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

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Abstract

Among the major transitions in the recent history of UK electricity market one of the most prominent was represented by the change of Gate Closure interval, that moved from 3.5 to 1 hour before real time in July, 2 2002. We demonstrate that this change has determined a permanent alteration in price dynamics, providing more certainty on market fundamentals.

Changes in price dynamics have been assessed by means of Recurrence Plots and Recurrence Quantification Analysis used to investigate the dynamics of electricity spot markets in the United Kingdom from 2001 to 2008. By making the assumption that the temporal evolution of the spot price is governed by an unknown complex dynamical system, depending crucially on the information available on market conditions and system fundamentals, we show that the dynamical regime shift of the price may be significantly linked to the gate closure change.

A possible explanation of this phenomenon is that shorter Gate Closure intervals may facilitate the forecasting activity of market operators, and therefore it may lead to changes in the spot price trends and dynamics.

Key words: Recurrence Plots, Energy markets. PACS: 05.40; 05.45

1 Introduction

Utilities around the world have been historically organized as a vertically integrated industry where prices were set by the regulator (or by the competent minister). Those prices reflected the total cost of the supply chain (generation, transmission and distribution), were administered and stable, and they only changed in a deterministic way. This paradigm has changed dramatically over the last 25 years. In this time frame most of western economies have embarked on a process of deregulation aiming to create a competitive market where possible. In particular, generation and supply activities have been firstly liberalized in countries like Australia, Chile, and United Kingdom starting from early 90's [17].

This process, among other consequences, has created a "market" price for the electricity that fluctuates depending on the equilibrium of supply and demand. In the "real time market", when the amount of electricity demanded by each individual supplier (and thus by the final costumers) and the amount of contracted generation becomes final, generators and suppliers place their bids to buy or sell electricity for the amount non contracted ahead of real time.

The electricity supply industry (ESI) has important physical characteristics that shape its optimal regulatory design [1]. It involves (i) large sunk costs which 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 at all nodes. Liberalization of such an industry involves the creation of a combination of competitive energy and retail markets, and regulated transmission and distribution activities. Successful liberalization requires 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 at all times balanced . This is done in UK by traders, suppliers and generators in the competitive wholesale market. Trading can take place bilaterally or on exchanges and over different timescales. It is therefore of the utmost relevance that market structure and market participant behaviors are able to convey efficient price signals to market operators. Therefore, establishing wholesale and retail electricity markets is essential for liberalizing the sector.

[1] The discussion around Energy market design has been summarized in the seminal paper by Wilson, R. (2002)[48]

Wholesale market design needs to take account of of the specific conditions of the sector and of various technical, economic, and institutional issues associated with pricing, contracts, scheduling, balancing, and network congestion [1]. Reforming countries have adopted different market models and these have evolved in stages, reflecting a learning process and a reminder that liberalization remains a work in progress [2,3,18–20]. Looking at the literature on electricity market it is evident that one of the most relevant focus of the debate has been market design (see [4–7,21] for markets, [8–11] from a regulatory point of view, and [12,13,22] for the market structure evaluation). In the literature however we find limited examples of mathematical representation able to identify how spot prices respond to market design intervention. Only [38] have studied the evolution of North Pool market showing a positive correlation between the number of market participants with the volatility of the time series. In order to respond to this vacuum we have analysed the dynamic and statistical performance of the electricity spot prices from the UK Power exchange using Recurrence Plots (RP) and Recurrence Quantification Analysis (RQA) in conjunction with volatility measures in order to explore the impact of major changes in market architecture to the inner characteristics of electricity spot trading and exchange.

In this paper we apply RP and RQA to analyse spot price data highlighting the dynamic dimension of spot price trend and the "learning" processes and bidding behavior that occur during major market structural changes (with high level of detail) that could shed a light to evaluate how major changes in the regulatory architecture affect electricity markets dynamics. Our analysis also reminds us that the interactions within an electricity market constitute a repeated game, therefore a process of experimentation and learning changes the behavior of the firms in the mark and produces its effect over time.

Our analysis is based on the British electricity supply industry. As case study we selected the UK market because the liberalization and successive privatization process started in the late 1980s and already in 1990 the electricity industry was split into generation, transmission, distribution and supply, which were then privatized separately. Furthermore, spot price data are available for a significative time span (from 2002 to 2008).

The aim of this paper is to capture how regulatory intervention affect, via cash out arrangement, spot price dynamics. It is well known in that generators and retailers use a succession of contracts to secure the necessary availability , normally beginning with longer term contacts (such as base season and peak) and the fine tune their position, closer to delivery using week and day base contracts. A functioning electricity market then requires liquid trading in spot, prompt and forward markets able to convert in efficient price mechanism the scarcity signals that derive from balancing.

Besides this introduction, the rest of the paper is organized as follows. In Section 2 we describe the UK wholesale market, in section 3 nonlinear methods and recurrence plots are described, while section 4 introduces our empirical analysis and illustrate the main results, also tested by means of a robustness check based on the spectral analysis of the time series. Finally, Section 5 contains results of our work and offers some concluding remarks. All figures and graphs are placed in the appendix at the end of the paper.

2 UK Wholesale market and the power exchange price

Electricity systems are subject to a strong real time constraint of permanent equilibrium between generation and consumption. Even small deviation 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 systems in Europe were designed to operate at a frequency of 50Hz. Sustained divergences from the reference frequency can destabilize or arm the system and could eventually escalate to dangerous events such as blackouts and brownouts [2].

The burden of continuously balancing the system is further complicated by the impossibility to store electricity 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 and the actual conditions of supply and demand are only known when most of the uncertainties disappear, leading to the reason why balancing need to be operated as close as possible to real time. The sources of the possible uncertainties are usually errors in demand forecasts due to the unpredictability of climate or social events, errors in output forecast, such as intermittence in wind power and outages, transmission constraints or trips.

In addition, there are further inter-temporal constraints on generation preventing the ability of certain plants to generate in a short time frame. Flexibility in generation depends in particular on the technology used, leaving aside transmission capacity. Not all technology 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 hours) the maintenance of the overall equilibrium cannot be managed by a decentralized market ([48]). This is why the operation of the system in real time is entrusted to a central authority (the System Operator) managing the transmission grid. In

[2] Reduction of voltage level below the normal minimum level specified for the system.

addition, given the relative arbitrariness enjoyed by SO in managing the system, the rules of operation during this specific period are defined *ex ante* in a balancing agreement.

In Europe the majority of the national balancing arrangements are based on a process that is organized into successive steps [3] (Figure 1). According to the prevailing process, every 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. The discrepancies are subsequently financially settled in a successive phase.

Therefore, the SO controls the functioning of the transmission system [4]. Balancing mechanisms [5] (BM), constitute a small fraction of the electricity traded (Figure 2) but it is still a fundamental part of the system for both technical and economical reasons. This is true for the above mentioned characteristics of the electricity sector.

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 ([49]). In practice real-time power exchange is the only form of power that is physically tradable among wholesale market operators, and the price formed in the BM is the basis of the chains of forward prices, ranging from futures to day-ahead. The day-ahead physical notification of schedules is solely indicative and could be modified until a certain point in time, until the so called "Gate Closure" (GC), after which all schedules are finalized. In this way the time of the gate closure represents the boundary between forward and real time market, in which only the SO is allowed 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 operators analyse the schedules collected and the underlying pattern of withdrawal/injections and 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 [6]. It may well happen that, because of a constraint in the network, the available power level and the number of market participants that are effectively able to

[3] See ETSO 2003 [**?**]

[4] Which constitutes a natural monopoly

[5] It is a more general description of the real time module. When certain conditions apply, such as absence of penalties, then a balancing mechanism could eventually constitute a market.

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

provide services in real-time is substantially limited or that the market is illiquid. Thus not all participants will be able to find counterparts to offer them additional contracts to modify their daily schedule, moving, consequently, the effective position of the gate closure further ahead real-time.

Historically in UK the GC has been calibrated on the time necessary to the marginal provider to supply its service. For these reason GC in UK moved from 3.5 to 1 hour before real time [7], because of the progressive substitution of the coal generation with other form of more flexible plants (such as CCGT and gas turbine) that allowed the management of energy imbalances closer to real time. This reflects the different timing required to warm up and operate those two different type of plants, where the typical ramp rate for coal plants is around 3 hours, whereas for gas fired plants varies between 5 to 30 minutes (depending on efficiency and on generation capacity).

As said before, there are two different types of balancing arrangements emerging in liberalized markets: at one end of the spectrum we find a "real-time market" that relies on a single price for power, and this is prevalent in US. At the other end we find a "balancing mechanism", more typical in Europe, where there is a set of prices, at a premium (or a discount) to the marginal cost of balancing power.

In each of these markets' design the SO performs ongoing adjustment to the electricity system using supplies available on the market or on the balancing mechanism, or, in case of congestion, by resorting to options negotiated in advance. Every 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 in terms of quality or quantity, then the system operator may exercise previously acquired options on various categories of reserves.

The main difference between the two systems is the conception of imbalances. When they are perceived as a voluntary action of market agents, then the choice usually is to discourage them with a "mechanism". When the level of imbalance is perceived as unavoidable, then a "market" system is preferred.

The first of the two arrangements is based on the concept of two-or dual-prices. The main price is the price for imbalance trades in the same direction of the system as a whole. It will be the system buy price (SBP) when the system is short, meaning that there is a negative imbalance (i.e. demand for balancing electricity), in this case energy supplies below the schedule are priced higher then the marginal cost of system balancing. Then we have the system sell price (SSP) when the system is long, meaning that energy is supplied in excess of the schedule, and is remunerated at below the marginal cost of system balancing. The second price is the reverse price, that is for trades in the opposite direction

[7] Modification proposal P12, with implementation date as of 2nd of July 2002

to the system as whole. This gives rise to two cases. In the first one the sign of the individual imbalance can be in the same direction as the sign of the entire system, meaning that it will be penalized more severely since it contributes to the global imbalance. In the second one the individual sign may be of the opposite of the overall sign.

The SSP-SBP methodology is based on a simple concept: the desire to encourage parties to balance their position as an end itself (although there is no regulatory requirement as such that parties should do so or that they should be fully contracted). This approach means that if a trading party is out of balance against its contract nominations [8] it will tend to see a price that is a discount to the short term energy market price if it is spilling (exporting) or that is at a premium to it if it is taking a top-up supply (importing) from the system. The imbalance prices that the trading parties sees, levied by the SO, are linked to actions taken by the SO that are treated as restoring the system to energy balance. These balancing actions are typically sourced from higher cost plant or plant with specific dynamic characteristics.

If the markets are operating efficiently, players should be able to arbitrage 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 ([14]). 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 be normal, but skewed toward higher prices - prices tend to jump up more than they jump down [9]. Figure 3 summarizes how an efficiently functioning market provides the signals for different players to take actions that impact 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, in order to infer how the market behavior has evolved over time in the wholesale electricity market, we can correctly concentrate our analysis to the wholesale spot market in UK in order to extract relevant information on the UK electricity market. As it is widely recognized in the literature the

[8] As adjusted for its bid/offer acceptances and measured against loss-adjusted metered volume.

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

British power market is considered to be fully competitive and one of the most mature ([15]). **NON HO CAPITO IL SENSO DELLA FRASE CHE SEGUE** In particular, following a significant reduction in generation concentration in the late 1990s and the introduction of wholesale market institutions (NETA) to replace the pool ([16]) in 2001.

3 Nonlinear methods and Recurrence Plots

Nonlinear methods are, by now, well established and widely described in a rich literature (see [44] and literature cites therein). The fact that apparently simple deterministic systems may exhibit complicated temporal behaviors in the presence of nonlinearity has influenced thinking and intuition in many fields. In particular, nonlinear methods have been successfully applied to a wide range of natural phenomena, giving insights and providing solution in different disciplines. Within nonlinear methods, nonlinear analysis of time series plays a fundamental role when analyzing experimental data, especially when mathematical models are hard to develop or give only poor information to the experimentalist[57]. 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 the hypothesis that a single or a multivariate recording represents the evolution of a 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 partly derived by means the method of *delays* [45,57], that allows for the reconstruction of the trajectory of the system in the phase space. In the last two decades a deep research has been performed on 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. (the reader is referred to Abarbanel [46] and Kantz [57] for an extensive description of methods and their applications).

Among nonlinear methods, the Recurrence Plot (RP) is a tool that in the last two decades has become one of the reference for the analysis of short, nonstationary and noisy time series [55]. Originally designed to display recurring patterns and to investigate non-stationarity in time series [25], the recurrence plot unveils an important characteristics of all dynamical systems: as stated by Poincaré, 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. In recent years, RPs found a wide range of applications when copying with nonstationary phenomena[62], such as energy systems and markets [53,52,39,40], biological systems [60,27,26,30], complex networks [64–66], speech analysis [68,67,61,32], financial time series [47], and earth and climate sciences [59,54,63,41,42]. The popularity of RPs 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 (see by example figure 6).

Given a time series $x_i = (x_1, x_2, \ldots, x_n)$, the Recurrence Plot is a two dimensional binary diagram representing the recurrences that occur in a reconstructed m-dimensional 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 $\vec{x}_i$ and $\vec{x}_j$ of the system:

$$\mathbf{R}_{ij} = \Theta(\varepsilon - ||\vec{x}_i - \vec{x}_j||), \quad \vec{x}_i \in \mathbb{R}^m, \quad i, j = 1, \ldots, N, \tag{1}$$

where N is the number of measured states $\vec{x}_i$, $\Theta(\cdot)$ is the step function, and $||\cdot||$ is a norm. In the graphical representation, each non-zero entry of $\mathbf{R}_{i,j}$ is marked by a black dot in the position (i, j). Since any state is recurrent with itself, the RP matrix fulfills $\mathbf{R}_{i,i} = 1$ and hence it contains the diagonal *Line of Identity* (LOI). 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. Furthermore, 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% [36].

After the computation of the matrix R_{ij}, the corresponding RP is characterized by typical patterns, whose structure is helpful for understanding the underlying dynamics of the time series. Such patterns areclassified 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, like long diagonal lines parallel to the LOI indicate periodic behaviors, while drifts in the structure of the recurrences are often due to slow nonstationarities in the unrelying system's parameters. White areas or bands indicate non strong stationarity and abrupt changes in the system's temporal dynamics. Finally, curved macrostructures have been related to very small frequency variations in periodic signals [43].

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 in phase space visit 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.

Because of the screen resolution and the length of the time series, it is difficult to analyse the RP only by means of visual inspection, which is anyway useful to detect, e.g. simple non-stationarities or irregular/periodic behaviors. By 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 are characterized by the distribution of diagonal lines of different lengths. To overcome this problem, a set of quantification measures, called Recurrence Quantification Analysis has been developed.

3.1 Recurrence Quantification Analysis

The recurrence quantification analysis [33] 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. 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), determinism (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 put in evidence the ability to find bifurcation points, chaotic transitions (especially chaos-order transitions) and dynamical regime shifts in stationary and nonstationary signals [34,58,56]. Focusing on isolated points and lines parallel to the LOI, we define the *Recurrence Rate* RR, the *Determinism* DET, and the *Average Line Length* $< L >$ starting from the distribution of the diagonal lines length $P(l)$:

In particular, the RR, defined as:

$$RR = \frac{1}{N^2}\sum_{i,j}^{N}\mathbf{R}_{i,j} = \frac{1}{N^2}\sum_{l=1}^{N} lP(l), \tag{2}$$

represents the fraction of recurrent points with respect to the total number of possible recurrences. It is a density measure of the RP.

The DET, defined as:

$$DET = \frac{\sum_{l=l_{min}}^{N} lP(l)}{\sum_{l=1}^{N} lP(l)}, \tag{3}$$

is the fraction of recurrent points forming diagonal structures with a minimum length l_{min} with respect to all the recurrences, l_{min} is usually selected as the first minimum of the signal's autocorrelation function. Choosing too large or too small values of l_{min} will introduce biases into the recurrence measures, e.g. $l_{min} = 1$ yields $DET = 100\%$, while choosing a large l_min does not capture the underlying dynamics Determinism provides a measure of the predictability of the system, because it accounts for the diagonal structures in the RP. High values of DET mean that the recurrence points are mainly organized in diagonal lines, indicating that the system is governed by a regular dynamics.

The average line length $< L >$, defined as:

$$< L >= \frac{\sum_{l=l_{min}}^{N} lP(l)}{\sum_{l=l_{min}}^{N} P(l)}, \tag{4}$$

gives an approximate measure of the average recurrence time of trajectories in the phase space. This measure gives a characteristic oscillation time of the system's dynamics.

4 Empirical analysis and results

We use a data set obtained from APX Power UK Reference Price Data (RPD) starting from March 2001 till August 2008. The recording starts on March 28, 2001 and ends on July 31, 2008. The sampling time is 30 min and the whole time series consists of 128544 samples.

Table 1 reports the main descriptive statistics while a complete plot of the recording is shown in Figure 4(a): as the reader can see, the recording is characterized by spikes, irregular oscillations and seasonal trends that can be easily identified (dotted lines indicate the position of each Jan. 1st).

In order to better characterize the irregularity of the prices, we have computed the logarithmic returns [10] , and figure 4(b) provides a further confirmation of he high volatility of the prices, especially in the first part of the time series (until the first quarter of 2003, or about until the 35000-the sample).

Going more in detail, Figures 5(a) and (b) provide a clearer visual inspection of the evolution of the prices, confirming their irregularity. In particular, the

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

daily oscillations in panel (a) -corresponding to the period 2/27-3/14 2002 (before the Gate Closure change)- are very noisy, and no regular oscillation can be identified, excluding the 24h. Time series in panel (b) -corresponding to the period 3/13-3/28 2008- look significantly different, showing a more periodic and smooth behavior, in which the typical intra-day double peak can be easily identified. 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 by example in [37]).

The significant differences observed in panles (a) and (b) of figure 5 suggest a further investigation of time series. We then compute the recurrence plots of the time series of Figure 5, and we compute the measure DET in order to characyerize the regularity of the dynamics searching for events that have contioned the observed shift in the dynamics.

Figure 6 shows the two recurrence plots: panel (a) corresponds to the period 02/27/2002–03/14/2002 (in the following indicated by period I) and panel (b) corresponds to the period 03/13/2008–03/28/2008 (in the following indicated by period II). As expected, the two recurrence plot look significantly different. The one corresponding to period I, shows an aperiodic pattern, with a limited number of short lines parallel to the LOI, while the one 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 $DET = 0.23$, while for period II $DET = 0.64$. The same behavior is observed for other time series extracted from years 2002 and 2008.

The significative difference between the RPs of 2002 and 2008 suggests a more extensive analysis of the time series. Following Strozzi et Al. [38], Barkoulas et Al. [39], and Bigdeli et Al. [40] we compute DET for windows of 30 days (1440 samples), and volatility for increasing windows of 30, 60, and 90 days. Figure 7 (a) and (b) show the result of this computation. The computation of the windowed DET is shown in panel (b). For the sake of comparison with the volatility, the panel reports the values $1-DET$ [11] . The main result is that the values of $1 - DET$ are high (~ 0.8, $DET \sim 0.2$ – low regularity) in the period March 2001–June 2002, then decrease rapidly from June 2002 to Jan. 2004, and reaches a plateau (~ 0.4, $DET \sim 0.6$, 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), with the difference that the values oscillate around the plateau because of the seasonal trends visible in Figure 4. Under 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. Under the dynamics

[11] In this case, the $1 - DET$ more the value is high, the more irregular is the time series.

point of view, the abrupt change in the values of DET suggests a change in the structure of the system [12], as observed by Trulla et Al. for the values of DET in the logistic map [34].

4.1 Spectral analsysis

We now check the robustness of our results by performing the spectral analysis of the of the logarithmic returns of the analysed data. This methodology is widely used to analyse the volatility of electricity loads and prices in the energy markets. A recent application of the spectral analysis to the UK wholesale electricity market is provided by [75], for a detailed literature review on spectral analysis and other frequency-domain approaches to time series analysis in the energy markets see [51].

The main idea is that the regular behavior of a time series is to be periodic. This approach then proceeds 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 time domain, the dependent variable evolves over time because of random shocks. The autocovariances γ_j, $j \in \{0, 1, \ldots, \infty\}$, of a covariance-stationary process y_t specify its variance and dependence structure, and the autocorrelations ρ_j, $j \in \{1, 2, \ldots, \infty\}$, provide a scale-free measure of its dependence structure. The autocorrelation at lag j specifies whether realizations at time t and realizations at time $t - j$ are positively related, unrelated, or negatively related.

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 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 $(\omega, \omega + d\omega)$.

More technical presentations of spectral density analyses can be found in [69], [70], [71], [72], [73] and [74]. Here it is sufficient to underline that the spec-

[12] 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 [44].)

tral density function plays a central role in summarizing the contributions of cyclical components to the variation of a stationary 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 [50].

Before modelling the dynamics of daily electricity prices, we first conduct a stationarity test. Then we examine electricity prices using frequency domain analyses. In general, we the time domain analysis helps specify the AR process and the frequency domain analysis helps specify the correct frequencies in periodic sine and cosine functions included as additional explanatory variables to model weekly seasonality. The purpose of our procedure is to evaluate if there is a change in the frequencies that model seasonality in our sub-samples.

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 modelling step is undertaken. The main reason is that many modelling procedures and techniques are applicable to only stationary time series. In particular, the periodogram techniques, discussed in section **??** requires the stationarity of a time series.

In order to test for a unit root in the time series of the UK electricity prices, we performs the modified Dickey-Fuller t test (known as the DF-GLS test) on the series of prices. Essentially, the test is an augmented Dickey-Fuller test except that the time series is transformed via a generalized least squares (GLS) regression before performing the test.

Table 2 reports the computed test statistics and the critical values using lags 1-71. In order to choose the lag of interest we may use different criteria. In particular, table 2 reports the lags suggested by the Ng-Perron sequential t criterion, the minimum Schwarz information criterion (SIC), and the Ng-Perron modified Akaike information criterion (MAIC). Using all criteria, the unit-root null hypothesis was rejected and therefore we can conclude that hourly electricity prices are stationary. Furthermore the results of the DF-GLS test are robust for higher and lower order choices of the maximal lag.

In order to check the previous results obtained by means of the recurrence plots analysis, we are interested in modelling the time series variability in three different periods. We analyse separately the first 20,000 observations (the period before the regulatory changes), the second 20,000 observations (transition period) and the last 20,000 observations of the series (last period).

The frequency domain analysis allows us to identify frequencies explaining a large portion of seasonal variations in electricity prices. We analyse the frequency domain of the log price series using the techniques of the spectral

(Fourier) analysis. In general, the power spectrum of a time series describes the distribution of power into frequency components composing that signal. According to Fourier analysis a time series can be approximated by a number of discrete frequencies, or a spectrum of frequencies over a continuous range.

The simplest technique to estimate the spectrum of a signal is the periodogram.

Suppose that a signal is sampled at N different times, with the samples uniformly spaced by Δt, giving values x_n. The periodogram of the series is given by the modulus squared of the discrete Fourier transform,

$$S(f) = \frac{\Delta t}{N} \left| \sum_{n=0}^{N-1} x_n e^{-i2\pi n f} \right|^2, \qquad -\frac{1}{2\Delta t} < f \leq \frac{1}{2\Delta t} \tag{5}$$

where $1/(2\Delta t)$ is the Nyquist frequency.

We estimate [13] the periodograms of the three sub-series described above, calculating the sinusoidal amplitudes for a discrete set of "natural? frequencies *(1/n, 2/n, ... , q/n)*. The results are presented in figures 8-10.

A relatively large value of the periodogram $P(j/n)$ indicates relatively more importance for the frequency j/n (or near j/n) in explaining the oscillation in the observed series. $P(j/n)$ is proportional to the squared correlation between the observed series and a cosine wave with frequency j/n. The dominant frequencies might be used to fit cosine (or sine) waves to the data, or might be used simply to describe the important periodicities in the series.

Figures 8-10, reports the the estimated periodograms over the different periods considered. We can see that in figure 8 high frequencies describe a relatively greater part of the series if compared to figure 10. Furthermore, figure 9 suggest the existence of a transition phase in which high frequencies become less dominant.

By other words, in the first period, when the time necessary for the marginal provider to supply its service was 3.5 hours, the time series variability is dominated by low frequencies fluctuations, 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 hour interval) the time series variability is due mainly to high frequencies cycles, that is the long-term cycle. The second period is a period of transition from the old regime to the new one.

[13] We use the STATA "pergram" module. See "pergram" documentation for details.

5 Conclusions

Summarizing, both volatility and the recurrence quantification measure DET show that the three different regions can be clearly identified: in the beginning of the observation period the recordings are characterized by highly irregular dynamics (high values of $1 - DET$) and high stochasticity (high values of volatility), while from February 2004 to July 2008, the dynamics becomes significantly more regular and the stochasticity is consistently reduced (low $1-DET$ values and low volatility values). These two regions are separated by a transition region, from January 2002 to January 2004, showing continuously decreasing and values for volatility and $1 - DET$. The literature on nonlinear systems dynamics and recurrence plots suggests that a structural transition occurred to the unknown system governing the price.

Our empirical results confirm that the change of the regulatory framework has directly impacted the structure of the market, deeply influencing the dynamics of the spot price, both under the dynamical and under the statistical point of view. This fact is demonstrated by the change of both DET and volatility. An higher determinism suggests that the spot prices become more regular, following with greater precision the national baseload curve, while lower values of volatility suggest that a reduction of the gate closure to 60 minutes ahead of real time also decreases the uncertainty around market fundamentals, resulting in a reduced oscillation of the prices. Market operators after July 2002 were able to operate closer to real time, thus with a better understanding upon existing market conditions. In electricity markets, information does not flow at the same time of trading . Traders buy and sell electricity at different hours of the day mainly to fulfil their industrial, commercial or consumption needs. But the sequence of forward markets crucially depend on the accuracy by which balancing markets operates in real time.

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Appendix: tables and figures

	Obs	Mean	Std. Dev.	Min	Max
Full sample	128544	28.64364	22.23741	0.36861	553.3
Fist 20,000 obs.	20000	16.88641	7.558001	1.2762	134.53
Last 20,000 obs.	20000	50.10214	30.39781	8.49	553.3

Table 1. Summary statistics for hourly electricity prices (£/MWh) across sub-samples.

Lags	DF-GLS tau Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value	Lags	DF-GLS tau Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
71	-15.768	-3.48	-2.837	-2.55	35	-25.919	-3.48	-2.838	-2.55
70	-15.654	-3.48	-2.837	-2.55	34	-26.883	-3.48	-2.838	-2.55
69	-15.602	-3.48	-2.837	-2.55	33	-28.201	-3.48	-2.838	-2.55
68	-15.523	-3.48	-2.837	-2.55	32	-28.792	-3.48	-2.838	-2.55
67	-15.626	-3.48	-2.837	-2.55	31	-30.195	-3.48	-2.838	-2.55
66	-15.464	-3.48	-2.838	-2.55	30	-31.628	-3.48	-2.838	-2.55
65	-15.569	-3.48	-2.838	-2.55	29	-33.32	-3.48	-2.838	-2.55
64	-15.592	-3.48	-2.838	-2.55	28	-34.325	-3.48	-2.838	-2.55
63	-15.67	-3.48	-2.838	-2.55	27	-36.591	-3.48	-2.838	-2.55
62	-15.715	-3.48	-2.838	-2.55	26	-38.369	-3.48	-2.838	-2.55
61	-15.858	-3.48	-2.838	-2.55	25	-40.164	-3.48	-2.838	-2.55
60	-15.914	-3.48	-2.838	-2.55	24	-41.527	-3.48	-2.838	-2.55
59	-15.919	-3.48	-2.838	-2.55	23	-44.578	-3.48	-2.838	-2.55
58	-15.922	-3.48	-2.838	-2.55	22	-46.389	-3.48	-2.838	-2.55
57	-16.082	-3.48	-2.838	-2.55	21	-47.81	-3.48	-2.838	-2.55
56	-16.042	-3.48	-2.838	-2.55	20	-48.874	-3.48	-2.838	-2.55
55	-16.198	-3.48	-2.838	-2.55	19	-50.836	-3.48	-2.838	-2.55
54	-16.165	-3.48	-2.838	-2.55	18	-51.312	-3.48	-2.838	-2.55
53	-16.17	-3.48	-2.838	-2.55	17	-51.806	-3.48	-2.838	-2.55
52	-16.193	-3.48	-2.838	-2.55	16	-52.055	-3.48	-2.838	-2.55
51	-15.703	-3.48	-2.838	-2.55	15	-53.377	-3.48	-2.838	-2.55
50	-15.615	-3.48	-2.838	-2.55	14	-52.736	-3.48	-2.838	-2.55
49	-15.857	-3.48	-2.838	-2.55	13	-52.975	-3.48	-2.838	-2.55
48	-15.809	-3.48	-2.838	-2.55	12	-53.033	-3.48	-2.838	-2.55
47	-9.963	-3.48	-2.838	-2.55	11	-54.146	-3.48	-2.838	-2.55
46	-9.207	-3.48	-2.838	-2.55	10	-55.358	-3.48	-2.838	-2.55
45	-10.545	-3.48	-2.838	-2.55	9	-55.679	-3.48	-2.838	-2.55
44	-12.051	-3.48	-2.838	-2.55	8	-55.409	-3.48	-2.838	-2.55
43	-14.131	-3.48	-2.838	-2.55	7	-58.696	-3.48	-2.838	-2.55
42	-16.183	-3.48	-2.838	-2.55	6	-60.242	-3.48	-2.838	-2.55
41	-17.84	-3.48	-2.838	-2.55	5	-61.519	-3.48	-2.838	-2.55
40	-19.129	-3.48	-2.838	-2.55	4	-63.169	-3.48	-2.838	-2.55
39	-21.189	-3.48	-2.838	-2.55	3	-67.479	-3.48	-2.838	-2.55
38	-22.437	-3.48	-2.838	-2.55	2	-69.537	-3.48	-2.838	-2.55
37	-23.42	-3.48	-2.838	-2.55	1	-72.858	-3.48	-2.838	-2.55
36	-24.416	-3.48	-2.838	-2.55	-	-	-	-	-

Maxlag = 71 chosen by Schwert criterion

Opt Lag (Ng-Perron seq t) = 71 with RMSE 4.851298

Min SC = 3.163923 at lag 52 with RMSE 4.8527

Min MAIC = 3.167664 at lag 68 with RMSE 4.851592

Table 2. Modified Dickey-Fuller t test for hourly electricity prices (£/MWh).

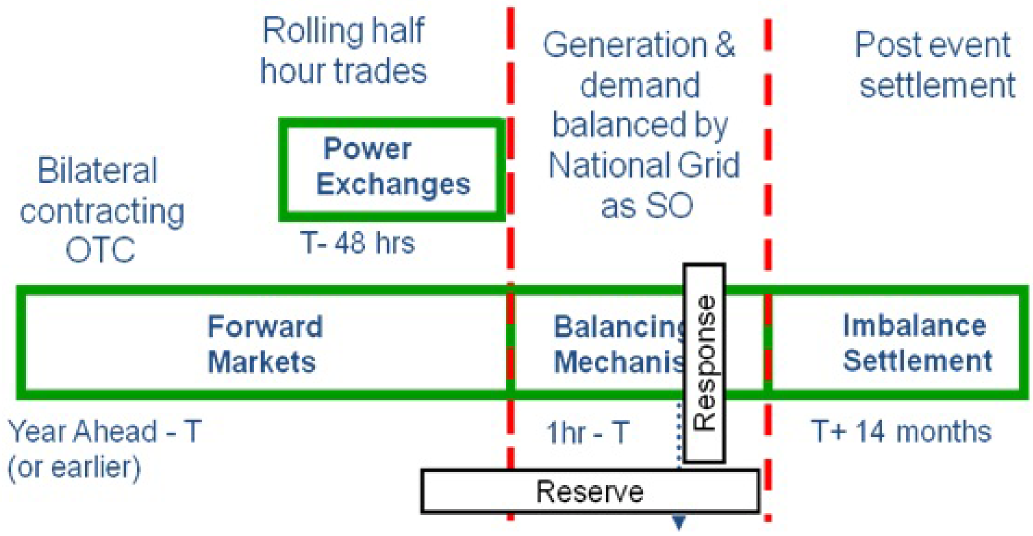

Fig. 1. Electricity market timeline (Source: National grid).

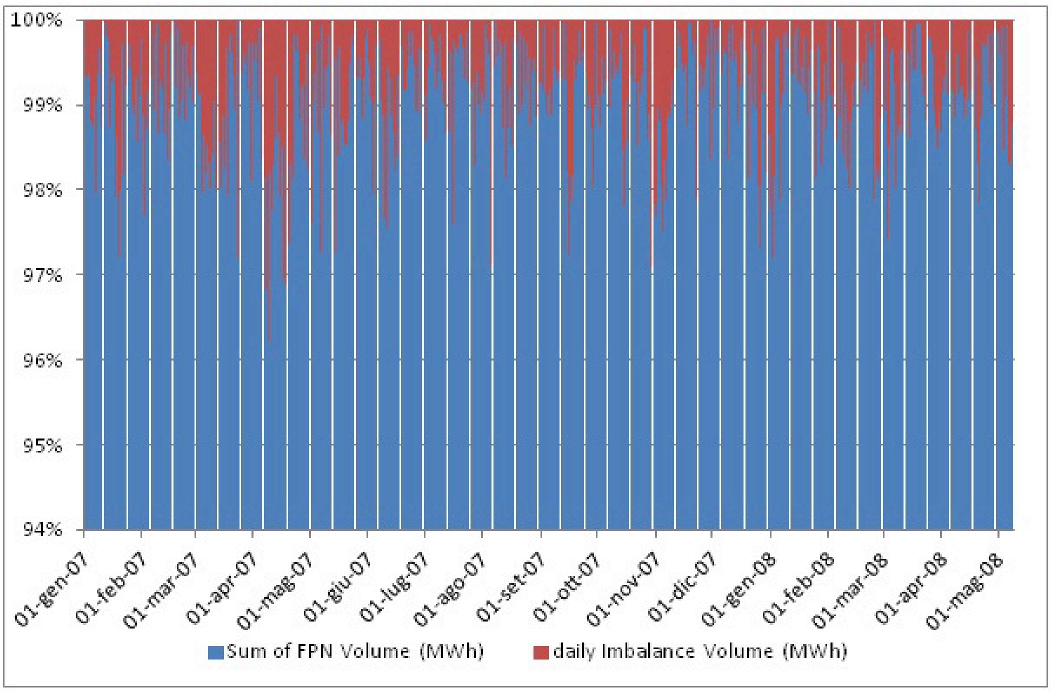

Fig. 2. Daily imbalance volume, Final Physical notification ratio - UK (Source: Netareport - National Grid).

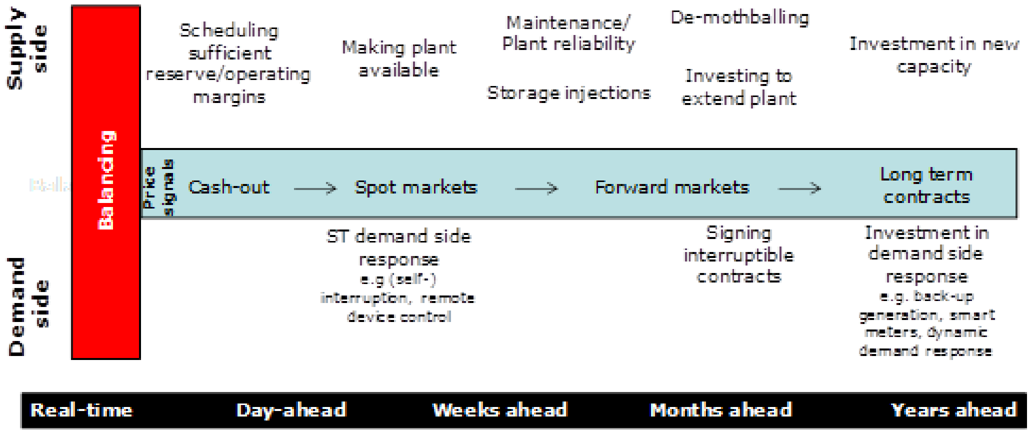

Fig. 3. Price signal sequence

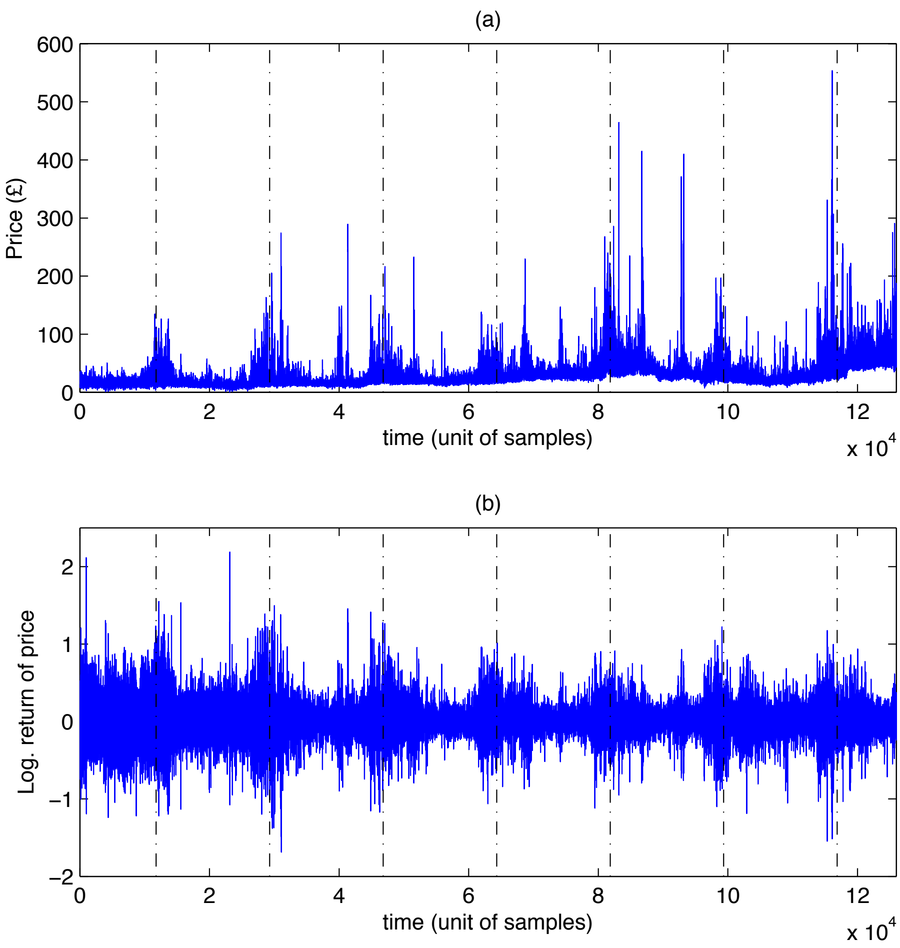

Fig. 4. Time series of the UK electricity price in the period March 2001-August 2008. Panel (a) shows the time series, panel (b) shows the logarithmic returns.

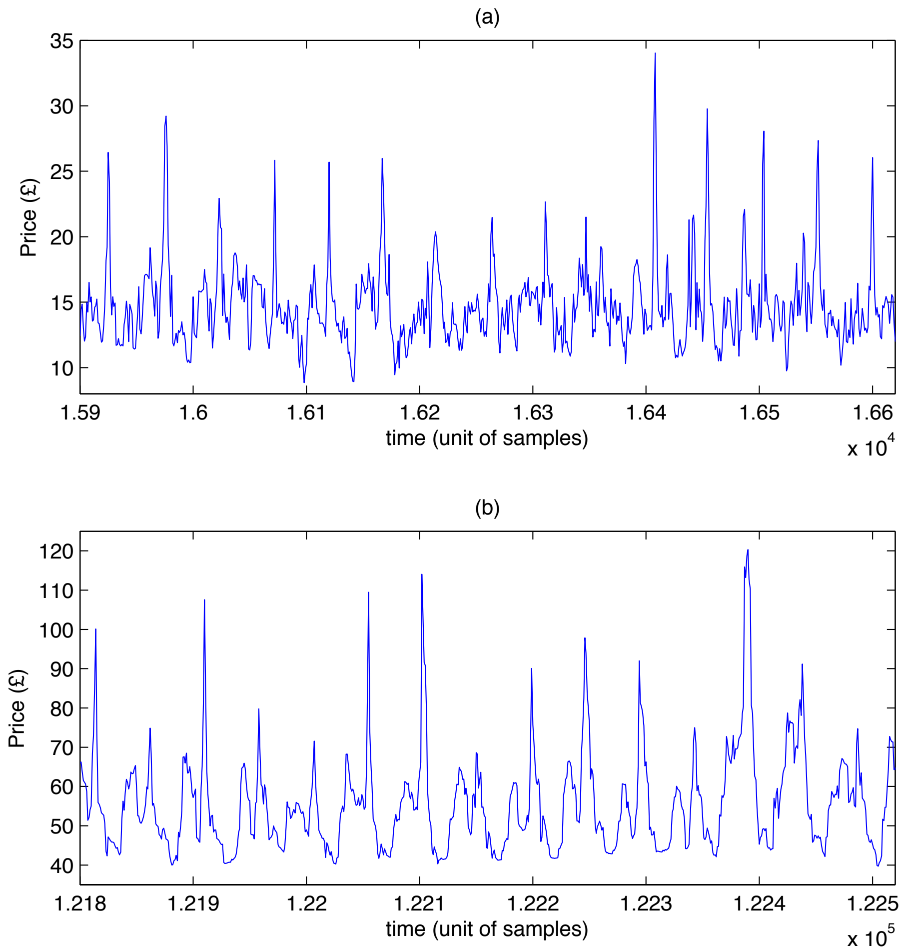

Fig. 5. Detail of time series. (a) typical oscillation in the period I 02/27/2002-03/14/2002; (b) typical oscillations in the period II 03/13/2008-03/28/2008, showing a less noisy and regular behavior.

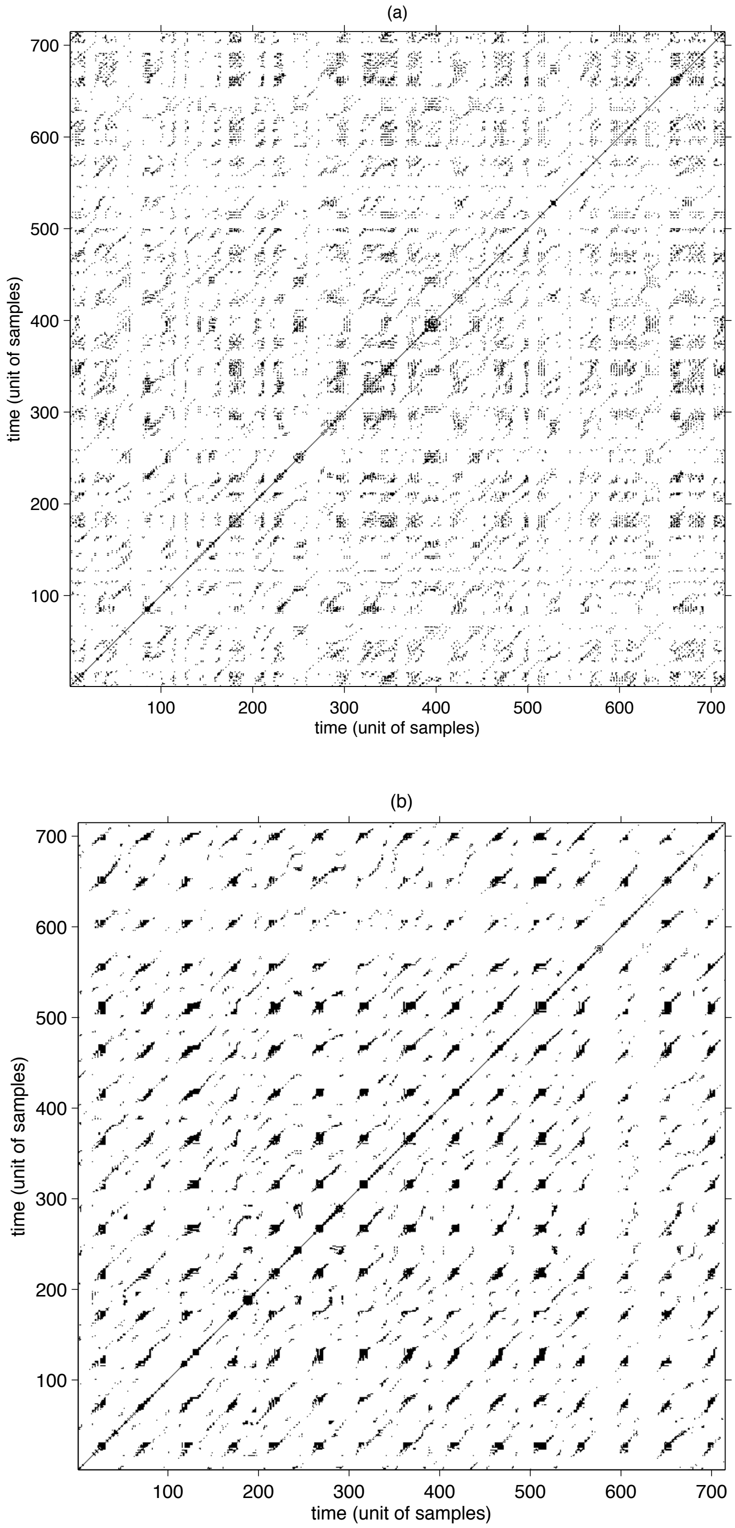

Fig. 6. Recurrence plots of the time series showed in figure 5. (a) The RP of period I shows irregular structures characterized by a distribution of isolated points, while the daily periodicity is difficult to identify; (b) The recurrence plot of period II shows a periodic behavior: a significative fraction of point is organized in lines, while the daily and weekly periodicity are more visible.

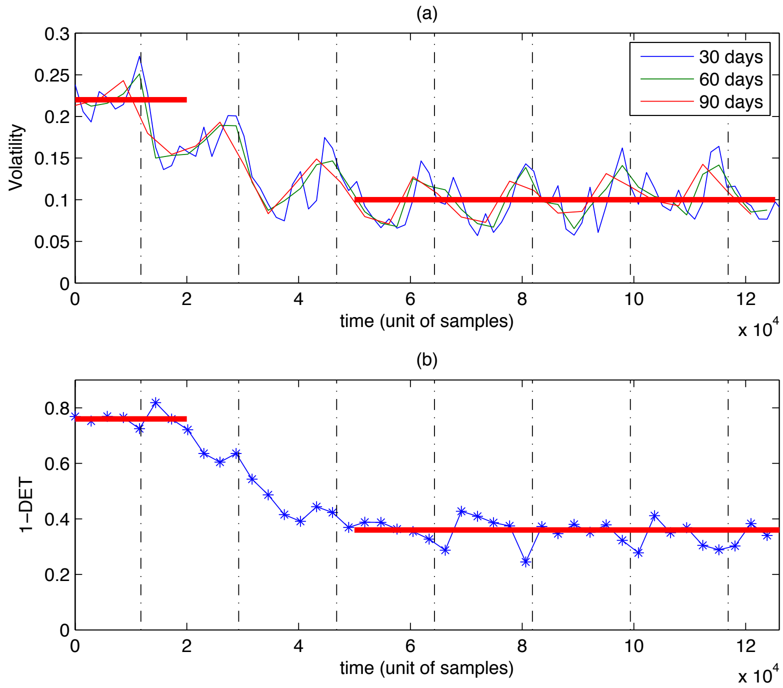

Fig. 7. Volatility and recurrence analysis of the time series. Panel (a) shows the volatility computed for time intervals of 30,60, and 90 days. Panel (b) reports the computation of $1 - DET$. Both indicators clearly identify two regions separated by a transition period.

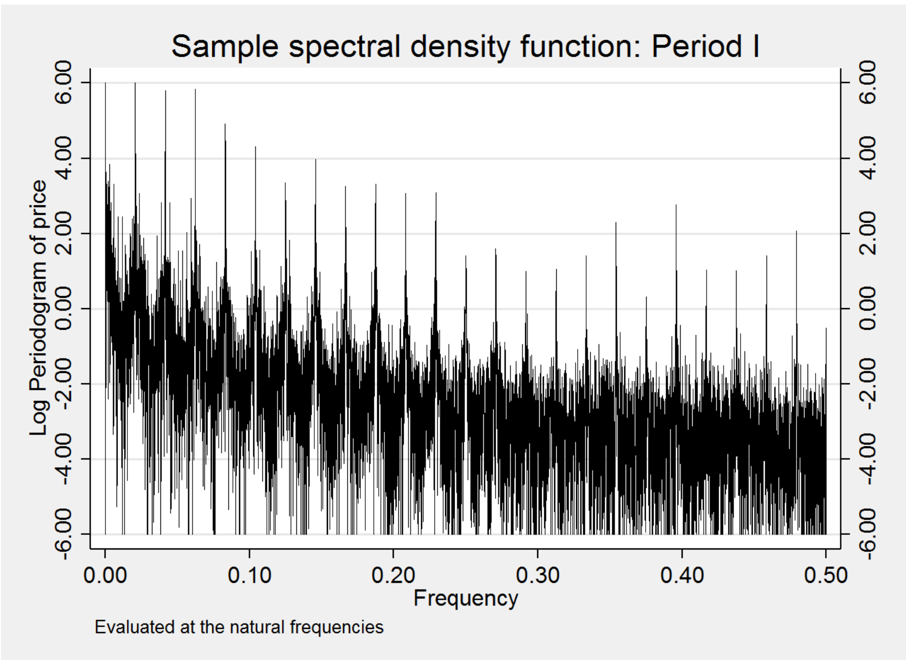

Fig. 8. Spectral densities of the price logarithm series over Period I = first 20,000 observations

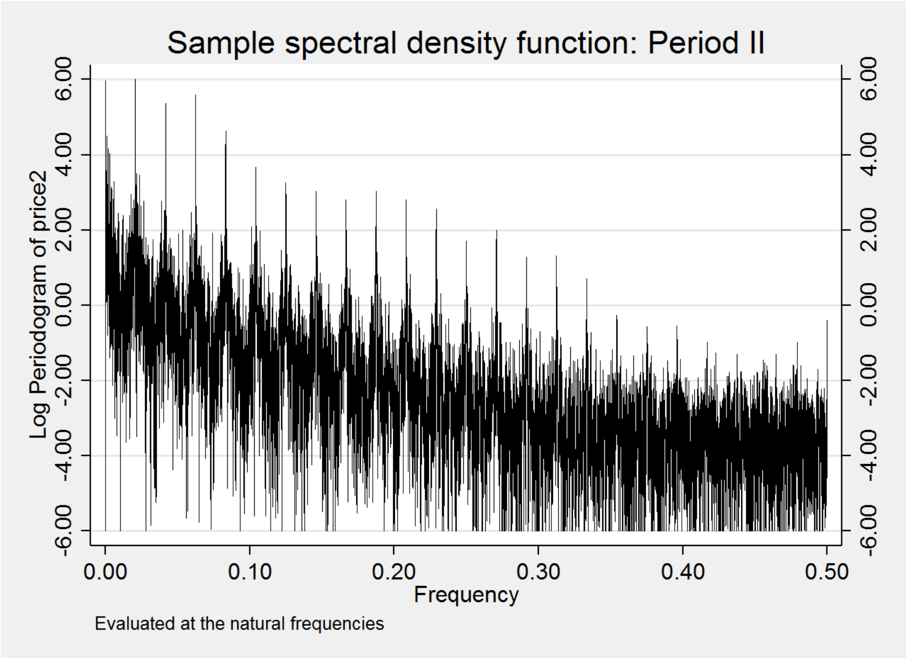

Fig. 9. Spectral densities of the price logarithm series over Period II = second 20,000 observations

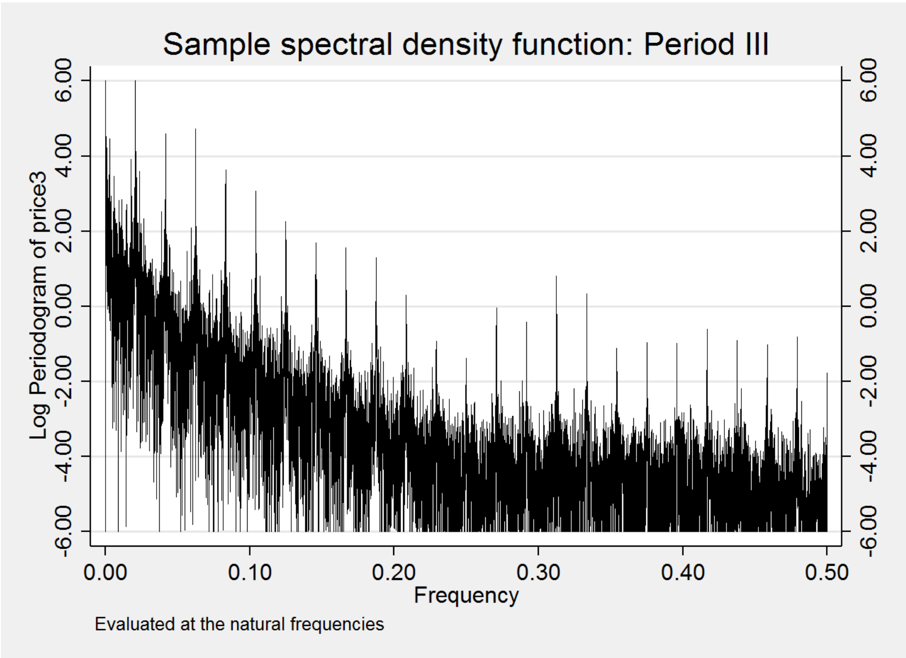

Fig. 10. Spectral densities of the price logarithm series over Period III = last 20,000 observations