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LEM
Working Paper Series

Market Design, Bidding Rules, and Long Memory in Electricity Prices

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2004/07 **April 2004**

ISSN (online) 2284-0400

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January 29, 2005

Abstract

In uniform price, sealed-bid, day-ahead electricity auctions, the market price is set at the intersection between aggregate demand and supply functions constructed by a market operator. Each day, just one agent - the marginal generator - owns the market-clearing plant. Moreover, day-ahead auctions are embedded in multi-segment systems, wherein diverse protocols coexist and change over time.

This complex environment leads to adoption of simple, adaptive bidding rules. Specifically, such a market design enables the emergence of two different types of routines, depending on whether the agent is a likely marginal or inframarginal generator. However, because of the uniform price mechanism, only the bidding behavior of the former can be reflected into market prices.

Depending on the specific way marginal generators process past information to set their bids - 'hyperbolic' or 'exponential' - electricity prices are likely to display long- or short-memory. Using an analogy with the hyperbolic discounting - a quite robust behavioral bias in humans - a long-memory view of electricity prices can be supported. This

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insight is confirmed by spectral analysis of daily data from NordPool and CalPX markets, in sharp contrast with most previous empirical studies.

This paper underlines the importance of institutional settings in determining the relationship between individual behavior and market outcomes, and proposes an interesting mapping of bidding rules and models of information processing into the time series properties of market prices.

JEL Classification: C22,D00,D21,D81,G14,L94.
Keywords: Market Design, Electricity Markets, Hyperbolic Discounting, Long Memory, Fractional Processes.

1 Introduction

There are many reasons to believe that the representative agent hypothesis, so widely employed in traditional economic models, does not generally hold (Stoker, 1986; Kirman, 1992). In a series of articles, Alan Kirman has underlined that no simple direct correspondence exists between individual and aggregate regularities (Kirman, 1999). Aggregation may add structure and regularity to noisy individual behaviors (Hildenbrand, 1994), giving rise to the well-behaved demand and supply functions one usually finds in economics textbooks. However, as shown by Sonnenschein (1972) and Debreu (1974), even if given properties happen to be satisfied at the individual level, it may well be that the aggregate does not display them. Hence, aggregate outcomes may not reflect individual behaviors. The structure of interactions between agents, as shaped by the market design, is proved to be crucial in this respect.

The impact of market design is very clear from a number of studies on very diverse markets, from stock exchanges (Amihud and Mendelsohn, 1987; Stoll and Whaley, 1990; Gode and Sunder, 1993; Bottazzi, Dosi and Rebesco, 2002), all the way to markets for perishable commodities. Kirman and Vignes' (1991) analysis of the Marseille fish market shows that, due to the complex network of local interactions enabled by the market design, aggregate properties fail to reflect the behavior observed in individual transactions.

The market for electric power, in terms of non-storability, is quite similar. Indeed, most empirical studies of electricity pools utilize econometric models originally chosen to describe the statistical properties of perishable commodity prices (see Schwartz, 1997). Using analytical tools (Newbery, 1998) as well as computational ones (Mount, 2000; Bower and Bunn, 2001), comparisons between uniform- and discriminatory-price auctions, as well as between different bidding protocols, have focused on the static efficiency properties of electricity markets. Results of the cited literature prove that significant differential effects are obtained under different market designs, holding constant the assumptions about individual rationality and cognition. This is consistent with Dosi's (1995) argument that institutions should be taken as the primitives in economic analysis. In the same vein, this paper stresses that market architecture provides the conditions for a differentiation of bidding rules, and in turn for whether the bidding behavior of a particular subset of agents gets reflected in the dynamic properties of the market price.

The institutional design most commonly adopted in electricity markets (bilateral, sealed-bid, uniform price auctions) is characterized by a simple structure of interactions. The price paid (received) to buy (sell) electricity is uniform, and set at the intersection between aggregate demand and supply curves constructed by the market operator. Thus, the market price is set by one agent at a time: the marginal generator. Coupled with the complexity of a multi-object, multi-segment and evolving market architecture, this justifies the emergence of different types of routines for marginal and inframarginal plants. As an implication of the pricing mechanisms, price dynamics is likely to reflect only the bidding rules of the former - i.e., price might be qualitatively similar just to the bids submitted by one type of agents. However, before believing that behind aggregate regularities there is the bidding behavior of marginal generators, one has to find a plausible behavioral mechanism.

Evidence from cognitive psychology on hyperbolic discounting (Loewenstein and Prelec, 1992; Laibson, 1997) demonstrates that agents frame information about periods far from the present according to a hyperbolic model. This paper conjectures that hyperbolic discounting provides a possible clue for the interpretation of behaviors whereby a specific statistical property - long-memory - characterizes electricity prices.

In Section 2, this argument is justified through a description of the main features of liberalized electricity markets. In Section 3, a theoretical analysis gives it a formal representation, and shows its equivalence to the statistical property of long-memory. In Section 4, estimation in the spectral domain on data from two electricity pools generally confirms the propositions of this work. Conclusions are drawn in Section 5.

2 Background

2.1 Market Design

Despite states of high and low economic activity follow each other in a deterministic fashion - within the day, the week and the year - the corresponding changes in the electricity market conditions are due to a large number of technological, behavioral and institutional causes, interacting in complex ways. These engender uncertainty, affecting the nature of market outcomes. Indeed, theoretical models of electricity auctions often incorporate uncertainty about either demand (Green and Newbery, 1992; von der Fehr and Harbord, 1993; Green, 1996; Newbery, 1998) or marginal costs (Wolfram, 1999; Bosco and Parisio, 2001).

Relatedly, from an institutional viewpoint two aspects are of primary relevance: (i) complexity of the market design; (ii) the uniform price and the merit order rules.

First, in the wholesale day-ahead market, each day 24 bilateral sealed-bid uniform price auctions simultaneously determine the quantities to be delivered and withdrawn the day after at the corresponding hours, as well as the related prices. Electricity day-ahead markets are equivalent to multiple object bilateral auctions (von der Fehr and Harbord, 1993; Wolfram, 1998; Brunekreeft, 2001; Ausubel and Cramton, 2002). As an implication, operators have to choose at the same time their strategies with respect to 24 daily auctions.

The need to guarantee system reliability has justified setting up further segments (i.e. over-the-counter, adjustment, reserve, real-time, and derivative markets); some with sessions held in parallel, some sequentially, and some with different rules (notably, continuous trading in over-the-counter, derivative, and adjustment markets). [1]

Furthermore, new segments have often been introduced well after the inset of the market (for instance, derivative markets in the NordPool: see Glachant and Finon, 2003). Agents have thus faced the need to revise their sets of behavioral rules as new profit opportunities have appeared. It is

[1] An example of what this implies in terms of uncertainty is provided by Bosco and Parisio (2001). When day-ahead market participants are allowed to trade power in other market segments, whether and to what extent competitors actually do so affects the cost structure of plants actually submitted in the day-ahead market. However, such information is not public knowledge.

then clear that participation to many market segments, with different and changing protocols, makes the decision problem extremely complex. And in highly complex and evolving environments, agents tend to stick to simple, possibly adaptive decision rules, such as routines (see, among others, Nelson and Winter, 1982; Dosi and Egidi, 1991; Dosi, Marengo and Fagiolo, 2003).

Second, the market price is set at the intersection between aggregate demand and supply functions, built by the market operator according to the so-called merit order. All agents admitted to inject (withdraw) power are paid (pay) the same uniform price. Besides the highly inelastic aggregate demand curve, supply bids are ordered from the lowest to the highest, until total demand is satisfied.[2] Furtherly, efficiency considerations require plants with the highest quasi-fixed costs to be selected for providing the base-load, i.e. to supply continuously their power.[3] Due to this, not all generating firms have the same probability to set the price. Actually, price is set by just one generator at a time. Let us call 'marginal generators' those who are most likely to set the price, and 'inframarginal' those who are higher in the merit order (i.e., the most efficient ones).[4]

The foregoing description of the market design has provided some preliminary clue as to the properties of bidding rules in electricity markets. Specifically, it is plausible that such rules are simple, adaptive, and heterogeneous. The empirical evidence on prices gives complementary insights for drawing a more complete picture.

[2]The elasticity of electricity demand to price is very low. There are two main reasons for this. First, because retail electricity prices are regulated, they do not reflect the dynamics of wholesale prices. Hence, final consumers are not directly exposed to wholesale price signals, and their demand is only responsive to idiosyncratic changes in their needs. Second, electricity is a necessary and pervasive good.

[3]Quasi-fixed costs are independent of the output level - just like fixed costs - but are born only if the plant is switched on. Costs for bringing the plant to the minimum efficient load belong to this category. Steam turbines, such as those using oil or coal as a fuel, are characterized by high quasi-fixed costs. Nuclear plants are similar in this respect. At the other end of the spectrum there are natural gas and hydroelectric plants, while combined-cycle plants are an intermediate solution. See Checchi (2003).

[4]Multi-plant generators can be considered marginal if at least one of their plants is likely to be market-clearing, due to high operating costs.

2.2 Existing Empirical Literature: Short- vs. Long-Memory

In the existing empirical literature, the analogy between electricity and perishable commodities - both are non-storable - has made traditional econometric models of commodity prices the reference point also for the analysis of the former.[5] Discrete Ornstein-Uhlenbeck and ARMA processes model prices as short-range correlated, mean-reverting, and stationary. The spiky behavior commonly observed is modeled through jump-diffusion processes.[6] Long-memory in the first and second order correlation structure of the data is either neglected, or empirically rejected. Mean-reversion and short-memory have been found by many authors. Among them, Wolak (1997), Ethier and Mount (1998), Lucia and Schwartz (2000), Mount (2000), Bystroem (2001), Knittel and Roberts (2001), Bellini (2002), De Jong and Huisman (2002), Escribano, Pena and Villaplana (2002), and Weron, Simonsen and Wilman (2004).

On the other hand, some studies have shown that electricity day-ahead price series can be described by long-memory processes. DeVany and Walls's (1999) finding of a zero-frequency unit root in data from Australian markets is the first in this stream of literature. In Leon and Rubia (2001), HEGY tests cannot reject the hypothesis that electricity prices from the Omel market (Spain) have unit roots at the long-run frequency, as well as at frequencies of one week, half a week, and a third of a week. After rejecting both the I(1) and the I(0) hypotheses, through Dickey-Fuller, modified R/S analysis, and KPSS tests, Atkins and Chen (2002) provide evidence of a fractional differencing order at zero frequency in prices from the Canadian market of Alberta, large enough as to imply non-stationarity. Fractional differencing and non-stationarity are also detected by Carnero, Koopman, and Ooms (2003) in a periodic time series framework.[7] All these latter outcomes of

[5] See Schwartz (1997) for a survey of the empirical literature about commodity markets.

[6] The use of jump-diffusion models in finance has first been proposed by Press (1967), and later by Merton (1976).

[7] See: HEGY tests (Hylleberg, Engle, Granger, and Yoo, 1990) generalize the traditional Dickey-Fuller test under the null that increments of the process over, say, τ observations form a stationary sequence. For instance, it can be used to test whether weekly electricity price increments are stationary. Lo's (1991) modified R/S test has I(0) as the null. The test is based on the range of the partial sums of the process, rescaled by its variance. The KPSS test (Kwiatowski, Phillips, Schmidt, and Shin, 1992) is similar to the R/S, but uses the second moment. Periodic time series analysis (Franses, 1994) treats observations

diverse testing and estimation procedures support a long-memory view of electricity price dynamics.

2.3 Bidding Rules, Information Processing, and Time Series Properties

Conditional on the market design commonly adopted, the empirical evidence just described can be mapped into specific bidding rules and ways of processing past information.

Because of the uniform price mechanism, different generators may learn to use different routines, depending on their position in the merit order. Specifically, inframarginal generators are mainly interested in avoiding to bid higher than the expected marginal generator's bid. Within this threshold, any bidding rule is, in principle, as profitable as any other. Plausibly, it can be soon learned that past prices have been set by just a few generators. This is supported by some evidence on bidding behaviors. For instance, Wolfram (1998; 1999) shows that, on average, mark-ups set by generating companies in the England and Wales pool are increasing in their marginal cost level. If it is known that only few generators own plants with high marginal costs, then high-bidding generators are known to be at most those few, and are known to bid approximately the same. Hence, inframarginal generators might take the series of past prices as the relevant information to predict the threshold. But in order to understand how actually such a threshold is established, one has to investigate on the bidding rules of the marginal generators.

Bidding by potentially marginal generators might be based on their own past bidding behavior, most probably equal to past prices.[8] Bids actually taken into account should be those regarding past sessions of the market, when demand and supply conditions were similar to the current ones (say, the week before if there is a weekly pattern in demand). Such a backward-looking approach involves assessing the outcomes of past actions, which in turn requires using memory and critically evaluating past events. Memory constraints and biases may be binding, especially if one has to remember and make sense of what happened in a complex environment.

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for each day of the week - or each month, or each season - as realizations of a different stochastic process. In a way, this amounts to analyzing univariate series in a multivariate framework.

[8]Notice that, because prices are set according to a sealed-bid auction, each generator knows only past market prices and their own bids.

Extensive studies in cognitive psychology have shown that, when humans face dynamical decision-making problems, some behavioral biases emerge (Loewenstein and Prelec, 1992). An analogous of the hyperbolic discounting (Laibson, 1997) seems relevant here. In comparing pairs of recent bids, agents on the electricity market (i.e., the managers responsible for bidding strategies) may give the most recent one a high relative weight, while assigning to pairs of far-off bids roughly the same weights. An hyperbolically-decaying function models this much better than the exponential one traditionally used in decision theory.[9] Interestingly, an exponential decay corresponds to the definition of short-memory given in stochastics, while hyperbolically-decaying weights describe the property of long-memory.[10] Hence, finding long- or short-memory in electricity prices might signal the use of different bidding rules by the potentially marginal generators, rooted in different perceptions of the past.

In sum, due to the market design commonly adopted, electricity prices are set by one generator at a time, among a small group of potentially price-setting agents. Their bidding rules are different from those of the infra-marginal, and the dynamics of market prices should only reflect their behavioral biases. One of such biases, robustly observed in experiments - hyperbolic discounting - may suggest a source of long-memory in electricity day-ahead prices. Conditional on the pricing mechanism, long-memory in electricity prices is thus a reasonable hypothesis.

3 Theoretical Analysis

3.1 A Model with Hyperbolic Bidding Rules

In most electricity auctions, the uniform price is set by the marginal generator, namely the one who owns the less efficient plant among those selected in the merit order. However, because of uncertainty about demand and costs, the marginal generator is not known ex-ante. One can rather assign to each

[9] In the literature mentioned here, hyperbolic decay is used to model discounting of expected utility. However, one can use it also to model perception of past events. What matters is the asymmetric treatment of pairs of recent events versus pairs of far-off ones. On the contrary, a constant discount rate is consistent with an unbiased perception of events that are far from the present.

[10] See Beran (1992) and Baillie (1996) for formal definitions of long- and short-memory.

generator a probability to be marginal. Reasonably, such probability is close or equal to zero for plants providing the base-load.

In general, suppose m generators have positive probabilities φ_a, $\sum_{a=1}^{m} \varphi_a = 1$, for $a = 1, ..., m$, to set the market price. The remaining $N - m$ are the inframarginal. For simplicity, and without loss of generality, let us assume $m = 2$. Bids b_{at}, $a = 1, 2$, satisfy the following $\forall t$:

$$b_{at} = P_t + \delta_{at} \tag{1}$$

where δ_{at} is the deviation of a's bid from the actual market price. $\delta_{at} > 0$ means that a has not been selected in the merit order, while $\delta_{at} < 0$ indicates that a is the second less efficient generator among the selected ones. $b_{at} = P_t$ when a is marginal. Let us assume δ_{at} is an iid, zero mean and finite variance shock.

Here, it is proposed that agents set their bids according to a backward-looking rule, taking their own past bidding behavior into account. The following representation is analogous to the one that best matches discounting by economic agents, as observed in experiments (Loewenstein and Prelec, 1992; Laibson, 1997):

$$b_{at} = \bar{b_a} + d b_{a,t-\tau} - \frac{d(d-1)}{2} b_{a,t-2\tau} + ... - (-1)^r \frac{d(d-1)...(d-r+1)}{r!} b_{a,t-r\tau} + ... \tag{2}$$

with $\bar{b_a} > 0$, and $d \geq 0$. Notice that, similar to the experimental evidence, in which expected future values are weighted hyperbolically, here past bids are assigned hyperbolically decaying weights. That is, when choosing a bid, generators refer to the past by weighting pairs of recent bids very differently. On the other hand, they assign roughly the same weights to behaviors very far in time. d tunes the asymmetry between weights of recent and remote information. It is assumed constant across generators. $d = 0$ is the case of a constant bid. The hyperbolic discounting bias might characterize agents even if information is regularly recorded and collected: in fact, what matters is how agents process such information.

Because of the periodic behavior of electricity demand, it can be assumed that agents only refer to own bids submitted in past periods when market conditions resembled the current ones. For instance, when setting bids for a Wednesday, generators for sure take as references the past Wednesdays, perhaps also the day before, and simply discard the information regarding all other days of the week. More generally, agents take only account of the information about τ, 2τ, 3τ, ... days before, $\tau \in \aleph_+$.

By assumption, the price is set by either generator 1 or by 2. Hence, the expected price at time t reads:

$$E(P_t) = \varphi_1 b_{1t} + \varphi_2 b_{2t} \tag{3}$$

Plugging lagged versions of (1) into (2), and (2) into (3), after some algebra we get

$$E(P_t) = \bar{P} + dP_{t-\tau} - \frac{d(d-1)}{2}P_{t-2\tau} + ... + \left[d\tilde{\delta}_{t-\tau} - \frac{d(d-1)}{2}\tilde{\delta}_{t-2\tau} + ...\right] \tag{4}$$

where $\bar{P} \equiv \varphi_1\bar{b}_1 + \varphi_2\bar{b}_2$; and $\tilde{\delta}_t \equiv \varphi_1\delta_{1t} + \varphi_2\delta_{2t}$ has mean zero and variance $\sigma^2_{\tilde{\delta}}$. A more compact expression for the market price process is the following:

$$(1 - L^\tau)^d P_t = \bar{P} + \theta(L)\tilde{\delta}_t + \epsilon_t \tag{5}$$

where ϵ_t is $iid(0, \sigma^2_\epsilon)$, and orthogonal to $\tilde{\delta}_t$, $\forall t$; $\theta(L) \equiv dL^\tau[1 - \frac{(d-1)}{2}L^\tau + ...]$, and $L^\tau P_t = P_{t-\tau}$. Correspondingly, the spectral density function $f_P(\omega)$ reads

$$f_P(\omega) = \frac{1}{2\pi}\left[\sigma^2_\epsilon + |\theta(e^{-i\omega})|^2\sigma^2_{\tilde{\delta}}\right]\prod_{j=1}^{k}|1 - e^{-i\tau\omega}|^{-2d} \tag{6}$$

with $\omega \in [-\pi, \pi]$, and $k \geq 1$. Such a power spectrum has k singularities at frequencies corresponding to the roots of $1 - z^\tau = 0$. The factor $g_P(\omega) \equiv \prod_{j=1}^{k}|1 - e^{-i\tau\omega}|^{-2d}$ is the long-memory component.

The short-memory component is $h_P(\omega) \equiv \frac{1}{2\pi}[\sigma^2_\epsilon + |\theta(e^{-i\omega})|^2\sigma^2_{\tilde{\delta}}]$, bounded at all frequencies. Its behavior depends on the properties of $\theta(L)$, which conveys, in the current price, differences between actual past prices and past bids by potentially-marginal generators. Notice that $\theta(L) = 0$ for $d = 0$; $\theta(L) = L^\tau$ for $d = 1$. The short-memory component has more structure when $|d| \in (0, 1)$, which sheds light on an interesting interaction with the long-memory factor.

To put things into perspective, let us compare the above with the case in which agents weight exponentially their past bidding; i.e.:

$$b_{at} = \bar{b_a} + \alpha b_{a,t-\tau} + \alpha^2 b_{a,t-2\tau} + \alpha^3 b_{a,t-3\tau}... \tag{7}$$

with $|\alpha| < 1$. Then,

$$E(P_t) = \bar{P} + \alpha P_{t-\tau} + \alpha^2 P_{t-2\tau} + ... + [\alpha\tilde{\delta}_{t-\tau} + \alpha^2\tilde{\delta}_{t-2\tau} + ...] \tag{8}$$

or, more compactly, for ε_t $iid(0, \sigma_\varepsilon^2)$, and $\phi(L) = 1 - \alpha L^\tau - (\alpha L^\tau)^2 - ...$:

$$\phi(L)P_t = \bar{P} + \frac{\alpha L^\tau}{1 - \alpha L^\tau}\tilde{\delta}_t + \varepsilon_t \tag{9}$$

with spectral density

$$f_P(\omega) = \frac{1}{2\pi}\left[\frac{\sigma_\varepsilon^2 + |1 - \alpha e^{-i\tau\omega}|^{-2}|\alpha e^{-i\tau\omega}|^2\sigma_{\tilde{\delta}}^2}{|\phi(e^{-i\tau\omega})|^2}\right] \tag{10}$$

bounded at all frequencies. Hence, prices in an electricity market with 'exponential' agents would display just short-memory, the property found by most empirical analyses of electricity prices (see Section 2.2). It is worth noting that exponential agents are not commonly observed in experiments. For this reason, it is unlikely that electricity prices display just short-memory dynamics.

The parameters defined above - d and τ - are likely to assume different values in peak-load and in off-peak hours. The two cases are analyzed below.

Off-peak case. As shown by von der Fehr and Harbord (1993), the off-peak (or low-demand) Nash equilibrium strategy for generators is to bid at marginal cost; i.e., $b_{at} = c_{at}$. The intuition is that, as long as demand is below system capacity, bidding above marginal cost engenders the risk of not being called into operation.[11] If generators play the Nash equilibrium, and marginal cost is constant ($c_{at} = c_a$), then it makes sense to assume away any behavioral bias. Putting it another way, in this case marginal generators have no memory problems: own cost information is constant, whether it is about very recent or very remote periods. Hence, $d = 0$ seems a reasonable hypothesis for the marginal cost-bidding strategy. On the other hand, bounded rationality implies that agents may not play the low-demand Nash equilibrium. $d > 0$ would signal this.

[11] More specifically, an equilibrium in pure strategies only exists when demand is low and deterministic. If demand uncertainty is assumed, then agents face a trade-off between submitting a high bid (which increases the likelihood to become the marginal generator), and a safer, but potentially less profitable, low bid.

Typically, demand conditions in off-peak hours do not change significantly from day to day. Electricity demand during the night is low regardless of the day of the week. Thus, generators are assumed to take the day before as reference point for their bidding strategy: $\tau = 1$.

Finally, an interesting consequence of the $d = 0$ hypothesis is that in off-peak times, the short-memory component has no structure - basically, just an *iid* sequence.

All this is summarized in the following

Proposition 1. If bidding is at marginal cost, i.e. $b_{at} = c_a$, $\forall a = 1, ..., m$, and if there is no weekly pattern in demand, then the off-peak price P_t^{off} is governed by the following process:

$$P_t^{off} = \bar{P} + \epsilon_t \tag{11}$$

with spectral density function, for $\omega \in [-\pi, \pi]$:

$$f_{off}(\omega) = \frac{\sigma_\epsilon^2}{2\pi} \tag{12}$$

Proposition 1 allows to test the marginal cost bidding hypothesis: finding $d > 0$ and a rich short-memory structure might signal that generators bid above costs, although discarding other hypotheses (such as constant marginal costs over time) might lead to the same empirical result.

Peak-load case. When demand approaches system capacity, all generators, even the less efficient ones, are very likely to be called into operation. Because the risk of not being selected is low, bidding above marginal cost is the rule.[12] Generators are then 'free' to set their bids, and to change them over time. To the extent that behavioral biases emerge in such a case, d ought to be between 0 and 1.

The existence of weekly patterns in electricity consumption suggests generators take the week before as a reference point. However, the weekly pattern

[12] Von der Fehr and Harbord (1993) show that, when demand is high and deterministic, the uniform price converges to the highest admissible price, say, to the price cap imposed by regulators. Demand uncertainty makes this conclusion only a bit milder. Wolfram (1998; 1999) derives a 'bid shading function', mapping marginal costs into bids through a mark-up, and empirically shows that mark-ups set by generating companies in the England and Wales pool are increasing in their marginal cost level. The extent of market power during the 2001 California crisis has been assessed by Joskow and Kahn (2002): it accounted for a significant share of the total increase in prices during the crisis.

in electricity demand does not look symmetric: dramatic changes in demand levels are observed between Fridays and Saturdays, and between Sundays and Mondays; less so in other days. Because market conditions change little across most days of the week, the day before can also be considered as a reference point for bidding. Thus, at peak-load, marginal generators might give hyperbolically decaying weights to information from $\tau' = 1$ and $\tau'' = 7$ days before, with memory tuned by d' and d'' respectively.

Finally, some structure in the short-memory component should characterize the process: $\theta(L)$ has many lags because of the fractional d, meaning that the current price reflects many past deviations of bids by non-marginal generators from the actual past prices. All of this leads to the following:

Proposition 2. If marginal generators use hyperbolic bidding rules, and if they use day and week before as references, then the peak-load price P_t^{peak} is governed by the following process:

$$(1-L)^{d'}(1-L^7)^{d''}P_t^{peak} = \bar{P} + \theta(L)\tilde{\delta}_t + \epsilon_t \tag{13}$$

with spectral density function, for $\omega \in [-\pi, \pi]$:

$$f_{peak}(\omega) = \frac{1}{2\pi}\left[\sigma_\epsilon^2 + |\theta(e^{-i\omega})|^2\sigma_{\tilde{\delta}}^2\right]|1-e^{-i\omega}|^{-2(d'+d'')}\prod_{j=1}^{3}|1-2\cos(\eta_j)e^{-i\omega}+e^{-2i\omega}|^{-2d''} \tag{14}$$

and $\eta = [\frac{2\pi}{7}\frac{4\pi}{7}\frac{6\pi}{7}]$.

Because $f_{peak}(\omega) \to \infty$ as $\omega \to 0$ and as $\omega \to \eta_j$, $j = 1, 2, 3$, at peak-load one is supposed to find long-memory at long-run and weekly frequencies. The memory associated to the long-run frequency is expected to be equal to $d' + d''$, higher than the one related to weekly frequencies (d'').

3.2 Generalized Fractional Processes

The processes suggested by the foregoing analysis belong to a rather general class of stochastic time series models: generalized fractional processes.

Indeed, if one approximates the short-memory component $h_P(\omega)$ by a truncated Fourier series, (13) corresponds to a generalized version of the Fractional Exponential (FExp) model introduced by Beran (1993).

Given a covariance-stationary sequence $\{x_t\}$, the Generalized Fractional Exponential (GFExp) model is defined by the following factorization of the spectral density function $f_x(\omega)$

$$f_x(\omega) = g_x(\omega)h_x(\omega) \tag{15}$$

with

$g_x(\omega) = \prod_{j=1}^{k} |1 - 2\cos(\eta_j)e^{-i\omega} + e^{-2i\omega}|^{-d_j}$

and

$h_x(\omega) = exp\{\sum_{h=0}^{s} \xi_h \cos(h\omega)\}$

Notice that $g_x(\omega)$ is in turn factorized in k sets of polynomials with complex roots of modulus one. Such polynomials are generating functions of Gegenbauer polynomials (see Gradshteyn and Ryzhik, 1980). The so-called Gegenbauer frequencies η_j model the periodic fluctuations in the data. Special cases of the GFExp model are: the FExp if $k = 1$; the Exponential model (Bloomfield, 1973) if $k = 1$, $d = 0$; and the ARFIMA$(0, d, 0)$ if $k = 1$, $s = 0$.[13]

The GFExp has the following properties. Assuming that the η_js are distinct, the process is stationary if $d_j < 0.5$ whenever $|\cos\eta_j| < 1$ for $j = 1, ..., k$, and $d_j < 0.25$ when $|\cos\eta_j| = 1$. Mean-reversion holds if $d_j < 1$ (if $d_j < 0.5$ when $|\cos\eta_j| = 1$). Interestingly, such a process can be at the same time mean-reverting, and non-stationary. The process is invertible if $d_j > -0.5$ whenever $|\cos\eta_j| < 1$ for $j = 1, ..., k$ and $d_j > -0.25$ when $|\cos\eta_j| = 1$. Notice that, as $\omega \to \eta_j$, the spectral density function becomes unbounded from above when $d_j > 0$, and vanishes when $d_j < 0$. The spectrum is bounded at all other frequencies.

[13]The GFExp process bears a strong resemblance with the Multiple Frequency Generalized ARMA (MFGARMA) model (see Woodward, Cheng and Gray, 1998), defined as

$$A(L)\prod_{j=1}^{k}(1 - 2\cos(\eta_j)L + L^2)^{d_j}(x_t - \mu) = B(L)\varepsilon_t \tag{16}$$

where: ε_t an i.i.d.$(0,\sigma^2)$ shock; μ is the mean;$A(.)$ an autoregressive polynomial of order p; and $B(.)$ a q-dimensional moving average polynomial. All roots to $A(z) = 0$ and $B(z) = 0$ are outside the unit circle. The MFGARMA model includes GARMA(p, d, η, q), ARFIMA(p, d, q) and ARMA(p, q) models as special cases. See Gray, Zhang and Woodward (1989) on GARMA processes.

4 Empirical Evidence

4.1 Estimation

The processes just reviewed provide a natural framework to test the propositions presented in this work. As a first step, the Gegenbauer frequencies (G-frequencies henceforth) are detected through periodogram maximization, as usually done in the related literature. Then, various methods can be used in order to estimate coefficients.[14] Drawing on Beran (1993), a simple way is to consider natural logarithms of the spectral density function, and estimate coefficients in the frequency domain through generalized linear regression with logarithmic link function. The log-spectrum of the GFExp process reads:

$$\ln f_P(\omega) = \sum_{h=0}^{s} \xi_h \cos(h\omega) - 2 \sum_{j=1}^{k} d_j \ln(2|\cos\omega - \cos\eta_j|) \qquad (17)$$

Because the LHS of the above equation is defined on a continuous interval, $[-\pi, \pi]$, it needs to be estimated. The periodogram is the typical choice in the log-periodogram regression approach (Geweke and Porter-Hudak, 1983; Robinson, 1995). However, it is an unbiased but not consistent estimate of the spectrum, so it has to be smoothed before taking logarithms. The averaged periodogram approach is used here: periodograms are computed over subsamples, and then averaged.[15] In order to assess the robustness of results, different lengths of the fast Fourier transform are considered (corresponding to 150, 200, 250, 300, and 350 datapoints). Not all of the log-spectrum ordinates are actually used: in order to avoid infinities, those corresponding to the localized G-frequencies are eliminated. Finally, restrictions on coefficients are tested through usual likelihood-based information criteria (Akaike Information Criterion, AIC; Bayesian Information Criterion, BIC; and Hannan-Quinn Information Criterion, HIC).

[14] Building on Geweke and Porter-Hudak (1983), Robinson (1995) proposes the log-periodogram regression, based on a linear approximation of the spectrum in a neighborhood of G-frequencies. Ferrara and Guegan (2001) use a two-stage procedure that allows also estimation of short-memory coefficients. Smallwood and Beaumont (2003) prove that consistent, unbiased and efficient estimates can be obtained if all coefficients are estimated simultaneously by maximum likelihood, an approach already used by Chung (1996).

[15] As shown by Bloomfield (1973), coefficients of an exponential model are asymptotically distributed according to a Gaussian. The averaged periodogram is shown to preserve this important result.

The assumption of covariance-stationarity is crucial for the spectral representation theorem to hold. Stationarity of the process cannot be taken for granted: it has to be tested for. One can tentatively perform the estimation on log-prices, and retain results only if they indicate stationarity. Otherwise, if non-stationarity is due to stochastic trends, differenced series should be used. Let us define the τ-days log-return by $R_t \equiv (1 - L^\tau)P_t$. The time-domain representation is as follows:

$$(1 - L^\tau)^{d-1} R_t = \theta(L)\tilde{\delta}_t + \epsilon_t \tag{18}$$

and the log-spectrum reads:

$$\ln f_R(\omega) = \sum_{h=0}^{s} \xi_h \cos(h\omega) + 2\sum_{j=1}^{k}(d_j - 1)\ln(2|\cos\omega - \cos\eta_j|) \tag{19}$$

The only difference with respect to the log-price process resides in the fractional differencing exponent: $d-1$ instead of d. Hence, one can estimate the memory of the τ-days log-return process and then retrieve the differencing degree of the log-price process by simply adding 1.

4.2 Data and Results

The data analyzed in this work consist of prices from two among the most widely studied markets: the NordPool and the California Power Exchange (CalPX). They are very different in many dimensions, including the composition of the supply stack, the degree of State ownership of generating plants, participation rules, and the structural evolution.[16] For this reason, they represent a nice 'sample' for assessing the robustness of price properties. However, they share a market design based on 24 daily bilateral uniform price auctions.

The available time series are the following. First, NordPool day-ahead log-prices from October 1, 2000 to November 20, 2002 (780 observations).

[16] There exists a vast literature on the institutional characteristics of electricity markets and on their evolution. Discussions about the NordPool are included in the book by Glachant and Finon (2003). Cameron and Cramton (1999), Joskow (2001), and Joskow and Kahn (2002) analyze different aspects of the CalPX setting. More general overviews are in Joskow (1996), Wolak and Patrick (1997), Green (2002), Holburn and Spiller (2002), and Newbery (2002).

Over time, NordPool has experienced major changes - institutional as well as technological, such as the introduction of a futures market in 1995, and the enlargement to Sweden, Finland and Denmark between 1996 and 2000. The latter process has altered NordPool's supply stack and, in turn, cost structures. The period analyzed here is the 'steady state' of NordPool's evolution. It can be considered homogeneous in structural terms. Moreover, the end of sample is set just before the crisis experienced at the end of 2002, in order to avoid spurious results.

Second, CalPX day-ahead log-prices from July 6, 1998, to May 31, 2000 (696 observations).[17] Actually, the market started on April 1, 1998, and it continued operating until January 31, 2001. A problem with missing values leads to discarding roughly the first three months of observations. The last month of price observations is discarded, because it reflects the intervention of the California Department of Water Resources as buyer of electricity, after insolvency of the Investor Owned Utilities (see Joskow, 2001). Also in this case, the time series is cut just before the inset of the crisis.[18]

Because of intradaily patterns, time series recorded at different hours of the day may display different dynamics. Specifically, significant differences are supposed to exist between prices in peak-load and off-peak hours. Here, we consider as off-peak prices those recorded at hours when mean demand (and in turn mean prices) has been the lowest. Similarly, hours when prices have been the highest on average are referred to as peak-load hours. For the markets at hand, the selected off-peak hours are 5 am (for NordPool) and 4 am (for CalPX). Peak-load hours are 9 am (NordPool) and 5 pm (CalPX). These can be considered as representative of broader sets of hours. Prices in hours from 1 am to 6 am resemble the chosen off-peak series, and prices in the remaining hours are similar to the peak-load series.

NordPool and CalPX normalized log-price series are shown in Figure 1. Weekly patterns are clearer in peak-load series than off-peak. Summary

[17]Sample sizes are not very large, for an analysis of long-memory behavior. One of the implications is that stochastic yearly seasonality cannot be detected in the spectral domain: one should have at least 6-7 years of daily observations (Granger, 1964). For the NordPool, the whole sample information (3993 obs.) could have been used. However, structural and institutional change has been quite radical. A trade-off exists between having a larger sample and satisfying the assumption of a stable data generating process.

[18]The CalPX and NordPool observations being discarded here have been used in Cavallo, Sapio and Termini (2003) for an analysis of how different aspects of the market design determine different properties of crises.

Figure 1: Plots of NordPool and CalPX day-ahead log-prices, normalized by the mean. Top-left: NordPool, 5 am. Top-right: NordPool, 9 am. Bottom-left: CalPX, 4 am. Bottom-right: CalPX, 5 pm.

statistics are displayed in Table 1 (Appendix). As often found in the empirical literature on electricity markets, log-prices have fat-tailed and asymmetric densities. The relative standard deviation is highest in the CalPX.

Tables 3 to 6 in the Appendix display estimates of the GFExp model on log-prices, for off-peak and peak-load hours in both markets, and for various lengths of the fast Fourier transform. t-values and likelihood information criteria are also reported. In both markets, off-peak prices are characterized by just one G-frequency (the 0 frequency), while 4 G-frequencies are detected in peak-load series (long-run, one week, half a week, one third of a week). Estimates indicate that day-ahead log-prices are non-stationary in both markets, for off-peak as well as peak-load hours. Notice, indeed, that off-peak fractional differencing coefficients are between 0.25 and 0.30; in peak-load hours, they tend to be well beyond 0.25 at zero frequency, and sometimes above 0.50 at the weekly ones. Taking account of the detected number of G-frequencies, all of this suggests considering differenced series, i.e. daily log-returns for off-peak, and weekly log-returns for peak-load hours. For these series, summary statistics are reported in Table 2, while results are in Tables 7 to 10. In Fig. 2, fitted log-spectra are superimposed to empirical ones. The implied fractional differencing coefficients are defined as the estimated fractional coefficients on log-returns, plus one. Because estimated differencing coefficients are always negative, the following description refers to stationary processes, as desired.

The main intuitions behind this paper are confirmed. First, long-memory holds generally across hours and across markets. The implied fractional differencing coefficients are indeed positive and significant for all series. As to magnitudes, off-peak prices have an implied zero-frequency fractional differencing coefficient of about 0.70 in the NordPool, and 0.80 in the CalPX markets, slightly lower than those in peak-load series (closer to 1). Weekly frequencies display less memory, even though occasionally, as in the NordPool case, the corresponding implied coefficients are greater or equal than 0.50. More memory at the long-run frequency is consistent with marginal generators bidding according to two different references: day before and week before. In sum, log-prices are long-memory and non-stationary in both markets, and almost always mean reverting.

Second, results are more similar across markets than across hours. Similar dynamics might be governing electricity prices in both markets, because demand patterns are alike and, less trivially, because market design and individual behaviors interact in similar ways. It is important to stress here that the basic design of electricity auctions (24 daily uniform price auctions) is common to the markets at hand. In both, the institutional design allows behavioral characteristics of one type of generators to be reflected in the dynamics of prices more than anything else. Hence, if behavioral biases - such as hyperbolic discounting - are typical of the human nature as such, similarity of results across markets is not surprising.

Third, off-peak fractional differencing coefficients are significantly greater than 0 in both markets. Given the historical accounts, one of the crucial hypotheses of Proposition 1 - constant marginal costs over time - seems realistic at least for the CalPX: in that market, almost no investments in new generating capacity were accomplished during the period analyzed (see Joskow, 2001). No dramatic changes occurred in the supply structure. As an implication, generators might not have played the low-demand Nash equilibrium. This can be taken as preliminary evidence that bidding above marginal cost occurs even off-peak.

Fourth and last, there is not very much structure in the short-memory

Figure 2: Empirical and fitted log-spectra of NordPool and CalPX day-ahead log-returns. Top-left: NordPool, 5 am, daily log-returns. Top-right: NordPool, 9 am, weekly log-returns. Bottom-left: CalPX, 4 am, daily log-returns. Bottom-right: CalPX, 5 pm, weekly log-returns. Length of the fast Fourier transform: 350 datapoints.

components. In NordPool off-peak prices, all coefficients but one in the short-memory polynomial have been restricted to zero, except in one case. Some more structure exists in the peak-load CalPX log-price process. A quite parsimonious representation can be given to the short-memory component of all series.

Summarizing, long-memory in day-ahead electricity log-prices is a property of off-peak as well as peak-load time series in two markets (NordPool and CalPX). Because price dynamics across markets is similar, conditional on the hour of the day, a possible explanation is that long-memory reflects the hyperbolic information processing of the generator who, enabled by the market mechanism, time by time turns out to set the price. Off-peak and peak-load price dynamics differ considerably, but fractional differencing provides evidence against marginal cost bidding in both states of the market.

5 Conclusions

In this paper, it has been shown that long-memory in day-ahead electricity prices is grounded on the bidding rules used by a specific type of agents, the marginal generators. One can conjecture that, because of the market design, two different types of routines emerge for marginal and inframarginal agents. These rules are supposed to be simple and adaptive, due to the complexity of a multi-segment, evolving market system. The uniform price and the merit order rules imply that only bidding by marginal generators is likely to affect market price dynamics. Relatedly, what actually seems to discriminate between long- and short-memory characterizations is the specific model according to which past information is processed by the price-setting agents. Estimation in the spectral domain, using data from the NordPool and CalPX markets, supports a long-memory view of electricity prices, and points at hyperbolic information processing as a plausible mechanism behind the bidding behavior of marginal generators.

Hence, within the stream of a growing related literature, this paper confirms the importance of institutional settings in shaping behaviors and, through them, market outcomes. Furthermore, it sheds light on an interesting mapping of bidding rules and ways of processing past information into the time series properties of market prices.

It is not clear whether, and to what extent, other market architectures would give rise to the same patterns. Pay-as-bid, sealed-bid auctions would eliminate the clear dichotomy between different types of routines: inframarginal generators would have much less degrees of freedom in their bidding. Open auctions would introduce wider interaction opportunities. This would be even more true of continuous trading: local interaction patterns and a multiplicity of local prices, unrelated to congestion issues, would emerge. Epidemics of opinion, such as those formalized by Scharfstein and Stein (1990) and Kirman (1991; 1993), are supposed to lead to a divergence between individual bidding and aggregate price properties, in contrast with the market dynamics analyzed here.

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mkt	n.obs	mean	std.dev.	c.v.	skewness	kurtosis
NordPool, 5am	780	4.9401	0.3200	0.0648	-0.7089	4.4176
CalPX, 4am	696	2.8217	0.5161	0.1829	-3.2356	28.6198
NordPool, 9am	780	5.1903	0.3355	0.0646	1.9343	13.1808
CalPX, 5pm	696	3.5336	0.4821	0.1364	1.3770	6.7565

Table 1: Summary statistics, NordPool and CalPX daily day-ahead log-prices, for off-peak and peak-load hours.

mkt	n.obs	mean	std.dev.	c.v.	skewness	kurtosis
NordPool, 5 am, daily log-returns	773	0.0086	0.2974	34.5226	-0.0962	25.1162
CalPX, 4 am, daily log-returns	689	0.0415	0.5978	14.3901	2.5034	20.1644
NordPool, 9 am, weekly log-returns	773	0.0014	0.2742	192.4018	0.1773	29.7922
CalPX, 5 pm, weekly log-returns	689	0.0025	0.3790	148.8238	-1.6925	45.8107

Table 2: Summary statistics, NordPool and CalPX day-ahead log-returns, for off-peak and peak-load hours.

par	150	200	250	300	350
d_1	**0.3298**	**0.3074**	**0.2697**	**0.2414**	**0.2412**
	17.8597	11.7290	10.3338	10.0907	11.1100
ξ_0	**-5.5468**	**-3.8549**	**-3.5151**	**-3.5710**	**-3.7855**
	-90.1136	-42.6767	-38.8267	-42.8070	-49.8129
ξ_4	**0.3763**	-	-	-	-
	4.2545	-	-	-	-
ξ_7	**0.3255**	-	-	-	-
	3.6844	-	-	-	-
AIC	-82.1410	110.5014	185.2604	226.7999	252.1477
BIC	-70.2616	117.1279	192.2383	234.1534	259.8173
HIC	-77.4737	113.1465	188.0103	229.6939	255.1583

Table 3: Estimates of the GFExp model on NordPool day-ahead log-prices, off-peak hour (5 am), different lengths of the fast Fourier transform. Point estimates are in bold figures when 95 percent significant (t-values are reported below them).

par	150	200	250	300	350
d_1	**0.3297**	**0.1801**	**0.2748**	**0.2619**	**0.2667**
	15.5128	3.9433	12.9526	15.6621	17.8129
ξ_0	**-3.3218**	**-2.8811**	**-1.9832**	**-1.7761**	**-1.9044**
	-45.8989	-30.8009	-29.4565	-33.3091	-39.7462
ξ_1	-	**0.5257**	-	-	-
	-	2.3654	-	-	-
ξ_2	-	-	**-0.5651**	**-0.5832**	**-0.5724**
	-	-	-5.4671	-7.1202	-7.7750
ξ_7	-	-	**0.4671**	**0.4674**	**0.4314**
	-	-	4.8437	6.1247	6.2965
AIC	-34.1581	126.0920	36.6831	-43.4168	-72.5205
BIC	-28.1637	136.0020	50.6718	-28.6825	-57.1579
HIC	-31.7697	130.0300	42.2159	-37.6016	-66.4758

Table 4: Estimates of the GFExp model on CalPX day-ahead log-prices, off-peak hour (4 am), different lengths of the fast Fourier transform. Point estimates are in bold figures when 95 percent significant (t-values are reported below them).

par	150	200	250	300	350
d_1	**0.4372**	**0.4189**	**0.4331**	**0.4445**	**0.4561**
	8.8137	7.3735	8.8659	9.3451	10.3702
d_2	**0.4539**	**0.3912**	**0.3775**	**0.3492**	**0.4276**
	5.3141	3.8385	4.3579	4.0776	5.5621
d_3	**0.6506**	**0.5983**	**0.5991**	**0.5372**	**0.5688**
	7.3096	6.0336	6.7622	6.3303	7.2170
d_4	**0.4182**	**0.3630**	**0.3635**	**0.3758**	**0.4131**
	5.0620	3.6901	4.3899	4.5620	5.4780
ξ_0	**-2.7500**	**-3.0916**	**-3.6544**	**-4.1865**	**-4.4732**
	-34.9027	-33.1647	-45.0661	-52.4675	-60.5060
ξ_7	**-0.8563**	**-0.7380**	**-0.7522**	**-0.6806**	**-0.7384**
	-4.5543	-3.3430	-3.9326	-3.6226	-4.2594
AIC	-4.4563	127.2123	132.7797	203.2132	236.1812
BIC	13.1940	146.8505	153.6636	225.2325	259.1549
HIC	2.3758	134.9064	140.9798	211.8538	245.1781

Table 5: Estimates of the GFExp model on NordPool day-ahead log-prices, peak-load hour (9 am), different lengths of the fast Fourier transform. Point estimates are in bold figures when 95 percent significant (t-values are reported below them).

par	150	200	250	300	350
d_1	**0.2197**	**0.4170**	**0.3970**	**0.3435**	**0.3724**
	4.0384	8.8626	6.8583	6.4454	8.6494
d_2	**0.3874**	**0.3907**	**0.5474**	**0.5270**	**0.4900**
	5.0071	4.6301	6.1218	6.4876	7.6561
d_3	**0.2307**	**0.2154**	**0.3927**	**0.3320**	**0.3506**
	2.8126	2.6232	3.7921	3.6984	4.7639
d_4	0.1187	**0.3691**	**0.2616**	0.1633	**0.1809**
	1.9196	4.5315	2.8589	1.9040	2.6244
ξ_0	**-2.9362**	**-3.7407**	**-3.8930**	**-3.6440**	**-3.4292**
	-54.2124	-48.4571	-47.0407	-48.3601	-55.9925
ξ_2	**0.7396**	-	-	-	-
	4.4696	-	-	-	-
ξ_3	**0.3702**	-	-	-	-
	2.1773	-	-	-	-
ξ_4	**0.3742**	-	-	-	-
	2.7582	-	-	-	-
ξ_7	**-0.3442**	-	-	-	-
	-2.6535	-	-	-	-
AIC	-116.6194	48.3656	144.1826	169.4194	103.9262
BIC	-90.5368	68.0038	168.4887	195.0602	130.6876
HIC	-106.7640	56.0598	153.6909	179.4517	114.3813

Table 6: Estimates of the GFExp model on CalPX day-ahead log-prices, peak-load hour (5 pm), different lengths of the fast Fourier transform. Point estimates are in bold figures when 95 percent significant (t-values are reported below them).

par	150	200	250	300	350
$d_1 - 1$	**-0.3308**	**-0.3168**	**-0.2957**	**-0.2810**	**-0.3083**
	-12.2900	-10.7305	-11.6472	-11.3805	-2.5542
ξ_0	**-2.7995**	**-3.1315**	**-3.6837**	**-4.2150**	**-4.4901**
	-30.5416	-30.7794	-41.8345	-48.9620	-57.0933
ξ_2	-	-	-	-	**-0.2441**
	-	-	-	-	-10.0038
AIC	38.6214	160.2343	171.1082	245.8786	277.3973
BIC	44.6158	166.8607	178.1350	253.2728	288.9366
HIC	41.0097	162.8793	173.9071	248.8133	281.9482

Table 7: Estimates of the GFExp model on NordPool day-ahead daily log-returns, off-peak hour (5 am), different lengths of the fast Fourier transform. Point estimates are in bold figures when 95 percent significant (t-values are reported below them).

par	150	200	250	300	350
$d_1 - 1$	**-0.1719**	**-0.2067**	**-0.2214**	**-0.2354**	**-0.2317**
	-8.0524	-7.7361	-10.3297	-13.8004	-15.4988
ξ_0	**-3.3279**	**-2.8413**	**-1.9773**	**-1.7762**	**-1.9044**
	-45.7709	-30.8512	-29.0721	-32.6619	-39.8055
ξ_2	-	-	**-0.5726**	**-0.5900**	**-0.5739**
	-	-	-5.4830	-7.0630	-7.8066
ξ_7	-	-	**0.4706**	**0.4716**	**0.4324**
	-	-	4.8310	6.0602	6.3193
AIC	-32.7344	118.6035	41.8467	-31.4501	-73.5519
BIC	-26.7400	125.2299	55.8354	-16.7158	-58.1894
HIC	-30.3461	121.2486	47.3795	-25.6349	-67.5073

Table 8: Estimates of the GFExp model on CalPX day-ahead daily log-returns, off-peak hour (4 am), different lengths of the fast Fourier transform. Point estimates are in bold figures when 95 percent significant (t-values are reported below them).

par	150	200	250	300	350
$d_1 - 1$	**-0.2250**	**-0.2449**	**-0.1427**	-0.0399	-0.0511
	-3.4997	-3.3937	-2.3354	-0.8434	-1.1630
$d_2 - 1$	**-0.8321**	**-0.9044**	**-0.7599**	**-0.6498**	**-0.6441**
	-8.4067	-7.8336	-7.8009	-7.6220	-8.3921
$d_3 - 1$	**-0.5013**	**-0.4375**	**-0.4008**	**-0.4532**	**-0.4797**
	-5.5852	-4.4068	-4.5882	-5.3630	-6.0958
$d_4 - 1$	**-0.6030**	**-0.5383**	**-0.5053**	**-0.6053**	**-0.6270**
	-6.2803	-4.6436	-5.3289	-7.3803	-8.3285
ξ_0	**-2.8593**	**-3.1899**	**-3.7137**	**-4.2317**	**-4.5149**
	-36.0326	-34.3147	-46.5626	-53.2656	-61.1689
ξ_1	**1.1084**	**1.7102**	**1.1062**	-	-
	2.3166	3.0132	2.3489	-	-
ξ_7	**-0.6586**	**-0.5803**	**-0.7172**	**-0.6845**	**-0.6781**
	-3.4638	-2.6315	-3.8018	-3.6590	-3.9180
AIC	-1.1728	127.1084	125.3840	200.5579	235.0438
BIC	19.3187	149.9475	149.6901	222.5772	258.0175
HIC	6.6975	136.0128	134.8923	209.1985	244.0406

Table 9: Estimates of the GFExp model on NordPool day-ahead weekly log-returns, peak-load hour (9 am), different lengths of the fast Fourier transform. Point estimates are in bold figures when 95 percent significant (t-values are reported below them).

par	150	200	250	300	350
$d_1 - 1$	**-0.2755**	-0.0838	**-0.1548**	**-0.2090**	**-0.1854**
	-4.8640	-1.7610	-2.2378	-3.3798	-4.3222
$d_2 - 1$	**-0.5149**	**-0.5913**	**-0.6317**	**-0.7393**	**-0.7018**
	-6.3916	-6.9302	-5.9884	-7.7629	-11.0037
$d_3 - 1$	**-0.7632**	**-0.7613**	**-0.7314**	**-0.8113**	**-0.8460**
	-8.9383	-9.1692	-8.3502	-10.3723	-11.5378
$d_4 - 1$	**-0.7901**	**-0.5994**	**-0.4328**	**-0.5781**	**-0.9703**
	-12.2739	-7.2776	-4.1435	-5.8192	-14.1275
ξ_0	**-2.9571**	**-3.7780**	**-3.8779**	**-3.6344**	**-3.4612**
	-52.4462	-48.4043	-48.6208	-49.9430	-56.7198
ξ_1	-	-	**1.6337**	**1.6845**	-
	-	-	2.6651	2.9558	-
ξ_2	**0.6711**	-	-	-	**0.5298**
	3.8958	-	-	-	2.8915
ξ_3	**0.4763**	-	-	-	-
	2.6906	-	-	-	-
ξ_4	**0.4623**	-	-	-	-
	3.2735	-	-	-	-
ξ_6	-	-	**0.3652**	**0.4449**	-
	-	-	2.4691	3.2686	-
ξ_7	**-0.4484**	**-0.5092**	**-0.4263**	**-0.4145**	**-0.3104**
	-3.3201	-2.7548	-2.2562	-2.4143	-2.1677
AIC	-104.2275	48.1723	126.4058	149.2925	101.3573
BIC	-78.1449	71.0114	154.1167	178.5406	128.1187
HIC	-94.3722	57.0767	137.2050	160.7023	111.8124

Table 10: Estimates of the GFExp model on CalPX day-ahead weekly log-returns, peak-load hour (5 pm), different lengths of the fast Fourier transform. Point estimates are in bold figures when 95 percent significant (t-values are reported below them).