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Electricity prices, large-scale renewable integration, and policy implications

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ABSTRACT

This paper investigates the effects of intermittent solar and wind power generation on electricity price formation in Germany. We use daily data from 2010 to 2015, a period with profound modifications in the German electricity market, the most notable being the rapid integration of photovoltaic and wind power sources, as well as the phasing out of nuclear energy. In the context of a GARCH-in-Mean model, we show that both solar and wind power Granger cause electricity prices, that solar power generation reduces the volatility of electricity prices by scaling down the use of peak-load power plants, and that wind power generation increases the volatility of electricity prices by challenging electricity market flexibility.

1. Introduction

Electricity markets are gaining increasing importance on the global energy scene. Through adjustments in their market design, electricity markets endeavour to adapt to new challenges and integrate renewable energy sources into the power generation mix. Renewables pledge to mitigate climate change and diversify the energy mix, increase the security of energy supply, and decouple economic growth from increasing energy demand. However, the use of renewables has profound effects on the power systems with which they are integrated, and challenge the economics and operation of the electricity markets through their intermittent nature. See, for example, Pérez-Arriaga and Batlle (2012). It is subject to market design whether intermittent power volatility, caused by nature, will penetrate into the power system and pass-through to electricity prices.

Electricity prices reflect the physical peculiarities and economics of the power system as these are captured by supply and demand forces. On the one hand, there is the instantaneous nature of electricity and transmission constraints, and on the other the highly inelastic short-term demand (Sensfuss et al., 2008) and limited economic possibilities of large-scale storage rendering the behavior of electricity prices special and dynamic. Pricing methods that work in the case of financial assets often break down when applied to electricity markets, because the latter are driven by multiple factors and exhibit different underlying data generating processes. Deregulation of electricity markets, which already counts for more than two decades, has provoked fundamental reforms within electricity industries, by introducing increased competition and driving electricity prices to phases of relative tranquility followed by periods of high volatility. In this already challenging power system, intermittent renewables influence electricity prices according to the so-called 'merit-order principle,' which has its origins in the standard microeconomic concept of perfect competition. In line with this, the price of electricity should be equal to the marginal cost of the last needed electricity generation technology, otherwise called marginal plant, to meet electricity demand. Renewables penetrate into the supply curve of the day-ahead market with nearly zero marginal cost and thus get priority dispatch compared to other electricity generation technologies. Accordingly, they shift the supply curve to the right, resulting in a lower electricity price and complex electricity market dynamics.

The effects of renewables on electricity prices are of great concern, not only to energy market participants such as, for example, risk managers who must have a clear understanding of price dynamics, but also to policymakers who need to adjust the market design based on new challenges in order to improve market efficiency and thus social welfare. As Huisman et al. (2015, p. 151) recently put it, "an incomplete understanding of these relations could lead to an unintended outcome of the implied policy." Hence, as the role of intermittent renewables increases, it is expected to have remarkable and unprecedented effects on electricity price dynamics, while testing the adequacy and flexibility of electricity market design.

Germany is a pioneer country for renewables integration, and 2015

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has been a landmark year, with the growth of renewables in the power generation mix at its highest ever recorded. Energiewende (2016), a leading energy policy instrument in Germany, points out that "2015 goes down on record as the year in which renewables dominated the power system for the first time ever, becoming by far the most important energy source." The large-scale integration of intermittent renewables has been a natural development in the German electricity industry, especially after its decision in March 2011 to scale down nuclear power plants. This transition of Germany's energy system, known as 'Energiewende,' has been assisted by the German renewable support scheme, which promotes investments in renewable energy generation through the implementation of policy instruments. Accordingly, we can safely argue that the German electricity market has experienced such drastic reforms during the energy transition, that nowadays it constitutes a different electricity market.

This paper contributes to the literature on the effects of renewable power on electricity prices in several ways. First, it fills the gap by disentangling the differential effects of solar and wind power on German day-ahead electricity prices, using daily data, which is as recent as June 2015. Apart from a few studies such as, for example, Clò et al. (2015), the majority of the literature focuses on the effects of wind power on electricity prices (because in past years solar power penetration was limited), or treats both solar and wind power as a combination under the name of intermittent renewables. Hence, they ignore the unique features of solar power as well as the corresponding implications for the power system; see Gullì and Balbo (2015). Secondly, since electricity supply nowadays consists largely of stochastic solar and wind power, while electricity demand is captured by electricity load, we are interested in exploring the dynamic relationship between day-ahead electricity prices and supply and demand forces in a multivariate context.

We estimate a univariate GARCH-in-Mean model in order to investigate the effects of solar and wind power on electricity price formation, and therefore explore their different implications in relation to market design. Only a few studies, with the most notable being Ketterer (2014), investigate the effects of renewables on day-ahead electricity price volatility, and most of them do not consider the recent period of high renewable penetration in the German electricity market. Finally, in line with Jónsson et al. (2010), we explore the impact of solar and wind power on the distributional properties of German day-ahead electricity prices, under different scenarios of solar and wind power penetration. By doing so, we understand better the effects of solar and wind power on the complex behavior of electricity prices, for instance negative or extreme prices, and consider it in relation to the market design and economics of the German power market.

The paper is structured as follows. In Section 2, we give an overview of the deregulation of electricity markets, the subsequent transition towards renewables, as well as the merit-order effect. We also discuss the new challenges of the German electricity market derived from the combination of large-scale integration of intermittent renewables and the limited flexibility of the electricity market. An analysis of negative electricity prices concludes this section. In Section 3, we describe the data and investigate their time series properties, while in Section 4 the effects of solar and wind power on the distributional properties of electricity prices are investigated. In Section 5, we present the GARCH-in-Mean model and discuss the empirical evidence, while in Section 6 we conduct a multivariate Granger causality investigation. The last section concludes the paper.

2. Challenges in electricity markets

Although electricity markets were traditionally designed merely for delivering electricity, nowadays they play numerous important roles in society. For example, sustainable development of energy supply, energy security, environmental protection, climate change mitigation, employment opportunities, and economic efficiency are some of their policy targets. In order to achieve these goals, electricity markets experience profound restructuring, with the most notable being their deregulation and the integration of renewable energy sources into their electricity production mix.

2.1. Deregulation and stylized facts

The deregulation of electricity markets has provoked fundamental reforms within their industries. Before deregulation, the electricity sector used to be vertically integrated and the public utility commissions set the prices in such a way as to ensure the solvency of the firm. Hence, price variation was minimal and under the rigorous control of regulators (Knittel and Roberts, 2005). After deregulation, however, competition was introduced and price variation rose significantly. Deregulation, in combination with the physical peculiarities and economics of the power system, introduced distinct dynamic properties in electricity prices, which are considerably different from those of financial assets (see Keles et al., 2013). These properties, or stylized facts, have been investigated by a substantial body of literature, including studies by Knittel and Roberts (2005), Higgs and Worthington (2008), Karakatsani and Bunn (2008), Escribano et al. (2011), and Fanone et al. (2013).

Seasonality is one of the most interesting characteristics of electricity prices, which is predominantly attributed to the highly inelastic short-term electricity demand (see Sensfuss et al., 2008). This can be viewed as a result of the limited efficient storage capabilities that preclude any kind of inventory strategy to be implemented in both the residential and commercial sectors. In combination with the transmission constraints and the instantaneous nature of electricity, any supply and demand shocks will be transmitted immediately to electricity prices, resulting in price spikes and high volatility. Ullrich (2012) investigates the realized volatility and the frequency of price spikes in eight wholesale electricity markets and underlies the need for better understanding of price spikes and volatility. Some other interesting studies on these stylized facts are Huisman and Mahieu (2003), Worthington et al. (2005), Karakatsani and Bunn (2010), and Efimova and Serletis (2014). Finally, mean reversion is another specific characteristic of electricity prices, mainly driven by weather conditions (Koopman et al., 2007); it refers to the tendency of electricity prices to revert to a long-run level reflecting the long-run cost of electricity generation.

Stationarity !!!

2.2. Transition towards renewables

Although Germany had not been a pioneer country in the deregulation of electricity markets, as for instance the United Kingdom and Norway, nowadays it attracts special attention as a prominent example of a country integrating renewable energy sources. In fact, 30.1 per cent of its electricity in 2015 came from renewables such as wind and solar, up from 16.6 per cent in 2010 (see Table 1). This energy transition, known as Energiewende, is characterized by high growth in renewable energy, and is a natural development in the German electricity industry after the German government's decision in 2011 to phase out nuclear power. Therefore, significant changes have occurred in the German energy mix over the following years with the nuclear power generation falling by 21 per cent during the first year.

Germany achieved this rapid transition through a generous renewable support scheme that relies on three policy instruments: (a) fixed-feed in tariffs for renewables accompanied by a take-off obligation, (b) a priority dispatch for renewables, and (c) very restrictive rules for renewables curtailment that takes place only for security reasons — see Brandstätt et al. (2011) and Henriot (2015). Although this support scheme inspired confidence for investors, thus boosting renewable energy investments (Klessmann et al., 2008), it raised a broad discussion related to its high cost that consumers are eventually required to finance (Tveten et al., 2013). Some notable studies that

Table 1
Electricity production in Germany by source (%).

Source	2010	2011	2012	2013	2014	2015
Hard coal	18.5	18.3	18.5	19.9	18.9	18.1
Lignite	23.0	24.5	25.5	25.2	24.8	23.8
Nuclear	22.2	17.6	15.8	15.2	15.5	14.1
Natural Gas	14.1	14.0	12.1	10.6	9.7	9.1
Oil	1.4	1.2	1.2	1.1	0.9	0.8
Others	4.2	4.2	4.1	4.1	4.3	4.1
Renewable energies from which	16.6	20.2	22.8	23.9	25.9	30.1
Biomass	4.7	5.3	6.3	6.5	6.9	6.8
Hydro power	3.3	2.9	3.5	3.6	3.1	3.0
Photovoltaic	1.8	3.2	4.2	4.9	5.7	5.9
Waste-to-energy	0.7	0.8	0.8	0.8	1.0	0.9
Wind	6.0	8.0	8.0	8.1	9.1	13.5

Source: AG Energiebilanzen (2016).

discuss the renewable electricity support instruments are Falconett and Nagasaka (2010), Frondel et al. (2010), and Verbruggen and Lauber (2012).

2.3. Price formation and the merit-order effect

Similar to every other economic system, the setting of electricity prices is based on the law of supply and demand. Renewables constitute a large part of the current electricity supply in the German electricity market and therefore their influence on electricity prices, through the supply and demand mechanism, should not be disregarded. Economic aspects and peculiarities of electricity markets are actually reflected in the pricing mechanism. That is to say, electricity demand is highly inelastic, capturing the limited ability of consumers to alter their consumption patterns in the short-run, while electricity supply or merit-order curve is discontinuous, convex, and sharply increasing at the high demand level (Karakatsani and Bunn, 2008), indicating the special characteristics of the electricity power generation mix.

The electricity supply curve is constructed based on the aforementioned merit-order principle, according to which supply offers are ranked dependent on their short-run marginal costs (Morales et al., 2014). Therefore, the left part of the curve traditionally consists of supply offers from power plants with low marginal cost such as lignite and hard coal, while the right part of the curve represents the supply offers from electricity generating units with high marginal cost, for instance gas and oil fired power plants. Renewable energy generation faces very low, or even negative marginal cost if renewable support schemes are taken into account, and therefore is usually prioritized in comparison to other electricity generation technologies. Consequently, offers from renewables are located on the left part of the supply curve, thereby replacing more expensive supply offers and shifting the entire curve to the right as illustrated in Fig. 1. Subject to a specific inelastic demand curve, this results in a lower electricity price and the so-called merit-order effect. The latter simply describes the price diminishing mechanism that is attributed to the renewable electricity generation, which penetrates into the power system.

The magnitude of the merit-order effect depends, predominantly, on three factors: (a) the level of electricity demand, (b) the slope of the supply curve, which in this context will also be referred to as the merit-order curve, and (c) the renewable electricity generation (Sensfuss et al., 2008 and Keles et al., 2013). Electricity demand and more particularly residual demand, which must be served by conventional power plants, determines the marginal technology that sets the electricity price based on its production cost. The slope of the merit-order curve plays the most important role in the size of the merit-order effect, and depends on numerous factors. Thus, fuel prices influence

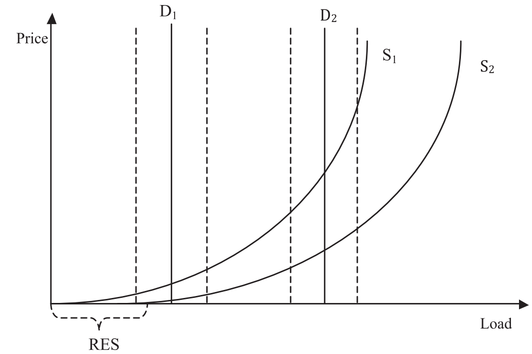

Fig. 1. Merit-order effect during peak and off-peak hours.

the value of the merit-order effect, but not all of them have the same impact. Therefore, the prices of the underlying fuels for the base-load power plants are not expected to have a significant impact on the volume of the merit-order effect, since these power plants are rarely substituted by renewables. On the contrary, the prices of fuels that support the mid-load and especially the peak-load power plants, have a greater effect on the size of the price reduction. In fact, Sensfuss et al. (2008) investigate the merit-order effect on the German electricity market, and conclude through simulation runs with different fuel prices that although a 20% price change of the fuels for lignite and nuclear power plants affects the merit-order effect by only 2%, a 20% price reduction in the price of natural gas reduces the size of the merit-order effect by around 30%. Moreover, they underline the significant effect of the ratio of fuel prices, for instance of gas and coal prices on the final result.

Some additional driving factors on the slope of the supply curve are the price of the emission allowances, the capacity of the renewable electricity generation, and the various efficiencies of the power plant portfolio. See Sensfuss et al. (2008) and Keles et al. (2013). Huisman et al. (2015) investigate the impact of fuel and emission cost on Nordpool day-ahead electricity prices, and provide empirical evidence of nonlinear dependence. Market power is also an important driving factor for the slope of the merit-order curve, which has seldom been studied in the literature. Gullì and Balbo (2015) investigate the impact of solar production on the Italian electricity prices and analyze the role of the market power in the final outcome. They conclude that solar production can lower the electricity price but only below a specific threshold. The reason is that operators of thermal power plant units may adapt their price strategy based on the expected availability of the renewable power generation in order to offset their reduced revenues which occur during times of renewable penetration. The latter refers primarily for the case of solar power, since it exhibits less intermittent power generation patterns compared to wind. Therefore, renewable power generation does not affect electricity price formation only in a direct way, but also by challenging the economics of the electricity markets with their intermittent nature. Clò et al. (2015) provide an interesting literature review of empirical studies regarding the merit-order effect in several countries, including Denmark, Germany, and Spain.

2.4. Renewable energy intermittency

Although renewable energy sources provide essential benefits for our environment, health, and economy, their intermittent nature challenges the design and operation of electricity markets. As Pérez-Arriaga and Batlle (2012, p. 2) put it, “intermittency comprises two separate elements: non-controllable variability and partial unpredictability.” Non-controllable variability refers to those situations in which renewable power plants are either unavailable when increased energy requirements occur in the system, or inject substantial amount of energy into the grid irrespective of the electricity demand level. The main reason for this is that renewable energy is determined by weather conditions such as solar radiation or wind speed, contrary to dispatchable generators that adapt their output as a reaction to economic incentives, and therefore the current energy requirements (Hirth, 2013). On the other hand, partial unpredictability describes the limited knowledge about future renewable power generation, due to the stochastic nature of weather conditions.

It is worth noting that similar to other applications, the forecasting horizon is an important factor of precision, and therefore the shorter the time horizon, the more accurate the weather predictions become. Accordingly, electricity markets should be designed in such a way that power systems are getting updated frequently with more accurate forecasts. Although a detailed description of each individual type of electricity market is not within the scope of this paper, it is important to underline that uncontrollable variability effects of renewables impact the day-ahead electricity markets primarily, while unpredictability issues influence the intraday and balancing markets through forecast errors (Morales et al., 2014). This work focuses on the non-controllable variable nature of renewables and its effects on the German day-ahead electricity price, which constitutes a European reference due to its underlying liquidity.

The replacement of dispatchable, conventional power plants with non-controllable variable renewables is a complex procedure, which introduces uncertainty with respect to the market design and particularly for the renewable support mechanism. The main reason is that electricity demand is time-varying and the upstream electricity market should have short-term flexibility to serve the required load. Nicolosi (2010, p. 7257) defines the flexibility of the electricity markets as "their ability to efficiently cover fluctuating electricity demand," and he adds "this flexibility is influenced by the installed power plant mix and the interaction with other markets." Traditionally, the German power generation mix consisted of thermal power plants that were designed and scheduled to cover dispatch requirements, which were merely subject to the varying demand forces. However, the integration of renewables increased the variability of residual demand and therefore the operating modes of thermal power plants. Hence, the number of start-ups and shutdowns in thermal production increased significantly in order to balance electrical load and avoid power blackouts. Therefore it can be seen that the role of the conventional power plants is currently twofold; firstly, to adjust to the intermittent renewable power generation, and secondly, to cover the time-varying electricity demand. This significantly increases the call for power system flexibility, as well as the need for the necessary regulatory and operational adjustments. Pérez-Arriaga and Batlle (2012) underline the importance of flexibility for the cost of economic dispatch, and comment on their inversely proportional relation. Shutting down and starting up thermal power plants implies increased operation costs due to lower power efficiencies. So the higher the flexibility of the power generation fleet is, the lower the overall cost that is incurred and vice versa.

2.5. Negative prices and their implications

In the same way that natural resource prices reflect the underlying market scarcities, negative electricity prices represent the limited system's flexibility. The first negative electricity prices in the European Energy Exchange were observed in October 2008, after the European Energy Exchange (EEX) decided to correct inefficient incidents and more particularly situations when energy oversupply needed to be cut (Nicolosi, 2010). Since then, they have become increasingly common events attracting considerable attention in the literature. Fanone et al. (2013) study the case of negative day-ahead electricity prices in the German day-ahead spot market and underline their considerable challenge in energy risk management activities. In a similar study, Genoese et al. (2010) show that a sufficient condition for the appearance of negative prices is either a low system load, combined with a moderate wind generation or a moderate system load combined with high wind generation. Besides the other factors, they find wind generation to be the most important influential factor, while they comment on the occurrence of all negative prices during the off-peak period.

Negative electricity prices are not problematic per se, since they are basically efficient for non-storable goods (Nicolosi, 2010). They arise mainly as a result of the large-scale renewable power generation, and the priority dispatch that the renewable support scheme provides them (Brandstätt et al., 2011). Hence in some hours, when the aforementioned sufficient conditions are satisfied, inflexible conventional power plants are forced to ramp-down and give priority to renewables. However, renewables may stop generating electricity only few hours later, and thereby base-load plants need to ramp-up quickly in order to serve the electricity demand. High opportunity costs may occur in these following hours, when prices are above variable costs for conventional power plants, due to their limited flexibility and expensive ramp-ups. This results in the fact that conventional plant operators are willing to bid negative prices into the market in order to avoid these ramp-downs and continue to produce, increasing their revenues. They can follow this pricing strategy as long as the opportunity costs and start-up costs are higher than the negative prices that they need to bid. It is worth mentioning that apart from these costs, long minimum standstill periods and accordingly revenue losses arise for the conventional power plants, before they can start producing again (Genoese et al., 2010). In fact, these long inactive periods threaten the sustainability of the conventional power plants that need high utilization in order to cover their high investment costs (Nicolosi, 2010). Furthermore, they create higher system costs, since a part of demand needs to be produced by other power plants that exhibit lower response time, but more expensive generation.

Another implication of negative electricity prices is the creation of investment incentives for flexible power generation. However, these incentives can be very inefficient and costly to society (Brandstätt et al., 2011). That is to say, although during some hours conventional power plants exhibit negative marginal costs and bid negative electricity prices to avoid their ramp-down, renewables penetrate into the system with zero marginal costs, owing to their priority dispatch. Brandstätt et al. (2011) discuss how the operation of renewable energy sources constraints the two leverages of the electricity market, namely prices and quantities; prices are established through fixed-feed in tariffs, while quantities are fixed through priority dispatch and restrictive curtailment. In fact, Brandstätt et al. (2011, p. 3736) underline the fact that "market loses degrees of freedom to perform its market-clearing function, at the expense of system-wide economic efficiency." Therefore they suggest voluntary curtailment agreements, as well as maintenance of the priority rule for renewables. Henriot (2015) comments on the limited literature on the economic curtailment, and argues that negative prices are the first market signals for economic curtailment of renewables. Finally, motivated by the aforementioned discussions, we proceed to the next section with the data description.

3. The data

We use daily German electricity spot prices, solar (s_t) and wind (w_t) power generation, and total electricity load (l_t) over the period from January 1, 2010 to June 30, 2015 — a total of 2007 observations. Specifically, we use the day-ahead spot electricity price, Phelix Day Base, which is calculated as the average price of the 24 h of one day; the Phelix Day Peak, which is the average electricity price of the peak hours; and the average electricity price of the off-peak hours. It is worth mentioning that peak hours cover hours 9–20, while off-peak hours cover hours 1–8 and hours 21–24.[1] The main reason for distinguishing

[1] *The definition of peak and off-peak hours remains the same during all the months of the year.*

between peak and off-peak hours is the fact that during these hours electricity markets exhibit different characteristics, for instance, flexibility, and economic efficiency, which are accordingly reflected in the electricity price dynamics. In fact, as Ballester and Furió (2015, p. 1606) put it, “the picture has become more informative when peak and off-peak hours are analyzed separately, confirming the fact that these price series should be viewed as different commodities, with different features.” All electricity prices and renewable power generation are from the European Energy Exchange, while total electricity load is from the European Network of Transmission System Operators for Electricity (ENTSO-E).

It is worth mentioning that since we investigate the effects of variable solar and wind power generation on day-ahead electricity prices, the predicted, rather than the actual power generation should be employed in the analysis. The main argument behind this is that the actual power generation does not affect the day-ahead electricity volumes and prices directly, but through their predictions that are placed in the market to be cleared (Morales et al., 2014). However, in this analysis we employ the actual renewable power generation and total load for two reasons. First, the data availability for predicted solar and wind power generation is limited, and second, since the predicted total load data is not available we would have to construct our own prediction model. However, this would render our estimation results subject to the generated regressor problem studied in detail by Pagan (1984), since the estimated predictions of total load would only be a proxy for the market expectations. Hence, we follow Nicolosi (2010) and accordingly use the actual solar and wind power generation, as well as the actual total electricity load. Nicolosi (2010, p. 7261) argues that “since, in this article, the actual market situation is analyzed, the realized values are used.” From a similar point of view, Mauritzen (2013), who investigates the effect of wind power production on Danish and Norwegian day-ahead prices, uses the actual wind power generation data, as an approximation of the forecasted wind.

Table 2 presents summary statistics for the electricity prices, solar and wind power generation, and total electricity load. Figs. 2 and 6–10 depict the development of the series from January 2010 to June 2015. This is the period after the latest profound modification which occurred in Germany's renewable energy policy in 2010. Significant changes followed in the electricity production mix [see Table 1], with the most important being the nuclear phase-out, and the rapid integration of photovoltaic and wind power systems. Despite the aggressive renewable energy transition, Germany currently produces more electricity from coal (hard coal and lignite) than renewables, with coal being at a slightly higher level than in 2010. This comes about as a result of the fact that energy transition towards renewables is a long-term and complex process, and therefore the major part of nuclear power production has to be replaced by other energy sources, such as coal. Natural gas also remains a considerable source of the electricity production mix, despite its decline in recent years, since it supports the flexible peak-load power generation that complements the variable nature of renewables. So in fact, Germany is still strongly dependent on heavily polluting fossil-fuels, and therefore far from meeting the emission reduction target of 40% by 2020, compared to 1990 levels.

Some stylized facts of electricity prices are discernible from Fig. 2. A

Table 2
Summary statistics.

Variable	Mean	Standard deviation	Skewness	Excess kurtosis	J-B normality
p_t	40.710	12.144	−0.637	6.558	1194.673
$p_{peak,t}$	46.018	14.516	−0.113	4.155	115.817
$p_{off-peak,t}$	35.403	11.130	−2.878	37.184	100490.115
s_t	67090.677	52857.637	0.673	2.433	178.431
w_t	131069.269	110880.605	1.652	6.169	1752.855
l_t	1326660.182	164759.086	−0.390	2.399	81.027

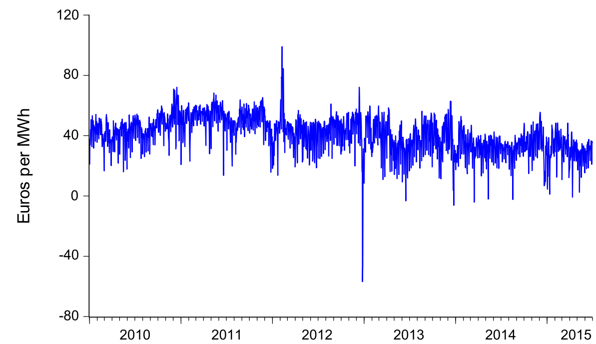

Fig. 2. All hours electricity prices.

yearly season is present with the price showing a tendency to decrease during the first half of the year and recover gradually by the end of it. The pattern becomes more obvious during the last years of our sample period, possibly due to implications of the energy transition. In addition, we identify a mean reverting behavior, and a slight tendency for the price to decrease over the last six years, signifying the success of the regulatory changes. Some periods of high volatility followed by periods of relative tranquility can also be identified. Another interesting stylized fact of electricity prices is sudden price spikes. Ullrich (2012) defines price spikes as the combination of an upward jump and a reversal, while he underlines their risky nature for wholesale electricity markets. Electricity price spikes can be attributed to limited economic possibilities of large-scale electricity storage, but should also be investigated in relation to renewable energy sources. Due to these price spikes, the electricity price distributions exhibit high kurtosis and fat tails (see Figs. 3–5), thus leading to substantial challenges for the operations of energy risk management.

Figs. 6 and 7 show the actual solar and wind power generation during the sample period. We find out that each energy source has its own advantages and areas where compromise is necessary. Wind power production provides the power market with high amounts of energy most of the year, but its output is highly volatile due to its intermittent nature. In contrast, solar power production is more stable than wind power production, and therefore easier to incorporate into medium-term planning (Kovacevic et al., 2013). However, a consistent pattern related to the seasons of the year becomes obvious in the solar production that reaches its maximum during the summer and decreases again gradually during the winter. The inverse seasonal pattern is partly identified in wind power production, thus indicating the extent to which the complementary nature of the solar and wind power generation can be exploited in the future for a hybrid power generation system. The high penetration rate of solar power into the electricity generation mix is also discernible from Fig. 6, as a result of generous policy incentives and sharp decline in installation costs.

Electricity demand is an equally important factor in price formation as the electricity supply. In the power systems, it is captured by the total electricity load which is illustrated in Fig. 8. We can see clearly

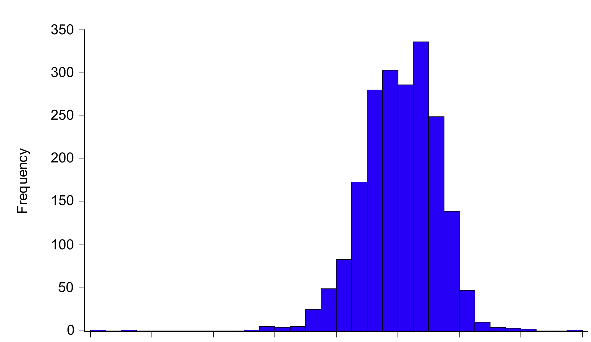

Fig. 3. Histogram of all hours electricity prices.

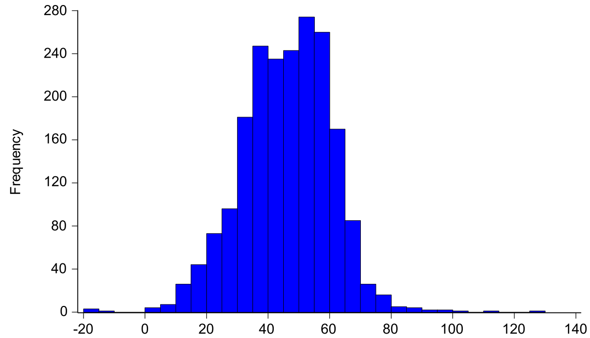

Fig. 4. Histogram of peak electricity prices.

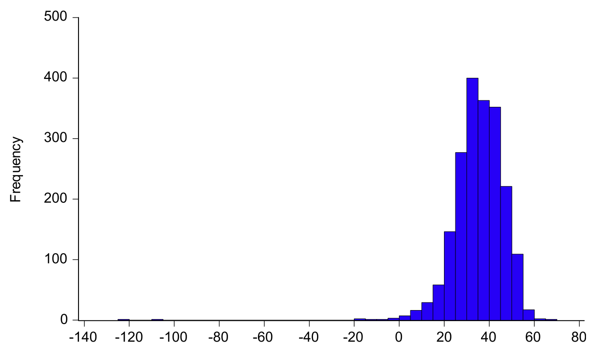

Fig. 5. Histogram of off-peak electricity prices.

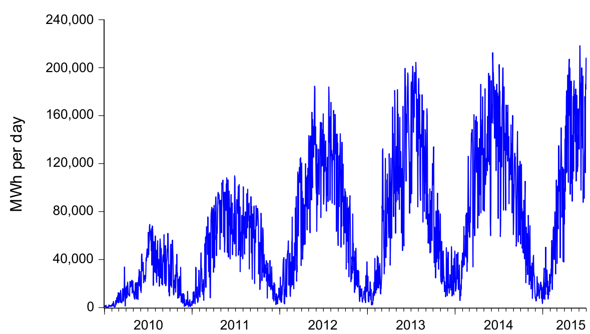

Fig. 6. Solar power production.

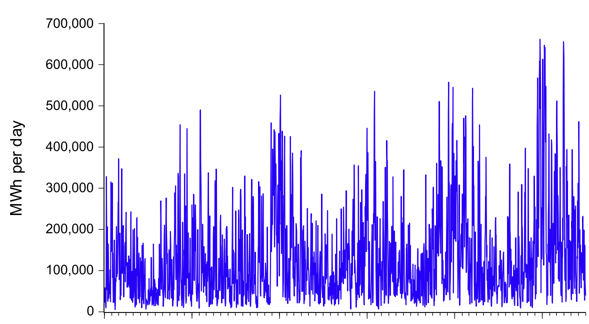

Fig. 7. Wind power production.

that electricity demand is well aligned to wind power production, reaching its maximum during the winter, and falling off gradually during the summer. In fact, as Agora (2015, p. 15) puts it, “Germany continues to be a winter peaking country primarily due to the demands of lighting and water and space heating; 6.1% of space heating is fueled electrically, including night storage systems and heat pumps.” In fact, electricity demand follows an inverse seasonal pattern than solar power production, which pushes down the peak electricity price. By looking at Figs. 6, 9 and 10, we notice that peak electricity prices get lower values

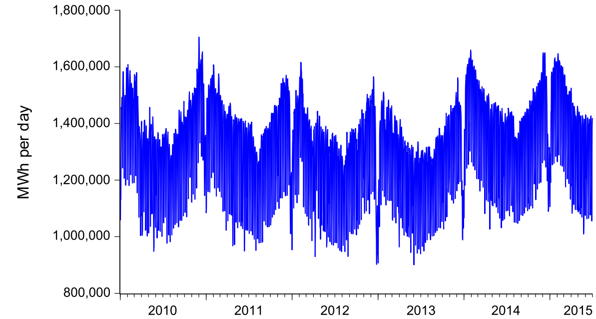

Fig. 8. Electricity load.

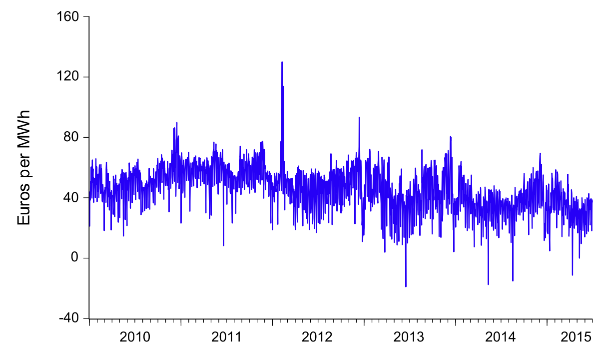

Fig. 9. Peak electricity prices.

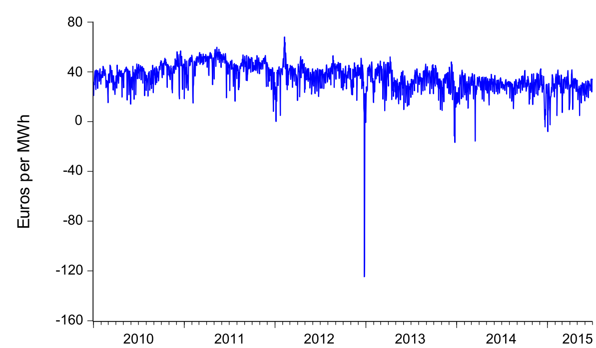

Fig. 10. Off-peak electricity prices.

than off-peak electricity prices during the spring and summer seasons. So, we may conclude that the spread between peak and off-peak electricity prices decreases when solar power generation reaches its maximum and vice versa. However, this conclusion might rely only on some coincidental facts, and therefore additional empirical investigation is necessary.

Before we continue with the empirical analysis, we conduct some necessary unit root and stationary tests in each of the employed series in Table 3, in order to test for the presence of a stochastic trend in the autoregressive part of the series. The Augmented Dickey-Fuller (ADF)

Table 3
Unit root and stationarity tests.

Variable	ADF τ_μ	DF-GLS μ	KPSS $\hat{\eta}_\mu$	KPSS $\hat{\eta}_\tau$
p_t	−4.458*	−1.894	3.699*	0.408*
$p_{peak,t}$	−3.969*	−1.656	3.455*	0.332*
$p_{off-peak,t}$	−4.845*	−2.340*	3.455*	0.396*
s_t	−2.613	−1.098	1.597*	0.107
w_t	−11.805*	−8.286*	1.107*	0.101
l_t	−4.838*	−1.647	0.399	0.307*

* Significance at the 5% level.

Table 4
Price distribution properties for different solar power penetration levels.

	0–7%	7–14%	14–21%
Mean	43.307	36.023	28.031
Standard deviation	12.128	9.725	9.676
Skewness	−1.026	−0.180	−0.757
Kurtosis	5.837	0.472	0.955
Observations	1378	550	79

Table 5
Price distribution properties for different wind power penetration levels.

	0–5%	5–10%	10–15%	15–20%	20–25%	25–55%
Mean	46.066	42.258	39.312	36.026	32.371	22.866
Standard deviation	10.218	10.578	9.498	9.533	10.938	14.337
Skewness	−0.164	0.264	−0.278	−0.151	0.182	−2.165
Kurtosis	0.350	1.021	0.507	−0.458	−0.414	9.029
Observations	684	562	353	174	100	134

test [see Dickey and Fuller, 1981] and the Dickey-Fuller GLS test [see Elliot et al., 1996] evaluate the null hypothesis of a unit root against an alternative of stationarity. We assume a constant, and select the optimal lag length based on the Bayesian information criterion (BIC). In addition, Kwiatkowski et al. (1992) tests are used in order to test the null hypothesis of stationarity (around a constant, for test statistic $\hat{\eta}_\mu$, and around a trend, for $\hat{\eta}_\tau$). We note that electricity prices during all hours and peak hours are not very informative regarding their unit root properties, although they should be stationary based on their mean reverting behavior [see Schwartz, 1997; Simonsen et al., 2004; Weron et al., 2004; Cartea and Figueroa, 2005], which is also verified by their historical development. Since overdifferencing may be more harmful than including a unit root series in levels, we use the levels of these series alongside the careful checking of the stationarity of the residuals in the model. An examination of the unit root and stationarity tests for the rest of the series, in combination with their historical development in Figs. 6–8, and 10, suggest that their levels are stationary, or integrated of order zero, $I(0)$. Last, we check for multicollinearity by using auxiliary regressions, as well as by examining the correlation matrix of the independent variables. Both of them suggest that there is no sign of severe multicollinearity.

4. The effects of solar and wind

Having analyzed the descriptive statistics and characteristics of the employed series, the question remains how solar and wind power generation affects day-ahead electricity prices. Therefore, in this section we analyze the way that the main properties of the electricity price distribution react to different amounts of solar and wind power generation, while taking into account total electricity load. We follow Jónsson et al. (2010) and divide our data into intervals, according to solar and wind power penetration; penetration here is defined as the ratio of each electric power source to the total electricity load. Tables 4, 5 summarize the properties of price distribution for different scenarios of solar and wind power penetration respectively, while Figs. 11 and 12 illustrate the corresponding histograms of electricity prices.

In the case of solar, the first two lines of the table show that both the mean and standard deviation of the electricity price decrease as solar power penetration increases. Moreover, the third and fourth central moments are calculated for each interval. Skewness, which is a measure of the degree of asymmetry of a distribution, takes always negative values indicating the left long tail, while kurtosis is high in the beginning, thus capturing the heavy tails of the distribution, and decreases significantly for solar power penetration higher than 7%. Hence, there is statistical evidence that the probability of extremely low electricity prices decreases when solar power penetration gets larger. Fig. 11 verifies this change in the distributional properties of electricity prices.

The mean of the electricity price also decreases for higher levels of wind power penetration. It is important to state that for wind power penetration higher than 25%, the mean of electricity price declines by around 50%. However, the standard deviation of the electricity price distribution increases as wind power penetration gets larger, providing some evidence of augmented volatility — see Jónsson et al. (2010). Skewness and kurtosis do not provide any obvious pattern, apart from the last interval where electricity price distribution exhibits negative skewness and high kurtosis. That is to say, the probability of very low electricity prices increases when wind power serves more than 25% of the electricity demand. This rapid change of distributional properties during the large interval might be an indication of non-linear effects of wind power generation on electricity prices.

5. GARCH modelling

This section presents three univariate GARCH-in-Mean models for three different electricity prices. In particular, we estimate three GARCH(1,1) models that apply to German day-ahead electricity prices during all hours, peak hours, and off-peak hours. In each case, we specify the mean equation based on the Schwarz Information Criterion (SIC), the Akaike Information Criterion (AIC), and the Hannan-Quin Information Criterion (HQC) (see panels A, B, and C of Table 6), which all suggest the AR(7) as the optimal model specification. Accordingly, the three mean equations are represented as

$$p_t = \alpha + \beta_1\sqrt{h_t} + \sum_{i=1}^{7}\beta_{1+i}p_{t-i} + \beta_9 s_t + \beta_{10}w_t + \beta_{11}l_t + \varepsilon_t \tag{1}$$

$$p_{peak,t} = \alpha + \beta_1\sqrt{h_t} + \sum_{i=1}^{7}\beta_{1+i}p_{t-i} + \beta_9 s_t + \beta_{10}w_t + \beta_{11}l_t + \varepsilon_t \tag{2}$$

$$p_{off-peak,t} = \alpha + \beta_1\sqrt{h_t} + \sum_{i=1}^{7}\beta_{1+i}p_{t-i} + \beta_9 s_t + \beta_{10}w_t + \beta_{11}l_t + \varepsilon_t \tag{3}$$

where $\sqrt{h_t}$ is the conditional standard deviation, s_t the solar power generation, w_t the wind power generation, and l_t is the total electricity load.

The variance equation of the model is a classic GARCH(1,1) equation augmented with additional regressors — the solar power generation, wind power generation, and the total electricity load. The resulting variance equation is

$$h_t = c_0 + a_1\varepsilon_{t-1}^2 + b_1h_{t-1} + b_2s_t + b_3w_t + b_4l_t \tag{4}$$

where h_t is the conditional varianceand ε_{t-1}^2 are the squared residuals.

It is noteworthy that in contrast to a large part of the literature, we actually include the negative electricity prices in our analysis, since we consider them useful for a better understanding of the market functioning, and also because there is some evidence for a direct relation between them and renewable power generation. The empirical consideration of negative electricity prices for the case of the German/Austrian electricity market is rarely found in the literature since they were not present until 2009 (Ziel et al., 2015). However, Keles et al. (2012) include them in their simulation study and get better results, while Fanone et al. (2013) also argue in favor of their inclusion. Therefore, we include the negative prices in our analysis without cutting off or shifting the series. Moreover, we do not apply any extreme value theory, and we merely filter values that exceed, by ten times, the standard deviation of the original price series.[2] We replace

[2] It is a common practice in the literature, for outlier detection purposes to filter values that exceed three times the standard deviation of the original series. However, we use the threshold of ten times, so that we solve some potential numerical problems and at the same time include as many observations as possible.

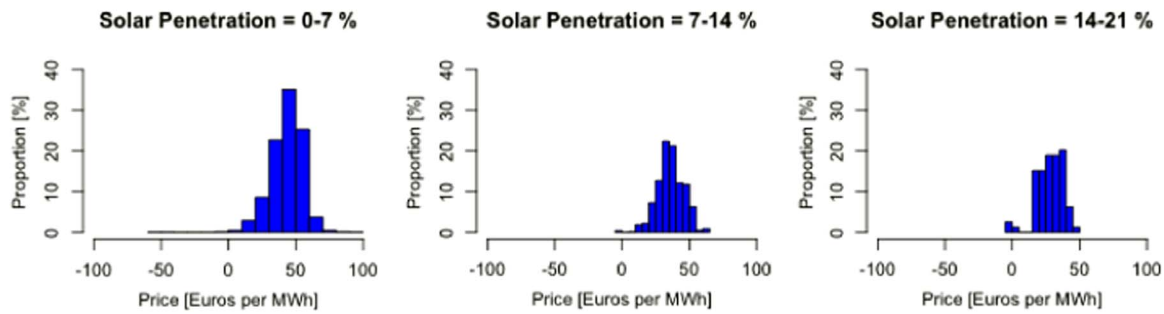

Fig. 11. Distribution of prices for different intervals of solar power penetration.

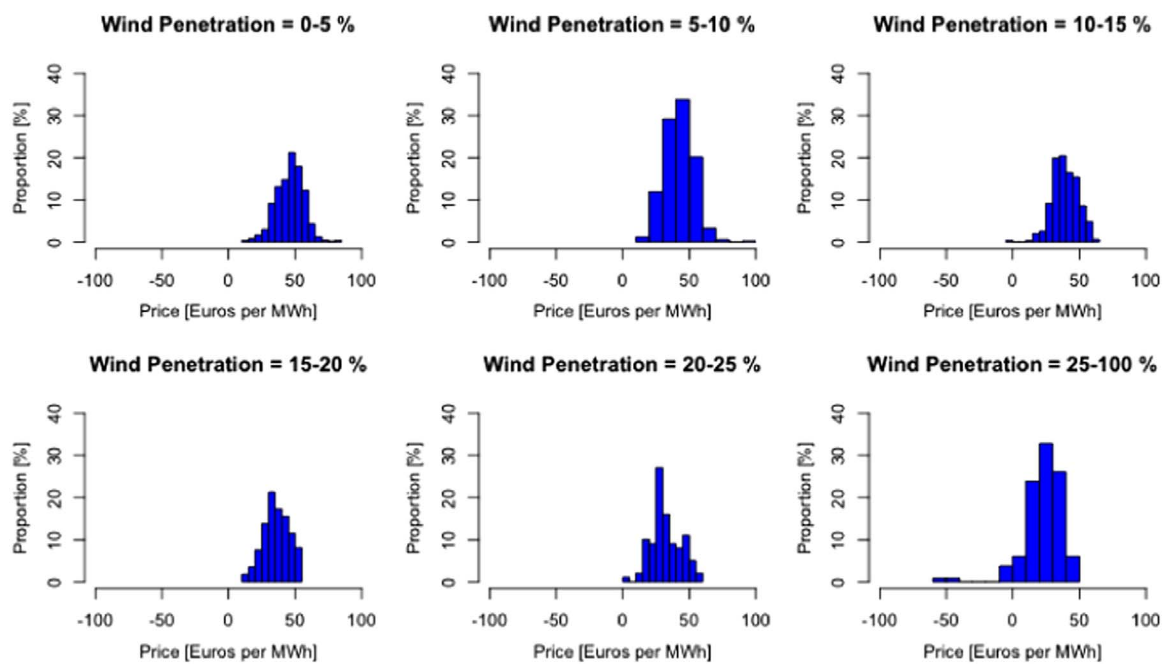

Fig. 12. Distribution of prices for different intervals of wind power penetration.

the outliers, which arise from the combination of exceptional high wind penetration and low demand, with the median of the respective series, which is a robust statistic.[3]

The empirical estimates for the three models, Eqs. (1) and (4), Eqs. (2) and (4), and Eqs. (3) and (4), are presented in panels A and B of Tables 7–9. All autoregressive coefficients, with the exception of the fifth during all hours and off-peak hours, as well as the fourth and fifth during peak hours, are found positive and statistically significant at the 1% level, while GARCH-in-Mean effects are found significant at the 5% level, but only for the case of electricity prices during peak hours. Hence, risk captured by electricity price volatility seems to propagate towards electricity prices during peak hours and affect them in a positive way. The most striking feature in the mean equation is the negative effect of solar and wind power generation on electricity prices, which is in line with the literature. In fact, wind exhibits a more severe effect than solar during all hours of the day, while the solar effect is significant during peak hours, but not during off-peak hours. In contrast, the total electricity load has, as expected, a positive impact on electricity prices throughout all hours of the day, while its effect becomes more prominent during peak hours when the electricity system is tight. Consequently, electricity prices increase with higher demand, and this rise is even greater when demand is high, relative to the other hours of the day and the power system capacity.

In the variance equation, the GARCH coefficient on h_{t-1}, which reflects the persistence of past shocks on the variance, is moderately high (0.552) during peak hours, and low (0.278) during off-peak hours. The ARCH coefficient on ε_{t-1}^2, which captures the impact of new shocks, is always found very low, while total electricity load which reflects the electricity demand profile, surprisingly, decreases electricity price volatility during all hours of the day. Finally, the most interesting feature in the variance equation is the significant effect of solar and wind power generation on electricity price volatility. Specifically, solar power production reduces electricity price volatility in contrast to wind power production that augments it. This finding is in accordance with

Table 6
Optimal AR lag in the mean equation.

Lag	A. All prices			B. Peak prices			C. Off-peak prices		
	AIC	SIC	HQ	AIC	SIC	HQ	AIC	SIC	HQ
1	5.558	5.591	5.570	6.095	6.128	6.107	5.464	5.497	5.476
2	6.097	6.134	6.111	6.354	6.390	6.367	5.684	5.720	5.697
3	5.859	5.898	5.873	6.405	6.444	6.419	5.787	5.826	5.802
4	5.753	5.794	5.768	6.164	6.206	6.179	5.643	5.685	5.658
5	5.411	5.456	5.428	5.918	5.963	5.934	5.303	5.348	5.320
6	5.389	5.437	5.407	5.891	5.939	5.909	5.275	5.323	5.293
7	5.363	5.413	5.382	5.848	5.898	5.867	5.259	5.309	5.277
8	5.548	5.601	5.567	5.849	5.903	5.869	5.260	5.313	5.279

[3] Only 2 observations out of 2007 for the electricity price during off-peak hours are replaced with the median of the series.

Table 7
Univariate GARCH base model.

A. Conditional mean equation	
Constant	10.850 (0.3252)
$\sqrt{h_t}$	0.086 (0.0867)
p_{t-1}	0.463 (0.0000)
p_{t-2}	0.097 (0.0005)
p_{t-3}	0.075 (0.0060)
p_{t-4}	0.068 (0.0081)
p_{t-5}	0.042 (0.0755)
p_{t-6}	0.069 (0.0026)
p_{t-7}	0.162 (0.0000)
s_t	−3.465E−05 (0.0000)
w_t	−4.481E−05 (0.0000)
l_t	4.037E−05 (0.0000)
B. Conditional variance equation	
Constant	23.159 (0.0000)
ε_{t-1}^2	0.226 (0.0000)
h_t	0.447 (0.0000)
s_t	−1.483E−05 (0.0000)
w_t	1.385E−05 (0.0000)
l_t	−1.436E−05 (0.0000)
C. Standardized residual diagnostics	
$Q(30)$ p-value	0.0001
$Q^2(30)$ p-value	0.9958

Table 8
Univariate GARCH peak model.

A. Conditional mean equation	
Constant	−7.033 (0.3232)
$\sqrt{h_t}$	0.121 (0.0233)
p_{t-1}	0.390 (0.0000)
p_{t-2}	0.124 (0.0000)
p_{t-3}	0.062 (0.0096)
p_{t-4}	0.043 (0.0719)
p_{t-5}	0.057 (0.0116)
p_{t-6}	0.082 (0.0001)
p_{t-7}	0.207 (0.0000)
s_t	−6.838E−05 (0.0000)
w_t	−5.035E−05 (0.0000)
l_t	5.557E−05 (0.0000)
B. Conditional variance equation	
Constant	26.318 (0.0000)
ε_{t-1}^2	0.198 (0.0000)
h_t	0.552 (0.0000)
s_t	−1.476E−05 (0.0018)
w_t	1.953E−05 (0.0000)
l_t	−1.656E−05 (0.0000)
C. Standardized residual diagnostics	
$Q(30)$ p-value	0.0000
$Q^2(30)$ p-value	0.9011

the previous results from the analysis of distributional properties of electricity prices under different renewable power penetration, where the standard deviation of electricity prices was found to decrease with higher solar power penetration, but to increase with higher wind power penetration.

The effects of solar and wind power generation on electricity price characteristics can be understood better through the analysis of the merit-order effect (see Fig. 1). First of all, every type of renewable power generation technology induces a merit-order effect, since they can always replace expensive fossil-fuel power generation due to their low, short-run marginal cost and priority dispatch. What really differentiates the effect of each renewable power source on electricity prices, is the relation of its power generation pattern with the special power system characteristics. In the case of solar, it is common knowledge that its greatest amount of production occurs during the same hours of peak electricity demand and therefore expensive peak-load power generation. Hence, solar power generation is expected to exhibit the strongest merit-order effect, compared to different renewable power sources, during peak hours. Accordingly, by looking at Fig. 1, we notice that the new electricity price, after solar power penetration, is set by the intersection of the demand curve D_2 and the new supply curve S_2. What is really noteworthy in this case, is not only the significantly lower system price but also the lower gradient of the new merit-order curve, where the demand curve crosses it. Thus, a new electricity price is set by 'cheaper' power generation, and demand variation can be handled adequately without high cost peak power plants penetrating into the system.

Moreover, solar power generation exhibits low variability, and therefore mid-load power plants can adjust their power production to residual demand efficiently, through their flexibility. In this way, solar power generation manages to reduce electricity price volatility which is characterized by large and frequent price spikes. On the other hand, wind power capacity is more than double that of solar and so, it is expected to induce a larger merit-order effect in total during the day. Combined with high variable power production, wind challenges the operation of power system, and more particularly its flexibility. That is to say, large amounts of wind power penetrate the system with high variability, and alternate the level of residual demand that conventional power plants need to serve. Thus, increased cycle effects and technology switching occur, causing frequent price spikes and increased price volatility. This effect becomes more prominent during off-peak hours, when system flexibility is even lower; base-load power plants, such as lignite or hard coal, bid negative prices in order to avoid ramp-downs, and thereby introduce negative price spikes and increase electricity price volatility.

Finally, Panel C of Tables 7–9 reports the Ljung-Box test statistics for the residuals. The Ljung-Box Q test for residual autocorrelation does not pass at conventional significance levels for all the lags; however, autocorrelation plots for residuals show very little autocorrelation and certainly no particular pattern that can be due to non-stationarity or seasonality. Overall, the diagnostic tests suggest that all GARCH models are correctly specified.

Table 9
Univariate GARCH off-peak model.

A. Conditional mean equation	
Constant	3.834 (0.2747)
$\sqrt{h_t}$	−0.054 (0.1417)
p_{t-1}	0.476 (0.0000)
p_{t-2}	0.092 (0.0002)
p_{t-3}	0.070 (0.0024)
p_{t-4}	0.060 (0.0049)
p_{t-5}	0.039 (0.0766)
p_{t-6}	0.099 (0.0000)
p_{t-7}	0.120 (0.0000)
s_t	−1.503E−06 (0.6436)
w_t	−3.861E−05 (0.0000)
l_t	2.552E−05 (0.0000)
B. Conditional variance equation	
Constant	22.663 (0.0000)
ε_{t-1}^2	0.143 (0.0000)
h_t	0.278 (0.0000)
s_t	−1.723E−05 (0.0000)
w_t	3.313E−05 (0.0000)
l_t	−1.394E−05 (0.0000)
C. Standardized residual diagnostics	
$Q(30)$ p-value	0.0000
$Q^2(30)$ p-value	0.0001

Table 10
p-values for Granger causality.

Causal variable	Electricity price		
	All hours	Peak hours	Off-peak hours
Solar	0.0000	0.0000	0.0000
Wind	0.0000	0.0000	0.0000
Load	0.0000	0.0000	0.0000
Solar & wind	0.0000	0.0000	0.0000

6. Granger causality

In this section, we test for Granger causality from solar power generation, wind power generation, and total electricity load to day-ahead electricity prices, within the already specified GARCH framework given by the Eqs. (1) and (4), Eqs. (2) and (4), and Eqs. (3) and (4). In fact, we investigate in the spirit of Granger (1969) whether past information about solar power generation, wind power generation, or total electricity load improves the prediction of electricity prices, beyond predictions that are based merely on past electricity prices.[4] We do that in a multivariate context, and use the Wald (1943) test in order to investigate whether the coefficients of solar, wind, or load, respectively, are zero, thus not Granger-causing electricity prices.

First, we test for Granger causality between electricity prices and solar power generation. Hence, we test the null hypothesis that the set of coefficients of solar, in the mean and variance equations, are jointly zero. If the null hypothesis is rejected, then we can safely conclude that solar Granger-causes the corresponding electricity price distribution. In addition, we explore the same causal relations for the case of wind power generation as well as total electricity load. Table 10 reports the results of these tests for electricity prices during all hours, peak hours, and off-peak hours; *p*-values lower than 0.01 indicate rejection of the null hypothesis of no Granger causality at the 1% significance level. The results clearly indicate that solar power generation, wind power generation, and total electricity load Granger-cause electricity prices at the 1% significance level.

Moreover, we investigate the combined impact of the two most important, intermittent, renewable energy sources in the German electricity market, solar and wind on electricity prices. Hence, we test the null hypothesis that the four coefficients of solar and wind power generation in the mean and variance equations are jointly zero. By looking at Table 10, we conclude that their combined impact Granger-causes electricity prices and modifies their distributions. Hence, we arrive at the conclusion that with our data, there is statistically significant evidence for Granger causality from solar power generation, wind power generation, and total electricity load to electricity prices. An interesting direction for future research would be to investigate the same causal relations in the context of non-linear models, while exploring the complex intraday dependence of hourly prices.

7. Conclusion

Climate change, environmental degradation, growing energy demand, depletion of natural resources, and limited energy security, all render the deployment of renewable energy sources in the electricity industry of high importance for decades to come. However, despite their many advantages, renewables challenge the operation of electricity markets with their intermittent nature. This paper discusses the ongoing transition of the German electricity market towards renewables, as well as the effects of intermittent solar and wind power generation on electricity price formation through the supply and demand mechanism. More importantly, it provides a study of the relationship between day-ahead electricity prices and solar and wind power generation and total electricity load for all hours, peak hours, and off-peak hours, using data over the period from 2010 to 2015. It also investigates the distributional properties of electricity prices under different scenarios of solar and wind power penetration.

We find that there are causal relationships from solar power generation, wind power generation, and total electricity load to electricity prices during all hours, peak hours, and off-peak hours. We provide evidence that although both solar and wind power generation induce a merit order effect, they have different effects on the volatility of electricity prices and their higher order moments. In particular, solar power generation reduces the volatility of electricity prices while it reduces the probability of electricity price spikes. On the other hand, wind power volatility passes through to electricity prices volatility, and introduces electricity price spikes. While the volatility of renewable power is driven by the stochastic nature of weather conditions, the volatility of electricity prices is also subject to market design.

The findings of this paper underline that effective and sustainable integration of large-scale renewable energy begins with a clear understanding of the distinct properties of each renewable energy source, as well as of its interaction with different parts of the power system. Increased flexibility seems to be the crucial element for addressing different aspects of renewable energy intermittency, such as variability or uncertainty, and rendering renewable energy sources viable and reliable. Hence, flexible conventional power generation, adequate transmission grid, and contribution of renewable energy to system stability are some of the potential ways to increase system flexibility. However, reducing the flexibility requirements through policy measures, such as economic curtailment of renewable generation, energy storage, demand response, and market interconnection can achieve similar results. Lastly, optimal management of renewable resources, for example, through geographic decorrelation, or resource complementarity is another key consideration for future deployment of large-scale renewables.

[4] Market forecasts about solar power generation, wind power generation, and total electricity load are provided before daily auction takes place at 12.00pm.

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