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Changes to Gate Closure and its impact on wholesale electricity prices: The case of the UK

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ABSTRACT

The electricity supply industry in the United Kingdom underwent a number of regulatory reforms since late 80's that have transformed the trading and pricing of the energy market. Herein we provide empirical evidence that the Modification Proposal P12 (Mod P12) - that took place in 7/2/2002 - moving the Gate Closure (GC) interval from 3.5 h to 1 h before real time has caused a permanent alteration in the UK spot price volatility. Using a combination of Recurrence Plot (RP) and Recurrence Quantification Analysis (RQA) we find that, after the the change in the GC time, short term price volatility significantly decreased between 2001 and 2008 while long term price volatility is not affected by CG change. Similar results are obtained by means of spectral analysis on the price series, showing a significant reduction in its variability. The results of our analysis suggest that a dynamical regime shift of the price occurred, and such shift is linked to the GC change whereby shorter GC intervals facilitate short-term forecasting on electricity demand and better reliability on the supply side. Therefore, GC closer to real time is associated to reduced price fluctuations in the wholesale market.

1. Introduction

Electricity utilities around the world have been historically organized as a vertically integrated industry where prices were set by the regulator or by the competent ministry, in order to cover the total cost of the supply chain, including generation, transmission and distribution. Consequently, prices have been changing in a deterministic way.

This scenario has changed dramatically in the last 30 years. In this period, a number of countries embarked on a process of market liberalisation, aiming at creating competitive markets where possible. In particular, generation and supply activities have been firstly liberalised in states and countries like Texas, Chile, and the United Kingdom starting from the early 90's (Glachant and Perez, 2011). This process led to important fluctuations of electricity market prices, that now depend on the temporary equilibrium of supply and demand generated at each relevant timeframe (Hogan, 1998).

Electricity market as a whole is organized in a sequence of negotiations, different in duration and vintage, from long term contracts to cash out (Fig. 1), each providing price signals towards the demand and supply side. Prices are now typically characterized by significant fluctuations and persistent seasonality (Geman and Roncoroni, 2006). In particular, in the last market sequence, the “real time market”, generators and suppliers place their bids to buy or sell electricity for the amount non contracted ahead of real time. Once the electricity demand (by individual suppliers and thus by final costumers) matches the amount of decided generation, the equilibrium price is reached. Hence, price signals derived from real time market provide relevant information and scarcity signals to generators and consumers alike in order to inform their long term and short-term decisions.

In the real time marcket, the GC defines the point of time prior to a Settlement Period[1] (SP) by which all notifications relating to each half hour period shall be submitted. Currently, in the UK the GC deadline falls one hour before real-time delivery, so that Generators can define their physical outputs and notify their expected production for the

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[1] A SP is each of the 48 half hours in which electricity is traded in the wholesale market, with generators and suppliers entering into contracts. Also non-physical traders such as investment banks participate in this trading. Each day (Settlement Day) is split into 48 SPs, with SP 1 equivalent to 00:00–00:30, SP 2–00:30–01:00, SP 3–01:00–01:30 and so on, through to SP 47 (23:00–23:30) and SP 48 (23:30–00:00) - see Elexon Balancing & Settlement Code.

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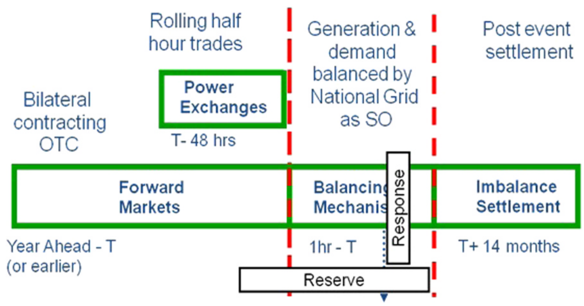

Fig. 1. Timing and functioning of the energy market in UK.

following SP to the System Operator (SO). The Parties then forward the information for each Balancing Mechanism (BM) Unit,[2] and the final expected operating level for the SP, to each BM Unit to be submitted by GC.

However, the timing of the GC crucially depends on different factors and it might shift over time in order to follow the development of the energy mix in different countries. Recently the literature started to consider GC a key parameter for energy system management, specifically considering the increased integration of renewable energy resources (Couto et al., 2016; Holttinen et al., 2016; Weber, 2010). In the UK, CG moved from 3.5 h before real time to 1 h in 2002 (see discussion below). Recently a recommendation from the Agency for the Cooperation of Energy Regulators (ACER) indicates that all European transmission SOs shall move GC time "as close as possible to real time".[3] In the UK, on the bases of this recommendation, Elexon - the body in charge for delivering the Balancing and Settlement Code in the British electricity supply industry - raised a proposal[4] to further move the GC time to 30 min. However, this proposal was not adopted since the standing modification group closed the debate waiting for more information on the impact that a shorter GC might have on electricity prices and volumes. Indeed, there is very little understanding of the implications that a shift of the GC might produce on price dynamics in the electricity market. The aim of this paper is to close this gap by providing evidence on how regulatory interventions on GC timing affect, via cash out arrangement, spot price dynamics. We do that by studying the dynamic and statistical characteristics of the electricity spot prices of the UK Power Exchange, using RP and RQA jointly with volatility measures.

The UK market is particularly interesting since the GC distance from real time set after the implementation of Mod P12 in 2002[5] has been shortened. Mod P12 was introduced just after the launch of the New Electricity Trading Arrangements (NETA).[6] NETA was designed to cope with a number of issues that characterized the previous regime (pool) including, but not limited to, BM, transparency and contract market[7] liquidity. Furthermore, since the beginning of the new NETA regime, entered into force in March 2001, there has been an intense debate about the way in which cash out prices are calculated[8] and a number of modification have been made (Henney, 2011, p. 57). Ofgem recognised as well that the initial cash out arrangements were not able to reflect the true balancing costs[9] of the SO, confirming the relevance of this fundamental price signal. Finally, the National Audit Office, reported that "…during the first year of NETA a total of 46 proposals were put forward to Ofgem, which approved 18 and rejected 18. A further 10 were amalgamated or withdrawn […] the most significant [was] the reduction of "Gate Closure" to one hour ahead of real time" (The National Audit Office, 2003 page 18). For these reasons, this paper investigates at the changes in the market price signals determined by the change in GC, trying to explore the consequences that the GC shift has implied for the UK electricity market under the price dynamics point of view.

The paper is structured as follows: Section 2 provides the reader with background concepts and literature review, in Section 3 we discuss the UK wholesale market arrangements, and in Section 4 nonlinear methods and recurrence plots are described. Section 5 introduces our empirical analysis and main results, including a robustness check based on the spectral analysis of the time series. Finally, Section 6 provides concluding remarks and policy implications.

2. Background and literature review

The Electricity Supply Industry (ESI) has important physical characteristics that shape its optimal regulatory design. They are characterized by (i) large sunk costs that limit entry possibilities, (ii) vertical stages (generation, transmission, distribution and retailing) of production with different optimal scales, and (iii) a non-storable good delivered via a network which requires instantaneous physical balance of supply and demand in each node (Wilson, 2002).

In particular, ESIs are subject to a strong real time constraint of permanent equilibrium between generation and consumption. Even small deviations from a balance situation affect the frequency at which the system operates, expressed in Hz, until a change in generation or consumption allows the normal state to be re-established. In fact, the majority of the electricity supply industries in Europe were designed to operate at a frequency of 50 Hz. Sustained divergences from the reference frequency can destabilize or harm the system and could eventually escalate to dangerous events such as blackouts and uncontrolled brownouts.[10]

The burden of continuously balancing the system is further complicated by the impossibility to store electricity (in large quantities) and by the uncertain consumption profile, which is subject to random fluctuations with no forewarning or commitment. These characteristics require that generation is continuously adapted to maintain equilibrium, given the status of the network and the actual demand. For these

[2] BM Units are used as units of trade within the Balancing Mechanism. Each BM Unit accounts for a collection of plant and/or apparatus, and is considered the smallest grouping that can be independently controlled. As a result, most BM Units contain either a generating unit or a collection of consumption meters. Any energy produced or consumed by the contents of a BM Unit is accredited to that BM Unit.

[3] Recommendation No 03/2015 Refer to art. 35, 4 (a) - Annex II issued on 20 July 2015 on the Network Code on Electricity Balancing.

[4] Issue 61 'Changes to Gate Closure for Energy Contract Volume Notifications' has been raised in October 2015 and discussed at the Standing Modification group at ELEXON available here: https://www.elexon.co.uk/change/standing-modification-group-issues/.

[5] Modification proposal P12 "Reduction of Gate Closure From 3.5 h To1 Hour" has been initially presented by Elexon on 9th of May 2001. The Mod P12 are available here: https://www.elexon.co.uk/mod-proposal/p012-reduction-of-gate-closure-from-3–5-h-to-1-h/.

[6] NETA is a system of bilateral trading between generators, suppliers and consumers on the UK market, the aim of which is to reduce wholesale electricity prices. Introduced in 2001, after the joining of Scotland, NETA became known as British Electricity Trading Transmission Arrangements (BETTA) in 2005.

[7] Other topics include new governance arrangements, demand side potential, CHP schemes, Vertical integration, Incentive for the system operator, transmission access, transmission losses, cost, and benefits. NETA arrangements comprise volume 1 and 2 and A draft specification for the balancing mechanisms and imbalance settlement, Ofgem, July 1999.

[8] Details of all proposed modifications together with their assessment and decisions are on Elexon's website www.elexons.co.uk.

[9] See Ofgem (2007), page 8, 2.11.

[10] "An uncontrolled brownout is a condition where excessively low voltage is experienced on an electric grid. This condition can persist for long periods of time and can result in equipment failure (i.e., motors or other constant power devices). Some loads, such as lighting and resistive heating, might show flicker or heat reduction from low-voltage conditions but not become damaged." (Blume, 2016).

reasons, balancing needs to be operated as close as possible to real time. Sources of the possible uncertainties include errors in demand forecasts due to the unpredictability of weather or social events, errors in output forecast, such as variability in wind and solar power and outages, transmission constraints or trips (Wilson, 2002).

In addition, there are further inter-temporal constraints on generation preventing the ability of certain plants to generate in a short time frame. In particular, flexibility in generation depends on the technology used, leaving aside transmission capacity. Not all technologies are able to respond to short-term signals, so the actual preparation for real time balancing begins before the actual moment of short-term signals. A practical consequence descending from these characteristics is that in short periods (from 1 to 3 h) the maintenance of the overall equilibrium cannot be managed by a decentralized market (Wilson, 2002). This is why the operation of the system in real time is entrusted to a central authority - the SO - managing the transmission grid. In addition, given the relative arbitrariness of SO in managing the system, the operational rules during this specific period are defined ex ante in a balancing agreement. It follows that efficient electricity systems require well-organized energy, associated ancillary services, and transmission capacity markets to achieve competition with physical balancing and appropriate regulation of monopoly power.

In particular, the fact that electricity cannot be currently stored (in large amounts) implies that supply and demand must be always balanced. In the UK, this is ensured by traders, suppliers and generators trough the competitive wholesale market. Trading can take place bilaterally or through exchanges and over different timescales (Fig. 1). Therefore, it is of the utmost relevance that market structure and market participant behaviours are able to convey efficient price signals to market operators. Consequently, establishing wholesale and retail electricity markets is essential for liberalizing the sector (Defeuilley, 2009; Littlechild, 2009).

Wholesale market design needs to take account of the specific conditions of the sector and of various technical, economic, and institutional issues associated with pricing, contracts, scheduling, balancing, and network congestion (Hogan, 1998). Reforming countries have adopted different market models that has often evolved over time, reflecting a learning-by-doing process reminding us that liberalisation remains still a work in progress (Pollitt, 2012; Wolak, 2001; Fiorio and Florio, 2013; Glachant and Ruester, 2014).

To the best of our knowledge, in the literature we found limited examples of mathematical representation able to identify how spot prices respond to regulatory intervention. Strozzi et al. (2008) have studied the evolution of NordPool market, showing a positive correlation between the number of market agents and the volatility of the price time series, while Evans and Green (2003), using monthly data on capacity ownership and electricity prices, show that increases in market competition are chiefly responsible for a decrease of the price level during the late 90 s. More recently, Petrella and Sapio (2012) looked at the impact of market design on the statistical properties of the Italian wholesale electricity prices. They found that the electricity price level and its volatility increased after the adoption of contracts for difference. In addition, following retail liberalisation and the beginning of white certificates trading,[11] the price level and its volatility increased. Bosco et al. (2013), using 2007–2010 real auction data, show that bidding behaviour (and profit function) of Enel, the main Italian energy supplier, has changed in response to price-cap regulation and competitive measures. Finally, Tashpulatov (2013) analysed how institutional changes and regulatory reforms affected the dynamics of daily electricity prices in the England and Wales wholesale electricity market during 1990–2001. He finds that the introduction of price-cap regulation generated higher price volatility, and average prices decreased until 1996. Later, after the first series of divestments, it has been successful at lowering price volatility.

These studies follow the present trend in energy econometrics and are limited to analyse the dynamics of *daily* and *intradaily* electricity prices, as in Kiesel and Paraschiv (2017), Pape et al. (2016) and many other recent papers.

We contribute to the existing literature by studying how price responds to changes in the gate closure using *half-hourly* prices time series. To the best of our knowledge, this is the first time that the impact of changes in the gate closure is analysed at this detail.

3. UK Wholesale market and the power exchange price

In Europe, the majority of the national balancing arrangements are based on a process that is organized into steps (ENTSO-E Network Code on Electricity Balancing[12]) (See Fig. 2). According to the prevailing arrangements, each player aggregates the position of contracts previously concluded on the forward markets, into settlement schedules. Those schedules are transmitted to the SO, which uses this final physical notification to compute the imbalances by comparisons with the actual measurement of injections and withdrawals off the transmission grid in real time. Subsequently, the discrepancies are financially settled in a successive phase. Therefore, the SO controls the functioning of the transmission system.[13] Balancing Mechanisms (BM)[14] constitutes a small fraction of the electricity traded but are fundamental part of the system for both technical and economic reasons.

Leaving aside the physical role in balancing global volumes of supply and demand, the BM provides the chain of electricity markets with the only real time price formation mechanism (Hirst and Kirby, 2001). Real-time power exchange is the only form of power that is physically tradable among wholesale market operators, and where the price is formed in real time. These characteristics combine to make the BM as the basis of the chains of forward prices, ranging from futures to day-ahead (Klæboe et al., 2015). The day-ahead physical notification of schedules is solely indicative and could be modified until a certain point in time, until the so-called GC, after which all schedules are finalised. In this way the GC time represents the boundary between forward and real time market, in which only a SO is allowed to operate. The temporal position of the gate closure is thus a fundamental parameter in the design of the balancing market and in determining both the level and quantity of information available and the level of uncertainty.

After the submission of the Final Physical Notification (FPN), the SO analyses the schedules collected and the underlying pattern of withdrawal/injections to compare this analysis with the state of the grid and the system, in order to be able to guarantee the security of the system.[15] It may well happen that, because of a constraint in the network, the available power level and the number of market participants effectively able to provide services in real-time is substantially limited, or that the market is illiquid. Thus, not all participants will be able to satisfy their needs.

In the UK, historically the GC has been calibrated on the time needed to the marginal provider to supply its service. For this reason,

[11] In environmental policy, white certificates are documents certifying that a certain reduction of energy consumption has been attained. In most applications, the white certificates are tradable and combined with an obligation to achieve a certain target of energy savings.

[12] A revised version of the Network Code on Electricity Balancing (EB) is now under evaluation and an updated draft of the Electricity Balancing guidelines will be discussed in the next electricity cross-border committee. The latest draft version is available here https://ec.europa.eu/energy/sites/ener/files/documents/informal_service_level_ebgl_10-10–2016nov.pdf.

[13] Which constitutes a natural monopoly.

[14] Balancing mechanism refers to the more general description of the real time module. When certain conditions apply, such as absence of penalties, the balancing mechanism applied to the real time module could substituted by a balancing market (see Glachant and Saguan, 2007).

[15] This is the main criterion driving the operation of each national SO.

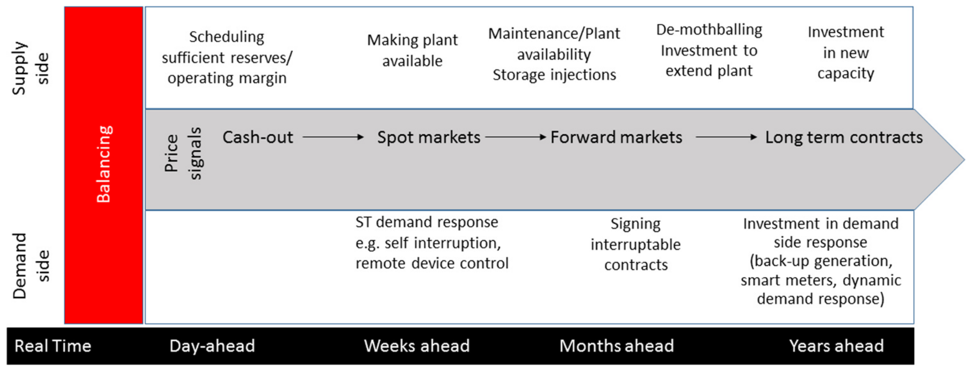

Fig. 2. Steps of the electricity balancing process.

the UK moved the GC from 3.5 to 1 h before real time,[16] because of the progressive substitution of the coal generation with other form of more flexible plants - Combined Cycle Gas Turbine (CCGT) - that allowed for the management of energy imbalances closer to real time. This reflects the different timing required to warm up and operate those two different types of plants: about 3 h for coal plants and 5 up to 30 min (depending on efficiency and on generation capacity) for gas fired plants.

There are two extremes that define the different types of balancing arrangements emerging in liberalised markets. On the one hand there are "Real-time market" that relies on a single price for power is prevalent in US and on the other extreme there exist the so called "Balancing Mechanisms", where there is a set of prices at a premium (or a discount) to the marginal cost of balancing power, depending on some form of cost activation scheme. In between there various combinations of these different approaches that can broadly cover the variety of methods and mechanisms that can be employed in the BM. For an overview of the existing approach please refer to Rivero et al. (2011) and van der Veen et al. (2012).

In both cases the SO performs ongoing adjustment to the electricity system using supplies available on the market or on the BM, or, in case of congestion, by resorting to options negotiated in advance. Each supplier booked by the SO is then paid on either a pay-as-bid or a marginal pricing basis. If the available supply of power is not sufficient or not available where needed, then the SO may exercise previously acquired options on various categories of reserves. The main difference between the two systems is the perception of imbalances. When they are viewed as a voluntary action of market agents, usually the choice is to discourage them by means of price mechanisms built in to dampen trading. Alternatively, when the level of imbalance is perceived as unavoidable then a "market'" system is preferred.

If markets are operating efficiently, players should be able to manage any systematic differences between short-term and long-term prices, meaning that there should be a close relationship between prices across all time horizons. Hence, short-term signals in cash-out should be reflected through the spot and forward markets, and provide longer-term signals for investment (Glachant and Saguan, 2007). Any differences between the average spot and longer-term prices reflect the risk premium associated with contracting forward, which can be positive or negative depending on future expectations of market tightness. If the market is expected to be short, then producers are in a stronger position and can charge an additional risk premium, whereas if the markets are expected to be long, suppliers may be able to demand a discount. The relationship between risk premia and market tightness may not be symmetrical since the distribution of spot prices tends not to be normal, but skewed toward higher prices - prices tend to jump up more than they jump down.[17] Fig. 2 summarises how an efficiently functioning market provides the signals to different players to take actions impacting on supply adequacy over different timeframes, from investing in long-term capacity on the right to real-time balancing on the left.

Considering the price transfer process along successive markets, briefly described above, the spot market price represents the relevant market price that will allow us to infer how market and bidding behaviours has evolved over time in the wholesale electricity market. It follows that, looking at the wholesale spot price market dynamics in the UK, we could determine the impact of the regulatory decision to move GC closer to real time operation. This will allow us to extract relevant information on the price dynamics in place in the UK electricity supply industry.

The British electricity market is considered to be among the most competitive and mature (Karakatsani and Bunn, 2008), following a significant reduction in generation concentration in the late 90 s and the introduction of wholesale market institutions by introducing NETA to replace the pool (Newbery, 1998) in 2001. NETA's stated intention was that of reducing wholesale and thereby retail prices, however, Giulietti et al. (2010) show that the shift in the institutional framework did not lead to significant changes in the price dynamic.

It follows that the results emerging from our study may represent a benchmark for other markets willing to undertake similar reforms, and can inform the current discussion on shifting GC as close as possible to real time, as recommended by ACER.

We study the British ESI, because of its international relevance and its recent attempts to shorten the GC time significantly, partially as a response to a rapid change in the generation mix. Furthermore, prior research suggests that the British wholesale electricity market is not characterized by strategic convergence of producers' behaviour (Bunn et al., 2015), despite the repetitive nature of the spot market. It follows that the price dynamic in this market is mainly due to the demand-supply mechanism instead of strategic interactions between market actors.

In the rest of the paper, in order to conduct our empirical analyses we employ nonlinear methods and spectral analysis of price series that will be introduced in the next section.

4. Methodology

4.1. Nonlinear time series analysis and Recurrence Plots

Nonlinear methods have been successfully applied to a wide range of natural phenomena, giving insights and providing solution in different fields of study. Within nonlinear methods, nonlinear analysis of time series plays a fundamental role when analysing experimental data, especially when mathematical models are hard to develop or provide

[16] See Modification proposal P12, with implementation date as of 7/2/2002.

[17] This is true because plants are subject to unplanned failures.

only poor information to the experimentalist (Bradley and Kantz, 2015). The main task of nonlinear time series analysis (NTSA) is therefore to extract information on the nonlinear system from the observation of its evolution, assuming that a single or a multivariate recording represents the evolution of an unknown dynamical system (i.e. a systems described by a set of nonlinear differential equations) and its past evolution contains information about the (unknown) model that has produced the time series itself. Such information can be partially derived by means the method of delays (Kantz et al., 2005; Bradley and Kantz, 2015), which allows for the reconstruction of the trajectory of the system in the phase space. There is a growing literature studying the identification of nonlinear and chaotic dynamics starting from time recordings: chaos and other nonlinear phenomena have been successfully identified in a wide range of phenomena like mechanical systems, markets (including energy and commodities), biological and biophysical systems, ecology etc. Regarding the energy and commodities markets the reader is referred to Abarbanel (1997); Bradley and Kantz (2015) for an extensive description of methods and their applications.

Among nonlinear methods, the RP is now a reference instrument for the analysis of short, non-stationary and noisy time series (Webber and Marwan, 2015). Originally designed to display recurring patterns and to investigate non-stationarity in time series (Eckmann et al., 1987), the RP unveils important characteristics of all dynamical systems. Recurrence is the most important feature of nonlinear systems, while non-stationarity is typical of natural systems, and may arise from different reasons, such as parameter drifting, time varying driving forces, sudden changes in dynamics etc.

Recently, RPs found a wide range of applications when coping with nonstationary phenomena (Ioana et al., 2014), such as energy systems and markets (Barkoulas et al., 2012; Bigdeli and Afshar, 2009; Kyrtsou et al., 2009; Bigdeli et al., 2013), biological systems (Kaluzny and Tarnecki, 1993; Hirata et al., 2014; Zbilut et al., 2004; Martis et al., 2014), complex networks (Jacob et al., 2016; Schultz et al., , 2015; Donner et al., , 2012), speech analysis (Facchini et al., 2005; Lopes et al., 2014; Lancia et al., 2014), financial time series (Strozzi et al., 2007), and earth and climate sciences (Marwan et al., 2002a, 2002b, 2003; Pedro and Coimbra, 2015; Panagoulia and Vlahogianni, 2014; Diodato and Bellocchi, 2014). The popularity of RP lies in the fact that their structure is visually appealing and allows for the investigation of complex dynamics by means of a simple two-dimensional plot.

In order to extract and define the dynamic characteristic of the UK spot market we use RP and RQA to analyse the UK spot price data. Our results show that, from a dynamic and spectral point of view, a change in the GC time triggered structural changes in the electricity markets and the analysis proposed (with high level of detail) shed a light on how major changes in rules affect electricity markets dynamics. Our analysis also reminds us that the interactions within an electricity market constitute a repeated game, and the process of experimentation and learning is able to change gradually over time the behaviour of firms in the market.

RPs have been recognised as a reliable tool to cope with time series showing irregular behaviours like trends and noise as well a irregular oscillations (Marwan, 2007; Marwan et al., 2014).

We start from considering the time series of the spot price $p_i = (p_1, p_2, \ldots, p_N)$, and we reconstruct a m-dimesional phase space by using the embedding method as described by (Kantz and Schreiber, 2005). The RP is a two dimensional binary diagram representing the recurrences that occur in the reconstructed phase space within an arbitrarily defined threshold ε at different times i, j. The RP is easily expressed as a two dimensional square matrix with ones and zeros representing the occurrence (ones) or not (zeros) of states $\vec{p_i}$ and $\vec{p}_j$ of the reconstructed trajectory of system:

$$\boldsymbol{R}_{ij} = \Theta(\varepsilon - \|\vec{p_i} - \vec{p_j}\|), \quad \vec{p_i} \in \mathbb{R}^m, \quad i, j = 1, \ldots, N \tag{1}$$

Where N is the number of measured states $\vec{p_i}$, $\Theta(\bullet)$ is the Heaviside step function, m is the dimension of the reconstructed phase space, and $||\cdot||$ is the chosen norm. In the graphical representation, each non-zero entry of $\boldsymbol{R}_{ij}$ is marked by a black dot in the position *(i,j)*. Since any state is recurrent with itself, the RP matrix fulfils $\boldsymbol{R}_{ii} = 1$and hence it contains the diagonal *Line of Identity* (LOI).

Special attention must be paid to the choice of the threshold ε. Although there is not a general rule for the estimation of ε, the noise level of the time series plays an important role in its choice, and usually, ε is chosen as a percentage of the diameter of the reconstructed trajectory in the phase space, not greater than 10%, while another criterion is to select ε such that the Recurrence Rate is under 5–10% (Marwan et al., 2007). A norm must be defined to compute an RP: usually the l_∞ norm is used, because it is independent of the phase space dimension and no rescaling of ε is required.

After the computation of the matrix $\boldsymbol{R}_{ij}$ the corresponding RP is characterized by typical patterns, whose structure is helpful in understanding the underlying dynamics of the time series. Such patterns are classified according to two features: *typology* and *textures. Typology* catches the global appearance of the RP, and allows for a first understanding of the time series dynamics: homogeneous distribution of points is usually associated with stationary stochastic processes, e.g. Gaussian or uniform white noise. Periodic structures, such as long diagonal lines parallel to the LOI, indicate periodic behaviours, while drifts in the structure of the recurrences are often due to slow non stationarities in the underlying system's parameters. White areas or bands indicate weak stationarity and abrupt changes in the system's temporal dynamics. Finally, curved macrostructures have been related to very small frequency variations in periodic signals (Facchini and Kantz, 2007).

The *textures* are the small structures forming the patterns in the RP. They may be: (a) single points, if the state does not persist for a long time; (b) diagonal lines of length l, indicating that portion of distinct trajectories visits the same portion of the phase space at different times, and that for l time steps they are closer than ε; (c) vertical and horizontal lines, indicating that the state changes very slowly in time.

RPs are useful to detect simple non-stationarities or irregular/periodic behaviours. However, it is difficult to analyse the RP by means of the sole visual inspection, because of insufficient screen resolution and the length of the time series. As an example, visual inspection reveals that the RP of white noise mainly shows isolated black points and few short lines, while long diagonal lines are typical of periodic signals. Chaotic systems, instead, are characterized by the distribution of diagonal lines of different lengths. For these reasons, a set of quantification measures, called RQA, has been developed to complement visual inspection techniques.

4.2. Recurrence quantification analysis

The RQA is a tool based on the statistical description of the textures distribution of the RP. It was introduced for the analysis of time series with non-stationarity or high levels of noise (Webber and Zbilut, 1994). The RQA is a set of quantitative measures defined using the recurrence point density and diagonal structures in the recurrence plot. Among the measures defined by researchers, the most common and informative are recurrence rate (RR), DET, average diagonal line length (L), and entropy (ENT). Furthermore, the computation of these measures on moving windows yields the time dependency of these measures, giving further insight on the underlying dynamics of the time series. Studies based on RQA measures highlight their appropriateness to identify structural changes like bifurcations, transitions and dynamical regime shifts in stationary and non-stationarity signals (Trulla et al., 1996; Alex et al., 2015; Pedro and Coimbra, 2015).

In the following we describe only the measures that will be useful to the purposes of the paper. For a complete review about RPs and RQA the reader is referred to Marwan (2007). We define DET starting from the distribution function of the diagonal lines length $P(l)$:

Table 1
Descriptive statistics of APX Power UK Reference Price Data (RPD) – observations from 4/2/2001–7/31/2008.

Variable	Obs.	Mean	Std. Dev.	Min	Max	SKEWNESS	KURTOSIS
Price	128,544	28.64364	22.23741	0.36861	553.3	4.079949	36.8867

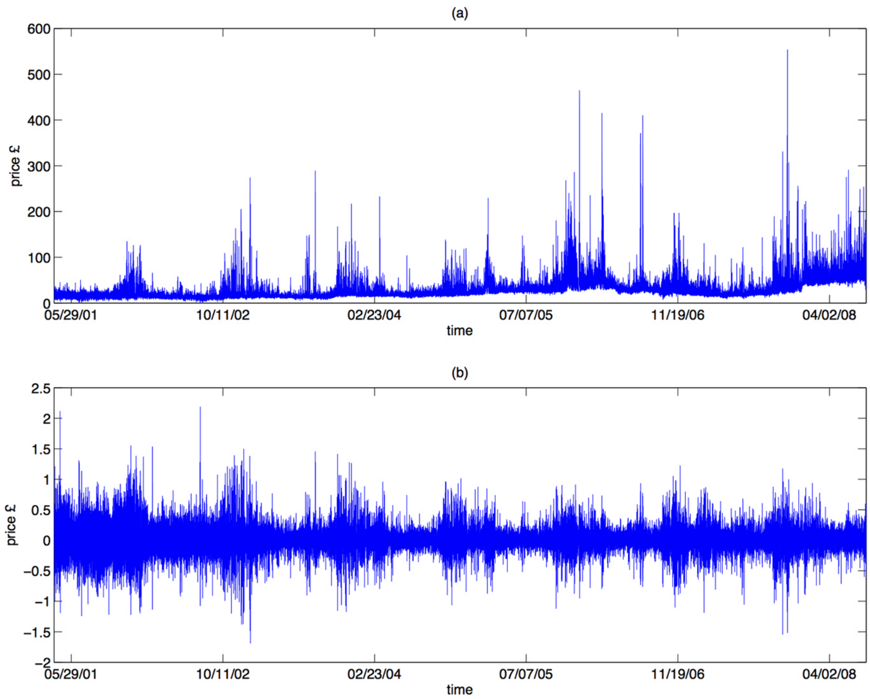

Fig. 3. Price (a) and logarithmic (b) return time series plot – whole sample.

$$DET = \frac{\sum_{l=l_{min}}^{N} lP(l)}{\sum_{l=1}^{N} lP(l)}, \tag{2}$$

where l is the generic diagonal line length in the range (l_{min}, N). DET indicates the fraction of recurrent points forming diagonal structures with a minimum length l_{min} with respect to all recurrences. l_{min} is usually selected as the first minimum of the signal's autocorrelation function (Marwan et al., 2007). Under the systes dynamics point of view, DET provides a measure of the predictability of the system, high values of DET mean that the recurrence points are mainly organized in diagonal lines, indicating that the system is characterized by regular dynamics.

5. Data, empirical analysis and results

We use a data set obtained from APX Power UK Reference Price Data (RPD) starting from 4/2/2001–7/31/2008, Table 1 shows the main descriptive statistics of the price series. The time series captures the replace the Pool with NETA in 2001 subsequently expanded to incorporate Scotland in BETTA - British Electricity Trading and Transmission Arrangements, creating for the first time a single Great Britain electricity market. The sampling time is 30 min and the whole time series consists of 128,544 observations.

The complete plot of the recording is shown in Fig. 3(a): Wholesale spot prices in the sample are characterized by spikes, irregular oscillations and seasonal trends that can be easily identified. In order to better characterize the irregularity of the prices, we also compute the logarithmic returns[18] of the price series: Fig. 3(b) provides a further confirmation of the high volatility of the prices, especially in the first part of the time series (until the first quarter of 2003, or about until the 35,000-the sample).

Fig. 4(a) and (b) provide a clearer visual inspection of the evolution of the prices, confirming their irregularity. In particular, the daily oscillations in panel (a) - corresponding to the period 4/12/2001–5/4/2001 (before the GC change) - are very noisy, and no regular oscillation can be identified, excluding the daily pattern that is clearly recognisable. Time series in panel (b) - corresponding to the period 7/24/2007–8/14/2007 - appear significantly different, showing a more periodic and smooth behaviour, in which the typical intra-day double peak is easily identifiable. It is worth noticing that in both cases is not possible to detect the 7-day periodicity, i.e. different dynamics on Saturdays and Sundays, typical of this class of signals (as observed in Paoletti et al., 2011, and literature cited therein).

The significant differences of the temporal behaviour observed in panels (a) and (b) of Fig. 4 suggest a further investigation of the time series underlying dynamics by computing and visualizing the RPs of the time series. In performing the RP based analysis, we refer to the whole time series, not following the common practice to analyse separately the half-hour observations. This choice is driven by the fact that each temporal observation embeds the past history of all the states of such system, and the analysis of the whole recording embeds a complete picture of the evolution of the dynamical system's state. Within these considerations, Recurrence plots indicators are therefore able to quantify such evolution shedding light on possible transitions and structural changes otherwise not detectable with other statistical-based methods (Kantz, 2005).

Our aim is now to understand if the price dynamics has been affected by the GC shifting time. RPs and RQA have been used to study the original time series (i.e. not considering the logarithmic returns).

[18] The logarithm of the ratio of the prices x at time t and t-1, $\log(x_t/x_{t-1})$.

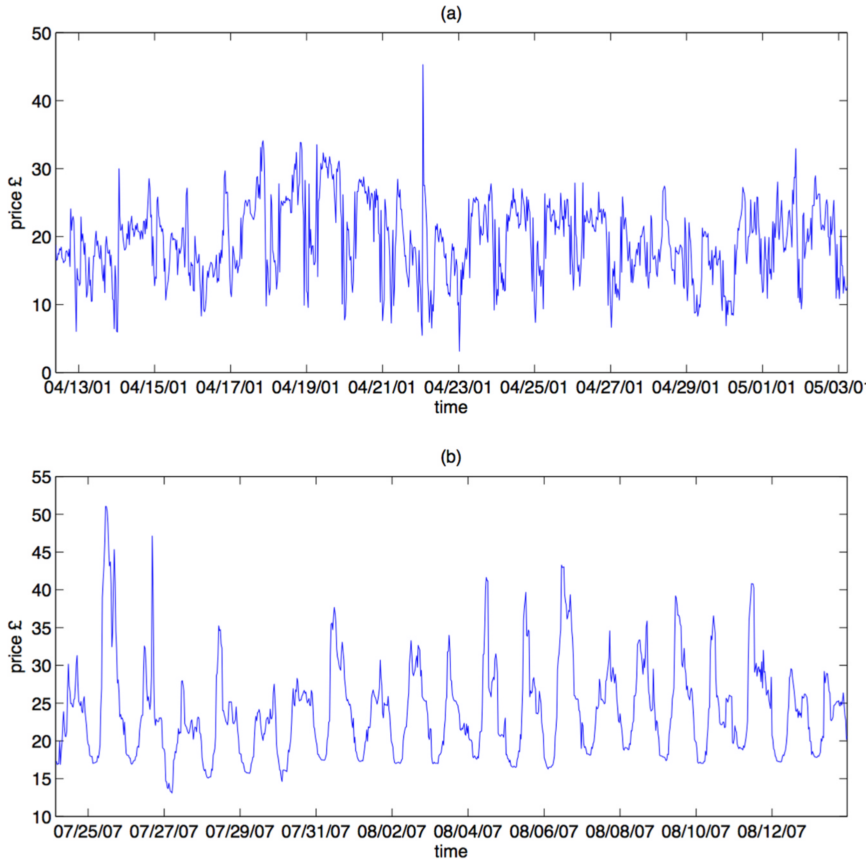

Fig. 4. Price time series plot. Detail of period I from 4/12/2001–5/4/2001 (a) and period II from 7/24/2007–8/14/2007 (b).

RPs and RQA have been computed using $D_E = 3$ and selecting the threshold ε in order to have $RR \sim 5\%$, DET has been computed using $l_{min} = 4$. Fig. 5 shows the two recurrence plots: panel (a) corresponds to the period 4/12/2001–5/4/2001 (period I) and panel (b) corresponds to the period 7/24/2007–8/14/2007 (period II).

As expected, the two recurrence plots look significantly different: the one corresponding to period I shows an aperiodic pattern with a limited number of short lines parallel to the LOI; the other, corresponding to period II, looks more periodic and with a limited number of isolated points.

The values for DET confirm the visual inspection: for period I we obtain DET $= 0.23$, while for period II we observe DET $= 0.64$. The same behaviour is observed for other time series extracted from years 2002 and 2008.

Considering this substantial difference between the RPs of 2001 and 2007, we performed a more extensive analysis of the time series. Following Strozzi et al. (2008), Barkoulas et al. (2012), and Bigdeli and Afshar (2009) we analysed the whole time series by computing DET for windows of 30 days (1440 samples), and volatility for increasing windows of 30, 60, and 90 days. Panels (a) and (b) of Fig. 6 show the result of this analysis. The computation of the windowed DET is shown in panel (b), that for the sake of comparison with the volatility reports on the y axis the values 1-DET.[19] The main result is that the values of 1-DET are high ($\sim$ 0.8, corresponding to DET $\sim$ 0.2 - low regularity) in the period March 2001 - June 2002, then decrease rapidly from June 2002 to January 2004, and reach a plateau ($\sim$ 0.4, corresponding to DET $\sim$ 0.6, high regularity) starting from February 2004. After that date, the values remain almost stable. The same is observed for the volatility shown in panel (a), however, here values oscillate around the plateau because of the seasonal trends visible in Fig. 3. From the stochastic point of view, a reduction of the volatility from 0.22 to 0.1 indicated a reduction of variability in the return prices, resulting in a more compact oscillation of the prices themselves. From the dynamic point of view, the abrupt change in the values of DET suggests a structural change of the system,[20] as observed by Trulla et al. regarding the values of DET in the logistic map (Trulla et al., 1996).

5.1. Spectral analysis

We now check the robustness of our results by performing the spectral analysis of price series. This methodology is widely used to analyse the volatility of electricity loads and prices in the energy markets.[21] The main idea that drives this kind of approach is that the regular behaviour of a time series is to be periodic. It follows that we can proceed to determine the periodic components of the time series by computing the associated periods, amplitudes, and phases. Following the frequency-domain approach to time series, a stationary process can be decomposed into random components that occur at frequencies $\omega \in [0, \pi]$. The spectral density of a stationary process describes the relative importance of these random components. In the frequency domain, the dependent variable is generated by an infinite number of random components that occur at the frequencies $\omega \in [0, \pi]$. The

[19] This choice is made for the sake of comparison with volatility, showing both curves decreasing with time. In this case, the higher 1-DET is, the more irregular is the time series.

[20] In the field of nonlinear systems dynamics, this phenomenon is known as bifurcation, and corresponds to a structural modification of the system, as one or more parameters are changed. (for further information the reader is referred to Strogatz (2014).

[21] See Weron (2006, 2014) for a detailed literature review on spectral analysis and other frequency-domain approaches to time series analysis in energy markets.

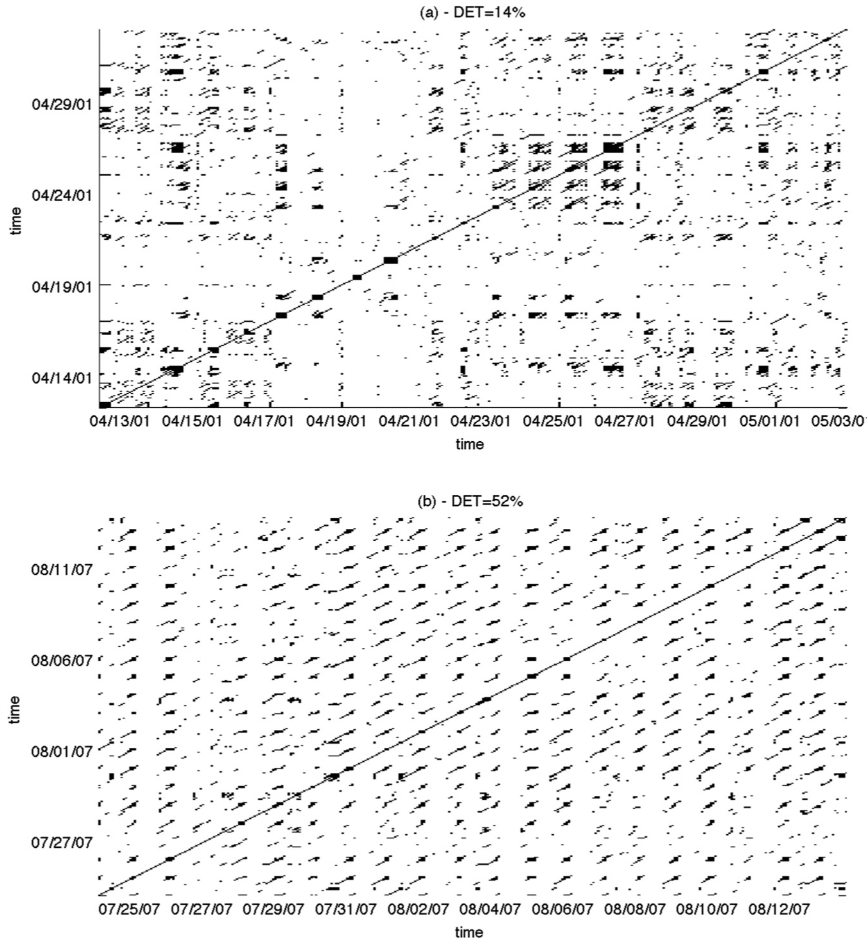

Fig. 5. Recurrence plots of the price series: period I from 4/12/2001–5/4/2001 (a) and period II from 7/24/2007–8/14/2007 (b).

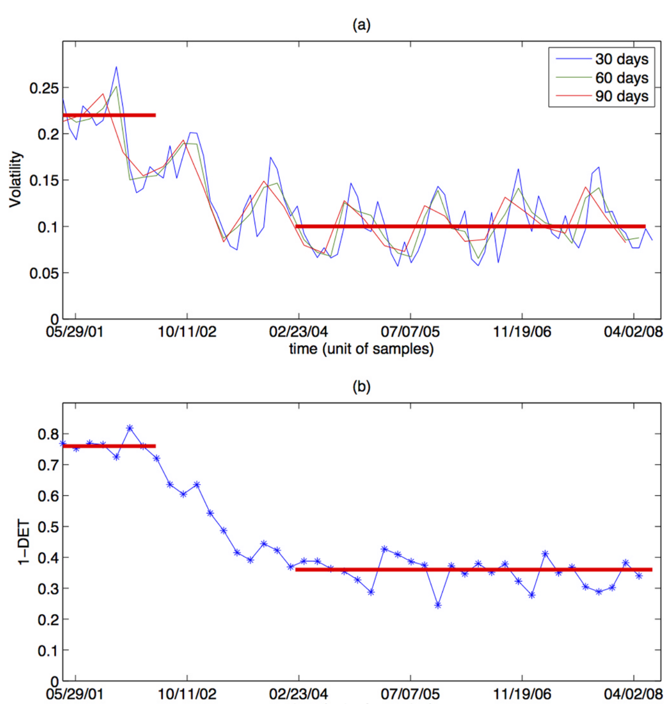

Fig. 6. Volatility for increasing windows of 30, 60, and 90 days (a) and 1-DET (b) computed on the price series.

spectral density specifies the relative importance of these random components. The area under the spectral density in the interval $(\omega, \omega + d\omega)$ is the fraction of the variance of the process than can be attributed to the random components that occur at the frequencies in the interval $(\omega, \omega + d\omega)$.

Here it is sufficient to underline that the spectral density function plays a central role in summarising the contributions of cyclical components to the variation of a time series. The spectral density at frequency zero is particularly important because of its direct link to the variance of a time series sample average, that is, the long-run variance (Vogelsang, 2008). Technical presentations of spectral density analyses can be found in Priestley (1981), Harvey (1989, 1993), Hamilton (1994), Fuller (1996) and Wei (2006). In order to check the previous results, obtained by means of the recurrence plots, we follow the approach provided by Granger and Morgenstern (1963) and Monge et al. (2017).

In particular, we use the first 20,000 observations and the last 20,000 observations of the series. We present nonparametric estimates of the spectral density of the price series $p_1,\ldots,p_N$ by means of periodograms. As seen above, a time series of interest can be decomposed into a unique set of sinusoids of various frequencies and amplitudes, and a plot of the sinusoidal amplitudes (ordinates) versus the frequencies of a time series gives us the spectral density. If we calculate the sinusoidal amplitudes for a discrete set of "natural" frequencies $\left(\frac{1}{N}, \frac{2}{N}, \ldots, \frac{q}{N}\right)$, we obtain the periodogram. Let $p_1,\ldots p_N$ be a price time series, and let $\omega_k = \frac{(k-1)}{N}$ denote the natural frequencies for $k = 1,\ldots, \frac{N}{2} + 1$. Define

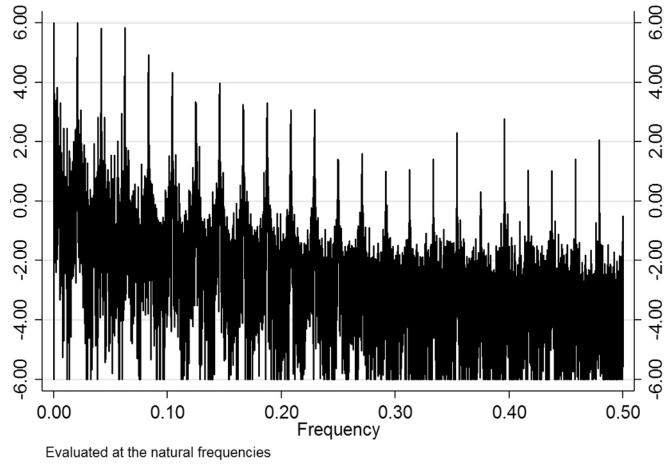

Fig. 7. Periodogram of price series – first 20,000 observations.

$$C_k^2 = \frac{1}{N^2}\left|\sum_{t=1}^{N} p_t e^{-2\pi(t-i)i\omega_k}\right|^2. \tag{3}$$

A plot of NC_k^2 versus ω_k is then called the periodogram.

Since the periodogram is symmetric about $\omega = 0.5$, we can further standardize the periodogram of the price time series such that

$$\frac{1}{N}\sum_{t=1}^{N}\frac{NC_k^2}{\hat{\sigma}^2} = 1, \tag{4}$$

where $\hat{\sigma}^2$ is the sample variance of the price series so that the average value of the ordinate is one. Once the amplitudes are standardised, we may take the natural log of the values $p_1,\ldots p_N$ and produce the *log-standardized periodogram*. In doing so, we truncate the graph at $\pm$ 6. For simplicity, we will refer to the log-standardized periodogram as the "periodogram" in the rest of the paper.

We estimate periodograms of the first 20,000 observations and the last 20,000 observations and the results are presented in Figs. 7 and 8. A relatively large value of the periodogram $P(\frac{q}{N})$ indicates relatively more importance for the frequency $\frac{q}{N}$ (or near $\frac{q}{N}$) in explaining the oscillation in the observed series. Fig. 7 reports the periodogram of the first 20,000 observations; we can see that high frequencies describe a relatively greater part of the series. On the contrary, the periodogram of the last 20,000 observations of the series reported in Fig. 8 shows that high frequencies determine a relatively smaller part of the series behaviour. That is, in the first period, when the time necessary for the marginal provider to supply its service was 3.5 h, high frequencies fluctuations are an important component of the time series variability, suggesting high fluctuations in the spot prices before the provider service supply. In the last period, where it has been made possible to manage energy imbalances closer to real time (1-h interval) the time series variability is due mainly to low frequency cycles, that is the long-term cycle.

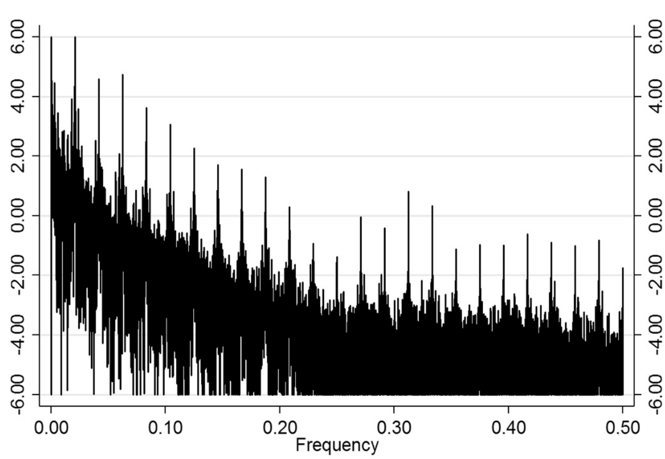

Fig. 8. Periodogram of price series – last 20,000 observations.

Table 2
UK half-hourly spot average price (APX Power UK Reference Price Data) – full series.

Time	Price	Time	Price
4:30	*18.97471*	9:30	29.81529
5:00	18.98081	21:00	30.52318
5:30	19.01166	15:30	30.71167
4:00	19.29757	15:00	30.93662
3:30	19.94286	16:00	31.18938
3:00	20.04691	14:30	31.25408
6:00	20.23738	14:00	32.04052
2:30	20.74172	20:30	32.04737
6:30	20.9614	10:00	32.20389
2:00	21.0535	16:30	33.13547
1:00	21.47305	10:30	33.18315
1:30	21.48846	13:30	33.83792
0:30	21.98442	20:00	34.45282
7:00	22.54827	11:00	34.7456
0:00	22.64567	13:00	35.27449
23:30	23.79659	11:30	35.44636
7:30	23.88609	12:30	36.42144
23:00	25.21944	12:00	36.57714
8:00	25.24531	19:30	36.76477
22:30	25.78587	17:00	36.83278
8:30	26.58524	19:00	37.71629
22:00	27.40309	17:30	39.99192
9:00	28.9532	18:30	41.05302
21:30	29.24213	*18:00*	*43.23426*

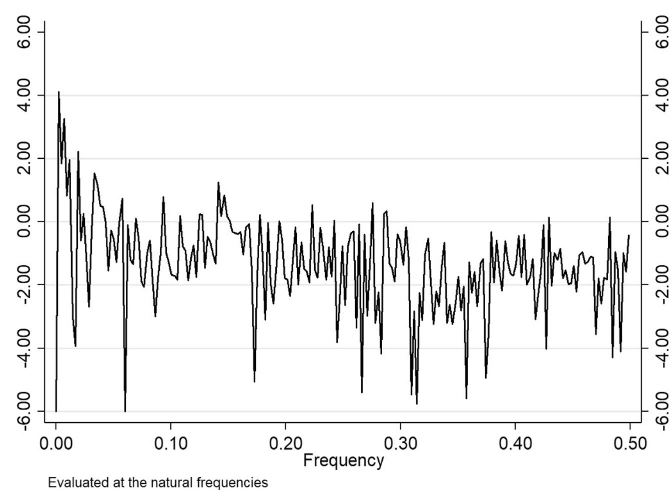

Fig. 9. Periodogram of price series at time 4.30 - first 417 observations.

We conclude the spectral analysis of the price series presenting periodograms based on time of the day-specific half-hourly prices, corresponding to peak and off-peak, in order to check if there are changes in daily peaks. Table 2 presents average prices computed on the full series for each half hour of the day. As we can see, on average, the peak is observed at 18:00 while the off-peak is observed at 4:30.

Fig. 9 and 10 report the periodograms on observations at time 4:30 included in the sample used above for Fig. 7 and 8.[22]

As we can see from Fig. 9 and 10, the behaviour of the off-peak periodograms suggest that in the last period high frequencies are relatively less important in describing the off peak-price series. That is, in

[22] In each subsample of 20,000 observations we have 20,000/48 off-peak/peak observations. That is, 417 observations.

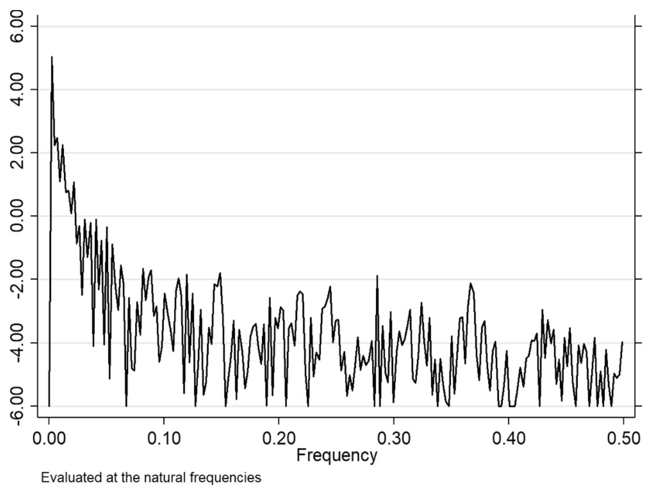

Fig. 10. Periodogram of price series at time 4.30 - last 417 observations.

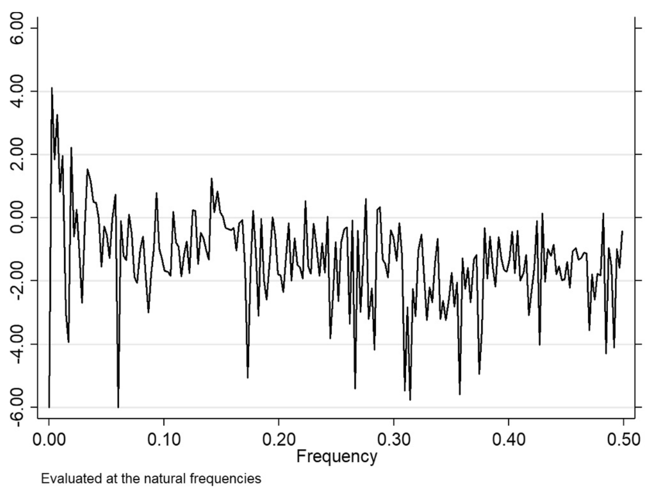

Fig. 11. Periodogram of price series at time 18.00 - first 417 observations.

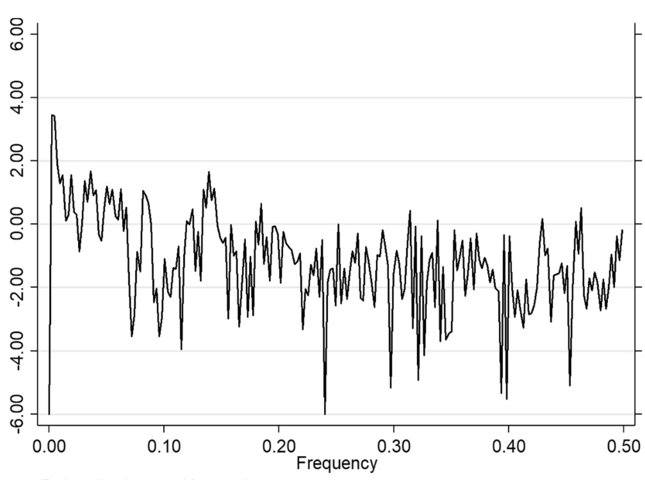

Fig. 12. Periodogram of price series at time 18.00 - last 417 observations.

the last period large part of volatility is due to the long run cycle instead of short-term fluctuations.

Fig. 11 and 12 report the same analysis using observations at time 18:00. In this case, we cannot observe any significant difference in periodograms.

Here it is important to note that the meaning of "short-term" is different if referred to peak subseries or to the full sample. In fact, peak series are daily series, while the full sample includes information about intra-daily fluctuations.

As a general result of our empirical analysis, we have obtained that longer term price volatility is not impacted while the very short term volatility (hourly/half hourly time scale) decreased after the CG change. This result are not surprisingly since changes in the GC are likely to directly affect short-term, intra-daily, price volatility and they have less relevance in determining medium and long term fluctuations. In fact, in the real time market, traders buy and sell electricity in order to fulfil their needs in the next few hours.

To conclude, it is important here to underline that our regression sample includes observations starting just after the launch of the NETA. Similar analyses based on observations referring to the previous regime (Pool) show that volatility of the Pool price started increasing after the expiration of coal contracts, which were imposed at vesting (Robinson and Baniak, 2010). Furthermore, according to Weron (2014), we can exclude the existence of new forecasting methods able to reduce volatility in the period considered.

On the contrary, previous empirical analyses (Schroeder and Weber, 2011, p.7) suggest that shortening the gate closure has a considerable effect on reducing forecasting errors. Furthermore, Joos and Staffell (2018) observe that significant flexibility already exists in energy markets of Britain and Germany and that gate closure closer to real time has been a way to transfer more balancing responsibility from the SO to market participants and make the balancing process more efficient with more accurate forecasts being available closer to real time.

6. Conclusion and policy implications

This study analysed the complex dynamics of the UK half-hourly spot price (2001–2008, APX Power UK Reference Price Data) both studying the temporal recurrence dynamics and the spectral properties of the price time series. We have identified the impact on the dynamics of the UK spot market in terms of volatility and on RQA. The value of DET shows that two clear areas can be identified, interspersed by a transition region. In the first part of the time series the recordings are characterized by highly irregular dynamics (high values of $1 - DET$) and high volatility. Our study shows that from February 2004 to July 2008, the dynamic becomes significantly more regular (low $1 - DET$) and the volatility is consistently reduced.

The literature on nonlinear systems dynamics and recurrence plots suggests that a structural transition, i.e. a permanent change in the dynamics, of the system underlying the price dynamics occurred.

Our empirical results confirm that after the change in CG time the spot price time series exhhibits a structural (permanent) change that has influenced the dynamics of the spot price. This is confirmed by the change of both DET and volatility. We have found that the newly introduced regime shows a higher determinism suggesting that the spot prices become more regular, following with greater precision the national baseload curve. At the same time lower values of volatility suggest that a reduction of the gate closure to 60 min ahead of real time contributes to decreasing the market uncertainties, resulting in a reduced fluctuations and spiking of the prices.

In particular, we have observed that longe term price volatility is not impacted by the change in the GC while the very short term volatility (hourly/half hourly time scale) decreased after the change. While it is not possible to insulate potential spill over effects in the early years of the new NETA regime, we consider that the introduction of NETA represents a natural experiment where new (and different) market rules and regulatory incentives have been adopted to the UK electricity system. In this context, market operators after July 2002 were able to operate closer to real time, thus with a better understanding on the existing market conditions. Electricity markets are characterized by the fact that information does not flow at the same time of trading, and this means that traders buy and sell electricity at different time of the day mainly to fulfil their industrial, commercial or consumption needs and the sequence of forward markets crucially depends on the accuracy by which BM operates in real time.

Our study represents the first attempt to look jointly at the dynamic and spectral behaviour of the spot price in the UK, providing evidence that reducing GC distance to real time had a positive and permanent impact on the wholesale electricity market, leading to a greater regularity in the price behaviour over time. This also provides a useful guidance to decision makers and regulators that are increasingly considering moving GC further closer to real time, as recently recommended by ACER. As suggested in Section 3, shortening the GC crucially depends on the specific characteristics of the generation mix available, and in particular on its flexibility. However, since in the UK market renewables are grew from under 4% in 2008–22% by 2017, projected at 30 + % by 2020 (Grubb and Newbery, 2018) we can rasonably expect further changes in the CG in the future.

Given the relevance of the technological aspects of power generation, we consider that our conclusions are important in shedding a light on how a competitive electricity market responds to GC shifts, but further evidence is needed to generalise these results to other markets in EU. Therefore, our result suggest that ACER recommendation needs to be tested against the dynamic and spectral performance of the electricicty spot price before implementation.

Our future research will look at the impact of a shift in the GC on the volumes traded. As GC distance to the real time approaches to zero (real time market) the effects on the liquidity of the market are still to be investigated.

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