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Liberalization of Electricity Supply Industry

Habilitation Thesis

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Contents

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Abstract

The habilitation thesis consists of papers analyzing the impact of regulatory reforms on market outcomes and bidding behavior of electricity producers. Each paper uses a different methodology to answer various research questions. In the first paper I analyze the impact of price-cap regulation and divestment series on the electricity price during the peak-demand period over trading days. In order to reflect the impact of divestment series, the market share of each incumbent producer is included in the analysis. The next paper analyzes changes in the incentive and disincentive to exercise market power by submitting price bids in excess of marginal production costs during the peak-demand period. I again focus on the peak-demand period over trading days because producers typically exercise market power namely during the periods when demand is at the peak. The third paper investigates another means of raising electricity prices when electricity producers may withhold cheaper production capacity during the peak-demand period compared to a low-demand period on the same trading day. In such a situation the market operator may need to use more expensive production facilities to satisfy demand for electricity. In the last paper I analyze changes in the price level and volatility over different regulatory regime periods. Such an analysis could be important for detecting tacit collusion when, for example, we observe a higher price level associated at the same time with lower volatility.

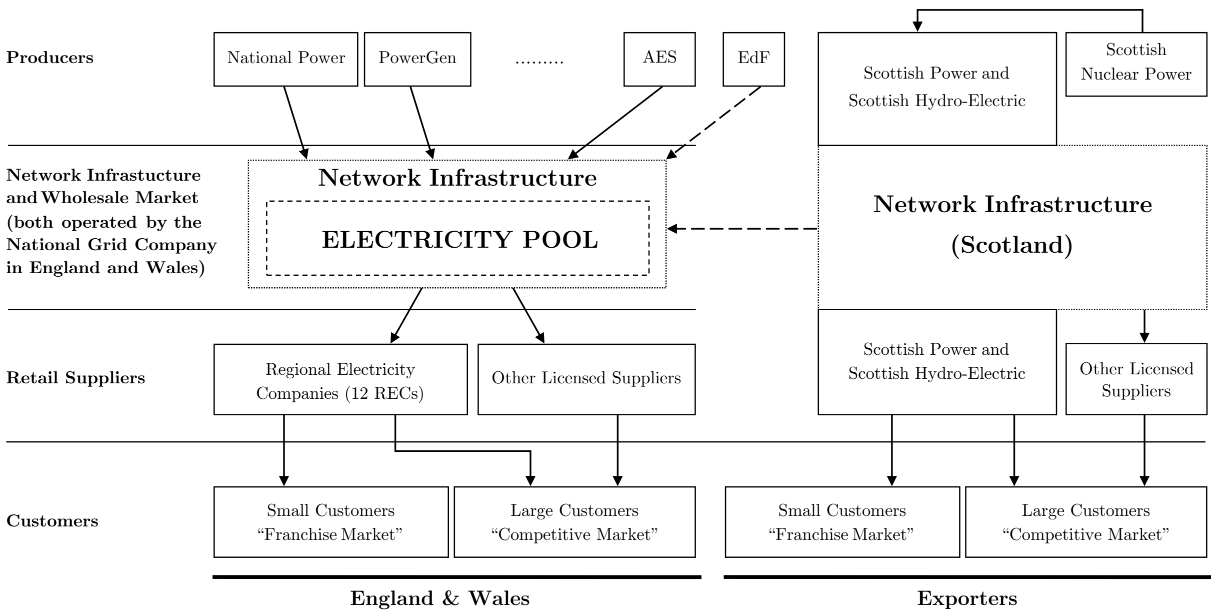
Keywords: liberalization; regulation; electricity markets; market power; uniform price auction; price bids; capacity bids; electricity price; skew generalized error distribution; conditional volatility

JEL Classification: C22; C51; D21; D22; D44; L50; L90; L94

General introduction

The habilitation thesis consists of a compilation of the author's works, which deal with the liberalization of electricity supply industry in Great Britain. According to Joskow (2008), privatization, restructuring, market design, and regulatory reforms pursued in the liberalization process of the electricity industry in England and Wales can be characterized as the international gold standard for energy market liberalization.

The liberalization of electricity supply industry in Great Britain included splitting the previously vertically integrated monopoly structure into electricity production, transmission, and distribution parts. Electricity producers traded electricity through the wholesale electricity market. This is summarized in Figure 0.1.



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

Figure 0.1: Description of the electricity supply industry in Great Britain in 1998

As described in Figure 0.1, in England and Wales, electricity producers sold electricity to retail suppliers (i.e., distribution companies) through the wholesale market known as the Electricity Pool, which was created in April 1990. This market was managed by the network operator, the National Grid Company (NGC), which was also responsible for transmitting electricity to retail suppliers.

Electricity trading on the wholesale market was organized as a uniform price auction. For each production unit electricity producers were asked to submit on a daily basis a start-up cost, a no-load cost, (at most) three price-offer bids, two elbow points, and half-hourly capacity bids, which were used in calculating half-hourly price bids (Electricity Pool, 1990). For each half-hourly period, based on ordered price bids, the market operator (i.e., NGC) constructed an aggregate supply schedule (also known as a merit order). The market operator was also responsible for preparing half-hourly demand forecasts, where the forecasting methodology was common knowledge (Wolak, 2000; Wolak and Patrick, 2001) and independent of producers' bidding on the auction (Green, 2006). The intersection of the merit order and forecast demand determines the wholesale price called the System Marginal Price (SMP). This represented the half-hourly uniform price paid the same to all producers whose production units were scheduled for electricity production.

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 0.1, the production and transmission were kept vertically integrated and not unbundled as was done, for example, in England and Wales.

The liberalization process of the electricity supply industry 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 electricity supply industry in Great Britain.

The first change was related to the expiry on April 1, 1993 of coal and other initial contracts imposed by the government. Hence, April 1, 1993 is considered as the *first structural break*. Later, the regulatory authority, the Office of Electricity Regulation (Offer),[1] introduced price-cap regulation that would set an explicit ceiling on annual average prices charged for electricity production by the two incumbent electricity producers:

[1] Later renamed the Office of Gas and Electricity Markets (Ofgem).

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 the literature, price-cap regulation is referred to as a behavioral remedy.

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 July 1996 and July 1999. These dates define the next two structural breaks. In the literature, introducing divestment series is also referred to as applying a structural remedy.

In March 2001, in order to introduce bilateral trading arrangements, the wholesale electricity market was replaced by the New Electricity Trading Arrangements (NETA). A transition to bilateral trading arrangements should not serve as an indication that all problems stem from the use of wholesale trading. Firms with a dominant position on the market could raise prices under any set of market rules (Green, 2003).

The habilitation thesis includes four paper reprints in the form they have been published or submitted to the Elsevier publisher. The first paper analyzes the impact of behavioral and structural remedies on the wholesale electricity price during the peak-demand period using the case of the England and Wales electricity market. This case study is unique because the two different kinds of remedies were introduced in the same market at different points of time, which enables conducting a comparative analysis. Even if I do not find a clear advantage of a structural remedy, I still suggest that a structural remedy in the form of horizontal restructuring could be a preferred measure at promoting competition in the electricity market. In particular, I find that after divestment series the effect of market share of the larger incumbent producer is statistically insignificant and that the volatility of electricity prices is lower. The paper also analyzes the weekly seasonality pattern using the time and frequency domain approaches, which is important in justifying the application of clustered robust standard errors by the day of the week in the analysis of producers' bidding on the electricity market. This paper is submitted for publication consideration to the Energy Economics journal.

The next two papers analyze the bidding behavior of electricity producers at the uniform price auction. In the second paper 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. This paper is published in the Utilities Policy journal.

The third paper investigates if electricity producers apply a capacity cutting (i.e., withholding) strategy to increase prices. This strategy may be profitable 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 production facilities to satisfy demand. We analyze whether the regulatory reforms decreased the extent of strategic capacity bidding. This paper is coauthored with Lubomír Lízal and is published in the Energy Economics journal.

Strategic submission of price bids or capacity bids may make equilibrium prices in a market more volatile. Hence, in the next paper, I analyze and discuss the dynamics of daily price level and volatility in relation to the introduced regulatory reforms. 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 this fourth paper, which is published in the Energy Policy journal.

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). Moreover, the England and Wales electricity market was one of the first examples of a competitive wholesale electricity market in the world. This market was copied, almost in entirety in some cases, by a number of other countries seeking to reform their electricity supply industry (Bower, 2002). In this respect, the new findings documented in this habilitation thesis 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 The impact of behavioral and structural remedies on electricity prices: The case of the England and Wales electricity market

Currently under review in the Energy Economics journal.

The Impact of Behavioral and Structural Remedies on Electricity Prices: The Case of the England and Wales Electricity Market

Sherzod N. Tashpulatov*

Abstract

During the liberalization process the UK regulatory authority introduced behavioral and structural remedies in order to mitigate an exercise of market power and lower electricity prices. We study the impact of a behavioral remedy implemented through price-cap regulation and a structural remedy implemented through divestment series on the dynamics of electricity price during the peak-demand period over trading days. An AR–$ARCH$ model with a novel skew generalized error distribution is used. This distribution allows to capture the features of asymmetry, excess kurtosis, and heavy tails. The model is extended to include individual incumbent producers' market shares and other explanatory variables reflecting seasonal patterns and regulatory regimes.

We find that before and during price-cap regulation the effect of market share on electricity price is statistically significant for both incumbent producers. But after the divestment series the effect is statistically insignificant (with the exception of the effect of market share for the smaller incumbent producer after the second series of divestments). However, later price volatility increased compared to the price-cap regulation period. Nevertheless, the second series of divestments could be regarded as more successful than the first series in terms of reduced price volatility.

Keywords: *electricity price, uniform price auction, skew generalized error distribution, conditional volatility, regulation*

JEL Classification: C22, C5, L90, L94

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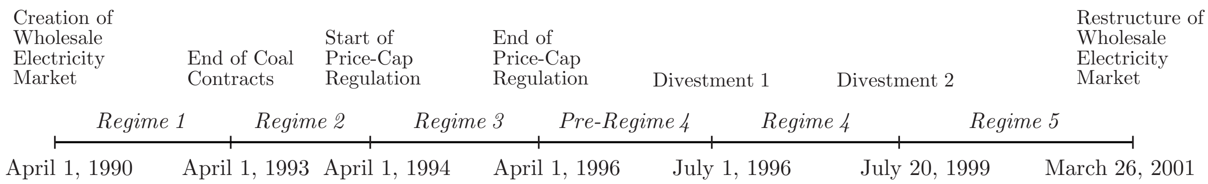
1 Introduction

Great Britain was the first among the OECD countries to liberalize its electricity supply industry. The production level of the electricity supply industry consisted of several firms where National Power (NP) and PowerGen (PG) had dominant positions. During the liberalization process, the regulatory authority, Office of Electricity Regulation (later renamed the Office of Gas and Electricity Markets), introduced a behavioral remedy (through price-cap regulation) and a structural remedy (through divestment series) at different points of time, which were targeted at the NP and PG producers and are presented in Figure 1.1.



Sources: Department of Trade and Industry (1997–2002), National Grid Company (1994–2001), Newbery (1999), Newbery (2005), Robinson and Baniak (2002), Wolfram (1999); author's illustration.

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

Price-cap regulation set an explicit ceiling on time-weighted and demand-weighted annual average prices charged for electricity production by the two incumbent electricity producers: NP (the larger producer) and PG (the smaller producer), which together sometimes produced more than 70% of electricity in the early 1990s. Later, divestment series were introduced in order to mitigate an exercise of market power and decrease the influence of the incumbent electricity producers. Following divestment series, the market shares of the incumbent electricity producers declined. Market share is an important factor affecting a firm's behavior and eventually market prices.

Generally, there is no consensus regarding the optimal remedy choice (behavioral or structural) to address market failures. Behavioral remedies try to redress specific conduct in a context where incentives remain essentially unchanged. Structural remedies, on the other hand, are aimed at changing the incentives of the firm(s) in the market, which is achieved once the structural remedies are implemented (Hellström et al., 2009).

European Union antitrust policy prioritizes the imposition of behavioral remedies above structural remedies because antitrust investigations typically concern infringements which are behavioral in nature. In the United States, on the other hand, there is a preference for structural remedies because they are simple and relatively easy to administer (Alexiadis and Sependa, 2013).

However, in 2008, following the investigation of E.ON (the world's largest utility company) on the German wholesale electricity market, for the first time the European Commission decided to apply a structural remedy. Specifically, it was agreed that E.ON would divest 5000 MW of generation capacity representing about 20% of the company's German generation portfolio (Chauve et al., 2009).

As discussed in Maier-Rigaud (2016), the advantage of a structural remedy is that it allows reducing a firm's market share and preventing the emergence or strengthening of a dominant position. Moreover, there will be no need for subsequent monitoring and enforcement. According to Council Regulation (2003), structural remedies should only be imposed either where there is no equally effective behavioral remedy or where any equally effective behavioral remedy would be more burdensome for the firm concerned than the structural remedy.

The wholesale electricity market in England and Wales presents an interesting case study where the regulatory authority introduced behavioral and structural remedies at different points of time. This enables us to compare the impact of each of the remedy on electricity price. In particular, we analyze changes in the price level and volatility during different regulatory regime periods. On the one hand, a price level affects revenues of producers and costs to consumers. On the other hand, price volatility reflects market uncertainty. Generally, both price level and volatility are important for investment and new entry decisions, too.

For the analysis of the price level and volatility, we use an autoregressive and autoregressive conditional heteroscedasticity (AR–$ARCH$) model with skew generalized error distribution (SGED). The model is extended to include regime dummy variables, incumbents' market shares calculated as a ratio of respective residual demand (in our case, incumbents' scheduled production capacity in the day-ahead auction) to forecast demand, and the seasonal component. We do not find statistical evidence for a clear advantage of a structural remedy over a behavioral remedy. Nevertheless, we find that after divestment series the effect of market share on electricity price is statistically insignificant for the larger incumbent producer. Moreover, after the second series of divestments price volatility is lower than during the price-cap regulation period.

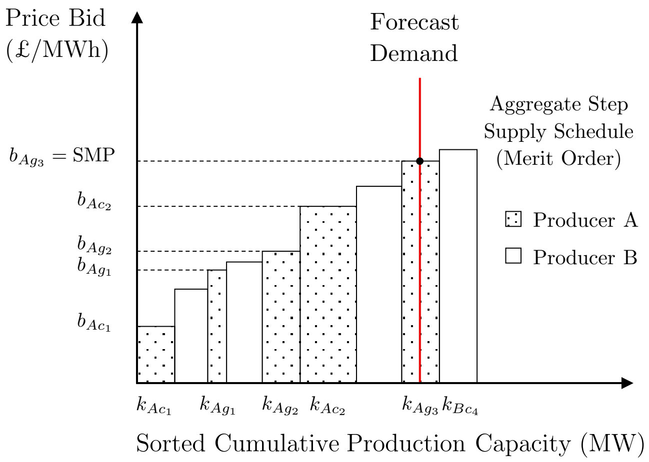
We limit our analysis to the period prior to 2001 because after March 26, 2001 the wholesale electricity market in England and Wales was restructured in order to introduce bilateral trading. Restructuring of the wholesale spot market (more precisely, a day-ahead market) for the dispatch and pricing of electricity however should not provide evidence to avoid the use of spot markets in the future. That is, a lesson that all problems stem from the use of a central auction would be wrong. Dominant producers could raise prices under any set of market rules (Green, 2003).

The measures designed to promote competition during the liberalization process were more extensive in Great Britain as compared to Germany, France, Italy, or Sweden (Bergman et al., 1998). Privatization, restructuring, market design, and regulatory reforms pursued in the liberalization process of the electricity industry in England and Wales can be characterized as the international gold standard for energy market liberalization (Joskow, 2008; Joskow, 2009). The England and Wales electricity market could, therefore, serve as an important source of lessons, especially for countries which have adopted a similar market design operated by several dominant firms.

2 Description of the electricity auction

At the start of liberalization, a wholesale market for electricity trading was created in order to introduce competition among electricity producers. Trading was organized as a uniform price auction, where all electricity producers were asked to submit price offers (up to three) and available capacity for each production unit. These multi-part bids were used by the market operator (i.e., the National Grid Company, or NGC) in the Generator Ordering and Loading (GOAL) algorithm in order to calculate half-hourly price bids (Electricity Pool, 1990; Sweeting, 2007).

In Figure 2.1, we schematically illustrate how the electricity market would have operated in a given half-hourly trading period.



Source: Author's illustration.
Notes: On the vertical axis, b_{Ac_1} refers to the price bid of electricity producer A's first production unit, whose production capacity is k_{Ac_1}. For the sake of simplicity, it is assumed that electricity producer A has 2 coal and 3 gas types of production unit. Price bids of all production units are ordered as would have been done by the market operator (i.e., the NGC) to create the least expensive production schedule. The intersection of the constructed production schedule and forecast demand (the vertical line) determines the System Marginal Price (SMP), the wholesale electricity price. In this hypothetical example, it is electricity producer A's third gas production unit that determines the SMP.
Figure 2.1: Determination of an SMP

For each half-hourly trading period the pairs of a price bid and respective production capacity of all production units were ordered based on price bids so that to construct a production schedule (also called a merit order) that would indicate the least expensive way to meet price-inelastic forecast demand. Methodology of forecasting demand for electricity by the market operator was common knowledge (Wolak, 2000; Wolak and Patrick, 2001) and independent of producers' bidding behavior (Green, 2006).

The production unit whose price bid in this production schedule intersects forecast demand is called the marginal production unit. Its price bid determines the System Marginal Price (SMP), which represented the wholesale price paid the same to all producers that were scheduled to produce electricity during a half-hourly trading period (Electricity Pool, 1990).

3 Literature review

Various approaches have been applied for studying electricity prices and an exercise of market power in restructured electricity markets. The seminal approach considered in Green and Newbery (1992) for the case of the England and Wales electricity market applies the supply function equilibrium model. The authors consider that a producer submits a continuously differentiable supply function that maximizes its profits given the residual demand it faces. This approach is 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 National Power and PowerGen incumbent electricity producers in the early 1990s.

By analyzing the later period, Wolfram (1999), however, finds that the supply function equilibrium model does not describe the market very well because electricity prices were much lower than the model predicted. She also finds that during price-cap regulation (April 1994 – March 1996) the industry supply curve rotated counterclockwise, which is explained as producers' attempt to increase prices when demand is high and decrease prices when demand is low and at the same time to satisfy the cap on annual average prices.

Another approach for studying an exercise of market power leading to higher electricity prices is a discrete bid auction model. Ciarreta and Espinosa (2010) find that for the Spanish wholesale electricity market, which is operated as a multiunit uniform price auction similarly to the original model of the England and Wales electricity market and where two firms (Endesa and Iberdrola) own most of capacity, the supply function equilibrium model better fits data than the discrete bid auction model. This result is, however, based on the analysis of bids for only oil fired thermal plants. Von der Fehr and Harbord (1993), Wolfram (1998), Crawford et al. (2007), and Tashpulatov (2015) consider a discrete bid auction model for the analysis of an exercise of market power in the England and Wales electricity market.

These two approaches measure market power based on differences between price bids and marginal costs. Approximation of marginal costs was possible for the case of the England and Wales electricity market thanks to the availability of data on the efficiency rates of production units and quarterly fuel prices paid by major power producers (Figure A.3).

Methodologies considering competitive benchmark prices and capacity withholding are relatively recent and have been applied in the analysis of restructured electricity markets in the US and Europe. In particular, Borenstein et al. (2002) apply the methodology of competitive benchmark prices in the analysis of electricity crisis in the California wholesale market. Sweeting (2007) similarly applies this methodology for the British electricity market. The application of competitive benchmark prices allows to estimate the scope and severity of departures from competitive bidding over time by measuring deviations of wholesale prices from the expected marginal cost of the most expensive production unit needed to serve demand for electricity.

Wolak and Patrick (2001), Dechenaux and Kovenock (2007), Fridolfsson and Tangerås (2009), Castro-Rodriguez et al. (2009), Green (2011), Lízal and Tashpulatov (2014) analyze a capacity withholding strategy. In the theoretical model, reflecting the design of the wholesale electricity market in England and Wales, Dechenaux and Kovenock (2007) find that capacity withholding in a uniform price auction could be even necessary to sustain tacit collusion. The literature identifies that producers may increase prices by withholding part of production capacity in order to force the market operator to use more expensive and probably less efficient production units to satisfy demand for electricity. In this case producers may increase output prices without driving a wedge between output prices and marginal production costs (Fridolfsson and Tangerås, 2009).

The next approach to study electricity prices and an exercise of market power is based on residual demand. This approach allows a producer to incorporate competitors' bidding behavior in its profit maximization problem (Marques et al., 2008; Prete and Hobbs, 2015). Another application of residual demand in day-ahead auctions is to analyze the effect of growing penetration of renewable energy sources (Vázqueza et al., 2014).

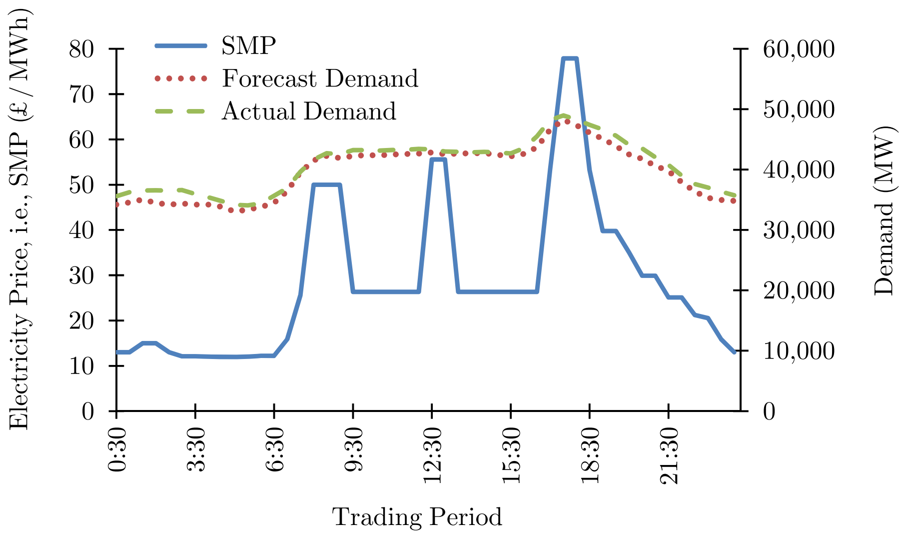
We use a firm's residual demand (i.e., a firm's scheduled production capacity in the day-ahead auction) in order to calculate its market share. More precisely, a firm's market share is calculated as a ratio of its residual demand to forecast demand. Generally, market share affects firms' behavior and eventually market prices. Using residual and forecast demand in calculating market shares is consistent with the market rules because these data were used in determining the wholesale price in the day-ahead electricity market in England and Wales.

Market shares can also be used to calculate the Herfindahl index. Evans and Green (2005) consider the monthly Herfindahl index to examine the effect of competition on electricity prices.

In our research we analyze the effect of incumbent producers' market shares on the wholesale electricity price during the peak-demand period over trading days in relation to the price-cap regulation and divestment series. We focus on the peak-demand period during each trading day because, as documented in the literature, market power is most often observed during namely the peak-demand period (Borenstein et al., 2002).

4 Data

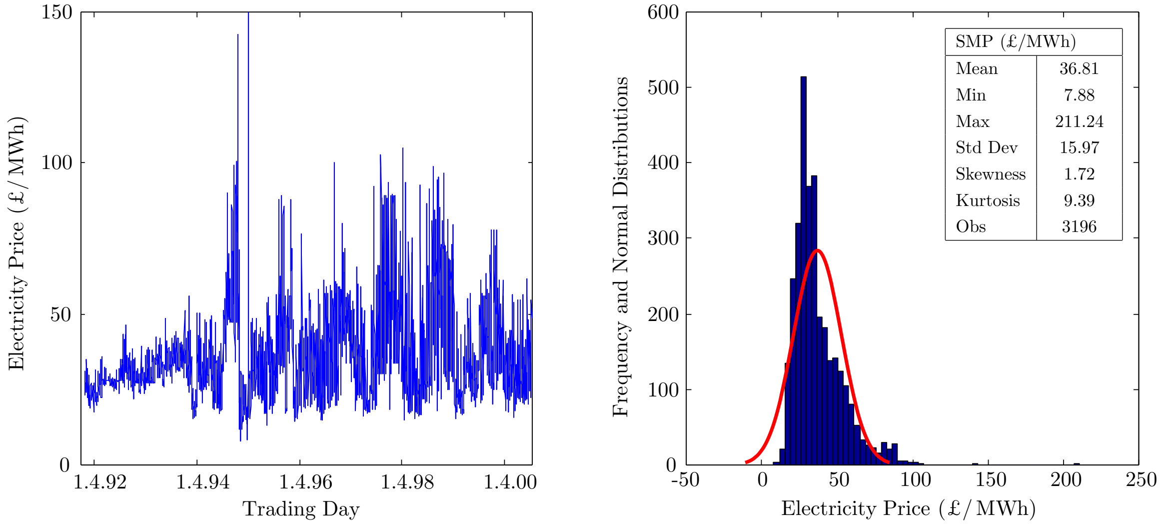
The first data set covers the period January 1, 1992 – September 30, 2000. This data set includes half-hourly observations on the wholesale electricity price (System Marginal Price (SMP)) and demand for electricity (load).



Source: Author's illustration.
Figure 4.1: SMP, forecast demand, and actual demand (Jan 6, 2000)

In Figure 4.1 we provide an illustration of market data for January 6, 2000. The peak-demand period on this trading day is during 17:30–18:00, when the forecast demand is at the peak of 48 215 MW and electricity price is £77.89 per MWh. Changes in forecast demand can be considered as exogenous when analyzing changes in electricity price because the forecasting methodology was independent of producer's bidding.

Figure 4.2 presents changes and distribution of the electricity price of the half-hourly peak-demand period over trading days. The empirical distribution (depicted through the histogram) differs a lot from the normal distribution (depicted through the smooth curve). The differences are also confirmed by our calculations of positive skewness and excess kurtosis.



Source: Author's calculations.
Figure 4.2: Electricity price during the peak-demand period over trading days (Jan 1, 1992 – Sept 30, 2000)

In Table 4.1 we present a detailed analysis of changes in the SMP of the peak-demand period across different regulatory periods summarized in Figure 1.1. For comparison purposes, we consider the price-cap regulation period (i.e., Regime 3) as the reference period.

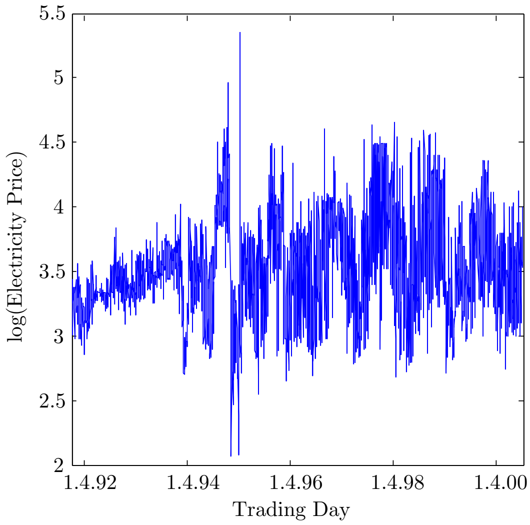
For testing the equality of means we first needed to test the equality of variances using F-test. The results indicate that during the price-cap regulation prices on average are statistically higher than in the earlier periods (i.e., Regime 1 and Regime 2). The prices on average rose further after the first series of divestments were introduced (i.e., Regime

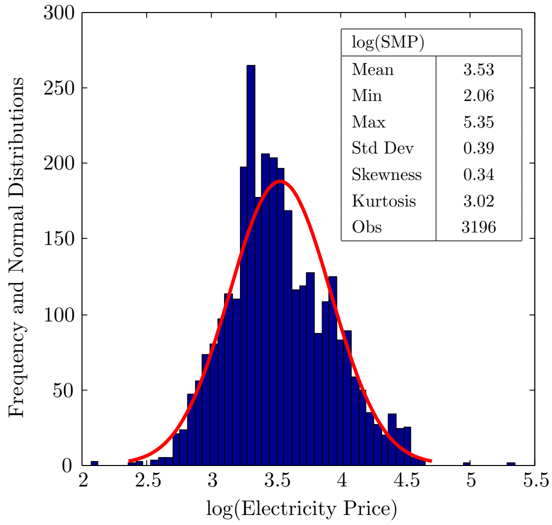
Table 4.1: Summary statistics for electricity price (£/MWh) during the peak-demand period over trading days

SMP	Regime 1 (Jan 92–Mar 93)	Regime 2 (Apr 93–Mar 94)	Regime 3 (Apr 94–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
Mean	27.5	32.9	37.2	35.3	42.0	36.3
Change of Mean	-9.7	-4.3		-2.0	4.8	-0.9
t-test	-14.4	-5.9		-1.4	5.5	-1.1
t-critical	-2.0	-2.0		-2.0	2.0	-2.0
Min	17.3	14.9	7.9	17.2	14.5	15.5
Max	46.2	55.9	211.2	76.7	105.1	77.9
St Dev	3.7	6.5	17.6	11.4	19.3	12.1
F-test	23.0	7.3		2.4	1.2	2.1
F-critical	1.2	1.2		1.3	1.1	1.2
Coef of Var (%)	13.4	19.8	47.4	32.3	45.9	33.5
Obs	456	365	731	91	1114	439

Source: Author's calculations.

4). During Pre-Regime 4 and Regime 5 periods the average prices were about the same as during the price-cap regulation period.





Source: Author's calculations.
Figure 4.3: Log of electricity price during the peak-demand period over trading days (Jan 1, 1992 – Sept 30, 2000)

Similar to Figure 4.2, in Figure 4.3 we present log transformed electricity price (i.e., the natural logarithm of electricity price), which is used in the empirical part. Using log transformed time series may help to mitigate the effect of outliers[1] and also allow to

[1]We observe a high price of about £211/MWh during the peak-demand period on April 4, 1995.

interpret regression results in terms of elasticities.

The results in Figure 4.3b show that the distribution of log of electricity price is positively skewed and has a peak higher than the peak of normal distribution. These issues could be addressed by considering skew generalized error distribution (SGED).

The second data set covers the period January 1, 1993 – September 30, 2000 and includes half-hourly data on capacity bids and price bids. Using publication materials of the National Grid Company (1994–2001), we can identify production units that were divested from NP and PG during horizontal restructuring, which is important in determining residual demand for these incumbent producers.

We consider market share as the ratio of residual demand to forecast demand from the day-ahead bidding data.[2] A firm's residual demand is represented by its scheduled capacity based on submitted available capacity of various production units as described in Figure 2.1. Market share can be considered as an independent variable when analyzing price changes because the electricity price was determined after the bidding of producers (i.e., after their submission of price and capacity bids). Sometimes the inclusion of market share may however lead to the endogeneity problem. For example, like in the feed-in tariff principle, when first the electricity price is announced and then bidding of electricity producers takes place.

In Tables 4.2–4.3 we present summary statistics for market shares of the NP and PG producers, which in the early years sometimes served more than 70% of demand.

This price spike was brought about by a mistaken mix of technical parameters that the GOAL algorithm had to accept. This explanation is based on a comment from Richard Green.

[2]The usual interpretation of a market share could be the share of electricity sold on the market, which is not what we consider in the paper.

Table 4.2: Summary statistics for NP's market share during the peak-demand period over trading days

	Regime 1 (Jan 93–Mar 93)	Regime 2 (Apr 93–Mar 94)	Regime 3 (Apr 94–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
Mean	0.449	0.426	0.367	0.297	0.229	0.124
Min	0.341	0.286	0.165	0.227	0.086	0.062
Max	0.506	0.503	0.501	0.350	0.317	0.181
St Dev	0.037	0.038	0.047	0.028	0.034	0.022
Coef of Var (%)	8.21	8.93	12.68	9.44	14.98	17.96
Obs	90	365	731	91	1114	439

Source: Author's calculations.

Table 4.3: Summary statistics for PG's market share during the peak-demand period over trading days

	Regime 1 (Jan 93–Mar 93)	Regime 2 (Apr 93–Mar 94)	Regime 3 (Apr 94–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
Mean	0.278	0.247	0.245	0.230	0.202	0.141
Min	0.219	0.128	0.123	0.166	0.096	0.069
Max	0.346	0.318	0.331	0.277	0.284	0.193
St Dev	0.033	0.035	0.035	0.025	0.028	0.017
Coef of Var (%)	11.98	14.06	14.21	10.84	13.97	11.99
Obs	90	365	731	91	1114	439

Source: Author's calculations.

Based on the analysis of the coefficient of variation we find that during almost all regime periods the market share of PG changes more than the market share of NP. However, after the second series of divestments, when on average the market share of NP is lower than the market share of PG, we find that changes in the market share of NP are higher. This could be the result of an unequal horizontal restructuring where NP divested more of generation capacity than did PG. Therefore, it is interesting to see how changes in the market shares due to divestments affected the price dynamics.

5 Methodology

In order to analyze the dynamics of the electricity price during the peak-demand period over trading days we consider the following model:

$$
\begin{aligned}
lprice_t &= a_0 + \sum_{i=1}^{P} a_i \, lprice_{t-i} + w_t' \cdot b + \varepsilon_t && (1) \\
h_t &= \alpha_0 + \sum_{i=1}^{p} \alpha_i \, \varepsilon_{t-i}^2 + z_t' \cdot \delta. && (2)
\end{aligned}
$$

The first equation is called the mean equation and is analyzed using an autoregressive process with maximum lag order P, that is, $AR(P)$. In this equation, the dependent variable $lprice_t$ is natural logarithm of the wholesale price of electricity (i.e., SMP) during the peak-demand period of trading day t in the day-ahead auction. The $AR(P)$ process for $lprice_t$ with selected lags of up to order P allows to take into account partial adjustment effects and seasonality (cyclical or periodic) features.

Next in the mean equation (1), w_t is a vector of explanatory variables including incumbent producers' market shares, natural logarithm of forecast demand, sine and cosine periodic functions. Incumbent producers' market shares are calculated as a ratio of their individual residual demand to forecast demand. Residual and forecast demand data were used in determining the wholesale price in the day-ahead electricity auction described in Figure 2.1. The inclusion of market shares is also partly consistent with the methodology in Evans and Green (2005) considering the effect of market concentration measured through the Herfindahl index on electricity prices. Interacting the market shares with regime dummy variables should in particular allow us for a more detailed analysis of the impact of divestment series on electricity prices.

Finally, ε_t is the disturbance term such that $E\left(\varepsilon_t | I_{t-1}\right) = 0$, where I_{t-1} represents the information set at time $t-1$. The disturbance term may be heteroscedastic, which then does not allow for statistical inference about the significance of estimated parameters in the mean equation.

In case the disturbance term has serial correlation or heteroscedasticity problems, one could apply a correction to the standard errors (e.g., Newey-West) or apply the generalized least squares method based on normal distribution (like in Evans and Green, 2005). These approaches take into account serial correlation and heteroscedasticity problems in the disturbance term, which then allows for statistical inference.

Another approach to address the heteroscedasticity problem in the disturbance term could be to consider the autoregressive conditional heteroscedasticity process with maximum lag order p, that is, $ARCH(p)$. This approach was first introduced and applied in Engle (1982) to estimate the means and variances of inflation in the UK.

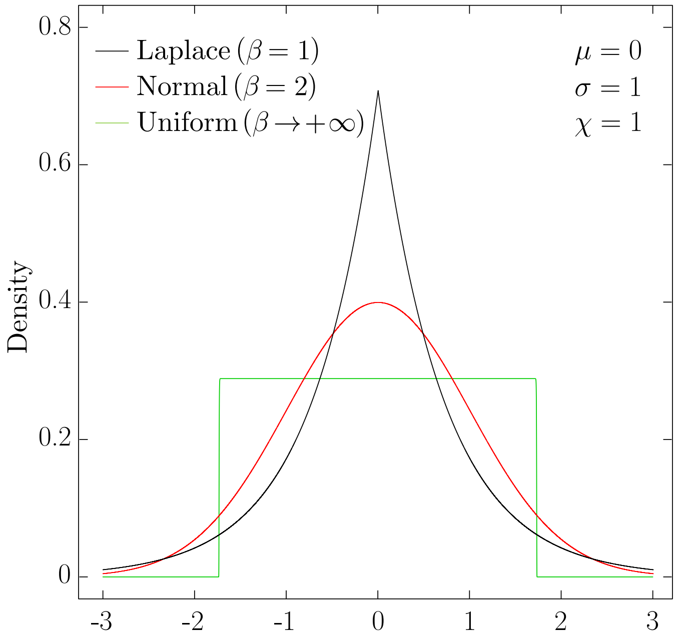
The heteroscedasticity can, therefore, be modeled by the second equation, which is called the volatility equation. Conditional variance and volatility[3] terms are used interchangeably in the literature, which is denoted by $var\left(\varepsilon_t|I_{t-1}\right) = h_t$, where I_{t-1} represents the information set at time $t-1$.[4] In this volatility equation (2), z_t is a vector including regime dummy variables, sine, and cosine periodic functions.

The mean equation (1) and volatility equation (2) are jointly called the $AR(P)$–$ARCH(p)$ model, which we extend by including external regressors. In order to estimate these two equations jointly, a distributional assumption needs to be made for the so-called standardized residuals $\nu_t = \varepsilon_t/\sqrt{h_t}$. Engle (1982) assumes that ν_t are independent and identically distributed (i.i.d.) and follow standard normal distribution. In our extended $AR(P)$–$ARCH(p)$ model we assume that ν_t are independent and identically distributed (i.i.d.) and follow skew generalized error distribution. This distribution is characterized by four parameters: mean μ, standard deviation σ, shape parameter β ($\beta < 2$ corre-

[3]Here conditional is in the sense of conditional on information at time $t-1$.

[4]Volatility can also be rewritten in the following way $h_t = var\left(\varepsilon_t|I_{t-1}\right) = E\left(\left(\varepsilon_t - E(\varepsilon_t)\right)^2|I_{t-1}\right) = E\left(\varepsilon_t^2|I_{t-1}\right)$, where we used $E\left(\varepsilon_t|I_{t-1}\right) = 0$.

sponds to a leptokurtic distribution with heavy tails and with a peak more acute and higher than in normal distribution),[5] and skewness parameter χ ($\chi > 1$ corresponds to a positively skewed distribution). Skew generalized error distribution is denoted by SGED (μ, σ, β, χ).[6]



Source: Author's calculations.
Notes: We describe special cases of the shape parameter $\beta = 1$, $\beta = 2$, and $\beta \to +\infty$ which correspond to Laplace (black), Standard Normal (red), and Uniform (green) distributions, respectively. When the skewness parameter exceeds 1, i.e., $\chi > 1$, then we obtain a positively skewed distribution.

Figure 5.1: SGED (μ, σ, β, χ)

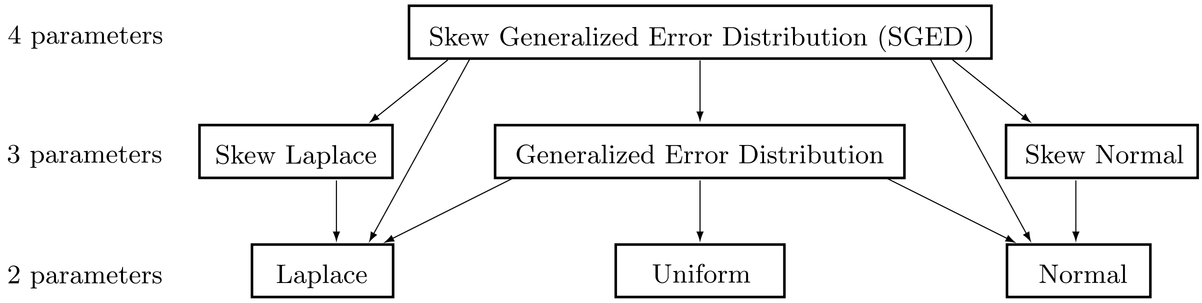
Figure 5.1 describes three special cases of SGED (μ, σ, β, χ) depending on the value of shape parameter β and fixed values of $\mu = 0$, $\sigma = 1$, and $\chi = 1$: Laplace distribution when $\beta = 1$, normal distribution when $\beta = 2$, and uniform distribution when $\beta \to \infty$. The symmetric case of SGED when $\chi = 1$ is known as generalized error distribution

[5] In cases of heavy tails and a peak lower than in normal distribution, Student's t distribution could be applicable.

[6] Skewness coefficient and skewness parameter are not the same concepts. Sample skewness coefficient is a sample statistic, whereas skewness parameter is the fourth parameter describing SGED. For a positively skewed distribution (i.e., with a longer right tail) the skewness coefficient is positive and skewness parameter is greater than one.

where β is a free parameter.

Below in Figure 5.2 we schematically illustrate related distributions, where SGED depending on four parameters represents the most flexible and general type of distribution.



Source: Author's illustration.

Figure 5.2: Special cases of SGED (μ, σ, β, χ)

As presented in Figure 4.3b, the peak in the distribution of electricity price is higher than that in the normal distribution. Since Student's t distribution has a lower peak than the normal distribution, we do not include Student's t distribution in Figure 5.2. At the same time, though, as the number of degrees of freedom increases, Student's t distribution approaches normal distribution.

In Appendix C, we examine model adequacy by verifying the validity of distributional assumptions of standardized residuals $\hat{\nu}_t$ based on the Brock–Dechert–Scheinkman (BDS) test (Brock et al., 1996), Ljung–Box Q-test (Ljung and Box, 1978), skewness and kurtosis measures, kernel density and quantile-quantile plots, Jarque–Bera and Kolmogorov–Smirnov normality tests (Hazewinkel, ed, 1990). Rejecting normality may not mean that the empirical distribution is SGED. That is why, we additionally perform the goodness of fit test. Finally, in order to test if the volatility model is correctly specified we perform the sign bias test developed by Engle and Ng (1993). Verifying the validity of distributional assumptions is important in analyzing economic time series with time-varying volatility and for the subsequent interpretation of results.

6 Results

Because stationarity in the time series analysis is a usual requirement in order to allow for modeling and statistical inference, we first provide the results of the stationarity test. Then we analyze seasonality properties using the correlogram and periodogram plots. Next we provide our estimation results for the mean and volatility equations.

6.1 Stationarity test

We test the stationarity of log of electricity price during the half-hourly peak-demand period over trading days using the Augmented Dickey–Fuller (ADF) test with a constant term (Dickey and Fuller, 1981). This test allows us to control for the possible presence of serial correlation in the residuals. The maximum lag order is reduced to 21 based on the Schwarz information criterion (SIC). The results of the ADF test are summarized in Table 6.1.

Table 6.1: ADF test for log of electricity price time series

Null hypothesis: log of electricity price time series has a unit root Exogenous: constant Lag length: 21 (Automatic based on SIC)	
ADF test statistic for log price time series	-5.349

Note: MacKinnon critical values for the rejection of the hypothesis of a unit root: 1% critical value = -3.432, 5% critical value = -2.862, and 10% critical value = -2.567.

The unit-root null hypothesis is rejected and therefore we conclude that log of electricity price time series is stationary. This test result allows us to apply the correlogram and periodogram plots for seasonality analysis which are presented in the next section.

In Table 6.2 we similarly present the stationarity test results for the log of forecast demand time series, which is included as an exogenous variable in modeling the dynamics of electricity price.

Table 6.2: ADF test for log of forecast demand time series

Null hypothesis: log of forecast demand time series has a unit root Exogenous: constant Lag length: 28 (Automatic based on SIC)	
ADF test statistic for log price time series	-3.650

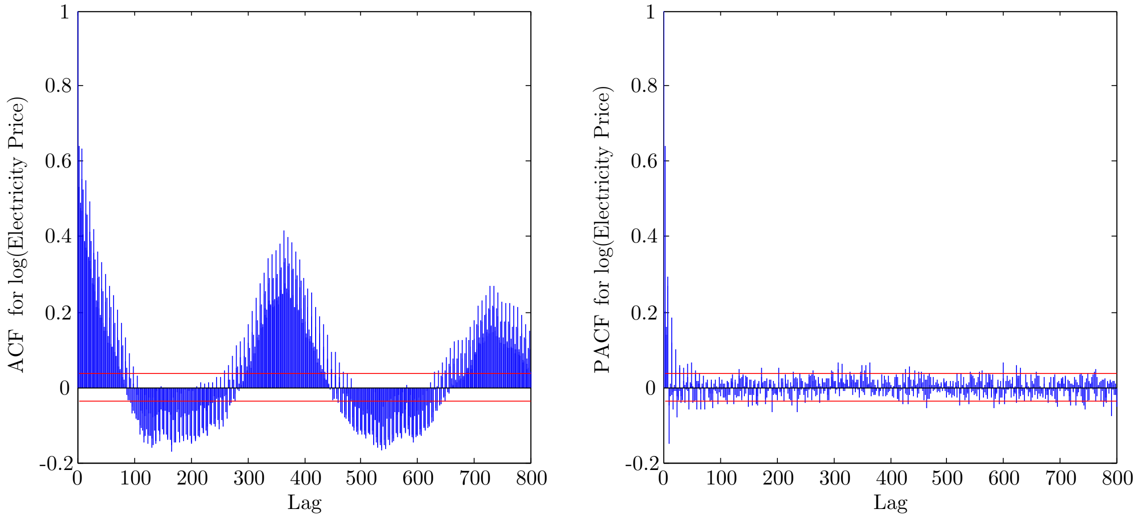
Note: MacKinnon critical values for the rejection of the hypothesis of a unit root: 1% critical value = -3.432, 5% critical value = -2.862, and 10% critical value = -2.567.

The unit-root null hypothesis is rejected and therefore we conclude that the log of forecast demand time series is stationary. This test result allows us to apply the Fourier transform in order to construct the periodogram plot for the log of forecast demand time series. We believe that there may be common frequencies with those of electricity price related to seasonality pattern. Including log of forecast demand may, therefore, lead to a parsimonious model without all frequencies of $2\pi/7$, $4\pi/7$, and $6\pi/7$ necessarily being used in sine and cosine periodic functions in order to model seasonality pattern.

6.2 Seasonality analysis

In order to analyze seasonality properties and partial adjustment effects on the time domain we use the autocorrelation function (ACF) and partial autocorrelation function (PACF) plots, respectively. They are summarized in the correlogram presented in Figure 6.1.

We find that the ACF plot contains spikes at lags of multiples of 7 and 364, which reflect the weekly and annual seasonality patterns in electricity prices, respectively. These results are empirically important not only for our specification of the $AR(P)$ process but also for the analysis of firm level data in general. For example, Puller (2007) in the analysis of firm level data of the California electricity market allows for heteroscedasticity and serial correlation in the shocks by computing Newey-West standard errors with a 7-day-lag moving-average structure.

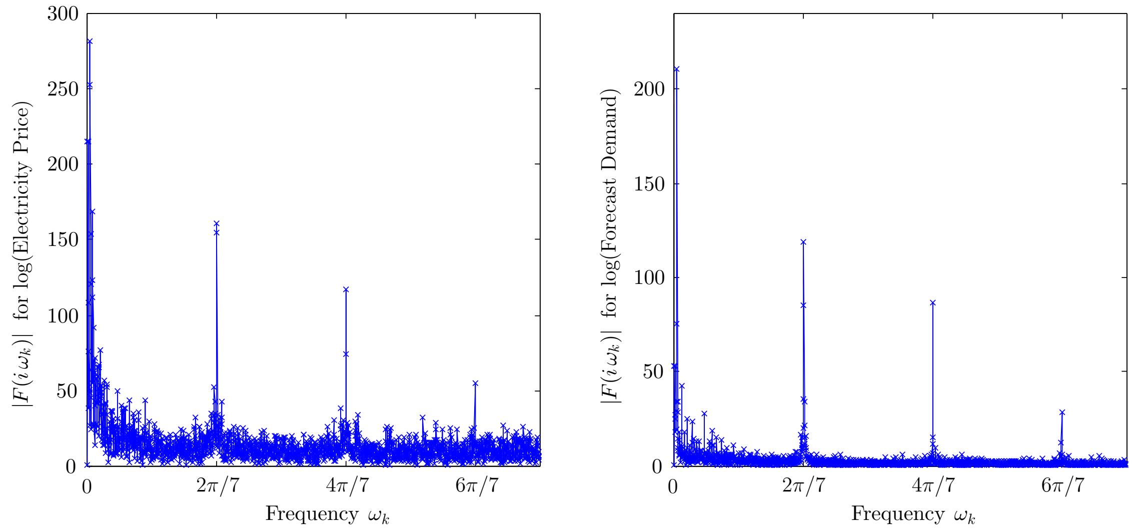


Source: Author's calculations.
Figure 6.1: Correlogram for log of electricity price time series

Fourier transform (FT) allows for the analysis of seasonality patterns on the frequency domain.[7] The frequencies ω_k where the absolute values of Fourier transform $|F(i\omega_k)|$ achieve local maxima could be used in sine and cosine functions in order to explain seasonal variation in the data.

In Figure 6.2 we summarize in periodogram plots the results of the absolute values of Fourier transform $|F(i\omega_k)|$ for the log of electricity price and log of forecast demand time series.

[7]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 numerical procedure computes $|F(i\,\omega_k)| \approx \left|\sum_{t=0}^{T-1} p_t\, e^{-i\omega_k t}\right| \approx |(p_t, \cos\omega_k t) - i\,(p_t, \sin\omega_k t)| = \sqrt{(p_t, \cos\omega_k t)^2 + (p_t, \sin\omega_k t)^2}$, where $\omega_k = \frac{k}{N-1} \cdot 2\pi$, $\;k = 0, 1, 2, \ldots, N-1$, and N determines the grid. The expressions in parentheses represent scalar products, which in statistical terms measure covariation between the price time series and cosine or sine functions for different values of frequency ω_k. The optimization finds such values of ω_k that would explain a large portion of variation in electricity prices. A graph where the absolute values of the Fourier transform are plotted on the frequency domain is known as a periodogram.



Source: Author's calculations.
Figure 6.2: Periodogram plots for log of electricity price and log of forecast demand time series

The periodogram plot suggests using $\frac{2\pi}{7}$, $\frac{4\pi}{7}$, and $\frac{6\pi}{7}$ as frequencies for the sine and cosine periodic functions. However the disadvantage of the Fourier transform is that it does not tell us directly which functions should be used with these identified frequencies: only sine, only cosine, or both. For this purpose we look at correlations presented in Table 6.3.

Table 6.3: Correlation of log of electricity price and log of forecast demand with periodic functions

Variable	$\cos\left(\frac{2\pi}{7}t\right)$	$\sin\left(\frac{2\pi}{7}t\right)$	$\cos\left(\frac{4\pi}{7}t\right)$	$\sin\left(\frac{4\pi}{7}t\right)$	$\cos\left(\frac{6\pi}{7}t\right)$	$\sin\left(\frac{6\pi}{7}t\right)$
log(SMP)	-0.18 ***	0.14 ***	-0.10 ***	0.10 ***	-0.06 ***	0.02
log(Forecast demand)	-0.44 ***	0.20 ***	-0.19 ***	0.19 ***	-0.07 ***	0.07 ***

Note: *, **, and *** stand for the 10%, 5%, and 1% significance levels, respectively.

The correlation analysis presented in Table 6.3 suggests not including variable $\sin\left(\frac{6\pi}{7}t\right)$ because correlation between this variable and the dependent variable log(SMP) is not statistically significant.

6.3 Estimation of the mean and volatility equations

Based on the detailed analysis of the correlogram and periodogram plots, we specify the lag structure and frequencies for the sine and cosine functions in the mean and volatility equations. The results presented in Tables 6.4 and 6.5 include standard errors of parameter estimates based on maximum likelihood estimation. These standard errors are correct because all distributional assumptions for ν_t are satisfied. In particular, in Appendix C we test in detail the distributional assumptions for ν_t of being i.i.d. and following SGED. The test results confirm the validity of our distributional assumptions.

Table 6.4: Mean equation $lprice_t = a_0 + \sum_{i=1}^{P} a_i \, lprice_{t-i} + w_t' \cdot b + \varepsilon_t$

Intercept term and lagged terms $lprice_{t-i}$	Coef $\hat{a}_i$	Std Err	Exogenous variables	Coef $\hat{b}_j$	Std Err
$\hat{a}_0$	-1.09005***	0.00290	$Regime\ 1_t \cdot S_t^{NP}$	0.03584***	0.00011
$lprice_{t-1}$	0.30204***	0.00073	$Regime\ 2_t \cdot S_t^{NP}$	0.28354***	0.05289
$lprice_{t-2}$	0.11736***	0.00031	S_t^{NP}	-0.01995***	0.00007
$lprice_{t-3}$	0.06675***	0.00017	$Pre\text{-}Regime\ 4_t \cdot S_t^{NP}$	0.90364	0.60383
$lprice_{t-4}$	0.06126***	0.00016	$Regime\ 4_t \cdot S_t^{NP}$	0.26883**	0.14972
$lprice_{t-6}$	0.12551***	0.00035	$Regime\ 5_t \cdot S_t^{NP}$	-0.59855	0.38660
$lprice_{t-7}$	0.19530***	0.00049	$Regime\ 1_t \cdot S_t^{PG}$	-0.28930***	0.00078
$lprice_{t-9}$	-0.09317***	0.00024	$Regime\ 2_t \cdot S_t^{PG}$	-0.52879***	0.08924
$lprice_{t-12}$	-0.05304***	0.00014	S_t^{PG}	0.30861***	0.00083
$lprice_{t-14}$	0.11632***	0.00031	$Pre\text{-}Regime\ 4_t \cdot S_t^{PG}$	-1.08304	0.77633
$lprice_{t-21}$	0.09109***	0.00023	$Regime\ 4_t \cdot S_t^{PG}$	-0.17788	0.17213
$lprice_{t-22}$	-0.05007***	0.00013	$Regime\ 5_t \cdot S_t^{PG}$	0.54115	0.33167
$lprice_{t-24}$	-0.04189***	0.00011	$\sin(2\pi t/7)$	0.02114***	0.00007
$lprice_{t-44}$	-0.04919***	0.00013	$\sin(4\pi t/7)$	0.02690***	0.00008
$lprice_{t-49}$	0.05135***	0.00013	$\cos(6\pi t/7)$	-0.01248***	0.00004
$lprice_{t-55}$	-0.02990***	0.00008	$ldemand_t$	0.16719***	0.00031
$lprice_{t-111}$	-0.04056***	0.00011			
$lprice_{t-164}$	-0.04248***	0.00011	R^2	0.606	
$lprice_{t-364}$	0.06847***	0.00018	Obs	2823	

Notes: The inclusion of some of the lags of the dependent variable helps as a correction for serial correlation in the error term. In the table, $lprice_t$ and $ldemand_t$ stand for the natural logarithm of SMP and forecast demand during the peak-demand period of trading day t ($t = 1, 2, \ldots, 3196$), respectively. The number of included observations is less because of lagged terms. w_t is a vector of exogenous variables including market shares interacted with regime dummy variables, periodic functions, and forecast demand. Standard errors are based on maximum likelihood estimation. *, **, and *** stand for the 10%, 5%, and 1% significance levels, respectively.

In Table 6.4 we provide our estimation results for the mean equation, which includes lags of the dependent variable and exogenous variables (market shares interacted with regime dummy variables, periodic functions, and forecast demand).

The price-cap regulation period (i.e., Regime 3 described in Figure 1.1) is considered as a reference period. The interaction terms between the regime dummy variables and market shares of incumbent producers allow to analyze changes in the effect of incumbents' market shares on electricity price.

Changes in the effect of market shares on electricity price are statistically significant before the price-cap regulation period. However these changes are mostly statistically insignificant after the divestment series.

The estimation results for the volatility equation including regime dummy variables and periodic functions as exogenous variables are presented in Table 6.5.

Table 6.5: Volatility equation $h_t = \alpha_0 + \sum_{i=1}^{p} \left(\alpha_i\, \varepsilon^2_{t-i} + \gamma_i\, I_{t-i} \cdot \varepsilon^2_{t-i}\right) + z'_t \cdot \delta$

Intercept term and ARCH terms ε^2_{t-i}	Coef	Std Err	Exogenous variables	Coef $\hat{\delta}_j$	Std Err
$\hat{\alpha}_0$	0.03824 ***	0.00012	*Regime* 1_t	-0.03342 ***	0.00011
ε^2_{t-1}	0.09687 ***	0.00035	*Regime* 2_t	-0.02853 ***	0.00107
ε^2_{t-2}	0.07501 ***	0.00032	*Pre-Regime* 4_t	0.02269	0.01484
ε^2_{t-4}	0.04659 ***	0.00018	*Regime* 4_t	0.00589 **	0.00341
ε^2_{t-5}	0.05782 ***	0.00019	*Regime* 5_t	-0.00667 **	0.00364
ε^2_{t-6}	0.07095 ***	0.00024	$\sin(2\pi t/7)$	0.00203 ***	0.00001
ε^2_{t-7}	0.00479 ***	0.00003	$\cos(2\pi t/7)$	0.00468 ***	0.00001
$I_{t-1} \cdot \varepsilon^2_{t-1}$	0.15345 ***	0.00053			
$I_{t-7} \cdot \varepsilon^2_{t-7}$	0.04791 ***	0.00023	SGED parameters		
			Shape parameter, $\hat{\beta}$	1.46803 ***	0.05237
			Skewness parameter, $\hat{\chi}$	1.05424 ***	0.02471

Notation: h_t stands for conditional volatility as described in footnote 4. I_{t-i} is an indicator function equal to 1 if $\varepsilon_{t-i} < 0$ and 0 otherwise. z_t is a vector of exogenous variables including regime dummy variables and periodic functions. Standard errors are based on maximum likelihood estimation. *, **, and *** stand for the 10%, 5%, and 1% significance levels, respectively.

Again the price-cap regulation period is considered as a reference period. Coefficient estimates in front of regime dummy variables represent estimates of changes in the intercept term during other regime periods. These estimates are all statistically significant except for the Pre-Regime 4 period. Interestingly, we find that the second series of divestments was more successful in terms of reduced price volatility since the negative change in the intercept term is also statistically significant.

In estimating the volatility equation we allow for volatility asymmetry. In other words, we allow for the asymmetric effects of past positive and negative shocks ε_{t-i} on volatility following Glosten et al. (1993). In this approach, α_i measures the direct effect of past shock ε_{t-i} and γ_i captures the additional effect of negative shock ε_{t-i} (in case $\varepsilon_{t-i} < 0$) on volatility.

The sum of coefficients in front of the lagged terms in the mean equation is 0.8 and in front of the $ARCH$ terms in the volatility equation is 0.5. This is consistent with the stability requirement of being less than 1. Moreover the positivity of the coefficients of $ARCH$ terms and the intercept term in the volatility equation guarantees positivity of conditional volatility.

The estimates of the shape and skewness parameters of SGED (μ, σ, β, χ) suggest that the empirical distribution of standardized residuals $\hat{\nu}_t$ has higher kurtosis (because shape parameter $\beta < 2$) than in the case of normal distribution and is positively skewed (because skewness parameter $\chi > 1$).[8] These are summarized in Table C.3.

7 Discussion

In the specification of the mean and volatility equations we consider the price-cap regulation period (i.e., Regime 3) as a reference period. In the mean equation, in particular, coefficient estimates in front of regime dummy variables interacted with market share reflect changes in the effect of market share in comparison to the reference period. This approach allows us to understand if compared to the price-cap regulation period the

[8]Normal distribution has kurtosis coefficient equal to 3 (i.e., shape parameter $\beta = 2$) and skewness coefficient equal to 0 (i.e., skewness parameter $\chi = 1$).

observed changes during the other regime periods are economically and statistically significant.

In the mean equation incumbent producers' market shares calculated as a ratio of residual demand to forecast demand is an important factor for the policy analysis of the impact of divestment series. As summarized in Table 6.4, changes in the slope coefficient of market shares for both incumbent producers are statistically significant before price-cap regulation, but are mostly statistically insignificant after divestment series.

The finding that changes in the effect of market shares are statistically insignificant may not mean that the effect of market shares on electricity price after divestment series is also statistically insignificant. We need to test the significance of the effect of market shares for each regime period separately. Since Regime 3 in Table 6.4 represents the reference period, first we calculate for the other regime periods the slope coefficient in front of incumbents' market shares by adding the coefficient value during Regime 3 (i.e., coefficient $\hat{b}_3$) and the respective change coefficient (i.e., the coefficient in front of market share interacted with the regime dummy variable). In particular, the slope coefficient of NP's market share for Regime 1 would be the sum of $\hat{b}_1 = 0.03584$ and $\hat{b}_3 = -0.01995$, which is approximately 0.0159. These calculations are presented in Table 7.1.

Table 7.1: The effect of market share of NP and PG on electricity price across different regimes

	Regime 1 (Jan 93–Mar 93) $\hat{b}_1 + \hat{b}_3$	Regime 2 (Apr 93–Mar 94) $\hat{b}_2 + \hat{b}_3$	Regime 3 (Apr 94–Mar 96) Price-cap $\hat{b}_3$	Pre-Regime 4 (Apr 96–Jul 96) $\hat{b}_4 + \hat{b}_3$	Regime 4 (Jul 96–Jul 99) Divestment 1 $\hat{b}_5 + \hat{b}_3$	Regime 5 (Jul 99–Sept 00) Divestment 2 $\hat{b}_6 + \hat{b}_3$
Coef of S_t^{NP}	0.0159	0.2636	-0.0200	0.8837	0.2489	-0.6185
Std Err	0.0001	0.0529	0.0001	0.6038	0.1497	0.3866
t-value	121.8835	4.9836	-307.3769	1.4635	1.6623	-1.5998
t-critical	2.0	2.0	-2.0	2.0	2.0	-2.0
Coef of S_t^{PG}	0.0193	-0.2202	0.3086	-0.7744	0.1307	0.8498
Std Err	0.0011	0.0892	0.0008	0.7763	0.1721	0.3317
t-value	17.1774	-2.4672	372.2598	-0.9975	0.7594	2.5621
t-critical	2.0	-2.0	2.0	-2.0	2.0	2.0
Obs	90	365	731	91	1114	439

Source: Author's calculations based on Table 6.4.

The dependent variable is the natural logarithm of electricity price and market shares are represented as a number. That is why, the estimated slope coefficients in front of market shares in Tables 6.4 and 7.1 can be interpreted in percentages. For example, for Regime 1, when the market share of NP increases by 1%, then we can expect that the price would increase by 0.0159%. Larger market share associated with higher prices is not consistent with competitive bidding and may be the result of capacity withholding. That is, a producer may reduce output from low-cost plants and instead increase output from more expensive plants. This strategy is not consistent with competitive bidding because equilibrium price will be higher.

Capacity withholding was already raised in the literature for various energy markets. However, sometimes it may be hard to analyze this issue as firms could reduce available capacity because of, for example, maintenance reasons. Indeed, when demand is expected to be high, even small decreases in the available capacity may lead to higher prices because the equilibrium takes place at the steeper part of the aggregate supply schedule.

On the other hand, if a producer behaves competitively by submitting price bids reflecting marginal costs, then this may lead to more of its capacity being scheduled for electricity production, hence, larger market share. At the same time, thanks to competitive bidding, equilibrium price is expected to be lower. So, increased output (i.e., larger market share) associated with lower electricity price is consistent with competition. We observe this effect, for example, for PG during Regime 2.

In order to test if the effect of market shares is statistically significant, we need to calculate the respective t-test values, which requires the knowledge of standard errors. These standard errors are calculated based on the variance-covariance matrix of estimated coefficients. In particular, in order to test if the effect of market share of NP is statistically significant in Regime 1 we test the following null hypothesis: $b_1 + b_3 = 0$. For this purpose we calculate the t-test value in the following way:

$$t\text{-test} = \frac{\hat{b}_1 + \hat{b}_3 - 0}{s.e.(\hat{b}_1 + \hat{b}_3)} = \frac{\hat{b}_1 + \hat{b}_3}{\sqrt{var(\hat{b}_1) + var(\hat{b}_3) + 2cov(\hat{b}_1, \hat{b}_3)}}. \tag{3}$$

The results are presented in Table 7.1. We find that the effect of market shares on electricity price is significant during and before price-cap regulation. After divestment series, however, the effect of the larger incumbent producer's market share on electricity price is statistically insignificant. This could be regarded as the structural remedy being effective in mitigating the effect of market share on electricity price for the larger incumbent producer. After the second series of divestments, the effect of market share on electricity for the smaller incumbent producer is however statistically significant. Hence, the two incumbent producers were affected differently by divestment series and the structural remedy was effective only for the larger producer. This could be related to unequal horizontal restructuring where the larger producer divested more of its capacity than the smaller producer (Tables 4.2 and 4.3).

These results of the effect of market shares on electricity price during the peak-demand period across trading days are new. In the related literature, there were studies analyzing high-demand periods. For example, market power analysis in Sweeting (2007) and supply curves during high- and low-demand periods in Wolfram (1999).

We also find that an increase in forecast demand by 1% is associated with higher electricity price by about 0.17%. This positive relationship is consistent with the market design presented in Figure 2.1.

Similar to the calculations in Table 7.1, we use the results in Table 6.5 in order to present in Table 7.2 intercept estimates for different regime periods in the volatility equation. In order to test the significance of the intercept term during Regime 1 we test

$H_0: \ \delta_1 + \alpha_0 = 0$. Here we again calculate the t-test value in the following way:

$$t\text{-test} = \frac{\hat{\delta}_1 + \hat{\alpha}_0 - 0}{s.e.(\hat{\delta}_1 + \hat{\alpha}_0)} = \frac{\hat{\delta}_1 + \hat{\alpha}_0}{\sqrt{var(\hat{\delta}_1) + var(\hat{\alpha}_0) + 2cov(\hat{\delta}_1, \hat{\alpha}_0)}}. \tag{4}$$

Table 7.2: Volatility across different regimes

	Regime 1 (Jan 93–Mar 93)	Regime 2 (Apr 93–Mar 94)	Regime 3 (Apr 94–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
	$\hat{\delta}_1 + \hat{\alpha}_0$	$\hat{\delta}_2 + \hat{\alpha}_0$	$\hat{\alpha}_0$	$\hat{\delta}_3 + \hat{\alpha}_0$	$\hat{\delta}_4 + \hat{\alpha}_0$	$\hat{\delta}_5 + \hat{\alpha}_0$
Intercept	0.0048	0.0097	0.0382	0.0609	0.0441	0.0316
Std Err	0.0002	0.0011	0.0001	0.0148	0.0034	0.0036
t-value	23.8783	9.1378	321.3917	4.1052	12.9518	8.6768
t-critical	2.0	2.0	2.0	2.0	2.0	2.0
Obs	90	365	731	91	1114	439

Source: Author's calculations based on Table 6.5.

The intercept term for each regime period is found statistically significant. The results also indicate that during the price-cap regulation period volatility was higher than in the previous periods. Robinson and Baniak (2002) also find that price volatility increased during the price-cap regulation period. The authors suggest that the incumbent electricity producers could have been deliberately increasing price volatility in order to enjoy higher risk premia in the contract market.

After the second series of divestments price volatility reduced, which we again attribute to the effectiveness of the structural remedy.

Volatility of electricity prices in this market was analyzed before in Robinson and Baniak (2002) and Tashpulatov (2013). Robinson and Baniak (2002) applies a non-parametric approach for weekly average prices. Tashpulatov (2013) applies a parametric approach for daily average prices using generalized error distribution in order to incorporate the features of heavy tails and excess kurtosis. Heavy tails could also be modeled by using Student's t distribution as is done in Koopman et al. (2007) for daily average prices. In our research however we use a more flexible skew generalized error distribution which reflects the features of not only heavy tails and excess kurtosis but also the asymmetry of distribution. Moreover, in this research we do not use the average price but the price during the peak-demand period over trading days. We do not consider fuel prices because they are available as quarterly average prices, which are presented in Figure A.3.

Our findings do not indicate a clear advantage of the structural remedy over the behavioral remedy. In particular, we find that after the first series of divestments price volatility increased, and then reduced after the second series of divestments. On the other hand, the effect of market share is qualitatively similar during the price-cap regulation period and after the second series of divestments were introduced. Nevertheless, the effect of market share on electricity price for the larger incumbent producer is found statistically insignificant after the divestment series were introduced.

8 Conclusions

This paper analyzes the dynamics of prices in the England and Wales electricity market in relation to the behavioral remedy (through price-cap regulation) and structural remedy (through divestment series). For this purpose we consider an extended AR–$ARCH$ model and include incumbents' market shares. We consider skew generalized error distribution, which is characterized by four parameters and therefore represents a more general and flexible type of distribution. We also conduct several statistical tests in order to verify the relevance of applying this distribution. This is necessary for checking the model adequacy and subsequent interpretation of results.

The effect of market shares in relation to divestment series during the peak-demand period across trading days has not been analyzed before. We find that the effect of incumbent producers' market shares is sometimes mutually opposite. On the one hand, larger market share associated with higher electricity price may be related to the incentive to reduce available capacity in order to increase prices. On the other hand, if a firm bids competitively, then it may have larger market share and tend to decrease equilibrium price.

When comparing the two kinds of remedies, we find qualitatively similar results of the effect of market share during the price-cap regulation period and after the second series of divestments. Statistically, however, the effect of market share after the divestment series is insignificant for the larger incumbent producer. Furthermore, price volatility reduced after the second series of divestments.

We do not find an absolute advantage of the structural remedy over the behavioral remedy because the effect of market share on electricity price for the smaller incumbent producer is statistically significant. The regulatory office may however prefer the structural remedy which does not involve monitoring costs as in the case of the behavioral remedy. Moreover, structural remedies in the form of divestment series may make the market more competitive (Puller, 2007). Then we can expect the effect of a firm's market share on electricity price to be small or statistically insignificant.

The England and Wales electricity market has served as a model for much of the electricity industry restructuring worldwide (Wolak, 2000). The findings of this paper regarding the impact of behavioral and structural remedies on electricity prices could therefore be of interest to countries that adopted similar trading arrangements.

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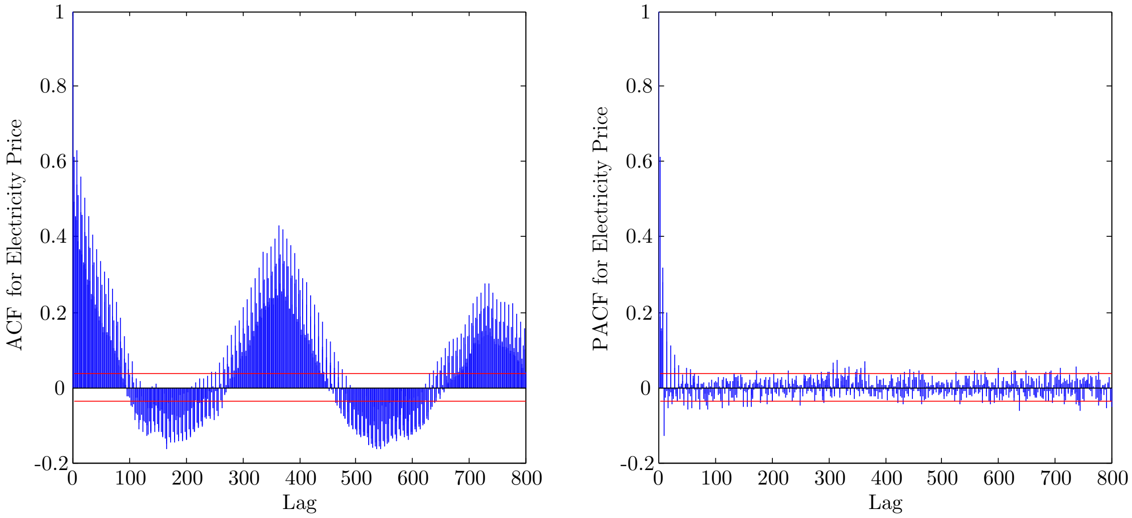
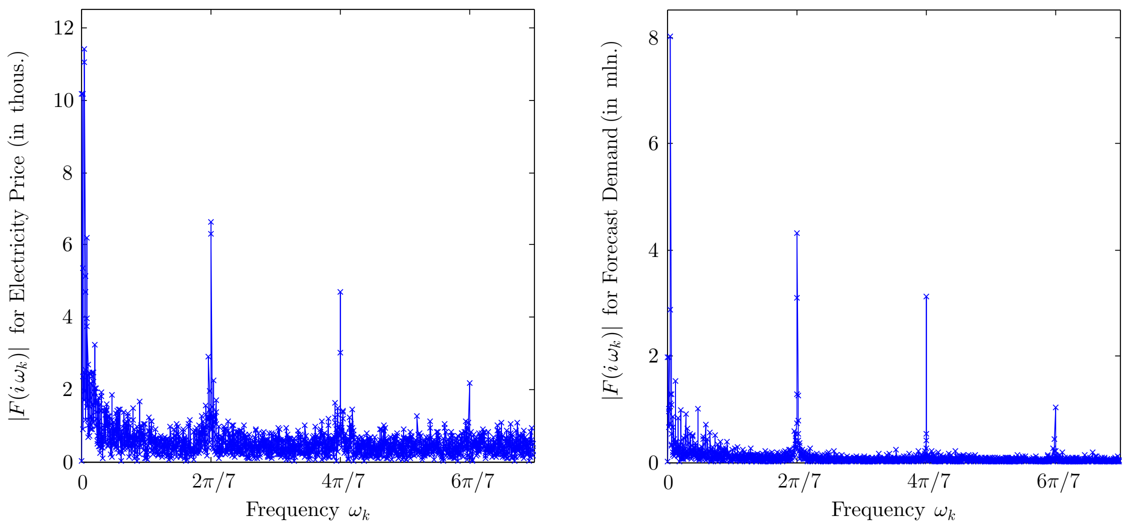
Supplemental Material

Appendices

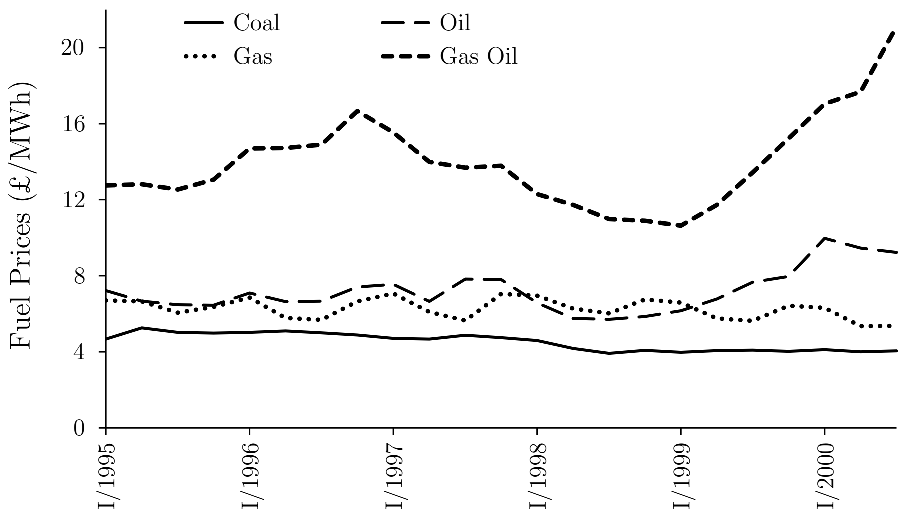
A Figures



Source: Author's calculations.
Figure A.1: Correlogram for electricity price time series



Source: Author's calculations.
Figure A.2: Periodogram plots for electricity price and forecast demand time series



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

Figure A.3: Quarterly fuel prices for major power producers in Great Britain

B Tables

Table B.1: ADF test for electricity price time series

Null hypothesis: price time series has a unit root		
Exogenous: constant		
Lag length: 13 (Automatic choice based on SIC)		
ADF test statistic for price time series -5.217		
	1% critical value	-3.432
	5% critical value	-2.862
	10% critical value	-2.567

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

Table B.2: ADF test for forecast demand time series

Null hypothesis: forecast demand time series has a unit root		
Exogenous: constant		
Lag length: 28 (Automatic choice based on SIC)		
ADF test statistic for forecast demand time series -3.756		
	1% critical value	-3.432
	5% critical value	-2.862
	10% critical value	-2.567

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

Table B.3: Correlation of electricity price and demand with periodic functions

Variables	$\cos\left(\frac{2\pi}{7}t\right)$	$\sin\left(\frac{2\pi}{7}t\right)$	$\cos\left(\frac{4\pi}{7}t\right)$	$\sin\left(\frac{4\pi}{7}t\right)$	$\cos\left(\frac{6\pi}{7}t\right)$	$\sin\left(\frac{6\pi}{7}t\right)$
Electricity price (SMP)	-0.17***	0.14***	-0.09***	0.10***	-0.06***	0.02
Forecast demand	-0.43***	0.20***	-0.18***	0.19***	-0.07***	0.06***

Note: *, **, and *** stand for the 10%, 5%, and 1% significance levels, respectively.

C Testing model adequacy

The adequacy of the estimated model generally depends on the validity of assumptions made prior to estimation. For the maximum likelihood estimation procedure applied in our research we assume that standardized residuals $\nu_t = \varepsilon_t/\sqrt{h_t}$ are independent and identically distributed (i.i.d.) and follow skew generalized error distribution (SGED). These assumptions are tested and discussed in Sections C.1 and C.2. Finally, in Section C.3, using the sign bias test, we examine if in the volatility process there are any asymmetric effects of positive and negative shocks left.

C.1 Testing the i.i.d. assumption for the standardized residuals

We verify the i.i.d. assumption for the standardized residuals by using two approaches: the Brock–Dechert–Scheinkman (BDS) test (Brock et al., 1996) and Ljung–Box Q-test (Ljung and Box, 1978). These tests allow to see if there is any information left in standardized residuals $\hat{\nu}_t$.

As summarized in Table C.1, for different values of the embedding dimension m and a default option of the proximity parameter ε we do not reject the null hypothesis that $\hat{\nu}_t$ is i.i.d. time series.

Table C.1: BDS test for $\hat{\nu}_t$

Dimension	BDS Stat	Std Err	p-value
2	-0.0006	0.0014	0.6798
3	-0.0004	0.0022	0.8411
4	-0.0001	0.0026	0.9802
5	-0.0005	0.0027	0.8598
6	-0.0007	0.0026	0.7897

Because the above conclusion is based on the parameters of m and ε, for robustness check we additionally use the Ljung–Box Q-test. The Q-test allows to verify if $\hat{\nu}_t$ and $\hat{\nu}_t^2$ are serially correlated. Serial correlation in $\hat{\nu}_t$ is interpreted as an autocorrelation problem in $\hat{\nu}_t$ and serial correlation in $\hat{\nu}_t^2$ is interpreted as a heteroscedasticity problem in $\hat{\nu}_t$. The results of the Ljung–Box Q-test for $\hat{\nu}_t$ and $\hat{\nu}_t^2$ are presented in Table C.2.

Table C.2: Ljung–Box Q-test for $\hat{\nu}_t$ and $\hat{\nu}_t^2$

	$\hat{\nu}_t$				$\hat{\nu}_t^2$			
Lag	ACF	PACF	Q-Stat	p-value	ACF	PACF	Q-Stat	p-value
1	-0.01	-0.01	0.44	0.51	-0.02	-0.02	0.94	0.33
5	0.03	0.03	6.77	0.24	0.00	0.00	1.49	0.91
10	-0.01	-0.01	8.17	0.61	0.03	0.03	7.83	0.65
50	0.01	0.01	41.18	0.81	0.01	0.00	47.12	0.59
100	-0.02	-0.01	106.40	0.31	0.04	0.04	98.69	0.52
200	-0.01	-0.01	198.74	0.51	0.00	0.01	189.73	0.69
300	0.01	0.01	316.63	0.24	0.00	0.02	297.89	0.52

As all p-values from the Ljung–Box Q-test are above 10%, we do not reject the null hypothesis and conclude that time series $\hat{\nu}_t$ and $\hat{\nu}_t^2$ are not serially correlated.

C.2 Testing the distributional assumption for the standardized residuals

The distributional assumption for the standardized residuals is examined in three steps. In the first step we analyze descriptive statistics. Then we use Jarque–Bera normality test, Kolmogorov–Smirnov test, and the quantile-quantile plot in order to compare the empirical distribution with normal distribution. Finally, in the third step, we test if the standardized residuals follow SGED (μ, σ, β, χ) using the goodness of fit test.

We find that the empirical distribution of standardized residuals $\hat{\nu}_t$ has excess kurtosis and heavy tails (kurtosis coefficient greater than 3 and shape parameter less than 2). The empirical distribution of $\hat{\nu}_t$ is also skewed to the right (skewness coefficient greater than 0 and skewness parameter greater than 1). Based on standard errors of $\hat{\beta}$ and $\hat{\chi}$ presented in Table 6.5, we also find that shape and skewness parameters are statistically different from 2 and 1, respectively. These findings are not in line with normal or Student's t distributions. The results are summarized in Table C.3 and Figure C.1a.

Table C.3: Descriptive statistics for standardized residuals $\hat{\nu}_t$

Mean ($\hat{\mu}$)	-0.0233
Standard deviation ($\hat{\sigma}$)	1.0022
Kurtosis coefficient	4.7464
Shape parameter ($\hat{\beta}$)	1.4680
Skewness coefficient	0.2316
Skewness parameter ($\hat{\chi}$)	1.0542

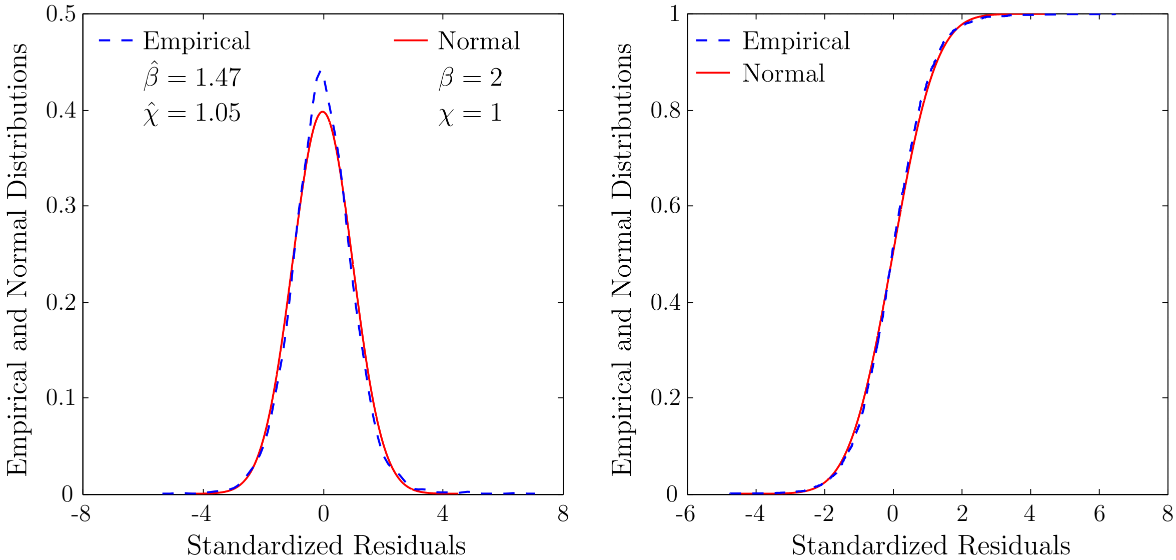


Figure C.1: Comparison of the empirical distribution of standardized residuals to normal distribution

Jarque–Bera test allows to test if the observed excess kurtosis and positive skewness of standardized residuals $\hat{\nu}_t$ are jointly statistically significant in order to conclude that the empirical distribution of standardized residuals $\hat{\nu}_t$ is different from normal distribution. The results of Jarque–Bera test presented in Table C.4 suggest rejecting the null hypothesis of normal distribution.

Table C.4: Normality tests for standardized residuals $\hat{\nu}_t$

Jarque–Bera test		Kolmogorov–Smirnov test	
Jarque–Bera statistic	384.946	Kolmogorov–Smirnov statistic	0.0270
p-value	0	p-value	0.0319

Another way how to test if data follow some theoretical distribution (not necessarily normal distribution as was in Jarque–Bera test) is to apply Kolmogorov–Smirnov test. The idea of this test is based on comparing the differences in cumulative distribution functions (CDF) of empirical and theoretical distributions. We compare the CDFs of empirical and normal distributions. Again we reject the null hypothesis stating that the empirical distribution of standardized residuals $\hat{\nu}_t$ is normal at the 5% significance level.

In other words, the differences observed between the empirical and normal distributions in Figure C.1 are statistically significant. Following Figure C.1a, we suggest that the major reason for rejecting the null hypothesis could be related to excess kurtosis (i.e., kurtosis coefficient greater than 3), heavy tails, and positive skewness observed in the empirical distribution of standardized residuals.

Indeed, when comparing the CDF of the empirical distribution of standardized residuals $\hat{\nu}_t$ and normal CDF in Figure C.1b we note some differences in tails. The quantile-quantile plot in Figure C.2 illustrates more clearly observations in the tails located outside the 95% confidence interval when comparing the empirical and normal distributions.

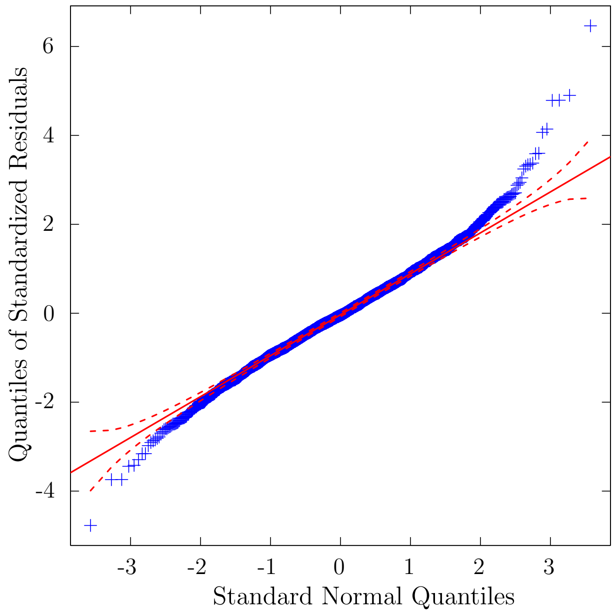


Figure C.2: Quantile–quantile plot for standardized residuals

The finding that the standardized residuals do not follow normal distribution may not necessarily mean that the standardized residuals follow SGED, even if SGED nests normal distribution as a special case. In order to test if the standardized residuals follow SGED we apply the goodness of fit test.

In the goodness of fit test an important parameter is the number of bins (i.e., groups, intervals). Since there are several empirical rules how to set the number of bins, we consider 4 possibilities for the number of bins. The test results in Table C.5 suggest not rejecting the null hypothesis stating that the empirical distribution is the same as theoretical (i.e., SGED in our case).

Table C.5: Pearson goodness of fit test

Group	χ^2-stat	p-value
20	25.28	0.15
30	33.42	0.26
40	48.50	0.14
50	54.24	0.28

These tests, therefore, support the application of SGED. This distribution coincides with normal distribution when the shape parameter is two (i.e., kurtosis coefficient is three) and skewness parameter is one (i.e., skewness coefficient is zero).

C.3 Testing model specification

Asymmetry of positive and negative shock effects on volatility was addressed in our methodology following the approach in Glosten et al. (1993) by introducing parameter γ_i in the volatility equation. The presence of remaining asymmetries in the effect of positive and negative shocks on volatility would indicate that the model is misspecified. Hence, we use the sign bias test developed in Engle and Ng (1993) in order to test the null hypothesis stating that the conditional volatility model is correctly specified.

Table C.6: Sign bias test

	t-value	p-value
Sign bias	0.25	0.81
Negative sign bias	0.20	0.84
Positive sign bias	0.87	0.38
Joint effect	0.82	0.84

The test results indicate not rejecting the null hypothesis since all p-values are above 10%. This conclusion suggests that our conditional volatility model has been correctly specified.

D Abbreviations

ACF	Autocorrelation Function
ADF	Augmented Dickey–Fuller
AR	Autoregressive
ARCH	Autoregressive Conditional Heteroscedasticity
BDS	Brock–Dechert–Scheinkman
CDF	Cumulative Distribution Function
Coef of Var	Coefficient of Variation
FT	Fourier Transform
GOAL	Generator Ordering and Loading
i.i.d.	independent and identically distributed
NGC	National Grid Company
NP	National Power
Obs	Observations
PACF	Partial Autocorrelation Function
PG	PowerGen
SGED	Skew Generalized Error Distribution
SIC	Schwarz Information Criterion
SMP	System Marginal Price
St Dev	Standard Deviation

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2 Analysis of electricity industry liberalization in Great Britain: How did the bidding behavior of electricity producers change?

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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. This paper empirically examines 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 we consider a duopoly case, based on which a regression model is specified. The estimation of the regression model allows for 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.

1. Introduction

Great Britain was the first among the OECD countries to liberalize its electricity supply industry. 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.

Research has shown, however, that producers have exercised market power by submitting price bids significantly exceeding marginal costs (for example, Crawford et al., 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. 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 is the possible loss 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 market power issues are also discussed in Bergman et al. (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. Other 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.

As part of the liberalization process, in order to mitigate an

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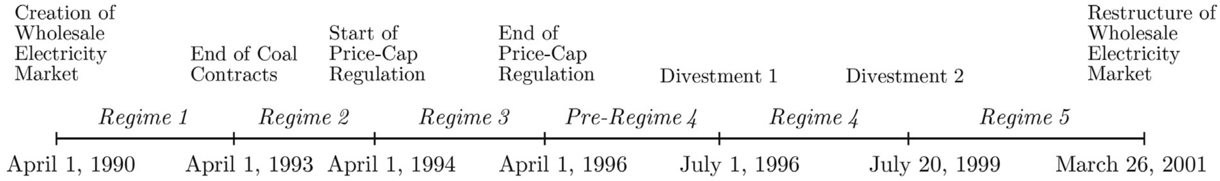


Fig. 1. : Institutional changes and regulatory reforms during 1990–2001.
Sources: Department of Trade and Industry (1997–2002), National Grid Company (1994–2001), Newbery (1999), Robinson and Baniak (2002), Wolfram (1999); author's illustration.

exercise of market power by incumbent electricity producers, the regulatory authority, the Office of Electricity Regulation (Offer, later constituted as the Office of Gas and Electricity Markets, or Ofgem), introduced several reforms. This paper analyzes how the regulatory reforms affected the bidding behavior of electricity producers. In particular, we quantify and document new empirical evidence about how the incentive and disincentive to exercise market power changed over the 1995–2000 period.

The measures designed to mitigate an exercise of market power and promote competition during the liberalization process were more extensive in Great Britain when compared to Germany, France, Italy, or Sweden (Bergman et al., 1998). Joskow characterizes the privatization, restructuring, market design, and regulatory reforms pursued in England and Wales as the international gold standard for energy market liberalization (Joskow, 2008, 2009). In this respect, the new findings documented in this research could be of interest to countries that have structured or are about to structure their electricity markets similar to the original model adopted in England and Wales.

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 the 1990–2001 period are summarized in Fig. 1 and described in detail in the following paragraphs.

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

Earlier research (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 that took place in 1996 and 1999.

When defining regime periods for an ex-post regulation analysis, we 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). In this case, choosing a structural break slightly different from the actual date of the transfer would have resulted in a short time series (either PowerGen just before transferring medium coal production facilities if the cut-off were early, or Eastern Group just after acquiring medium coal production facilities if the cut-off were after the transfer), which would be difficult to analyze.

Hence, it is assumed here that the structural breaks are exogenously given by the dates when the reforms were introduced. 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.

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.

Her main finding is that electricity producers submit price

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

[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).

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 submit higher price bids than smaller producers for comparable production units (i.e., production units using the same fuel to produce electricity and having almost the same marginal costs).

The findings of Wolfram (1998) are in line with those of Green and Newbery (1992), 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. Both studies 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 fuel prices. They 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 subsequent time 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. He finds that electricity producers were exercising increased market power during 1995–2000 and notes the contradiction with oligopoly models that, given falling market concentration during this period, would have predicted a reduction in market power. The author also finds that starting in 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.

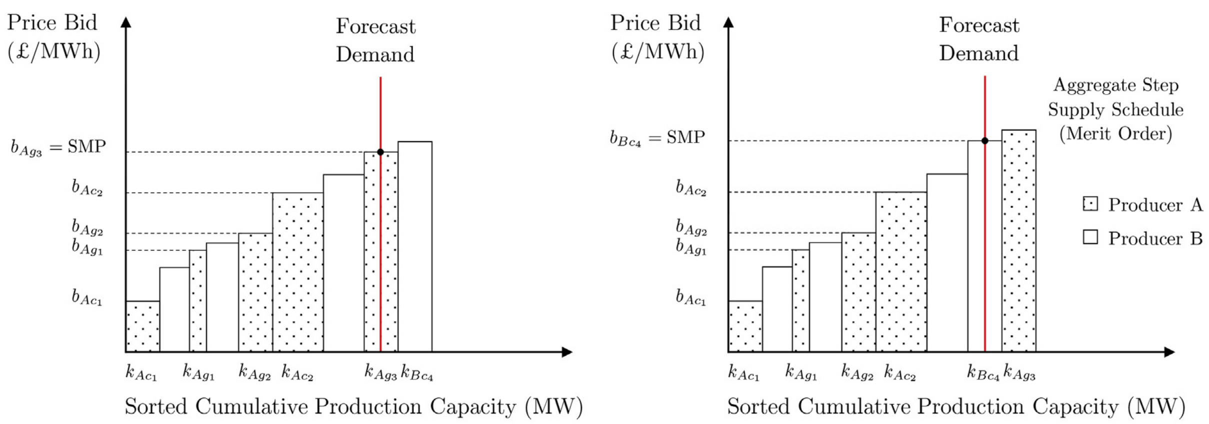
As explained in Borenstein et al. (2002), the application of competitive benchmark prices to analyze whether an electricity market, as a whole, is setting competitive prices has an advantage of being less vulnerable to the arguments of coincidence and bad luck. This approach also allows for estimating 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, we consider 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, we 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 also in line with the methodology adopted in Crawford et al. (2007). Moreover, the choice of peak-demand trading periods is in agreement with the analysis by 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.

4. Methodology

For the analysis of the bidding behavior of electricity producers, we assume no uncertainty in the forecast 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



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

Fig. 2. : Determination of the SMP: a hypothetical example. *Notes:* Given price bid b_{Bc_4} of producer B we analyze at the intersection of the supply schedule and forecast demand two possible scenarios, which depend on the price bid of producer A. In (a) we assume that $b_{Bc_4} > b_{Ag_3}$, in which case producer A will set the price so that $b_{Ag_3} = \text{SMP}$. In (b) we assume that $b_{Bc_4} \leq b_{Ag_3}$, in which case producer B will set the price so that $b_{Bc_4} = \text{SMP}$. In case when price bids are equal, according to market rules, both production units are scheduled. Cases (a) and (b) are reflected in the first and second addenda of equation (1) describing the expected profit maximization problem of producer A.
Source: Author's illustration.

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 on the thermal efficiency rate and capacity type of production units.

In Section 4.1, we 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 4.2 in order to analyze the bidding behavior of electricity producers.

4.1. Analysis of a duopoly case with an asymmetric technology structure

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

Assume that there are two risk-neutral electricity producers, A and B, where producer A has several production unit types and producer B has one production unit type. For the explanation of the model, we refer to the hypothetical example in Fig. 2. More general cases demand complex notations, which would complicate the illustration of derivation results important for the construction of the regression model described in Section 4.2.

Let $k_{A\tau}$ denote the production capacity of type τ submitted by producer A. 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 Fig. 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 $c_{Bc} = c_{Bc_4}$.

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 $[\underline{b}, \overline{b}]$, where $\underline{b}, \overline{b} \in \mathbb{R}^+$ and $\underline{b} < \overline{b}$. 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 Fig. 2, this is the price bid of the third gas production unit that could be used for strategic bidding by producer A. In other words, $b_{Ag} \in [\underline{b}, \overline{b}]$ is producer A's strategic choice variable.

Submitted price and capacity bids[3] for 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 price bid b_B of producer B, we define the expected profit maximization problem of producer A:

$$\begin{aligned} E[\pi_A(b_{Ag}, b_B)] &= E\left[\pi_A \middle| \underbrace{b_B > b_{Ag}}_{\text{Asets}}\right] + E\left[\pi_A \middle| \underbrace{b_B \le b_{Ag}}_{\text{Bsets}}\right] \\ &= \int_{b_{Ag}}^{\overline{b}} \left[(b_{Ag} - c_{Ac}) \cdot \frac{1}{2} k_{Ac} + (b_{Ag} - c_{Ag}) \cdot \frac{1}{2} k_{Ag}\right] \cdot f(b_B) db_B \\ &+ \int_{\underline{b}}^{b_{Ag}} \left[(b_B - c_{Ac}) \cdot \frac{1}{2} k_{Ac} + (b_B - c_{Ag}) \cdot \frac{1}{2} \alpha_{Ag} k_{Ag}\right] \cdot f(b_B) db_B. \end{aligned} \tag{1}$$

In the calculation of the expected profit,[4] producer A considers two possible scenarios depending on whether producer A or producer B sets the uniform auction price as described in Fig. 2(a) and (b), respectively. 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 of 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

$$\begin{aligned} \log(b_{Ag} - c_{Ag}) = \log(k_{Ac} + k_{Ag}) - \log(1 - \alpha_{Ag}) k_{Ag} \\ + \log(1 - F(b_{Ag})) - \log(f(b_{Ag})). \end{aligned} \tag{2}$$

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

By $k_{A\tau}$ we denote the capacity of production units of type τ submitted by producer A. Then, $k_{Ac} + k_{Ag}$ denotes the capacity of production units with price bids below price bid b_{Ag} in the aggregate supply schedule. The optimality condition represented by Equation (2), suggests that a larger production capacity below creates an incentive to submit a higher price bid because when that price bid sets the uniform auction price it is applied to producer A's entire 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 of producer A that might not be scheduled to produce electricity due to a higher 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 of 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,

[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.

[4] We use a factor of 1/2 to convert MW to MWh because the duration of a trading period is 30 min.

[5] For differentiation, we use the Leibniz's formula provided in Sydsæter et al. (2008).

$1 - F(b_{Ag})$ 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 time-variant probabilities is a difficult task in the case of several producers. Probabilities are generally different across producers and are also expected to vary across capacity types of production units. In order to assess 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 relevant. Given the market outcomes, we 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.

4.2. Specification of the 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:

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

In this regression model, subscript i stands for an electricity producer and subscript j stands for the capacity type of marginal and extra-marginal production units. In other words, producers' production units located at and above the forecast demand are considered. If a producer has several extra-marginal production units of the same capacity type located above the forecast demand, then a production unit closest to the forecast 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 logarithm following the derivation results from the duopoly case. The variable $Markup_{ijt}$ under logarithm denotes the price bid minus marginal cost of a production unit of type j of producer i. There are two advantages of incorporating marginal costs into the definition of the dependent variable. Firstly, this allows for 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}.

Fig. 3, using an example of producer A with two types of production unit, we summarize the definitions of variables used in the regression model.

The effect of the first explanatory variable is generally assumed to be different across producers. This assumption is consistent with the earlier theoretical and empirical research (for example, Wolfram, 1998 and Crawford et al., 2007). 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 markup: when this price bid sets the 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.

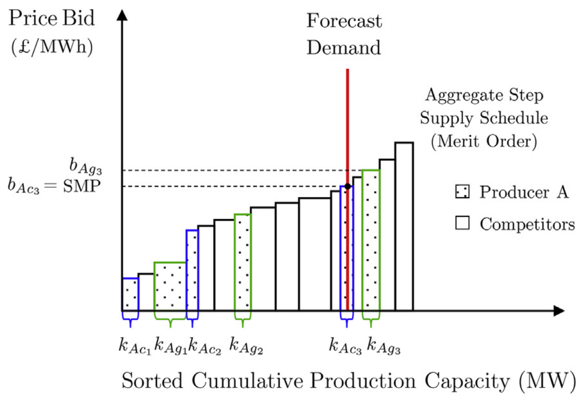


Fig. 3. Explanation of variables used in the regression model. *Notes:*

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	:	$b_{Ag_3} - k_{Ag_3}$

Source: Author's illustration.

The effect of the second explanatory variable is assumed to vary across not only producers but also capacity 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 reflects an incentive, whereas the second explanatory variable reflects 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, we assume that the parameters in front of the explanatory variables can change during the different regime periods described in Fig. 1. The validity of this assumption is verified by testing whether the explanatory variables interacted with the regime dummy variables have statistically significant coefficients (denoted by δ's; see Equation (4), footnote 8, and Block 2 of Table 8).

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

[6] Weekly seasonality is a feature inherent to electricity markets. For the case of electricity prices, the weekly seasonality properties are studied in Tashpulatov (2013).

5. Data

The two data sets used cover the period from January 1, 1995 to September 30, 2000. The first data set contains half-hourly market data on the forecast demand for electricity and System Marginal Price (SMP). Summary statistics for the market data are presented in Table 1.

The maximal value of the SMP corresponds to the highest spike in 1995, which was brought about by a mistaken mix of technical

Table 1
Descriptive statistics for market data during all trading periods.

	Mean	Min	Max	Std Dev	Frequency	Obs
Forecast demand (MW)	32991.6	19,026	51,065	5965.6	30 min	100,798
SMP (£/MWh)	21.1	0	836.2	13.3	30 min	100,798

Source: Author's calculations.

Table 2
Summary statistics for capacity bidding during peak-demand trading periods.

Pr	Type	Production capacity below bid b_{ijt} (MW)				Production capacity at bid b_{ijt} (MW)				
		Mean	Min	Max	St Dev	Mean	Min	Max	St Dev	Obs
NP	Large coal	8851.9	1990.0	17346.0	2779.7	488.7	105.0	645.0	45.3	1516
	Medium coal	9364.0	1780.0	16608.0	2393.9	288.6	2.5	340.0	65.0	1328
	Small coal	11634.8	6707.0	20049.0	2627.6	113.9	96.0	115.0	0.8	993
	Oil	10820.2	2560.0	18459.0	3595.7	655.5	210.0	685.0	72.4	2017
	OCGT	13131.6	3729.0	20468.0	4038.9	64.1	17.0	70.0	13.2	2482
PG	Large coal	7319.7	1959.0	13092.0	1895.8	485.8	160.0	517.0	26.4	1627
	Medium coal	9826.1	5523.0	13035.0	1376.4	239.6	189.0	333.0	63.9	291
	Oil	9400.7	3785.0	13820.0	2187.3	662.0	95.1	675.0	61.4	1612
	OCGT	10475.7	3941.0	15602.0	2549.8	67.5	28.0	68.0	2.6	2042
EDF	Export	2008.0	0.2	2778.0	583.4	61.2	1.0	989.0	223.9	1160
SI	Export	2351.7	311.0	4397.0	1113.9	255.8	1.0	600.0	152.0	131
	CCGT	1476.6	237.0	2330.0	569.9	185.1	168.0	590.0	74.0	33
TXU	Large coal	2864.3	0.2	6084.0	1329.6	484.2	91.2	503.0	21.5	896
	Medium coal	4192.8	913.0	6360.0	1161.5	235.1	125.3	333.0	67.0	682
	OCGT	4773.5	350.0	6644.0	1340.9	24.3	20.0	25.0	1.7	1480
Ed	Large coal	1884.1	0.2	3900.0	693.4	473.5	235.0	506.0	55.0	224
	OCGT	4384.7	2475.0	6055.0	755.5	17.0	17.0	17.0	0.0	1731
	PSB	865.4	0.2	4673.0	1038.3	252.9	48.0	288.0	75.7	2036
BE	Large coal	6430.3	4638.0	7572.0	650.8	477.0	300.0	495.0	41.7	98
AES	Large coal	2608.5	895.0	3692.0	739.9	645.0	645.0	645.0	0.0	63
	OCGT	2894.5	0.2	4467.0	1487.3	60.1	25.0	140.0	51.0	567

Source: Author's calculations.

Table 3
Descriptive statistics for nominal and real markups (£/MWh) of marginal and extra-marginal production units during peak-demand trading periods.

Pr	Type	Nominal markup (£/MWh)				Real markup (£/MWh)				
		Mean	Min	Max	St Dev	Mean	Min	Max	St Dev	Obs
NP	Large coal	14.3	0.2	49.5	8.3	13.1	0.2	44.1	7.5	1516
	Medium coal	21.3	0.0	79.0	21.4	19.3	0.0	70.0	18.9	1328
	Small coal	23.3	0.6	86.7	19.4	21.9	0.5	86.7	19.1	993
	Oil	36.4	0.0	254.9	14.6	33.6	0.0	252.6	13.5	2017
	OCGT	59.1	4.3	689.1	83.6	56.1	4.0	682.9	83.3	2482
PG	Large coal	14.2	0.1	60.2	10.0	13.1	0.1	56.4	9.1	1627
	Medium coal	13.2	0.1	36.4	8.9	12.8	0.1	34.8	8.5	291
	Oil	38.6	0.4	91.8	11.9	35.5	0.3	83.2	10.8	1612
	OCGT	50.2	9.1	694.8	54.7	47.0	8.0	690.1	54.5	2042
EDF	Export	9.4	1.0	93.0	19.4	8.8	0.9	91.3	18.5	1160
SI	Export	14.3	1.0	75.0	12.0	13.8	0.9	71.3	11.4	131
	CCGT	4.9	2.4	7.3	1.5	4.9	2.4	7.3	1.5	33
TXU	Large coal	9.3	0.0	55.7	7.9	8.4	0.0	52.9	7.3	896
	Medium coal	11.6	0.1	74.0	7.9	10.6	0.0	67.0	7.3	682
	OCGT	17.3	0.1	60.5	16.2	16.0	0.1	57.5	15.4	1480
Ed	Large coal	12.5	3.1	32.9	5.9	11.0	2.8	29.3	5.2	224
	OCGT	44.9	21.5	64.4	12.3	39.7	18.9	57.3	11.0	1731
	PSB	18.5	0.8	71.9	9.5	17.0	0.7	63.7	8.5	2036
BE	Large coal	11.3	3.8	18.5	3.0	10.0	3.4	16.4	2.6	98
AES	Large coal	9.1	4.5	18.7	3.0	8.1	4.0	16.6	2.6	63
	OCGT	39.9	0.0	203.8	25.8	35.4	0.0	186.3	22.9	567

Source: Author's calculations.

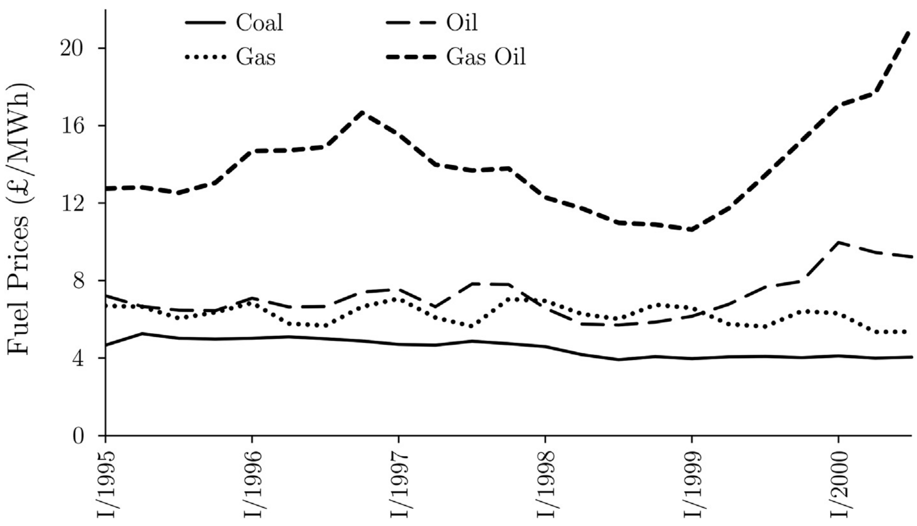


Fig. 4. Quarterly fuel prices for major power producers in Great Britain.
Sources: Department of Trade and Industry (1993–2000), Department of Trade and Industry (1997–2002); author's calculations.

Table 4
Descriptive statistics for SMP (£/MWh) during peak-demand trading periods.

	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
Mean	36.6	35.3	42.0	36.3
Change of Mean		−1.3	5.4	−0.3
t-test		−0.9	5.0	−0.3
t-critical		−2.0	2.0	−2.0
Min	7.9	17.2	14.5	15.5
Max	211.2	76.7	105.1	77.9
St Dev	19.2	11.4	19.3	12.1
F-test		2.9	1.0	2.5
F-critical		1.3	1.1	1.2
Coef of Var (%)	52.5	32.3	45.9	33.5
Obs	456	91	1114	439

Source: Author's calculations.

The second data set contains half-hourly bid data on production capacity and price bids. This data set is used for preparing variables in regression model (3) and are summarized in Tables 2 and 3.

Using data on half-hourly price bids, quarterly fuel prices, and the efficiency rates of production units, we calculate nominal markups. In order to calculate real markups we divide nominal markups by quarterly producer price index for the electricity industry. Summary statistics for markups are presented in Table 3.

Fig. 4 describes quarterly fuel prices, which are used to approximate the marginal costs of production units.

Results reported in Table 4 indicate that the average of electricity prices during peak-demand trading periods was higher after the first series of divestments. As the two-sample *t*-test indicates (with equal variances based on the *F*-test), the difference is also statistically significant. During the other periods the average price level was similar to the one during the price-cap regulation period.

Calculations shown in Tables 5–7 reveal an interesting finding. After the divestments, average markups (nominal and real) for several capacity types belonging to the incumbent electricity producers were higher by more than the decrease in their respective inframarginal capacities. This suggests the possibility that greater market power was actually exercised even with the lesser market concentration following the divestment series. A more detailed analysis of changes in the exercise of market power, based on the estimate of the producer specific β_{1i}, is summarized in the next section.

Table 5
Descriptive statistics for inframarginal capacity (MW) during peak-demand trading periods for NP and PG.

	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	
	NP	PG	NP	PG	NP	PG	NP	PG
Mean	13842.9	9966.6	10368.0	8050.9	8877.1	7822.1	4914.7	5548.0
% Scale for Mean	100	100	75	81	64	78	36	56
Min	6307.4	4574.0	6753.0	4709.0	2695.0	2933.7	1780.0	1959.0
Max	19149.0	14651.0	14098.0	10646.0	14072.0	12427.0	9045.0	8840.0
St Dev	2874.4	2210.4	1835.1	1512.7	1887.1	1607.7	1450.5	1162.5
Coef of Var (%)	20.8	22.2	17.7	18.8	21.3	20.6	29.5	21.0
Obs	401	401	91	91	1111	1111	439	439

Source: Author's calculations.

parameters that the Generator Ordering and Loading (GOAL) algorithm had to accept.[7] 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).

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

Table 6
Capacity-weighted average of nominal and real markups (£/MWh) of marginal and extra-marginal production units of NP during peak-demand trading periods.

Capacity type	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			
	Nominal	Real	Nominal	Change (%)	Real	Change (%)	Nominal	Change (%)	Real	Change (%)	Nominal	Change (%)	Real	Change (%)
Large coal	9.1	9.0	10.6	16	10.1	12	15.5	70	14.2	58	15.5	70	13.8	53
Medium coal	6.2	6.1	11.3	83	10.8	78	17.7	188	16.2	167	46.8	660	41.6	587
Small coal	33.9	33.8	10.2	−70	9.7	−71	21.6	−36	19.8	−41				
Oil	25.0	24.7	46.1	85	44.1	79	37.8	51	34.7	41	40.3	61	35.6	45
OCGT	83.5	82.9	39.5	−53	37.7	−55	47.9	−43	43.9	−47	44.9	−46	39.8	−52
All types	27.5	27.2	27.1	−1	25.9	−5	27.8	1	25.5	−6	35.4	29	31.4	15

Source: Author's calculations.

Table 7
Capacity-weighted average of nominal and real markups (£/MWh) of marginal and extra-marginal production units of PG during peak-demand trading periods.

Capacity Type	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			
	Nominal	Real	Nominal	Change (%)	Real	Change (%)	Nominal	Change (%)	Real	Change (%)	Nominal	Change (%)	Real	Change (%)
Large coal	10.6	10.5	4.9	−54	4.7	−55	15.1	43	13.9	33	14.6	38	12.9	23
medium coal	10.7	10.6	22.2	107	21.3	100								
Oil	29.1	28.7	52.0	79	49.7	73	39.5	36	36.3	26	41.2	41	36.5	27
OCGT	80.6	79.8	34.9	−57	33.3	−58	48.5	−40	44.5	−44	29.4	−64	26.1	−67
All types	25.0	24.7	33.6	34	32.1	30	29.5	18	27.1	9	30.8	23	27.3	10

Source: Author's calculations.

6. Results and discussion

Section 4.2 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 4.1. Log-linear regression models are often used in empirical research, in part because the estimated slope coefficients in this specification can be directly interpreted as elasticities.

This 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 $\widehat{\beta}_{1i}$ and $\widehat{\beta}_{2ij}$ slope parameters in front of the explanatory variables during the reference period are presented in Block 1 of Table 8. These slope parameters in Equation (3) reflect the incentive and disincentive to exercise market power, respectively. Results of $\widehat{\beta}_{1i}$ and $\widehat{\beta}_{2ij}$ in Table 8 vary across producers (subscript i) and capacity types (subscript j), which suggests that considering producer and capacity type specific parameters has been correct.

It is also assumed that these slope parameters 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 estimations are presented in Block 2 of Table 8.[8]

The validity of our assumption is verifiable by formal testing. For example, a test for the equality of the first slope parameter for NP during January 1995 to March 1996 and pre-regime 4 can be represented as testing the following null hypothesis:

$$H_0 : \beta_{1,NP}^{\text{Pre-Regime 4}} - \beta_{1,NP}^{\text{Jan 95–Mar 96}} = \delta_{1,NP}^{\text{Pre-Regime 4}} = 0. \tag{4}$$

The value of

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

suggests rejecting H_0 at the 1% significance level.

Similarly, other estimation results in Block 2 of Table 8 allow for evaluating in detail the impact of the regulatory reforms on the bidding behavior of electricity producers during the subsequent regime periods. In particular, $\widehat{\delta}_1$ reflects a change in the incentive and $\widehat{\delta}_2$ reflects a change in the disincentive to exercise market power by submitting price bids in excess of marginal costs.

Estimation results presented in Table 8 suggest findings related to the theoretical predictions and the impact of regulatory reforms. The results generally support the assumption that the slope parameters need not be the same across producers and capacity types. Moreover, changes in the slope parameters during later regime periods, presented in Block 2 of Table 8, are in most cases statistically and economically significant. This makes it possible to analyze in detail changes in the bidding behavior of electricity producers in relation to the adopted 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 $\widehat{\beta}_{1i}$ generally confirm this prediction consistent with earlier research by Green and Newbery (1992) and Wolfram (1998).

The results also provide statistical evidence that following the

[8] More precisely, we use the following notation: $\widehat{\beta}_{1i}^{\text{Pre-Regime 4}} = \widehat{\beta}_{1i}^{\text{Regime 3}} + \widehat{\delta}_{1i}^{\text{Pre-Regime 4}}$, $\widehat{\beta}_{1i}^{\text{Regime 4}} = \widehat{\beta}_{1i}^{\text{Regime 3}} + \widehat{\delta}_{1i}^{\text{Regime 4}}$, $\widehat{\beta}_{1i}^{\text{Regime 5}} = \widehat{\beta}_{1i}^{\text{Regime 3}} + \widehat{\delta}_{1i}^{\text{Regime 5}}$, where $\widehat{\delta}_{1i}^{\text{Pre-Regime 4}}, \widehat{\delta}_{1i}^{\text{Regime 4}}, \widehat{\delta}_{1i}^{\text{Regime 5}}$ are the estimates of a change presented in the first part of Block 2 of Table 8. Similarly, $\widehat{\beta}_{2ij}^{\text{Pre-Regime 4}} = \widehat{\beta}_{2ij}^{\text{Regime 3}} + \widehat{\delta}_{2ij}^{\text{Pre-Regime 4}}$, $\widehat{\beta}_{2ij}^{\text{Regime 4}} = \widehat{\beta}_{2ij}^{\text{Regime 3}} + \widehat{\delta}_{2ij}^{\text{Regime 4}}$, $\widehat{\beta}_{2ij}^{\text{Regime 5}} = \widehat{\beta}_{2ij}^{\text{Regime 3}} + \widehat{\delta}_{2ij}^{\text{Regime 5}}$, where $\widehat{\delta}_{2ij}^{\text{Pre-Regime 4}}, \widehat{\delta}_{2ij}^{\text{Regime 4}}, \widehat{\delta}_{2ij}^{\text{Regime 5}}$ are the estimates of a change presented in the second part of Block 2 of Table 8.

Table 8
Estimation results of Equation (3) $\log(Markup_{ijt}) = \beta_0 + \beta_{1i}\cdot\log(Production\ Cap.\ below\ Bid\ b_{ijt}) + \beta_{2ij}\cdot\log(Production\ Cap.\ at\ Bid\ b_{ijt}) + \varepsilon_{ijt}$.

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	$\widehat{\beta}_{1i}$	NP		0.037	0.289						
		PG		0.258**	0.107						
		EDF		0.262***	0.057						
		SI		0.294***	0.080						
		TXU						0.128	0.133		
		Ed		0.058***	0.006						
		BE								0.571***	0.173
		AES						0.033	0.036		
	$\widehat{\beta}_{2ij}$	NP	Large coal	0.168	0.431						
			Medium coal	0.077	0.469						
			Small coal	0.389	0.568						
			Oil	0.273	0.417						
			OCGT	0.738	0.643						
		PG	Large coal	−0.151	0.151						
			Medium coal	−0.152	0.167						
			Oil	0.032	0.141						
			OCGT	0.282	0.219						
		EDF	Export	0.365***	0.062						
		SI	Export	−0.063	0.101						
			CCGT	−0.204*	0.104						
		TXU	Large coal					0.038	0.180		
			Medium coal					0.105	0.206		
			OCGT					0.344	0.355		
		Ed	Large coal							0.052	0.035
			OCGT							0.508***	0.083
			PSB	0.295***	0.074						
		BE	Large coal							−0.503**	0.246
		AES	Large coal							−1.255***	0.026
			OCGT					0.165*	0.085		
Block 2: Estimation of a change in comparison to a reference period	$\widehat{\delta}_{1i}$	NP				1.365***	0.264	0.586**	0.238	0.489*	0.273
		PG				0.309**	0.148	0.347**	0.168	0.555***	0.116
		EDF						−0.263***	0.015	−0.211***	0.012
		SI				0.195	0.234	0.021	0.102		
		TXU								−0.269**	0.117
		Ed				−0.102***	0.011	−0.019***	0.003	0.162***	0.039
		AES								1.220***	0.070
	$\widehat{\delta}_{2ij}$	NP	Large coal			−2.006***	0.403	−0.749**	0.365	−0.538	0.420
			Medium coal			−2.118***	0.448	−0.732*	0.402	−0.351	0.459
			Small coal			−2.814***	0.532	−1.108**	0.481		
			Oil			−1.815***	0.391	−0.690*	0.356	−0.476	0.408
			OCGT			−3.159***	0.605	−1.331**	0.549	−1.108*	0.628
		PG	Large coal			−0.506**	0.220	−0.401*	0.242	−0.635***	0.171
			Medium coal			−0.304	0.248				
			Oil			−0.305	0.211	−0.402*	0.236	−0.639***	0.165
			OCGT			−0.802**	0.328	−0.811**	0.369	−1.352***	0.253
		EDF	Export					−0.068	0.061	−0.231***	0.084
		SI	Export			−0.423	0.361	0.009	0.157		
		TXU	Large coal							0.363**	0.148
			Medium coal							0.416**	0.184
			OCGT							−0.203	0.302
		Ed	PSB			0.066***	0.006	0.109***	0.005	−0.149**	0.058
		AES	OCGT							−2.271***	0.088
			Intercept	0.481	0.415						

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 [8].
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.

divestment series, the incentive to exercise market power increased for the National Power and PowerGen incumbent producers. 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 AES, $\widehat{\beta}_{1i}$ 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 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 Lízal and Tashpulatov (2014). This possibility was analyzed by Joskow and Kahn (2002) who, similar to Sweeting (2007), used competitive benchmark prices to study market behavior during the California electricity crisis of 2000–2001. The authors suggest 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). The relatively higher incentive to exercise market power by NP, PG, and AES during the late 1990s along with possible capacity cutting may explain differences between wholesale prices and competitive benchmark prices found by Sweeting (2007).

The incentive to submit a price bid reflecting a high markup is moderated by the presence of a threat that the production unit at stake may not be scheduled to produce electricity. This effect does not need to be the same across producers. Moreover, as mentioned earlier, if a single producer has several types of production units, then this disincentive may also vary across types of production unit. Hence, the disincentive to exercise market power is reflected by the estimated producer and capacity type specific slope parameter $\widehat{\beta}_{2ij}$ of the second explanatory variable log(*Production Capacity at Bid* b_{ijt}). In particular, $\widehat{\beta}_{2ij}$ 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 $\widehat{\beta}_{2ij}$ should be negative. However, in some instances, especially during the price-cap regulation period, the estimates of $\widehat{\beta}_{2ij}$ are positive, but statistically insignificant. Exceptions are related to the new entrant producers, TXU and Edison, which acquired the divested production facilities.

Following the divestment series, we find statistical evidence for the presence of the disincentive to exercise market power for the incumbent electricity producers, which was not observed during the price-cap regulation period. This follows from the negative estimates of δ_{2ij} for NP and PG in Block 2 of Table 8, which based on notation in footnote 8 suggests that $\widehat{\beta}_{2ij}$ is negative for NP and PG after the divestment series. However, it took place at the expense of an increased incentive to exercise market power by the incumbent producers, as discussed earlier. These results suggest that the structural remedies were generally more successful than behavioral remedies at creating the disincentive, but not necessarily at decreasing the extent of exercising market power. Nevertheless, since in a less concentrated market structure it is easier to promote competitive bidding, structural remedies could be superior.

For the robustness check we also consider peak-demand trading periods with real price markups. 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.

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 model is considered in order to identify the incentive and disincentive to exercise market power. As the model suggests, a producer has an incentive to submit a higher price bid in excess of marginal cost for a production unit when that producer has a larger capacity below it. However, this incentive is moderated by the potential threat that this production unit may be out of schedule if a very high price bid is submitted. The functional form of the regression model is also based on the conclusions of the duopoly case.

During the period of price-cap regulation, we do not find statistical evidence for the presence of the disincentive to exercise market power for the incumbent producers. However, after the divestment series were introduced, we find the presence of the disincentive to exercise market power reflected by the negative coefficient of the second explanatory variable. At the same time, however, we find statistical evidence for the increased incentive to exercise market power described by the coefficient of the first explanatory variable in the regression model.

Generally, structural remedies implemented through divestment series might be preferred to behavioral remedies implemented through price-cap regulation. After divestments, market concentration decreases, which facilitates promoting competitive bidding among electricity producers.

The findings and conclusions of this research could be of interest to other countries using a day-ahead market for electricity trading since the experience in England and Wales has served as a model for much of the electricity industry restructuring worldwide (Wolak, 2000).

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Appendix A. Supplementary data

Supplementary data related to this article can be found at http://dx.doi.org/10.1016/j.jup.2015.07.004.

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Supplemental Material

The material is available at http://dx.doi.org/10.1016/j.jup.2015.07.004

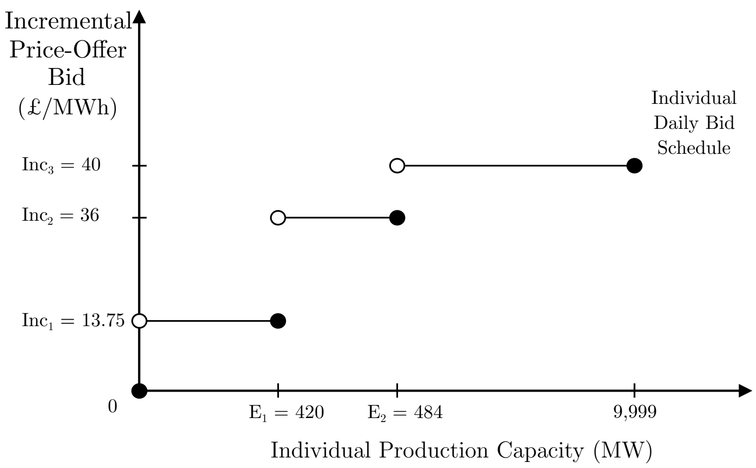
Appendices

A Bidding on the England and Wales electricity market

The wholesale electricity market in England and Wales consisted of three participants: producers, the market operator, and retail suppliers. Electricity producers sold electricity to retail suppliers through the wholesale market, also known as the Electricity Pool. This wholesale electricity market was managed by the network operator, the National Grid Company (NGC).

Trading in the England and Wales wholesale electricity market was conducted every day through a uniform price auction. The trading day consisted of 48 half-hourly trading periods, which the NGC divided into high- and low-demand trading periods. The NGC invited electricity producers to submit daily and half-hourly bids for each production unit for the following trading day.

The daily bids for each individual production unit included a start-up cost, a no-load cost, (at most) three incremental price-offer bids, and two elbow points. The start-up cost (measured in £) represented the cost to start up a production unit. The no-load cost (measured in £/h) represented the cost to keep a production unit from shutting down. The two elbow points (measured in MW) defined ranges over which the incremental price-offer bids (measured in £/MWh) applied. Figure A.1 illustrates what PowerGen submitted for its coal production unit KINO_02Z, which belonged to the Kingsnorth plant. The submitted bids for the start-up and no-load costs for this production unit were £4,200 and £5,103/h, respectively.



Source: Author's illustration.

Figure A.1: Submission of daily bids by PowerGen (January 14, 2000)

1

Electricity producers were also asked to submit for each individual production unit half-hourly bids on production capacity (measured in MW). The market operator used all these submitted daily and half-hourly bid data for individual production units to compute the respective half-hourly price bids (PBs) for the next trading day. The computation of PBs measured in £/MWh was common knowledge and was also different for high- and low-demand trading periods. This computation is described in Wolfram (1998) and Sweeting (2007).

Let Inc_1, Inc_2, Inc_3 denote three incremental price-offer bids, E_1 and E_2 denote two elbow points, and k denote production capacity. For high-demand trading periods the Average Bids (ABs) are first constructed:

$$
\begin{aligned}
&\textbf{a)}\text{ if } k=0,\ \text{then} \begin{cases} AB_1 = \text{£}0/\text{MWh} \\ AB_2 = \text{£}999/\text{MWh} \\ AB_3 = \text{£}999/\text{MWh} \end{cases} ; \\
&\textbf{b)}\text{ if } k \in (0; E_1],\ \text{then} \begin{cases} AB_1 = \frac{NoLoad}{k} + Inc_1 \\ AB_2 = 999 \\ AB_3 = 999 \end{cases} ; \\
&\textbf{c)}\text{ if } k \in (E_1; E_2],\ \text{then} \begin{cases} AB_1 = \frac{NoLoad}{E_1} + Inc_1 \\ AB_2 = \frac{NoLoad}{k} + \frac{Inc_1 \cdot E_1 + Inc_2 \cdot (k - E_1)}{k} \\ AB_3 = 999 \end{cases} ; \\
&\textbf{d)}\text{ if } k \in (E_2; 9999\text{ MW}],\ \text{then} \begin{cases} AB_1 = \frac{NoLoad}{E_1} + Inc_1 \\ AB_2 = \frac{NoLoad}{E_2} + \frac{Inc_1 \cdot E_1 + Inc_2 \cdot (E_2 - E_1)}{E_2} \\ AB_3 = \frac{NoLoad}{k} + \frac{Inc_1 \cdot E_1 + Inc_2 \cdot (E_2 - E_1) + Inc_3 \cdot (k - E_2)}{k} \end{cases} .
\end{aligned}
\tag{1}
$$

This choice of presentation allows for interpreting

$$AB = \frac{NoLoad}{k} + \frac{Inc_1 \cdot E_1 + Inc_2 \cdot (E_2 - E_1) + Inc_3 \cdot (k - E_2)}{k}$$

as consisting of two components. The first component uniformly distributes the no-load cost over the production capacity and the second term represents a capacity-weighted average of submitted incremental price-offer bids. Similarly, it can be shown that the start-up cost is uniformly distributed over high-demand trading periods during which a production unit produces electricity and then added to the half-hourly ABs. Depending on the value of production capacity k for each production unit, the minimum among the final AB_1, AB_2, and AB_3 define the half-hourly PBs.

In low-demand trading periods, the PB is set equal to one of the incremental price-offer bids depending on the value of the submitted half-hourly production capacity k:

$$\begin{array}{ll} \textbf{a)} \text{ if } k = 0, \text{ then } PB = 0\,; & \textbf{c)} \text{ if } k \in (E_1; E_2], \text{ then } PB = Inc_2\,; \\ \textbf{b)} \text{ if } k \in (0; E_1], \text{ then } PB = Inc_1\,; & \textbf{d)} \text{ if } k \in (E_2; 9999 \text{ MW}], \text{ then } PB = Inc_3\,. \end{array} \tag{2}$$

For each half-hourly trading period, the pairs of the PB and respective production capacity are ordered based on the PB to construct an aggregate supply schedule known also as a merit order.

B Approximation of marginal costs

Marginal costs of production units are approximated based on the definition of the thermal efficiency rate and data on quarterly fuel 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 for expressing the thermal efficiency rate κ of production unit X using fuel Y to produce 1 MWh of electricity in the following way:

$$\kappa(X, Y) = \frac{\big(1 \text{ MWh of electricity}\big) \cdot \text{factor } E}{\text{fuel } Y \cdot \text{factor } Y}\,, \tag{3}$$

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

Equation (3) for $\kappa(X, Y)$ suggests that the marginal cost of production unit X using fuel Y to produce 1 MWh of electricity can be approximated by

$$\begin{aligned} MC(X, Y) &= \big(\text{price of fuel } Y\big) \cdot \text{fuel } Y = \\ &= \big(\text{price of fuel } Y\big) \cdot \frac{\big(1 \text{ MWh of electricity}\big) \cdot \text{factor } E}{\kappa(X, Y) \cdot \text{factor } Y}\,. \end{aligned} \tag{4}$$

If fuel prices are given in £/MWh, then equation (4) simplifies to

$$MC(X, Y) = \big(\text{price of fuel } Y\big) \cdot \frac{1}{\kappa(X, Y)}\,. \tag{5}$$

As summarized in Table B.1, there are ten types of production unit. Nuclear and hydro types of production unit are far from being pivotal because they mainly operate 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 natural gas, respectively (Department of Trade and Industry, 1997–2002). Marginal costs of OCGT production units are approximated according to equation (4) because originally the price data on gas oil are available in £/liter. Based on Department of Trade and Industry (1997–2002), first we convert liters to tons (using 1163 liters per ton) and then to gigajoules (using calorific values of 45.5 gigajoules per ton) for the gas oil fuel.

Marginal costs of production units using coal, oil, and gas fuels are approximated according to equation (5) because quarterly fuel prices are available in £/MWh.

The efficiency rate of a production unit varies within a capacity type. The differences could be related to the age or size of a production unit. That is why, for approximating marginal costs we 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 for approximating their marginal costs using equation (4) or (5). Therefore, their marginal costs are also approximated using quarterly minimal price bids.

Table B.1: 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.

C Robustness check

Table C.1: Estimation results of equation (??) 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		0.040	0.289						
		PG		0.263**	0.107						
		EDF		0.270***	0.057						
		SI		0.296***	0.079						
		TXU						0.129	0.133		
		Ed		0.058***	0.006						
		BE								0.569***	0.173
		AES						0.027	0.036		
	$\hat{\beta}_{2ij}$	NP	Large Coal	0.176	0.431						
			Medium Coal	0.085	0.469						
			Small Coal	0.399	0.568						
			Oil	0.280	0.417						
			OCGT	0.750	0.643						
		PG	Large Coal	-0.147	0.151						
			Medium Coal	-0.147	0.166						
			Oil	0.036	0.141						
			OCGT	0.288	0.219						
		EDF	Export	0.372***	0.062						
		SI	Export	-0.052	0.099						
			CCGT	-0.192*	0.102						
		TXU	Large Coal					0.037	0.179		
			Medium Coal					0.103	0.204		
			OCGT					0.340	0.353		
		Ed	Large Coal							0.049	0.035
			OCGT							0.503***	0.082
			PSB	0.308***	0.074						
		BE	Large Coal							-0.507**	0.247
		AES	Large Coal							-1.254***	0.026
			OCGT					0.165*	0.085		
Block 2: Estimation of a change in comparison to a reference period	$\hat{\delta}_{1i}$	NP				1.365***	0.264	0.587**	0.238	0.483*	0.274
		PG				0.307**	0.147	0.361**	0.168	0.555***	0.116
		EDF						-0.271***	0.015	-0.224***	0.012
		SI				0.197	0.233	0.024	0.101		
		TXU								-0.271**	0.118
		Ed				-0.102***	0.011	-0.019***	0.003	0.159***	0.038
		AES								1.220***	0.070
	$\hat{\delta}_{2ij}$	NP	Large Coal			-2.011***	0.403	-0.762**	0.365	-0.547	0.421
			Medium Coal			-2.123***	0.448	-0.745*	0.402	-0.360	0.459
			Small Coal			-2.821***	0.532	-1.126**	0.482		
			Oil			-1.820***	0.391	-0.703*	0.356	-0.485	0.409
			OCGT			-3.167***	0.605	-1.351**	0.549	-1.124*	0.628
		PG	Large Coal			-0.508**	0.220	-0.433*	0.242	-0.652***	0.172
			Medium Coal			-0.307	0.247				
			Oil			-0.307	0.211	-0.434*	0.236	-0.655***	0.166
			OCGT			-0.804**	0.327	-0.859**	0.368	-1.377***	0.254
		EDF	Export					-0.077	0.062	-0.238***	0.084
		SI	Export			-0.433	0.360	-0.004	0.155		
		TXU	Large Coal							0.358**	0.150
			Medium Coal							0.412**	0.185
			OCGT							-0.209	0.305
		Ed	PSB			0.060***	0.006	0.097***	0.005	-0.165***	0.058
		AES	OCGT							-2.269***	0.087
			Intercept	0.399	0.414						

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 ??.
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 $R^2 = 0.602$.

D 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
Ofgem	Office of Gas and Electricity Markets
PG	PowerGen
SFE	Supply Function Equilibrium
SI	Scottish Interconnector
SMP	System Marginal Price
TXU	Texas Utilities (formerly, Eastern Group)

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3 Do producers apply a capacity cutting strategy to increase prices? The case of the England and Wales electricity market

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Do producers apply a capacity cutting strategy to increase prices? The case of the England and Wales electricity market ☆

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A B S T R A C T

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.

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 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 et al. (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 is relatively high could be another means of increasing prices.

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[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.

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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 et al. (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 Fig. 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.

2. Electricity auction and the 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 et al., 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 is called the System

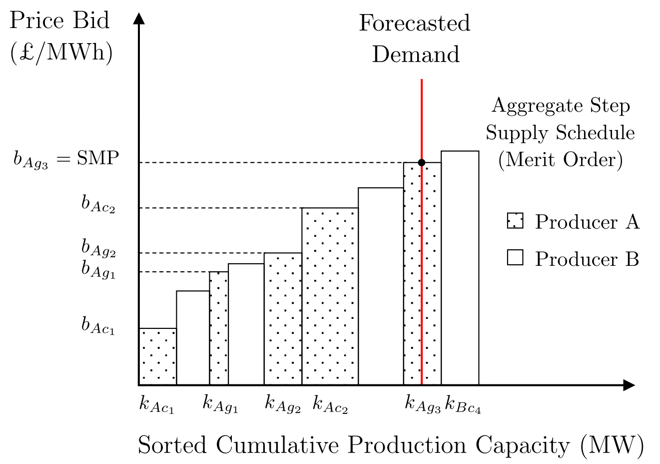

Fig. 2.1. Determination of the SMP during a half-hourly trading period.
Source: Authors' illustration.

Marginal Price (SMP) and represents 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 Fig. 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.

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 Fig. 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 to all production units needed to satisfy demand for electricity, and thereby, to enjoy higher profits on their scheduled units.

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 a shaded area in Fig. 2.2a and Fig. 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 to competitors. As Dechenaux and Kovenock (2007) find, capacity cutting may even be necessary to sustain tacit collusion. 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

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

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

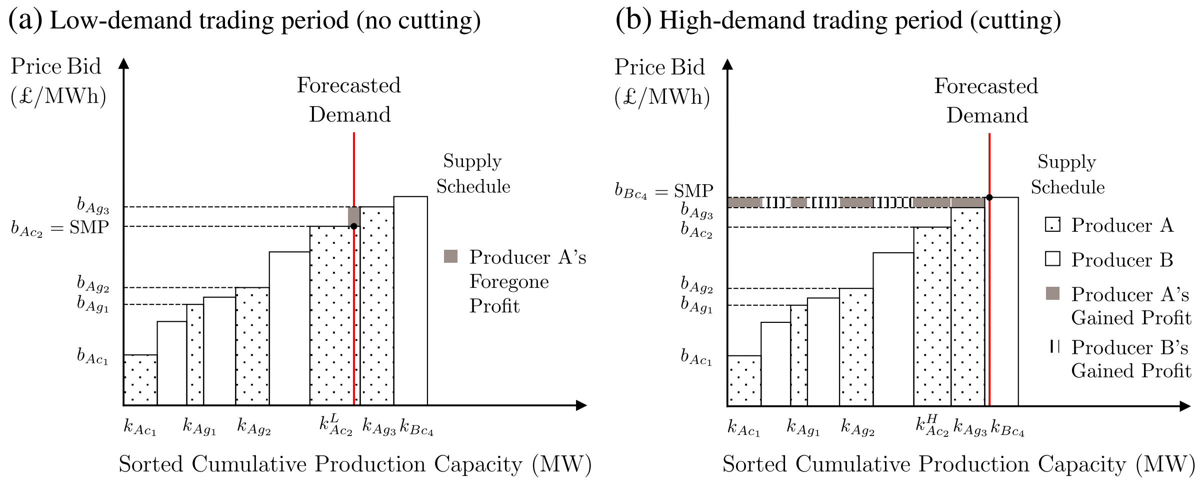

Fig. 2.2. Capacity strategy. *Notes*: In (a) we depict part of production capacity k_{Ac_2}, which could have been withheld for the high-demand period. The shaded area depicts the associated loss if capacity cutting were applied. In (b) we illustrate a change in SMP when part of capacity for k_{Ac_2} 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.
Source: Authors' illustration.

(1992), Von der Fehr and Harbord (1993), Wolfram (1998), Crawford et al. (2007), and Sweeting (2007).

As described in Fig. 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 et al., 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, the 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 Fig. 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 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 when 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 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.

Similar to Borenstein et al. (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.

[5] This is also a limitation of research by (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.

[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.

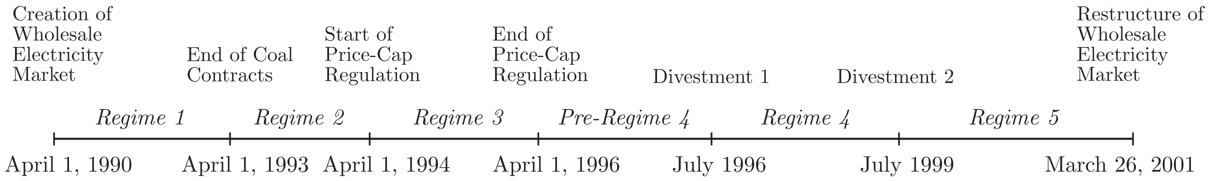

Fig. 2.3. Institutional changes and regulatory reforms in the ESI in Great Britain during 1990–2001.
Sources: Department of Trade and Industry (1997–2002), National Grid Company (1994–2001), Newbery (1999), Robinson and Baniak (2002), Wolfram (1999); authors' illustration.

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 from substantial gaps between maximal and submitted capacity bids at peak hours, 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 also 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 the 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. However these conclusions 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 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 presents 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; 2) increasing wholesale prices.[8] Firstly,

Table 2.1
Structural impact of National Power and PowerGen divestments.
Source: Reproduced from Bishop and McSorley (2001).

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

Note: HHI stands for Herfindahl–Hirschmann Index (sum of squared shares: monopoly = 1).

[7] Capacity payments are computed as $CP = LOLP \cdot (VLL - SMP)$, where LOLP stands for Loss of Load Probability (an estimated probability that demand will exceed supply), VLL 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).

[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.

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 Fig. 2.2.

4. Binding theory and empirics

4.1. Data and its 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 Figs. A.1 and A.2 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 provided in Table 4.1.

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:

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

where t denotes trading day.

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

$$\text{growth in SMP}_t = \frac{\text{SMP}_{t,(\text{peak}-\text{demand period})}}{\text{SMP}_{t,(\text{peak}-\text{demand period}-\text{five hours})}} - 1, \qquad (2)$$

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. But 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).

Table 4.1
Sample of descriptive statistics for market data (January 1, 2000–January 31, 2000).
Source: Authors' calculations.

	Forecasted demand (MW)	SMP (£/MWh)
Mean	38,464.60	24.39
Min	25,001.00	8.00
Max	49,945.00	77.89
Std. Dev.	5247.83	12.54
Frequency	30 min	30 min
Obs.	1488	1488

Table 4.2
Relative changes in market demand (MW) and SMP (£/MWh) during January 6, 2000.
Source: Authors' calculations.

$\text{Demand}_{t,(\tau-5\text{hrs})}$	$\text{Demand}_{t\tau}$	Growth in demand_t	$\text{SMP}_{t,(\tau-5\text{hrs})}$	$\text{SMP}_{t\tau}$	Growth in SMP_t
42,825	48,215	0.126	55.56	77.89	0.402

Notes: Subscript t is trading day (January 6, 2000) and τ is peak-demand trading period (17:30).

Table 4.3
Sample of descriptive statistics for capacity bidding data (January 1, 2000–January 31, 2000).
Source: Authors' calculations.

	Capacity bids (MW)
Mean	175.41
Min	0.00
Max	989.00
Std. Dev.	248.12
Frequency	30 min
Obs.	450,336

The application of Eqs. (1)–(2) for market data of a trading day on January 6, 2000 is presented in Table 4.2.

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 presented in Table 4.3.

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.[9]

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

$$\Delta k_{ijt} = \frac{\sum_{l\in j} k_{ilt,(\text{peak}-\text{demand period})}}{\sum_{l\in j} k_{ilt,(\text{peak}-\text{demand period}-\text{five hours})}} - 1, \qquad (3)$$

where subscripts i, j, l, t denote producer, capacity type, production unit, trading day, respectively and $\sum_{l\in j} k_{ilt,(\text{peak}-\text{demand period})}$ denotes producer i's capacity of type j during the peak-demand period of trading day t.

The application of Eq. (3) for submitted (declared) capacity bids on January 6, 2000 is presented in Table 4.4.

In Table 4.5, based on the comparison between the peak- and low-demand trading periods within a day, we present the incidence of non-competitive and competitive capacity bidding behaviors.

The first block in Table 4.5 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 B.1.

Cases when producers either do not change or increase declared available capacity when an increase in demand is forecasted are defined

[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.

Table 4.4
Application of Eq. (3) for capacity bids during January 6, 2000.
Source: Authors' calculations.

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

Notes: k denotes capacity and Δk_{ijt} denotes a relative change in capacity, which is computed using Eq. (3). Subscript i is producer, j is capacity type, l is production unit, t is trading day (January 6, 2000), 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.

to be consistent with competitive bidding behavior. Their incidence results are presented in the last two blocks in Table 4.5. The incidence results can be explained as producers applying a mixed strategy approach between bidding noncompetitively and competitively.

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 4.5 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 lead to an increase of wholesale prices.

4.2. Empirical methodology

When demand is forecasted to increase producers may bid capacity either noncompetitively (by applying a capacity cutting strategy) or

Table 4.5
Incidence of noncompetitive and competitive capacity bidding during January 1, 1995–September 30, 2000.
Source: Authors' calculations.

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	–	–

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.

competitively (by increasing or at least not changing declared available capacity). The incidence of noncompetitive and competitive capacity bidding is summarized in Table 4.5. We use a regression analysis to examine the noncompetitive capacity bidding. Specifically, we consider the following regression model:

$$\Delta k_{ijt} = \alpha + \beta_{ij} \cdot \text{growth in demand}_t + \varepsilon_{ijt}, \tag{4}$$

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 Eq. (3). 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 the 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 Eq. (4) 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).

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]

[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.

[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.

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:

$$\mathrm{P}(\text{Decision} = 1|\mathrm{x}) = \Phi\left(a + b_{ij} \cdot \text{growth in demand}_t + c_{ij} \cdot \text{growth in SMP}_{\mathbf{t}}\right) \tag{5}$$

$$\Delta k_{ijt} = \alpha + \beta_{ij} \cdot \text{growth in demand}_t + \gamma \cdot \hat{\lambda}_{ijt} + \varepsilon_{ijt}, \tag{6}$$

where in Eq. (5) 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 Eq. (6), 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.

Therefore, regression Eq. (4) describing capacity cutting behavior is modified according to Eq. (6). 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 Fig. 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.

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 4.5. 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.

5.1. Selection equation

The analysis includes cases of noncompetitive and competitive capacity bidding. They represent 3970 and 35,043 observations, respectively. Decision = 1 corresponds to noncompetitive capacity bidding when a producer applies a capacity cutting strategy. In Table 5.1 we present our estimation results for the probit selection equation.

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

Table 5.1
Probit selection equation. P(Decision = 1|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.

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 Eq. (6) describing the noncompetitive bidding behavior at the level of individual producers' capacity types.

5.2. Effect of a regulatory regime change

In estimating amount Eq. (6) we assume that the producer and capacity type specific slope parameter β_{ij} may additionally vary during different regime periods described in Fig. 2.3. We present our estimation results in Table 5.2. 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 Eq. (6). In Table 5.2 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 one 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}.

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.

5.2.1. Incumbent producers: National Power and PowerGen

Our estimation results presented in the first block of Table 5.2 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 5.2, 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.

Table 5.2
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 = 3970 and $R^2 = 0.376$.

But 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 $j \in$ {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 only exception for the CCGT type.

Qualitatively, the estimation results related to the noncompetitive bidding behavior 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 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.

[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 5.2.

5.2.2. 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 non-competitive 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.

5.2.3. 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 5.2 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 3 (Ofgem, 2000a). However, we do not find statistical evidence for applying capacity cutting for the PSB type when demand is forecasted to increase.

5.2.4. 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 the 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 5.2 indicate noncompetitive bidding behavior of BE with respect to the large coal capacity (a negative estimate for the slope parameter). However, as the incidence of cutting is relatively very low (see Table 4.5), 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 5.2, indicate weak evidence for capacity cutting 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 4.5 is the same for this producer's large coal capacity.

[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).

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 consistent 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 in line with Ofgem's official investigation of capacity withdrawal by this producer (Ofgem, 2000a,b). 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 an interesting evidence in reasoning why the BE and AES producers did not wish to join the MALC code of conduct.

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Appendix A. Supplementary data

Supplemen tary data to this article can be found online at http://dx.doi.org/10.1016/j.eneco.2014.02.007.

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Supplemental Material

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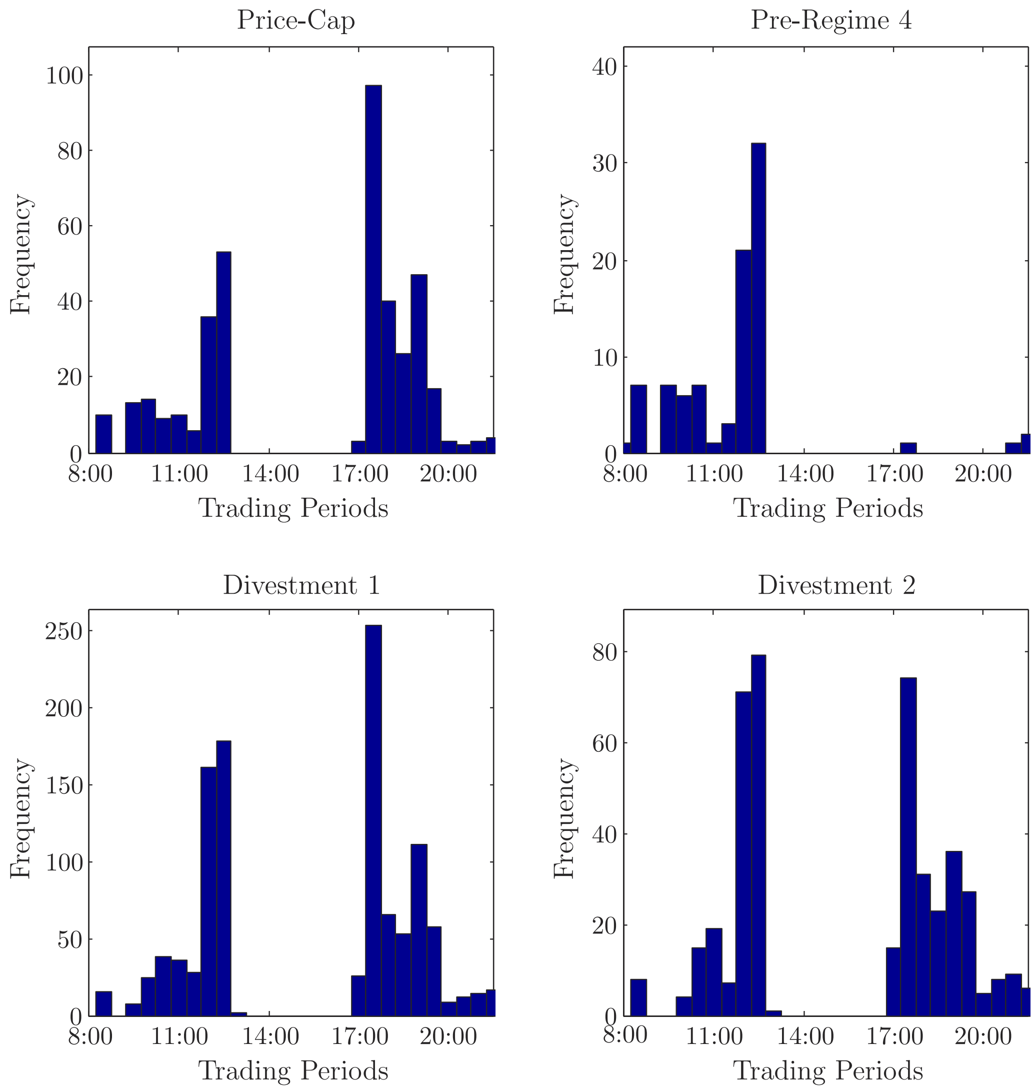
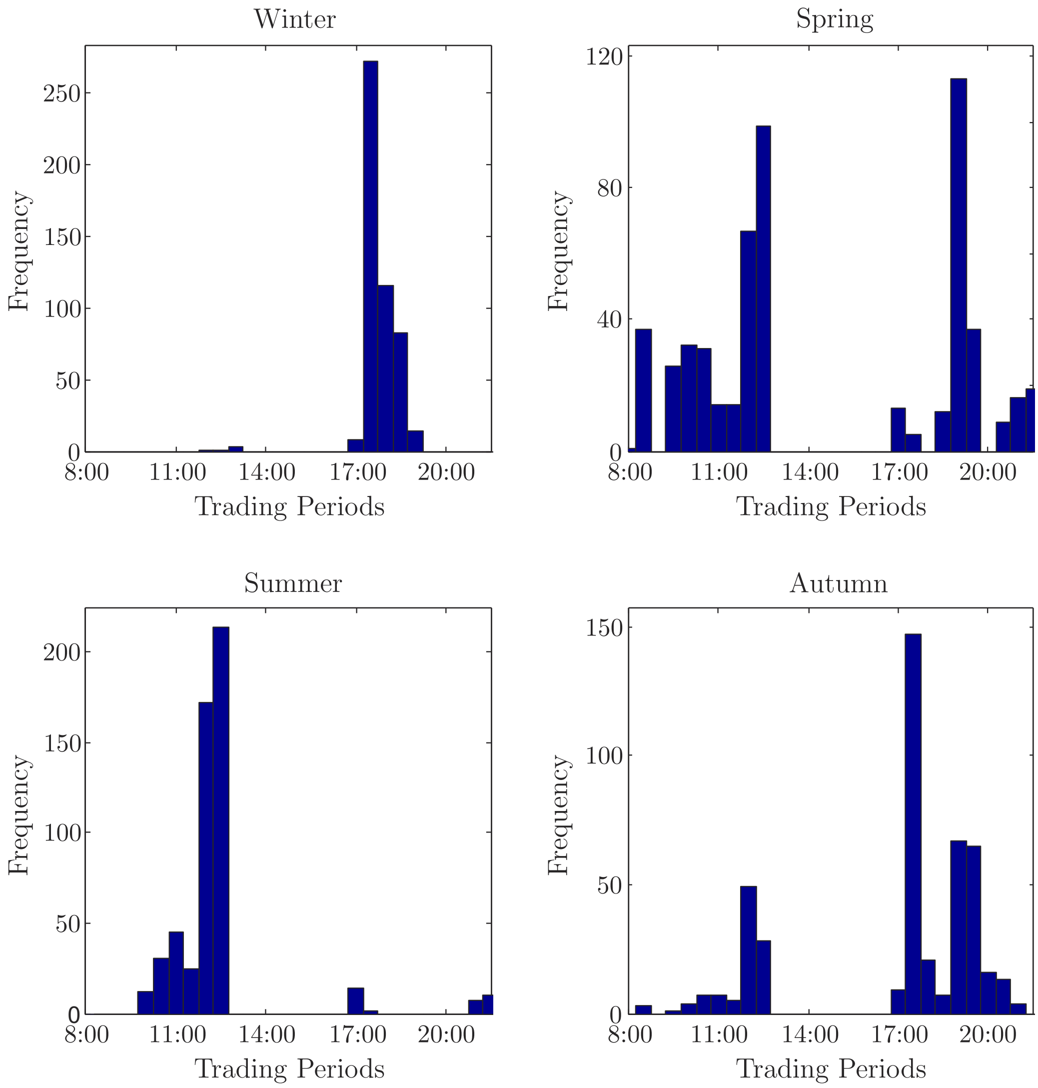
Appendices

A Figures



Sources: Authors' calculations.

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



Sources: Authors' calculations.

Figure A.2: Incidence of peak-demand periods across seasons during January 1, 1995 – September 30, 2000

B Tables

Table B.1: 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.

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, the OFFER)
PG	PowerGen
PSB	Pumped Storage Business
SI	Scottish Interconnector
SMP	System Marginal Price

4 Estimating the volatility of electricity prices: The case of the England and Wales wholesale electricity market

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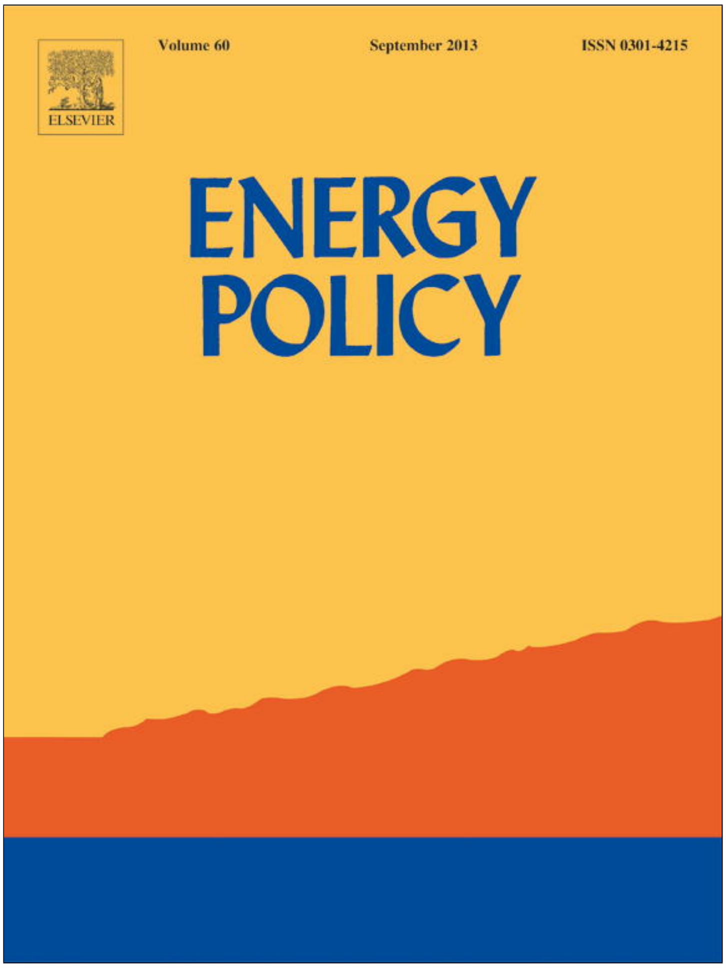
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Estimating the volatility of electricity prices: The case of the England and Wales wholesale electricity market

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AUTHOR-HIGHLIGHTS

- The impact of regulation on the dynamics of electricity prices is examined.
- Price-cap regulation has decreased the level at the cost of higher volatility.
- The first series of divestments has reversed the trade-off.
- The reversed trade-off is explained as an indication of tacit collusion.
- The second series of divestments is found generally successful.

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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.

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

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; NEM, New Zealand Electricity Market; NGC, National Grid Company; OFFER, Office of Electricity Regulation; OFGEM, Office of Gas and Electricity Markets (formerly, the 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.

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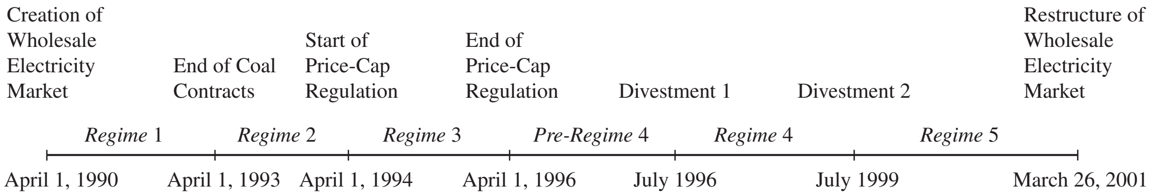

Fig. 1. Institutional changes and regulatory reforms in the ESI in Great Britain during 1990–2001. *Sources:* Department of Trade and Industry (1997–2002), National Grid Company (1994–2001), Newbery (1999), Robinson and Baniak (2002), Wolfram (1999); author's illustration.

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 Fig. 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 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.

Joskow (2009) 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. In this respect, the findings and conclusions of this research could be of interest to countries that 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.

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 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. The authors 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 et al. (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 that 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 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 et al. (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 et al. (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 et al. (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 et al. (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 et al. (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, as well as the presence of spikes and volatility clustering in electricity prices.

Koopman et al. (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 5.

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 Fig. 1.

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 when the reforms were introduced. This approach, which in particular better corresponds to the nature of the divestment series introduced by the regulatory authority, is also applied in Tashpulatov (2010). For example, the introduction of the first series of divestments for PowerGen led to

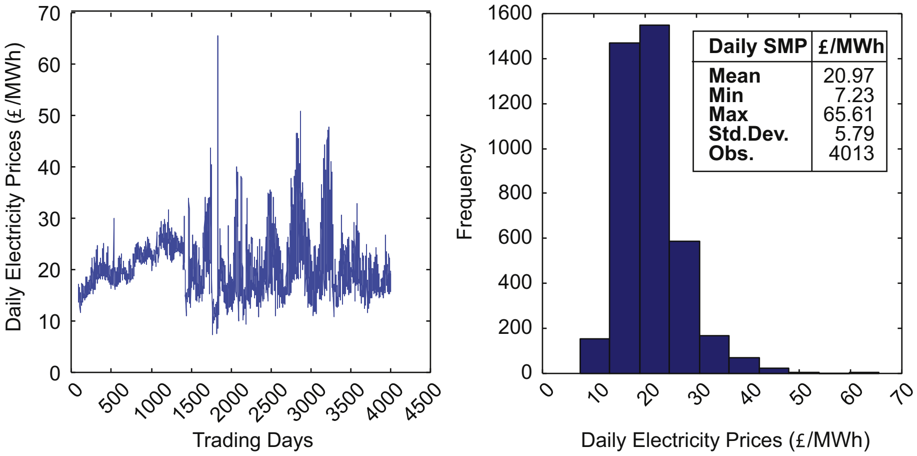

Fig. 2. Daily electricity prices (April 1, 1990–March 26, 2001). *Source*: Author's calculations.

the transfer of all medium coal production facilities to Eastern Group (National Grid Company, 1994–2001). In that study 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, in this study 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.

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).

Fig. 2 above describes the development and distribution of daily electricity prices for the whole history of the England and Wales wholesale electricity market.

The observed excessively high 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 (see Robinson and Baniak, 2002).

In Table 1 I summarize the descriptive statistics of daily electricity prices during the different regime periods described in Section 3.

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

Table 1
Summary statistics for daily electricity prices (£/MWh) across regimes.

	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.

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 5.

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 the institutional changes and regulatory reforms that took place in the ESI in Great Britain during 1990–2001.

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 Sections 5.2 and 5.3, respectively, also require the stationarity of a time series (see, for example, Gençay et al., 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 10, which was then changed to 8 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 2.

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).

Table 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

MacKinnon critical values for the rejection of the hypothesis of a unit root.

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 Fig. 3 (a lag of order 1000 corresponds to approximately 25% of the sample size).

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, … (integer multiples of 7), and annual seasonality observed through the spikes in the sample ACF at lag orders of 364, 728, … (integer multiples of 364).

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

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 A.

A graph where the frequency domain is plotted against the absolute values of the Fourier transform is known as a periodogram. In Fig. 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 Fig. 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

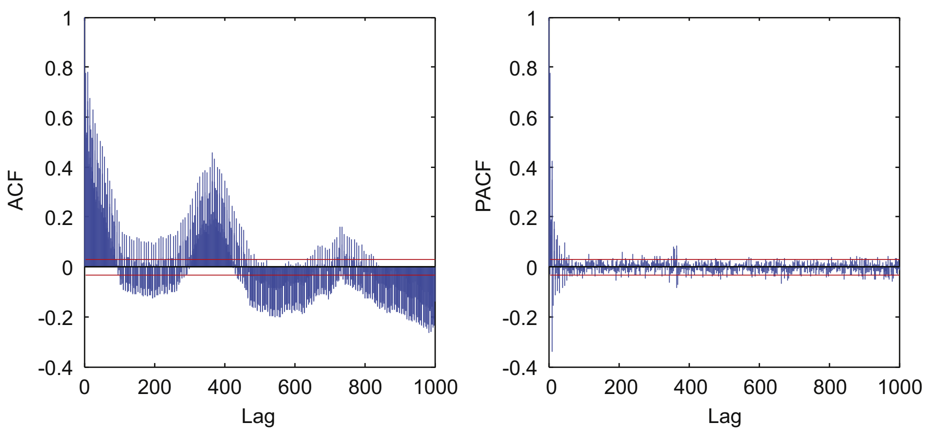

Fig. 3. Correlogram for daily electricity prices. *Source*: Author's calculations.

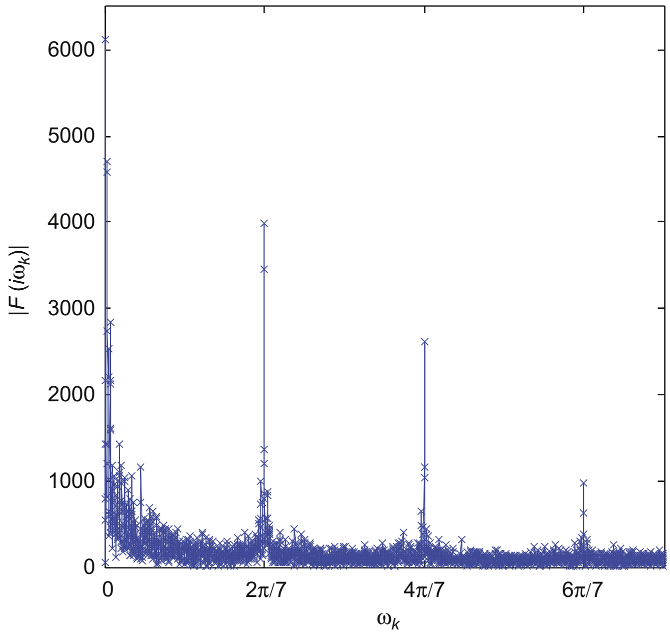

Fig. 4. Periodogram for daily electricity prices. *Source*: Author's calculations.

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 mentioned in Koopman et al. (2007).

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:

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

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

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:

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

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

where $h_t = E_{t-1}[\varepsilon_t^2]$ 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 in particular 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 the 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 the volatility. This is investigated by a threshold *ARCH* process developed in Glosten et al. (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, $\hat{\nu}_t = \hat{\varepsilon}_t / \sqrt{\hat{h}_t}$, is an i.i.d. sequence. For this purpose, I apply the BDS test developed by Brock et al. (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.

6. Results and discussion

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

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

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

where z_t is a vector of additional explanatory variables including periodic sine and cosine functions and regime dummy variables. In Figs. B1 and B2 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.

Table 3
Estimation results of the extended AR–ARCH model.

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

$$h_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i\, \varepsilon^2_{t-i} + z'_t \cdot \delta,$$

Mean equation Variable	Coef.	Std. Err.	*Conditional volatility equation* 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^2_{t-1}	0.174***	0.027
$price_{t-2}$	0.068***	0.016	ε^2_{t-3}	0.019*	0.012
$price_{t-3}$	0.033**	0.014	ε^2_{t-4}	0.092***	0.021
$price_{t-4}$	0.048***	0.014	ε^2_{t-5}	0.110***	0.020
$price_{t-6}$	0.084***	0.013	ε^2_{t-7}	0.293***	0.039
$price_{t-7}$	0.241***	0.019	$\varepsilon^2_{t-7} \cdot I_{t-7}$	−0.124**	0.054
$price_{t-8}$	−0.101***	0.017	ε^2_{t-9}	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.

* stands for the 10% significance level.
** stands for the 5% significance level.
*** stands for the 1% significance level.

The estimation results obtained using the Marquardt algorithm are summarized in Table 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.

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 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 Fig. 5, in comparison with the normal distribution, suggests that the assumption of the generalized normal distribution for ν_t works reasonably well.

In order to check 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,

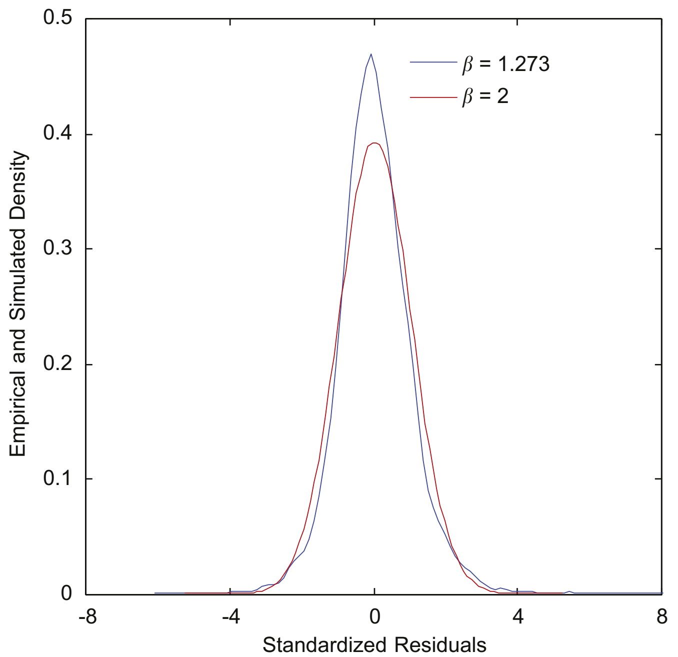

Fig. 5. Density of $\hat{\nu}_t$ and the normal distribution.

confirms the adequacy of the estimated *AR–ARCH* model. The test results are summarized in Table 4.

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 if 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 Fig. 6.

The test results presented in Fig. 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, 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 Fig. 7.

Table 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

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 hard 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

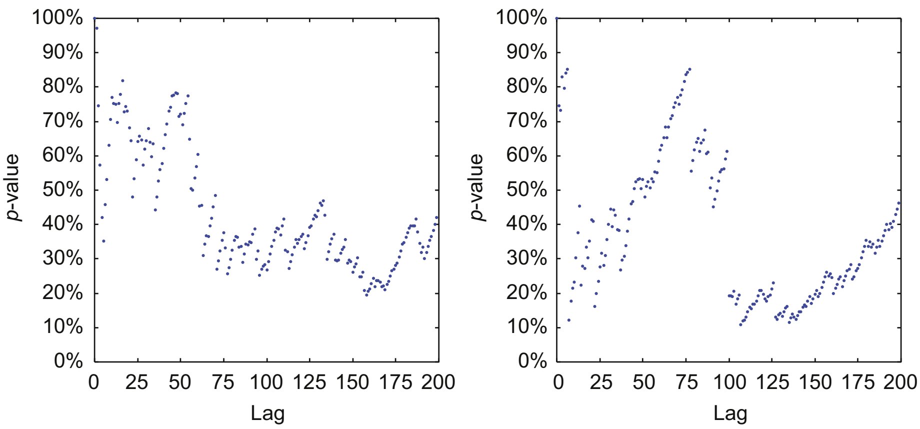

Fig. 6. Ljung–Box Q-test for standardized residuals $\hat{\nu}_t$ and $\hat{\nu_t^2}$. *Source*: Author's calculations.

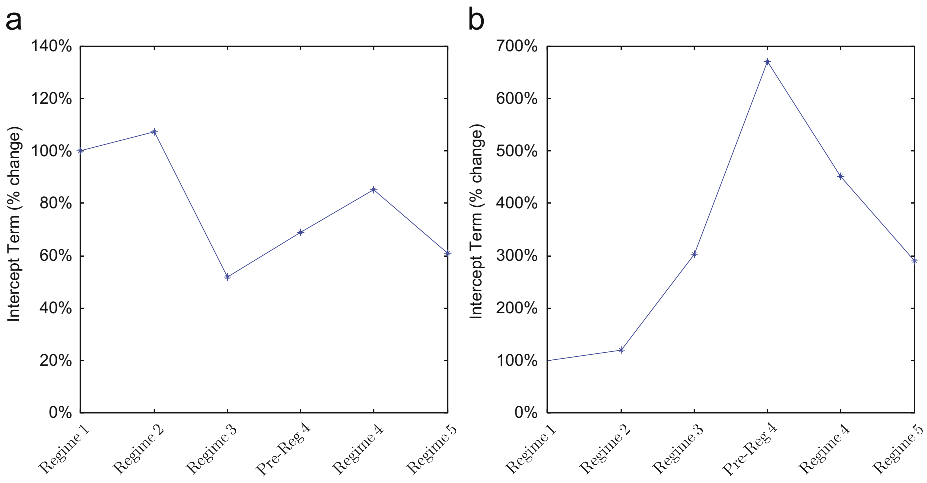

Fig. 7. Impact of the institutional changes and regulatory reforms on price and volatility dynamics: (a) Mean equation and (b) conditional volatility equation. *Source*: Author's calculations.

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 is measured through a Herfindahl concentration index, are chiefly responsible for a decrease in the price level.

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.

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I would like to express my gratitude to Lubomír Lízal, Jan Kmenta, Evžen Kočenda, Petr Zemčík, and anonymous referees for comments and suggestions. I am also very grateful to Richard Green, the Department for Business, Innovation and Skills (formerly, the Department of Trade and Industry), National Grid plc, and OFGEM for providing access to data on electricity prices and publication materials.

Appendix A. A Fourier transform

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

$$F(i\omega) = \mathcal{F}\{p(t)\} = \int_0^T p(t) \cdot e^{-i\omega t}\, dt,$$

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 $\omega_k = k/(N-1) \cdot 2\pi$, $k = 0, 1, 2, \ldots, N-1$, 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.

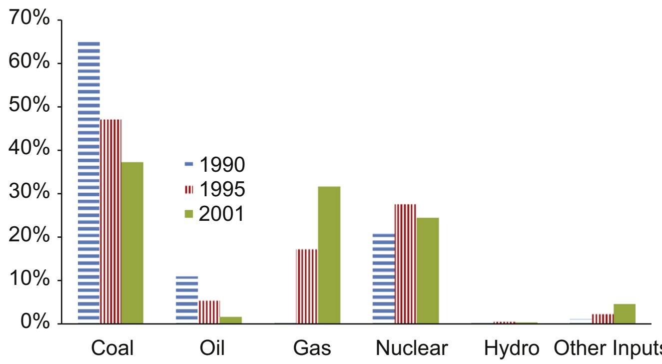

Fig. B1. Distribution of input types for electricity production. *Source*: Department of Trade and Industry (1997–2002); author's calculations.

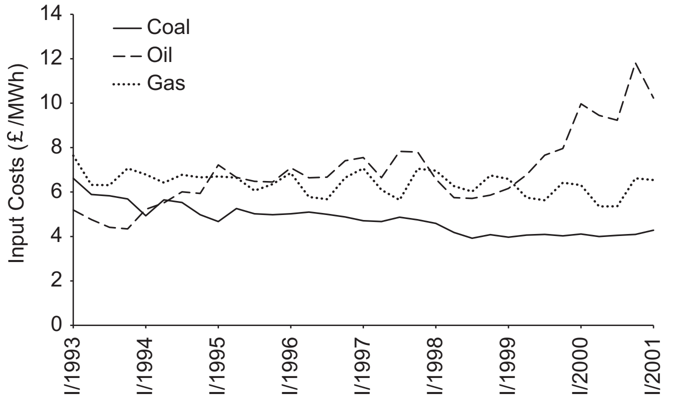

Fig. B2. Quarterly average input costs of electricity producers in the UK. *Source*: Department of Trade and Industry (1993–2000); author's calculations.

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

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

where $\omega_k = k/(N-1)\cdot 2\pi$, $k = 0, 1, 2, \ldots, N-1$, 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.

Appendix B

Distribution of input types for electricity production and quarterly average input costs of electricity producers in the UK are shown in Figs. B.1 and B.2.

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Directions for further research

In the first paper I analyze the dynamics of the wholesale electricity price during the peak-demand period. I propose to use skew generalized error distribution (SGED), which captures the features of heavy tails, excess kurtosis (i.e., kurtosis above three), and asymmetry. This distribution is relatively novel and has not been used much in the literature. Instead, other simpler distributions have been used. For example, Koopman et al. (2007) for the autoregressive integrated moving average model with generalized autoregressive conditional heteroscedasticity ($ARFIMA$–$GARCH$ model) use Student's t distribution, which captures the feature of heavy tails and assumes kurtosis below three. It would be interesting to use the $ARFIMA$–$GARCH$ model with SGED in case time series have additionally the features of excess kurtosis and asymmetry.

There are two frequently used models to analyze the bidding behavior of producers on electricity markets: supply function equilibrium and discrete bid auction. The first model of a supply function equilibrium is used, for example, in Green and Newbery (1992). This approach assumes that production units are small enough or that each producer has a sufficiently large number of production units, as was the case with the National Power and PowerGen incumbent electricity producers in the early 1990s. Ciarreta and Espinosa (2010) similarly applies the supply function equilibrium model for the Spanish wholesale electricity market.

The second model of a discrete bid auction is used in Von der Fehr and Harbord (1993), Wolfram (1998), Brunekreeft (2001), and Crawford et al. (2007). In the second paper I also use the discrete bid auction model to analyze the bidding behavior of producers on the wholesale electricity market during the liberalization process in Great Britain (Tashpulatov, 2015).

Until now there is no clear consensus regarding which modeling approach is better. On the one hand, Ciarreta and Espinosa (2010) finds that the supply function equilibrium model better fits data than the discrete bid auction model. On other hand, when analyzing the later period, Wolfram (1999), however, finds that for the British wholesale electricity market the supply function equilibrium model does not describe the market very well because electricity prices were much lower than the model predicted. Both of these wholesale electricity markets share a lot in common: a similar market design operated by two incumbent electricity producers. Because the result of Ciarreta and Espinosa (2010) is based on the analysis of bids for only oil fired thermal plants, it could be interesting to extend the analysis for all plants.

Withholding output could be another possible way how to increase prices without the need to price output above marginal production cost. This is also an important issue in energy markets. In the third paper we compare capacity bidding of producers during low- and high-demand periods in order to analyze if producers behave competitively or noncompetitively. Capacity withholding was also an issue in the German electricity market where the E.ON AG electricity producer was investigated by the European Commission (European Commission, 2009). The situation of a firm producing less for a higher price is a frequent consequence of the firm's dominant or monopoly position on the market. Hence, understanding the bidding behavior of producers is important for ensuring reasonable energy prices for end consumers.

In the literature, under daily prices we usually see time-weighted average prices. However, for some market participants and regulators it could be also of interest to see the analysis of demand-weighted average prices. For the British electricity market it was possible to analyze only time-weighted average daily prices as presented in the last paper because demand data are not available for the whole sample period. The presented methodology based on time and frequency domains with the generalized error distribution could however be easily applied to the new price time series. In case the distribution is asymmetric, then one could apply skew generalized error distribution similar to the methodology in the first paper.

Conclusions

In the presented four papers we discussed the liberalization process of the electricity supply industry in Great Britain. The purpose of liberalizing the electricity supply industry was to promote competition and to lower prices for end consumers. We focus on the analysis of the peak-demand period during which, as documented in the literature, producers may exercise market power.

In the first and fourth papers we analyze the effect of regulatory reforms on market outcomes. In particular, we analyze the effect of reforms on the electricity price during the peak-demand period and on the daily electricity price, respectively. Both of these papers find weekly seasonality pattern in electricity prices, which was later important for analyzing firm behavior.

The second and third papers address producers' bidding behavior. In particular, in the second paper, we analyze the exercise of market power manifested in submitting price bids in excess of marginal production costs. In the third paper, we analyze the capacity withholding strategy aimed at creating artificial deficit during the peak-demand period with a view to increase the wholesale electricity price when the market operator may need to schedule more expensive production facilities.

We find that the second series of divestments was generally more successful at promoting competition and at lowering price level and volatility. However, the incumbent producers were affected differently possibly because of an unequal horizontal restructuring introduced through divestment series.

The documented results from the analysis of the England and Wales electricity market could be interesting for countries which adopted a similar market design operated by several dominant firms. This market could be used as a model for liberalizing energy markets in other countries (Wolak, 2000; Joskow, 2008; Joskow, 2009).

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