2ij} \cdot \log\left(\mathit{Production\ Capacity\ at\ Bid}\ b_{ijt}\right) + \varepsilon_{ijt}\,. \tag{3}$$

In this regression model, subscript i stands for an electricity producer and subscript j stands for the type of marginal and extra-marginal production units. In other words, producers' production units located at and above the forecasted demand are considered. If a producer has several extra-marginal production units of the same input type located above the forecasted demand, then a production unit closest to the forecasted demand is considered. We analyze producers' bidding behavior during the peak-demand period of trading day t.

The variables Markup_{ijt}, *Production Capacity below Bid* b_{ijt}, and *Production Capacity at Bid* b_{ijt} enter under a logarithm following the derivation results from the duopoly case. The variable Markup_{ijt} under logarithm denotes the price bid minus the marginal cost of a production unit of type j belonging to producer i. There are two advantages of incorporating marginal costs into the definition of the dependent variable. Firstly, this allows analyzing an exercise of market power explained by other variables. Secondly, the approximation of marginal costs may involve a measurement error. Therefore, incorporating marginal costs into the definition of the dependent variable may at most lead to an overestimation of standard errors of coefficient estimates.

The two explanatory variables in the regression model are log(*Production Capacity below Bid* b_{ijt}) and log(*Production Capacity at Bid* b_{ijt}). The variable *Production Capacity below Bid* b_{ijt} denotes the total amount of declared (submitted) capacity of production units that belong to producer i and have price bids lower than b_{ijt}. The variable *Production Capacity at Bid* b_{ijt} denotes the amount of declared (submitted) capacity of a production unit of type j for which producer i submits price bid b_{ijt}.

In Figure 1.3, using an example of producer A with two types of production unit, I summarize the definitions of variables used in the regression model.



Source: Author's illustration.

Notes:
Production Capacity below Bid b_{Ac_3} : $k_{Ac_1} + k_{Ag_1} + k_{Ac_2} + k_{Ag_2}$
Production Capacity at Bid b_{Ac_3} : k_{Ac_3}
Markup$_{Ac_3}$: $b_{Ac_3} - c_{Ac_3}$
Production Capacity below Bid b_{Ag_3} : $k_{Ac_1} + k_{Ag_1} + k_{Ac_2} + k_{Ag_2} + k_{Ac_3}$
Production Capacity at Bid b_{Ag_3} : k_{Ag_3}
Markup$_{Ag_3}$: $b_{Ag_3} - c_{Ag_3}$

Figure 1.3: Explanation of variables used in the regression model

The effect of the first explanatory variable is generally assumed to be different across producers. Moreover, the producer specific slope parameter β_{1i} is expected to be positive because, as the theoretical predictions suggest, a larger total production capacity would create an incentive to submit a price bid reflecting a higher bid markup: when this price bid sets a uniform auction price, it is applied to a producer's entire scheduled production capacity. This intuition is consistent with Mount (2001), where the author states that the increasing difference between the price bid and marginal cost observed when the amount for sale increases is an example of how market power can be used to raise the final price.

The effect of the second explanatory variable is assumed to vary across not only producers but also input types. Moreover, the producer and type specific slope parameter β_{2ij} is expected to be negative because, as the theoretical predictions suggest, a larger production unit at stake moderates a producer's willingness to submit a price bid reflecting a higher markup. Thus, a producer faces the trade-off between bidding high to set a high price and bidding low to ensure that the production unit at stake is scheduled to produce electricity. In this respect, the first explanatory variable can reflect an incentive, whereas the second explanatory variable can reflect a disincentive to exercise market power by submitting price bids in excess of marginal costs.

In order to evaluate the impact of regulatory reforms on the bidding behavior of electricity producers, I assume that the parameters in front of the explanatory variables can change during different regime periods described in Figure 1.1. The validity of this assumption is verified by testing if the explanatory variables interacted with the regime dummy variables have statistically significant coefficients (denoted by δ's; see equation (4), footnote (7), and Block 2 in Table 1.3).

Finally, it is assumed that a disturbance term, ε_{ijt}, is orthogonal to the explanatory variables. For statistical inference I use producer–capacity type–day robust clustered standard errors. This approach allows taking into account producer related heteroscedasticity and weekly seasonality features.[6]

1.5 Data

The data consist of two data sets and cover the period January 1, 1995–September 30, 2000. The first data set contains half-hourly market data on the forecasted demand for electricity and System Marginal Price (SMP). A sample summary of these data with the associated measurement units is presented in Table 1.1.

The first data set also includes information about the production unit that sets the SMP: the name of the production unit, its input type, and the name of the corresponding plant and electricity producer.

The second data set contains half-hourly bid data on production capacity and price bids. This data set also includes information about the production unit, its input type,

[6]Weekly seasonality is a feature inherent to electricity markets. For the case of electricity prices, the weekly seasonality properties are studied in the last chapter.

Table 1.1: Sample of descriptive statistics for market data (January 1, 2000–January 31, 2000)

	Forecasted Demand (MW)	SMP (£/MWh)
Mean	38464.60	24.39
Min	25001.00	8.00
Max	49945.00	77.89
Std Dev	5247.83	12.54
Frequency	30 min	30 min
Obs	1488	1488

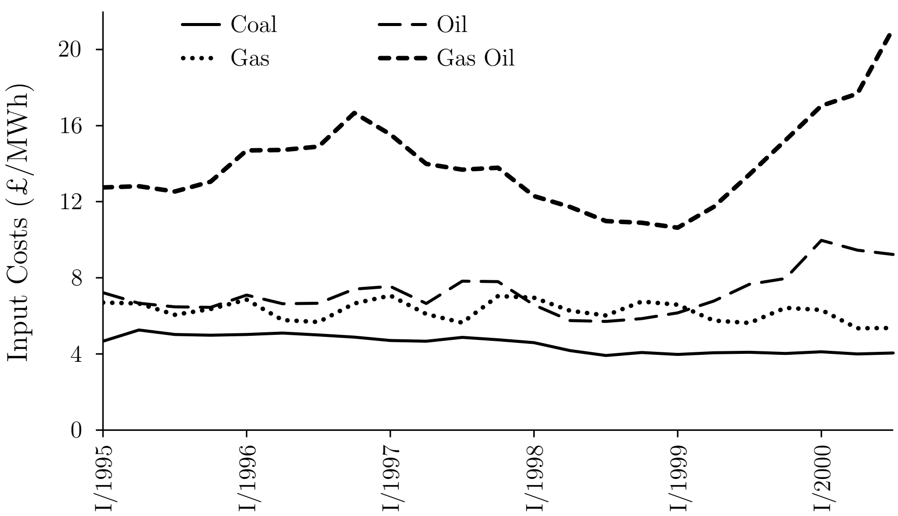
Source: Author's calculations.

and the name of the corresponding plant and electricity producer. A sample summary of these data with the associated measurement units is presented in Table 1.2.

Table 1.2: Sample of descriptive statistics for bid data (January 1, 2000–January 31, 2000)

	Capacity Bid (MW)	Price Bid (£/MWh)
Mean	175.41	39.54
Min	0.00	0.00
Max	989.00	37865.50
Std Dev	248.12	106.68
Frequency	30 min	30 min
Obs	450336	450336

Source: Author's calculations.



Sources: Department of Trade and Industry (1993–2000), Department of Trade and Industry (1997–2002); author's calculations.

Figure 1.4: Quarterly input costs of major power producers in Great Britain

Figure 1.4 describes the quarterly input costs of electricity producers, which are used to approximate the marginal costs of production units.

1.6 Results and discussion

In Section 1.4.2 we have introduced the specification of the regression model to evaluate the impact of the regulatory reforms on producers' bidding behavior. The choice of a log-linear functional form of the regression model is based on the first-order condition from the expected profit maximization problem in the duopoly case discussed in Section 1.4.1. Generally, log-linear regression models are often used in empirical research. One of the advantages of a log-linear regression model is that the estimated slope coefficients in this specification can be directly interpreted as elasticities.

The analysis includes all major power producers except for BNFL Magnox because production units belonging to this producer were always infra-marginal (i.e., not pivotal) during peak-demand trading periods. Focusing on peak-demand periods is consistent with the finding in Borenstein et al. (2002) that noncompetitive bidding behavior is most commonly observed during peak-demand periods.

Estimation results of $\hat{\beta}_{1i}$ and $\hat{\beta}_{2ij}$ slope parameters in front of the explanatory variables during the reference period are presented in Block 1 of Table 1.3. These slope parameters in equation (3) reflect the incentive and disincentive to exercise market power, respectively. Results of $\hat{\beta}_{1i}$ and $\hat{\beta}_{2ij}$ in Table 1.3 vary across producers (subscript i) and input types (subscript j), which suggests that considering producer and input type specific parameters has been correct.

I also assume that these slope parameters in front of the explanatory variables can vary during later regime periods. For this purpose, the interactions of the explanatory variables with the regime dummy variables are considered. The slope parameters of the interaction terms are denoted by δ's and their estimation results are presented in Block 2 of Table 1.3.[7]

[7] More precisely, I use the following notation: $\hat{\beta}_{1i}^{\text{Pre-Regime 4}} = \hat{\beta}_{1i}^{\text{Regime 3}} + \hat{\delta}_{1i}^{\text{Pre-Regime 4}}$, $\hat{\beta}_{1i}^{\text{Regime 4}} =$

The validity of my assumption is verifiable by formal testing. For example, a test for the equality of the first slope parameter for NP during Jan 95–Mar 96 and pre-regime 4 can be represented as testing the following null hypothesis:

$$\mathrm{H}_0: \ \beta_{1,\mathrm{NP}}^{\text{Pre-Regime 4}} - \beta_{1,\mathrm{NP}}^{\text{Jan 95–Mar 96}} = \delta_{1,\mathrm{NP}}^{\text{Pre-Regime 4}} = 0. \tag{4}$$

The value of

$$t\text{-stat} = \frac{\hat{\delta}_{1,\mathrm{NP}}^{\text{Pre-Regime 4}} - 0}{s.e.(\hat{\delta}_{1,\mathrm{NP}}^{\text{Pre-Regime 4}})} = \frac{1.306 - 0}{0.255} \approx 5.122 \tag{5}$$

suggests rejecting H_0 at the 1% significance level.

Similarly, other estimation results in Block 2 of Table 1.3 allow evaluating in detail the impact of the regulatory reforms on the bidding behavior of electricity producers during the subsequent regime periods. In particular, $\hat{\delta}_1$ reflects a change in the incentive and $\hat{\delta}_2$ reflects a change in the disincentive to exercise market power by submitting price bids in excess of marginal costs.

$\hat{\beta}_{1i}^{\text{Regime 3}} + \hat{\delta}_{1i}^{\text{Regime 4}}$, $\hat{\beta}_{1i}^{\text{Regime 5}} = \hat{\beta}_{1i}^{\text{Regime 3}} + \hat{\delta}_{1i}^{\text{Regime 5}}$, where $\hat{\delta}_{1i}^{\text{Pre-Regime 4}}, \hat{\delta}_{1i}^{\text{Regime 4}}, \hat{\delta}_{1i}^{\text{Regime 5}}$ are the estimates of a change presented in the first part of Block 2 in Table 1.3.

Similarly, $\hat{\beta}_{2ij}^{\text{Pre-Regime 4}} = \hat{\beta}_{2ij}^{\text{Regime 3}} + \hat{\delta}_{2ij}^{\text{Pre-Regime 4}}$, $\hat{\beta}_{2ij}^{\text{Regime 4}} = \hat{\beta}_{2ij}^{\text{Regime 3}} + \hat{\delta}_{2ij}^{\text{Regime 4}}$, $\hat{\beta}_{2ij}^{\text{Regime 5}} = \hat{\beta}_{2ij}^{\text{Regime 3}} + \hat{\delta}_{2ij}^{\text{Regime 5}}$, where $\hat{\delta}_{2ij}^{\text{Pre-Regime 4}}, \hat{\delta}_{2ij}^{\text{Regime 4}}, \hat{\delta}_{2ij}^{\text{Regime 5}}$ are the estimates of a change presented in the second part of Block 2 in Table 1.3.

Table 1.3: Estimation results of equation (3)

$$\log\big(Markup_{\,ijt}\big)=\beta_0+\beta_{1i}\cdot\log(Production\ Cap.\ below\ Bid\ b_{\,ijt})+\beta_{2ij}\cdot\log(Production\ Cap.\ at\ Bid\ b_{\,ijt})+\varepsilon_{ijt}$$

Dependent Variable: $\log(Markup_{\,ijt})$				Regime 3 (Jan 95–Mar 96) Price-cap		Pre-Regime 4 (Apr 96–Jul 96)		Regime 4 (Jul 96–Jul 99) Divestment 1		Regime 5 (Jul 99–Sept 00) Divestment 2	
		Pr	Type	Coef	Std Err	Coef	Std Err	Coef	Std Err	Coef	Std Err
Block 1: Estimation during a reference period	$\hat{\beta}_{1i}$	NP		0.029	0.275						
		PG		0.247**	0.100						
		EDF		0.286***	0.057						
		SI		0.283***	0.079						
		TXU						0.107	0.132		
		Ed		0.058***	0.006						
		BE								0.550***	0.169
		AES						0.031	0.036		
	$\hat{\beta}_{2ij}$	NP	Large Coal	0.159	0.428						
			Medium Coal	0.055	0.472						
			Small Coal	0.415	0.588						
			Oil	0.277	0.413						
			OCGT	0.836	0.679						
		PG	Large Coal	-0.170	0.149						
			Medium Coal	-0.174	0.166						
			Oil	0.037	0.138						
			OCGT	0.338	0.229						
		EDF	Export	0.370***	0.066						
		SI	Export	-0.070	0.103						
			CCGT	-0.234**	0.107						
		TXU	Large Coal					0.036	0.182		
			Medium Coal					0.115	0.211		
			OCGT					0.431	0.407		
		Ed	Large Coal							0.041	0.033
			OCGT							0.629***	0.091
			PSB	0.291***	0.071						
		BE	Large Coal							-0.513**	0.250
		AES	Large Coal							-1.166***	0.024
			OCGT					0.133	0.083		
Block 2: Estimation of a change in comparison to a reference period	$\hat{\delta}_{1i}$	NP				1.306***	0.255	0.559**	0.227	0.483*	0.260
		PG				0.307**	0.145	0.349**	0.168	0.556***	0.111
		EDF						-0.298***	0.018	-0.254***	0.018
		SI				0.179	0.226	0.021	0.099		
		TXU								-0.232**	0.115
		Ed				-0.102***	0.011	-0.019***	0.003	0.159***	0.036
		AES								1.112***	0.066
	$\hat{\delta}_{2ij}$	NP	Large Coal			-1.995***	0.405	-0.728**	0.362	-0.537	0.418
			Medium Coal			-2.121***	0.457	-0.706*	0.404	-0.322	0.461
			Small Coal			-2.938***	0.557	-1.141**	0.498		
			Oil			-1.779***	0.391	-0.663*	0.352	-0.468	0.404
			OCGT			-3.361***	0.647	-1.410**	0.580	-1.220*	0.662
		PG	Large Coal			-0.528**	0.225	-0.411	0.252	-0.647***	0.171
			Medium Coal			-0.300	0.257				
			Oil			-0.302	0.215	-0.413*	0.245	-0.651***	0.164
			OCGT			-0.894**	0.357	-0.909**	0.409	-1.512***	0.269
		EDF	Export					-0.091	0.072	-0.237***	0.089
		SI	Export			-0.432	0.366	0.016	0.159		
		TXU	Large Coal							0.327**	0.150
			Medium Coal							0.379**	0.190
			OCGT							-0.448	0.345
		Ed	PSB			0.061***	0.007	0.122***	0.005	-0.143**	0.058
		AES	OCGT							-2.254***	0.085
			Intercept	0.749**	0.349						

Notes: The first block contains coefficient estimates of explanatory variables for a reference period. The second block contains coefficient estimates of the interaction terms between regime dummy variables and explanatory variables. The notation for coefficient estimates is described in footnote (7).
Producer–capacity type–day clustered robust standard errors are used for statistical inferences. *, **, and *** stand for the 10%, 5%, and 1% significance levels, respectively. Annual seasonal dummy variables are omitted because they are found statistically insignificant. Obs = 23 009 and $R^2 = 0.601$.

Estimation results presented in Table 1.3 allow one to draw conclusions related to the analysis of the theoretical predictions and the impact of regulatory reforms. The results generally support my assumption that the slope parameters need not be the same across producers and input types. Moreover, changes in the slope parameters during later regime periods presented in Block 2 in Table 1.3 are in most cases statistically and economically significant. In this way it is possible to analyze in detail changes in the bidding behavior of electricity producers in relation to the introduced regulatory reforms.

The first theoretical prediction suggests that larger total capacity creates an incentive to submit a price bid in excess of marginal cost. Estimates of $\hat{\beta}_{1i}$ generally confirm this theoretical prediction and is, therefore, consistent with earlier research by Green and Newbery (1992) and Wolfram (1998).

The results also provide statistical evidence that during later regime periods the incentive to exercise market power has increased for the National Power and PowerGen incumbent electricity producers. In other words, I find that the incentive to exercise market power is greater after divestment series were introduced. For the other electricity producers, with the exception of AES, the incentive to exercise market power during later regime periods has either decreased or been relatively low. For the AES producer, however, $\hat{\beta}_{1i}$ during the last regime period is not only statistically, but also economically significant. The estimation results for NP, PG, and AES are partly in line with the findings in Sweeting (2007), where the author using the methodology of competitive benchmark prices shows that the extent of exercising market power has generally increased during the late 1990s.

Besides submitting price bids in excess of marginal costs, producers may apply a capacity cutting strategy in order to raise wholesale prices above competitive benchmark prices. The capacity cutting strategy and related literature is discussed in detail in the next chapter. The suggestion is consistent with the finding of Joskow and Kahn (2002), who similar to Sweeting (2007) also use competitive benchmark prices to study the California electricity market during the California electricity crisis. The authors find that capacity cutting, which is observed through substantial gaps between maximal and submitted capacity bids during peak-demand periods, could explain the remaining deviations in wholesale prices from competitive benchmark prices (after accounting for low levels of imports, high demand for electricity, and high prices of NO_x emissions permits). Relatively a higher incentive to exercise market power by NP, PG, and AES during the late 1990s and possible capacity cutting may explain differences between wholesale prices and competitive benchmark prices found in Sweeting (2007).

The incentive to submit a price bid reflecting a high markup is however moderated by the presence of a threat that the production unit at stake may not be scheduled to produce electricity. This effect also generally does not need to be the same across producers. Moreover, as mentioned earlier, if a single producer has several types of production unit, then this disincentive may additionally vary across types of production unit. The detailed analysis of inter- and intra-firm differences produced significantly better estimation results in contrast to the case when symmetry was assumed.

Hence, the disincentive to exercise market power is reflected by the estimated producer and input type specific slope parameter $\hat{\beta}_{2ij}$ in front of the second explanatory variable $\log(Production\ Capacity\, at\, Bid\, b_{ijt})$. In particular, $\hat{\beta}_{2ij}$ measures the percentage change in the markup, when the capacity of a production unit at stake is larger by 1%.

The second theoretical prediction suggests that $\hat{\beta}_{2ij}$ should be negative. However, in some instances, especially during the price-cap regulation period, the estimates of $\hat{\beta}_{2ij}$ are positive, but statistically insignificant. Exceptions are related to the TXU and Edison new entrant producers, which were the recipients of divested production facilities.

The estimation results provide statistical evidence that the divestment series were more successful than price-cap regulation at fostering bidding behavior consistent with theoretical predictions. However, this took place at the expense of an increased incentive to exercise market power by the incumbent producers, which was discussed earlier. This, therefore, suggests that the structural remedies were generally more successful than behavioral remedies at fostering bidding behavior consistent with theoretical predictions, but not necessarily at decreasing the extent of exercising market power. Nevertheless, because in a less concentrated market structure it is easier to promote competitive bidding, structural remedies could be superior.

For the robustness check, in Table 1.5, I also consider peak-demand trading periods with real price markups. The real price markups are calculated using producer price indices for the electricity industry published by the Office for National Statistics. Qualitatively, conclusions regarding the analysis of the theoretical predictions and the evaluation of the impact of regulatory reforms are similar to those for nominal price markups. The results are therefore generally robust.

1.7 Conclusions

This paper examines the impact of regulatory reforms introduced during the liberalization process of the electricity supply industry in Great Britain on the bidding behavior of electricity producers. For this purpose, a duopoly case is considered in order to identify the incentive and disincentive to exercise market power. The functional form is also based on the conclusions of the duopoly case.

During the price-cap regulation the theoretical prediction regarding the disincentive to exercise market power was not confirmed for the incumbent producers due to statistically insignificant estimation results. However, after the divestment series were introduced, the bidding behavior of the incumbent producers conformed to the theoretical predictions. At the same time, though, I find statistical evidence for the increased incentive to exercise market power.

Structural remedies implemented through divestment series are therefore found to be more successful at promoting bidding behavior consistent with theoretical predictions but not necessarily at mitigating the exercise of market power. Generally structural remedies could be preferred to behavioral remedies implemented through the price-cap regulation. After divestments, the market concentration decreases, which facilitates promoting competitive bidding among electricity producers.

In addition to the analysis of the bidding behavior of electricity producers during peak-demand trading periods with nominal price markups, I also analyze the bidding behavior of electricity producers with real price markups. Qualitatively, the results generally conform to those with nominal price markups.

References

Bergman, L., Doyle, C., Gual, J., Hultkrantz, L., Neven, D., Röller, L.-H., Waverman, L., 1998. Europe's Network Industries: Conflicting Priorities – Telecommunications. Vol. 1 of Monitoring European Deregulation. Center for Economic Policy Research, London.

Borenstein, S., Bushnell, J. B., Wolak, F. A., 2002. Measuring market inefficiencies in California's restructured wholesale electricity market. American Economic Review 92 (5), 1376–1405.

Crawford, G. S., Crespo, J., Tauchen, H., 2007. Bidding asymmetries in multi-unit auctions: implications of bid function equilibria in the British spot market for electricity. International Journal of Industrial Organization 25 (6), 1233–1268.

Department of Trade and Industry, 1993–2000. Energy Trends. Department of Trade and Industry, London.

Department of Trade and Industry, 1997–2002. Digest of United Kingdom Energy Statistics. Department of Trade and Industry, London.

Electricity Pool, 1990. Pooling and Settlement Agreement for the Electricity Industry in England and Wales. Electricity Pool of England and Wales, London.

Evans, J. E., Green, R. J., 2005. Why did British electricity prices fall after 1998? mimeo, University of Surrey and University of Birmingham.

Geradin, D., 2006. Twenty years of liberalization of network industries in the European Union: Where do we go now? mimeo, Tilburg University.

Green, R. J., 2006. Market power mitigation in the UK power market. Utilities Policy 14 (2), 76–89.

Green, R. J., 2011. Did English generators play Cournot? Capacity withholding in the electricity pool. mimeo, University of Birmingham (updated version).

Green, R. J., Newbery, D. M., 1992. Competition in the British electricity spot market. Journal of Political Economy 100 (5), 929–953.

Joskow, P. L., 2009. Foreword: US vs. EU electricity reforms achievement. In: Glachant, J.-M., Lévêque, F. (Eds.), Electricity Reform in Europe. Edward Elgar Publishing Limited, Cheltenham.

Joskow, P. L., Kahn, E., 2002. A quantitative analysis of pricing behavior in California's wholesale electricity market during summer 2000. Energy Journal 23 (4), 1–35.

Mount, T., 2001. Market power and price volatility in restructured markets for electricity. Decision Support Systems 30 (3), 311–325.

National Grid Company, 1994–2001. Seven Year Statement. National Grid Company, Coventry.

Newbery, D. M., 1999. The UK experience: privatization with market power. mimeo, University of Cambridge.

Robinson, T., Baniak, A., 2002. The volatility of prices in the English and Welsh electricity pool. Applied Economics 34 (12), 1487–1495.

Sweeting, A., 2007. Market power in the England and Wales wholesale electricity market 1995–2000. Economic Journal 117 (520), 654–685.

Sydsæter, K., Hammond, P., Seierstad, A., Strøm, A., 2008. Further Mathematics for Economic Analysis. Pearson Education Limited, Essex.

Von der Fehr, N.-H. M., Harbord, D., 1993. Spot market competition in the UK electricity industry. Economic Journal 103 (418), 531–546.

Wolak, F. A., 2000. Market design and price behavior in restructured electricity markets: an international comparison. In: Deregulation and Interdependence in the Asia-Pacific Region. Vol. 8. NBER-EASE, pp. 79–137.

Wolak, F. A., Patrick, R. H., 2001. The impact of market rules and market structure on the price determination process in the England and Wales electricity market. NBER working paper series no. 8248.

Wolfram, C. D., 1998. Strategic bidding in a multiunit auction: an empirical analysis of bids to supply electricity in England and Wales. RAND Journal of Economics 29 (4), 703–725.

Wolfram, C. D., 1999. Measuring duopoly power in the British electricity spot market. American Economic Review 89 (4), 805–826.

1.A Approximation of marginal costs

Marginal costs of production units are approximated based on the definition of the thermal efficiency rate and data on quarterly input prices provided in Department of Trade and Industry (1997–2002, 1993–2000).

Definition: The thermal efficiency rate is the efficiency rate with which heat energy contained in fuel is converted into electrical energy (Department of Trade and Industry, 1997–2002).

This definition allows expressing the thermal efficiency rate κ of production unit X using input Y to produce 1 MWh of electricity in the following way:

$$\kappa(X,Y) = \frac{\big(\text{1 MWh of electricity}\big) \cdot \text{factor } E}{\text{input } Y \cdot \text{factor } Y}, \tag{6}$$

where the additional terms denoted by factor E and factor Y are multipliers used to convert 1 MWh of electricity and input Y necessary to produce 1 MWh of electricity into the commonly used energy measurement unit, for example, gigajoule (GJ). In particular, because 41.868 GJ = 11.63 MWh, it follows that factor $E = 3.6$ GJ/MWh.

Equation (6) for $\kappa(X,Y)$ suggests that the marginal cost of production unit X using input Y to produce 1 MWh of electricity can be approximated by

$$\begin{aligned} MC(X,Y) &= \big(\text{price of input } Y\big) \cdot \text{input } Y = \\ &= \big(\text{price of input } Y\big) \cdot \frac{\big(\text{1 MWh of electricity}\big) \cdot \text{factor } E}{\kappa(X,Y) \cdot \text{factor } Y}. \end{aligned} \tag{7}$$

If input prices are given in £/MWh, then equation (7) simplifies to

$$MC(X,Y) = \big(\text{price of input } Y\big) \cdot \frac{\big(\text{1 MWh of electricity}\big)}{\kappa(X,Y)}. \tag{8}$$

As summarized in Table 1.4, there are ten types of production unit. Nuclear and hydro types of production unit are far from being pivotal because they mainly operate

Table 1.4: Distribution of types of production unit during January 1, 2000–January 31, 2000

Producer	Types of Production Unit										
	Large Coal	Medium Coal	Small Coal	Oil	Nuclear	CCGT	OCGT	PSB	Hydro	Export	*Subtotal*
National Power	11	6	4	7	–	6	22	–	2	–	58
PowerGen	12	–	–	4	–	8	11	–	4	–	39
BNFL Magnox	–	–	–	–	26	–	–	–	1	–	27
EDF		–	–	–	–	1	–	–	–	11	12
SI	–	–	–	–	–	7	–	–	–	19	26
TXU	8	8	–	–	–	2	8	–	–	–	26
Edison	8	–	–	–	–	–	4	10	–	–	22
British Energy	–	–	–	–	12	–	–	–	–	–	12
AES	6	–	1	–	–	1	4	–	–	–	12
Subtotal	45	14	5	11	38	25	49	10	7	30	234

Source: National Grid Company (1994–2001) publications for various years; author's calculations.

as base-load and are located in the beginning of the aggregate supply schedule. This excludes the necessity to approximate their marginal costs.

Open cycle gas turbine (OCGT) and combined cycle gas turbine (CCGT) production units use gas oil and gas inputs, respectively (Department of Trade and Industry, 1997–2002). Marginal costs of OCGT production units are approximated according to equation (7) because originally the price data on gas oil are available in £/liter. Based on Department of Trade and Industry (1997–2002), first I convert liters to tonnes (using 1163 liters per tonne) and then to gigajoules (using calorific values of 45.5 gigajoules per tonne) for the gas oil input.

Marginal costs of production units using coal, oil, and gas inputs are approximated according to equation (8) because quarterly input prices are available in £/MWh.

The efficiency rate of a production unit varies within an input type. The differences could be related to the age or size of a production unit. That is why, for approximating marginal costs I use production unit specific thermal efficiency rates. For some production units, updated estimates of thermal efficiency rates are available. Using, however, older thermal efficiency rates could, at times, overestimate or underestimate the true marginal costs, leading, thereby, to a measurement error.

The production units of pumped storage business (PSB) have turbines that pump water up to a hill-top reservoir during off-peak periods, which then allows the production of electricity during peak-demand periods or during unexpected shortfalls in system supply. The marginal costs of these pumped facilities are approximated by quarterly minimal price bids.

EDF and Scottish Interconnector are producers that exported electricity into the England and Wales wholesale electricity market. No data describing their technological characteristics are available, which does not allow approximating their marginal costs using equation (7) or (8). Therefore, their marginal costs are also approximated using quarterly minimal price bids.

1.B Robustness check

Table 1.5: Estimation results of equation (3) based on the real markup

Dependent Variable: log($Real\ Markup_{ijt}$)				Regime 3 (Jan 95–Mar 96) Price-cap		Pre-Regime 4 (Apr 96–Jul 96)		Regime 4 (Jul 96–Jul 99) Divestment 1		Regime 5 (Jul 99–Sept 00) Divestment 2	
		Pr	Type	Coef	Std Err	Coef	Std Err	Coef	Std Err	Coef	Std Err
Block 1: Estimation during a reference period	$\hat{\beta}_{1i}$	NP		0.032	0.275						
		PG		0.253**	0.100						
		EDF		0.295***	0.057						
		SI		0.286***	0.077						
		TXU						0.109	0.131		
		Ed		0.058***	0.006						
		BE								0.548***	0.170
		AES						0.025	0.036		
	$\hat{\beta}_{2ij}$	NP	Large Coal	0.167	0.429						
			Medium Coal	0.063	0.472						
			Small Coal	0.426	0.588						
			Oil	0.285	0.413						
			OCGT	0.849	0.679						
		PG	Large Coal	-0.166	0.149						
			Medium Coal	-0.169	0.166						
			Oil	0.040	0.138						
			OCGT	0.345	0.229						
		EDF	Export	0.378***	0.066						
		SI	Export	-0.059	0.101						
			CCGT	-0.221**	0.105						
		TXU	Large Coal					0.035	0.181		
			Medium Coal					0.112	0.210		
			OCGT					0.426	0.404		
		Ed	Large Coal							0.038	0.032
			OCGT							0.623***	0.090
			PSB	0.305***	0.071						
		BE	Large Coal							-0.517**	0.251
		AES	Large Coal							-1.166***	0.024
			OCGT					0.132	0.083		
Block 2: Estimation of a change in comparison to a reference period	$\hat{\delta}_{1i}$	NP				1.306***	0.255	0.560**	0.227	0.476*	0.260
		PG				0.305**	0.145	0.362**	0.168	0.554***	0.111
		EDF						-0.307***	0.017	-0.269***	0.018
		SI				0.180	0.225	0.023	0.098		
		TXU								-0.234**	0.116
		Ed				-0.102***	0.011	-0.019***	0.003	0.155***	0.036
		AES								1.111***	0.066
	$\hat{\delta}_{2ij}$	NP	Large Coal			-2.001***	0.405	-0.742**	0.362	-0.547	0.418
			Medium Coal			-2.126***	0.457	-0.720*	0.404	-0.332	0.461
			Small Coal			-2.946***	0.557	-1.160**	0.498		
			Oil			-1.784***	0.392	-0.676*	0.353	-0.478	0.404
			OCGT			-3.371***	0.647	-1.432**	0.580	-1.237*	0.663
		PG	Large Coal			-0.530**	0.225	-0.444*	0.252	-0.665***	0.171
			Medium Coal			-0.302	0.257				
			Oil			-0.304	0.215	-0.444*	0.245	-0.668***	0.165
			OCGT			-0.897**	0.357	-0.960**	0.409	-1.539***	0.270
		EDF	Export			-0.101	0.072			-0.245***	0.089
		SI	Export			-0.442	0.364	0.002	0.158		
		TXU	Large Coal							0.322**	0.151
			Medium Coal							0.374*	0.191
			OCGT							-0.455	0.348
		Ed	PSB			0.054***	0.007	0.107***	0.005	-0.161***	0.057
		AES	OCGT							-2.250***	0.085
			Intercept	0.668*	0.348						

Notes: The first block contains coefficient estimates of explanatory variables for a reference period. The second block contains coefficient estimates of the interaction terms between regime dummy variables and explanatory variables. The notation for coefficient estimates is described in footnote (7).
Producer–capacity type–day clustered robust standard errors are used for statistical inferences. *, **, and *** stand for the 10%, 5%, and 1% significance levels, respectively. Annual seasonal dummy variables are omitted because they are found statistically insignificant. Obs = 23 009 and $R^2 = 0.602$.

1.C Abbreviations

BE	British Energy
BNFL	British Nuclear Fuels Limited
CCGT	Combined Cycle Gas Turbine
Ed	Edison
EDF	Électricité de France (Electricity of France)
ESI	Electricity Supply Industry
GOAL	Generator Ordering and Loading
MMC	Monopolies and Mergers Commission
NETA	New Electricity Trading Arrangements
NGC	National Grid Company
NP	National Power
OCGT	Open Cycle Gas Turbine
Offer	Office of Electricity Regulation
PG	PowerGen
SFE	Supply Function Equilibrium
SI	Scottish Interconnector
SMP	System Marginal Price
TXU	Texas Utilities (formerly, Eastern Group)

2. Do Producers Apply a Capacity Cutting Strategy to Increase Prices? The Case of the England and Wales Electricity Market*

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CERGE-EI‡

Abstract

Promoting competition among electricity producers is primarily targeted at ensuring fair electricity prices for consumers. Producers could, however, withhold part of production facilities (i.e., apply a capacity cutting strategy) and thereby push more expensive production facilities to satisfy demand for electricity. This behavior could lead to a higher price determined through a uniform price auction. Using the case of the England and Wales wholesale electricity market we empirically analyze whether producers indeed did apply a capacity cutting strategy. For this purpose we examine the bidding behavior of producers during high- and low-demand trading periods within a trading day. We find statistical evidence for the presence of capacity cutting by several producers, which is consistent with the regulatory authority's reports.

Keywords: capacity bids; electricity prices; uniform price auction; regulation

JEL Classification: D22; D44; L50; L94

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2.1 Introduction

Prices of goods and services of general interest play a key role in determining the welfare of a society. Electricity, which usually accounts for a large share of energy consumption, is among those kinds of goods. Nowadays it also has a character of an essential good and understanding the sources and reasons of high electricity price changes therefore becomes an important task. Hence, the key question, given that the electricity industry contains a natural monopoly element and is monitored, is whether consumers face fair prices.

In general, there are several means by which producers could exercise market power. The most common is through an exercise of monopoly power, whereby producers charge prices significantly exceeding their marginal production costs. For the case of the England and Wales electricity market, this type of noncompetitive behavior of electricity producers has been thoroughly studied in, for example, Green and Newbery (1992), Von der Fehr and Harbord (1993), Wolfram (1998), Crawford, Crespo, and Tauchen (2007), and Sweeting (2007).

Another means by which producers on a semi-competitive market could set high prices is through the creation of an artificial deficit. Given a sufficiently high level of demand, this strategy could be successful at increasing prices.[1] Late in 2008, the E.ON AG electricity producer was investigated by the European Commission for abusing its dominant position to withhold available production facilities in the German electricity market with a view to raising electricity prices to the detriment of consumers (European Commission, 2009).

Fridolfsson and Tangerås (2009), using the case of the Nordic wholesale electricity market,[2] suggest that producers may have an incentive to withhold base-load nuclear plants to increase output prices without driving a wedge between output prices and marginal production costs. The authors therefore conclude that strategic withholding when demand

[1]In general, cases of creating an artificial deficit in order to increase prices have been observed in various contexts. One historical example is burning coffee beans in Brazil, which was successful at increasing Brazilian coffee prices in New York by more than 40% (Time, 1932). Another recent example is the artificial creation of a deficit of diesel fuel by oil companies in Russia, which resulted in excessively high prices. The artificial deficit in this case was created by shutting down plants for maintenance reasons (Avtonovosti – Automobile news, 2011).

[2]Most electricity is produced by means of hydro power plants.

is relatively high could be another means of increasing prices.

Exploitation of a capacity cutting strategy undermines the allocative efficiency of production resources. In other words, capacity cutting can introduce distortions to the least-cost production schedules intended to serve demand at lower prices. As a consequence, it may become necessary to operate more expensive production facilities to satisfy demand for electricity at higher prices, whose burden is then eventually transferred to consumers.

Comparing the two means, price bids and capacity bids, Castro-Rodriguez, Marín, and Siotis (2009) conclude that because a regulatory authority can relatively easily monitor the submission of price bids in excess of marginal costs, capacity bids could be regarded as an alternative instrument through which producers may affect prices.

In our research on the England and Wales electricity market, we define capacity cutting as a reduction of the amount of declared available capacity of a production unit when demand is forecasted to increase in the half-hourly day-ahead auction (see Figure 2.2 for a detailed description).[3] We examine producers' bidding behavior between high- and low-demand trading periods (usually evening and afternoon periods). The intra-day analysis of the bidding behavior during different trading days is advantageous for the day-ahead auction because producers are asked to submit capacity bids in advance for each half-hourly trading period of the next trading day. In contrast, an inter-day analysis may not be conclusive because capacity could have been reduced during the following day due to maintenance, fuel reload, etc.

In the following sections we first describe the market rules and institutional background. We then review the related literature. In the empirical methodology we describe the regression model, econometric assumptions, and estimation strategy. Finally we quantitatively assess whether the regulatory reforms during the liberalization process were successful at decreasing the extent of applying a capacity cutting strategy.

[3] An extreme case of applying a capacity cutting strategy is to declare a production unit as unavailable for electricity production, which may not be inexpensive in terms of the associated start-up costs.

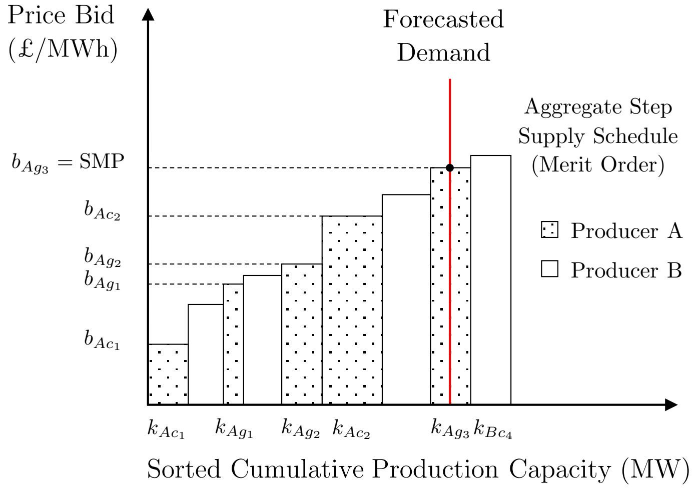
2.2 Electricity auction and market regulation

In this section we first describe the operation of the wholesale electricity market in England and Wales. In particular, using a hypothetical example, we explain the role of producers and the market operator (i.e., the auctioneer). We then proceed to the description of a capacity cutting strategy aimed at increasing the wholesale price. Finally, we describe the reforms introduced by the regulatory authority, the Office of Electricity Regulation (Offer), which were targeted at improving competition and ensuring lower electricity prices.

At the start of liberalization the power grids were separated from the energy production and a wholesale market for electricity trading was created (Bergman, Doyle, Gual, Hultkrantz, Neven, Röller, and Waverman, 1998). Trading was organized through a half-hourly uniform price auction, where electricity producers are asked to submit half-hourly capacity bids and daily bids for all production units. Daily bids include incremental price-offer bids, elbow points, start-up and no-load costs. Then half-hourly price bids for every production unit are calculated based on daily bids and half-hourly declared capacity bids. These rules are common knowledge and described in detail in the Electricity Pool (1990), which is a technical summary used by the market operator, the National Grid Company (NGC). A more intuitive description of trading rules, including the Generator Ordering and Loading (GOAL) algorithm, is also presented in Sweeting (2007).

The market operator orders all production units based on price bids to construct a half-hourly aggregate supply schedule. The market operator also prepares demand forecasts, where the forecasting methodology is common knowledge (Wolak, 2000; Wolak and Patrick, 2001). The forecasting methodology is also independent of producers' bidding behavior (Green, 2006). The production unit whose price bid in the aggregate supply schedule intersects price-inelastic forecasted demand is called the marginal production unit. Its price bid determined the System Marginal Price (SMP) and represented the wholesale price for electricity production during a given half-hourly trading period. This is the uniform auction price paid the same for producers' production units needed to satisfy demand for electricity.

In Figure 2.1, we schematically illustrate how the electricity market would have operated in a given half-hourly trading period. All production units are ordered according to half-hourly price bids.



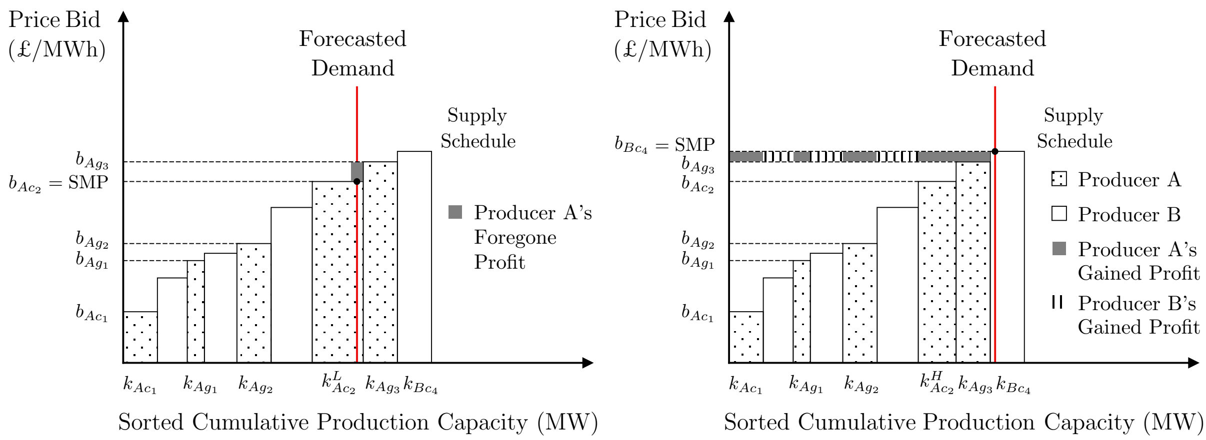
Source: Authors' illustration.

Figure 2.1: Determination of the SMP during a half-hourly trading period

Let b_{Ac_1} denote the price bid of electricity producer A's first coal production unit for which the submitted (declared) production capacity is k_{Ac_1}. For the sake of simplicity, it is assumed that electricity producer A has two coal and three gas types of production units. Price bids of all production units are ordered as would have been done by the market operator to create a half-hourly aggregate supply schedule. The vertical line in the graph is the forecasted demand. The intersection of the constructed aggregate supply schedule and price-inelastic forecasted demand determines the SMP, the wholesale electricity price. In this hypothetical example, it is electricity producer A's third gas production unit whose price bid determines the SMP.

Submitted price and capacity bids for individual production units represent private knowledge for each producer that owns those production units. This is a feature of a sealed-bid uniform price auction, where the bids of one producer are unknown to the other producers.

In the hypothetical example presented in Figure 2.2 we illustrate how a producer could have applied a capacity cutting strategy in order to increase the wholesale price, which is paid the same for all production units needed to satisfy demand for electricity, and thereby, to enjoy higher profits on their scheduled units.



(a) Low-demand trading period (no cutting) (b) High-demand trading period (cutting)

Source: Authors' illustration.
Notes: In (a) we depict part of production capacity k_{Ac_2}, which could have been withheld for the high-demand period. The shaded area depicts the associated loss if capacity cutting were applied. In (b) we illustrate a change in SMP when part of capacity for k_{Ac_2} is withheld (i.e., $k^H_{Ac_2} < k^L_{Ac_2}$). If there were no capacity cutting, then we would observe a lower SMP equal to b_{Ag_3}. The shaded area depicts, therefore, the gain associated with applying capacity cutting during the high-demand trading period.

Figure 2.2: Capacity strategy

For illustration purposes, in this example, we assume that producers submit price bids reflecting marginal costs. We also assume that during trading period H producer A had decided to restrict the capacity of its second coal production unit (i.e., $k^H_{Ac_2} < k^L_{Ac_2}$), which led to a higher SMP.[4] If there were no capacity cutting, then we would observe a lower SMP equal to b_{Ag_3}. Producer A's loss and gain associated with applying a capacity cutting strategy are depicted by the shaded area in Figures 2.2a and 2.2b, respectively.

From the presented example we see that applying capacity cutting may indeed be profitable and could also serve as a positive externality for competitors. As Dechenaux and Kovenock (2007) find, capacity cutting may even be necessary to sustain tacit collusion.

[4]Withholding a whole production unit can be interpreted as a special case of a capacity cutting strategy.

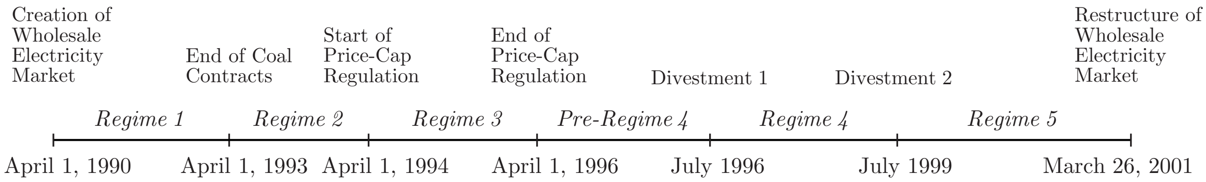
All of this tends to eventually decrease consumers' welfare. Moreover, the difference between gain and loss may be greater, resulting in an even larger SMP, if producers strategically submit price bids in excess of marginal costs, where the latter has been studied in, for example, Green and Newbery (1992), Von der Fehr and Harbord (1993), Wolfram (1998), Crawford et al. (2007), and Sweeting (2007).

As described in Figure 2.2, in our analysis we focus on strategic capacity bidding which may drive up spot wholesale prices (i.e., the SMP). We do not consider contracts for differences (CfD) that are linked to SMP because data on financial positions are commercially confidential.[5] Our approach is partly consistent with the methodology in Cramton, Ockenfels, and Stoft (2013) modeling the operation of capacity markets. The authors assume that electricity producers are paid spot prices even if most output is sold forward. This assumption is motivated by the fact that the prices for forward contracts are linked to expected spot market prices for electricity through intertemporal arbitrage. Moreover, because in the England and Wales electricity market the coverage of sales by CfDs generally decreased (Green, 1999; Herguera, 2000), we can consider that there may have been short-term incentives for producers' strategic capacity bidding.

The regulatory authority, Offer, noticed cases of excessively high electricity prices, which were attributed to the possible noncompetitive bidding behavior of the incumbent electricity producers (National Power and PowerGen). In order to decrease the influence of the incumbent producers on the wholesale electricity market, the regulatory authority introduced several reforms in the Electricity Supply Industry (ESI) in Great Britain. The time of the introduced institutional changes and regulatory reforms define different regime periods, which are summarized in Figure 2.3.

At the time of the creation of the wholesale electricity market, coal and other contracts were introduced by the government, which then expired in 1993. Later, the regulatory authority introduced price-cap regulation and divestment series. The price-cap regulation

[5]This is also a limitation in Robinson and Baniak (2002), where the authors state that producers could have been deliberately increasing price volatility in order to enjoy higher risk premia in the contract market. This statement, however, has not been empirically verified.



Sources: Department of Trade and Industry (1997–2002), National Grid Company (1994–2001), Newbery (1999), Robinson and Baniak (2002), Wolfram (1999); authors' illustration.

Figure 2.3: Institutional changes and regulatory reforms in the ESI in Great Britain during 1990–2001

during 1994–1996 was a temporary measure designed to control the annual average prices set by the incumbent electricity producers. In order to decrease market concentration and improve competition, the incumbent electricity producers were asked to divest part of their production facilities, which took place in 1996 and 1999. In March 2001, the wholesale electricity market was restructured to introduce bilateral trading arrangements.

When defining regime periods we consider the exact dates in which the reforms were introduced. This approach better reflects the nature of the divestment series introduced by the regulatory authority. For example, the introduction of the first series of divestments for PowerGen led to the transfer of all medium coal production facilities to Eastern Group, which was later renamed TXU (National Grid Company, 1994–2001).[6] Hence, we assume that the structural breaks are exogenously given by the dates when the reforms were introduced. It is also worth mentioning that the structural changes introduced through the two divestment series differ because the first series of divestments included the lease and the second series of divestments included the sale of production facilities (National Grid Company, 1994–2001). Hence, the impact of the two divestment series on the bidding behavior of electricity producers is likely to be different.

Table 2.1 describes the distribution of shares of production capacity and price setting among electricity producers between the financial years 1995/1996 and 1999/2000. To

[6] A separate analysis of the bidding behavior of PowerGen with respect to medium coal production facilities several days or weeks before the actual divestment took place may not be statistically reliable due to a small number of observations. For Eastern Group, it would not be possible because Eastern Group did not have coal production facilities before and therefore could not participate in the auction by submitting bids for coal production units.

the original table reproduced from Bishop and McSorley (2001) we add a measure of the Herfindahl–Hirschmann Index (HHI) computed as a sum of squared shares. The calculations show that thanks to the divestment series and new entry the concentration measure decreased by almost twofold.

Table 2.1: Structural impact of National Power and PowerGen divestments

Producer	Share of Capacity		Share of Price Setting	
	1995/1996	1999/2000	1995/1996	1999/2000
National Power	33.7	13.0	44.8	14.6
PowerGen	28.1	16.5	31.8	16.8
BNFL Magnox	5.8	5.4	0.0	0.0
EDF	3.3	3.3	0.7	10.7
Scottish Interconnector	2.3	2.2	1.7	0.4
TXU	1.6	9.2	7.3	11.8
Edison	3.8	8.9	13.2	21.1
British Energy	12.0	14.8	0.0	4.9
AES	0.5	7.6	0.0	19.3
Combined Cycle Gas Turbines	7.8	17.2	0.5	0.4
Others	1.3	2.0	0.0	0.0
HHI	0.22	0.12	0.33	0.16

Source: Reproduced from Bishop and McSorley (2001).
Note: HHI stands for Herfindahl–Hirschmann Index (sum of squared shares: monopoly = 1).

Similar to Borenstein, Bushnell, and Wolak (2002), we restrict our analysis to electricity producers located in Great Britain. In particular, we exclude the EDF exporter, which was not suspected of abusing market power. We also observe that the incidence of capacity cutting by this producer was very low and its capacity bidding was generally consistent with competitive bidding behavior.

The measures designed to promote competition during the liberalization were more extensive in Great Britain compared to Germany, France, Italy, or Sweden (Bergman et al., 1998). In particular, Joskow (2009) characterizes the privatization, restructuring, market design, and regulatory reforms pursued in the liberalization process of the electricity industry in England and Wales as the international gold standard for energy market liberalization. In this respect, Great Britain, with the longest experience of a liberalization process, can also serve as an important source of lessons.

2.3 Evidence on uniform price auction and incentives for capacity cutting in the literature

Le Coq (2002) and Crampes and Creti (2005) theoretically analyze a two-stage duopoly game, where producers first decide on capacity bids and then compete in a uniform price auction. The authors find that a uniform price auction creates an incentive for strategic capacity cutting when demand is known. This result is generalized for the case of stochastic demand in Sanin (2006).

Joskow and Kahn (2002) study the California spot electricity market during the California electricity crisis that cost $40 billion in added energy costs (Weare, 2003) and find that even after accounting for low levels of imports, high demand for electricity, and high prices of NO_x emissions permits, there are still large deviations of wholesale market prices from the competitive benchmark prices, i.e., the marginal cost of supplying additional electricity at the associated market clearing quantities. The authors find that capacity cutting, which is observed through substantial gaps between maximal and submitted capacity bids during peak-demand periods, could explain the remaining deviations from the competitive benchmark prices. Their observation of gaps between maximal and submitted capacity bids during peak hours has been important for the development of our regression analysis, where we compare capacity bids during low- and peak-demand trading periods within a trading day over time for the case of the electricity market in England and Wales.

The application of competitive benchmark prices to analyze whether an electricity market, as a whole, is setting competitive prices has an advantage of being less vulnerable to the arguments of coincidence and bad luck. This approach allows estimating the scope and severity of departures from competitive bidding over time (Borenstein et al., 2002).

Sweeting (2007) similarly applies the methodology of competitive benchmark prices to analyze the development of market power in the England and Wales electricity market. The author finds that electricity producers were exercising increased market power in the late 1990s. This finding, as the author indicates, is however in contradiction with oligopoly models, which, given that during this period market concentration was falling, would have predicted a reduction in market power.

Sweeting (2007) also finds that from the beginning of 1997 the National Power and PowerGen incumbent electricity producers could have increased their profits by submitting lower price bids and increasing output. From a short-term perspective, these findings are explained as tacit collusion. The latter finding on output could also be related to capacity cutting, which we empirically analyze in this research. This conjecture is consistent with findings in Dechenaux and Kovenock (2007), where the authors consider a symmetric oligopoly market structure with firms having equal sharing of profits. The authors show that in this market structure, operated as a uniform price auction, capacity withholding may even be necessary to sustain collusion.

Earlier, capacity bidding in the same electricity market was empirically studied in Wolak and Patrick (2001) and Green (2011). Wolak and Patrick (2001) show that capacity bids are a more "high-powered" instrument than price bids for strategic bidding. In particular, by analyzing the pattern of submitted half-hourly capacity bids, the authors conclude that the incumbent producers were strategically withholding capacity to increase wholesale prices. These conclusions, however, are mainly drawn from time series observations and probability distributions.

In contrast, in our research we use a regression model and consider the period during the late 1990s. This period also includes several new entrants like the TXU and AES producers. Our approach to consider demand increases within different trading days as producers' possible incentive for strategic capacity bidding is, in general, consistent with observations in Wolak and Patrick (2001) and Joskow and Kahn (2002).

On the other hand, withholding capacity may lead to an increase in the probability that demand will exceed supply, which will ultimately increase capacity payments.[7] Historically, PowerGen successfully applied this strategy during the summer and early fall

[7] Capacity payments are computed as CP = LOLP $\cdot$ (VOLL − SMP), where LOLP stands for Loss of Load Probability (an estimated probability that demand will exceed supply), VOLL for Value of Lost Load (the Pool's estimate of customers' maximum willingness to pay for electricity supply), and SMP for System Marginal Price (a wholesale price).

of 1991. The producer had to stop this practice in response to criticism by the regulatory authority. Almost a decade later, in June 2000, Edison similarly withdrew a large coal production unit of 480 MW capacity from the Fiddlers Ferry plant, which was again investigated by the regulatory authority. The withdrawn production capacity represents approximately 1% of total production capacity operated during peak-demand periods in England and Wales (National Grid Company, 1994–2001). In July, the producer agreed to return the plant to the system and the regulatory authority did not take any action (Ofgem, 2000a). The strategic withholding was calculated to cause a 10% increase in wholesale prices, which during June–July approximately amounted to a total increase in revenues by £100 million (Ofgem, 2000b).

In the analysis of the England and Wales electricity market, Green (2011) distinguishes two incentives for withholding capacity: 1) increasing capacity payments and 2) increasing wholesale prices.[8] Firstly, using Monte Carlo simulations, the author finds that during November–February in 1997–2001 low availability rates are not responsible for raising capacity payments above competitive levels computed based on US availability rates. Secondly, the author finds that the industry's annual truly excess outputs are lower after privatization, which suggests that after privatization producers' output was closer to the optimal pattern and, hence, matching of demand and supply improved.

Because from the long-term perspective neither of the two incentives for withholding capacity is found significant, Green (2011) concludes that the evidence for large-scale capacity withholding is weak. However, this conclusion is not completely in line with findings in Wolak and Patrick (2001) and the regulatory authority's investigation reports.

In our research, by analyzing producers' bidding behavior during peak- and low-demand trading periods within a trading day over time, we intend to add new evidence on whether producers apply capacity cutting to increase prices as described in the hypothetical example in Figure 2.2.

[8]Generally, high capacity payments or wholesale prices during peak-demand periods besides decreasing the economic welfare of consumers may also lead to wrong investment or new entry decisions and increased price volatility.

2.4 Binding theory and empirics

2.4.1 Data and their use

We use two data sets covering the period January 1, 1995–September 30, 2000. The first data set contains half-hourly market data for each trading period and includes observations on forecasted demand and wholesale prices, the System Marginal Price (SMP).

In Figures 2.4 and 2.5 we present the distribution of peak-demand half-hours across regime periods and across seasons, respectively.

A sample summary of the market data with the associated measurement units is presented in Table 2.2.

Table 2.2: Sample of descriptive statistics for market data (January 1, 2000–January 31, 2000)

	Forecasted Demand (MW)	SMP (£/MWh)
Mean	38464.60	24.39
Min	25001.00	8.00
Max	49945.00	77.89
Std Dev	5247.83	12.54
Frequency	30 min	30 min
Obs	1488	1488

Source: Authors' calculations.

Using data on the forecasted demand, we compute demand increases as a relative change in the forecasted demand during the peak-demand trading period compared to the same day preceding low-demand trading period. More precisely, we consider the following:

$$\text{growth in demand}_t = \frac{\text{forecasted demand}_{t,(\text{peak-demand period})}}{\text{forecasted demand}_{t,(\text{peak-demand period}-\text{five hours})}} - 1\,, \tag{9}$$

where t denotes trading day.

Similarly, we compute relative changes in the wholesale price (i.e., SMP):

$$\text{growth in SMP}_t = \frac{\text{SMP}_{t,(\text{peak-demand period})}}{\text{SMP}_{t,(\text{peak-demand period}-\text{five hours})}} - 1\,, \tag{10}$$

where t denotes trading day.

In our research we consider five-hour differences between the peak- and low-demand periods within a trading day. Qualitatively the results are similar to alternative choices of a low-demand period. Considering namely peak-demand periods is crucial because generally it has been documented in the literature that noncompetitive bidding behavior occurs most frequently during peak-demand periods (Joskow and Kahn, 2002).

The application of equations (9)–(10) for market data of a trading day on January 6, 2000 is presented in Table 2.3.

Table 2.3: Relative changes in market demand (MW) and SMP (£/MWh)

$\text{Demand}_{t,(\tau-5\text{hrs})}$	$\text{Demand}_{t\tau}$	Growth in Demand_t	$\text{SMP}_{t,(\tau-5\text{hrs})}$	$\text{SMP}_{t\tau}$	Growth in SMP_t
42825	48215	0.126	55.56	77.89	0.402

Source: Authors' calculations.
Note: Subscript t is trading day (January 6, 2000) and τ is peak-demand trading period (17:30).

The second data set contains data on half-hourly capacity bids (i.e., declared availability) for each trading period, which also includes the identity of an electricity producer, plant, production unit, and capacity (input) type. A sample summary of capacity bidding data is provided in Table 2.4.

Table 2.4: Sample of descriptive statistics for capacity bidding data (January 1, 2000–January 31, 2000)

	Capacity Bid (MW)
Mean	175.41
Min	0.00
Max	989.00
Std Dev	248.12
Frequency	30 min
Obs	450336

Source: Authors' calculations.

In order to exclude the ambiguity that some production capacity is not made available to the market due to, for example, maintenance and other technical reasons, we consider declared capacity bids on a daily basis. More precisely, for each trading day we compute a relative change in submitted capacity during the peak-demand trading period in comparison to the same day preceding low-demand trading period. This relative change in submitted capacity at producer and capacity type level is considered as the dependent (explained) variable in the regression analysis.

Algebraically, the definition of a relative change in capacity between periods can be summarized in the following way:

$$\Delta k_{ijt} = \frac{\sum_{l \in j} k_{ilt,(\text{peak-demand period})}}{\sum_{l \in j} k_{ilt,(\text{peak-demand period}-\text{five hours})}} - 1, \tag{11}$$

where subscripts i, j, l, t denote producer, capacity type, production unit, trading day, respectively and $\sum_{l \in j} k_{ilt,(\text{peak-demand period})}$ denotes producer i's capacity of type j during the peak-demand period of trading day t. The application of equation (11) for submitted (declared) capacity bids on January 6, 2000 is presented in Table 2.5.

Table 2.5: Application of equation (11) for capacity bids during January 6, 2000

Producer	Type	$\sum_{l \in j} k_{ilt,(\tau-5\text{hrs})}$ (MW)	$\sum_{l \in j} k_{ilt,\tau}$ (MW)	Δk_{ijt}	Case consistent with strategy
NP	Large Coal	4845	4350	-0.102	noncompetitive
	Medium Coal	1306	1306	0	competitive
	Oil	1180	1180	0	competitive
	CCGT	3265	3295	0.009	competitive
	OCGT	412	412	0	competitive
PG	Large Coal	4346	4346	0	competitive
	Oil	1350	1350	0	competitive
	CCGT	2991	3032	0.014	competitive
	OCGT	191	191	0	competitive
BNFL	Nuclear	2449	2449	0	competitive
SI	Export	1514	1514	0	competitive
	CCGT	2843	2843	0	competitive
TXU	Large Coal	3792	3792	0	competitive
	Medium Coal	1774	1774	0	competitive
	CCGT	595	595	0	competitive
	OCGT	90	90	0	competitive
Ed	Large Coal	2946	2946	0	competitive
	OCGT	68	68	0	competitive
	PSB	2088	1998	-0.043	noncompetitive
BE	Nuclear	5461	5483.4	0.004	competitive
AES	Large Coal	3225	3225	0	competitive
	CCGT	250	250	0	competitive
	OCGT	215	215	0	competitive

Source: Authors' calculations.
Notes: k denotes capacity and Δk_{ijt} denotes a relative change in capacity, which is computed using equation (11). Subscript i is producer, j is capacity type, l is production unit, t is trading day (January 6, 2000), and τ is peak-demand trading period (17:30). Capacity cutting (i.e., noncompetitive capacity bidding) is defined as a reduction of capacity during the peak-demand period compared to the same day preceding low-demand period.

In Table 2.6, based on the comparison between the peak- and low-demand trading periods within a day, we present the incidence of noncompetitive and competitive capacity bidding behaviors.

Table 2.6: Incidence of noncompetitive and competitive capacity bidding during January 1, 1995–September 30, 2000

Case		Producer	Large Coal	Medium Coal	Small Coal	Oil	Nuclear	CCGT	OCGT	PSB	Export
Competitive bidding consistent	No (cutting)	NP	186	112	17	29	–	885	143	–	–
		PG	346	16	–	18	–	1015	67	–	–
		BNFL	–	–	–	–	198	–	–	–	–
		SI	–	–	–	–		113	–	–	80
		TXU	214	89	–	–	–	173	22	–	–
		Ed	28	–	–	–	–	–	–	41	–
		BE	5	–	–	–	122	–	–	–	–
		AES	11	–	–	–	–	25	15	–	–
	Yes (no change)	NP	1437	1705	1380	1935	–	509	1597	–	–
		PG	1174	302	–	1528	–	371	1897	–	–
		BNFL	–	–	–	–	1588	–	–	–	–
		SI	–	–	–	–		1662	–	–	1570
		TXU	601	670	–	–	–	1510	1478	–	–
		Ed	332	–	–	–	–	–	–	905	–
		BE	139	–	–	–	1138	–	–	–	–
		AES	428	–	–	–	–	694	1312	–	–
	Yes (expanding)	NP	406	180	79	64	–	633	289	–	–
		PG	509	51	–	195	–	643	65	–	–
		BNFL	–	–	–	–	243	–	–	–	–
		SI	–	–	–	–		252	–	–	374
		TXU	705	501	–	–	–	290	48	–	–
		Ed	77	–	–	–	–	–	–	1072	–
		BE	85	–	–	–	377	–	–	–	–
		AES	11	–	–	–	–	19	13	–	–

Source: Authors' calculations.
Note: Capacity cutting (i.e., noncompetitive capacity bidding) is defined as a reduction of capacity during the peak-demand period compared to the same day preceding low-demand period.

The first block in Table 2.6 contains a summary of the incidence of noncompetitive bidding behavior manifested through an application of capacity cutting when demand is forecasted to increase. The distribution of the incidence of noncompetitive bidding across regime periods is presented in Table 2.9.

Cases where producers either do not change or increase declared available capacity when an increase in demand is forecasted are defined to be consistent with competitive bidding behavior. Their incidence results are presented in the last two blocks in Table 2.6. The incidence results can be explained as producers applying a mixed strategy approach between bidding noncompetitively and competitively.[9]

[9] The unexpected technical failures in real-time supply of energy do not affect our identification strategy as they can occur only after the day-ahead bidding is made.

An explanation of capacity cutting during peak-demand periods based on scheduled maintenance reasons is not economically justifiable. If a producer needs to run brief maintenance, then it is most probably done during the low-demand period of a day when prices are usually low. In this case a producer incurs minimal losses associated with not making the capacity available for electricity production.

Table 2.6 suggests that among major power producers Edison has relatively least withheld the PSB type of capacity. However, a more detailed analysis is required with respect to Edison's large coal production capacity, which the producer received during the second series of divestments. As mentioned in Ofgem (2000b), it was the reduction of the large coal capacity type, which led to an increase in wholesale prices.

2.4.2 Empirical methodology

When demand is forecasted to increase producers may bid capacity either noncompetitively (by applying a capacity cutting strategy) or competitively (by increasing or at least not changing declared available capacity). The incidence of noncompetitive and competitive capacity bidding is summarized in Table 2.6. We use a regression analysis to examine the noncompetitive capacity bidding. Specifically, we consider the following regression model:

$$\Delta k_{ijt} = \alpha + \beta_{ij} \cdot \text{growth in demand}_t + \varepsilon_{ijt}, \tag{12}$$

where subscripts i, j, t denote producer, capacity type, trading day, respectively. The dependent variable is defined as a relative change in submitted (declared) capacity during the peak-demand trading period compared to the same day preceding low-demand trading period. This is defined in equation (11). We consider negative values of the dependent variable, which reflect the extent of capacity cutting by producers across various capacity types. The explanatory variable, growth in demand, is defined as a relative increase in forecasted demand during the peak-demand trading period compared to the same day preceding low-demand trading period.

We consider five-hour differences between the peak- and low-demand trading periods. The results are generally similar to those which are based on alternative choices of a low-demand trading period as a comparison benchmark. More importantly, because noncompetitive bidding behavior could be observed mainly during high-demand trading periods, similar to Joskow and Kahn (2002) and Crawford et al. (2007), we analyze the bidding behavior of electricity producers in relation to peak-demand trading periods.[10]

The disturbance term in the regression model is assumed orthogonal to the explanatory variable. The exogeneity assumption of the explanatory variable is in line with the fact that the forecasting methodology the market operator applies is, firstly, common knowledge (Wolak, 2000; Wolak and Patrick, 2001) and, secondly, independent of producers' bidding behavior (Green, 2006).

The slope parameter is assumed to be producer and capacity type specific.[11] It measures the extent of cutting capacity when demand increases by 1%. The intuition that an increase in demand explains the extent of capacity cutting is testable. In particular, if the capacity cutting hypothesis holds, then we should obtain statistical evidence that an increase in demand explains a decrease in capacity made available for electricity production.

However, estimating regression equation (12) is expected to be subject to sample selection bias. The sample selection problem arises in our research because we have selected the noncompetitive sample based on the negative values of the dependent variable. In order to correct for the sample selection problem, we use Heckman's two-step procedure developed in Heckman (1979).

[10] This is the period when the SMP is usually determined at a steeper part of the aggregate supply schedule. In this case, even a small decrease in declared available capacity may have a large effect on the SMP.

[11] A producer can, in general, use different inputs (e.g., coal, gas, etc.) to produce electricity. Therefore, we distinguish production capacities that use different inputs. Moreover, coal input can be used in large-, medium-, and small-sized plants. Because the efficiency rate of production capacity in these plants is different, we also distinguish large coal, medium coal, and small coal types of production capacity. These types of production capacity are usually located in different parts of the aggregate supply schedule. For this reason, we consider not only producer but also capacity type specific parameters.

In the first step we estimate the selection equation using the probit model on the full sample. We assume that demand and wholesale price (i.e., the SMP) increases explain a producer's decision to submit capacity bids noncompetitively or competitively during the peak-demand trading period. Even if growth in SMP is not sufficient, we still can rely on growth in demand thanks to the nonlinearity of the probit model in correcting for the selection bias.[12]

The fitted values from the probit model are used to calculate λ_{ijt}, the inverse Mill's ratio, which is a decreasing function of the probability that an observation is selected into the sample. The calculated $\hat{\lambda}_{ijt}$ is then used in the second step as an additional explanatory variable to estimate the amount equation for the selected sample.

Below we formally summarize the estimation procedure:

$$\mathrm{P}(\text{Decision} = 1|\mathbf{x}) = \Phi(a + b_{ij} \cdot \text{growth in demand}_t + c_{ij} \cdot \text{growth in SMP}_t) \tag{13}$$

$$\Delta k_{ijt} = \alpha + \beta_{ij} \cdot \text{growth in demand}_t + \gamma \cdot \hat{\lambda}_{ijt} + \varepsilon_{ijt}\,, \tag{14}$$

where in equation (13) we use Decision = 1 to code the cutting case. The term $\hat{\lambda}_{ijt}$ is calculated as a ratio of $\hat{\phi}(\cdot)$ and $\hat{\Phi}(\cdot)$. Then equation (14), the amount equation (also called the second stage equation), is estimated only for the noncompetitive sample with Mill's inverse ratio included as a correction term.

This Heckman's two-step procedure is also described in Kmenta (2004). This procedure allows estimating the regression equation free of sample selection bias.

Our methodology is generally consistent with the game-theoretic point of view. In particular, we consider that a firm first decides which bidding strategy to adopt: noncompetitive or competitive. If, for example, in the first stage a firm has decided to bid noncompetitively, then in the second stage it decides on the amount (extent) of capacity cutting.

[12] Our method is robust even when a producer just uses a randomization strategy. The probit model estimates the probability of a particular bidding decision (noncompetitive or competitive capacity bidding). Moreover, our identification strategy is not dependent on random failures because we analyze bidding on a day-ahead auction.

Therefore, regression equation (12) describing capacity cutting behavior is modified according to equation (14). If $\hat{\gamma}$ is found statistically significant, then we can conclude that there would have been a sample selection bias had we not included $\hat{\lambda}_{ijt}$ in the amount equation (i.e., control for the probability of selecting a particularly observed strategy) and hence distorting the coefficient of interest β_{ij}.

For the regulation analysis, we assume that producer and capacity type specific slope parameter β_{ij} may vary during different regime periods described in Figure 2.3. This approach allows us to draw conclusions regarding the effectiveness of regulatory reforms in mitigating the noncompetitive capacity bidding. In particular, using our estimation results, we would be able to draw conclusions if the changes during later regime periods are economically and statistically significant.

2.5 Results and discussion

The discussion of estimation results is divided into two parts. First, we discuss the results of the probit selection equation. Decision = 1 corresponds to noncompetitive capacity bidding and Decision = 0 corresponds to competitive capacity bidding. The incidence of these strategic decisions is summarized in Table 2.6. The estimation of this selection equation is necessary to calculate $\hat{\lambda}_{ijt}$ for the amount equation. We then proceed to the discussion of results for the amount equation describing noncompetitive capacity bidding of producers.

2.5.1 Selection equation

The analysis includes cases of noncompetitive and competitive capacity bidding. They represent 3 970 and 35 043 observations, respectively. Decision = 1 corresponds to noncompetitive capacity bidding when a producer applies a capacity cutting strategy. In Table 2.7 we present our estimation results for the probit selection equation.

Table 2.7: Probit selection equation

$$\text{P(Decision} = 1|\mathbf{x}) = \Phi(a + b_{ij} \cdot \text{growth in demand}_t + c_{ij} \cdot \text{growth in SMP}_t)$$

Dependent Variable: Decision		Growth in Demand ($\hat{b}_{ij}$)		Growth in SMP ($\hat{c}_{ij}$)	
Producer	Type	Coef	Std Err	Coef	Std Err
NP	Large Coal	0.788 ***	0.237	0.031	0.025
	Medium Coal	0.506 *	0.305	-0.074 *	0.042
	Small Coal	-1.062	0.801	-0.341 ***	0.110
	Oil	-2.808 ***	0.453	-0.010	0.031
	CCGT	6.884 ***	0.283	-0.020	0.015
	OCGT	1.050 ***	0.338	-0.002	0.029
PG	Large Coal	3.191 ***	0.275	-0.045 **	0.020
	Medium Coal	-1.978	1.688	0.103	0.103
	Oil	-4.100 ***	1.012	-0.066	0.115
	CCGT	7.520 ***	0.367	0.017	0.053
	OCGT	-0.184	0.534	-0.092	0.078
BNFL	Nuclear	1.929 ***	0.276	-0.067	0.046
SI	Export	-0.241	0.537	-0.052	0.059
	CCGT	-0.331	0.235	0.030	0.027
TXU	Large Coal	0.233	0.328	0.079 *	0.047
	Medium Coal	-0.800	0.725	0.071	0.059
	CCGT	0.948 ***	0.272	-0.001	0.020
	OCGT	-0.754	0.633	-0.385 ***	0.127
Ed	Large Coal	-0.107	0.493	0.003	0.103
	PSB	-3.893 ***	0.453	0.012	0.038
BE	Large Coal	-1.533	1.788	-0.071	0.195
	Nuclear	0.974 ***	0.352	-0.074 *	0.040
AES	Large Coal	0.755	0.850	-0.445 ***	0.165
	CCGT	1.631 **	0.785	-0.383 *	0.231
	OCGT	-0.515	0.605	-0.395 ***	0.062
	Intercept	-1.541 ***	0.059		

Notes: Producer–capacity type–day clustered robust standard errors are used for statistical inferences. *, **, and *** stand for the 10%, 5%, and 1% significance levels, respectively. Obs = 39 013.

The estimation results suggest that the increase of demand and wholesale price (i.e., the SMP) has an asymmetric effect across producers and capacity types. This finding sheds light on producers' differing attitudes in the decision to apply capacity cutting across various types of production capacity and, therefore, supports our assumption that the model parameters may be producer and capacity type specific. In particular, we find that the effect of an increase in demand is the largest for the CCGT type (less profitable and more flexible) belonging to the incumbent producers.

We also find that sometimes the effect of an increase in demand and wholesale price is opposite, indicating the presence of a trade-off in deciding towards capacity cutting.

For statistical inference we apply producer–capacity type–day clustered robust standard errors. This approach allows one to take into account heteroscedasticity and weekly seasonality features. Volatility and seasonality of electricity prices in the given market are studied in Robinson and Baniak (2002) and Tashpulatov (2013).

The fitted values of the probit selection equation are used in calculating the inverse Mill's ratio, which is included as an additional explanatory variable in amount equation (14) describing the noncompetitive bidding behavior at the level of individual producers' capacity types.

2.5.2 Effect of a regulatory regime change

In estimating amount equation (14) we assume that the producer and capacity type specific slope parameter β_{ij} may additionally vary during different regime periods described in Figure 2.3. We present our estimation results in Table 2.8. This amount equation is estimated using observations corresponding to capacity cutting with sample selection correction for producers' capacity bidding as discussed in the previous section.

Our results indicate that the null hypothesis stating no sample selection problem is rejected. This finding justifies the validity of our assumption that firms first decide on their bidding strategy.

The extent of how much to cut when demand is forecasted to increase is reflected by the producer and capacity type specific slope parameter β_{ij} in amount equation (14). In Table 2.8 we present our estimation results for the slope parameter in front of the growth of demand in two blocks. In the first block we present coefficient estimates for the growth in demand during a reference period. In the second block we present coefficient estimates for the interaction terms between regime dummy variables and growth in demand. The second block in the estimation table allows us to observe changes for β_{ij} during later regime periods in the extent of capacity cutting associated with demand increases. The estimation results indicate that there are differences in the bidding behavior across not only producers but also capacity types. This generally supports our assumption of the producer and type specific parameter β_{ij}.

Table 2.8: Amount equation: $\Delta k_{ijt} = \alpha + \beta_{ij} \cdot \text{growth in demand}_t + \gamma \cdot \hat{\lambda}_{ijt} + \varepsilon_{ijt}$

Dependent Variable: Δk_{ijt}			Regime 3 (Jan 95–Mar 96) Price-cap		Pre-Regime 4 (Apr 96–Jul 96)		Regime 4 (Jul 96–Jul 99) Divestment 1		Regime 5 (Jul 99–Sept 00) Divestment 2	
	Pr	Type	Coef	Std Err	Coef	Std Err	Coef	Std Err	Coef	Std Err
Block 1: Growth in Demand ($\hat{\beta}_{ij}$) Estimation during a reference period	NP	Large Coal	0.068***	0.025						
		Medium Coal	-0.484***	0.089						
		Small Coal	-0.121	0.163						
		Oil	-0.164	0.135						
		CCGT	-0.410***	0.077						
		OCGT	-0.037	0.024						
	PG	Large Coal	-0.058	0.037						
		Medium Coal	-0.379	0.250						
		Oil	-0.020	0.184						
		CCGT	-0.383***	0.080						
		OCGT	0.090	0.064						
	BNFL	Nuclear	0.024	0.020						
	SI	Export	-0.509*	0.287						
		CCGT	-1.304***	0.274						
	TXU	Large Coal					0.180*	0.108		
		Medium Coal					-0.665***	0.105		
		CCGT	-0.213	0.278						
		OCGT					-0.466***	0.140		
	Ed	Large Coal							-0.355***	0.056
		PSB	0.096	0.123						
	BE	Large Coal							-0.770***	0.256
		Nuclear			0.166***	0.027				
	AES	Large Coal							-0.299***	0.052
		CCGT							0.140***	0.033
		OCGT							-0.186	0.135
Block 2: Regime × Growth in Demand ($\hat{\delta}_{ij}$) Change in comparison to a reference period	NP	Large Coal			0.056***	0.019	-0.095***	0.019	-0.658***	0.120
		Medium Coal			0.070	0.072	0.092	0.074	-0.463*	0.267
		Small Coal			NA		-0.205***	0.055		
		Oil			-0.553***	0.191	-0.784***	0.192	-0.195	0.711
		CCGT			0.132***	0.023	0.079**	0.031	0.075***	0.027
		OCGT			0.034	0.024	-0.006	0.018	-0.101	0.065
	PG	Large Coal			0.013	0.018	-0.030**	0.013	-0.167**	0.069
		Oil			0.372**	0.160	-1.257**	0.624		
		CCGT			-0.062***	0.022	-0.008	0.015	0.000	0.007
		OCGT			-0.050	0.092	-0.084	0.078	-0.483***	0.042
	BNFL	Nuclear			0.086***	0.027	0.003	0.030	0.021**	0.009
	SI	Export			0.423	0.308	0.270	0.289	0.136	0.342
		CCGT			1.123***	0.362	0.918***	0.259	1.471***	0.263
	TXU	Large Coal							-0.663***	0.117
		Medium Coal							0.185	0.138
		CCGT			0.249	0.322	0.037	0.293	-0.654***	0.183
		OCGT							0.185	0.152
	Ed	PSB			NA		0.042	0.180	0.498***	0.100
	BE	Nuclear					-0.136***	0.016	-0.260***	0.028
		$\hat{\gamma}$	-0.112***	0.019						
		Intercept	0.141***	0.032						

Notes: The first block contains coefficient estimates for a reference period and the second block for the interaction terms with regime dummy variables. Producer–capacity type–day clustered robust standard errors are used for statistical inferences. *, **, and *** stand for the 10%, 5%, and 1% significance levels, respectively. Obs = 3 970 and $R^2 = 0.376$.

In the following sections we first discuss estimation results for the incumbent electricity producers. Next we review the results for the state-owned British Nuclear Fuels Limited (BNFL) and exporting Scottish Interconnector (SI) producers. We then discuss in detail the findings for TXU and Edison, which received plants during the divestment series. We conclude our discussion with the British Energy and AES producers.

Incumbent producers: National Power and PowerGen

Our estimation results presented in the first block of Table 2.8 indicate statistical evidence for the presence of capacity cutting by the incumbent electricity producers (NP and PG) in peak-demand trading periods during price-cap regulation. Wolfram (1999) identifies that price-cap regulation led the industry supply curve to rotate counterclockwise. The author explains the change in the industry supply curve as the consequence of reducing prices when demand is low and increasing them when demand is high in order to satisfy the price cap. Our result on capacity cutting during peak-demand periods may therefore provide a possible alternative explanation of how the bidding behavior of producers during price-cap regulation led the industry supply curve to rotate counterclockwise.

Based on the estimation results presented in the second block of Table 2.8, we find that for NP (the larger incumbent producer) the extent of applying capacity cutting during peak-demand periods has generally decreased in the pre-regime 4 period (i.e., after price-cap regulation and before divestment series). The only exception is the oil type for which the extent of capacity cutting has increased. For the small coal type during pre-regime 4 we do not observe capacity cutting at all.

After the divestment series, the extent of capacity cutting compared to the price-cap regulation period (i.e., regime 3) has increased for almost all types. That is, we find that in absolute terms $\hat{\beta}_{ij}^{\text{Regime 4}}$ and $\hat{\beta}_{ij}^{\text{Regime 5}}$ are greater than $\hat{\beta}_{ij}^{\text{Regime 3}}$ for $i = \text{NP}$ and $j \in \{\text{Large Coal, Small Coal, Oil, OCGT}\}$.[13] An exception is related to the medium coal (during regime 4) and CCGT (during all later regimes) types for which the extent of capacity cutting has decreased. Generally, after the second series of divestments the extent of capacity cutting by NP has increased with the exception of the CCGT type.

Qualitatively, the estimation results related to the noncompetitive bidding behavior

[13] We use the following notation: $\hat{\beta}_{ij}^{\text{Pre-Regime 4}} = \hat{\beta}_{ij}^{\text{Regime 3}} + \hat{\delta}_{ij}^{\text{Pre-Regime 4}}$, $\hat{\beta}_{ij}^{\text{Regime 4}} = \hat{\beta}_{ij}^{\text{Regime 3}} + \hat{\delta}_{ij}^{\text{Regime 4}}$, $\hat{\beta}_{ij}^{\text{Regime 5}} = \hat{\beta}_{ij}^{\text{Regime 3}} + \hat{\delta}_{ij}^{\text{Regime 5}}$, where $\hat{\delta}_{ij}^{\text{Pre-Regime 4}}, \hat{\delta}_{ij}^{\text{Regime 4}}, \hat{\delta}_{ij}^{\text{Regime 5}}$ are the estimates of a change presented in the second block of Table 2.8.

of PG (the smaller incumbent producer) are similar to NP. However, there are differences in the magnitudes of the estimation results. Therefore, the regulatory actions, generally, did not have the same effect on the incumbents' bidding behavior. We explain the observed quantitative differences as the consequence of an unequal horizontal restructuring introduced through divestment series, which affected differently the individual incumbent producers' mix of capacity types.

Our estimation results indicating an increase in the extent of capacity cutting by the incumbent producers after the divestment series is partly consistent with Sweeting (2007), where the author finds that the incumbent producers could have increased their profits by lowering price bids and increasing output. This behavior is interpreted as an indication of possible tacit collusion. Dechenaux and Kovenock (2007) also finds that capacity cutting in a uniform price auction could be even necessary to sustain tacit collusion.

State-owned and exporter producers: BNFL and SI

British Nuclear Fuels Limited (BNFL) was a state-owned company using Magnox nuclear reactors for electricity production. We do not find any statistical evidence for this producer's capacity cutting when demand is forecasted to increase.

Scottish Interconnector (SI) was an exporter of electricity to the wholesale market. There is statistical evidence for this producer's noncompetitive bidding behavior in exporting electricity although to a smaller extent during later regime periods. A reduction in export could have however been related to the increased demand for electricity in Scotland. This producer also had CCGT production facilities located in England and Wales. We find that the extent of cutting for the CCGT type of capacity compared to the reference period has largely decreased during later regime periods.

Divestment recipients: TXU and Edison

TXU is the producer which received plants during the first series of divestments. We find statistical evidence that this producer's bidding behavior is consistent with applying capacity cutting when demand is forecasted to increase (except for the large coal type during regime 4).

During the second series of divestments, the plants were transferred to Edison. There is statistical evidence for this producer's withholding of the large coal capacity type. This is indicated in the first block of Table 2.8 by a statistically significant negative slope coefficient during regime 5. Our finding is consistent with the Ofgem's investigation report into the withdrawal of a large coal production unit by this producer discussed in Section 2.3 (Ofgem, 2000a). However, we do not find statistical evidence for applying capacity cutting for the PSB type when demand is forecasted to increase.

Code of conduct: British Energy and AES

In the following paragraphs we analyze the estimation results for producers that did not wish to join the market abuse license condition (MALC).[14]

Similar to the BNFL producer, there is weak evidence that BE applied capacity cutting for the nuclear capacity type during pre-regime 4 and regime 4 periods. However, because $\hat{\beta}_{ij}^{\text{Regime 5}} = \hat{\beta}_{ij}^{\text{Pre-Regime 4}} + \hat{\delta}_{ij}^{\text{Regime 5}}$ is negative for i = BE and j = Nuclear, we can state that during the last regime period there is statistical evidence for cutting nuclear capacity during peak-demand periods. Our finding from a short-term perspective is partly consistent with the suggestion in Fridolfsson and Tangerås (2009) that producers may restrict base-load nuclear capacity to increase electricity prices.

The estimation results presented in the first block of Table 2.8 indicate noncompetitive bidding behavior of BE with respect to the large coal capacity type (a negative estimate for the slope parameter). However, as the incidence of cutting is relatively very low (see Table 2.6), we can conclude that the evidence of capacity cutting for the large coal capacity is generally weak.

The second producer which did not sign the MALC was AES. Our estimation results presented in the first block of Table 2.8, indicate weak evidence for capacity cutting

[14]The regulatory authority proposed a license condition targeted at tackling market abuse in 2000. Because two major electricity producers, British Energy and AES, refused to accept the MALC, the regulatory authority referred the matter to the Competition Commission (CC). The CC subsequently did not approve the introduction of the MALC although it acknowledged the possibility that British Energy could profit from capacity cutting (Ofgem, 2000b).

with respect to CCGT and OCGT production facilities. However, we find statistical evidence consistent with capacity cutting for the large coal capacity type when demand is forecasted to increase. We also observe that the incidence of cutting and expanding patterns summarized in Table 2.6 is the same for this producer's large coal capacity.

2.6 Conclusions

Using the case of the England and Wales electricity market, we analyze whether producers apply a capacity cutting strategy to increase prices at a uniform price auction. The capacity cutting strategy may allow producers to artificially create deficit and drive up wholesale electricity prices and hence revenues and profits of all producers on the market.

Our results suggest that the extent of applying capacity cutting by the incumbent electricity producers has increased after the divestment series (with two exceptions for the NP producer). This result is partly consistent with the simulation study of Sweeting (2007), who finds that during the late 1990s the incumbent producers could have increased profits by lowering price bids and increasing output. Based on the findings in Dechenaux and Kovenock (2007), we suggest that restricting capacity could have been necessary to sustain tacit collusion, which is also consistent with the findings of possible tacit collusion discussed in Sweeting (2007).

Quantitatively, however, the estimation results differ for the incumbent producers. We explain this as the consequence of an unequal horizontal restructuring, which affected differently the capacity mix of the individual incumbent producers. Our results also suggest that divestment series were successful at reducing the extent of applying capacity cutting for the CCGT type of production capacity belonging to the NP producer.

Generally, statistical evidence for capacity cutting by BNFL during peak-demand periods is weak. This finding is partly in line with the simulation study of Green (2011), who also finds weak evidence for large-scale capacity withholding.

We find statistical evidence indicating capacity cutting by Edison with respect to the large coal type of capacity. This finding is consistent with Ofgem's official investigation of capacity withdrawal by this producer (Ofgem, 2000a; Ofgem, 2000b). Making less base-load or infra-marginal capacity available may force the market operator to use more expensive and sometimes less efficient production facilities, which in the end could lead to higher electricity prices to the detriment of consumers' welfare.

There is also statistical evidence that the BE and AES producers, which did not sign the market abuse license condition (MALC), restricted their nuclear and large coal capacity during peak-demand periods. This can be interesting evidence in reasoning why the BE and AES producers did not wish to join the MALC code of conduct.

References

Avtonovosti – Automobile news, 2011. Ceny na soljarku: polnyj absurd i naglost' – Prices of diesel fuel: complete absurdity and impudence. Available at: http://auto.mail.ru/article.html?id=34055 [Accessed: April 14, 2011].

Bergman, L., Doyle, C., Gual, J., Hultkrantz, L., Neven, D., Röller, L.-H., Waverman, L., 1998. Europe's Network Industries: Conflicting Priorities – Telecommunications. Vol. 1 of Monitoring European Deregulation. Center for Economic Policy Research, London.

Bishop, S., McSorley, C., 2001. Regulating electricity markets: experience from the United Kingdom. Electricity Journal 14 (10), 81–86.

Borenstein, S., Bushnell, J. B., Wolak, F. A., 2002. Measuring market inefficiencies in California's restructured wholesale electricity market. American Economic Review 92 (5), 1376–1405.

Castro-Rodriguez, F., Marín, P. L., Siotis, G., 2009. Capacity choices in liberalized electricity markets. Energy Policy 37 (7), 2574–2581.

Crampes, C., Creti, A., 2005. Capacity competition in electricity markets. Economia delle Fonti di Energia e dell'Ambiente 2, 59–83.

Cramton, P., Ockenfels, A., Stoft, S., 2013. Capacity market fundamentals. Economics of Energy and Environmental Policy 2 (2), 27–46.

Crawford, G. S., Crespo, J., Tauchen, H., 2007. Bidding asymmetries in multi-unit auctions: implications of bid function equilibria in the British spot market for electricity. International Journal of Industrial Organization 25 (6), 1233–1268.

Dechenaux, E., Kovenock, D., 2007. Tacit collusion and capacity withholding in repeated uniform price auctions. RAND Journal of Economics 38 (4), 1044–1069.

Department of Trade and Industry, 1997–2002. Digest of United Kingdom Energy Statistics. Department of Trade and Industry, London.

Electricity Pool, 1990. Pooling and Settlement Agreement for the Electricity Industry in England and Wales. Electricity Pool of England and Wales, London.

European Commission, 2009. Summary of Commission Decision of 26 November 2008 relating to a proceeding under Article 82 of the EC Treaty and Article 54 of the EEA Agreement (Cases COMP/39.388 – German Electricity Wholesale Market and COMP/39.389 – German Electricity Balancing Market). Official Journal of the European Union 52 (C 36), 8.

Fridolfsson, S.-O., Tangerås, T. P., 2009. Market power in the Nordic electricity wholesale market: a survey of the empirical evidence. Energy Policy 37 (9), 3681–3692.

Green, R. J., 1999. The electricity contract market in England and Wales. Journal of Industrial Economics 47 (1), 107–124.

Green, R. J., 2006. Market power mitigation in the UK power market. Utilities Policy 14 (2), 76–89.

Green, R. J., 2011. Did English generators play Cournot? Capacity withholding in the electricity pool. mimeo, University of Birmingham (updated version).

Green, R. J., Newbery, D. M., 1992. Competition in the British electricity spot market. Journal of Political Economy 100 (5), 929–953.

Heckman, J. J., 1979. Sample selection bias as a specification error. Econometrica 47 (1), 153–161.

Herguera, I., 2000. Bilateral contracts and the spot market for electricity: some observations on the British and the NordPool experiences. Utilities Policy 9 (2), 73–80.

Joskow, P. L., 2009. Foreword: US vs. EU electricity reforms achievement. In: Glachant, J.-M., Lévêque, F. (Eds.), Electricity Reform in Europe. Edward Elgar Publishing Limited, Cheltenham.

Joskow, P. L., Kahn, E., 2002. A quantitative analysis of pricing behavior in California's wholesale electricity market during summer 2000. Energy Journal 23 (4), 1–35.

Kmenta, J., 2004. Elements of Econometrics, 2nd Edition. The University of Michigan Press, Michigan.

Le Coq, C., 2002. Strategic use of available capacity in the electricity spot market. SSE/EFI working paper series no. 496.

National Grid Company, 1994–2001. Seven Year Statement. National Grid Company, Coventry.

Newbery, D. M., 1999. The UK experience: privatization with market power. mimeo, University of Cambridge.

Ofgem, 2000a. Ofgem's Investigation of Edison First Power under the Market Abuse License Condition: Initial Findings. Office of Gas and Electricity Markets, July.

Ofgem, 2000b. R/134 Competition Commission Rejects Market Abuse Licence Condition. Office of Gas and Electricity Markets, December.

Robinson, T., Baniak, A., 2002. The volatility of prices in the English and Welsh electricity pool. Applied Economics 34 (12), 1487–1495.

Sanin, M. E., 2006. Market design in wholesale electricity markets. CORE discussion paper series no. 2006/100.

Sweeting, A., 2007. Market power in the England and Wales wholesale electricity market 1995–2000. Economic Journal 117 (520), 654–685.

Tashpulatov, S. N., 2013. Estimating the volatility of electricity prices: the case of the England and Wales wholesale electricity market. Energy Policy 60, 81–90.

Time, 1932. Brazil: Destroy! Destroy! 19 (23), July.

Von der Fehr, N.-H. M., Harbord, D., 1993. Spot market competition in the UK electricity industry. Economic Journal 103 (418), 531–546.

Weare, C., 2003. The California electricity crisis: causes and policy options. Public Policy Institute of California, San Francisco.

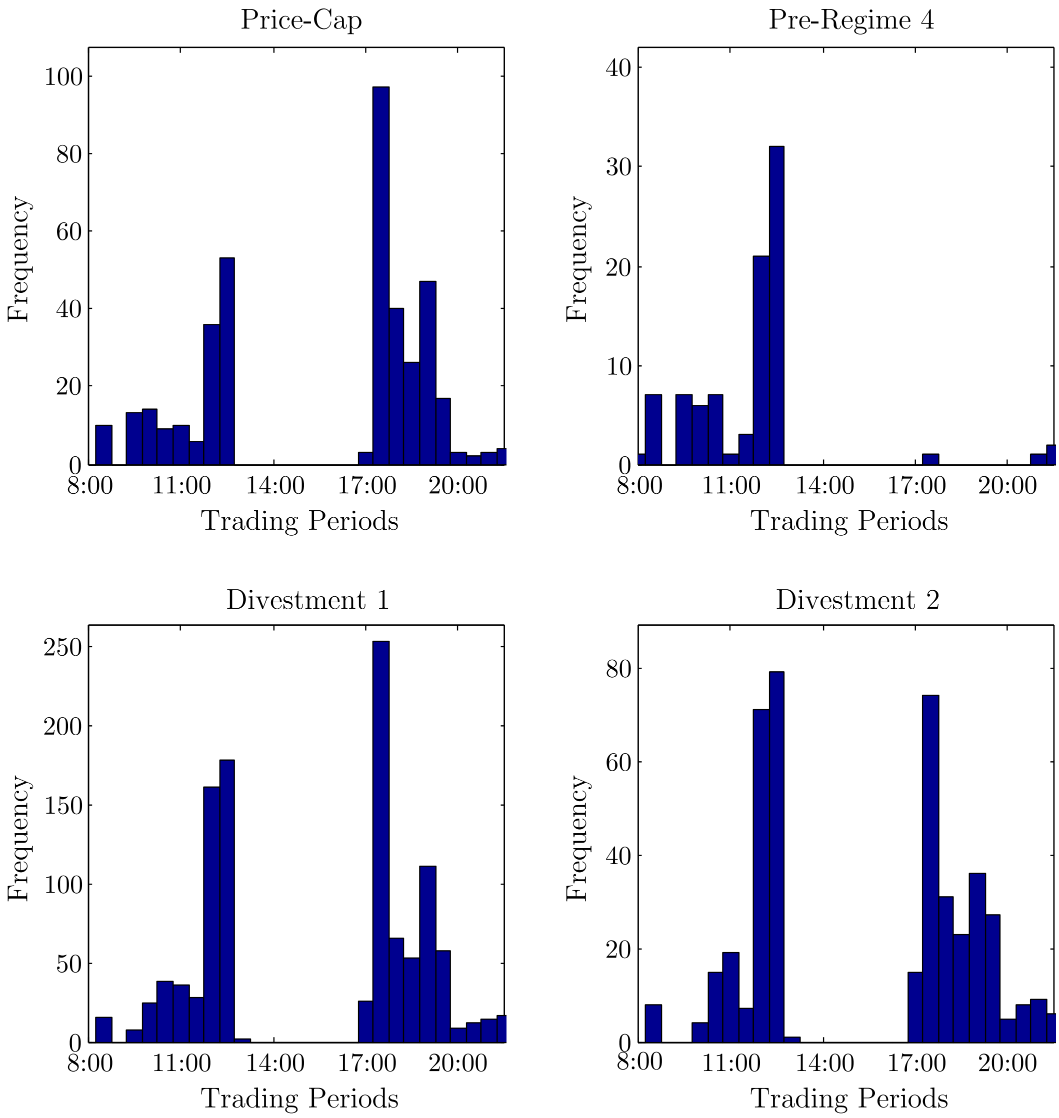
Wolak, F. A., 2000. Market design and price behavior in restructured electricity markets: an international comparison. In: Deregulation and Interdependence in the Asia-Pacific Region. Vol. 8. NBER-EASE, pp. 79–137.

Wolak, F. A., Patrick, R. H., 2001. The impact of market rules and market structure on the price determination process in the England and Wales electricity market. NBER working paper series no. 8248.

Wolfram, C. D., 1998. Strategic bidding in a multiunit auction: an empirical analysis of bids to supply electricity in England and Wales. RAND Journal of Economics 29 (4), 703–725.

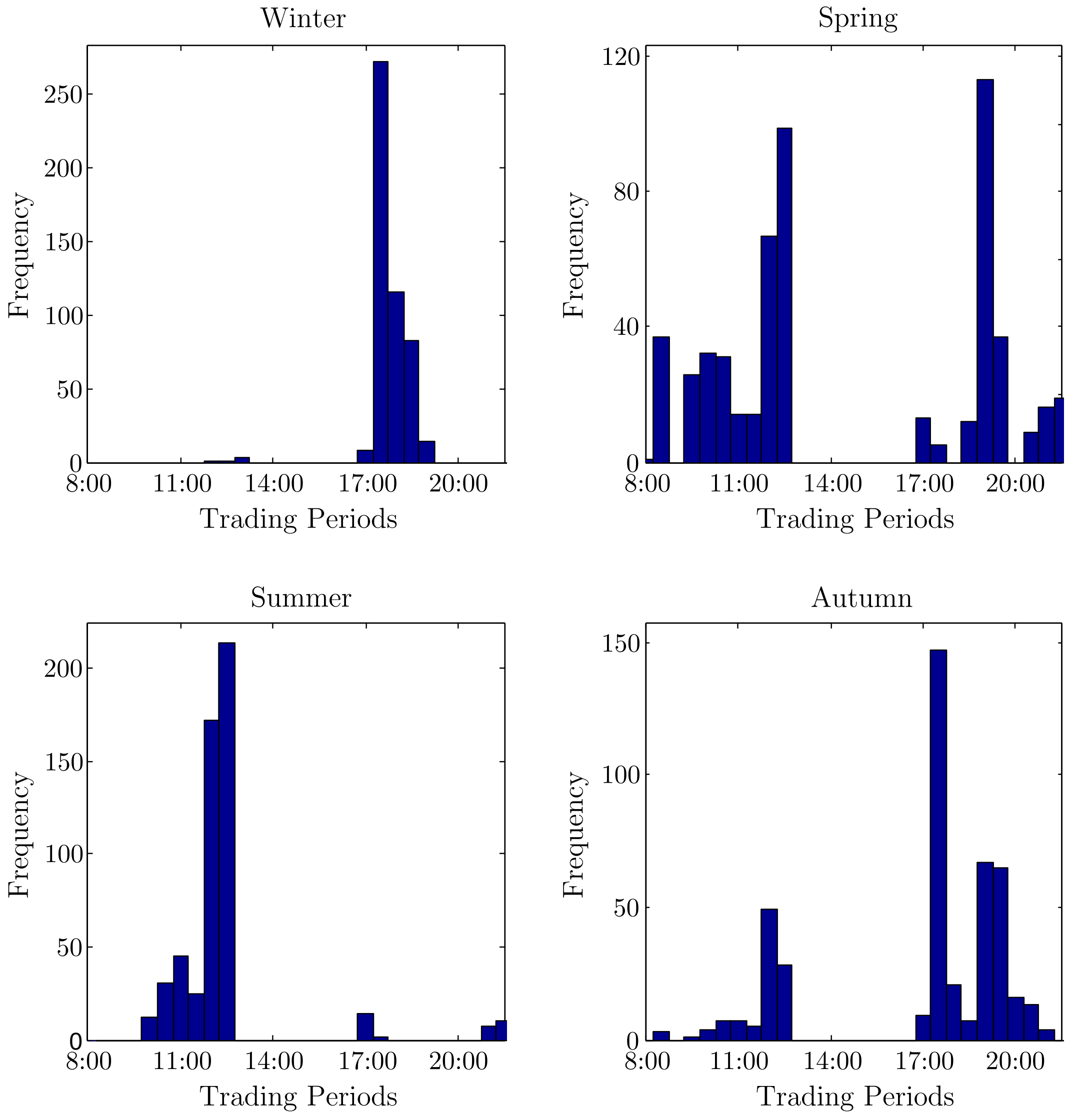
Wolfram, C. D., 1999. Measuring duopoly power in the British electricity spot market. American Economic Review 89 (4), 805–826.

2.A Figures



Sources: Authors' calculations.

Figure 2.4: Incidence of peak-demand periods across regimes during January 1, 1995–September 30, 2000



Sources: Authors' calculations.

Figure 2.5: Incidence of peak-demand periods across seasons during January 1, 1995–September 30, 2000

2.B Tables

Table 2.9: Incidence of noncompetitive capacity bidding across periods

Period	Producer	Large Coal	Medium Coal	Small Coal	Oil	Nuclear	CCGT	OCGT	PSB	Export	*Subtotal*
Regime 3 (Jan 95–Mar 96) Price-cap	NP	48	26	5	14	–	47	39	–	–	179
	PG	78	16	–	8	–	137	20	–	–	259
	BNFL	–	–	–	–	60	–	–	–	–	60
	SI	–	–	–	–	–	38	–	–	12	50
	TXU	–	–	–	–	–	6	–	–	–	6
	Ed	–	–	–	–	–	–	–	4	–	4
	Subtotal	126	42	5	22	60	228	59	4	12	558
Pre-Regime 4 (Apr 96–Jul 96)	NP	16	8	–	4	–	56	16	–	–	100
	PG	24	–	–	3	–	60	10	–	–	97
	BNFL	–	–	–	–	15	–	–	–	–	15
	SI	–	–	–	–	–	14	–	–	11	25
	TXU	–	–	–	–	–	11	–	–	–	11
	BE	–	–	–	–	18	–	–	–	–	18
	Subtotal	40	8	–	7	33	141	26	–	11	266
Regime 4 (Jul 96–Jul 99) Divestment 1	NP	88	67	12	4	–	554	75	–	–	800
	PG	221	–	–	7	–	600	31	–	–	859
	BNFL	–	–	–	–	51	–	–	–	–	51
	SI	–	–	–		–	34	–	–	29	63
	TXU	193	70	–	–	–	151	17	–	–	431
	Ed	–	–	–	–	–	–	–	10	–	10
	BE	–	–	–	–	78	–	–	–	–	78
	Subtotal	502	137	12	11	129	1339	123	10	29	2292
Regime 5 (Jul 99–Sept 00) Divestment 2	NP	34	11	–	7	–	228	13	–	–	293
	PG	23	–	–	–	–	218	6	–	–	247
	BNFL	–	–	–	–	72	–	–	–	–	72
	SI	–	–	–	–	–	27	–	–	28	55
	TXU	21	19	–	–	–	5	5	–	–	50
	Ed	28	–	–	–	–	–	–	27	–	55
	BE	5	–	–	–	26	–	–	–	–	31
	AES	11	–	–	–	–	25	15	–	–	51
	Subtotal	122	30	–	7	98	503	39	27	28	854
Subtotal for All Periods		790	217	17	47	320	2211	247	41	80	3970

Source: Authors' calculations.
Note: Noncompetitive capacity bidding is defined as a reduction of capacity during the peak-demand period compared to the same day preceding low-demand period.

2.C Abbreviations

BE	British Energy
BNFL	British Nuclear Fuels Limited
CC	Competition Commission (formerly, the MMC)
CCGT	Combined Cycle Gas Turbine
CfD	Contract for Differences
Ed	Edison
EDF	Électricité de France (Electricity of France)
ESI	Electricity Supply Industry
GOAL	Generator Ordering and Loading
HHI	Herfindahl–Hirschmann Index
MALC	Market Abuse License Condition
MMC	Monopolies and Mergers Commission
NGC	National Grid Company
NP	National Power
OCGT	Open Cycle Gas Turbine
Offer	Office of Electricity Regulation
Ofgem	Office of Gas and Electricity Markets (formerly, Offer)
PG	PowerGen
PSB	Pumped Storage Business
SI	Scottish Interconnector
SMP	System Marginal Price

3. Estimating the Volatility of Electricity Prices: The Case of the England and Wales Wholesale Electricity Market*

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CERGE-EI‡

Abstract

Price fluctuations that partially comove with demand are a specific feature inherent to liberalized electricity markets. The regulatory authority in Great Britain, however, believed that sometimes electricity prices were significantly higher than what was expected and, therefore, introduced price-cap regulation and divestment series. In this study, I analyze how the introduced institutional changes and regulatory reforms affected the dynamics of daily electricity prices in the England and Wales wholesale electricity market during 1990–2001.

This research finds that the introduction of price-cap regulation did achieve the goal of lowering the price level at the cost of higher price volatility. Later, the first series of divestments is found to be successful at lowering price volatility, which however happens at the cost of a higher price level. Finally, this study also documents that the second series of divestments was more successful at lowering both the price level and volatility.

Keywords: electricity prices; conditional volatility; regulation

JEL Classification: C22; C51; L50; L94

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3.1 Introduction

Fluctuations in electricity prices are usually explained by electricity being nonstorable and the critical need to continuously meet market demand. Prior to liberalization, price fluctuations were generally minimal and controlled. However, after liberalization, during the history of the England and Wales wholesale electricity market, price fluctuations, caused by frequent spikes, were sometimes excessively large. Large fluctuations in electricity prices generally introduce uncertainties about revenues for producers and costs for retail suppliers, which could result in higher prices paid by consumers.

The regulatory authority, the Office of Electricity Regulation (Offer), believed that excessively high prices and fluctuations were possibly the result of the exercise of market power by incumbent electricity producers (National Power and PowerGen). Hence, in order to decrease the influence of the incumbent producers, the regulatory authority introduced price-cap regulation and divestments.

This empirical study quantitatively evaluates the impact of institutional changes and regulatory reforms on price and volatility dynamics. For this purpose I consider an AR–$ARCH$ model, which is extended to include periodic sine and cosine functions to accommodate weekly seasonality. The application of periodic sine and cosine functions, rather than daily dummy variables, is found to lead to a more parsimonious model. Finally, in order to analyze the impact of institutional changes and regulatory reforms on price and volatility dynamics, I also include regime dummy variables, which are created based on the timeline described in Figure 3.1.

The adopted methodology allows evaluating the impact of regulation on price and volatility dynamics during the liberalization process. This research documents new evidence of the impact of price-cap regulation and divestment series on price level and volatility. In particular, I find that the price-cap regulation was successful at lowering the price level, which however happened at the cost of higher price volatility. Later, after the first series of divestments was introduced, the trade-off reversed. I explain this as the evidence of possible tacit collusion, which is also discussed in Sweeting (2007).

The research finally documents that the second series of divestments was more successful at ensuring a lower price level and volatility. The first result, that a lower price level is related to decreased market concentration is consistent with findings in Evans and Green (2003), where the authors using monthly data on capacity ownership and electricity prices show that increases in market competition are chiefly responsible for a decrease in the price level during the late 1990s.

Paul Joskow characterized the privatization, restructuring, market design, and regulatory reforms pursued in the liberalization process of the electricity industry in England and Wales as the international gold standard for energy market liberalization (Joskow, 2009). In this respect, the findings and conclusions of this research could be of interest to countries that have formed or are about to form the operation of their modern electricity markets based on the original model of the England and Wales wholesale electricity market.

3.2 Related literature

After the liberalization of energy industries started in different countries, it became important to model and forecast price development. This is of special interest to producers and retail suppliers because price fluctuations now introduce uncertainties about revenues and costs. A government is also usually interested in understanding price developments resulting, for example, from auctions because they eventually define the costs that consumers will have to face. High costs for energy, besides decreasing the economic welfare of consumers, may also at times undermine the political stability of a country.

Green and Newbery (1992) and Von der Fehr and Harbord (1993) are the seminal studies in modeling electricity auctions. Both of these studies apply their models for the case of the England and Wales wholesale electricity market. Green and Newbery (1992) use the framework of the supply function equilibrium (SFE), where it is assumed that each electricity producer submits a continuously differentiable supply function. This is usually applicable when producers' production units are small enough or when each producer has a sufficiently large number of production units as was the case, for example, with National Power and PowerGen in the early years of the wholesale electricity market. The authors show that a producer with a larger production capacity has more incentive to exercise market power by bidding in excess of marginal costs.

In contrast, Von der Fehr and Harbord (1993) consider the framework where each electricity producer submits a step supply function on the uniform price auction. In particular, the authors model the electricity market as a sealed-bid multiple-unit auction. They demonstrate that no pure-strategy bidding equilibrium exists when electricity demand falls within a certain range. Their result is explained by an electricity producer's conflicting incentives to bid high in order to set a high price and to bid low in order to ensure that its production unit is scheduled to produce electricity.

Similar to Von der Fehr and Harbord (1993), Wolfram (1998) and Crawford, Crespo, and Tauchen (2007) model the market as a sealed-bid multiple-unit auction and empirically examine the bidding behavior of electricity producers. Wolfram (1998) finds that electricity producers submit price bids reflecting higher markups for production units which are likely to be scheduled to produce electricity if that producer has a large infra-marginal production capacity. The author indicates that the incentive to submit a price bid reflecting a higher markup for a certain production unit is moderated by the presence of a threat that the production unit might not be scheduled to produce electricity. Wolfram (1998) also finds that larger producers tend to submit higher price bids than smaller producers for comparable production units (i.e., production units using the same input to produce electricity and having almost the same marginal costs).

Crawford et al. (2007) empirically establish the presence of asymmetries in the bidding behavior of marginal and infra-marginal electricity producers: during the highest-demand trading periods marginal electricity producers behave strategically by submitting price bids higher than their marginal costs, whereas infra-marginal electricity producers behave competitively by submitting price bids reflecting their marginal costs.

Sweeting (2007) analyzes the development of market power in the same electricity market. The author measures market power as the margin between observed wholesale market prices and estimates of competitive benchmark prices, where the latter is defined as the expected marginal cost of the highest-cost production unit required to meet electricity demand. Sweeting (2007) finds that electricity producers were exercising increased market power. This result, as the author indicates, is however in contradiction with oligopoly models, which, when market concentration was falling, would have predicted a reduction in market power. Sweeting (2007) also finds that from the beginning of 1997 the incumbent electricity producers could have increased their profits by submitting lower price bids and increasing output. These findings are explained as tacit collusion.

In the following paragraphs I describe the development of modeling techniques applied for price time series from deregulated electricity supply industries in different countries. This research has been important for my development of the modeling approach to analyze the impact of institutional changes and regulatory reforms on price and volatility dynamics for the case of the England and Wales wholesale electricity market during 1990–2001.

Crespo, Hlouskova, Kossmeier, and Obersteiner (2004) consider the AR and $ARMA$ models to analyze hourly electricity prices from the Leipzig Power Exchange during June 16, 2000–October 15, 2001. The authors' main finding is that models where each hour of the day is studied separately yield uniformly better forecasts than models for the whole time series. Guthrie and Videbeck (2007) analyze half-hourly prices during November 1, 1996–April 30, 2005 from the New Zealand Electricity Market (NEM). The authors similarly find that half-hourly trading periods naturally fall into five groups of trading periods, which can be studied separately. For modeling purposes, the price time series is decomposed into deterministic and stochastic parts. The deterministic part is modeled using a dummy variable approach to take into account the day-of-the-week and month effects. The residuals, which are also called "filtered prices," represent the stochastic part and are modeled using a periodic autoregressive process. For each group Guthrie and Videbeck (2007) consider a periodic model, where a half-hourly price is regressed on the price during the previous trading period and the previous day's price during the same trading period. A detailed overview of periodic time series models is provided, for example, in Franses and Paap (2004).

Huisman, Huurman, and Mahieu (2007) treat hourly electricity prices from the Amsterdam Power Exchange (APX), the European Energy Exchange (EEX; Germany), and the Paris Power Exchange (PPX) for the year 2004 as a panel in which hours represent cross-sectional units and days represent the time dimension. The authors apply the seemingly unrelated regressions (SUR) method.

The findings in Crespo et al. (2004), Guthrie and Videbeck (2007), and Huisman et al. (2007) that each trading period or a group of trading periods should be studied separately across trading days rather than as a whole hourly (or half-hourly) time series, may be the consequence of the application of hourly, daily, and monthly dummy variables for a time-varying intercept term (or the deterministic component), which could not accommodate multiple types of seasonality as well as, for example, smooth periodic sine and cosine functions considered in this research.

Conejo, Contreras, Espínola, and Plazas (2005) find evidence that dynamic modeling is preferable to seasonal differencing when dealing with time series containing multiple types of seasonality. In particular, using the Pennsylvania–New Jersey–Maryland (PJM) interconnection data for the year 2002, the authors find that the *ARMA* dynamic regression models for different seasons, which include hourly, daily, and weekly lags, are more effective in forecasting electricity prices than the *ARIMA* regression models for different seasons, which include hourly, daily, and weekly differencing. This finding justifies my inclusion of lags to accommodate seasonality patterns, which is crucial because otherwise the regulation analysis for a transformed time series (like the removal of a deterministic seasonal component or seasonal differencing) may be incorrect.

However, none of the above studies model the volatility process, which is important for the risk and uncertainty measures. In contrast, Garcia, Contreras, van Akkeren, and Garcia (2005) consider a *GARCH* methodology to model and forecast hourly prices in the Spanish and California electricity markets during 1999–2000. The authors find that in terms of forecasting, their *GARCH* model outperforms a general *ARIMA* model when volatility and price spikes are present. Bosco, Parisio, and Pelagatti (2007) also consider a *GARCH* methodology to model the dynamics of daily average prices of the Italian wholesale electricity market created in 2004. The deterministic part of the price time series is modeled using low-frequency components and the stochastic part using a periodic *AR–GARCH* process. The authors find that the periodic modeling approach seems most appropriate to account for the different amount of memory of past prices that each weekday carries and for the presence of spikes and volatility clustering in electricity prices.

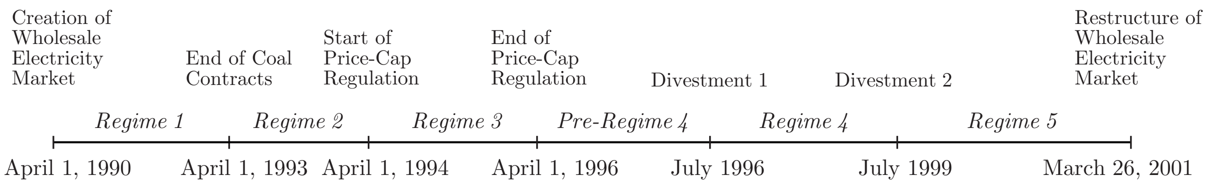
Koopman, Ooms, and Carnero (2007) similarly study daily average prices from the electricity markets in France, Germany, the Netherlands, and Norway. The authors find that a seasonal periodic autoregressive fractionally integrated moving average process with *ARCH* disturbances is the appropriate process to consider for the analysis of daily log-transformed electricity spot prices. This approach is however complex and dependent on the order of seasonal fractional integration, which should not violate the stationarity and invertibility conditions. Another challenging feature is that it is difficult to provide an intuitive interpretation to non-integer differencing.

In general, a major challenge of applying a periodic *AR* process considered, for example, in Guthrie and Videbeck (2007), Bosco et al. (2007), and Koopman et al. (2007) is the requirement to estimate a large number of parameters. In their study, Koopman et al. (2007) suggest, as possible extensions, applying smoothly time-varying parameters for modeling the dynamics of electricity prices, which may lead to a more parsimonious model. This suggestion is considered in Section 3.5.

3.3 The England and Wales electricity market

At the start of liberalization, a wholesale market for electricity trading was organized in England and Wales. This market operated through a half-hourly uniform price auction managed by the National Grid Company (NGC). The resulting half-hourly uniform auction price, which is also known as the System Marginal Price (SMP), determined a payment to producers for electricity production.

The regulatory authority, the Office of Electricity Regulation (Offer), noticed cases of excessively high electricity prices, which were attributed to the possible noncompetitive bidding behavior of the incumbent electricity producers (National Power and PowerGen). In order to decrease the influence of the incumbent electricity producers and thereby reduce the incidence of price spikes leading to price fluctuations being significantly higher than expected, the regulatory authority introduced several reforms in the Electricity Supply Industry (ESI) in Great Britain. The time of the introduced institutional changes and regulatory reforms define different regime periods, which are summarized in Figure 3.1.



Sources: Department of Trade and Industry (1997–2002), National Grid Company (1994–2001), Newbery (1999), Robinson and Baniak (2002), Wolfram (1999); author's illustration.

Figure 3.1: Institutional changes and regulatory reforms in the ESI in Great Britain during 1990–2001

At the time of the creation of the wholesale electricity market, coal and other contracts were introduced by the government, which then expired in 1993. The end of coal contracts is expected to lead to higher price volatility because of increased uncertainty about market prices of coal, which is one of the major inputs in electricity production.

Later, because the regulatory authority believed that the excessively high prices were resulting from the noncompetitive bidding behavior of the incumbent electricity producers, it introduced price-cap regulation and divestments. The price-cap regulation during 1994–1996 was a temporary measure designed to control annual average prices set by the incumbent electricity producers. Later, in order to decrease market concentration and improve competition, the incumbent electricity producers were asked to divest part of their production facilities, which took place in 1996 and 1999.

When defining regime periods for an ex-post regulation analysis, I consider the exact dates in which the reforms were introduced. This approach better corresponds to the nature of the divestment series introduced by the regulatory authority. For example, the introduction of the first series of divestments for PowerGen led to the transfer of all medium coal production facilities to Eastern Group (National Grid Company, 1994–2001). A separate analysis of the bidding behavior of PowerGen with respect to medium coal production facilities several days or weeks before the actual divestment took place may not be statistically reliable due to a small number of observations. For Eastern Group, it would not be possible because Eastern Group did not have coal production facilities before and therefore could not participate in the auction by submitting bids for coal production units. Hence, in order to be consistent with the earlier chapters, I assume that the structural breaks are exogenously given by the dates when the reforms were introduced.

It is worth mentioning that the structural changes introduced through the divestment series differ because the first series of divestments included the lease and the second series included the sale of production facilities (National Grid Company, 1994–2001). Therefore, the effect of the two divestment series, generally, need not be the same.

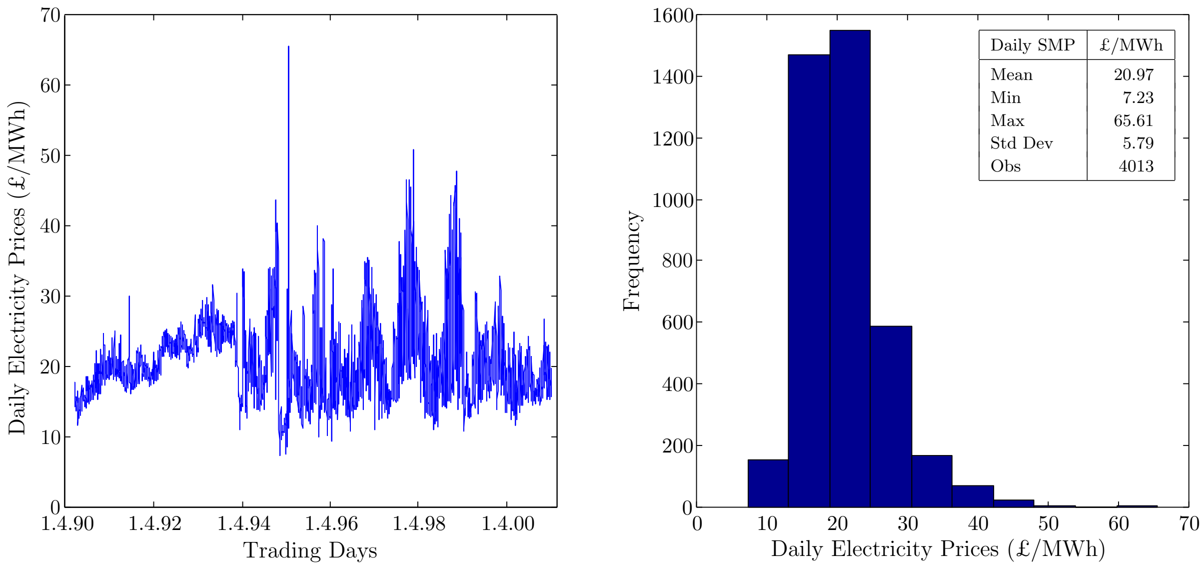
In March 2001, the wholesale electricity market was restructured to introduce bilateral trading arrangements.

3.4 Data

The uniform auction price, also known as the System Marginal Price (SMP), is the half-hourly wholesale price paid to producers for electricity production. Daily electricity prices are defined as daily averages of the half-hourly SMP.

Understanding the dynamics of daily prices from liberalized electricity markets is important because these prices are usually used as a reference price for market valuations and financial contracts (Huisman et al., 2007).

Figure 3.2 describes the development and distribution of daily electricity prices for the whole history of the England and Wales wholesale electricity market. The highest spike in 1995 was brought about by a mistaken mix of technical parameters that the Generator Ordering and Loading (GOAL) algorithm had to accept.[1] Other price spikes in the mid-1990s are probably associated with some plants not being available due to maintenance and interruption of gas supplies in England and Wales and disputes in France (Robinson and Baniak, 2002).



Source: Author's calculations.

Figure 3.2: Daily electricity prices (April 1, 1990–March 26, 2001)

In Table 3.1 I summarize the descriptive statistics of daily electricity prices during the different regime periods described in Section 3.3.

Table 3.1: Summary statistics for daily electricity prices (£/MWh) across regimes

Price	Regime 1	Regime 2	Regime 3	Pre-Regime 4	Regime 4	Regime 5
Mean	19.84	24.16	20.08	19.90	22.61	19.31
Min	11.49	10.98	7.23	12.38	10.71	11.55
Max	30.08	31.53	65.61	33.84	50.92	32.90
Std Dev	2.87	3.56	7.01	4.48	7.62	3.57
Obs	1096	365	731	91	1114	616

Source: Author's calculations.

The preliminary results based on descriptive statistics indicate that the mean and

[1] This explanation is based on a comment from Richard Green.

standard deviation of prices are higher after the expiration of the coal contracts. It is also interesting to note a large decrease in the mean of prices accompanied by a large increase in the standard deviation of prices during the price-cap regulation period. This could indicate a trade-off of attempting to control annual average prices at the expense of larger price fluctuations. The price fluctuations were finally stabilized after the two series of divestments, which were introduced by the regulatory authority as an attempt to decrease the overall influence of the incumbent electricity producers and thereby improve competition in the wholesale electricity market.

In order to draw statistical inferences in the analysis of the impact of institutional changes and regulatory reforms on price and volatility dynamics, I apply time series econometrics techniques. These are described in detail in Section 3.5.

3.5 Methodology

Before modeling the dynamics of daily electricity prices, I first conduct a stationarity test. Then I examine electricity prices using time and frequency domain analyses. The time domain analysis helps specify the AR process, and the frequency domain analysis helps specify the correct frequencies in periodic sine and cosine functions included as additional explanatory variables to model weekly seasonality. The volatility dynamics of electricity prices is modeled using an $ARCH$ process. Finally, in order to account for the presence of institutional changes and regulatory reforms, I enrich the set of explanatory variables to include regime dummy variables. The regime periods are determined based on the known time of institutional changes and regulatory reforms that took place in the ESI in Great Britain during 1990–2001.

3.5.1 Stationarity test

A time series is called covariance stationary if its mean and variance are constant over time and if its covariance depends only on the lag order. This is the weak form of stationarity usually employed in time series econometrics.

A stationarity test is usually conducted before any modeling step is undertaken. The main reason is that many modeling procedures and techniques are applicable to only stationary time series. In particular, correlogram and periodogram techniques, discussed in Section 3.5.2 and Section 3.5.3, respectively, also require the stationarity of a time series (see, for example, Gençay, Selçuk, and Whitcher, 2002).

I test the stationarity of daily electricity prices using the Augmented Dickey–Fuller (ADF) test with a constant term, which allows controlling for the possible presence of a serial correlation in the residuals. As the maximum number of lags I initially chose ten, which was then changed to eight based on the statistical significance of the coefficient on the highest lag and Akaike information criterion (AIC). The unit-root null hypothesis was rejected and therefore I conclude that daily electricity prices are stationary. The results of the ADF test are summarized in Table 3.2.

Table 3.2: Augmented Dickey–Fuller test for daily electricity prices

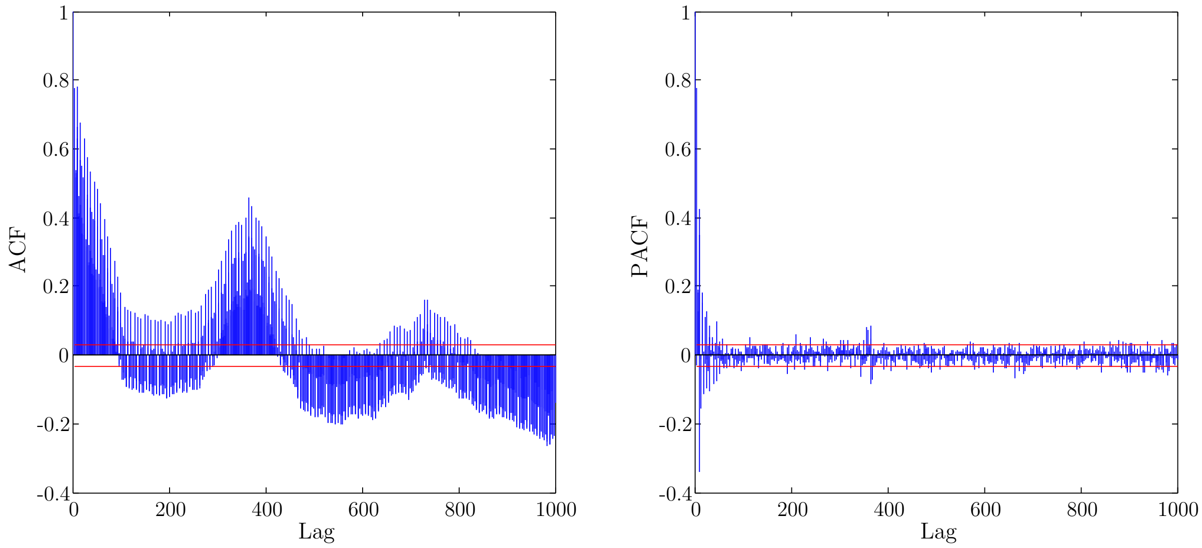
Null hypothesis: daily price time series has a unit root			
Exogenous: constant			
Lag length: 8 (based on AIC, maximal lag = 10)			
ADF test statistic	-8.304	1% critical value	-3.432
		5% critical value	-2.862
		10% critical value	-2.567

Note: I use MacKinnon critical values for the rejection of the hypothesis of a unit root.

The stationarity conclusion is robust for higher order choices of the maximal lag. However, the conclusion is usually less reliable when a very high order of the maximal lag is considered. This is due to a decrease in the power of the ADF test (Kočenda and Černý, 2007).

3.5.2 Time domain analysis

A time series can be analyzed on a time domain using the autocorrelation function (ACF) and partial autocorrelation function (PACF). I summarize the sample ACF and PACF for daily electricity prices in a correlogram presented in Figure 3.3 (a lag of order 1000 corresponds to approximately 25% of the sample size).



Source: Author's calculations.
Figure 3.3: Correlogram for daily electricity prices

A detailed analysis of the sample autocorrelation function (ACF) reveals the presence of two types of seasonality in electricity prices: weekly seasonality observed through the spikes in the sample ACF at lag orders of $7, 14, \ldots$ (integer multiples of 7), and annual seasonality observed through the spikes in the sample ACF at lag orders of $364, 728, \ldots$ (integer multiples of 364).

The sample partial autocorrelation function (PACF) suggests to additionally consider such lag orders as $9, 16, 28, 29, 61$, and 100 to accommodate weekend, monthly, and quarterly patterns. This knowledge is also used in specifying the AR process.

3.5.3 Frequency domain analysis

A frequency domain analysis allows us to identify frequencies explaining a large portion of seasonal variations in electricity prices. The identified frequencies can then be used in specifying the arguments of periodic sine and cosine functions that are included as additional explanatory variables. A frequency domain is examined using the techniques of the spectral (Fourier) analysis. The techniques of the Fourier analysis allow modeling a time series with seasonal components as a sum of periodic $A \cdot \sin(\omega t + \varphi)$ sinusoidal functions, where A denotes the amplitude of a sinusoidal wave, ω denotes the frequency, and φ denotes the phase shift (see, for example, Molinero, 1991; Wang, 2003; Prado and West, 2010). For practical considerations, the periodic sinusoidal function can be rewritten in the following way: $A \cdot \sin(\omega t + \varphi) = A \cdot \sin\varphi \cdot \cos(\omega t) + A \cdot \cos\varphi \cdot \sin(\omega t)$. The rewritten expression suggests using $\cos(\omega t)$ and $\sin(\omega t)$ trigonometric functions as explanatory variables for modeling the seasonal pattern of electricity prices. Assuming that ω is known (as described later, it will be determined based on the Fourier transform), estimates of the slope parameters can then allow calculating the respective amplitude and phase shift.

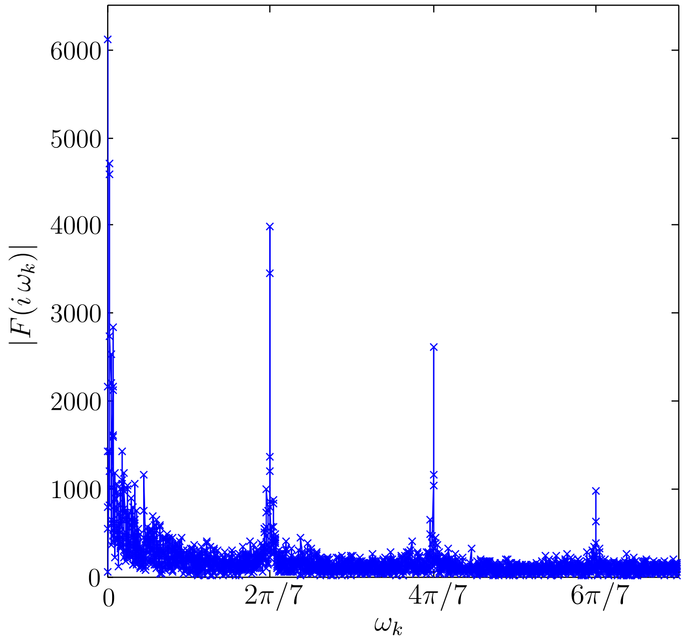
The Fourier transform of a real-valued function $p(t)$ on the domain $[0, T]$ is defined as $F(i\,\omega) = \mathcal{F}\{p(t)\} = \int_0^T p(t)\, e^{-i\omega t}\, dt$, where i is the imaginary unit such that $i^2 = -1$. Based on this definition, the FFT numerical procedure computes $F(i\,\omega_k) \approx \sum_{t=0}^{T-1} p_t\, e^{-i\omega_k t}$.

It is important to note that the values of the Fourier transform are complex numbers and are therefore not directly comparable. For this reason I use the absolute values of the Fourier transform. A detailed description is presented in Appendix 4.A.

A graph where the frequency domain is plotted against the absolute values of the Fourier transform is known as a periodogram. In Figure 3.4 I present a periodogram plot for daily electricity prices.

A detailed analysis of the frequency domain, where the absolute values of the Fourier transform achieve local maxima, as described in the periodogram in Figure 3.4, allows revealing frequencies that explain the seasonal pattern in the price time series. Hence, the frequencies at which the absolute values of the Fourier transform achieve local maxima can be used in specifying the argument of sine and cosine functions included as additional explanatory variables.

The application of sine and cosine functions in modeling weekly seasonality is preferred to the application of daily dummy variables because the former approach has resulted in a more parsimonious model. An application of smooth periodic functions rather than, for example, daily dummy variables is also in line with the suggestion for future extensions



Source: Author's calculations.
Figure 3.4: Periodogram for daily electricity prices

mentioned in Koopman et al. (2007).

3.5.4 *AR–ARCH* model specification

For the analysis of price and volatility dynamics I employ the *AR(P)–ARCH(p)* model, which was developed and applied in Engle (1982) to estimate the means and variances of inflation in the UK.

The *AR(P)–ARCH(p)* model applied for the estimation of volatility of electricity prices can be represented in the following way:

$$price_t = a_0 + \sum_{i=1}^{P} a_i \, price_{t-i} + \varepsilon_t \tag{15}$$

$$\varepsilon_t = \nu_t \sqrt{\alpha_0 + \sum_{i=1}^{p} \alpha_i \, \varepsilon_{t-i}^2} \; , \tag{16}$$

where similar to Engle (1982) and Koopman et al. (2007) I consider autoregressive conditional heteroscedastic residuals ε_t. ν_t is a sequence of an independent and identically distributed (i.i.d.) random variable with zero mean and unit variance, which are also known as the standardized residuals. The distributional assumption for ν_t is crucial for the joint estimation of the two equations using the maximum likelihood approach. As described, for example, in Hamilton (1994), usually a normal distribution, generalized normal distribution or t-distribution is considered. A normal distribution is a special case of a generalized normal distribution when a shape parameter is equal to two.

As the standardized residuals, ν_t, is the i.i.d. sequence with zero mean and unit variance, we can also specify the *AR(P)–ARCH(p)* model in the following way:

$$price_t = a_0 + \sum_{i=1}^{P} a_i \, price_{t-i} + \varepsilon_t \tag{17}$$

$$h_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i \, \varepsilon_{t-i}^2 \ , \tag{18}$$

where $h_t = E_{t-1}\left[\varepsilon_t^2\right]$ is the conditional variance or volatility.

The two equations describing the *AR(P)* and *ARCH(p)* processes are called the mean and conditional volatility equations, respectively. This specification captures such inherent properties of electricity prices as mean reversion, spikes, and volatility clustering.

The error term ε_t in the *AR(P)* process is assumed not to contain any serial correlation. The appropriateness of a chosen specification for the *AR(P)* process is examined using the ACF, PACF, and p-values of the Ljung–Box Q-test statistics.

To ensure that the conditional volatility h_t is positive, it is usually assumed that $\alpha_0 > 0$ and $\alpha_i \geq 0$. The implication of the *ARCH* term in the conditional volatility equation is reviewed, for example, in Kočenda and Černý (2007). In particular, the *ARCH* term ε_{t-1}^2 is designed to reflect the impact of a shock or news from the previous period that would affect the current conditional volatility. More precisely, a significant and positive α_i less than one would measure the extent of a past shock's effect on volatility, which is not destabilizing. Additionally, it is also possible to distinguish the impact of positive and negative shocks from a previous period, which can asymmetrically affect volatility.

This is investigated by a threshold *ARCH* process developed in Glosten, Jagannathan, and Runkle (1993).

Similar to Koopman et al. (2007), I extend the mean and volatility equations to include explanatory variables represented in this research by periodic sine and cosine functions with frequencies suggested by the Fourier transform. In order to evaluate the impact of institutional changes and regulatory reforms on the dynamics of electricity prices, I also additionally include regime dummy variables because I assume that the institutional changes and regulatory reforms could have affected the price development. The validity of the proposed assumption is verifiable by formal hypothesis testing. The regime periods are determined based on the known time of the institutional changes and regulatory reforms that took place in the ESI in Great Britain during 1990–2001.

The joint estimation of the mean and conditional volatility equations is dependent on the distributional assumption of ν_t. Usually a t-distribution or generalized normal distribution is considered. The adequacy of the overall *AR(P)–ARCH(p)* model is verified by testing if the standardized residuals, $\hat{\nu}_t = \dfrac{\hat{\varepsilon}_t}{\sqrt{\hat{h}_t}}$, is an i.i.d. sequence. For this purpose, I apply the BDS test developed by Brock, Dechert, Scheinkman, and LeBaron (1996). Because the conclusion of the BDS test can in general depend on the values of the embedding dimension and proximity parameters, I also additionally analyze the p-values of the Ljung–Box Q-test statistics to examine whether $\hat{\nu}_t$ and $\hat{\nu_t^2}$ contain any serial correlation. This is done as a robustness check for the judgement on model adequacy.

3.6 Results and discussion

Based on the presented methodology, the following dynamic model is estimated:

$$price_t = a_0 + \sum_{i=1}^{P} a_i \, price_{t-i} + z_t' \cdot \gamma + \varepsilon_t \tag{19}$$

$$h_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i \, \varepsilon_{t-i}^2 + z_t' \cdot \delta \ , \tag{20}$$

where z_t is a vector of additional explanatory variables including periodic sine and cosine functions and regime dummy variables. In Figures 3.8 and 3.9 changes in the distribution of input types in electricity production and changes in input prices are presented. Because data on input prices are available at a quarterly frequency, we cannot explicitly consider input prices in modeling the dynamics of electricity prices. I assume that electricity prices incorporate past changes in input prices, which are generally common for all producers.

The estimation results obtained using the Marquardt algorithm are summarized in Table 3.3. Attempts to model weekly seasonality through the application of daily dummy variables were not as successful as the application of smooth periodic sine and cosine functions, where the frequencies are chosen based on the Fourier transform. In particular, the application of sine and cosine functions has resulted in a more parsimonious model. Weekly seasonality is additionally modeled through a lag structure in both the mean and conditional volatility equations. The mean equation also includes a yearly lag, which is statistically significant.

It is interesting to note that weekly seasonality modeled in the conditional volatility equation is found to be complex to also contain asymmetries with respect to positive and negative shocks (or innovations). As the estimation results indicate, there is evidence at the 5% significance level that positive shocks from the previous week have a larger effect on the volatility. The sum of the coefficients of the lagged variables is less than unity (0.965 in the mean equation and 0.738 in the conditional volatility equation), which suggests that the effects of past prices and shocks are not destabilizing. Moreover, the nonnegativity requirement of the coefficients of the $ARCH$ terms is also satisfied. The latter is necessary to ensure that the conditional volatility is positive.

Table 3.3: Estimation results of the extended AR–ARCH model

$$price_t = a_0 + \sum_{i=1}^{P} a_i \, price_{t-i} + z_t' \cdot \gamma + \varepsilon_t$$

$$h_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i \, \varepsilon_{t-i}^2 + z_t' \cdot \delta \ ,$$

Mean Equation			*Conditional Volatility Equation*		
Variable	Coef	Std Err	Variable	Coef	Std Err
Dependent Variable: $price_t$					
a_0	0.836***	0.262	α_0	0.604***	0.069
$price_{t-1}$	0.600***	0.015	ε_{t-1}^2	0.174***	0.027
$price_{t-2}$	0.068***	0.016	ε_{t-3}^2	0.019*	0.012
$price_{t-3}$	0.033**	0.014	ε_{t-4}^2	0.092***	0.021
$price_{t-4}$	0.048***	0.014	ε_{t-5}^2	0.110***	0.020
$price_{t-6}$	0.084***	0.013	ε_{t-7}^2	0.293***	0.039
$price_{t-7}$	0.241***	0.019	$\varepsilon_{t-7}^2 \cdot I_{t-7}$	-0.124**	0.054
$price_{t-8}$	-0.101***	0.017	ε_{t-9}^2	0.051***	0.019
$price_{t-9}$	-0.107***	0.015	$\cos(4\pi t/7)$	-0.383***	0.091
$price_{t-14}$	0.096***	0.012	$\cos(6\pi t/7)$	0.554***	0.089
$price_{t-16}$	-0.065***	0.011	$\sin(2\pi t/7)$	0.646***	0.102
$price_{t-21}$	0.071***	0.011	$\sin(4\pi t/7)$	-0.308***	0.057
$price_{t-25}$	-0.038***	0.009	$\sin(6\pi t/7)$	-0.548***	0.087
$price_{t-28}$	0.070***	0.013	Regime 2	0.118	0.083
$price_{t-29}$	-0.069***	0.012	Regime 3	1.223***	0.240
$price_{t-42}$	0.044***	0.012	Pre-Regime 4	3.455***	1.343
$price_{t-43}$	-0.032***	0.011	Regime 4	2.130***	0.356
$price_{t-48}$	0.015*	0.009	Regime 5	1.152***	0.220
$price_{t-61}$	-0.009	0.007			
$price_{t-100}$	-0.024***	0.006	Shape parameter	1.273	0.036
$price_{t-207}$	-0.021***	0.007			
$price_{t-209}$	0.025***	0.007			
$price_{t-260}$	-0.018***	0.006			
$price_{t-270}$	0.013**	0.006			
$price_{t-341}$	0.026***	0.008			
$price_{t-344}$	-0.026***	0.007			
$price_{t-355}$	-0.041***	0.009			
$price_{t-357}$	0.037***	0.010			
$price_{t-364}$	0.043***	0.009			
$\cos(2\pi t/7)$	-0.131***	0.042			
$\cos(4\pi t/7)$	-0.252***	0.042			
$\cos(6\pi t/7)$	0.118***	0.033			
$\sin(4\pi t/7)$	-0.124***	0.036			
$\sin(6\pi t/7)$	-0.290***	0.036			
Regime 2	0.062	0.076			
Regime 3	-0.403***	0.081			
Pre-Regime 4	-0.261	0.280			
Regime 4	-0.123	0.075			
Regime 5	-0.328***	0.079			
Obs	3631				
Adj R^2	0.804				
AIC	4.031				

Notes: I_{t-7} is an indicator function equal to 1 if $\varepsilon_{t-7} < 0$ and 0 otherwise. The inclusion of a *GARCH* term has not improved the results. The functions $\sin(2\pi t/7)$ and $\cos(2\pi t/7)$ are excluded from the mean and volatility equations respectively because the corresponding estimated slope coefficients are statistically insignificant. *, **, and *** stand for the 10%, 5%, and 1% significance levels, respectively.

The assumption that the standardized residuals ν_t have a t-distribution is rejected at the 1% significance level. Therefore, a generalized normal distribution (also known as a generalized error distribution) is considered. The estimation results presented in Table 3.3 include an estimate of the shape parameter, which suggests that tails are leptokurtic, i.e., heavier than those of a standard normal distribution. This is an often-cited result in the literature dealing with modeling and forecasting electricity price dynamics (see, for example, Koopman et al., 2007). The distribution of $\hat{\nu}_t$ presented in Figure 3.5, in comparison with the normal distribution, suggests that the assumption of the generalized normal distribution for ν_t works reasonably well.

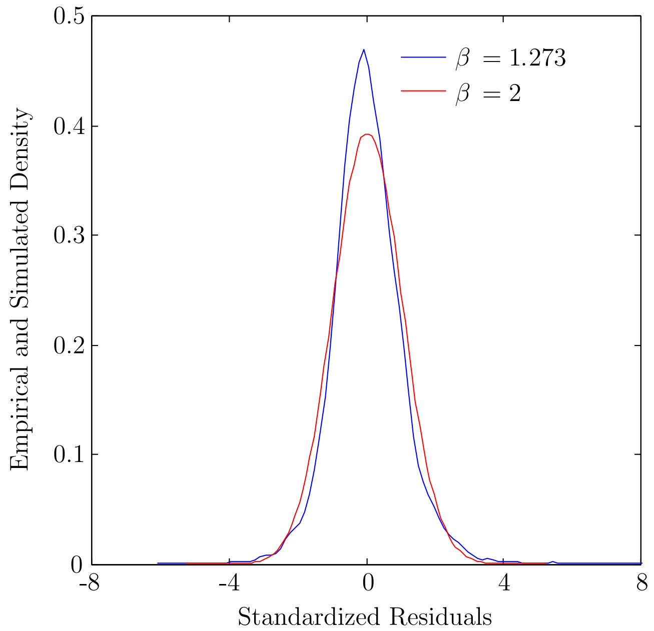


Figure 3.5: Density of $\hat{\nu}_t$ and the normal distribution

In order to check for the adequacy of the estimated extended *AR–ARCH* model, I also apply the BDS test developed by Brock et al. (1996) to test if the standardized residuals $\hat{\nu}_t$ are i.i.d. For the embedding dimension m equal to 2 and 3 and a default option of the proximity parameter ε, the null hypothesis that the standardized residuals are i.i.d. is not rejected. This test, therefore, confirms the adequacy of the estimated *AR–ARCH* model. The test results are summarized in Table 3.4.

Table 3.4: BDS test for standardized residuals $\hat{\nu}_t$

Dimension	BDS Stat	Std Err	p-value
2	-0.001	0.001	0.500
3	0.002	0.002	0.260

Because the conclusion of the BDS test can in general be sensitive to the choice of m and ε parameters, as a robustness check for model adequacy, I additionally examine whether the standardized residuals $\hat{\nu}_t$ and standardized residuals squared $\hat{\nu_t^2}$ contain any serial correlation. For this purpose I examine the p-values of the Ljung–Box Q-test statistics. The test results are summarized in Figure 3.6.

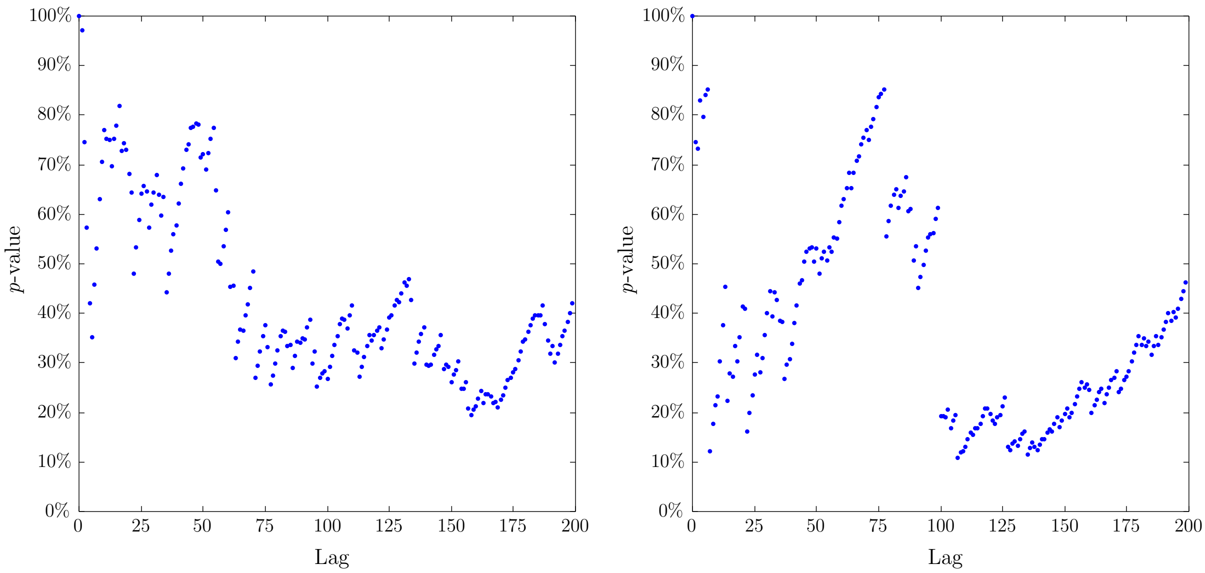
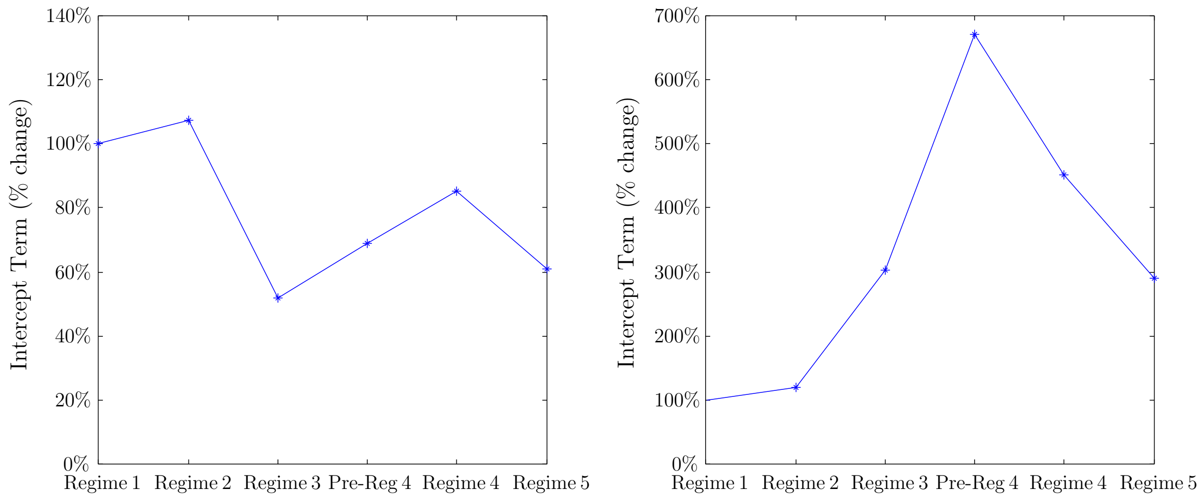


Figure 3.6: Ljung–Box Q-test for standardized residuals $\hat{\nu}_t$ and $\hat{\nu_t^2}$

The test results presented in Figure 3.6 provide evidence at the 5% significance level that the standardized residuals ($\hat{\nu}_t$) and standardized residuals squared ($\hat{\nu_t^2}$) do not have any serial correlation. These findings suggest that the residuals do not contain any further information and therefore justify the appropriateness of the joint estimation of the mean and conditional volatility equations. Overall, the estimated extended AR–$ARCH$ model explains about 80% of variations in electricity prices.

Using the estimation results presented in Table 3.3, I summarize in relative terms the effects of the institutional changes and regulatory reforms on price and volatility dynamics for the case of the England and Wales electricity market during 1990–2001. This is presented in Figure 3.7.



(a) Mean equation (b) Conditional volatility equation

Figure 3.7: Impact of institutional changes and regulatory reforms on price and volatility dynamics

When the initial coal contracts expired, the electricity prices on average became slightly higher and more volatile. These changes, however, are neither statistically nor economically significant compared to the reference period, i.e., regime 1.

During the price-cap regulation period (i.e., regime 3) we observe a decrease in the price level, which however happens at the cost of higher volatility. These changes are both statistically and economically significant. This result is also partly consistent with the finding in Wolfram (1999) that the price-cap regulation led the industry supply curve to rotate counterclockwise because in order to satisfy the price cap producers reduced prices when demand was low and increased them when demand was high.

Using nonparametric techniques for weekly electricity prices during December 10, 1990–March 11, 1996, Robinson and Baniak (2002) also find that after the expiry of the coal contracts in 1993 and during price-cap regulation, price volatility increased, for which the authors provide an alternative explanation. In particular, they state that the incumbent electricity producers could have been deliberately increasing price volatility in order to enjoy higher risk premia in the contract market. However, because data on contracts are confidential, it is difficult to empirically verify this statement.

During the period after price-cap regulation and before the first series of divestments took place, the price volatility increased dramatically, whereas an increase in the price level is only economically significant. This can possibly be characterized as a transitional feature of the pre-regime 4 period. During regime 4, when the first series of divestments took place, the volatility decreased, whereas the price level increased further compared to the pre-regime 4 period. This finding indicates that during regime 4 the trade-off has reversed: lower volatility is achieved at the cost of a higher price level. The increased price level and decreased price volatility during this period could be related to tacit collusion discussed, for example, in Sweeting (2007).

The estimation results indicate that the second series of divestments was more successful. In particular, the price level and volatility are both reduced. This finding supports the implementation of the second series of divestments.

From the perspective of the presented time series modeling approach, it follows that the price-cap regulation and divestment series led in the end to similar price levels and volatility. In other words, the structural remedy implemented through divestment series had a similar impact on the price level and volatility as the behavioral remedy implemented through the price-cap regulation. However, usually divestments could be superior to price regulation because the former allow for the creation of a less concentrated market structure, where it is easier to promote competitive bidding among electricity producers. This conclusion is consistent with the restructuring recommendation stated in Green and Newbery (1992). In particular, using empirical simulation the authors show that restructuring leads to a significantly lower equilibrium price and deadweight loss. The result that restructuring leads to lower electricity prices was later confirmed in Evans and Green (2003), where the authors show that increases in market competition, which are measured through a Herfindahl concentration index, are chiefly responsible for a decrease in the price level.

3.7 Conclusions

This study aims to analyze the impact of introduced institutional changes and regulatory reforms on price and volatility dynamics. For this purpose, time and frequency domain analyses are used to appropriately model seasonality in electricity prices. The methodology based on the application of sine and cosine functions, whose frequencies are determined from the Fourier transform rather than based on the application of the daily dummy variables, is found to be more appropriate for modeling weekly seasonality in electricity prices. As a result, a more parsimonious AR–$ARCH$ model has been considered. Moreover, the estimation results of the extended AR–$ARCH$ model indicate that innovations from the previous week have asymmetric effects on volatility. In particular, I find that positive innovations from the previous week have a larger effect on volatility.

This research also documents new results in quantifying the impact of institutional changes and regulatory reforms on price and volatility dynamics for the case of the England and Wales wholesale electricity market during 1990–2001. Firstly, I find the presence of a trade-off in introducing price-cap regulation, which is both statistically and economically significant. In particular, estimation results indicate that a lower price level was achieved at the expense of higher volatility. Secondly, the implementation of the first series of divestments was successful at lowering price volatility, which however happened at the cost of a higher price level. This is explained as the possible presence of tacit collusion. Thirdly, only during the last regime period, when the second series of divestments was implemented, was it possible to simultaneously reduce prices and volatility.

I also find that the structural remedy implemented through divestment series had a similar impact on price level and volatility as the behavioral remedy implemented through the price regulation. Because in a less concentrated market consisting of, for example, five–six major power producers it is easier to promote competition, divestment series could be superior.

The findings and conclusions of this study of the impact of the institutional changes and regulatory reforms on the dynamics of electricity prices could be of interest to, for example, Argentina, Australia, Chile, Italy, Spain, and some US states, which have organized the operation of their modern electricity markets similar to the original model of the England and Wales wholesale electricity market.

References

Bosco, B. P., Parisio, L. P., Pelagatti, M. M., 2007. Deregulated wholesale electricity prices in Italy: an empirical analysis. International Advances in Economic Research 13 (4), 415–432.

Brock, W. A., Dechert, W. D., Scheinkman, J. A., LeBaron, B., 1996. A test for independence based on the correlation dimension. Econometric Reviews 15 (3), 197–235.

Conejo, A. J., Contreras, J., Espínola, R., Plazas, M. A., 2005. Forecasting electricity prices for a day-ahead pool-based electric energy market. International Journal of Forecasting 21 (3), 435–462.

Crawford, G. S., Crespo, J., Tauchen, H., 2007. Bidding asymmetries in multi-unit auctions: implications of bid function equilibria in the British spot market for electricity. International Journal of Industrial Organization 25 (6), 1233–1268.

Crespo, J. C., Hlouskova, J., Kossmeier, S., Obersteiner, M., 2004. Forecasting electricity spot-prices using linear univariate time-series models. Applied Energy 77 (1), 87–106.

Department of Trade and Industry, 1993–2000. Energy Trends. Department of Trade and Industry, London.

Department of Trade and Industry, 1997–2002. Digest of United Kingdom Energy Statistics. Department of Trade and Industry, London.

Engle, R. F., 1982. Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation. Econometrica 50 (4), 987–1007.

Evans, J. E., Green, R. J., 2003. Why did British electricity prices fall after 1998? MIT Center for Energy and Environmental Policy Research working paper series no. 03-007.

Franses, P. H., Paap, R., 2004. Periodic Time Series Models. Advanced Texts in Econometrics. Oxford University Press, New York.

Garcia, R. C., Contreras, J., van Akkeren, M., Garcia, J. B. C., 2005. A GARCH forecasting model to predict day-ahead electricity prices. IEEE Transactions on Power Systems 20 (2), 867–874.

Gençay, R., Selçuk, F., Whitcher, B., 2002. An Introduction to Wavelets and Other Filtering Methods in Finance and Economics. Academic Press, San Diego.

Glosten, L. R., Jagannathan, R., Runkle, D. E., 1993. On the relation between the expected value and the volatility of the nominal excess returns on stocks. Journal of Finance 48 (5), 1779–1801.

Green, R. J., Newbery, D. M., 1992. Competition in the British electricity spot market. Journal of Political Economy 100 (5), 929–953.

Guthrie, G., Videbeck, S., 2007. Electricity spot price dynamics: beyond financial models. Energy Policy 35 (11), 5614–5621.

Hamilton, J. D., 1994. Time Series Analysis. Princeton University Press, Princeton.

Huisman, R., Huurman, C., Mahieu, R., 2007. Hourly electricity prices in day-ahead markets. Energy Economics 29 (2), 240–248.

Joskow, P. L., 2009. Foreword: US vs. EU electricity reforms achievement. In: Glachant, J.-M., Lévêque, F. (Eds.), Electricity Reform in Europe. Edward Elgar Publishing Limited, Cheltenham.

Koopman, S. J., Ooms, M., Carnero, M. A., 2007. Periodic seasonal Reg-ARFIMA-GARCH models for daily electricity spot prices. Journal of the American Statistical Association 102 (477), 16–27.

Kočenda, E., Černý, A., 2007. Elements of Time Series Econometrics: An Applied Approach. Karolinum Press, Prague.

Molinero, C. M., 1991. The autocorrelation function of a time series with a deterministic component. IMA Journal of Mathematics Applied in Business and Industry 3 (1), 25–30.

National Grid Company, 1994–2001. Seven Year Statement. National Grid Company, Coventry.

Newbery, D. M., 1999. The UK experience: privatization with market power. mimeo, University of Cambridge.

Prado, R., West, M., 2010. Time Series Modeling, Computation, and Inference. Texts in Statistical Science. CRC Press, Boca Raton.

Robinson, T., Baniak, A., 2002. The volatility of prices in the English and Welsh electricity pool. Applied Economics 34 (12), 1487–1495.

Sweeting, A., 2007. Market power in the England and Wales wholesale electricity market 1995–2000. Economic Journal 117 (520), 654–685.

Von der Fehr, N.-H. M., Harbord, D., 1993. Spot market competition in the UK electricity industry. Economic Journal 103 (418), 531–546.

Wang, P., 2003. Financial Econometrics: Methods and Models. Routledge Advanced Texts in Economics and Finance. Routledge, London.

Wolfram, C. D., 1998. Strategic bidding in a multiunit auction: an empirical analysis of bids to supply electricity in England and Wales. RAND Journal of Economics 29 (4), 703–725.

Wolfram, C. D., 1999. Measuring duopoly power in the British electricity spot market. American Economic Review 89 (4), 805–826.

3.A Fourier transform

The Fourier transform of a real-valued function $p(t)$ on the domain $[0, T]$ is defined as

$$F(i\,\omega) = \mathcal{F}\{p(t)\} = \int\limits_0^T p(t) \cdot e^{-i\omega t}\, dt\,,$$

where i is the imaginary unit such that $i^2 = -1$.

Using the above definition, we can write the following approximation for the Fourier transform:

$$\begin{aligned} F(i\,\omega_k) \approx \sum_{t=0}^{T-1} p_t \cdot e^{-i\omega_k t} &= \sum_{t=0}^{T-1} p_t \cdot (\cos\omega_k t - i \sin\omega_k t) = \\ &= \sum_{t=0}^{T-1} p_t \cdot \cos\omega_k t - i \sum_{t=0}^{T-1} p_t \cdot \sin\omega_k t = \\ &= (p_t, \cos\omega_k t) - i\,(p_t, \sin\omega_k t), \end{aligned}$$

where $\omega_k = \frac{k}{N-1} \cdot 2\pi, \quad k = 0, 1, 2, \ldots, N-1$, and N determines the grid.

Because the values of the Fourier transform are complex numbers, they are not directly comparable. For this reason we use the absolute values of the Fourier transform.

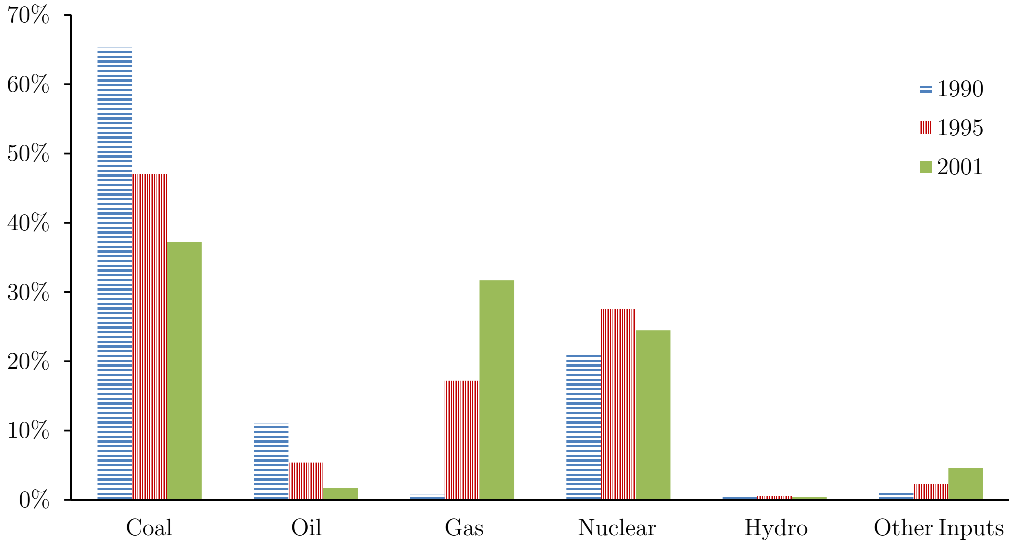
The optimization problem can therefore be described in the following way:

$$|F(i\,\omega_k)| \approx |(p_t, \cos\omega_k t) - i\,(p_t, \sin\omega_k t)| \longrightarrow \max_{\omega_k}$$

where $\omega_k = \frac{k}{N-1} \cdot 2\pi, \quad k = 0, 1, 2, \ldots, N-1$, and N determines the grid.

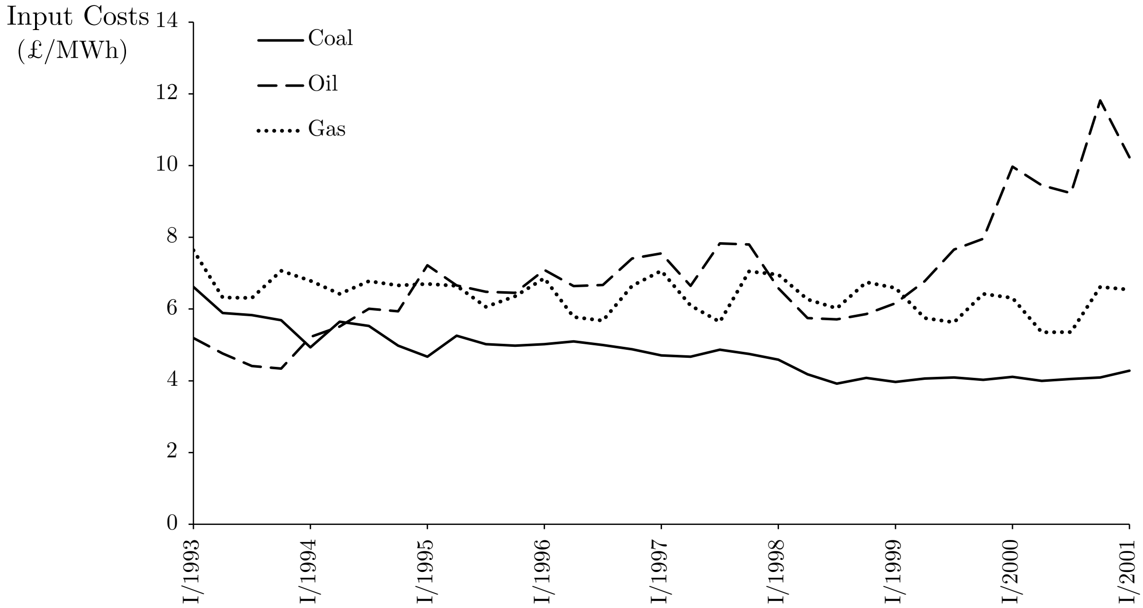
The expressions in parentheses represent scalar products. In statistical terms, they measure covariation between the price time series and cosine/sine functions for different values of ω_k. In this optimization problem, our task is to find such values of ω_k that would explain a large portion of variation in the electricity prices. The results have been computed using the FFT procedure implemented in MatLab.

3.B Figures



Source: Department of Trade and Industry (1997–2002); author's calculations.

Figure 3.8: Distribution of input types for electricity production



Source: Department of Trade and Industry (1993–2000); author's calculations.

Figure 3.9: Quarterly input costs of electricity producers in the UK

3.C Abbreviations

ACF	Autorcorrelation Function
ADF	Augmented Dickey–Fuller
AIC	Akaike Information Criterion
APX	Amsterdam Power Exchange
AR	Autoregressive
ARCH	Autoregressive Conditional Heteroscedasticity
ARIMA	Autoregressive Integrated Moving Average
ARMA	Autoregressive Moving Average
BDS	Brock Dechert Scheinkman
EEX	European Energy Exchange (Germany)
ESI	Electricity Supply Industry
FFT	Fast Fourier Transform
GARCH	Generalized Autoregressive Conditional Heteroscedasticity
GOAL	Generator Ordering and Loading
NEM	New Zealand Electricity Market
NGC	National Grid Company
Offer	Office of Electricity Regulation
Ofgem	Office of Gas and Electricity Markets (formerly, Offer)
PACF	Partial Autorcorrelation Function
PJM	Pennsylvania–New Jersey–Maryland
PPX	Paris Power Exchange
SFE	Supply Function Equilibrium
SMP	System Marginal Price
SUR	Seemingly Unrelated Regressions