The evolution of electricity price on the German day-ahead market before and after the energy switch

Abdolrahman Khoshrou[1], Eric J. Pauwels[1], and André B. Dorsman[2]

[1]CWI, Science Park 123, 1098 XG Amsterdam, The Netherlands
[2]VU, De Boelelaan 1105, 1081 HV Amsterdam, The Netherlands

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Abstract In Europe, Germany is taking the lead in the switch from fossil and nuclear energy to renewables. This creates new challenges as wind and solar energy are fundamentally intermittent and to some degree, unpredictable. It is therefore of considerable interest to investigate what effect these changes have on the overall trend and volatility of the electricity price. While market coupling promises to reduce price volatility, dependence on renewable energy sources (RES) might have the opposite effect. To elucidate the combined impact of these two developments, we investigate the evolution of the electricity price on the German day-ahead market over the course of the last 11 years (2006-2016). Our main observations are that price volatility has decreased rather than increased. Furthermore, excess wind production during off-peak hours correlates well with the occurrence of negative prices. Finally, daily price profiles show a gradual shift in peak-prices away from the day-light hours, and this shift is more pronounced during the summer than in winter. This points to a growing influence of solar production on prices.

Keywords Electricity network, day-ahead price, solar energy, wind energy, energy switch.

1 Introduction

In this paper we will look at the influence of the predicted supply of renewables on the realized electricity prices on the German day-ahead market. This research has clear practical implications. Indeed, if an abundance of German renewables substantially impacts the price and volatility of the electricity in Germany, it affects the position of fossil fuel suppliers. Price volatility will increase, causing additional market risks for suppliers and consumers on the German electricity market. It is also conceivable that it would negatively impact the reliability of the electricity grid. Due to the integration of the European grids the problems will not be limited to the German grid. Increasing instability on the German grid means also a higher instability on the neighboring grids.

Renewable Energy Sources (RES) are assuming an increasingly pre-eminent role in the German electricity production. Significant cost reductions, on the one hand, and tremendous technology advances and reliability improvements, on the other hand, have primed the growing interest in green electricity. Germany is pursuing an ambitious goal, a switch from fossil fuel to renewables, the so-called Energiewende (energy transition). It is planned that by 2050, the emission of greenhouse gases will have been reduced by 80-95%([1]). To achieve this, energy consumption will be reduced by 50% and at least 80% of electricity will come from renewables. In line with the above-mentioned ambitions, Germany has substantially expanded its RES-capacity, in particular wind and solar [2]. It is therefore to be expected that this evolution will have a significant impact on German electricity prices. This paper will investigate the combined result of both effects on the electricity price in the German day-ahead market. As explained below, the day-ahead market is an exchange for short-term electricity contracts to be executed on the next day. We have opted to focus on this market as it represents an important and growing segment where market mechanisms are clearly visible.

In particular, we will focus on the following question: What is the evolution of the day-ahead price and its volatility in Germany over the last 11 years (i.e. 2006-2016)? However, before we proceed, we will briefly explain the workings of the day-ahead market.

Day-Ahead Market The day-ahead market is an exchange for short-term electricity contracts. The trading in this market is driven by its participants. A buyer, typically a utility, needs to assess how much energy (MWh) it will need to fulfill its customers requirements for the following day, and how much its purchase price is going to be (Euro/MWh) hour by hour. The seller, for example the owner of a wind farm, also submits the quantity he is prepared to deliver the next day and at what price level on hourly basis. The deadline for the members to submit the price and the quantity for which they seek to make an agreement is 12h00 CET. These “bids” are fed into a complex algorithm to calculate the clearing price. This process typically takes around 42 minutes to clearing the market and settling the financial and physical transactions. From 00:00 CET the next day, the sellers deliver the power at the contracted rate.

Organisation of paper The rest of this paper is organised as follows: In Section 2 we will give an overview of the literature, followed by Section 3 that focuses on the data description and the analysis for Germany. This section explains the sources and some statistics of different types of data we have used in this work. The evolution of different types of volatility measures for the day-ahead price time series are investigated in Section 4. Section 5 presents the results and some discussion on the effect of RES on day-ahead markets. The concluding Section 6 also contains some policy implications.

2 Background and Literature Review

Recently, the impacts of variable generation on the electricity market has attracted a lot of attention. We briefly highlight some important contributions that are related to the topics discussed in this paper. Denny et al. [3] represent a case study where the functionality of the increased interconnection between Great Britain and Ireland to facilitating the integration of the wind farms into the power system was studied. That work suggests a reduction in average price and its volatility in Ireland as an outcome of this increased interconnection.

With the growing contribution of intermittent energy sources, transmission grid extensions and increasing the cross-border interconnections capacities seems inevitable. Schaber et al. [4] examines viability of this approach and its effects, based on projected wind and solar data until 2020. They conclude that expanding the grid is, indeed, helpful in coping with externalities which come with the deployment of renewable energies.

The positive outcomes of the substantial expansion of photovoltaic (PV) installations in Germany and Italy, and in particular, their role in daytime peak price fall have been discussed in [5]. This work also reports the benefits of the complementary nature of wind and PV resources in the UK.

The influence of renewables on the German day-ahead market has been investigated in [6] where the authors also take into account the priority that the German policies assigns to renewables over fossil fuels in case of adequate supply. The authors reported existence of convincing evidence for the impact of RES on the emerging of negative prices on the German day-ahead market.

3 Data

3.1 Data sources

In this study we have collected data from two sources.

European Power Exchange EPEX SPOT The European Power Exchange EPEX SPOT SE operates on the Central Western European (CWE) spot market, i.e. Switzerland, France, Germany and Austrian short-term electricity markets. Striving for the creation of a single integrated electricity market, EPEX SPOT functions as an organized wholesale market place for trading large quantities of electricity between the market members. These members are mostly non-final consumers and big players on the energy sector such as utilities and aggregators, industrial producers, the Transmission System Operators (TSOs), banks, financial service providers and energy trading entities that are working within the energy sector on a daily basis. In fact, this company offers its clients the technologies, electronic trading systems and platform to operate their orders based on reference prices.

Energy trading entities, banks and financial services providers have a prominent role in increasing liquidity of the wholesale power market. These members are mainly focused on market and trade cross borders, even though not necessarily owning any power assets. Some energy intensive industries also participate in the wholesale market as bargain hunters to get a deal at the most reasonable price. Grid losses compensation is a great prime for TSOs to intervene on the spot market. Moreover, regulating feed-in tariff schemes for marketing zero-carbon energy sources are extensively practiced by the TSO in Germany.

Since EPEX SPOT's markets allow for proxy trading, several members trade on behalf of smaller companies or aggregators that pool small assets. This is important since these small entities are mostly formed by decentralized green electricity producers (mainly hydro in France, wind and solar in Germany), demand response aggregators, or other very small suppliers, for whom direct trading would be too costly or cumbersome.

TenneT TSO GmbH TenneT is a transmission system operator active in The Netherlands and Germany within the framework of the Dutch and German laws and regulations. It publishes network-relevant data, such as cross-border load flows, actual and forecast wind and solar energy feed-in, vertical network load in accordance with legal provisions. The dissemination of information is carried out immediately after availability of the respective data. The time set of data is mostly for every quarter of hour. To be consistent with the time frame of the day-ahead market, we have replaced every four successive values obtained from TenneT website with its average to have hourly based data.

3.2 Data Description for the German Day-Ahead Market

In this paper we focus on the following data sets for the German day-ahead market[1]:

(Realized) Day-Ahead Price (in Euro/MWh) This is the price (for each time-slot of the next day) as set by the spot market. As mentioned previously, on the day-ahead market the hourly price of the traded quantity (in Euro/MWh) is set a day earlier. Figure 1 shows the profile of hourly price values on the day-ahead market in Germany and Austria from 2006 through 2016.

[1] In fact, data contains the day-ahead auction prices with delivery on the German/Austrian TSO zones.

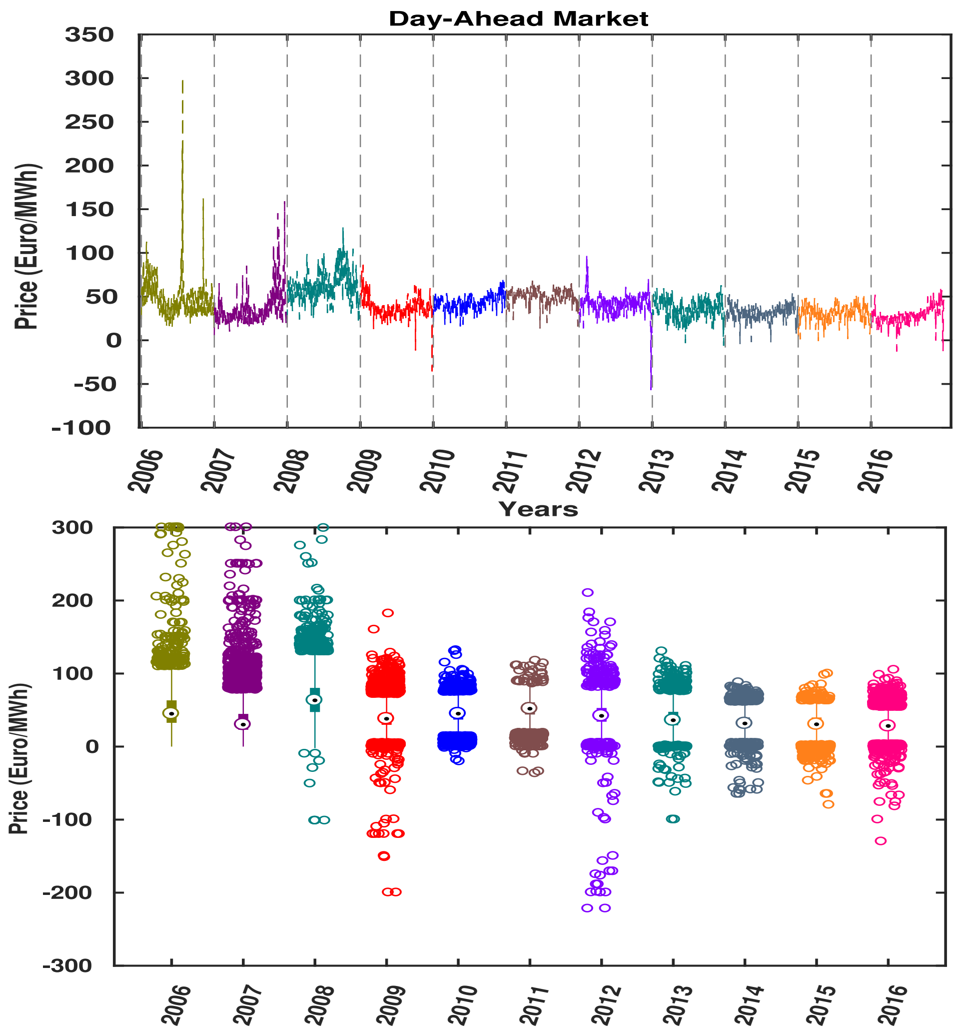

Figure 1: Top: Realized day-ahead price for each hour timeslot for the years 2006 through 2016. Both the positive and negative price spikes are quite obvious, especially during the first half of the decade. A cursory glance at this time series suggest that there is an overall downward trend in the day-ahead price, as well as in the volatility of the price. This will be further investigated in later sections. Bottom: Boxplot of the same data, for the sake of visualization only price values between the interval of $[-300, 300]$ has been illustrated.

Figure 2 also suggests a downward trend in the annual average as well as standard deviation (over a year) of the price profiles during the past 11 years.

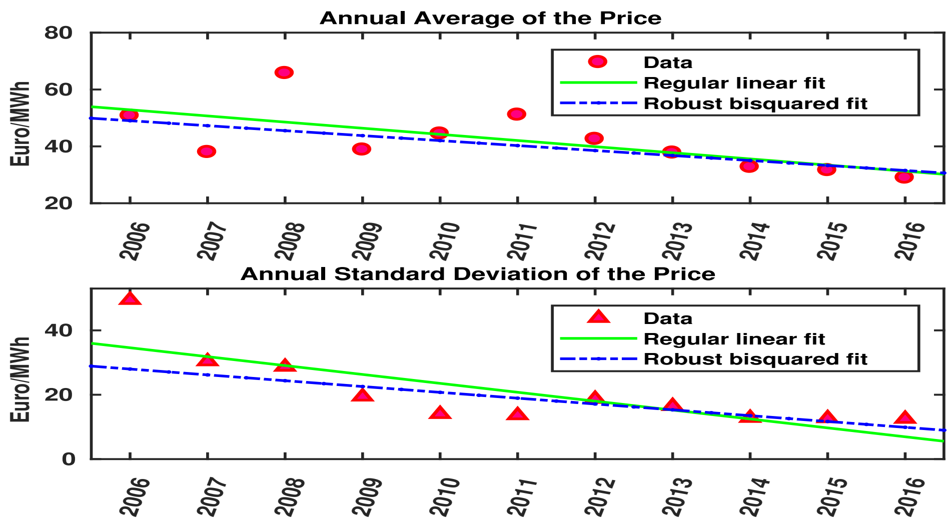

Figure 2: Annual means (top) and standard deviation (bottom) of prices on the day-ahead market. The data seem consistent with an overall downward trend in both the average and standard deviation. The latter can be seen as a proxy for the volatility.

Figure 3 displays an alternative way for exploring the trend of the price data; this time they have been averaged over a sliding window covering a month's worth of values. As a consequence the underlying trends are more pronounced, in particular the downward trend in the second half of the decade.

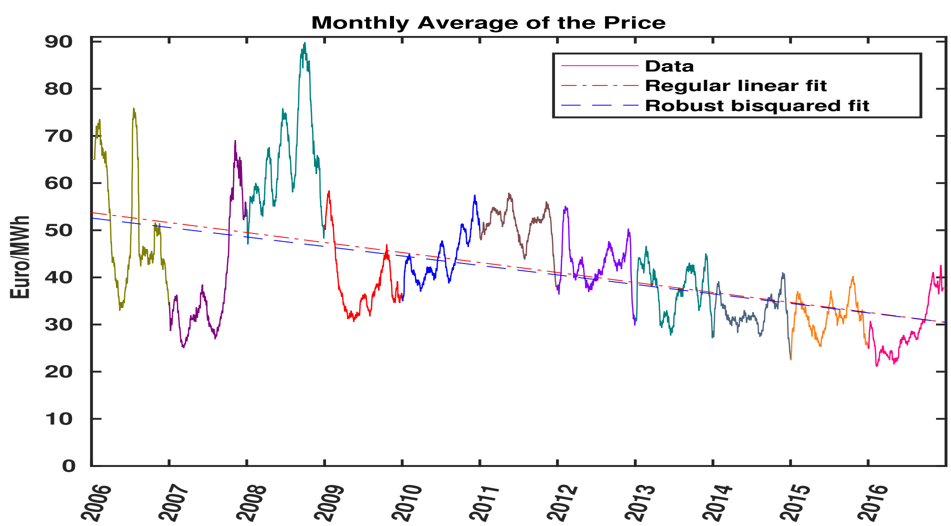

Figure 3: Day-ahead price averaged over a sliding window each time covering a month's worth of price values. An overall downward trend is noticeable, especially in the second half of the decade.

(Realized) Day-Ahead Traded Quantity (or Volume, in GWh) This is the total amount of energy (in GWh) that is being traded on the day-ahead market for each hourslot on a particular day. Recall that the volume to be exchanged on day T is traded and fixed on the previous day $(T-1)$. A general overview of the traded quantity in the GE day-ahead market over the last decade is presented as a series of boxplots in Figure 4. Two interesting features are readily apparent. In the top panel the occurrence of a considerable number of *outliers* (represented as individual points near the upper part of the boxplot) point to unusually high volumes that are being traded. The reason for this is suggested in the bottom panel where the averages (over each year) for each hour of the day are depicted. Again, the steady increase in the traded volume is evident. However, whereas in the first half of the decade, the traded volume is essentially constant over the course of the day, the latter part of the decade shows an increasingly more prominent bump that mirrors the average supply of solar energy, and could therefore be an indicator of surpluses generated by the renewable energy sources (in particular solar). In 2016, however, we witness a minor reduction in the traded volume, as it may be a direct outcome of warm winter in this year and, on the other hand, less solar feed-in in that year.

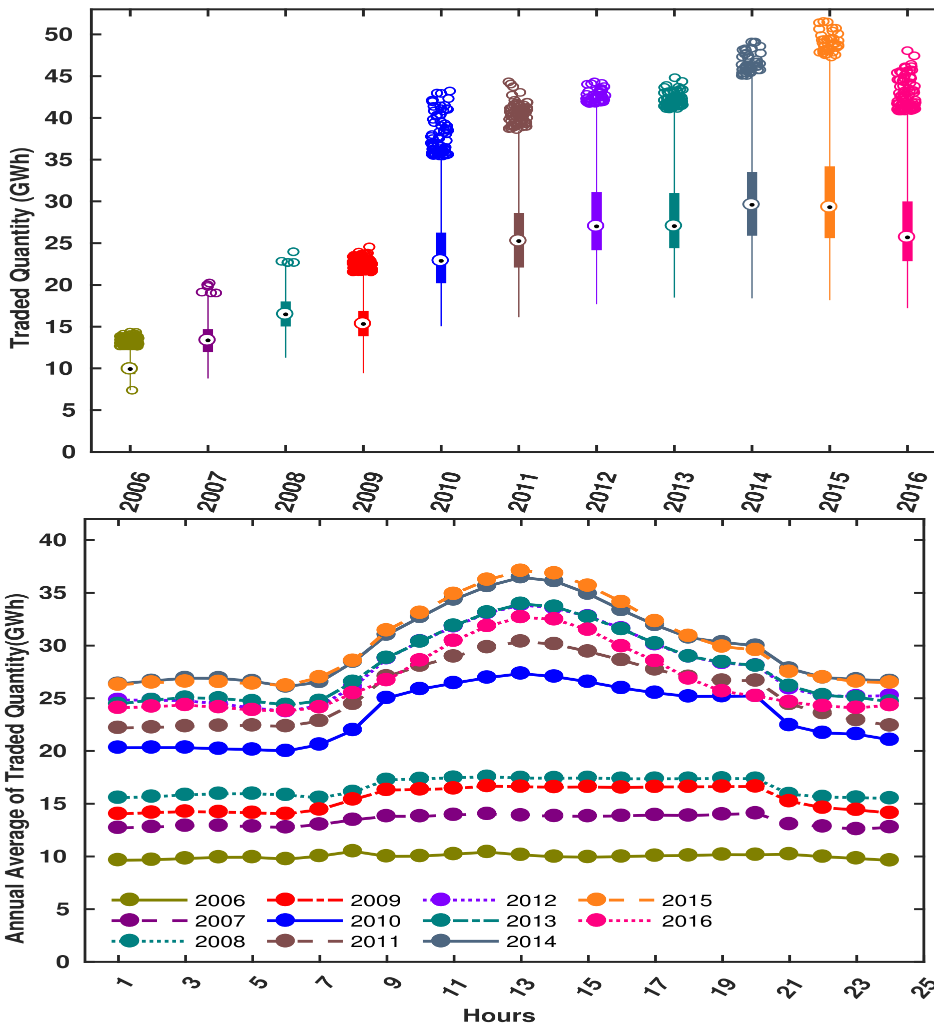

Figure 4: Top: Boxplots for the hourly values of traded volumes on the day-ahead market. Each box represents the data for one year (2006 through 2016). Notice how each box has a considerable number of (high-end) outliers indicating that substantially higher traded volumes (with respect to the annual mean) are quite common. The upward trend (indicated by rising tendency of the boxplot centre) is also evident. Bottom: Daily evolution of traded volume (averaged over a year) for each hourly timeslot. Again, the overall growth in the traded volume is clearly visible, as well as the gradual development of a midday "hump" indicating that volume increases in line with the available solar energy.

Actual Vertical Load Flow (in GWh) Vertical flow refers to the power flows between the high, medium and low voltage grids. The bulk of the flow is cascading down from the high voltage (traditional production and transmission) to low voltage (distribution and consumption). However, Figure 5 shows evidence that under certain circumstances, negative flows are possible (e.g. when there is copious rooftop solar production). The top panel illustrates that in addition to the negative averaged trend, there is also unambiguous proof of actual negative flow, indicative of surplus production in the low-to-medium voltage grids. This effect is also clearly visible in the averages for the hourslots (bottom panel). Over the course of the period 2010-2016 the total amount of vertical flow during the midday peak hours gradually decreases to levels that are comparable to off-peak flow. The continuous declining trend in the vertical load flow is interpreted as a sign of success of the Energiewende. The reasons for this reduction are twofold: 1) Improved energy efficiency and consumption reduction on the demand side; and 2) The renewable energy sources connected to the grid that feed the surplus into the high-voltage grid for transmission. Moreover, it can be seen that the descent around 13h00 becomes steeper. This timeslot corresponds the peak-value of solar feed-in.

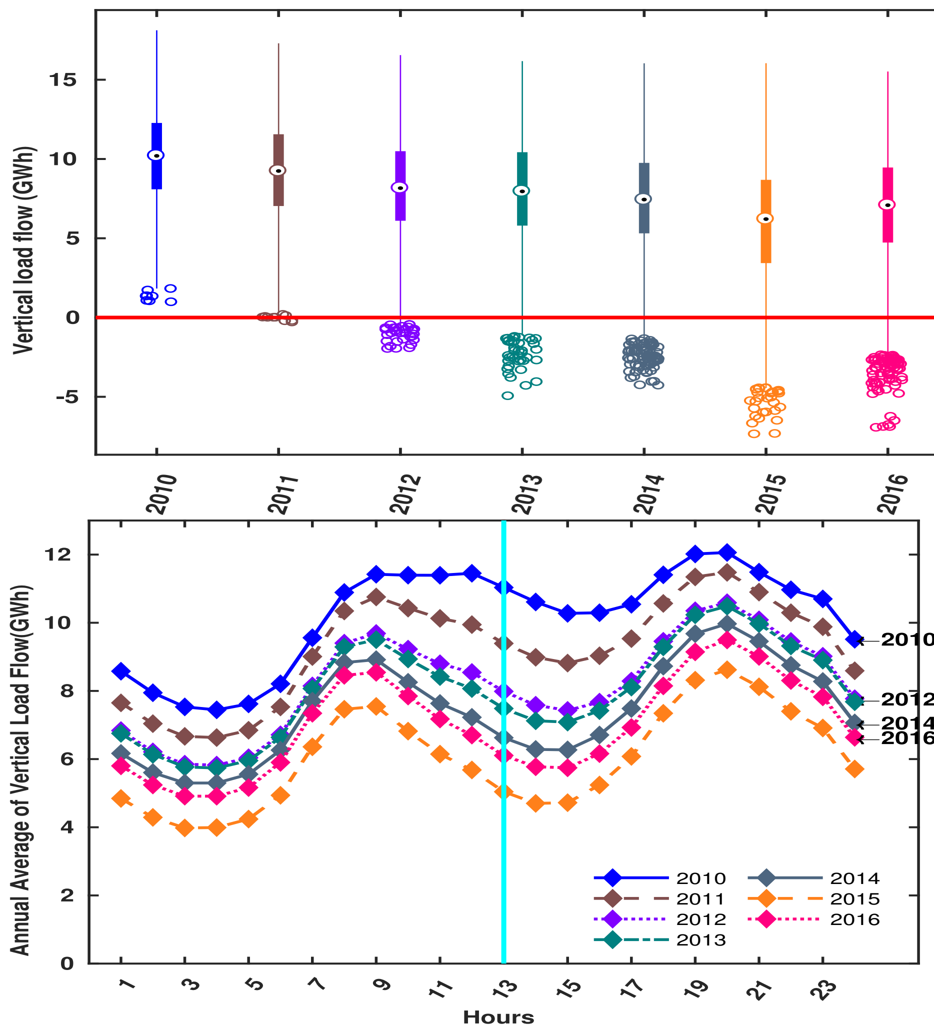

Figure 5: The emergence of the negative values and also the downward trend in average daily vertical load flow provoke the high effect of the renewable energy feed-in. From 2015 to 2016, there is an increase in the annual average of the vertical load. It can be an interpreted as a reflection of less traded quantity, which in turn is a result of less generation by the renewable sources in 2016. Top: The downward trend and emerging of negative load flow from high voltage (HV) to the low voltage (LV) is an indicator of RES connected to the distribution network. Bottom: The continuous declining trend in the annual average daily profile of vertical load flow(as in Figure 4) 2016 is an exception..

Day-Ahead Wind Energy Feed-in (in GWh) Figure 6 shows the annual forecast of wind energy feed-in over the course of six years. As seen in Figure 6 wind energy production is relatively constant around the clock.

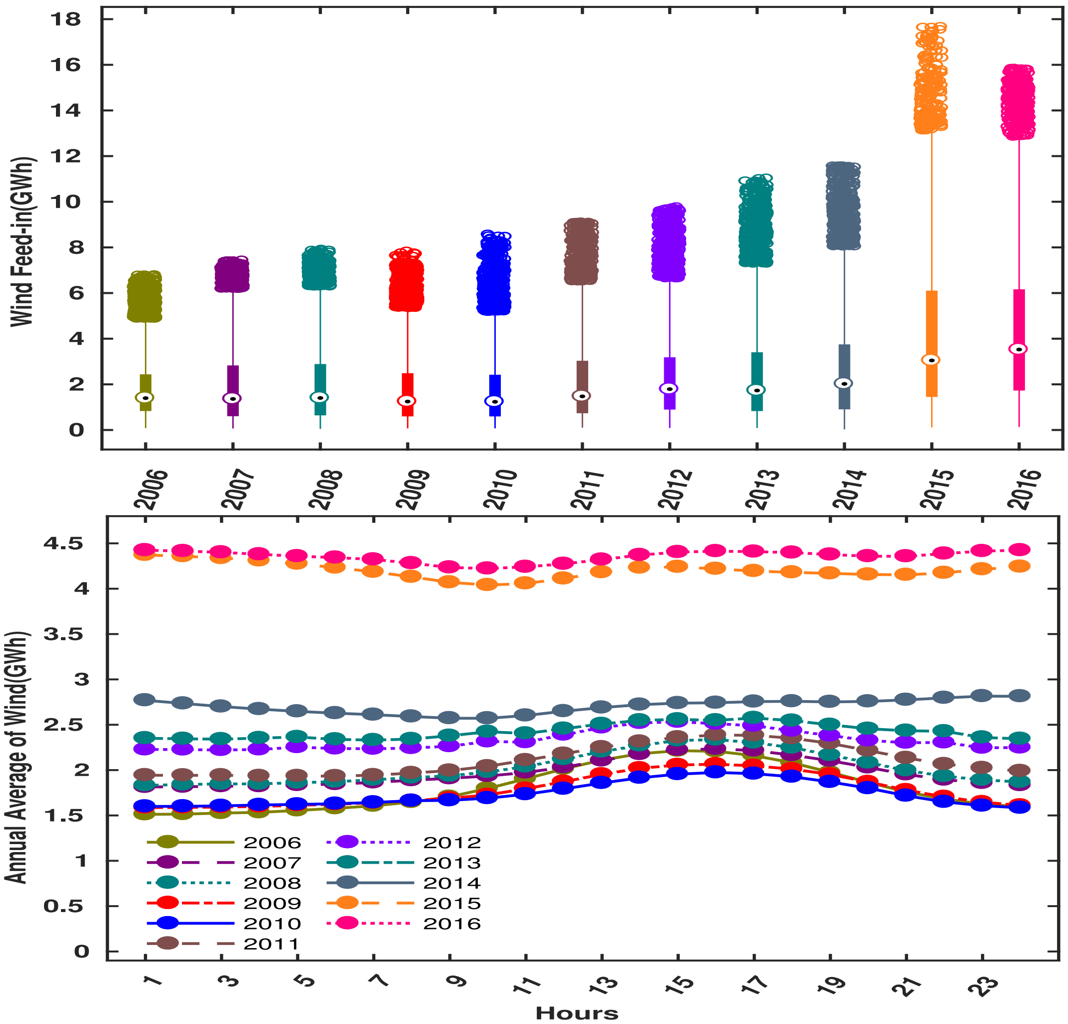

Figure 6: The consistent growth in wind energy feed-in over the years. The change in the daily profile in 2014 and 2015 is noticeable. peak production of the wind profile is eventually moving from early afternoon to late night or early morning. This can become an issue for the stability of the grid where there is not enough demand during those particular hours with high wind production.

Day-Ahead Solar Energy Feed-in (in GWh) The developments in energy storage technologies and also the falling costs of harvesting the solar power have made it increasingly attractive for the private households [7]. Figure 7 shows the day-time (non-zero values) solar energy feed-in forecast from 2010 to 2016. After the rapid rise in 2010 through 2013, solar feed-in has leveled off in the last two years.

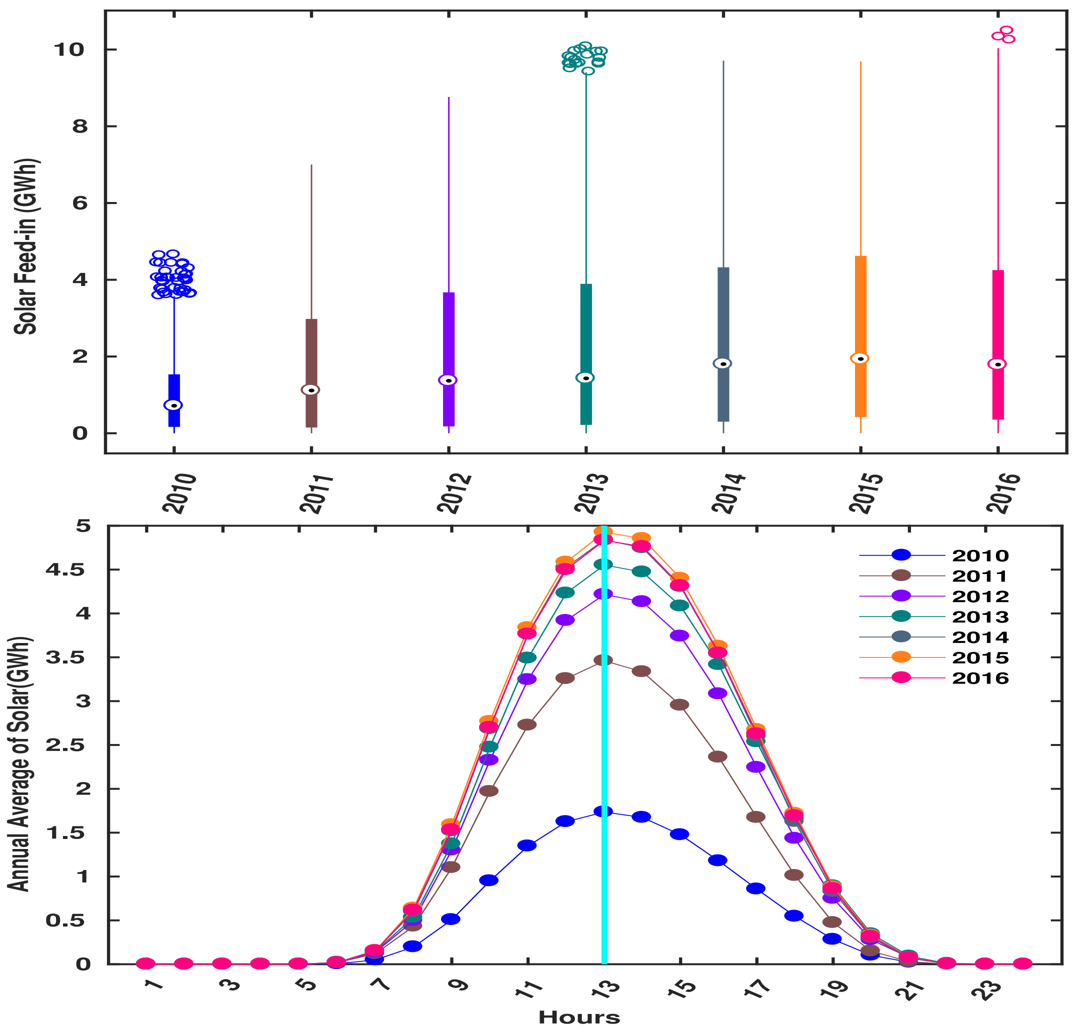

Figure 7: Top: Smooth growth in annual solar energy feed-in (only non-zero day-time values have been considered). Bottom: Annual averaged solar feed-in for each time-slot for the years 2010 through 2016. Peak of solar feed-in is around 13h00, and that coincide with high demand during the day.

4 Methodology

4.1 Evolution of German Day-Ahead Price

As mentioned above, the main focus in this work is on the day-ahead price in Germany (as depicted in Figure 1). In Figures. 2 and 3 we already highlighted the downward trend in price over the decade. Figure 8 displays a complementary viewpoint: in this figure, every value at any hour is the average (top) or the standard deviation (bottom) of all the records of that particular hour during a whole year. Hence, the graph shows the evolution of annually averaged (over the years 2006-2016) daily profile of the day-ahead price for each hourslot.

A continuous downward trend during the decade in the average value of the daily profile is noticeable in the top panel (Figure 8). More importantly, the change in the overall shape of the daily profile is even more telling. Whereas in the first period of the decade prices showed a pronounced elevation at peak hours (and higher volatility as testified by the high standard deviation depicted in Figure 8), the profiles in the second half of the decade are much flatter with little variation between peak and off-peak hours. Again this points to a marked decrease in price fluctuation.

Another intriguing feature of the data is the shift of the timeslot (during the day) for which electricity is most expensive. Before 2011, the midday peak price (around 12h00), was considerably higher than the early evening spike around 20h00. However after 2011, the first spike is not just lower than the second one, but also shows a clear shift to earlier hours. This makes sense in light of the higher contribution of renewables, in particular solar. Indeed, it is reasonable to assume that the typically high supply of solar power around midday is the reason for the drop in prices during these hours. Figure 8 also illustrates how the midday bulge of the daily standard deviation profile, especially before 2009, gradually transforms into indented shape with maximum values around 8h00. This corresponds to a decrease in the variability of the price profile over the years.

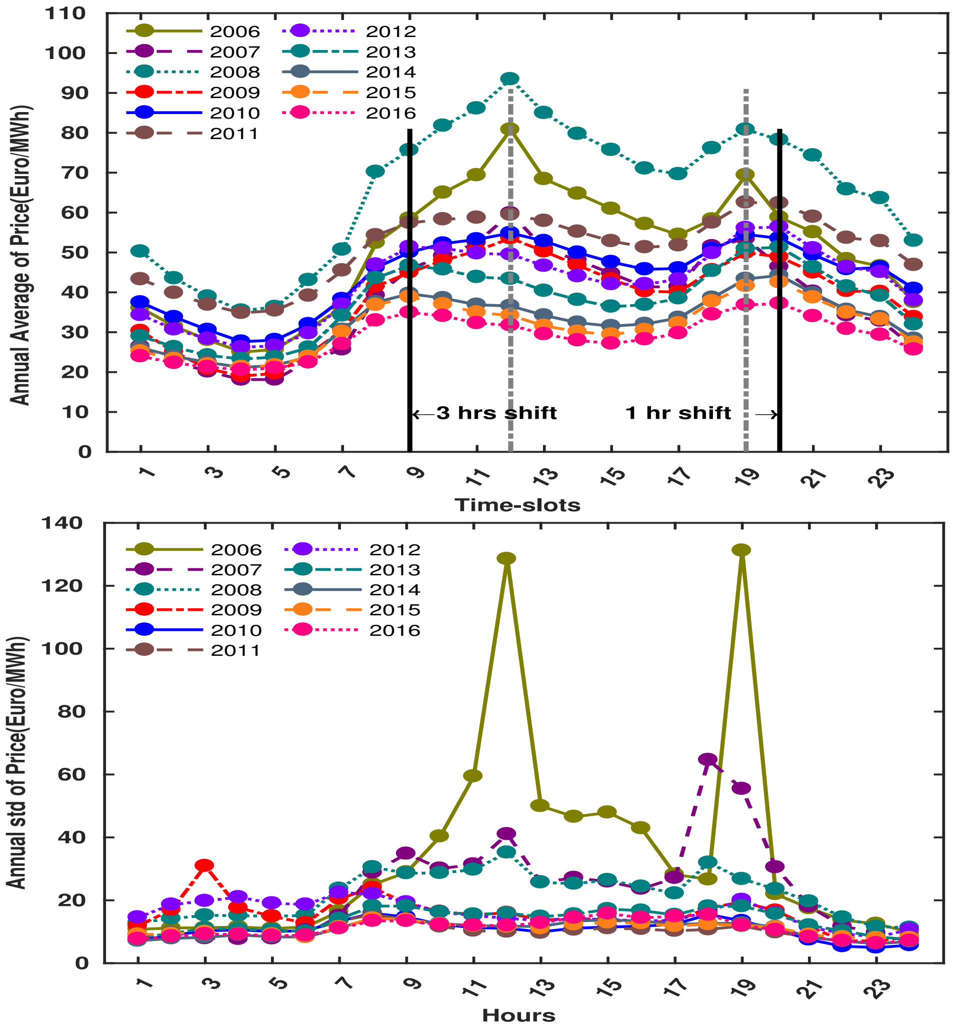

Figure 8: Averaged daily profiles of the day-head prices in the decade 2006-2016. Changes in these profiles from 2011 onwards in both daily average and standard deviation profile are clearly noticeable. Top: Change in timing and amplitude of daytime and evening time peak values after 2011. Bottom: Daily Profile of the standard deviation. Every values for each given hour equals the standard deviation of the price values during the year in that hour.

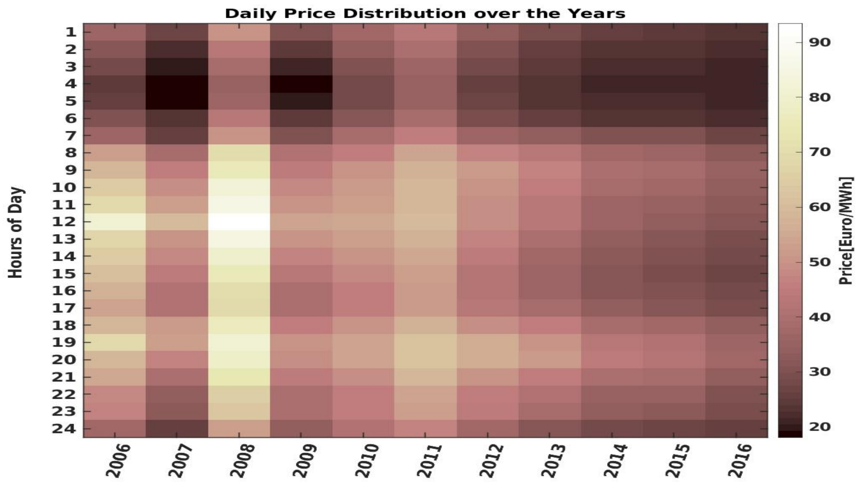

Figure 9: Less contrast in each column suggests less deviation in daily price over the year, also a consistent downward trend in average daily price values from 2011 afterwards in noticeable.

An alternative representation of the data in Figure 9 confirms the previous findings by showing the downward trend in the average daily price from left to right. The diminishing contrast in each column indicates a smoother price profile with lower daily spread over the years. Looking closely, the shift of the midday and afternoon peak hours is notable.

4.2 Evolution of German Day-Ahead Price During Winter and Summer

To illustrate the impact of solar energy on the price, we look at the data for the summer (June through August) and winter (December through February) periods separately. Since, in winters, days are shorter and the sun, if it emerges at all, traces out a lower path in the sky, a significantly smaller amount of solar energy is produced. Wind on the other hand, is fairly constant throughout the day, but there are marked difference between the seasons. This is illustrated in Figures. 10 and 11.

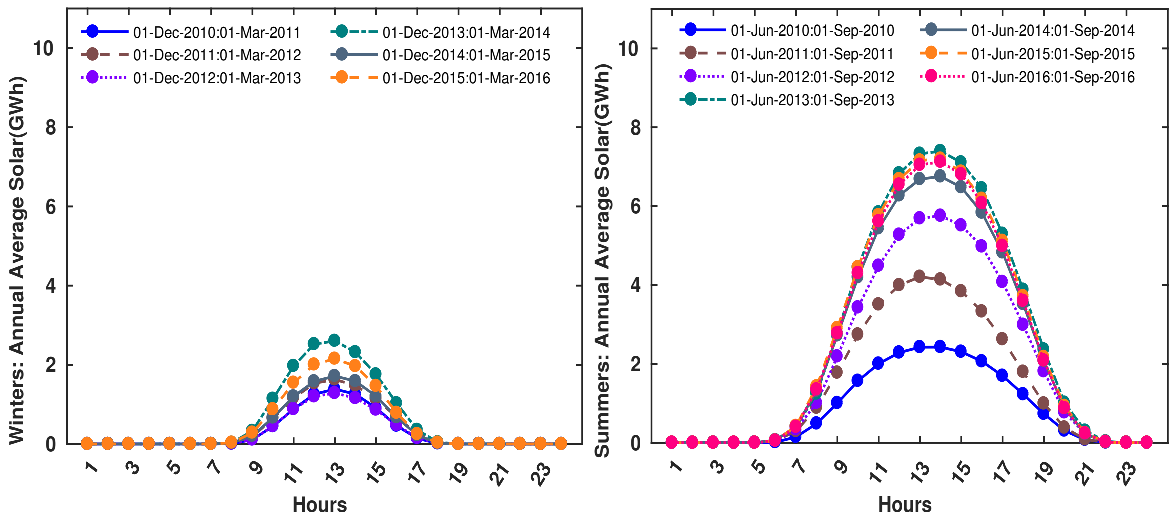

Figure 10: Low production of solar and also shorter occuring hours in winters, vs. high amount and longer period of solar production during summer.

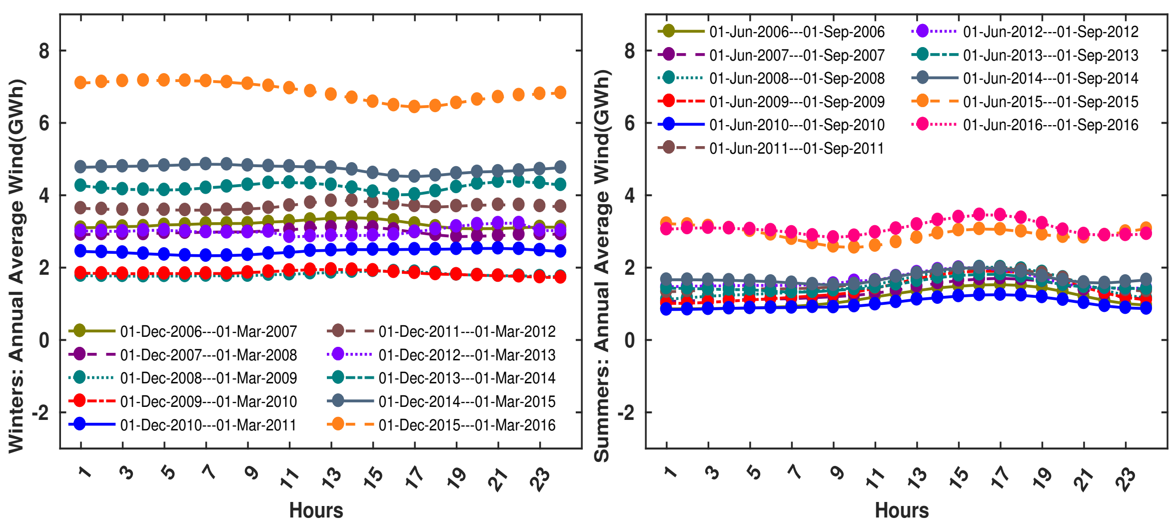

Figure 11: Almost smooth and steady harvest of constant wind breathe in winters, vs. low production of wind in summer. although the small bump in production during the summer afternoons is noteworthy.

Comparing the solar energy feed-in in winters and summers in Figures 10 and 12 and also considering the evolutions of the price profiles in Figure 13 allow us to conclude that solar energy, especially in summer, effectively flattens the daytime price profile.

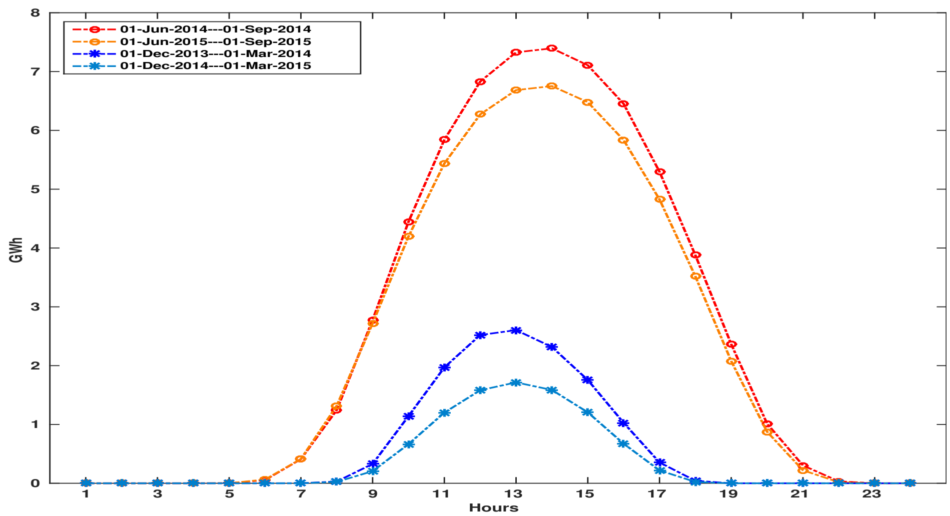

Figure 12: A comparison of the average daily solar energy feed-in during the last two summers and winters.

Figure 13 contrasts the evolution of the daily average of the price profile during the winter (December through February) and summer (June through August) season. During the observed period we see that for winter time the peak at 19h00 is reduced both in size and sharpness, most likely due to the increase in the wind energy. During the summer period, the morning peak at 12h00 disappears completely over the years, in all likelihood again due to the increasing supply of wind and especially solar energy. In other words, the increasing supply of wind and solar energy is not only reducing the electricity price, but it is also changing the daily profile substantially.

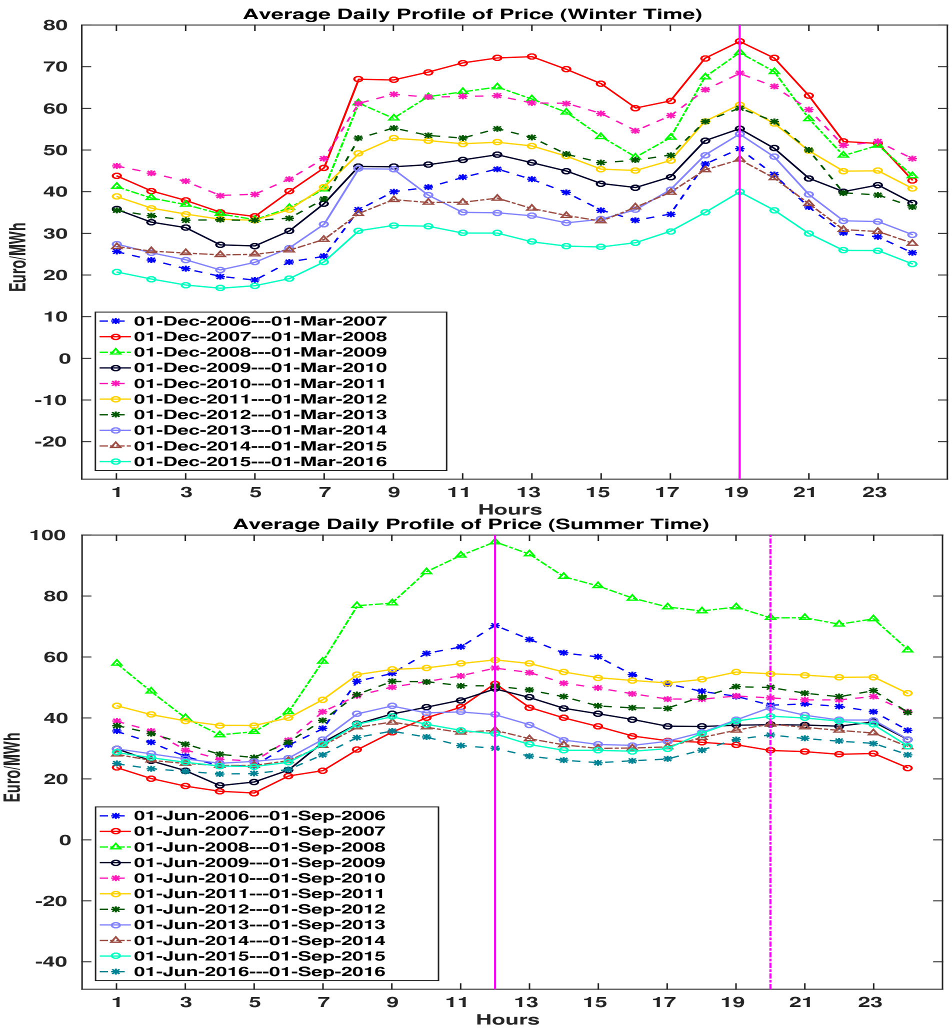

Figure 13: Contrasting the evolution of the daily average of the price profile during the winter (December through February) and summer (June through August) season. Every value is the average of the prices for that specific hour, with the average ranging over the specified period. Top: During the winter period the maximum values occur from 18h00 to 20h00, with peak at 19h00. Also, there is a steep increase in the morning (around 7h00). Bottom: During the summer, the price increase in the morning (5h00-9h00) is considerably flatter. Also the price-spike observed during winter evenings (around 19h00) is completely absent in the summer. Both observations underscore the impact of solar on the price.

4.3 Volatility of the Day-Ahead Price

It is reasonable to question whether the intermittency of renewables would render the price more erratic. For that reason we are interested in the volatility of the day-ahead price. Loosely speaking, volatility refers to the random fluctuations of a time series about its mean or expected value. There are various methods to define and quantify volatility, from old applied models like Garman/Klass to coefficient of variation and formal Stochastic Volatility models such as GARCH, Heston models and so on, see, e.g., [8, 9]. In this work, we focus on three different methods and compare the results for consistency.

4.3.1 Coefficient of Variation

As a first indicator of volatility we use the (localized) coefficient of variation. It simply compares the standard variation (denoted as σ) of the data (within a pre-defined, sliding window) to the mean (μ, in the same window) and expresses this as a fraction or percentage. More formally: $C_v = \sigma/\mu$. In practice, knowing that the price is lower bounded to -500 (see [10]) to avoid getting very small values in the denominator, the price data is shifted up by 500. Figure 14 contains the evolution of the daily C_v and its corresponding statistics. To be more precise, in top panel every data points equals $\sigma/\mu \times 100$ for a given day. Visually, the most striking observation is the decrease in roughness during the decade. Closer scrutiny also reveals a slight overall downward trend. This latter observation is even more obvious when we expand the averaging window to cover a year's worth of price data (middle panel). Based on these observations we can conclude that, when interpreting volatility as an appropriate coefficient of variation, volatility decreases over time.

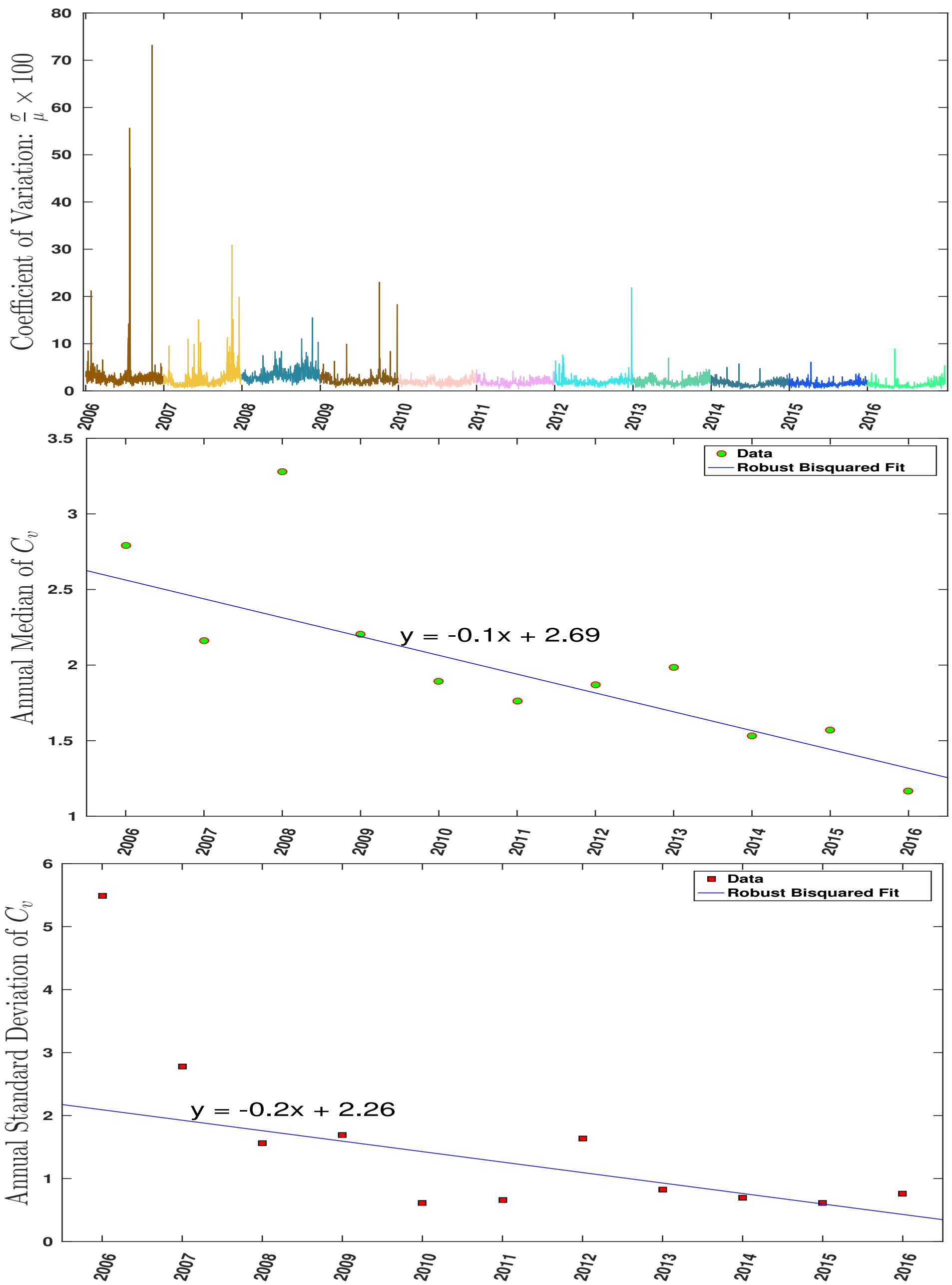

Figure 14: Top: every data point is the C_v of a given day. The downward trend in coefficient of variation of the hourly day-ahead price forecast. It is striking the reduction in the annual average of the variability from 2015 to 2016. Also in some instance we witness some high instances. In the middle and the bottom panels, the contrast between reduction in annual median and the increase in the annual standard deviation in 2016 is striking.

4.3.2 Roughness as a Smoothed Derivative

A roughness measure based on a smoothed derivative of the signal is another well-known method to quantify volatility. It is closely related to Savitzky-Golay filtering [11]. Let us assume that the hourly price data constitute a time series $\mathbf{p} = (p_1, p_2, \ldots, p_N)$ where p_1 is the price for the first hourslot in the series, whereas p_N is the last one. To compute the "roughness" of the time series we proceed as follows. First apply a Savitzky-Golay (7 point) convolution filter (denoted here by f_7) to the data. Because of the alternating structure of the coefficients in the filter and the fact that it is centered symmetrical about the point of interest, the convolution operation amounts to computing a smoothed estimate of a (first) derivative. More explicitly, the convolution of the original price signal $\mathbf{p}$ and the 7-point Savitzky-Golay filter $\mathbf{f}_7$ results in a new, derived time series $\mathbf{x} = \mathbf{p} * \mathbf{f}_7$ such that each value x_t is a specific linear combination of the corresponding neighbouring values in $\mathbf{p}$:

$$x_t = \frac{1}{60}(p_{t+3} - 9p_{t+2} + 45p_{t+1} - 45p_{t-1} + 9p_{t-2} - p_{t-3}), \quad t = 1, 2, \ldots, N$$

Since the (smoothed) derivative signal $\mathbf{x}$ will be high (in absolute value) whenever the $\mathbf{p}$-signal changes quickly, it makes sense to use the squared $\mathbf{x}$-signal (appropriately averaged) as a volatility measure. Hence, we define roughness (volatility) at a particular instant t in the time series as the root mean square (RMS or in mathematical parlance, the L_2 norm) of the $\mathbf{x}$-signal in a window of radius L centered at t:

$$R_t = \sqrt{\frac{1}{2L+1} \sum_{l=-L}^{L} x_l^2}, \qquad t = 1, 2, \ldots, N$$

Figure 15 shows the above-defined RMS measure of roughness over the period from 2006 through 2016. In this particular case the average was computed over a sliding window covering at each point a week's worth of hourly observations (i.e. $24 \times 7 = 168$ values). A cursory glance at the top panel in Figure 15 again shows a decreasing trend in volatility. The bottom panel which shows the averages computed over the timespan of a year, confirms this impression. The similarities with the figures for the coefficient of variation are obvious (in fact, the correlation coefficient exceeds 95%).

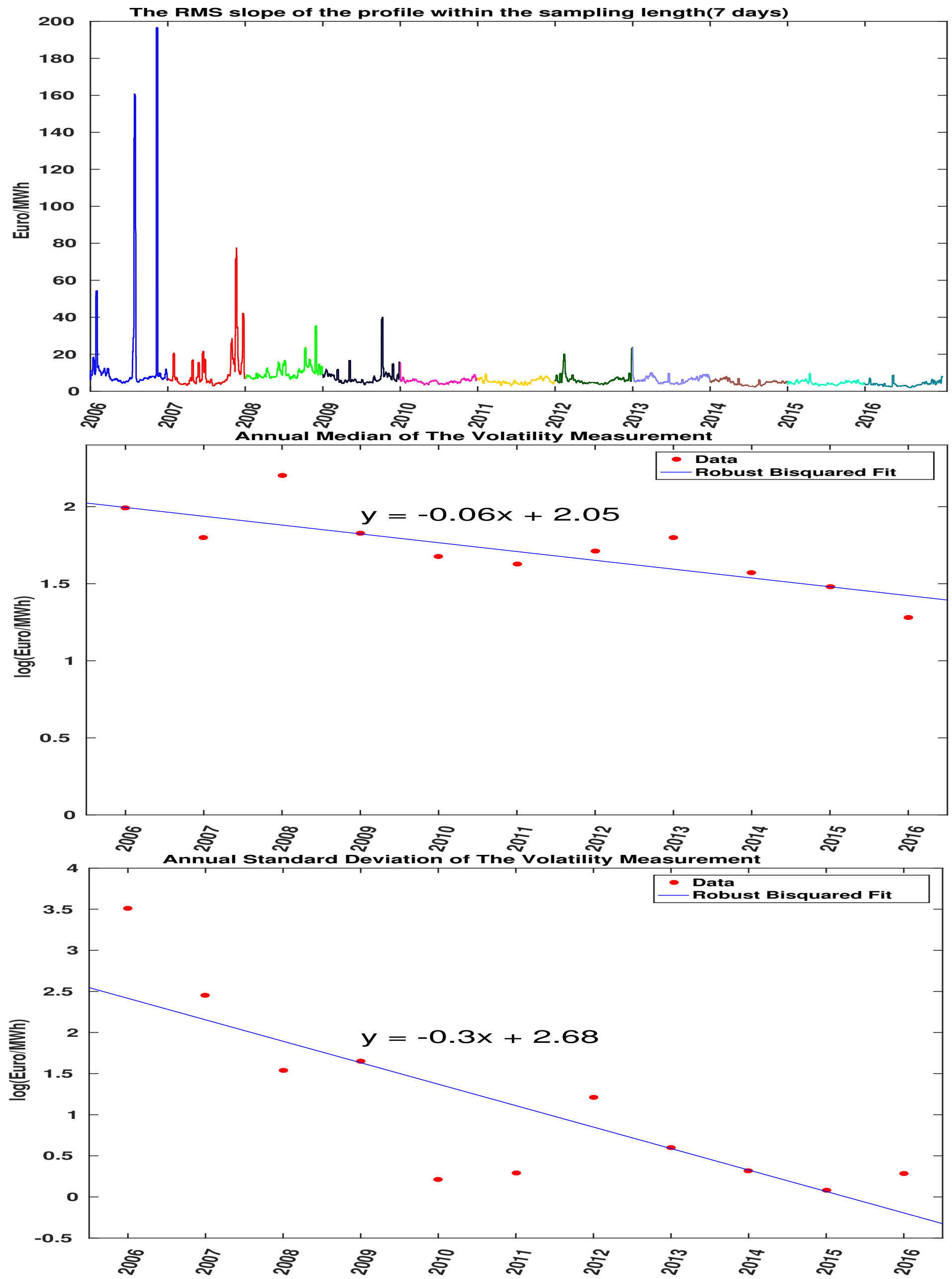

Figure 15: Top: Roughness R_t as measure for volatility. Each data point is obtained by averaging over a week's worth of data (i.e. $2L+1 = 24 \times 7 = 168$). Bottom: The overall annual median of the RMS roughness measurements (represented by the red spots). The blue line shows the best bi-squared fit. Notice that the results are displayed using a logarithmic scale for the y-axis. To highlight the underlying trend, each data point represents the corresponding annual average for the data in the top panel. Consistent with the previous results, the annual volatility during recent years has continuously decreased. In contrast, in 2016, its standard deviation has increased.

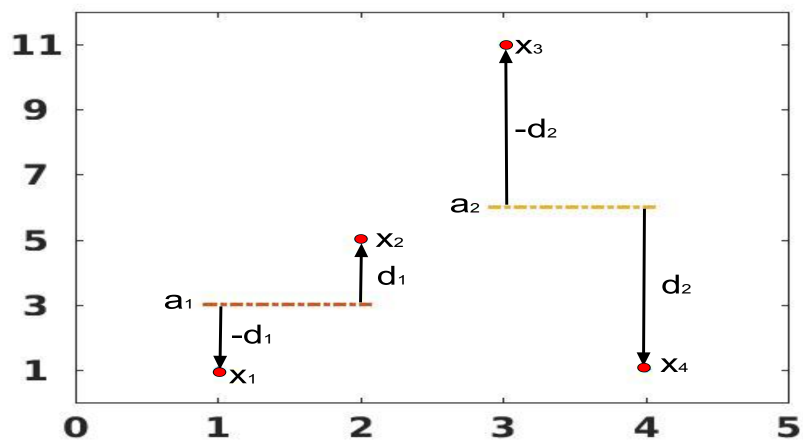

Figure 16: Schematic representation of the Haar wavelet decomposition for a (short) discrete signal $\mathbf{x} = (x_1, x_2, x_3, x_4)$. In the first analysis step, the original values (red dots) are paired, and each pair is replaced by its mean or approximation (a_i, yellow-ish dotted lines) and the symmetric deviation d_i with respect to the corresponding mean. As a consequence, the original signal $\mathbf{x}$ can equally well be represented by the approximation vector $\mathbf{a} = (a_1, a_2)$ and the vector of detail coefficients $\mathbf{d} = (d_1, d_2)$. The next analysis step (not depicted here) would repeat the procedure, this time starting with the approximation $\mathbf{a}$ as input (see Figure 17 for a schematic representation)
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4.3.3 Wavelet decomposition

For our third and final volatility measure, we turn to wavelet analysis. In modern mathematics, wavelets are one of the most efficient and widely used tools to analyse digital signals. As the name suggests, wavelet analysis is akin to Fourier analysis which decomposes the signal of interest as a linear combination of sine-waves of different frequency and phase. However, whereas sine-waves extend along the whole time-axis, wavelets are nonzero only for a finite duration (in technical parlance: they have finite support). As a consequence, wavelet analysis will not only tell us which frequencies are hidden in the signal, but can also pinpoint their location in the data stream. From this, it becomes clear that wavelets hand us a useful tool to probe the data for the occurrence and location of high-frequency fluctuations.

Time series decomposition using the Haar wavelet The Haar wavelet is arguably the simplest wavelet and lends itself to a straightforward interpretation. It basically takes any discrete signal $\mathbf{x} = (x_1, x_2, x_3, \ldots)$ and creates an approximation $\mathbf{a}$ and detail $\mathbf{d}$ signal by running the following simple recipe (also see Figure 16 for a schematic illustration):

1. Take the first two elements x_1 and x_2 and compute the mean (or approximation) $a = (x_1 + x_2)/2$ and $d = (x_1 - x_2)/2$. Notice that this implies $x_1 = a + d$ and $x_2 = a - d$, or more explicitly: the approximation coefficient equals the mean of the two values, and the detail coefficient the amount of deviation between the actual value and the approximation.

2. Store the results in the approximation and detail vector, respectively:

$$\mathbf{a}(1) = a \qquad \mathbf{d}(1) = d.$$

   Both vectors have a length equal to half the length of the original input $\mathbf{x}$.

3. Move on to the next pair (x_3, x_4) and continue until all $\mathbf{x}$-elements have been processed. This way we get the level-one approximation $(\mathbf{a}_1)$ and detail $(\mathbf{d}_1)$ coefficient (each vectors of half the length of the original $\mathbf{x}$-sequence).

4. To compute the level-two approximation and detail coefficients we repeat the whole procedure but use $\mathbf{a}_1$ as input (instead of $\mathbf{x}$).

5. This can be continued until we have reached a pre-defined level. A schematic representation of this procedure is shown in Figure 17.

As a concrete example, imagine that the time series is given by $\mathbf{x} = (1 \quad 5 \quad 11 \quad 1 \ldots)$, then

- Level 1 decomposition:

$$\mathbf{x} = (\underbrace{1 \quad 5}_{3\pm2} \quad \underbrace{11 \quad 1}_{6\pm(-5)} \ldots) \quad \longrightarrow \quad \mathbf{a}_1 = (3 \quad 6\ldots) \quad \text{and} \quad \mathbf{d}_1 = (2 \quad -5\ldots)$$

- Level 2 decomposition:

$$\mathbf{a}_1 = \quad \underbrace{(3 \quad 6}_{4.5\pm(-1.5)} \quad \ldots) \quad \longrightarrow \quad \mathbf{a}_2 = (4.5 \quad \ldots) \quad \text{and} \quad \mathbf{d}_2 = (-1.5 \quad \ldots)$$

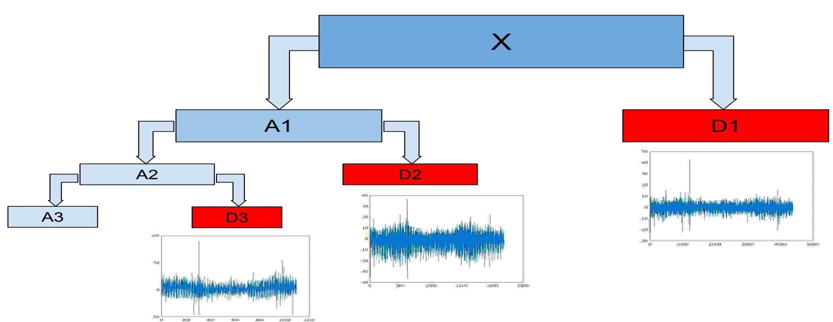

Figure 17: An overview of the decomposition of array X, down to three levels. The D coefficients (in red) have been considered as a notion of volatility.

Figure 17 illustrates an overview of the wavelet decomposition down to three levels. It is important to realise that the level-one detail coefficient capture the highest frequency oscillations.

Subsequent detail coefficients correlate with oscillations of successively lower frequencies. Hence the (averaged) size of the detail coefficients (especially the first level) are indicative of volatility. For this reason, we have implemented the wavelet decomposition to the price values, with maximum wavelet decomposition level equal to three. Figure 18 contains the absolute values of the Haar wavelet coefficients of the price values, each time averaged for a year's worth of values. Again, the downward trend underscores the decrease in volatility over the years.

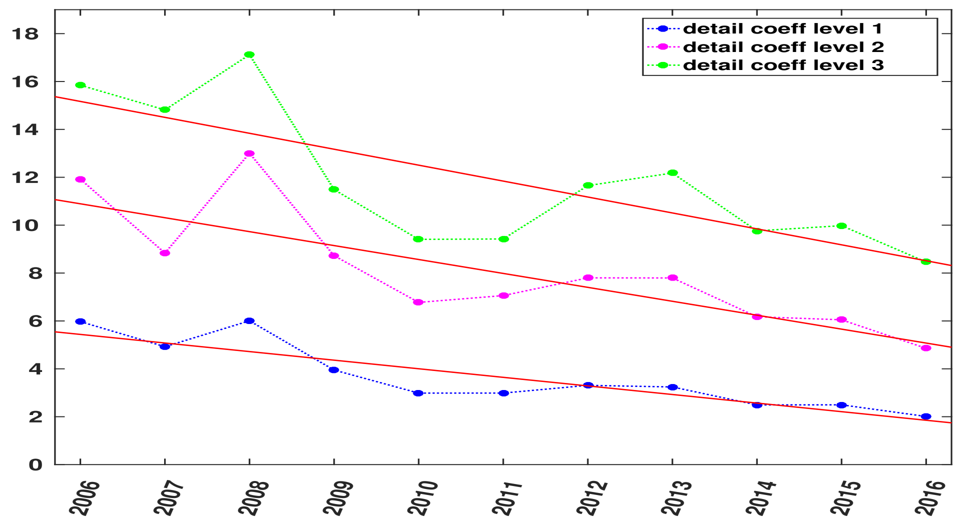

Figure 18: Evolution of the annual volatility as measured by the average values of the Haar wavelet detail coefficients for the first three levels. Again the overall downward trend is clearly visible.

5 Exploring the trend

5.1 Looking into Extreme Values on the German Day-ahead Market

Another way to characterize the market's performance is to scrutinize the extremes of the price range. In this section we will look at this problem from different points of view.

Evolution of extreme price values – convergence of range As a first step, the *extreme* values of the hourly prices during the years has been probed. More specifically, collecting all the hourslot values for each year in the period 2006 through 2016 yields a price distribution for each year. Extreme prices (both high and low) are characterized as prices outside the extreme 5% percentiles (again high and low). So we get a representative value for high (low) prices by focusing on the values of the 95% (5% respectively) percentile for the distribution of each year's worth of hourly price values. The results are shown in Figure 19 where we have plotted both values (high and low) for each year. There is a clearly pronounced continuous downward trend for the high prices, with 2008 being an obvious outlier. The lowest prices show a slight decrease over the years, but because it is much less pronounced, the overall spread of the prices is steadily decreasing, indicative of a more mature market.

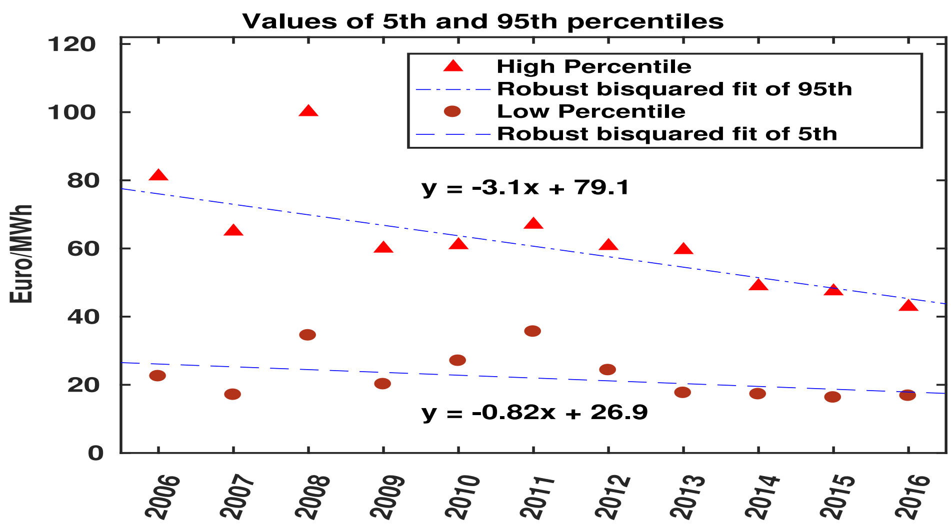

Figure 19: Evolution of extreme prices on the German day-ahead market. Representative values for both the high (triangles, representing the 95% percentile) and low (circles, representing the 5% percentile) prices are shown for each year. The downward trend for high prices is obvious, 2008 being an outlier. Understandably, the downward trend in the low prices is only slight as there is obviously less room for manoeuvre. Overall, there is convergence of both extremes, indicative of a less volatile market.

Distribution of high and low price values over the day In a next step, we explore the evolutions in the distribution of occurrences of the extreme prices over the course of the day. Recall that high (low) prices are defined as values outside the 95th (5th) percentile of price distribution for that year. Figure 20 (top panel) shows how the occurrence of low prices is distributed over the day (for the years 2006 through 2016). Whereas in the earlier years of the decade, there is a clear concentration of low price occurrences in the early morning (4h00-5h00), later years show a more uniform daily distribution. A similar distribution for the occurrence of high prices is shown in the bottom panel of Figure 20. It indicates a distinct shift (occurring around 2011) in the time slot of high prices. More precisely, the day time peak is shifted from noon to the earlier hour of 9h00, while the evening is postponed, shifting from 19h00 to 20h00. Also apparent is the fact that, starting in 2011, the afternoon spikes in the price profile exceed the daytime ones.

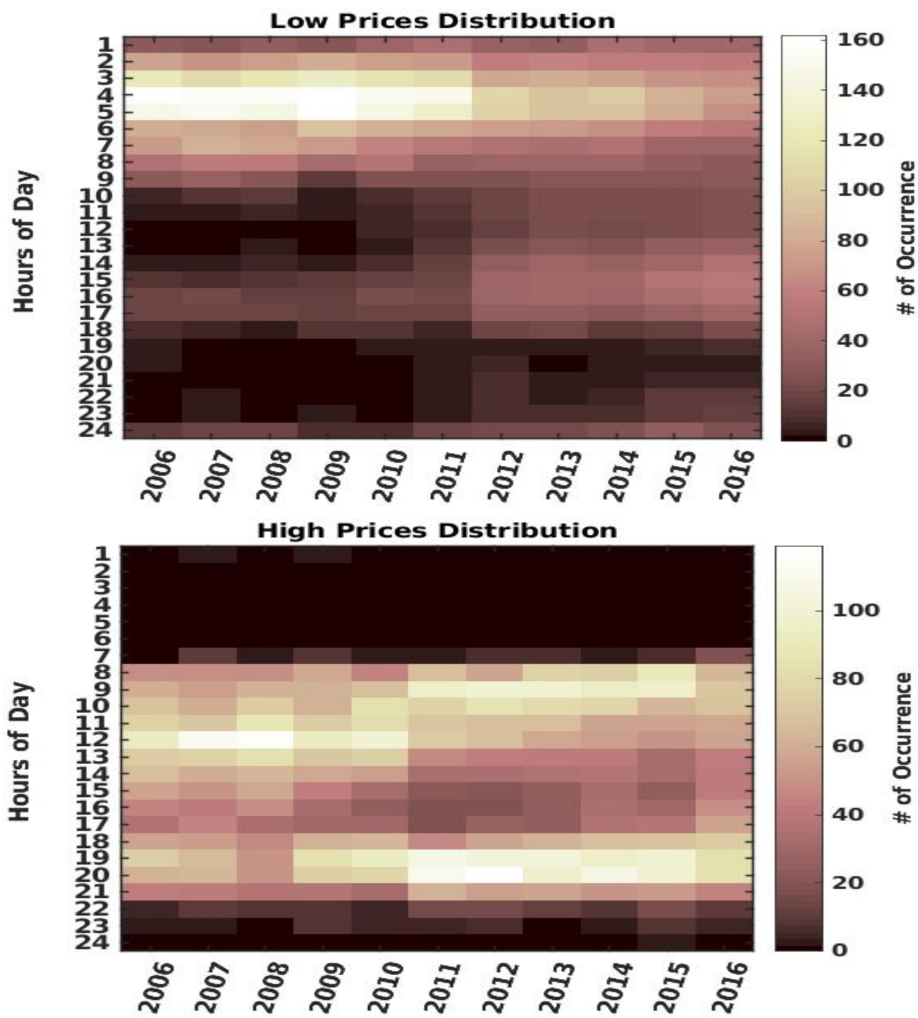

Figure 20: Top: The distribution of low prices over the day. In the first half of the decade low prices are typically clustered in the early hours of the morning. After 2012, the low price values are more evenly distributed over the day. Bottom: The distribution of high prices over the day. Before 2011, the daytime peak values were higher than the afternoon ones, and occurred around noon. After 2011, high prices occur predominantly at the beginning and end of the peak period. Each column represents 440 values, which is 5% of the total number of observations during one year.

5.2 Zero and Negative Prices

Distribution of zero or negative prices over the years Of special interest are zero or negative prices as they reflect the effect of cheap and non-conventional energy sources. Significant amounts of electricity in Germany are still produced by conventional sources. In 2015, for example, lignite, nuclear energy and hard coal were responsible for producing 24, 14.2 and 18.3 percent of gross electricity production, respectively (see [12]). The synchronization speed of these plants is slow and they can not be shut or ramped down very quickly. As a result, on some days when there is excess of electricity production by renewable energy sources, prices become negative and consumers can actually make a profit by consuming electricity. Figure 21 shows how although the number of occurrences of negative prices has been slightly increasing in recent years, the severity in terms of the magnitude is decreasing. More specifically, the width (on the x-axis) of the interval assigned to each year is proportional to the number of occurrences of negative (or zero) prices in that year. The y-axis depicts the corresponding values. Starting in 2012, the number of occurrences (length of the interval) seems to increase. However, the magnitudes of negative prices on these occasions is steadily decreasing.

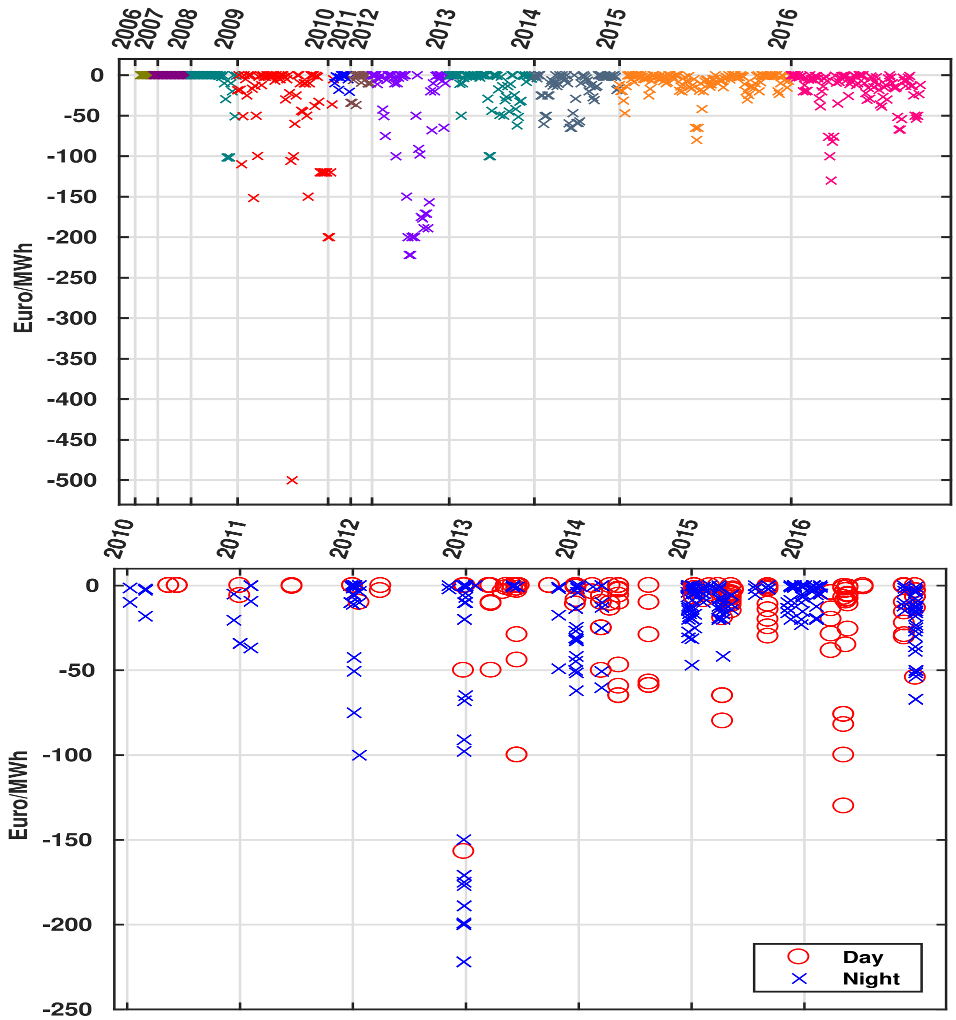

Figure 21: The length assigned to each year on the x axis is proportional to the number of negative or zero price occurrences in that year. The y-axis shows the magnitude of these negative prices. From this graph it transpires that there is a reduction in the magnitude of the negative prices in recent years, although their number is mildly increasing.

Distribution of zero or negative prices over the day Figure 22 provides an overview of the distribution of the growing number of instances of zero as well as negative prices over the days in the period 2006-2016. As was explained in the previous paragraph, as of 2008 negative prices have started to appear and the number of occurrences has increased over the years. Furthermore they seem to be increasingly clustered in the early hours of the morning. This points to the growth in capacity of RES (in particular wind) as the main cause. Before 2012, non-positive prices hardly occurred between 11h00 and 17h00, but this changes towards the end of the decade. Again this is exactly what one would expect as a consequence of the substantial increase in solar feed-in.

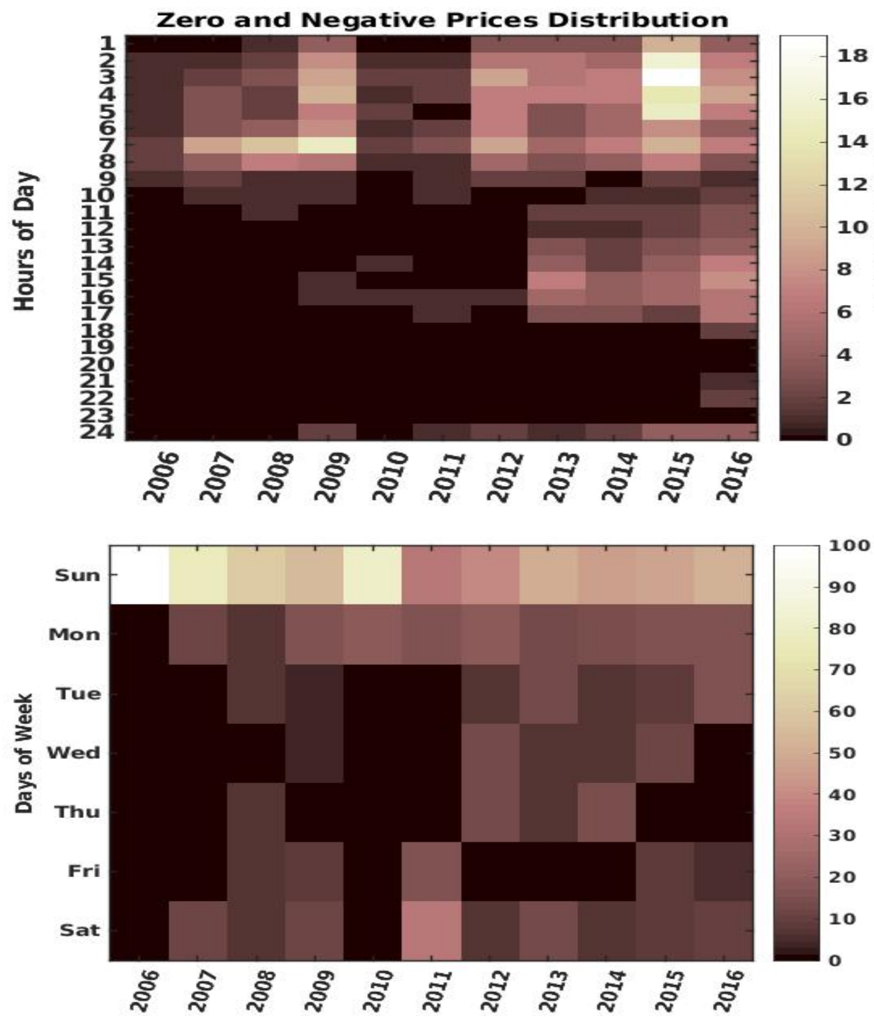

Figure 22: Top:Abundance of zero as well as negative prices during the period of absence of sunlight provokes the higher impact of wind than solar in this matter. Conversely, there are no negative prices in the evening hours 19h - 23h, as consumption is high, and solar input has vanished. Bottom: The percentage of the distribution of the zero or negative prices on the days of week.

This is further corroborated by Figure 23 which shows how the number of zero or negative prices nicely mirrors the capacity growth in wind feed-in. The parallels are especially striking during night time (the absence of solar feed-in) when consumption is low. As mentioned before, solar data only was available fro the period of 2010-2016.

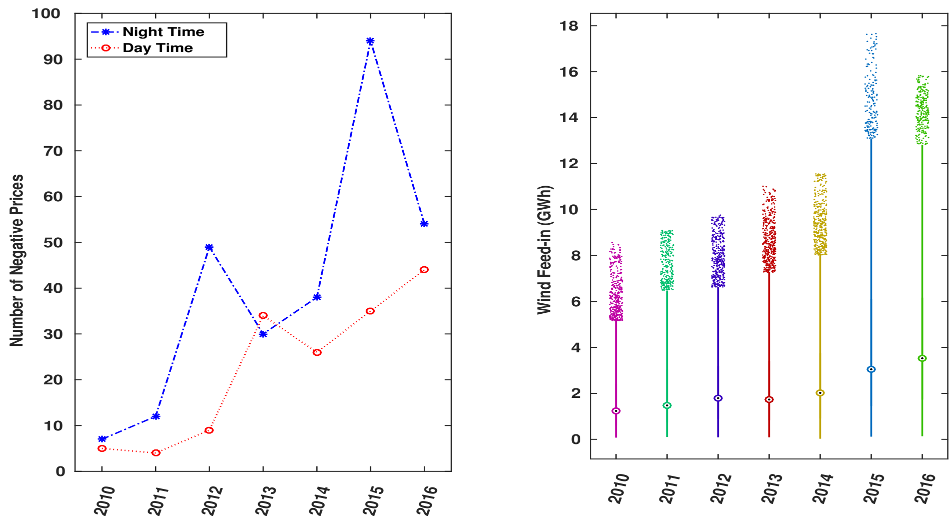

Figure 23: The number of negative prices each year (left panel) clearly mirrors the growth in wind capacity (right panel). The correspondence is most striking for night-time data. The decrease in the number of outliers in the wind feed-in in 2016 (despite the increase of its median) nicely mirrors the reduction in the number of zero or negative prices during night hours during that year. It again confirms the fact that during night times, zero or negative prices are the result of "pecularities" in the wind.

6 Conclusions and Policy Implications

The decision of the German government in 2011 to stimulate RES-generation has had a noticeable effect on the electricity day-ahead market. In this paper we focused on the day-ahead prices in the decade 2006 through 2016. Three general trends emerged.

First, there is an overall downward trend in the average electricity price. This has undoubtedly a number of causes, but the expanding penetration of solar and wind power accounts for at least part of it. Indeed, it is possible to clearly trace the impact of solar on the change of the daily price profile over the year. The traditional peaks during daytime are flattened out and shifted towards the night-time. Furthermore, this effect is most pronounced in the summer. The effect of the growth in wind power is most transparent in the shift in distribution of low and negative prices during the day. A further, and independent, pointer to the impact of renewables is provided by data on vertical flow, unambiguously indicating the growing occurrence of surpluses in the low- or mid-voltage production (read: solar and wind).

Second, we found that the daily profile of the electricity price during winter time deviates from the profile during summer time. In winter time we have a peak at 19h00, while during summer time the graph of the electricity price between 19h00 and 23h00 is flat. Looking at the morning peak at 12h00, the winter peak disappears during the observed period. Also the morning peak in summer time disappears. We conclude that the increasing supply of wind and solar energy during the period 2006-2016 does not only have a negative influence (lowering effect) on the electricity price, but also changes the daily profile of the electricity price.

Third, contrary to what one might expect, the shift towards more renewables (which by their very nature are intermittent and less controllable) has not resulted in an increase in price volatility.

Indeed, if anything, price volatility has been decreasing over the years, pointing to a gain in efficient due to market coupling across Europe.

Based on these observations, we think that policy makers should take the following point into consideration. The increase of the negative vertical flow (as witnessed in Figure 5) underscores the growing importance of solar, especially from so-called prosumers, e.g. privately owned rooftop installations. Given the developments in affordable, household-ready batteries (e.g. Tesla's PowerWall) it is conceivable that a substantial percentage of prosumers will strive to become grid-independent. This would have significant consequences for the grid-dependent customers as well as the grid operators, and needs to be monitored. For instance, a reversal in the current trends of vertical flows would most likely be due to an increased adoptation of privately owned, household-scale storage. This decentralization process means that there will no longer be one large grid, but several local grids with their own price developments. Arbitration between local grids is possible and might be the next development.

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References

[1] Fourth "energy transition" monitoring report, https://www.bmwi.de/BMWi/Redaktion/PDF/V/vierter-monitoring-bericht-energie-der-zukunft-englische-kurzfassung,property=pdf,bereich=bmwi2012,sprache=de,rwb=true.pdf.

[2] Information portal renewable energy, http://www.erneuerbare-energien.de/EE/Navigation/DE/Service/Erneuerbare_Energien_in_Zahlen/Zeitreihen/zeitreihen.htm.

[3] E. Denny, A. Tuohy, P. Meibom, A. Keane, D. Flynn, A. Mullane, M. O'malley, The impact of increased interconnection on electricity systems with large penetrations of wind generation: A case study of ireland and great britain, Energy Policy 38 (11) (2010) 6946–6954.

[4] K. Schaber, F. Steinke, T. Hamacher, Transmission grid extensions for the integration of variable renewable energies in europe: Who benefits where?, Energy Policy 43 (2012) 123–135.

[5] K. Barnham, K. Knorr, M. Mazzer, Benefits of photovoltaic power in supplying national electricity demand, Energy Policy 54 (2013) 385–390.

[6] N. Adaduldah, A. Dorsman, G. J. Franx, P. Pottuijt, The influence of renewables on the german day ahead electricity prices, in: Perspectives on Energy Risk, Springer, 2014, pp. 165–182.

[7] Duurzaam, http://www.duurzaambedrijfsleven.nl/industrie/15265/grootste-batterij-ter-wereld-wordt-game-changer-voor-energiesysteem.

[8] L. C. G. Rogers, S. E. Satchell, Estimating variance from high, low and closing prices, The Annals of Applied Probability (1991) 504–512.

[9] R. T. Baillie, C.-F. Chung, M. A. Tieslau, Analysing inflation by the fractionally integrated arfima–garch model, Journal of applied econometrics (1996) 23–40.

[10] Epexspot, day-ahead auction, https://www.epexspot.com/en/product-info/auction/germany-austria.

[11] A. Savitzky, M. J. Golay, Smoothing and differentiation of data by simplified least squares procedures., Analytical chemistry 36 (8) (1964) 1627–1639.

[12] Federal statistical office of germany, https://www.destatis.de/EN/FactsFigures/EconomicSectors/Energy/Production/Tables/GrossElectricityProduction.html.