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Forecasting electricity prices: The impact of fundamentals and time-varying coefficients

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Abstract

This paper investigates the day-ahead forecasting performance of fundamental price models for electricity spot prices, intended to capture: (i) the impacts of economic, technical, strategic and risk factors on intra-day prices; and (ii) the dynamics of these effects over time. A time-varying parameter (TVP) regression model allows for a continuously adaptive price structure, due to agent learning, regulatory and market structure changes. A regime-switching regression model allows for discontinuities in pricing due to temporal irregularities and scarcity effects. The models that invoke market fundamentals and time-varying coefficients exhibit the best predictive performance among various alternatives, in the British market.

Keywords: Electricity prices; Forecasting; Time-varying effects; Regime-switching

1. Introduction

Due to the idiosyncrasies of wholesale electricity markets, spot price dynamics are only partially understood, and their forecasting, even at the day-ahead horizon, remains an important challenge for market participants and system controllers. This complexity arises from a convolution of market characteristics, including: (i) the instantaneous nature of the commodity; (ii) the shape of the supply function, which, in the presence of diverse plant technologies, is intrinsically steeply increasing, discontinuous and convex; (iii) the exercise of market power, resulting from oligopolistic market structures, agents' asymmetries and the negligible demand elasticity of price in the short term; (iv) complex market designs; and (v) substantial agent learning, due to highly-repeated auctions, frequent regulatory interventions, and market structure changes. A clear implication of the interaction of all these complexities is that spot price forecasting is not trivial.

Firstly, forward prices convey limited signals about spot movements. Due to its non-storability, the convenience yield relationship, which links the forward curve to the spot price in many other commodities, does not hold for electricity. In addition, the forward premium, even at day-ahead horizons, exhibits an indefinite sign and unclear pattern across trading periods (Longstaff & Wang, 2004), which can

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be related, in some markets, to the diurnal heterogeneity of the plants operating, as well as to market design aspects (Karakatsani & Bunn, 2005). Secondly, while stylised stochastic models of spot prices (Escribano, Peaea, & Villaplana, 2002; de Jong & Huisman, 2003; Geman & Roncoroni, 2006) replicate the characteristics of the statistical distribution well, and allow derivatives pricing via analytical formulae or numerical simulations, their short-term forecasting performance is inadequate, partially due to the occurrence of abrupt, fast-reverting spikes. These can only be pre-signalled by predictions of relevant exogenous drivers, such a fuel prices or the capacity surplus, rather than from historical prices. Thirdly, in the presence of market power and significant asymmetries across agents, critical information on future market fundamentals may only be available to a subset of market participants, e.g. the dominant generators or integrated companies. A purely statistical model that does not invoke market fundamentals and agent behaviour may therefore be quite inadequate as a basis for forecasting.

Although intuitively appealing for forecasting, existing fundamental models for electricity prices also exhibit a number of limitations. Firstly, they are primarily constrained to autoregressive effects and the price responses to demand, fuel prices or weather conditions, such as temperature, precipitation and wind (e.g. Nogales, Contreras, Conejo, & Espinola, 2002; Kanamura & Ohashi, 2004; Vehvilainen & Pyykkonen, 2004; Kosater, 2006, Rambharat, Brockwell, & Seppi, 2005, Knittel & Roberts, 2005). In competitive electricity markets, however, particularly as they evolve towards less centralised designs, these factors are not sufficient. They need to be complemented with (i) aspects of plant dynamics, as suggested by technical and economic arguments, (ii) risk measures, as implied by Longstaff and Wang (2004), (iii) market design effects, manifested in various comparative studies (e.g., Wolak, 2000), (iv) agent learning, and (v) strategic behaviour. Although the exercise of market power has been documented extensively in market assessments, as well as competition models (e.g. e.g. Wolfram, 1999; Borenstein, Bushnell, & Knittel, 1999; Green & Newbery, 1992; Day, Hobbs, & Pang, 2002), relevant indicators do not appear in econometric price models. Secondly, price formation is contingent upon the market design and market structure (Wolak, 2000; Bower & Bunn, 2001). These specificities should be reflected in the price models in order to obtain precise market inferences and price predictions. Thirdly, most specifications tend to refer to daily average prices, which conceal intra-day patterns. However, each intraday trading period displays a rather distinct price profile, reflecting the dynamics of demand, supply and operational constraints. Still, high-frequency studies have appeared only recently (e.g. Longstaff & Wang, 2004; Guthrie & Videbeck, 2007; Huisman, Huurman, & Mahieu, 2007). Finally, most models generally estimate constant parameters, although the evolution of market conditions would suggest that this might be inadequate.

Even if price drivers are adequately represented, forecasting spot electricity prices with a fundamental model poses two main challenges. Firstly, it presupposes that forecasts of the predictor variables, such as the level of demand, and, more critically, the capacity margin, will be available. The errors implicit in these forecasts could be minor, relative to the uncertainty underlying the price process if these fundamentals are disregarded; on the other hand, they may be substantial, of an order that diminishes the marginal gain in price prediction. While demand forecasts are generally very accurate, the predictability of capacity margins remains under-researched. Whereas generators are often obliged to submit indications of their future plant availability to the system operator, these notifications are often interpreted with scepticism by grid controllers. Secondly, it is uncertain whether the equation of a fundamental price model, estimated from historical data, would generalise well out-of-sample. Electricity markets are subject to many shocks in fuel prices, demand, supply, and institutional involvement, including, most recently in Europe, carbon dioxide prices.

Motivated by the above issues, this paper investigates the impact on day-ahead price forecasting of two model characteristics: (i) the representation of the market fundamentals that influence price formation; and (ii) the specification of their time-varying effects. Our study focuses on three fundamental price models: (i) a linear regression, based on the market factors defined in Section 3, which captures the average price formation over the sample period; (ii) a time-varying parameter (TVP) regression model of random-walk coefficients, which postulates a continuously adaptive price structure, due to agents learning in response to frequent regulatory/market structure changes; and (iii) a Markov regime-switching regression model, which allows for discontinuities in pricing due to temporal irregularities, such as excessive scarcity rents being achieved when favourable conditions arise. These models are compared to autoregressive price models, with similar coefficient dynamics. All models are estimated at the level of the 48 half-hourly periods that constitute a trading day in the British market.

Our context is the British[1] electricity market over the first year after the reforms introduced in March 2001. An extensive investigation was performed across various intra-day periods, and the patterns that emerged were homogeneous to a large extent. To illustrate our findings, we report in this paper our analysis for two typical periods of peak demand: period 25 (11.00-11.30) and period 35 (16.00-16.30). In the latter, the price dynamics were particularly complex, whilst in the former they were more stable.

The empirical findings from the British market suggest that price models based on market fundamentals and their time-varying effects are the most effective and potentially useful in practice. Of course, the factors relevant for price formation are expected to vary across time periods and markets, depending on local specificities, such as the generation mix, the degree of market power, and the market design. Nevertheless, the inherent characteristics of electricity, including its non-storability and oligopolistic market structure, yield economic, technical, strategic and risk factors, similar to those defined in this paper, which are potentially influential in other periods and markets, while their highly adaptive nature renders time-varying effects substantial.

The paper is organised as follows. Section 2 describes the market design introduced in the British electricity market in March 2001. Section 3 defines potential price drivers of spot electricity prices. Section 4 focuses on regressions with time-varying coefficients and comments on their insights into the adaptation of price formation and its temporal irregularities. Section 5 presents forecasting results, and Section 6 concludes.

[1] For simplicity, the wholesale electricity market for England and Wales is referred to as British, although it did not include the Scottish region until 2005.

2. The market setting

2.1. Market design

The British electricity market, liberalised in the early 1990s, is currently fully competitive, and perhaps the most mature market in the world. The New Electricity Trading Arrangements (NETA), implemented in March 2001, introduced fully liberalised bilateral contracting and voluntary spot trading to replace the compulsory, day-ahead uniform auction Pool that had existed since 1990. These market design changes, which reflected a strong regulatory intent for the further commoditisation of electricity and the elimination of market power, occurred shortly after the final opening of retail competition in the domestic segment, and also coincided with a period of strategic re-orientation by the major players. In anticipation of the reforms, the dominant generators of the early 1990s, which had sustained high prices for a decade, sought to rebalance their physical market exposures by selling power stations and purchasing retail businesses. The market structure that emerged, characterised by substantial vertical integration, could be interpreted as a strategic response to (a) the greater emphasis upon bilateral trading in the new market regime; (b) a recognition that value was migrating to the retail end of the supply chain (as an excess of generating capacity was developing, while residential customers were proving to be quite price inelastic); and also (c) an increased exposure to new price risks, such as volatile prices in short-term markets, as well as increased counterparty credit risks following the demise of Enron, TXU Europe and other energy traders.

More specifically, the design of the reformed British market is based upon fully liberalised trading and plant self-scheduling, and hence, in this bilateral environment, most energy is traded with forward contracts. Close to physical delivery, agents fine tune their positions, from blocks (peak and baseload) to half-hourly resolution, in the Power Exchanges that have emerged. These operate continuously up to 1 hour (initially 3.5 hours) prior to each half-hourly physical delivery period, a point defined as Gate Closure, and are effectively the spot markets. After Gate Closure, the System Operator administers a market for system balancing, and invites offers and bids for load increases or decreases in real time. Based on the accepted offers and bids, two imbalance prices are calculated, with the price for energy deficiency (System Buy Price or SBP) being substantially higher than the price for energy surplus (System Sell Price or SSP). Every participant is exposed to these imbalance prices for consuming or delivering a different volume of power from his declaration at gate closure. Similar ex-post settlement systems for volume imbalances are found in many electricity markets.

2.2. Data

In the British market, the main reference for spot trading was the UKPX power exchange. The spot prices used are volume-weighted averages of all trades ahead of each trading period. Each day consists of 48 trading or load periods. Following the market definitions, Period 1 is defined as 23.00-23.30 (prior to the day), period 2 as 23.30-0.00, and so on, up to period 48 (22.30-23.00). Although UKPX started its operations in March 2001, June 2001 has been suggested by various traders as an appropriate initial point for credible analyses after the market had settled down. The intervention effects of this market mechanism change are still rather controversial (Bower, 2004; Evans & Green 2003; Fabra & Toro, 2004).

Our sampling period was specified as 6th June, 2001 – 1st April, 2002, yielding 300 days (or 216 weekdays) for each trading period. Overall, during this period, prices were generally considered to be low, and without any accusations of substantial market power abuse, despite the Enron collapse that occurred. For the forecasting exercise, the validation set for which price predictions were computed was specified as the last 50 weekdays of the sample (17 January – 1 April, 2002). The estimation set initially included the 166 preceding weekdays (6 June, 2001 – 16 January, 2002), and was recurrently augmented on a daily basis; i.e., all models were estimated on an expanding window. This decomposition of the sample provided sufficient observations for both model estimation and prediction, and was particularly challenging due to the emerging market conditions discussed in Section 5.1. In Section 4, which introduces fundamental models with time-varying coefficients, the entire sample (all 300 days) is used for model estimation, as the emphasis is on revealing market insights obtained from these models. These insights are not altered if weekdays and weekends are separated. However, for price prediction we focus on weekdays in order to reduce noise.

In electricity markets, each intra-day trading period (hourly or half-hourly) displays a rather distinct price profile reflecting the daily variation of demand, costs and operational constraints. In order to control for these dissimilarities, our price models are estimated separately for each period. This multi-model approach was also inspired by the extensive research on electricity demand forecasting, where a similar modelling strategy has generally improved forecasting accuracy (Bunn, 2000). As the lead time of our forecasts is one day ahead, this approach is reasonable. If instead predictions are required for a few hours ahead, then a model built on all price data up to the forecasting origin could possibly perform better.

The alternative of a single regression with binary variables for each trading period (e.g. Popova, 2004) is less appealing, as the coefficients and residual variances are then assumed to be constant across the day. Simultaneous estimation of all 48 half-hourly models through Seemingly Unrelated Regressions (SUR), though attractive for accounting for intra-day error cross-correlations, was both computationally infeasible, given the large number of periods and influential variables, and unappealing, given our day-ahead forecasting horizon.

Preliminary data analysis reveals that the spot price series displays the typical spot electricity price features of pronounced volatility, positive skewness, excess kurtosis, seasonality, jumps and conditional heteroscedasticity. Fig. 1 shows the average intra- and inter-day price levels and volatilities. Fig. 2 displays the prices in selected trading periods, illustrating the substantial intra-day variation in price behaviour, and the potential for misleading inferences, when diurnal patterns are averaged. Stationarity tests (the Augmented Dickey-Fuller and Phillips-Perron tests) for prices across trading periods, after adjusting for serial correlation and annual seasonality, rejected the unit root hypothesis at the 5% significance level. Long-memory tests were not significant, consistent with previous findings that long-memory arises in electricity markets which are dominated more by hydro than by thermal generation (Carnero, Koopman, & Ooms, 2007). Some authors (e.g. Pilipovic, 1998) apply

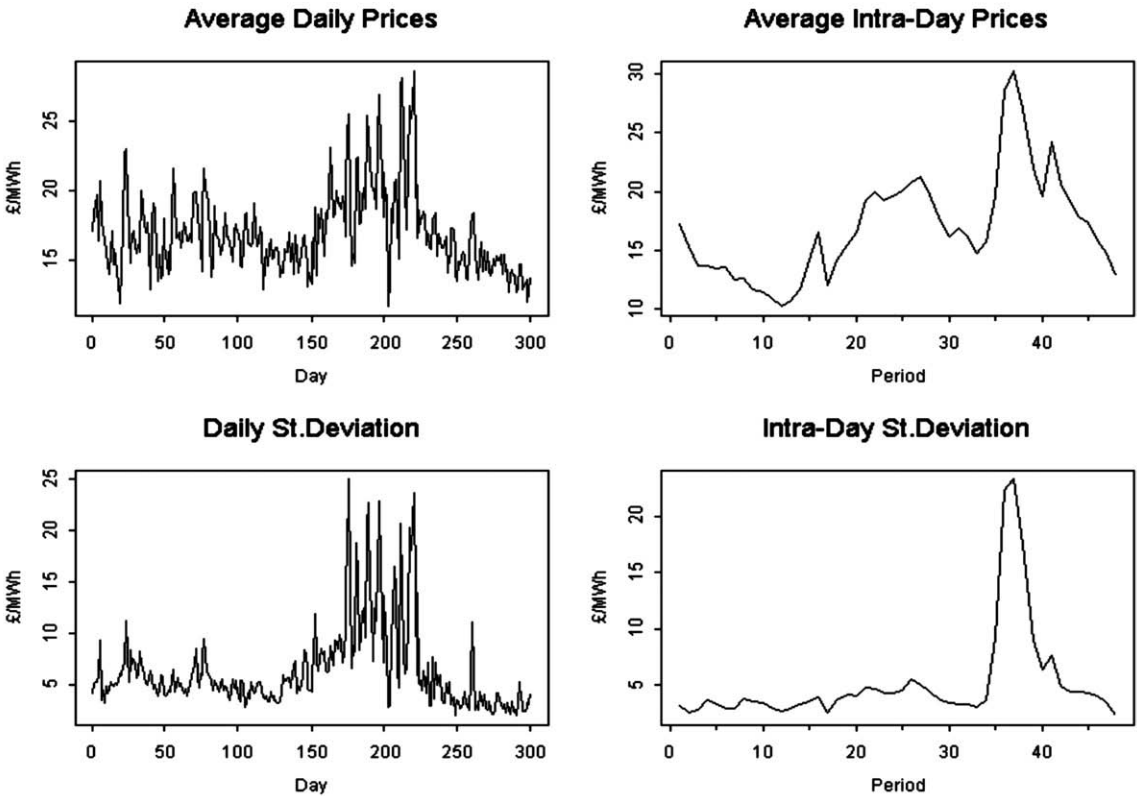

Fig. 1. Average inter- and intra-day level and volatility profiles of spot prices (6 June, 2001 – 1 April, 2002).

logarithms to daily average electricity prices to improve normality, but this transformation was not adopted here, as its variance stabilizing properties could mask the more detailed statistical price properties that we intended to model.

3. A fundamental price specification

3.1. Price drivers

Defining the systematic factors which determine the fine structure and dynamics of spot electricity prices is a non-trivial issue. Fundamental variables, such as demand (with temperature sometimes used as an instrumental variable) or fuel prices, are conventionally included in electricity price models (e.g. Nogales et al., 2002; Kanamura & Ohashi, 2004; Vehvilainen & Pyykkonen, 2004; Mount, Ning, & Cai, 2006). Our objective was to augment these factors, and include plant dynamics, strategic effects, risk perceptions, agents' learning, trading inefficiencies and market design implications in the underlying models. The variables discussed in this section are motivated by theoretical considerations, and constitute public information which is available to market participants in a timely way.

i) *Demand.* A proper specification of the effect of demand is crucial, both in itself as a primary influence on electricity prices, and in order to formulate a well-specified background from which to properly estimate other, more subtle effects. To reflect the timing of the spot electricity market, and the consequent operational and trading decisions, our demand variable was defined as the 12 p.m. day-ahead demand forecast, published by the system operator. The use of a demand forecast, together with the negligible price-demand elasticity in the

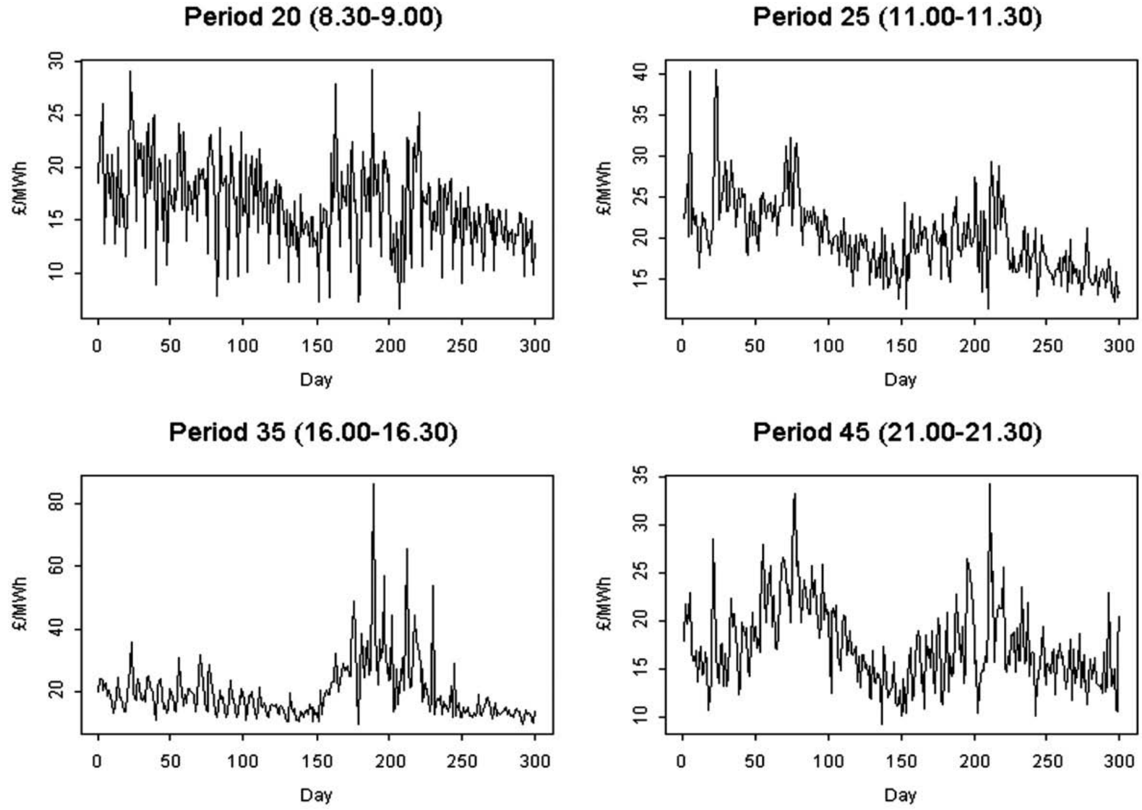

Fig. 2. Intra-day spot prices in selected trading periods.

very short term, reduces endogeneity concerns. Given the heterogeneity of plant technologies in terms of costs and flexibility, and the exercise of scarcity rents, the aggregate supply function is steeply increasing, convex and discontinuous. This non-linear mapping of demand into price is often approximated with a polynomial (Vucetic, Tomsovic, & Obradovic, 2001) or an exponential function (Eydeland & Geman, 1998). Among the various non-linear formulations tested, a quadratic polynomial was found to be the most adequate representation, with its convexity or concavity depending upon the time of the day. To resolve collinearity, the demand polynomial was decomposed into two orthonormal functions, a linear and a quadratic component, denoted as Demand.Lin and Demand.Quad.

ii) *Demand slope and curvature.* The existence of a balancing mechanism, operating after the spot market, could induce the backward migration of some pricing of plant dynamics into the preceding spot trading. To capture the intraday aspects of plant dynamics and its cost/strategic implications, we also considered the demand slope and demand curvature, which are approximated by the first and second time differences of demand respectively, and are denoted as DemandSl and DemandCurv. The former could be particularly influential in a market where rapid output adjustment and plant flexibility are rewarded. Technical reasons are also relevant. The transitory periods when stations are ramping up and down are the most risky state in the operating cycle of a plant and this justifies a premium price. The occurrence of higher imbalance prices at times of steep demand change, i.e. early in the morning and in the evening, endorses the appeal of these two variables.

iii) *Demand Volatility.* Demand variation, due to temporal, weather and consumption patterns, imposes difficulties in load prediction and plant scheduling, which are eventually translated into balancing costs. In addition, the degree of demand volatility influences agents' risk attitudes, and, given the asymmetric penalties for energy imbalances in the British market, could encourage over-contracting on the demand side as a risk management policy. Possible measures of demand uncertainty include unexpected demand, derived from a predictive demand model (e.g., Longstaff & Wang, 2004), or the historic volatility of demand. In this study, the latter, model-free, measure was adopted. DemandVol was defined as the coefficient of variation (standard deviation/mean) of demand in a weekly (7 day) moving window. Due to large demand fluctuations across the year, this standardisation was essential in order to avoid misleading inferences.

iv) *Margin*. This is a measure of excess generation capacity, and hence an indicator of scarcity. Forecasts are again published by the System Operator ahead of Gate Closure, and are computed as the maximum declared available output aggregated across all generating units minus the demand forecast. Margin would be expected to exert a negative effect on electricity prices. Transient low values tend to cause escalating imbalance buy prices (SBP), and this scenario may allow generators to extract scarcity rents, even in the preceding spot market. With its definition as a forecast, and aggregated measurement across all plants, Margin is not an endogenous supply variable, as was confirmed using some of the standard (e.g. Hausman, 1978) statistical tests. Instead, it can be perceived as an instrumental signal of price risk. In the longer term, of course, the capacity margin would be endogenous, as the expectation of higher prices would induce more capacity, and vice-versa. However, in the very short term, the available capacity is fixed ahead of the spot price determination.

v) *Lag-1 Margin*. The amount of excess capacity on the previous day was introduced to capture inter-day concerns about scarcity. Thus, generators with market power could seek to adjust the level of Margin, independently of current prices, in order to create a scarcity fear, and hence influence future prices. Lag-1 Margin is simply the value of Margin, defined above, on the previous day in the given trading period.

vi) *Scarcity*. This variable was intended to capture the steep impact of capacity margin on price above a threshold. Scarcity was based on the ratio = Margin/Demand, introduced by Visudhiphan and Ilic (2000), and defined as: max{*Lower Quartile of Ratio* − *Ratio*, 0}, where the lower quartile of the ratio is calculated from its sampling distribution in each load period. Analysing UK data, Bunn and Oliveira (2001) suggest that there is a threshold value of margin above which collusion is possible and sustainable. Similarly, Genc and Reynolds (2004) conclude that as excess capacity declines, the more competitive, low price, equilibria are eliminated.

vii) *Learning*. Three past values of spot price were considered: price in the same trading period on the previous day (P_{t-1}), price in the same trading period and day in the previous week (P_{t-7}), and daily average price on the previous day (MP_{t-1}), which creates a link between half-hourly bidding and price signals from the entire day. As this last variable becomes known only at the end of the trading day, it was excluded from the forecasting models.

viii) *Price Volatility*. This indicator of price instability and risk, denoted as PriceVol, was defined, similarly to demand volatility, as the coefficient of variation of spot prices for each period across the preceding 7 days.

ix) *Spread*. The difference between the two imbalance prices for energy deficiency and energy surplus (SBP-SSP) is a measure of unhedgeable risk exposure, which could be manifested in spot prices in the form of a forward premium. To avoid endogeneity, Lag-1 Spread on the previous day was considered.

x) *Seasonality*. Even with an extensive demand representation, a seasonal component is important, not least as a proxy for the yearly pattern of fuel prices. A sinusoidal function with a winter peak was the most adequate representation.

xi) *Trend*. A linear time trend was introduced to capture stabilisation effects in an evolving market.

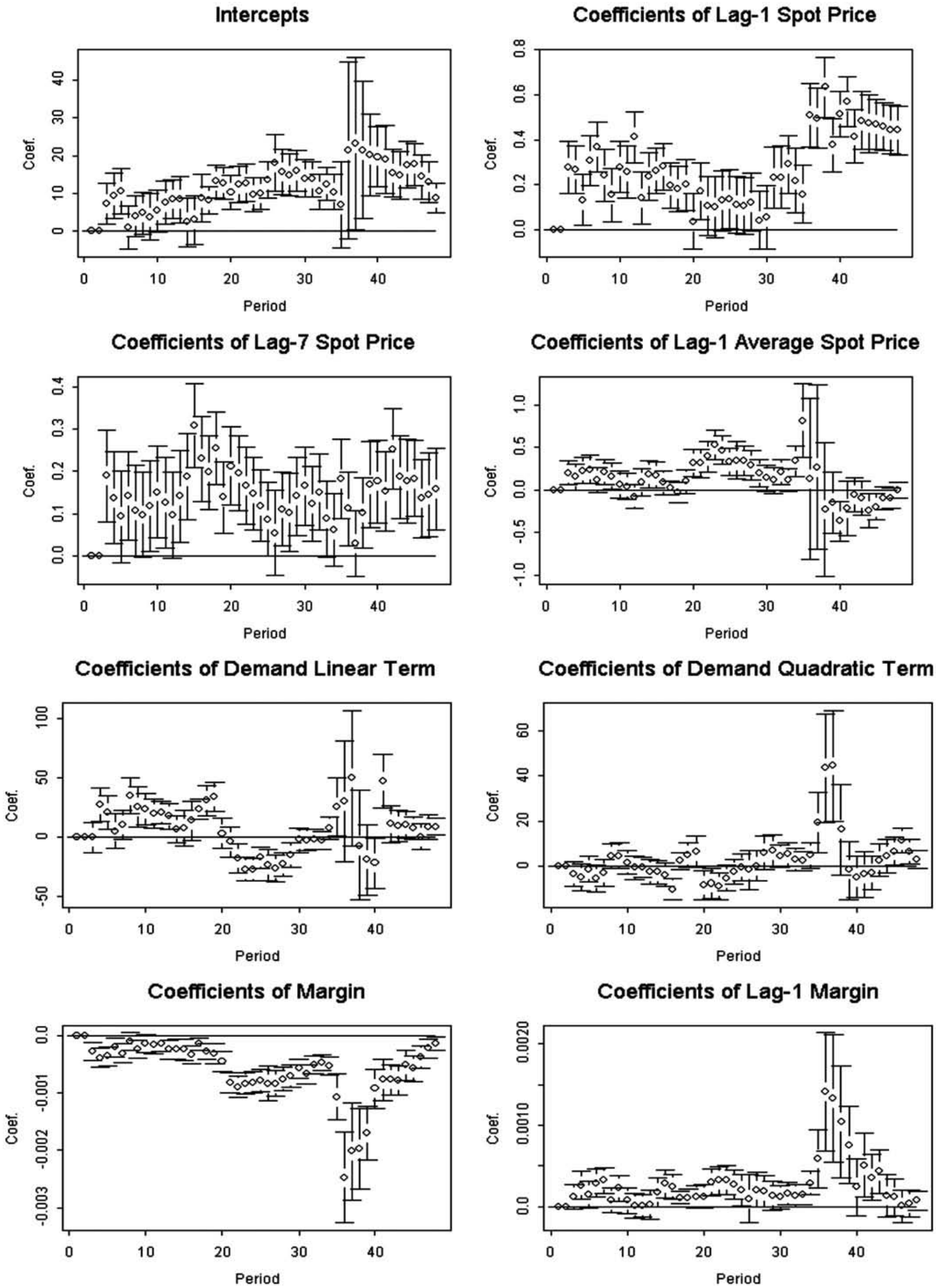

Fig. 3. Regression coefficients and 95% confidence intervals across intra-day periods.

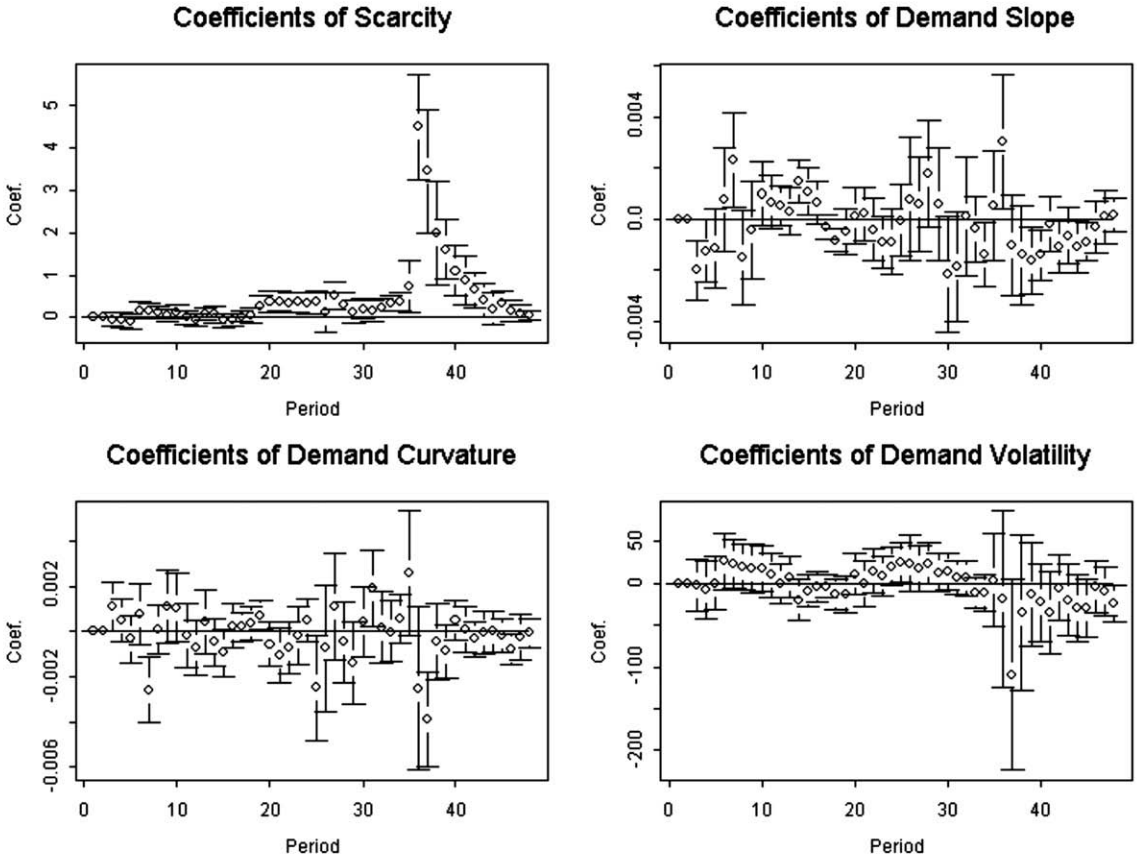

Fig. 3 (*continued*).

xii) *Diurnal and weekly effects*. Diurnal patterns were represented by modelling each half-hourly trading period separately. Regarding weekly effects, a separate modelling of weekdays and weekends did not change the inferences from model estimation, possibly due to a well-specified inclusion of demand and margin in the model. For forecasting purposes, however, we focused only on weekdays to maximise precision.

Some comment on various omitted variables is worthwhile:

a) *Fuel prices*. Although spot fuel prices represent the relevant operational/opportunity costs, they were not included in the fundamental model, as their evolution over the 10 months of the sample was quite slow. Other studies have also shown that fuel costs may not influence high-frequency electricity prices (Guirguis & Felder, 2004).

b) *Forward prices*. Forward prices were excluded for two reasons. Firstly, the sign of the forward electricity premium (Lucia & Schwartz, 2002; Longstaff & Wang, 2004) is ambiguous, while in the presence of trading inefficiencies and market power, large disparities tend to arise between day-ahead and spot prices (Borenstein, Bushnell, & Wolak, 2002). Secondly, as Roques, Newbery, and Nuttall (2004) emphasise, what forward prices reflect are the demand and supply for hedges, which are a reflection of the risk aversion of participants, speculative positions, and the perceived cost of risk, as well as the fundamental drivers of supply and demand for the physical commodity.

Given the explicit representation of market fundamentals and risk measures in our regression model, simultaneity effects could therefore arise.

3.2. Linear regressions

In order to elucidate the average characteristics of price formation over the sampling period and its intra-day variation, a linear regression model is estimated independently for each of the 48 intra-day trading periods. For a given trading period j, this model is specified as:

$$P_{jt} = X_{jt}'\beta_j + \varepsilon_{jt}, \varepsilon_{jt} \sim N\left(0, \sigma_j^2\right), \qquad \text{(Model 1.1)}$$

where P_{jt} denotes the spot price on day t in period j (t=1, 2,..., T, j=1, 2,...,48), T is the sample size (T=300), β_j a 16×1 vector of coefficients, ε_{jt} an i.i.d. error term, and a 16×1 vector of exogenous regressors defined as:

$$\begin{aligned} X_{jt} = \big(&1, P_{j(t-1)}, P_{j(t-7)}, MP_{t-1}, Demand.Lin_{jt}, \\ &Demand.Quad_{jt}, DemandSl_{jt}, DemandCurv_{jt}, \\ &Margin_{jt}, Margin_{j(t-1)}, Scarcity_{jt}, DemandVol_{jt}, \\ &PriceVol_{jt}, Spread_{j(t-1)}, Trend, Seasonality_{jt}\big)'. \end{aligned}$$

Conventional tests for multicollinerity, residual serial correlation, outliers' influence, endogeneity, and over-fitting all indicated that there were no particular mis-specification problems. To correct for error heteroscedasticity of unknown form, Huber-White robust standard errors were computed.

The estimated coefficients over the ten-month period (6 June, 2001 – 1 April, 2002) are displayed in Fig. 3. In summary, electricity prices over the first year of the reformed British market were found to: (i) respond to demand in a linear and/or quadratic way, consistent with the variation of plant costs and technical constraints across the day; (ii) display significant autocorrelation, indicative of trading inefficiencies; (iii) reflect financial risks, as measured by price volatility, demand volatility and spread in the balancing market, to some extent; (iv) be influenced by the demand slope and curvature, due to plant dynamic constraints; and (v) be sensitive to Margin throughout the day, with a substantial negative effect, possibly suggestive of scarcity rents in the peak periods; whereas Lag-1 Margin portrayed a positive impact, possibly indicative of some manipulation of capacity; and in particular, plant withdrawals at times of capacity surplus, in order to yield higher prices on the next day. Overall, these regressions revealed a market responding to economic fundamentals and plant operating constraints to a certain extent, with learning and emergent financial characteristics, but still some strategic manipulation of capacity, which becomes more intense during trading periods of peak demand.

In general, the linear regressions reveal a substantial, systematic component in spot electricity prices. The price responses to the various market factors exhibit pronounced diurnal variation, in terms of both magnitude and sign. This variation can be related to a large extent to the diurnal demand pattern, which implies the scheduling of heterogeneous plants across the day, with differential costs and market power potential. Given the significant intra-day variation in price formation, we will use some parsimonious refinements of our basic regression Model 1.1 in Section 4, below. These reduced models may vary slightly depending on the variable selection procedure (e.g. forward addition, backward elimination, two-direction stepwise, best subset selection) and the optimality criterion adopted (AIC, BIC, HQ).

4. Price models with time-varying coefficients

4.1. Continuous adjustment of price formation

Our first hypothesis is that price formation is dynamic, in that the responses of price to the various market fundamentals may change continuously, even within a given trading period. Such an adaptive pricing process is likely to emerge due to agents' learning, subtle rule modifications, regulators' announcements, institutional policies (e.g. regarding renewables), mergers and acquisitions in the electricity industry, or major events like the Enron collapse. To investigate this hypothesis, the linear regression model, assumed for prices in Section 3, is re-specified with time-varying parameters of random walk dynamics, as follows:

$$P_{jt} = X_{jt}'\beta_{jt} + \varepsilon_{jt} \quad \text{Measurement equation} \quad \text{(Model 1.2)}$$

$$\beta_{jt} = \beta_{j(t-1)} + v_{jt} \quad \text{Transition equation,}$$

where

$$\varepsilon_{jt} \sim i.i.d.N\left(0, \sigma^2_{\varepsilon j}\right), v_{jt} = \left(v_{j1t}, v_{j2t}, \ldots, v_{jkt}\right)',$$
$$v_{jt} \sim N_k\left(0, \Sigma_j\right), E\left(\varepsilon_{jt} v_{jt}\right) = 0, \text{ and}$$
$$\Sigma_j = \text{diag}\left\{\sigma^2_{v_{jk}}\right\},$$

k denotes the number of regressors after a variable elimination procedure is applied to model 1.1, in order to capture the distinct profile of each trading period and facilitate convergence.

In the above state-space formulation, the regression coefficients are not unknown constants but latent, stochastic variables that follow random walks, estimated by a Kalman Filter (Kim & Nelson, 1999). Stability tests (following Brown, Durbin, & Evans, 1975) tended to justify this, with the strongest evidence of time-varying parameters for periods around the morning and evening demand peaks. The coefficients' specification as random walk processes, following Rosenberg (1973), has been used in many contexts (Engle & Watson, 1985; Kim & Nelson, 1999; Song & Wong, 2003; Yao & Gao, 2004). The intuition for this is that the coefficients react to the arrival of new information. The alternative of mean-reverting coefficients could be appropriate for multi-year samples, but was found to be inferior for the relatively short and highly adaptive period investigated here.

Table 1 reports details of model formulae and parameter estimates for periods 25 and 35. Fig. 4 illustrates the evolution of some of these effects over the 300 days. Specification tests for the TVP models were satisfactory, and variable selection diagnostics were similar to the linear regressions. Overall, the evolution of the price structure can be summarised as follows:

i) The positive impact of price signals from the previous day and week on the spot price decreased over time for various load periods. One possible interpretation of this is that offers became progressively more sophisticated, relying upon other, more fundamental drivers.

ii) In contrast with past prices, the role of the historic spot price volatility increased dramatically in winter for some peak periods. In period 25, March 2002, this impact was three times as great as in July 2001. This implied that the hedging of risk via the day-ahead market became more expensive over time in response to the unpredictable imbalance risk, and primarily, perhaps, credit risks.

iii) The responses of prices to Margin evolved in a fairly uniform fashion across periods. In Fig. 4, the negative effects of Margin, which reflected scarcity rents, declined systematically, and this effect was even more pronounced in period 35. This decline of scarcity elements in the spot pricing could imply that the market was gradually converging to a more competitive state, given the evolving overcapacity and less concentrated market structure on the generation side; or, more simply, that with increased vertical integration, wholesale price support became less crucial to the profits of several key players.

iv) The effect of Lag-1 Margin on prices, although negative in the beginning, like Margin, reversed its sign during the winter, possibly suggesting dynamic counter-effects of capacity adjustments on the day to prior day-ahead signals of tight or slack capacity margins. This could imply some strategic behaviour on the part of generators with market power, and/or interventions in the spot market by the system operator.

v) The evolution of the Demand effect was quite variable, with no consistent pattern across periods. The lack of a strong relationship between prices and demand, both intra-day and annually, could

Table 1
Parameter estimates for time-varying parameter regression models

Panel A: Period 25		Panel B: Period 35	
Variable	σ_{v_k}	Variable	σ_{v_k}
Intercept	0.20	*Intercept*	0.03
P_{t-1}	0.012*	P_{t-1}	0.12*
P_{t-7}	0.0026	P_{t-7}	0.19*
$PriceVol_t$	0.0075*	MP_{t-1}	0.008
$Demand.Lin_t$	0.27*	$Demand.Lin_t$	0.54*
$Demand.Quad_t$	0.011	$Demand.Quad_t$	0.63*
$Margin_t$	0.00038*	$Margin_t$	0.000032*
$DemandVol_t$	0.00036	$Margin_{t-1}$	0.000012*
$DemandCurv_t$	0.00009	$DemandCurv_t$	0.0005
R^2	0.68	R^2	0.81
σ^2_ε	0.75	σ^2_ε	2.4

An asterisk denotes significance at the 5% level.

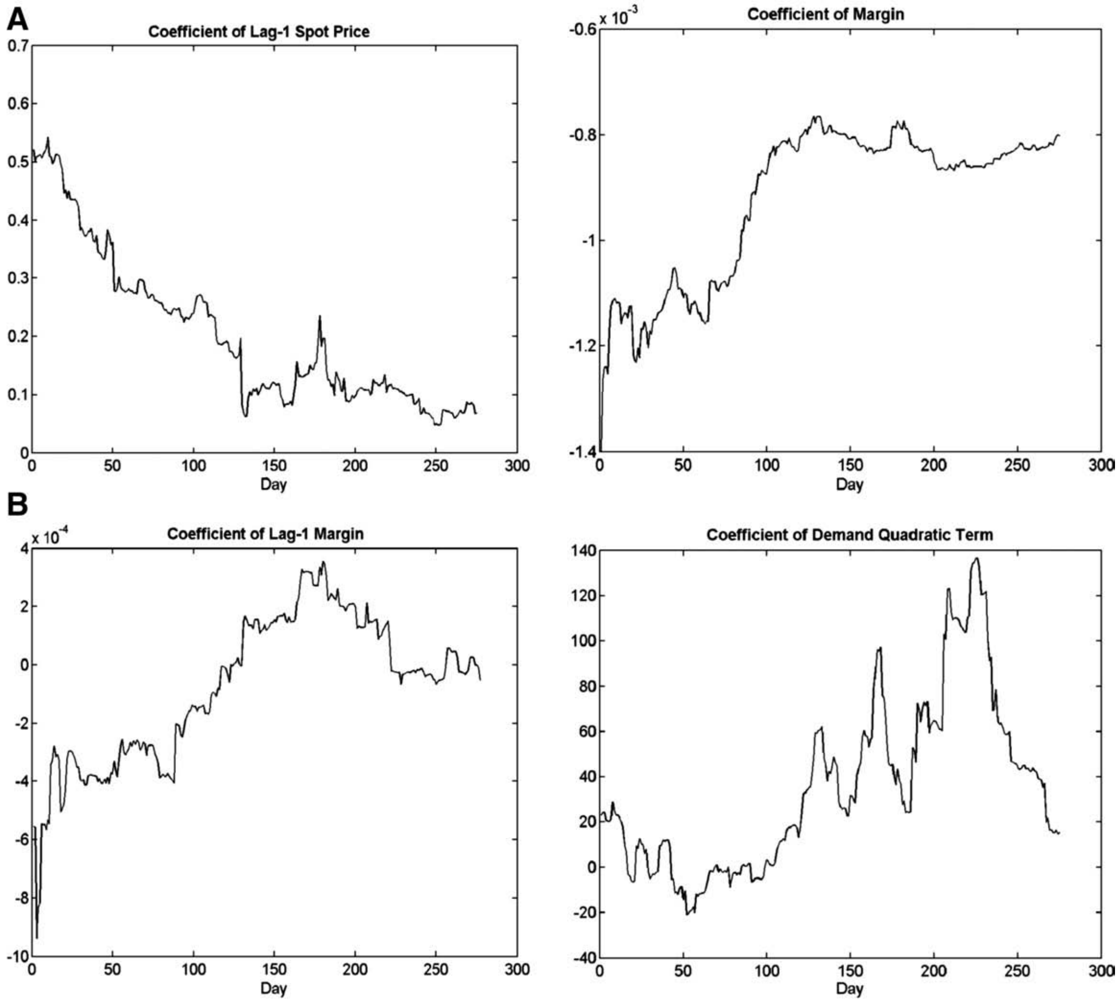

Fig. 4. Examples of the time-varying coefficients' evolutions. Panel A: Lag1 Spot and Margin, for Period 25. Panel B: Lag1 Margin and Demand-quadratic, for Period 35.

be attributed to the market design. With purely bilateral trading, instead of central dispatch, the marginal technology, which influences prices the most, becomes decoupled from the "merit order".

Hence, it is evident that the price formation process exhibits substantial adaptation over time.

4.2. Transient Pricing Irregularities

As spot electricity prices exhibit recurrent, fast-reverting spikes of unpredictable magnitude and timing, which induce severe financial risks, and auction theory predicts the existence of multiple equilibria (Green & Newbery, 1992; von der Fehr & Harbord, 1993), an appealing hypothesis to be tested is whether the price formation process itself exhibits regime shifts, even within a given trading period. To clarify possible switches in the magnitude of strategic effects and more generally, how agents react during transient abnormalities, such as plant outages and unexpected demand, as well as the ways in which pricing is altered as a result of agent reactions to such circumstances, Markov regime-switching is introduced to the regression price models. These non-linear models allow an assessment of extreme price risk after controlling for various market fundamentals, rather than purely from price levels, as in autoregressive regime-switching models (e.g. Ethier & Mount, 1998). Whether the magnitude of extreme prices is arbitrary, given that various different sources can induce irregularities, or still obeys some fundamental relationship, thereby indicating a systematic agent reaction to favourable market conditions, is an issue that has not been previously addressed.

Motivated by these questions, the linear regression Model 1.1 is refined with first-order Markov regime-switching, as follows:

$$P_t = X_t' \beta_{S_t} + \varepsilon_t, \qquad \text{(Model 1.3)}$$

where $\varepsilon_t \sim N(0, \sigma^2_{S_t})$, $\Pr(S_t = i | S_{t-1} = j) = p_{ij}$, $\forall i, j \in S$; P_t denotes the spot price on day t in a given trading period (the subscript j is omitted for simplicity); S_t is the latent regime at time t; $S = \{1, 2, \ldots, n\}$ is the set of possible states; X_t a $k \times 1$ vector of regressors at t; β_{S_t} a $k \times 1$ vector of coefficients in regime S_t; $\sigma^2_{S_t}$ the error variance in regime S_t; and P_{ij} the transition probability between states i and j. k denotes the number of regressors after a variable elimination procedure has been applied to Model 1.1, in order to capture the distinct profile of each trading period and facilitate convergence.

Following Hamilton (1990), the above model assumes that the market at each time point is in one of n possible states, indexed by an unobservable discrete variable S_t which evolves according to a first-order, irreducible, homogeneous and ergodic Markov process. Prices are not a priori classified into distinct regimes. Both their categorisation (i.e. the identification of the latent state at each point) and the model parameters are endogenously estimated with probabilistic inference. In general, transition probabilities could be specified as time-varying, either with seasonal variation or as a function of a covariate, such as the ratio of excess capacity over demand. However, constant probabilities were adequate in our context, and this can be attributed to two facts: firstly, our sample was not extended across multiple years, and secondly, the price model itself postulated a fine structure with seasonal components, which adequately captured a substantial fraction of the spikes.

Overall, the estimation of the regime-switching regressions revealed multiple pricing regimes within various intra-day periods, mainly those positioned at the peak demand segments. The regimes were generally differentiated by price levels, ‘low’ and ‘high’, although this was not a firm distinction, given the adjustments for market fundamentals. For instance, a moderate price was occasionally assigned to the irregular regime, if its value was perceived to be “high” for the underlying market conditions. The characteristics of pricing in the spike regimes were common across various periods, most evident in the coefficients of strategic effects (Margin and Lag-1 Margin). These coefficients were inflated compared to the regular regime, suggesting that players extracted different scarcity rents on these occasions.

Reduced regression specifications were derived for each trading period in order to facilitate the convergence of the estimation algorithm and ensure reliable estimates in the infrequent irregular category. Despite their simplicity, these models retained the essential elements of the spot price structure, i.e. Lag-1 Price, Price Volatility, Demand, Margin and Lag-1 Margin. Table 2 shows the estimated models, with two regimes identified for trading period 25, and three regimes for trading period 35. Table 3 reports regime transition and ergodic probabilities. For both periods, the Davies’ bounds test yields a p-value of zero, indicating the rejection of the null hypothesis of a linear model against the alternative of multiple regimes, while the Andrews (1993) test indicated no remaining non-linearities. The adequacy of the number of regimes was assessed with the Cheung and Erlandsson (2005) test. In general, three regimes were required for the most volatile periods, as two categories of spikes tended to emerge: one set generated from the same regression, and a minority which did not comply with the others.

To illustrate the characteristics of price formation during irregular regimes, we comment briefly on period 35. In this highly volatile period, three pricing regimes emerged: a normal regime (I) and two irregular ones (II, III), the last of which captured the most extreme spikes. The transition dynamics of regime III indicated persistence to the same state with probability 0.09, shift to the smoother regime II with probability 0.80, and abrupt reversion to normal levels with probability 0.04. This switching pattern suggests a two-stage spike reversal to normal prices. Under the two irregular

Table 2
Parameter estimates for Markov regime-switching regression models

Panel A: Period 25

Variable	Coefficients	
	Regular Regime (I)	Irregular Regime (II)
Intercept	11.47*	36.82*
P_{t-1}	0.44*	−0.10
$PriceVol_t$	10.87*	5.55
$Demand.Lin_t$	−8.89*	−33.57*
$Demand.Quad_t$	1.12	−0.42*
$Margin_t$	−0.0005*	−0.0014*
σ_ε	0.42	1.12
R^2	0.74	

Panel B: Period 35

Variable	Coefficients		
	Regular Regime (I)	Irregular Regime (II)	Irregular Regime (III)
Intercept	7.30*	40.72*	−18.10*
P_{t-1}	0.61*	0.04	1.4
$Demand.Linr_t$	16.09*	−63.6*	28.90
$Demand.Quad_t$	21.03*	115.3*	15.82
$Margin_t$	−0.0007*	−0.0028*	−0.0025*
$Margin_{t-1}$	0.0005*	0.001*	0.005*
σ_ε	0.82	1.97	2.84
R^2	0.92		

regimes, the effects of both Margin and Lag-1 Margin escalated, compared to their regular values in regime I. The former coefficient was multiplied by a factor of almost 4, implying high scarcity pricing, while the latter was doubled in regime II and ten-fold in regime III, indicating more intense capacity adjustments. It is hence evident that selective agent behaviour, exercised when temporal irregularities arise, creates substantial discontinuities in price formation.

5. Day-ahead forecasting

5.1. Forecasting schemes

This section evaluates the day-ahead forecasting performance of the three fundamental models previously specified. As a base comparator, an autoregressive (AR) model, i.e. a time-series specification which does not invoke market fundamentals, is considered. This model is still intuitive, as the highly repetitive nature of electricity auctions induces substantial agent learning, which leads to strong price autocorrelations. These could also relate to the mean-reverting nature of market fundamentals. In the British market at this time, autoregressive effects could be even stronger, as the reforms introduced at the time would intensify agents' need for re-learning.

It should be emphasised that all models are fitted separately for each half-hourly period, and hence, their parameters are allowed to vary across the day. To fully describe a price predictive scheme, three elements should be defined: (i) the price model; (ii) the estimation procedure; and (iii) the prediction scheme for the fundamental variables involved in the regressions. This is important, since, whilst day-ahead forecasts of demand are fairly accurate, this does not apply to Margin, which may be subject to manipulation by generators in order to create scarcity fears.

5.1.1. Price models

Model I is an autoregressive model of order optimised w.r.t. the AIC criterion. This formulation is then re-specified with time-varying coefficients, which are assumed to follow (a) random walk dynamics, to capture adjustments to new information, and (b) a first-order Markov process, to replicate regime shifts. In the former case, the refined model (TVP-AR) is denoted as Model Ia, and in the latter (RS-AR) as Model Ib.

Model II is a linear regression model which captures the average characteristics of price formation over the sample period. This is a reduced form of Model 1 (Section 3.2), after a variable elimination procedure is applied, in order to capture the distinct profile of each

Table 3
Transition and ergodic regime probabilities

Period 25

Regime	S_t=I	S_t=II
S_{t+1}=I	0.70	0.66
S_{t+1}=II	0.30	0.34
Ergodic Probabilities	0.69	0.31

Period 35

Regime	S_t=I	S_t=II	S_t=III
S_{t+1}=I	0.90	0.57	0.13
S_{t+1}=II	0.07	0.33	0.80
S_{t+1}=III	0.03	0.10	0.07
Ergodic Probabilities	0.82	0.14	0.04

trading period and facilitate converge. This basic model is then re-specified with time-varying coefficients, assumed to follow either (a) random-walk dynamics, reflective of an adaptive price formation process (yielding Model IIa) or (b) a first-order Markov process, which allows for discontinuities in pricing due to temporal irregularities, such as excessive scarcity rents (yielding Model IIb and Model IIc). As is explained below, these two variants of the regime-switching model differ only in the decision rule applied for regime-prediction (i.e., Eq. (2) vs. a minimum-distance rule). Finally, Model IId is a linear regression model in which a linear time trend is imposed. This trend emerges in the beginning of the 50-day forecasting sample, not from the beginning of the estimation sample. The intuition is that agents at this point could anticipate a new, declining path of prices given the eminent changes in the market conditions. A linear trend has been excluded from Model II.

The two variants of the RS-regression, i.e. Models IIb and IIc, differ in the regime-prediction decision rule. In general, in these models, a day-ahead price forecast can be formed as:

a) The expected value, i.e., a linear combination of predicted prices across regimes weighted by predicted regime probabilities:

$$f_{t+1} = \sum_{i=1}^{s} f_{t+1}^{i} \cdot \hat{\mathrm{P}}(S_{t+1} = i|I_t). \quad (1)$$

b) The predicted price from the regime with the highest predicted probability of occurrence, i.e.,

$$f_{t+1} = f_{t+1}^{i}, \text{ where } i = \arg\max_{s} \hat{\mathrm{P}}(S_{t+1} = s|I_t), \quad (2)$$

where f_{t+1} denotes the day-ahead spot price forecast for day $t+1$, and I_t the information set up to t.

Although smoothed regime probabilities may provide an accurate description of regime-transition dynamics ex-post, predicted probabilities of the irregular regime for the next period rarely exceed a conventional threshold level. This reflects the abrupt occurrence and fast reversion of electricity price spikes. Therefore, Eq. (1) over-estimates regular prices in the short term, whereas Eq. (2) tends to misclassify spikes. While this problem could be averaged out in medium-term price simulations, intended to evaluate contingent claims, it may prove critical for the precision required in day-ahead predictions.

An appealing alternative would be to abandon the Markovian assumption for the state variable and instead assume independent states, the probabilities of which are expressed as a function of a relevant variable indicating scarcity. Therefore, we allowed the regime probability p to be an S-shaped (logistic) function of the Margin to Demand ratio. Although this non-linear formulation could theoretically signal which regime is dominant, algorithmic convergence was not attained in our application. This could be attributed to the inability of the S-shaped function to capture kinked effects after a specific scarcity threshold. Threshold specifications in which the irregular regime occurs only when this ratio exceeds a certain value were also not successful. The conditional price densities under the two or three pricing regimes could perhaps be separated better if non-aggregated data were available, such as an index of capacity concentration or the amount of capacity allocated to the most influential generators.

To resolve the above complications and simultaneously exploit day-ahead market expectations, the following decision rule was proposed:

a) The expected "fundamental" profile $\hat{X}_{t+1}$ (i.e., the vector of price drivers) for the next day is compared to the average covariates profile in each estimated regime up to time t according to a distance measure. The Mahalanobis distance is defined as such, in order to account for the correlation among predictors, which can create an illusive effect. This distance is defined as $d_s^2 = (\hat{X}_{t+1} - \bar{X}_s)' C_s^{-1} (\hat{X}_{t+1} - \bar{X}_i)$, $s = 1,2, \ldots, S$, where S is the number of regimes. $\bar{X}_i$ is the vector of means, and C_s the covariance matrix of predictors in regime s, both computed from the data up to time t. Alternative distance measures from the cluster analysis literature could be considered.
b) The predicted regime, S_{t+1}, is defined as the one that displays the most similar profile to $\hat{X}_{t+1}$, i.e. $S_{t+1} = r = \arg\min_{s} d_s$.
c) The price forecast is computed from the regression model of the predicted regime, i.e. $f_{t+1} = f_{t+1}^{r}$.

5.1.2. Estimation procedure

In order to formulate a price forecast on day t for a certain trading period on day $t+1$, the models can be estimated from (i) a training set $[1{:}N]$, $N<t$, (ii) a rolling window of fixed length, or (iii) a daily expanding data

set [1:*t*]. The last procedure is selected here. Hence, consistent with the dynamic nature of electricity markets, inferences are updated recursively on a daily basis, even for parameters assumed to be constant. In the presence of a relatively short sample, the second procedure would imply substantial information loss, whereas the first would assume some of sort of equilibrium for the regression coefficients and/or the regime probabilities, despite the adaptive nature of the market.

5.1.3. Prediction of fundamentals

Day-ahead prediction of the variables X_t, which impact on prices, touches upon issues of information credibility. Both Demand and Margin forecasts are published by the System Operator and updated on a day-ahead basis. However, whereas the former are very accurate, the latter can be misleading, as the plant notifications submitted by generators before Gate Closure could be strategically manipulated, in order to influence prices. Market participants naturally adjust the predictions published according to their private information. The "correctness" or "distortion" of these beliefs may well relate to their size in the market.

As the published day-ahead forecasts of Margin tend to be received with scepticism, we take the view that market participants form expectations which either coincide with the true value (perfect foresight), or are correct on average (unbiased forecasts). Hence:

a) Assumption I postulates no uncertainty around Margin and uses its actual (ex-post) values, as declared at Gate Closure. Although such expectations may not be pragmatic, they would more closely resemble those of well-informed traders or large-portfolio, integrated players. This view allows the validation of the models out-of-sample, in the absence of uncertainty about an important price driver.
b) Assumption II postulates that the representative agent forms unbiased forecasts of Margin. Prediction errors are simulated from a normal distribution $N(0, \xi_i^2)$, where the variance is ξ_i specific to each trading period j, equal to the historical sample variance. (Alternatively, ξ_i could be the residual variance in a predictive model for Margin, such as an AR with a seasonal intercept.)

Table 4 summarises the models and formulae for day-ahead forecasting under the selected estimation procedure, i.e. recursive estimation in an expanding data set on a daily basis. These formulae would be identical under the two alternative estimation procedures previously outlined, but the parameters would instead be estimated from either a fixed subset or a rolling window.

5.1.4. Validation set

The validation set for out-of-sample forecasting was defined as the 50 weekdays in the period 17 January – 1 April, 2002, and the initial training set as the 166 preceding weekdays (6 June, 2001 – 16 January, 2002). This setting allowed an assessment of the fundamental price models under a complex set of market conditions. As Fig. 1 illustrates, British spot prices started declining substantially at this time, and this effect was more pronounced during peak periods. This price path was a response to a combination of market characteristics, such as overcapacity – which emerged due to the persistence of high prices in the previous decade – decreasing concentration, imposed by the regulator, and the abolishment of capacity payments. As a result, signals of financial distress started to emerge among generation-only companies, which led to the withdrawal of capacity from the market in the subsequent year, and even the exit of several players in winter 2002.

Given the new emerging risks, the price formation process would be expected to be refined, and this would penalise the predictive accuracy of fundamental models. Instead, autoregressive models, based solely on past prices, could adapt more easily to the new conditions. Given the market changes at the time, it would not be meaningful to extend the forecasting period further, i.e., beyond April 2002, as the price fundamentals would be different in the fairly unstable period that followed. In statistical terms, a structural break may have occurred at this time; however, this is beyond the scope of our paper. Fundamental models could still be successful in this turbulent period, if price drivers were revised appropriately to reflect the new risks and market structure.

5.2. Forecasting results

The forecasting approach outlined in the previous section is illustrated for the peak trading periods 25 (11.00-11.30) and 35 (16.00-16.30). The latter is one of the most volatile ones, while the former seems more stable, but still complex to model. Parsimonious linear

Table 4
Models for day-ahead price prediction

AR (Model I)	$f_{t+1} = \hat{c}^t + \sum_{l=1}^{q_t} \hat{\phi}_j^t P_{t+1-l},\ q_t = \arg\max AIC^t$
TVP-AR (Model Ia)	$f_{t+1} = \hat{c}_{t\|t-1} + \sum_{l=1}^{q} \hat{\phi}_{l,t\|t-1} P_{t+1-l}$
RS-AR (Model Ib)	$f_{t+1} = f_{t+1}^r = \hat{c}_r^t + \sum_{l=1}^{q} \phi_{l,r}^t P_{t+1-l}\ r = \arg\max_s P(S_{t+1} = s\|I_t)$
Linear Regression (Model II)	$f_{t+1} = \hat{X}'_{t+1}\hat{\beta}^t$
TVP-Regression (Model IIa)	$f_{t+1} = \hat{X}'_{t+1}\hat{\beta}_{t+1\|t}$
RS-Regression (Model IIb) Markov Regime Prediction	$f_{t+1} = f_{t+1}^r = \hat{X}'_{t+1}\hat{\beta}_r^t,\ r = \arg\max_s P(S_{t+1} = s\|I_t)$
RS-Regression (Model IIc) Min-Distance Rule	$f_t = f_{t+1}^i = \hat{X}'_{t+1}\hat{\beta}^{i(t)},\ r = \arg\min_s d_s$
Linear Regression + Trend (Model IId)	$f_{t+1} = \hat{X}'_{t+1}\hat{\beta}^{(t)} + \alpha(t+1-M)$, M: starting point of the emerging trend

For a given trading period, let f_{t+1} denote the day-ahead spot price forecast for day $t+1$, X_t the vector of predictors on day t, I_t the information set up to t, $\hat{X}_{t+1} = E_t(X_{t+1}|I_t)$ the expected market profile (in terms of the values of the fundamentals X_t) for day $t+1$ on t, β and ϕ vectors of regression coefficients and autoregressive parameters respectively, and c an intercept term. The superscript t on a parameter ($\hat{\beta}^t$,$\hat{\phi}^t$) indicates an estimated value from the training set [1, t]. r denotes the regime with the highest probability of occurrence at $t+1$ according to a pre-specified decision rule (Eq. (2) or the minimum-distance rule previously outlined). The subscript r on a parameter indicates the estimated value in regime r, and f_{t+1}^r is the day-ahead price forecast according to the price model under regime r.

regressions, denoted as Models IIa-d, were derived with stepwise variable-elimination procedures from Model 1, applied to the initial window (6 June 2001 – 16 January, 2002, weekdays), yielding the following equations for periods 25 and 35 respectively:

$$P_t = \beta_0 + \beta_1 P_{t-1} + \beta_2 Demand.Lin_t + \beta_3 Margin_t + \beta_4 PriceVol_t + \varepsilon_t$$

and

$$P_t = \beta_0 + \beta_1 P_{t-1} + \beta_2 Demand.Lin_t + \beta_3 Demand.Quad_t + \beta_4 Margin_t + \beta_5 Margin_{t-1} + \beta_6 DemandCurv_t + \varepsilon_t.$$

The above equations were used in the TVP regressions, where the coefficients were assumed to follow random walks. Issues of convergence and robustness to initial values dictated the exclusion of DemandCurv from the corresponding regime-switching model. The autoregressive price models were initially specified with orders 4 and 21 respectively, according to the AIC criterion. Tables 5 and 6 summarise the performance of the eight price models for the illustrative periods under the two alternative assumptions on Margin (perfect foresight vs. unbiased expectations). The following error statistics were computed: Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE) and Max Absolute Percentage Error (Max APE). The units for RMSE and MAE are £/MWh. Fig. 5 displays actual and predicted prices for the validation period under the assumption of unbiased margin forecasts for period 25.

Overall, despite the complexity of spot price dynamics and the validation period, fairly accurate forecasts were derived across the various periods considered. This suggests the validity of the fundamental specifications and their appeal in combination with a recursive estimation procedure. For a given trading period, the predictive accuracy of alternative models varied significantly, with deviations in MAPE often reaching levels of 8%. Although one would expect the appropriateness of a model to be contingent upon the profile of a load period, or at least its classification as peak or off-peak, the relative performance of the models was reasonably uniform across the day. This could be to some extent an implication of the specific validation period. As prices exhibited fairly untypical paths, time-varying coefficients became necessary even for conventionally quiet

Table 5
Prediction error statistics (Period 25)

	MAPE	MAE	RMSE	MaxAE	MaxAPE
Panel A: No uncertainty about Margin					
TVP-Regression (IIa)	3.56	0.56	0.69	1.89	12.93
RS-Regression, Min-Distance Rule (IIc)	4.40	0.68	0.79	1.53	10.75
Regression + Trend (IId)	5.35	0.83	0.96	2.28	13.92
RS-Regression, Markov (IIb)	5.69	0.83	1.01	2.99	20.9
TVP-AR (Ia)	6.72	0.92	1.32	3.09	18.98
RS-AR (Ib)	6.88	1.22	1.48	2.89	19.65
Linear Regression (II)	8.20	1.27	1.57	3.74	24.9
AR (I)	10.17	1.58	1.91	5.03	35.68
Panel B: Unbiased expectations about Margin					
RS-Regression, Min-Distance Rule (IIc)	4.09	0.94	1.01	2.45	16.77
TVP-Regression (IIa)	5.93	0.63	0.88	2.09	14.63
Regression + Trend (IId)	6.09	0.96	1.21	3.07	21.44
RS-Regression, Markov (IIb)	6.38	1.00	1.29	3.63	23.4
TVP-AR (Ia)	6.72	0.92	1.32	3.09	18.98
RS-AR (Ib)	6.88	1.22	1.48	2.89	19.65
Linear Regression (II)	9.16	1.51	1.49	4.14	25.47
AR (I)	10.17	1.58	1.91	5.03	35.68

periods, which could perhaps have been adequately captured by a linear model under more stable market conditions. More specifically:

i) Autoregressive or regression price models with time-varying coefficients (i.e. random walk or Markov) captured 'local' aspects of market dynamics, and yielded more accurate forecasts than the same models with constant coefficients, despite recursive estimation in both cases. This was anticipated given the strong adjustment of electricity price formation, which was possibly even more intense during our validation period. The introduction of time-varying coefficients

Table 6
Prediction error statistics (Period 35)

	MAPE	MAE	RMSE	MaxAE	MaxAPE
Panel A: No uncertainty about Margin					
RS-Regression, Min-Distance Rule (IIc)	5.50	0.80	1.00	2.55	14.21
TVP-Regression (IIa)	6.67	0.92	1.12	2.79	19.36
RS-Regression, Markov (IIb)	9.04	1.26	1.57	4.40	35.5
Regression + Trend (IId)	7.99	1.10	1.35	2.74	22.50
TVP-AR (Ia)	10.32	1.39	1.81	5.61	49.83
RS-AR (Ib)	11.03	1.53	1.84	5.14	33.64
Linear Regression (II)	11.8	1.66	1.96	4.91	33.6
AR (I)	13.14	1.76	2.28	5.61	49.56
Panel B: Unbiased expectations about Margin					
RS-Regression, Min-Distance Rule (IIc)	6.31	0.87	1.11	2.92	19.12
TVP-Regression (IIa)	8.12	1.14	1.48	4.43	29.63
RS-Regression, Markov (IIb)	9.23	1.24	1.53	4.28	36.2
Regression + Trend (IId)	8.72	1.25	1.56	3.75	22.9
TVP-AR (Ia)	10.32	1.39	1.81	5.61	49.83
RS-AR (Ib)	11.03	1.53	1.84	5.14	33.64
Linear Regression (II)	12.2	1.68	2.15	6.06	37.2
AR (I)	13.14	1.76	2.28	5.61	49.56

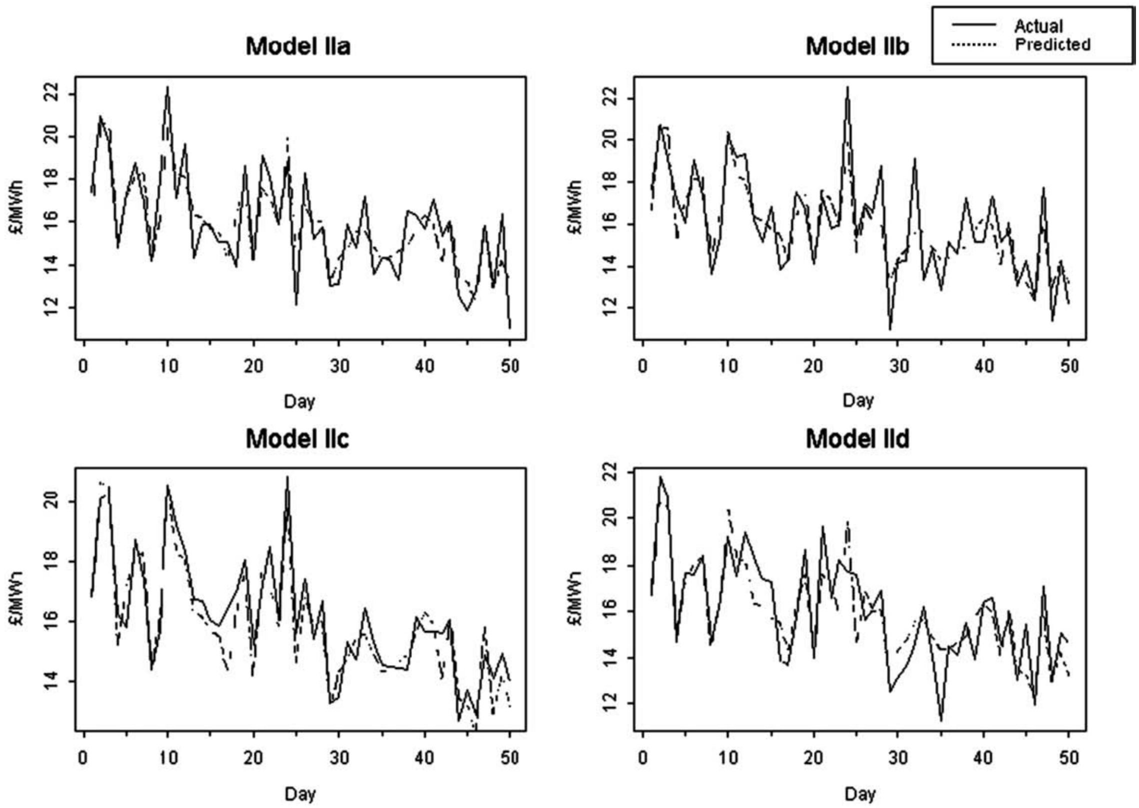

Fig. 5. Actual and predicted prices with fundamental and time-series models (Period 25) under unbiased expectations about capacity margin.

had a more dramatic effect on regression than on autoregressive models. This implies that the varying effects of fundamentals on prices could not easily be mapped to changes in the autocorrelation structure. For the periods studied, the highest reductions in MAPEs due to the introduction of time-varying coefficients were observed within the class of regression models, from 11.81% (Model II) to 5.50% (Model IIc) in period 35, and from 8.20% (Model II) to 3.56% (Model IIa) in period 25, when no uncertainty was assumed about the Margin.

ii) Regime-switching and time-varying parameter models were similar in terms of predictive accuracy. The latter captured the fast evolving aspects of price formation, whereas the former better captured irregular values, which were still present in the sample, despite the overall low prices, but were moderated in terms of magnitude and frequency.

iii) The time-varying parameter regression (IIa) captured the declining path of prices and performed better than a regression with an explicitly specified linear trend (IId). The MAPEs were 6.67% and 7.99% respectively in period 35, and 4.40% and 5.35% in period 25, under no uncertainty about Margin. For unbiased margin forecasts, the MAPEs were adjusted to 8.12% and 8.72% in period 35, and 4.09% and 6.09% in period 25.

iv) Price prediction was more accurate with the minimum-distance rule for regime prediction (Model IIc) than with Markov-predicted probabilities (Model IIb). Under no uncertainty about Margin, the following MAPEs were obtained from the two schemes: 5.50% and 9.04% in period 35; and 3.56% and 5.69% in period 25.

v) The maximum prediction error was substantially reduced under regression, relative to autoregressive models. This finding is appealing from a risk-management perspective, e.g. for Value-at-Risk calculations. In our example, even the linear regression reduced the Maximum APE by more than 10% compared to the AR model. In terms of this error statistic, the maximum deviation between the most sophisticated and simplest models was 35% and 23% for periods 35 and 25 respectively.

vi) Adjusting for the uncertainty about Margin by assuming unbiased forecasts had a minor impact on the average forecasting error, but substantially influenced the maximum absolute error. The effect on MAPE tended to be less than 1% for the more sophisticated specification, and less than 2% for the simplest regression. Nevertheless, the effect on MaxAPE occasionally reached values of 10%. These findings indicate that private information on capacity availability could differentiate agents at critical times. Such asymmetries could critically affect the predictive accuracy.

vii) Regarding the autoregressive models, their variants with time-varying coefficients (Models Ia and Ib) consistently performed better than the simplest linear regression (II). This was expected, given the strong autocorrelation structure in the reformed market and the transitory validation period, during which the price drivers were changing. Nevertheless, the more sophisticated regressions systematically outperformed the corresponding autoregressive models, even after adjusting for uncertainty around Margin.

viii) Despite the complexity of price prediction at the trading period level, the MAPEs attained with regressions of time-varying coefficients were comparable to, or better than, the lower bounds of 5% often reported in the literature. In previous studies, this high predictive accuracy has been attained for aggregated electricity prices, which are much smoother than high-frequency ones, typically with non-parametric or more complex methods, and for more stable environments than the reformed British market, such as the Spanish oligopoly (e.g. Conejo et al., 2005).

6. Summary and conclusions

Overall, price models which represent market fundamentals and their time-varying effects (either as continuously evolving or changing across a few market regimes) exhibited the best predictive performance for day-ahead horizons and intra-day trading periods among various alternatives, including autoregressive models with similar coefficient dynamics. This finding was retained after adjusting for agents' uncertainty around the value of a key driving variable, Margin, assuming unbiased expectations with variance equal to the historic sample variance. In off-peak periods, the value of fundamental models with time-varying coefficients was still substantial, although less than in peak periods. As the autoregressive models were expected to perform well under the specific market conditions, it appears that regressions with time-varying coefficients therefore offer a promising direction for electricity price forecasting.

Despite the complexity of prediction at the trading period level, the mean absolute percentage errors attained with the proposed models were comparable to or better than the lowest values reported by researchers elsewhere. Furthermore, in previous studies, this high accuracy was attained for average daily prices, which are much smoother than intra-day prices, using more complicated (or non-parametric) methods than our fundamental specifications, and involved more stable settings than the reformed British market. Given the fast reversion of electricity spikes, price forecasts with a new rule for regime prediction, which incorporates information on expected market fundamentals, were more accurate than Markov-predicted probabilities, which rarely indicated a spiky regime. Whilst adjusting for possible agent uncertainty on Margin had a negligible impact on the average forecasting error, the maximum absolute error was increased. This implies that private information on capacity availability can differentiate agents at critical times.

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