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Structure and stylized facts of a deregulated power market

Ingve Simonsen ^a, Rafał Weron ^b, Birger Mo ^c

^a*Department of Physics, NTNU, NO-7491 Trondheim, Norway*

^b*Hugo Steinhaus Center for Stochastic Methods,
Wrocław University of Technology, 50-370 Wrocław, Poland*

^c*Sintef Energy Research, NO-7491 Trondheim, Norway*

Abstract

Dramatic changes to the structure of the power sector have taken place over the past few decades. The major structural change being the introduction of competitive markets and power exchanges. In this paper, we conduct a detailed empirical study of the statistical properties of the Nordic power (Nord Pool) spot market. The aim of this study is to identify so-called stylized facts of the market. We address the structure of the market, and in particular, describe in detail the spot price forming process (equilibrium point trading). A collection of stylized facts is identified and discussed for the hourly system spot price, based on the entire 12 year history of available Nord Pool data. In particular we analyze: seasonality, weather effects, the human factor, return distributions, volatility, spikes, and mean-reversion (anti-correlation). The empirical study presented in this paper shed new light on the mechanisms, features and structures of these new commodity markets. The market features that distinguish them from more classic financial and commodity markets are pointed out.

Key words: Electricity market, Stylized facts, Deregulation, Econophysics, Interdisciplinary physics

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Email addresses: Ingve.Simonsen@phys.ntnu.no (Ingve Simonsen),
Rafal.Weron@pwr.wroc.pl (Rafał Weron), Birger.Mo@sintef.no (Birger Mo).

1 Introduction

Since the discovery of the light bulb, electricity has made a tremendous impact on daily life and the development of our society. Today, it represents a crucial component of modern way of life, and it is hard to imagine a life without it. There are nowadays just too many “gadgets” that are powered by electric power for such a situation to go on unnoticed. To provide every household with a sufficient supply of electric energy, power generator companies were set up. They used to serve dedicated geographical areas from which consumers *had* to buy their electricity (a monopoly situation). However, since the late 1980’s dramatic changes to the structure of the electricity business have taken place around the world. The original monopolistic situation was replaced by *deregulated markets*, where consumers in principle were free to choose their provider – the market place for electric power had become competitive. To facilitate trading in these new free markets, exchanges for electric power have been organized. Everything from spot contracts to derivatives, like forward and futures contracts, are traded. Even if a power exchange is not a necessity of a deregulated power market, it has been argued that the establishment of such exchanges has contributed to the high trading activity seen, for instance, in the Nordic power market. Its establishment has promoted competition and created liquidity in the market. Furthermore, it serves as a source for updated and independent market information.

In this paper, after briefly introducing the structure of the market, we point out and explain some of the many characteristics of a competitive power market. Herein, we focus on the Nordic spot power market, since this is one of the most developed and liquid electricity markets of today. However, many of the features that are described are not unique to this market, and can, in fact, be taken over to other market places as well. As the philosophy of a deregulated power sector spreads, and the amount of cross trading between the different regional markets becomes higher, one large, say, European competitive market will probably emerge.

This paper is organized as follows: We start by describing the market and the market place (Sec. 2). The first part of this section is devoted to a historical introduction to the Nordic spot market. Then the organizing principles and structure of the market are approached. Here it is described, for instance, how the bidding is being conducted. In the last part of Sec. 2 the so-called equilibrium trading is introduced that pinpoints the way that the spot price is being determined from the available offers. In Sec. 3, we start to identify and discuss a set of stylized facts for the Nordic power market. What is discussed, in particular, are: seasonality and its origin, mean reversion, spikes, return distributions, volatility. Many of the features are rather general and shared with other deregulated power markets. Finally in Sec. 4 the conclusions that

can be drawn from the results of this work is presented.

2 Nord Pool — the market place

2.1 *Some history*

The Nordic commodity market for electricity is known as Nord Pool [1]. It was established in 1992 as a consequence of the Norwegian energy act of 1991 that formally paved the way for the deregulation of the electricity sector of Norway. At this time it was a Norwegian market, but in 1996 and 1998 Sweden and Finland, respectively, joined in. With the dawn of the new millennium (2000), Denmark has become member as well. Only at this point in time was it fair to talk about a power exchange for the Nordic region. Presently there are no definite plans for Island, the last remaining Nordic country, to join this market.

Nord Pool was the worlds first international power exchange. In this market, participants from outside the Nordic region are allowed to participate on equal terms with “local” participants. To participate in the spot market it is required that the participants must have a grid connection enabling them to deliver or take out power form the main grid. For this reason the spot market is often also called the physical market. As for today, the physical market has a few hundred participants. More then one third of the total power consumption in the Nordic region is traded in this market, and the fraction has steadily been increasing since the inception of the exchange in the early 1990s. In addition to the physical market, there is also a financial market. Here, power derivatives, like forwards, futures, and options are being traded. This market presently has just under four hundred participants. For each of these two markets, about ten nationalities are being represented among the market participants.

2.2 *Market structure and equilibrium trading*

We will now try to describe the mechanism used by Nord Pool to determine the spot price. The spot price is a result of an hourly auction. It is determined from the various bids presented to the market administrator up to the time when the auction is closed. Before proceeding, we should stress that these procedures are specific to every exchange, and therefore are not general. However, the system used by Nord Pool shares many common features with other deregulated power markets.

At Nord Pool the auction based spot market for trading power for physical delivery is called Elspot. Strictly speaking, Elspot is a day-ahead (24-hours) forward market. What is traded are one-hour-long physical power contracts, and the minimum contract size is 0.1MWh. At noon (12:00 hours) each day, the market participants submit to the market administrator (Nord Pool) their (bid and ask) offers for the next 24 hours starting at 1:00 hours the next day. This information is provided electronically via the Internet (Elweb) with a resolution of one hour, *i.e.* one for each hour of the next day. Such information should contain both price and volume of the bids¹. The market participants are free (for hourly bidding) to provide a whole sell and/or buy stack for each hour. For instance, a power generator could be more interested in selling larger quantities of electricity if the price is high than if it is low. This is illustrated by Fig. 1 that depicts a bid/ask stack for a given hour for a fictitious power generator. From this figure, one observes that the generator is indeed interested in selling electric power if the price is p_1^A (or above). Furthermore, if the price is $p_2^A > p_1^A$ (or higher) the power generator wants to sell even larger quantities for that particular hour. Notice also from Fig. 1 that this market participant, in addition, is willing to buy electricity if the price is below p_1^B . That power generators also are willing to buy power is not uncommon at Nord Pool. They have typically committed themselves, at a mutually agreed upon price, to long term contracts with large consumers. These contracts they have to honor at any time during the contract period. A power generator is, of course, interested in optimizing his profit. This can also be achieved by buying electricity during low price periods, and thereby saving own production potential for periods when the price is higher. This strategy might work since a large fraction of the production in the Nord Pool area comes from hydro power that is easily tunable and where future production is directly related to the filling fraction of the dam (water reservoir).

By 12:00 hours Nord Pool closes the bidding for the next day and for each hour proceeds to make cumulative volume distributions (purchase and sale curves) *vs.* price for both bid ($V_B(p)$) and ask ($V_A(p)$) offers. Since there must be a balance between production and consumption in the electricity market, the so-called *system (spot) price*, $S(t)$, for that particular hour, t , is determined as the price where $V_A(S) = V_B(S)$. This is called the *market cross*, or *equilibrium point*. Trading based on this method is called equilibrium trading, auction trading or simultaneous price setting. If the data does not define an equilibrium point, no transactions will take place for that hour, and no spot price will

¹ To be formally correct, there are in fact three possible ways of bidding at Elspot. *Hourly bidding* consisting of pairs of price and volume for each hour. In *block bidding*, the bidding price and volume is fixed for a number of consecutive hours. *Flexible hourly bidding* is a fixed price and volume *sales* bid where the hour of the sale is flexible and determined by the highest (next day) spot price that is above the price indicated by the bid.

therefore be determined. So far, to our knowledge, this has never happened at Nord Pool.

After having determined the system price, $S(t)$ for a given hour of the next day's 24 hours period, Nord Pool continues by analyzing for potential *bottlenecks* (grid congestions) in the power transmission grid that might result from this system price. If no *bottlenecks* are found, the system price will represent the spot price for the whole Nord Pool area. On the other hand, if potential grid congestions may result from the bidding, so-called *area (spot) prices*, that are different from the system price, will have to be created. The idea behind the introduction of area prices is to adjust electricity prices within a geographical area in order to favor *local* trading to such a degree that the limited capacity of the transmission grid is not exceeded. How the area prices are being determined within Nord Pool differs between, say, Sweden and Norway, and we will not discuss it further here (see Ref. [1] for details).

What the reader should keep in mind is that the system price is the price determined by the equilibrium point (market cross) independent of potential grid congestions. The area prices will only differ from this price for those hours for which transmission capacity in the central grid is limited. The system price is therefore typically less volatile than the area prices where the characteristic spikes (see Subsec. 3.3) can be more pronounced due to grid congestions. In the rest of this paper we will focus on the system price.

3 Stylized facts

After having addressed the structure of Nord Pool's spot market, we will now proceed by considering the so-called *stylized facts* of this market. As will be seen below, some of its features are dramatically different from more well-studied financial and commodity markets.

The time series that will be considered in this work is depicted in Fig. 2. This is the Nord Pool system (spot) price, at an hourly time resolution, for the period from the beginning of May, 1992, and up to the same month of 2004 (12 years of data and 105216 samples in total). In the inset to this figure, the variation over an arbitrarily chosen week is presented so that the daily and weekly structure should be more apparent. Notice, that the system price data are regularly sampled in time, at an hourly interval, due to the way the market is defined.

3.1 Seasonality — the human factor and the weather conditions

Electric power can not be stored efficiently with today's technology. This implies that produced electric power has to be consumed instantaneously. To store electric power is not possible except for indirect methods like, for instance, water in a water reservoir, or a pile of coal. In contrast with conventional goods, inventory strategies cannot be used for electricity to even out large price fluctuations and cycles. In this section, we will also look into the influence of the human factor on the power prices, and how weather conditions and the climate influence the price setting of this commodity.

It is not hard to convince oneself that the level of human activity is reflected in the consumption data of electric power. When humans are active, they tend to demand more electricity than during their sleeping hours that, normally, are during nighttime. In the inset to Fig. 3, this daily cycle is indeed readily observed. The data seem also to support a “double” peak structure in the consumption curve; one in the morning and one late in the afternoon. This corresponds to the time of day when in the Nordic countries people normally get up in the morning and go to work (7–9h), and when they get home from work in the afternoon (17–19h) and start making dinner, watching TV, *etc.* It is also interesting to observe from the inset of Fig. 3 that the consumption is typically lower over the weekend, when major businesses are closed. In particular it seems to be the lowest during Sundays, for which the “double peak” structure seems to be less pronounced².

On a larger scale, one can observe a seasonal structure with high consumption during the winter period and lower consumption during summer time (Fig. 3). This structure can be attributed to the weather, and in particular to the outdoor temperatures. In the Nordic countries, and in particular in Norway, electricity is used to a large extent also for inhouse heating. Since the climate in northern Europe has cold winters, it is the enhanced consumption due to the cold that can be observed in the consumption data as a seasonal structure. It should be mentioned that for instance in California, where the summers are hot, and the winters “pleasant”, the highest consumption is in the summer months [13], and not during the winter period as is the case for Nord Pool. This situation is caused by the extensive use of air conditioning.

To summarize, we have seen that the consumption data have (at least) three types of periodicities: *daily*, *weekly*, and *annual*. The two first are caused mainly by the human activity cycles, while the latter in addition is a consequence of the climate. Notice that these cycles obviously are cultural dependent, and for other regions they might, and most probably will, be different.

² For a likely explanation for this effect, ask yourself when do you typically get out of bed during non work days?

By comparing the system spot price, $S(t)$, of Fig. 2 with the consumption data, $C(t)$, of Fig. 3, one indeed observes similar cycles for the price and the corresponding consumption: When the consumption is high, the system price is high and visa versa. Thus, one might suspect that the cyclic behavior that can be observed in the system price is a result of the consumption pattern. To see if this is the case, and to quantify this dependence in Fig. 4 we present the (normalized) cross-correlation function, defined as

$$C_{sc}(\Delta t) = \frac{\langle (S(t + \Delta t) - \langle S \rangle) (C(t) - \langle C \rangle) \rangle}{\sigma_s \sigma_c}, \quad (1)$$

where $\sigma_{s,c}$ are the (sample) standard deviation of the system price and consumption, respectively, and $\langle \cdot \rangle$ is used to denote the temporal average.³ Fig. 4 shows that there indeed is a significant correlation between the consumption and the system price. For zero lag ($\Delta t = 0$), this correlation function is 0.39, and is slowly decaying with increasing lag. After a one month period (30 days) the cross-correlation has dropped only slightly to a level just below 0.3 (see Fig. 4). Furthermore, the enhancement in the correlation for lags of integer number of days are also readily observed. It should be noted that the variation in correlation within a day is larger for the price-consumption correlation than the price auto-correlation itself (Fig. 4) defined in correspondence with Eq. (1). So, it can be concluded that the seasonality that can be observed in the system price can be attributed to the consumption patterns for electric power. Hence, it is fair to say that *consumption drives electricity prices!*

From Fig. 2 it can be observed that some years the overall price level seems to be higher than other years. This can for instance be noticed for the year 1996, and in particular for 2003. What happened during these years, was that the amount of water in the hydro power reservoirs, was lower than usual. This was caused by reduced amount of precipitation, and/or larger production earlier in the year. The media and some researchers have speculated that this situation partly was caused by the abuse of market power by some of the major market participants. This view is still controversial, though. Whatever caused such a situation, the result was that the prices typically were quite a bit higher during these periods. For year 2003, the above situation coincided with a rather harsh winter, resulting in unusually high prices that persisted to be high through large parts of the winter months of that year. Hence, the enhancement in the price levels of these years was a direct consequence of the weather and climatic conditions that then applied.

³ The correlation function defined in this way formally assumes that the time series involved are stationary. Since this assumption might be questionable for the system spot price process as well as the consumption time series, one should only use this expression for small values of Δt .

3.2 Mean reversion

The question of temporal price correlations in the Nord Pool system spot price will now be considered. For a classic (liquid) stock market, say, it is well documented that the logarithmic price changes are uncorrelated after a very short period of time (often just a few minutes) [5,6]. This implies that the (integrated) logarithmic price process is a Brownian motion⁴ that is characterized by a (self-affine) Hurst exponent of $H = 1/2$ [7]. Any deviation in the Hurst exponent from this value would signal a non-vanishing correlation in the underlying price process. When $H > 1/2$ one talks about positive correlations, while when $H < 1/2$ the correlation is negative, or what is called anti-correlation [7,9,12]. The presence of such correlations would give rise to so-called *arbitrage opportunities* [12]. This, however, would most likely be taken advantage of pretty soon in investment strategies, and will thus, as a consequence, disappear rather soon thereafter [16].

In Fig. 5 the so-called (1st order) wavelet coefficient (AWC) [9] $W_1[s](a)$ of the logarithmic Nord Pool system price, $s(t) = \ln S(t)$, is presented, where a corresponds to scale. If the analyzed signal has a self-affine scaling property [7], the (1st order) AWC-function is expected to scale as [9]

$$W_1[s](a) \simeq a^{H+1/2}. \quad (2)$$

A very prominent scaling regime can be observed in Fig. 5. It starts at approximately $a \simeq 1$ day and extends up to the sample size (several years of data). The corresponding Hurst exponent can be obtained from Eq. (2) as the slope of the curve, and one finds (see Ref. [9] for details)

$$H = 0.41 \pm 0.02. \quad (3)$$

This value is far from the uncorrelated case of $H = 1/2$, and this finding is thus somewhat surprising. It should be noted that a similar value has previously been reported for the Californian power market CalPX [13]. However, what is most remarkable about this result is the size and quality of the scaling regime. Scale invariance is present for almost three orders of magnitude in time, and the cyclic dependence of the spot price seems not to disrupt this invariance in any significant way.

Moreover, a drastic change in the scaling seems to take place for scales below one day. This is seen in Fig. 5 as a well-pronounced cross-over. To be able to clearly see such cross-overs, and more importantly, to not disrupt the scaling

⁴ The price process itself will then be what is called a geometrical Brownian motion.

above it, it is of uttermost importance to use analyzing techniques that decouple scales [11]. The average wavelet coefficient method suits this purpose rather well (see Ref. [9,11] for additional details).

According to Eq. (3), since $H < 1/2$, the spot price increments are *anti-correlated*. This means that, say, a positive price increment in the past is more likely to be followed by a price drop over an equal time period into the future, than a price increase. The price process is consequently non-Markovian [8]! Another way of saying this is that if you move away from an in principle time-dependent fundamental price level, you tend to be dragged back to this level again. In the economics literature, this phenomenon is therefore often termed mean-reversion [8,14]. So the spot electricity price process is a (non-Markovian) anti-correlated, or equivalently mean-reverting process. This is of importance when pricing, say, electricity options or futures. Not recognizing this fact increases your risk exposure if you are an option writer. The fundamental assumption of the celebrated Black-Scholes-Merton (BSM) option pricing formula [3,4,8] is that the underlying follows a geometric Brownian motion [5,8]. This is therefore *far* from being satisfied for the electricity spot price process. The same limitation and assumption apply to the important extension of the BSM-model for pricing of (European) futures options — the so-called Black 76 model [2] that is used extensively in the power industry.

Before closing this subsection, we will discuss why this anti-correlation seems to be so robust with time. Above we argued that a similar behavior for a stock market most likely would be shortly lived due to agents exploiting it [16,12]. So why does not the same thing happen in the power market. The key to understand this, comes from the fact that to hold a long position in a commodity has a certain price that normally is much higher than for, say, a stock. In the case of a commodity you may need to rent storage for it, the quality of the commodity may deteriorate with time *etc.*, or it may not be possible to store efficiently at all. The latter is the case for electric power for which there is no efficient technology (at a reasonable price) for storing vast amounts of power. Consequently, presently it has to be consumed immediately after production. Hence, there are no economical motives for exploiting the non-vanishing correlations. The anti-correlation does simply not represent an arbitrage opportunity like in a stock market. However, this may change in the future with the introduction of new technologies.

3.3 Price spikes

One of the most pronounced features of a spot electricity market are the spikes present in the spot price. Within a very short period of time, the system price can change substantially (Fig. 2). It is not uncommon that prices from one

day to the next, or even within just a few hours, can rise by a factor of ten or more. The time periods of considerable prices, are normally short, and prices tend to fall back down to more “normal” levels after just a few hours. For instance, on Monday February 5, 2001, the spot price for the 6th hour of that day was 190 NOK/MWh. Three hours later, it reached the all-day-high of 1952 NOK/MWh, an increase of more than a factor of ten. Moreover, at the end of the day electricity was again priced more moderately at 171 NOK/MWh.

Such rapid price changes are termed price *spikes* (or sometimes incorrectly jumps). They are of uttermost importance to take into consideration if one wants to understand and/or characterize the stochastic process of the electricity spot price. Hence, they are essential to consider when pricing derivatives that use the spot price as the underlying [?]. Failing to do so, will greatly underestimate, say, the option premium, and thus increase the risk for the writer of the option. For instance in the US, where the size of the spikes can be much more severe, there are examples of power companies having to file for bankruptcies after having underestimated or neglected the spikes. It should be mentioned, that the Nordic power market, is known for having less pronounced spikes than many other comparable markets. For the German market EEX [10], the Dutch APX power exchange, and the already mentioned US markets the spikes are much more pronounced. The presence of spikes in the spot price process is maybe the most characteristic stylized fact of a deregulated power market!

Price spikes of such a severity as for the spot electricity market are not known from stock markets or other commodity markets. So, what causes them to appear here, and not in other markets? [5,15] There is no single reason for this, nor a single simple explanation. Factors that contribute in this direction are the production stack and the demand curve (see definitions below), and how the spot price depends on those two. Some types of power generation are more expensive than others (see Fig. 10). If larger fractions of the power needed to satisfy demand comes from expensive sources, the price will go up. However, why may this result in spikes? To be able to understand this, one must consider the strategy used by some of the potential buyers in placing their bids. Since electric power is an essential commodity for many market participants, for which they hardly can operate without, some are willing to pay almost whatever it takes to secure a sufficient supply of power at any given time. As a result, some agents place, on a regular basis, bids at the maximum allowed level of 10,000 NOK/MWh for the amount of electric power they anticipate to need for that hour. Recall that the spot price is what a buyer has to pay for each unit of power independent of what he or she did bid initially as long as their bid was above (or equal to) the spot price. Hence, with this type of strategy, the worst case scenario is that a buyer has to stick with the high prices for a maximum of 24 hours. After this period, he or she is free to try to get power cheaper from alternative sources. With this type of

bidding strategies, there will always be some buyers that are willing to pay a considerable amount in order to cover their need of electricity.

Depending on the overall production capabilities at the time, only a slight increase in consumption may result in drastic increase in the spot price (see Fig. 10). This behavior is caused by more costly energy sources being put into production to fill demand. This is seen in Fig. 10 as a rapid rise in the supply stack for large total produced volumes. When the consumption drops slightly again, as we see that it does over the day, the price will quickly drop back to the average level, since now the more costly production facilities are no more needed for.

On the other hand, if the consumption stays almost constant, price spikes can still appear when considerable amount of “cheap” production capabilities are removed from the market. Then the quick rise in the supply stack will set in at a lower total production volumes, and the price will experience a rapid increase. There are several reasons why production capabilities are removed from the market: First, and the most obvious reason, is planned maintenance of plant and/or transmission grid. Second, there is always the possibility that plants and grids are taken out of production due to (unpredicted) technical problems. Last but not the least, there is the possibility of central market players abusing their market power. This is a rather controversial issue and the extent is hard to assess.

According to the above way of arguing, it should be expected that the likelihood of a spike is highest during the winter months, when the consumption is high in the Nordic area, and during consumption peak hours. By studying Fig. 2 one realizes that the spike frequency is definitely highest during the winter months. In particular, of the 100 largest spikes for the time period used to produce Fig. 2, more than 50% of the spikes took place in February, while the months November till February accounted for more than 90% of the spikes. The remaining spikes occurred in March and April, and no spike was hence present during the summer. In Subsec. 3.1 we saw that daily peaks occurred during the morning (7–9h) and in the afternoon. In Fig. 8 we present the distribution of the hour of the day when a spike appeared in the Nord Pool system price. This figure resulted from considering the 100 largest hourly logarithmic returns of the system price depicted in Fig. 2. This spike occurrence distribution is fully consistent with the hypothesis of spikes being caused mainly by *consumption constraints*.

Hence in conclusion, the price spikes are mainly a result of *supply shocks*. They are triggered by increased demand and/or the short-term disappearance of major production facilities, or transmission lines, due to failure or maintenance, or simply abuse of market power by central market players. There is simply just not enough energy available from “cheap” sources to cover the de-

mand. Due to the non-storability of electric power, these spikes are not easily removed by implementing inventory strategies as often is done for many other commodities.

3.4 Non-Gaussian return distribution characterized by fat tails

As we have seen in the previous subsections, prices can change drastically within rather short time periods. This means that the level of return can be considerable. In the power market it is not entirely clear if return is a fruitful quantity due to its non-storability. Even though, we will still study it here, if nothing else, to compare it to similar quantities found in more conventional markets. Before we do so, however, it is necessary to address the question of how to calculate returns. Return was originally introduced in order to measure how much one could gain/lose on an investment [8]. Typically the following two definitions are used in the literature ($\Delta p(t) = p(t + \Delta t) - p(t)$)

$$R_{\Delta t}(t) = \frac{p(t + \Delta t) - p(t)}{p(t)} = \frac{\Delta p(t)}{p(t)}, \quad (4)$$

and

$$r_{\Delta t}(t) = \ln \frac{p(t + \Delta t)}{p(t)} = \ln \left(1 + \frac{\Delta p(t)}{p(t)} \right). \quad (5)$$

The former is known simply as return and the latter as *logarithmic* return. In the literature, however, they are often not distinguished since whenever $\Delta p(t)/p(t) \ll 1$, as is the case for a stock market, say, these two definitions are equal to lowest order [6]. For the electricity market, on the other hand, we have seen explicitly above that $\Delta p(t)/p(t)$, is *not* necessarily small due mainly to the presence of the spikes in the spot price process. Hence, for a power market, one has to pay particular attention and distinguish between return and logarithmic return. For instance the daily return on the ninth hour (the hour of the spike) of the day before the “spiky” Monday (February 5, 2001) was $R = 10.3$ compared to the logarithmic return of $r = 2.4$.

Furthermore, for the notion of return to make sense as a measure of gain and loss, one assumes that there is no periodicity or seasonality in the analyzed data over the time window used in the calculation (see below). In our case, we have just seen that there indeed are such periodic structures on several time scales. One can therefore not easily interpret return for any time window without initially processing the spot price data in order to try to remove the cyclic behavior. However, to perform such periodic trend removal with confidence is not an easy task in general; it always leaves the open question to

what is being part of the trend and what is the contribution from statistical fluctuations. For the electricity market, this process is in particular delicate since the daily structure, caused by the consumption patterns, is so significant. It is therefore advisable to instead consider, returns calculated over a whole number days, or preferably whole weeks. On time scales of a few weeks, at the most, the annual cycle can be neglected to a good approximation.

In Fig. 6 we present the daily logarithmic return for the same set of data used to produce Fig. 2. The daily ($\Delta t = 24\text{h}$) volatility (see next Subsection) was found to be $\sigma_{\Delta t} = 0.16$, and it is this value that was used in the normalization of Fig. 6. It is evident from this figure that log-returns larger than several standard deviations are not uncommon. This is probably more apparent from Fig. 7 that depicts the probability distribution function of normalized logarithmic returns, $r_{\Delta t}/\sigma_{\Delta t}$. The dashed line in the same figure represents a standard Gaussian distribution. It is rather apparent that the distribution of daily returns is highly *non-Gaussian* and that its tails are fat. Its peakedness is quantified by the kurtosis, which for this pdf is found to be 73.9. Thus the pdf of daily returns is *leptokurtic*. These findings are similar to what is found for many financial markets if Δt is not too large [17,15,18–22]. Notice that the pdf of log-returns is slightly skewed. The skewness of this distribution was found to be 0.46, that would have been zero for symmetric pdf's.

Moreover, logarithmic returns (as well as returns) do not show long range correlations (see Fig. 9), a finding that replicates what has previously been found in many other markets [17,15,18–22]. There is, however, an enhanced correlation that can be associated with the seasonality of the system price, and that shows up as periodic patterns in the return auto-correlation function.

3.5 Volatility — its level, correlation, and clustering

Volatility (or logarithmic volatility) is defined as the standard deviation of the return (or logarithmic return) [5,6,8]. The daily (logarithmic) volatility was found to be $\sigma_{\Delta t} = 16\%$ for the dataset used to produce Fig. 6 ($\Delta t = 24\text{h}$). Typical values for daily volatilities found in other markets are: 1–1.5% for stock indecis, less than 4% for individual stocks, for bonds less than 0.5%, 2–3% for crude oil and about 3–5% for natural gas, and as low as 0.03% for short-term interest rates. We see that the electricity spot market has a considerably higher volatility than many other financial and commodity markets. This is indeed a characteristic feature of electricity spot markets. Surprisingly, the spot market at Nord Pool is known for its “low” volatility, and other liberalized power markets may have considerably higher volatility.

From the daily return data (Fig. 6) one can observe indications of so-called

volatility clustering, *i.e.* time periods where the volatility is consistently higher than in the other periods. Such fluctuations are reminiscent of similar intermittent patterns found in turbulence [6,23], and this observation has prompted efforts to compare turbulence to finance (See Ref. [6] and references therein). To make the time dependence of the volatility more explicit, we have taken a $T = 24$ hour period of daily return data as the basis for the calculation of the time dependent volatility $\sigma_{\Delta t}(t, T)$ (Fig. 11). From this figure, the volatility clustering should be evident. To quantify the volatility clustering, one may study the temporal volatility-volatility correlation function, $C_{\sigma\sigma}(\Delta t)$. It is defined in accordance with Eq. (1) for the variable $\sigma_{\Delta t}(t, T)$, and the result is presented in Fig. 12. Significant temporal correlations are indeed present for Nord Pool up to a time scale of approximately 100 days. Above this time scale, only correlation that can be distinguished from the noise result from the strong cyclic structure of the system price. The decay of $C_{\sigma\sigma}(\Delta t)$ with lag Δt is consistent with an inverse power law,

$$C_{\sigma\sigma}(\Delta t) \sim \Delta t^\nu \tag{6}$$

of a small exponent $\nu = 0.07$ (solid line of Fig. 12). For stock markets this exponent has been found to typically lie in the range 0.1–0.3 [24,25]. Notice the close-to monthly oscillation in the volatility correlation that is present in the results of Fig. 12. The origin of this monthly correlation we are still unsure about.

It is interesting to observe from Figs. 11 and 13 that there rather consistently is a high daily volatility period during the summer months. It should be recalled that for the same period, the system price is typically low due to the lower consumption. Hence, consumption constraints are not what is expected to explain this clustering phenomenon, since constraints are most frequent during the winter (cf. Subsec. 3.3). On the contrary, it is suspected that the explanation of this effect is to be found in so-called *forced production*. Large fractions of the Nordic power generation comes from hydro power. During the autumn and summer time, the filling fraction of the water reservoirs used by hydro-power plants are normally at their maximum. If, over time, the inflow of water to the reservoir is larger than the outflow needed to generate the power to satisfy demand, one may end up in the situation of so-called forced production. Under such circumstances the power generators will produce electricity almost whatever the price is, just to prevent the reservoir flooding. The dam owners are normally supposed to regulate the water flow, and they will be liable for potential damage caused by flooding. When many power generators go into the state of forced production, the system price may be very low, and possibly even negative.

On the other hand, there seems to be no, or very little, dependence in the absolute price change to the price level itself (Figs. 13). So, from day to day, say,

the change in absolute price will be approximately of the *same* level both for high and low price periods. This, of course, means that return (or logarithmic return) will be highest for the low price periods. Consequently, the volatility will also be highest for low price periods.

This phenomenon expresses itself as a negative correlation between volatility and price (not price difference). To our knowledge such a correlation has never been reported before for the power market, and it still remains to see if this is a unique characteristics of the Nordic market, or it may be extended to power markets in general.

Before, closing this section we should mention that we have tried to empirically identify the so-called leverage effect for the Nord Pool data [29,30,28,15,26]. This effect was observed by F. Black in the mid 1970s , when he observed that volatility of stocks tends to increase when the price drops [29]. Nowadays, the leverage effect is usually stated as the existence of a negative correlation between past returns and future volatility, but *not* the other way around. From the empirical volatility-return correlation function for the Nordic spot price data it has proven difficult to be conclusive on this issue due to the periodicity of the spot price data. Further work is need to clarify whether or not such higher order correlation effect also is present for in electricity market.

4 Conclusions

We have discussed the structure and some stylized facts of the deregulated Nordic spot power market — Nord Pool (Elspot). This market was the first international spot power market, and presently maybe, the most liquid market of its kind. The mechanism that fixes the spot price and the traded volume — the equilibrium method — was described and discussed. A brief discussion of how bottlenecks are resolved was also mentioned.

A deregulated power markets has many peculiarities, and we discussed several stylized facts for the Nord Pool market. The most characteristic feature of the spot electricity market is the presence of the spikes in the price. Empirically they were found to occur during the winter months and during hours of the day corresponding to peak consumption. Spikes we found to be associated with *supply shocks*, either by increased demand and/or a reduction in supply.

The return distribution was found to share many of the features of well-studied financial market — in particular the fat-tail phenomenon. Furthermore, returns poses only very short range correlation. Volatility on the other hand, shows long range power-law correlation, with clustering of high volatility during summer time. Additionally, a new type of negative correlation for the

Nordic market was identified between the volatility and the spot price. During low price periods, the volatility tends to be high and visa versa. This effect we attribute to forced production.

More well-known features of a liberalized power market were also surveyed; the seasonality of the spot price, and its mean-reverting character. The former finds its explanation in the weather conditions, and the human routines.

It is the hope that this work may prompt more interest in the deregulated power markets. There are many interesting problems to attack and that must be overcome in order to make the markets more efficient. In particular, how to price options and futures options in such markets with confidence is a great challenge where academic minded individuals can give substantial contributions, and where the benefits for the power sector, if successful, should not be underestimated.

Acknowledgement

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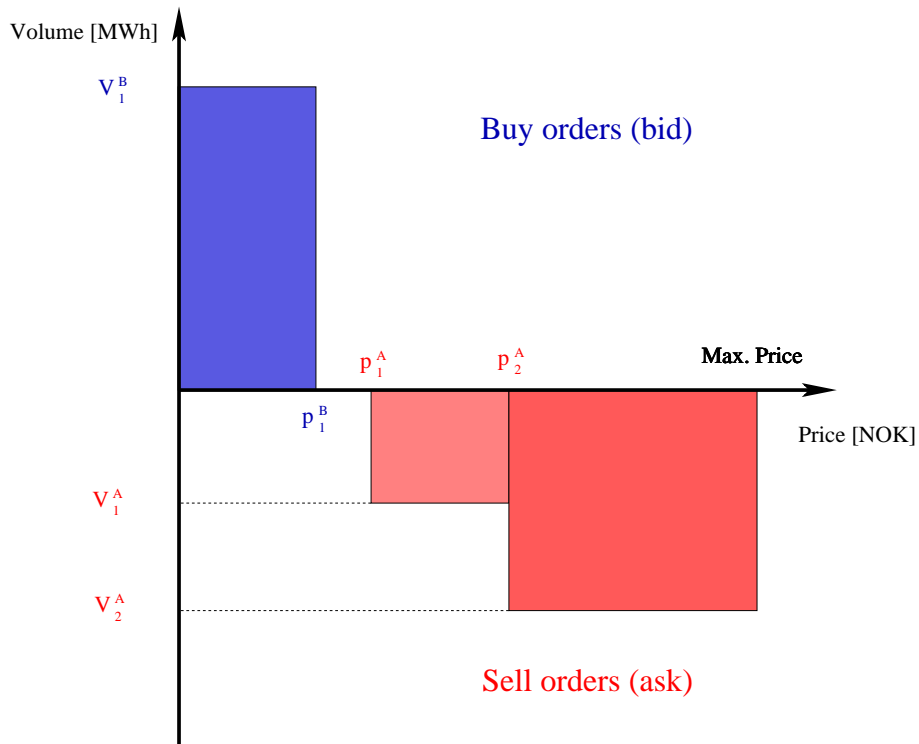


Fig. 1. The (bid and ask) orders for a given hour of a fictitious power generator. At Elspot buy orders are positive numbers, while those of sell orders are negative. In this particular example there is one purchase order of V_1^B MWh at a maximum price of p_1^B , and two sell orders. The two sell orders (asks) are for volumes V_1^A and V_2^A MWh and the sell prices are set to at least p_1^B and p_2^B , respectively.

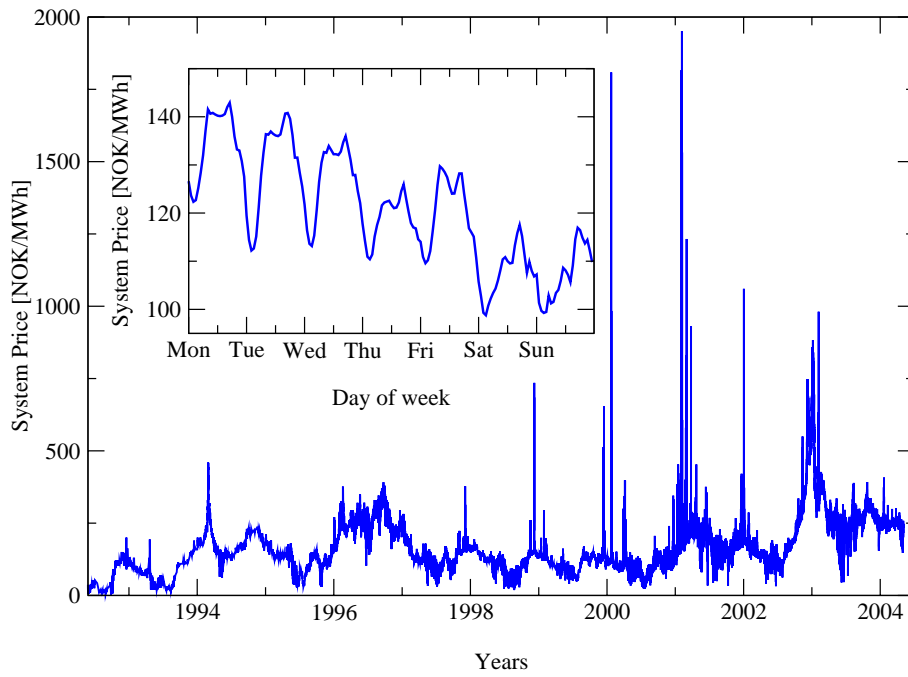


Fig. 2. Hourly system price for the spot market (Elspot) at the Nordic power exchange (Nord Pool) from May, 1992 up till May 2004 (12 full years of data). In total the data set contains 105216 data points. The inset depicts the system price for a typical week (1st week of 2000) chosen arbitrarily.

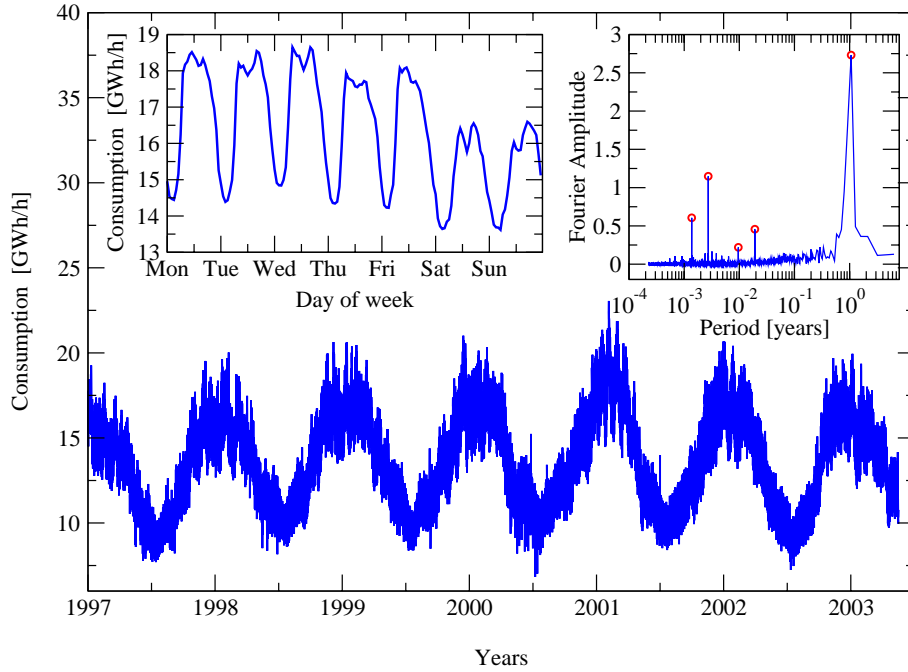


Fig. 3. Consumption data for Norway from the beginning of 1997 till mid-2003. In the left inset, the consumption for the 1st week of year 2000 is depicted. This is the same week for which the system price was presented in Fig. 2. The right inset shows the absolute value of the Fourier spectrum of the consumption data depicted in the main figure. The 5 open dots are used to indicate the main components. They correspond, from left to right, to a period of half-a-day, a day, half-a-week, a week, and finally a year. Those are the scales of the main periodicity of the consumption. Hence, a daily, weekly and annual cycle are supported in the data.

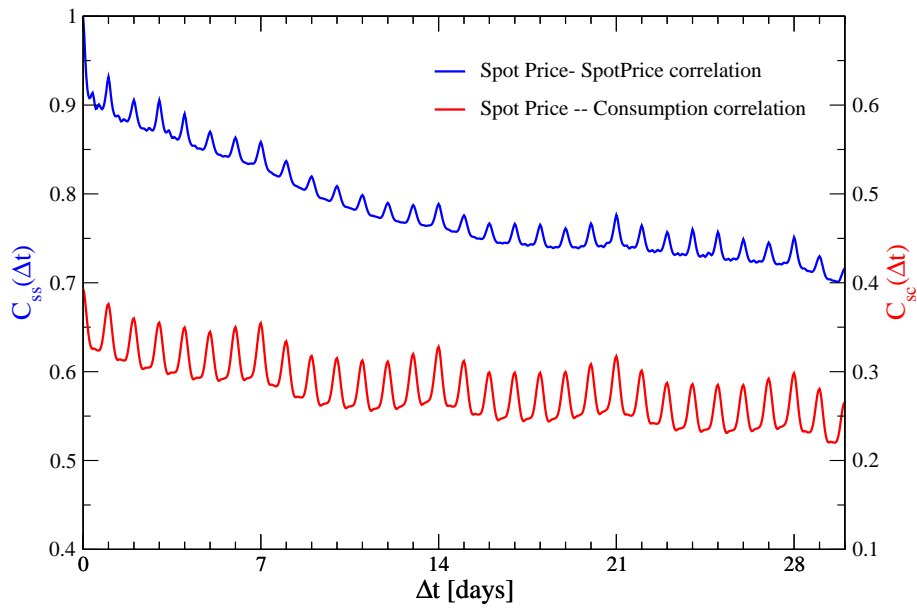


Fig. 4. The spot price auto-correlation function (left axis, upper curve), $C_{ss}(\Delta t)$, and the spot price consumption cross-correlation function (right axis, lower curve), $C_{sc}(\Delta t)$. These two correlation functions are defined in accordance with Eq. (1). Notice the daily and weekly cycles that are apparent in these functions.

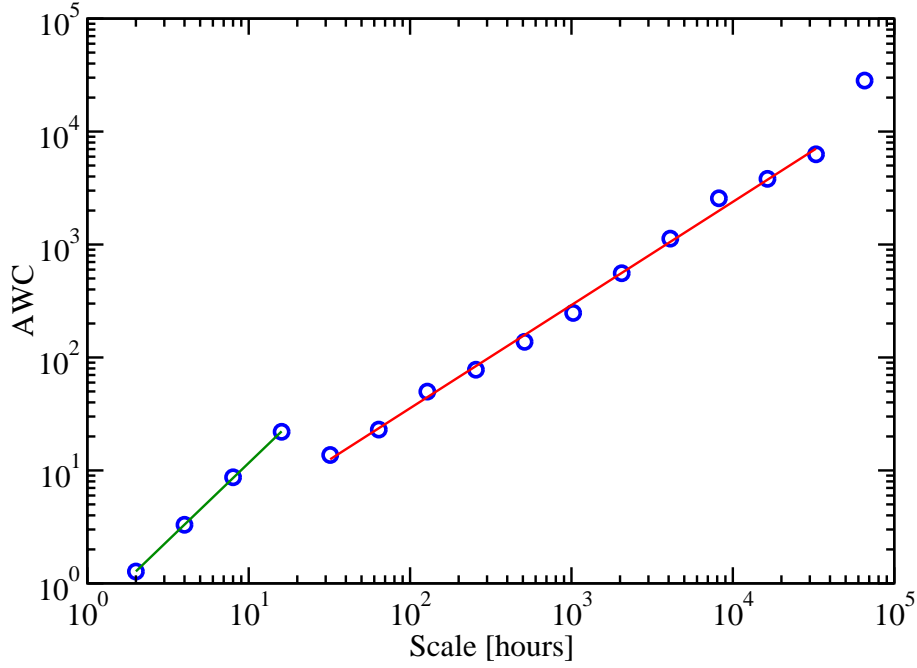


Fig. 5. The AWC spectrum, $W[p](a)$ vs. scale a , for the hourly Nordic electricity spot data presented in Fig. 2. A cross-over at $a_{\times} \sim 24 h$ is easily observed in the $W[p](a)$ -spectrum. The scaling region $a > a_{\times}$ corresponds to a Hurst exponent of $H = 0.41 \pm 0.02$ where the uncertainty is a pure regression error. The slope of the spectrum for $a < a_{\times}$ seems to indicate a persistent behavior ($H > 0.5$). The wavelet used in obtaining these results was of the Daubechies type (DAUB24). (Figure after Ref. [11].

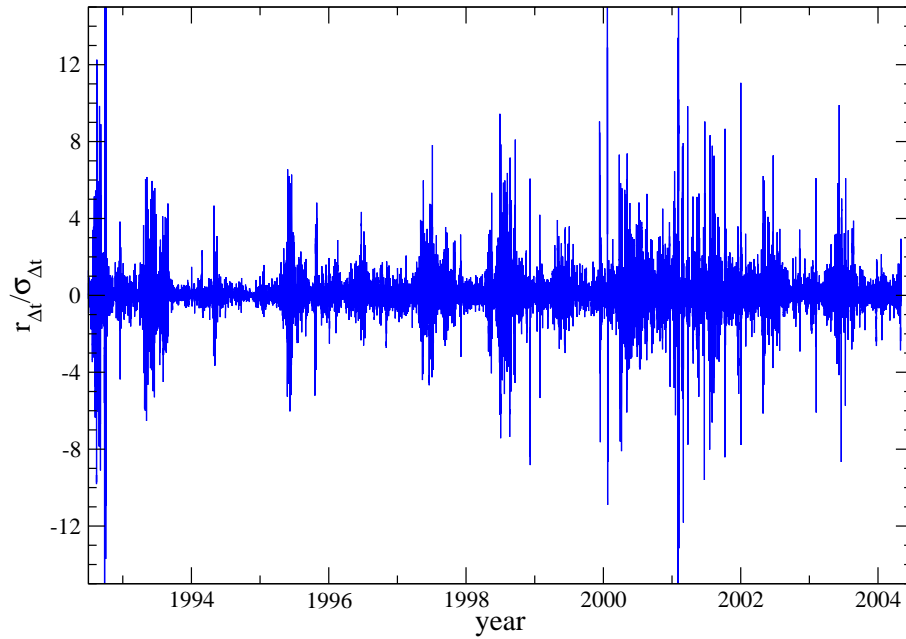


Fig. 6. The normalized daily ($\Delta t = 24h$) logarithmic return $r_{\Delta t}(t)/\sigma_{\Delta t}$. The normalization is done with respect to the sample mean $\sigma_{\Delta t} = 0.16$. The underlying data set is that of Fig. 2.

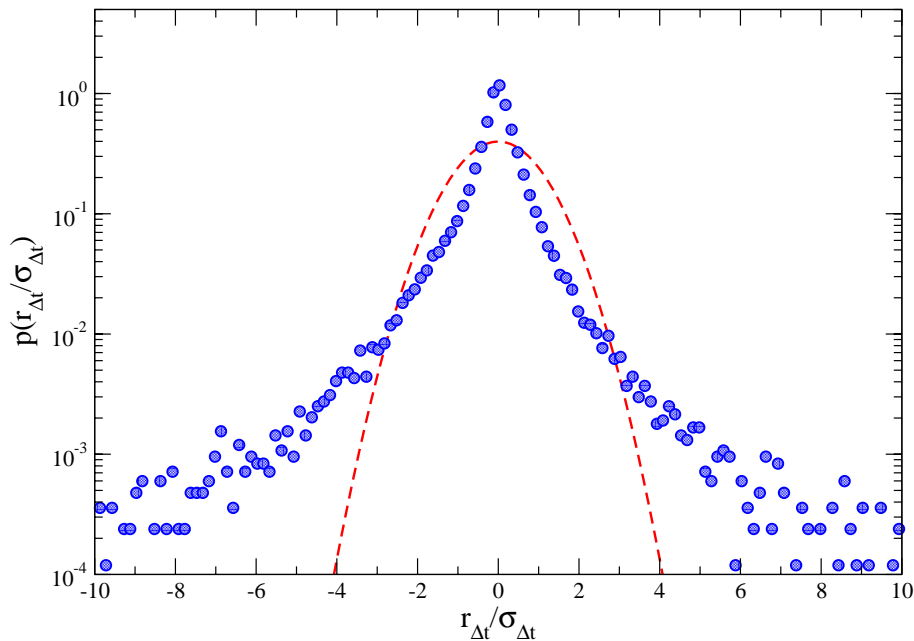


Fig. 7. The logarithmic return distribution, $p(r_{\Delta t}/\sigma_{\Delta t})$ for Nord Pool electricity spot price at the $\Delta t = 24$ hours. The volatility used in the normalization was $\sigma_{\Delta t} = 0.16$. The dashed line corresponds to a standardized Gaussian distribution. The data set analyzed was that of Fig. 2.

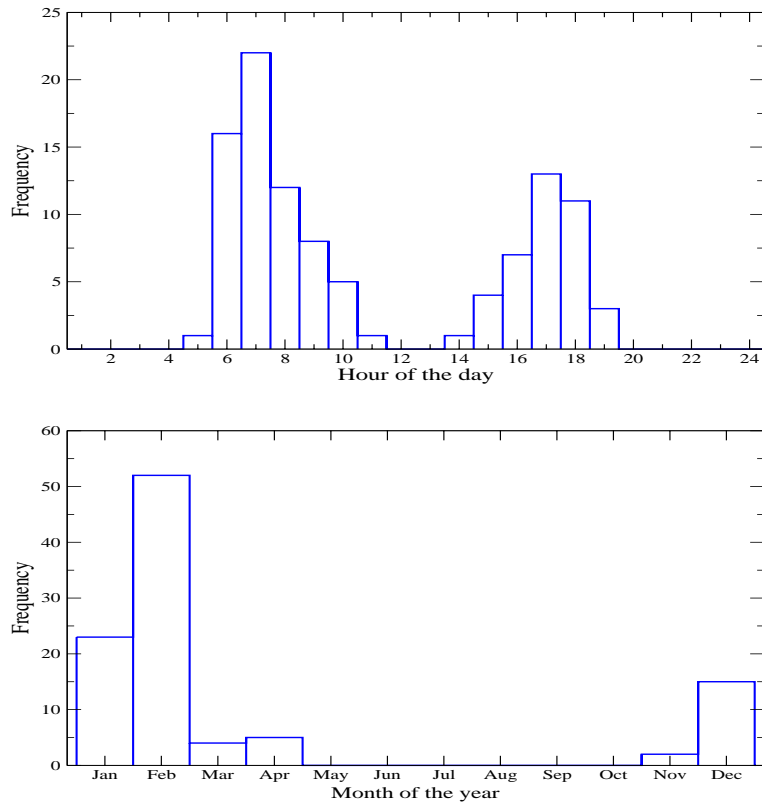


Fig. 8. The distribution of spot price spikes for the 100 largest events that took place over the period 1992–2004 (analyzed data shown in Fig.2). The top figure depicts the distribution of spikes over the hours of the day, while the bottom figure represents the same figure, but showing the monthly spike distribution.

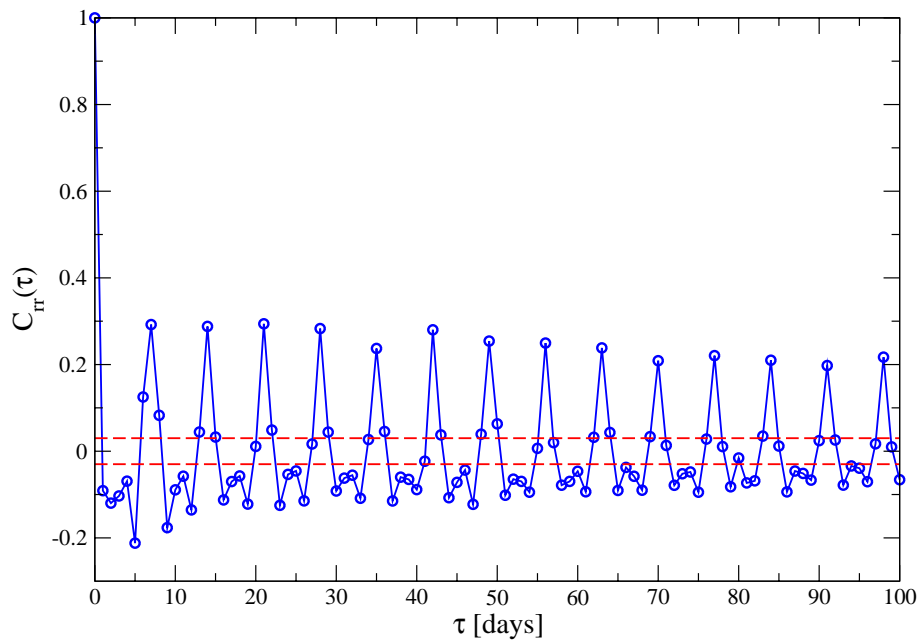


Fig. 9. The auto-correlation function, $C_{rr}(\tau)$, of daily mean daily return $r_{\Delta t}$ (with $\Delta t = 24h$). Returns are shortly correlated. The dashed horizontal line correspond to the 95% confidence interval. Notice the periodic structure that is associated with the weekly structure.

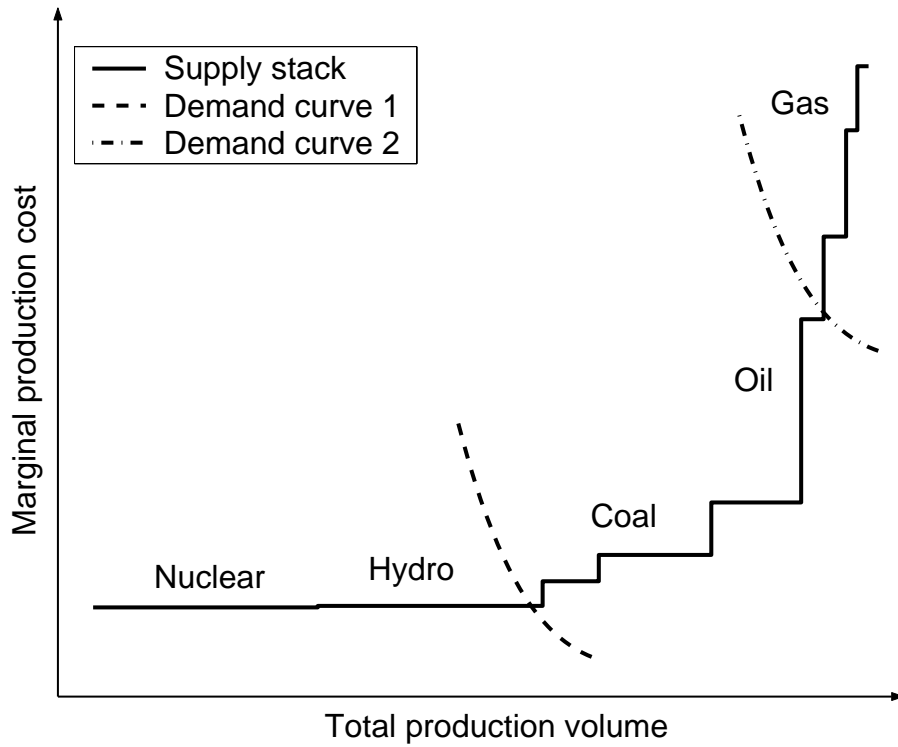


Fig. 10. A schematic supply stack with two potential demand curves superimposed on it. The spot price, given as the intersection between demand and supply, is not very sensitive to demand shifts when the demand is low (curve 1), since the supply stack is typically flat in the low-demand region. However, when demand is high only small increments in demand can have huge effects on the price (curve 2).

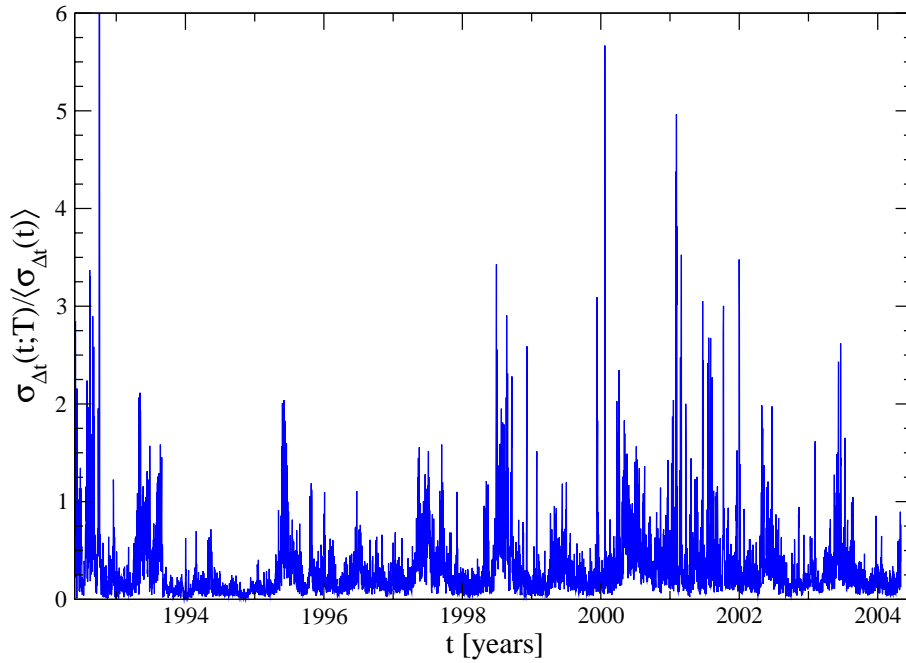


Fig. 11. The time dependent daily volatility $\sigma_{\Delta t}(t, T)$ for $\Delta t = T = 1$ day of the data shown in Fig. 2. This quantity is defined as $\sigma_{\Delta t}(t, T) = \langle r_{\Delta t}(t) \rangle_T$ where $r_{\Delta t}(t)$ is used to denote the logarithmic return (as defined in Eq. (5)), and T is the time interval over which the average is taken. The globally (sample) averaged daily volatility used in the normalization was $\langle \sigma_{\Delta t}(t) \rangle = 0.16$.

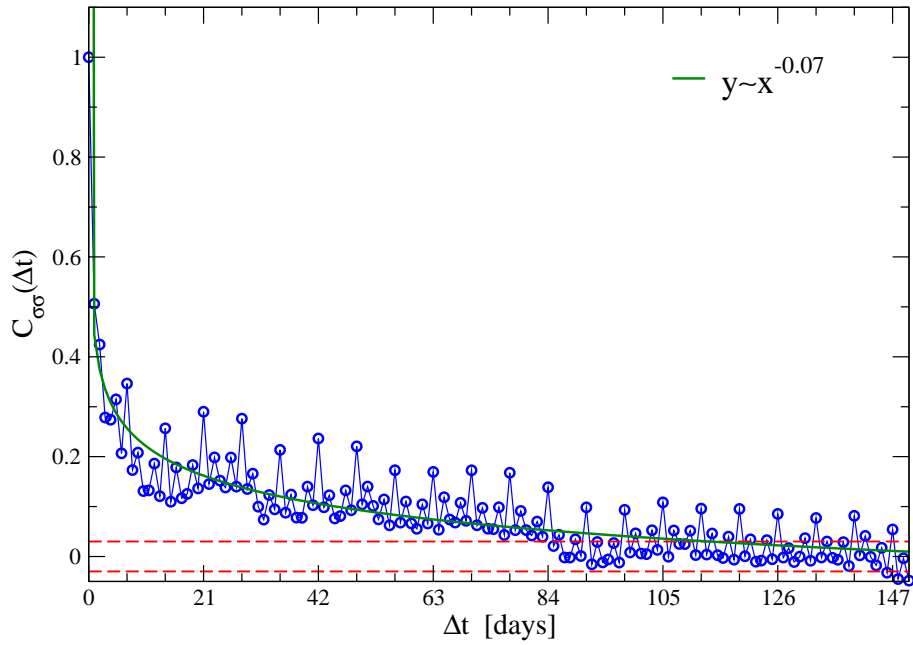


Fig. 12. The volatility-volatility correlation, $C_{\sigma\sigma}(\Delta t)$, vs. lag Δt for the Nord Pool system price. It is observed that after about a 100 days, no significant correlation is present in the volatility except for what can be attributed to the strong weekly cycle. The solid line represent an inverse power law fit to the data : $y \sim x^{0.07}$. The horizontal dashed lines represent the 95% confidence intervals. Notice the close to monthly oscillations in the $C_{\sigma\sigma}(\Delta t)$.

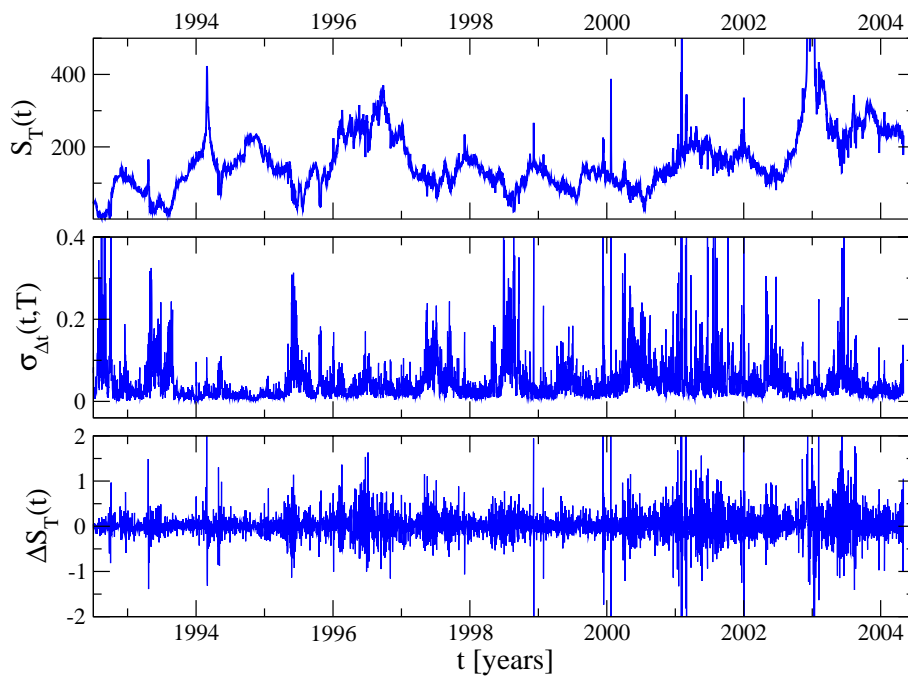


Fig. 13. A comparison of the daily ($T = \Delta t = 24h$) mean system price (top), $S_T(t)$, the daily volatility (middle) $\sigma_{\Delta t}(t, T)$, and the change in daily mean system price (bottom), $\Delta S_T(t)$. Notice the increase in the volatility whenever the system price is low. Moreover, from the bottom figure, it should be noted that the absolute price change seems to be more or less independent of the overall price level.