ESTIMATING THE VOLATILITY OF ELECTRICITY PRICES: THE CASE OF THE ENGLAND AND WALES WHOLESALE ELECTRICITY MARKET

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

Sherzod N. Tashpulatov†

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.

The 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 in lowering price volatility, which however happens at the cost of a higher price level. Finally, the study also documents that the second series of divestment was more successful in lowering both the price level and volatility.

Abstrakt

Cenové fluktuace, jež se částečně spolupohybují s poptávkou, jsou specifickým rysem liberalizovaných trhů s elektřinou. Regulační orgán ve Velké Británii se však domníval, že ceny elektřiny byly někdy výrazně vyšší, než se očekávalo, a z toho důvodu tedy zavedl regulaci cenovými omezeními a sérii divestitur. V tomto výzkumu analyzuji, jaký dopad zavedení institucionálních změn a regulačních reforem mělo na dynamiku denních cen elektřiny na anglickém a velšském velkoobchodním trhu v letech 1990–2001.

Tento výzkum dospívá k závěru, že zavedení regulace pomocí cenových omezení dosáhlo zamýšleného snížení cenové úrovně za cenu vyšší cenové volatility. Dále je zjištěno, že první vlna divestitur byla úspěšná při snižování cenové volatility, což se ale stalo za cenu vyšší cenové hladiny. Výzkum také nakonec přináší důkazy, že druhá vlna divestitur byla úspěšnější při snižování jak cenové úrovně, tak volatility.

Keywords: electricity prices, seasonality, Fourier transform, conditional volatility, regulation

JEL Classification: C22, C51, L50, L94

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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. The 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 the case of the wholesale electricity market in England and Wales during 1990–2001. For this purpose I consider an *AR–ARCH* model, which is extended to include periodic sine and cosine functions to accommodate weekly seasonality. The application of periodic sine and cosine functions rather than daily dummy variables is found to lead to a more parsimonious model. Finally, in order to analyze the impact of institutional changes and regulatory reforms on price and volatility dynamics, I also include regime dummy variables, which are created based on the timeline described in Figure 3.1.

Paul L. Joskow characterized the privatization, restructuring, market design, and regulatory reforms pursued in the liberalization process of the electricity industry in England and Wales as the international gold standard for energy market liberalization (cited in Glachant and Lévêque, eds, 2009). In this respect, the findings and conclusions of this research could be of particular 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 Literature Review

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 for producers and costs for retail suppliers. The government is also usually interested in understanding price developments, 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. Green and Newbery (1992) use the framework of supply function equilibrium (SFE), where it is assumed that electricity producers submit a continuous 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 England and Wales wholesale electricity market. The authors show that a producer with larger production capacity has more incentive to exercise market power by submitting price bids in excess of marginal costs.

Von der Fehr and Harbord (1993) consider N electricity producers serving the British electricity market operated as a uniform price 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 to set a high price and bid low to ensure that its production unit is scheduled to produce electricity.

Wolfram (1998) and Crawford et al. (2007) empirically examine the bidding behavior of electricity producers in the wholesale electricity market in England and Wales. 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 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 the threat that the production unit might be left out of the production schedule. 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 in the British electricity market: 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 finding, 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.

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.

Cuaresma 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 yielded uniformly better forecasts than models for the whole time series. Similar to Cuaresma et al. (2004), Guthrie and Videbeck (2007) analyze half-hourly prices from the New Zealand Electricity Market (NEM) operated as a uniform price auction. For the period November 1, 1996 – April 30, 2005, 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 (PAR) process.[1] 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.

The findings in Cuaresma et al. (2004) and Guthrie and Videbeck (2007) that each trading period or a group of trading periods should be studied separately across trading days, rather than as a whole hourly time series, can be the consequence of the application of hourly, daily, and monthly dummy variables for a time-varying intercept term (or the

[1] A detailed overview of periodic time series models is provided, for example, in Franses and Paap (2004).

deterministic component) in modeling the dynamics of the whole hourly (or half-hourly) time series, which could not accommodate multiple types of seasonality as well as, for example, smooth periodic sine and cosine functions. In general, a major concern in their approach is the necessity to estimate a large number of parameters.

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 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.

However, none of the above studies examine in detail the nature of the residuals, which in general is crucial for statistical inference and model specification. In contrast, Garcia et al. (2005) consider a *GARCH* methodology to model and forecast hourly prices in the Spanish and Californian electricity markets during September 1, 1999 - November 30, 2000 and January 1, 2000 - December 31, 2000, respectively. 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 seemed most appropriate to account for the different amount of memory of past prices that each weekday carried, as well as the presence of spikes and volatility clustering in electricity prices.

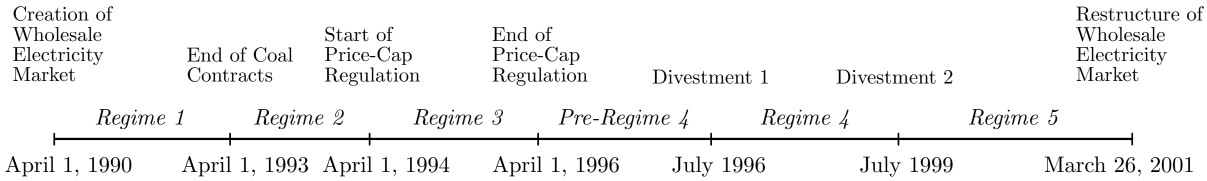
The challenge of applying the periodic modeling approach considered, for example, in Guthrie and Videbeck (2007) and Bosco et al. (2007) is the requirement to estimate a large number of parameters. Koopman et al. (2007), for example, mention that the application of smoothly time-varying parameters could be preferred, because it might suggest a more parsimonious model.

Koopman et al. (2007) study daily average prices from electricity markets in France, Germany, the Netherlands, and Norway. The dynamics of daily log-transformed electricity spot prices is modeled using a seasonal periodic autoregressive fractionally integrated moving average process with autoregressive conditional heteroscedastic disturbances. However, this modeling approach is in general 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. As possible extensions, the authors suggest considering smoothly time-varying parameters for modeling the dynamics of electricity prices. This suggestion is examined in Section 5 of this paper by applying periodic sine and cosine functions to model weekly seasonality in electricity prices.

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 absurdly 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 prices and price fluctuations being significantly higher than expected, the regulatory authority introduced several reforms in the Electricity Supply Industry (ESI) in Great Britain. The time of the introduced institutional changes and regulatory reforms define different regime periods, which are summarized in Figure 3.1.



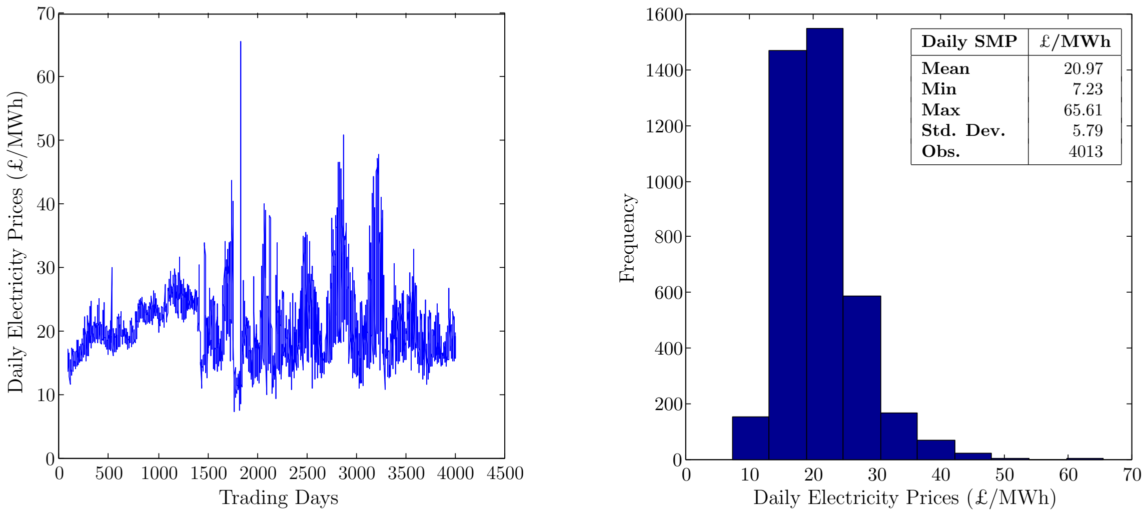
Sources: Department of Trade and Industry (1997–2002), National Grid Company (1994–2001), Newbery (1999), Robinson and Baniak (2002), Wolfram (1999); author's illustration.

Figure 3.1: Institutional Changes and Regulatory Reforms in the ESI in Great Britain during 1990–2001

At the time of the creation of the wholesale electricity market, coal and other contracts were introduced by the government, which then expired in 1993. Later, because it was believed that the excessively high prices were resulting from the noncompetitive bidding behavior of the incumbent electricity producers, the regulatory authority introduced price-cap regulation and divestments. The price-cap regulation during 1994–1996 was a temporary measure designed to control annual average prices. 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.

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. Figure 4.1 describes the development and distribution of daily electricity prices for the whole history of the England and Wales wholesale electricity market.



Source: Author's calculations.
Figure 4.1: Daily Electricity Prices (April 1, 1990 – March 26, 2001)

Detailed information and my acknowledgments to people and organizations I was in contact with in the process of collecting data and materials will be listed at a later stage of the dissertation research.

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, for example, Robinson and Baniak, 2002).

In Table 4.1 I summarize the descriptive statistics of daily electricity prices during the different regime periods described in Section 3.

Table 4.1: 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.

The results indicate that the mean and standard deviation of prices are significantly higher after the expiration of the coal contracts. It is also interesting to note a significant decrease in the mean of prices accompanied by a significant 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 introduced by the regulatory authority as an attempt to decrease the overall influence of the incumbent electricity producers and thereby improve competition in the electricity market.

However, in general, a quick view at the summary statistics without formal econometric modeling and hypothesis testing can be deceptive and, therefore, cannot be regarded as a reliable approach in regulation analysis. This is especially related to cases when seemingly economically significant differences are later found to be statistically insignificant. In order to draw statistical inferences in the analysis of the impact of institutional changes and regulatory reforms on price and volatility dynamics, the application of formal testing and modeling techniques of time series econometrics are usually required. This is pursued 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 correct frequencies in periodic sine and cosine functions included as additional explanatory variables to model weekly seasonality. The application of sine and cosine functions to capture weekly seasonality in electricity prices is found to yield a more parsimonious model than the application of the daily dummy variables. 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. If the test provides evidence that a time series is nonstationary, then one can decide to apply, for example, detrending or differencing transformations. The main reason for attempting to apply transformations to achieve stationarity is that many modeling procedures and techniques are only applicable to stationary time series. In particular, correlogram and periodogram techniques, discussed in Section 5.2 and Section 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 choose 10, which is 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 is rejected and therefore we conclude that daily electricity prices are stationary. The results of the ADF test are summarized in Table 5.1.

Table 5.1: 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

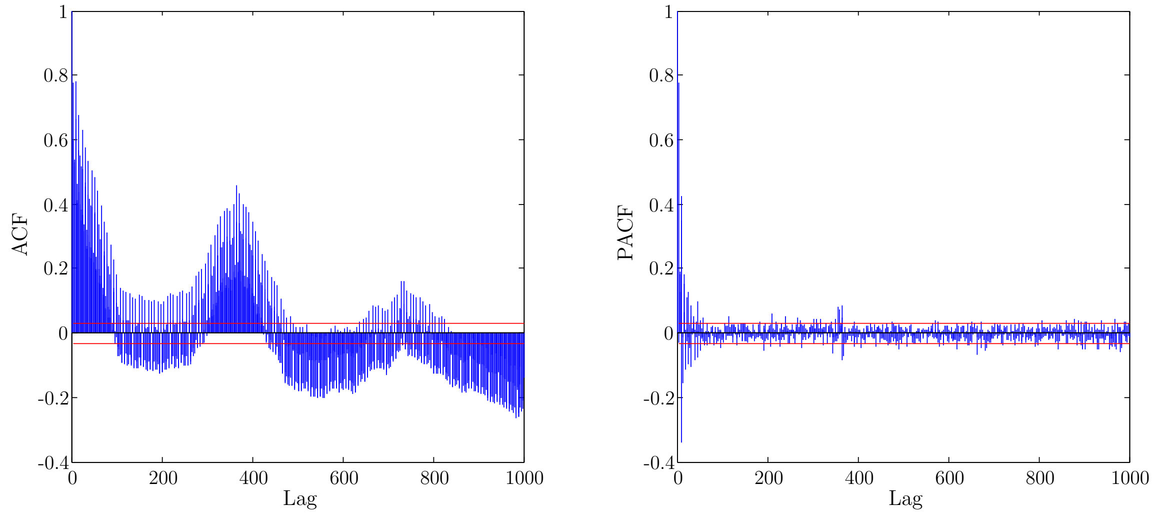
*MacKinnon critical values for the rejection of the hypothesis of a unit root.

Source: Author's calculations.

5.2 Time Domain Analysis

A time series can be analyzed on a time domain using the autocorrelation function (ACF) and partial autocorrelation function (PACF). I summarize the sample ACF and PACF for daily electricity prices in a correlogram presented in Figure 5.1 (a lag of order 1000 corresponds to approximately 25% of the sample size).

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



Source: Author's calculations.

Figure 5.1: Correlogram for Daily Electricity Prices

The sample partial autocorrelation function (PACF) suggests to additionally consider such lag orders as $9, 16, 61, 100$ to accommodate the effects of weekends, 2-month and 3-month periods. This knowledge is also used in specifying the AR process.

5.3 Frequency Domain Analysis

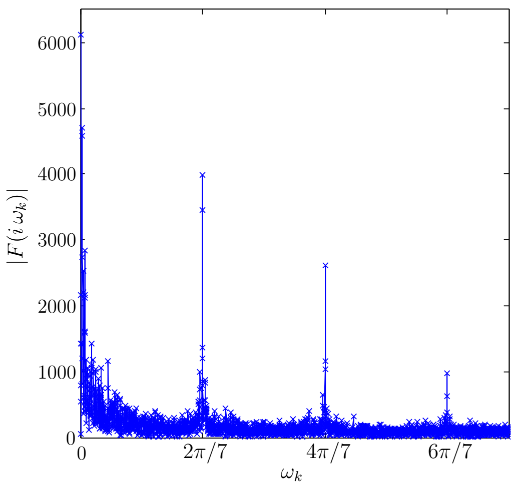
A frequency domain analysis allows to identify frequencies explaining a large portion of seasonal variations in electricity prices. The identified frequencies can then be used in specifying the arguments of periodic sine and cosine functions that are included as additional explanatory variables. I find that the application of sine and cosine functions is superior to the application of daily dummy variables, because the former approach has resulted in a more parsimonious model.

A frequency domain is examined using the techniques of spectral (Fourier) analysis. The techniques of 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 a frequency, and φ denotes a 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), parameter estimates can then allow calculating the respective amplitude and phase shift.

The Fourier transform of a real-valued function $p(t)$ on $[0, T]$ 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 graph where the frequency domain is plotted against the absolute values of the Fourier transform is known as a periodogram. In Figure 5.2 I present a periodogram plot for daily electricity prices.



Source: Author's calculations.

Figure 5.2: Periodogram for Daily Electricity Prices

Detailed analysis of the frequency domain, where the absolute values of the Fourier transform achieve local maxima, as described in the periodogram in Figure 5.2, allows revealing frequencies that explain the seasonal pattern in the price time series. Hence, the frequencies at which the absolute values of the Fourier transform achieve local maxima can be used in specifying the argument of sine and cosine functions included as additional explanatory variables.

The application of sine and cosine functions 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 2.

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

The two equations describing the *AR(P)* and *ARCH(p)* processes are called the mean and conditional volatility equations, respectively. This specification captures 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 "shocks" or "news" from the previous period that would affect the current conditional volatility. More precisely, a significant and positive α less than 1 would measure the extent of the shocks' effect on the volatility, which is not destabilizing. Additionally, it is also possible to distinguish the impact of positive and negative shocks from the previous period, which can asymmetrically affect the volatility. This is investigated by a treshhold *ARCH* process developed by 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 April 1, 1990 – March 26, 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, $\hat{\nu}_t = \frac{\hat{\varepsilon}_t}{\sqrt{\hat{h}_t}}$, 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 Estimation Results

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. The estimation results obtained using the Marquardt algorithm are summarized in Table 6.1.

Table 6.1: Estimation Results of the Extended AR-ARCH Model

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

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

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

Source: Author's calculations.

Notes: I_{t-7} is an indicator function equal to 1 if $\varepsilon_{t-7} < 0$ and 0 otherwise. *, **, and *** stand for the 10%, 5%, and 1% significance levels, respectively.

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 "news"). 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 6.1 also provide an estimate of the shape parameter. The estimated shape parameter suggests that tails are leptokurtic, i.e., heavier than those of a 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).

In order to check the adequacy of the estimated AR–$ARCH$ model, I apply the BDS test developed by Brock et al. (1996) to test if the standardized residuals $\hat{\nu}_t$ are i.i.d.

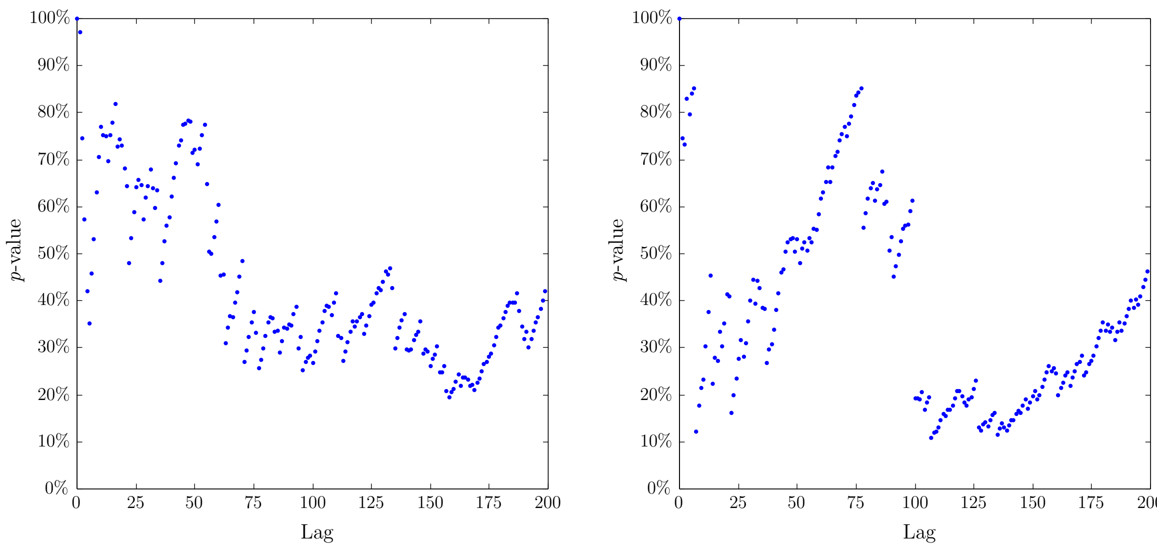
For the embedding dimension m equal to 2 and 3 and a default option of the proximity parameter ε, the null hypothesis that the standardized residuals are i.i.d. is not rejected. This test, therefore, confirms the adequacy of the estimated *AR–ARCH* model. The test results are summarized in Table 6.2.

Table 6.2: 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

Source: Author's calculations.

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 Figure 6.1.

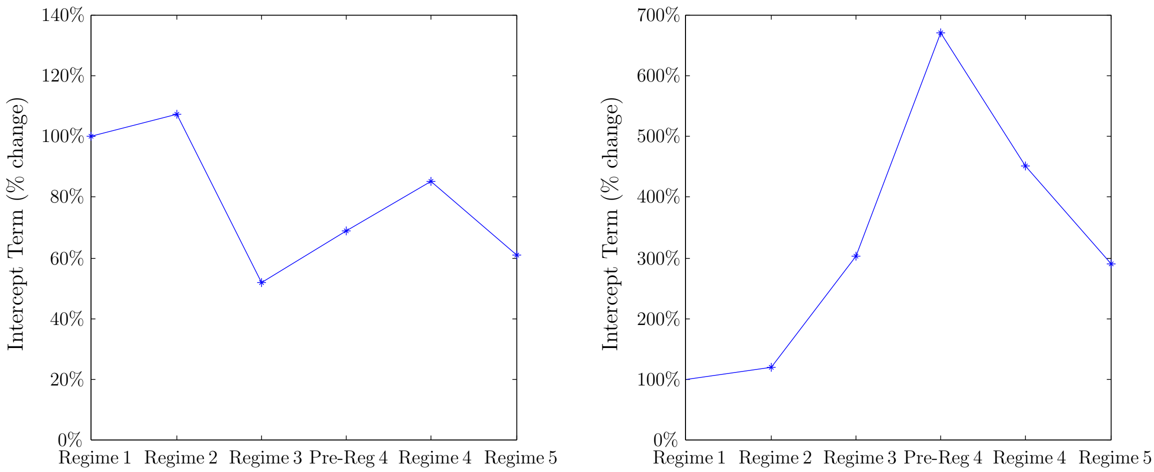


Source: Author's calculations.

Figure 6.1: Ljung-Box Q-Test for Standardized Residuals $\hat{\nu}_t$ and $\hat{\nu_t^2}$

The test results presented in Figure 6.1 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 *AR–ARCH* model explains about 80% of the variations in electricity prices.

Using the estimation results provided in Table 6.1, I summarize in relative terms the effects of the institutional changes and regulatory reforms on price and volatility dynamics for the case of the England and Wales electricity market during 1990–2001. This is presented in Figure 6.2.



(a) Mean Equation (b) Conditional Volatility Equation

Source: Author's calculations.

Figure 6.2: Impact of the Institutional Changes and Regulatory Reforms on Price and Volatility Dynamics

When the initial 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 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, 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.

During the period after price-cap regulation and before the first series of divestments took place, the price volatility increased dramatically, whereas a change 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 as compared to the pre-regime 4 period. This finding indicates that during the regime 4 period 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 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 price-cap regulation and divestment series led in the end to similar price levels and volatility. However, usually divestment series could be superior to price regulations because they allow for the creation of a less concentrated market structure, where it will be easier to promote competitive bidding among electricity producers.

7 Conclusion

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 in lowering price volatility, which however happened at the cost of a higher price level. Thirdly, only during the last regime period, when the second series of divestments was implemented, was it possible to simultaneously reduce prices and volatility.

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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