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The effect of wind and solar energy on the tails of the German electricity price distribution

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Abstract

Increased levels of wind and solar energy penetration in the German energy system are accompanied by increased uncertainty in electricity prices. This is a result of the highly intermittent nature of solar and wind energy generation and the instantaneous nature of electricity consumption. Moreover, German policy objectives aim at an efficient and sustainable future energy market with 100% renewable energy supply. This reinforces the increased desire to understand tail behaviour of electricity prices in relation to solar and wind energy penetration. This paper confirms the findings of Hagfors et al. (2016b), who revealed substantial differences in how wind and solar energy generation affect negative and positive price spikes. Besides, this paper adds to the findings of Kyritsis et al. (2017), who found that solar power generation reduces volatility and wind power generation increases volatility. Volatility, as a measure of risk, does not reveal information on the direction of the volatility in terms of positive and negative price spikes. This research improves insight on price estimation and risk assessment by providing distinctive estimations on the tails of electricity prices. Quantile regression techniques are applied to the 5^{th} and the 95^{th} quantile for on-peak and off-peak electricity prices and sensitivity analysis clearly reveals differences between the effects of solar and wind energy penetration on the left tail and the right tail. Improved understanding of the 90% confidence interval of electricity prices can, for example, enhance trading strategies with batteries such that expected gains and the corresponding risk can be judged more accurately for different levels of wind and solar energy generation. This increases the validity to invest in batteries, which could ultimately lead to an efficient and sustainable energy market with 100% renewable energy supply by balancing supply and demand.

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Chapter 1: Introduction

The German energy market has been subject to two major changes in the supply of energy. Firstly, deregulation of the energy market caused increased competition. Secondly, the role of renewable energy sources became of greater importance in the power generation mix, while at the same time nuclear power plants were scaled down. This transition towards renewables was announced by the government in 2011 and is referred to as the *Energiewende:* the country's planned transition to a low-carbon, nuclear-free economy (Renn & Marshall, 2016). Hereby Germany became a leader in renewable energy within Europe (Bederidge & Kern, 2013). The drastic reforms related to the energy transition led to changes in the dynamics of the electricity market. The growing role of intermittent renewable energy sources, mainly in terms of wind and solar energy, asks for a better understanding of the effects of renewables on electricity prices. This is of great concern for market participants, such as 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 with the aim to improve efficiency (Kyritsis, Andersson & Serletis, 2017).

The combination of the intermittency of renewable energy supply, the inelastic short-term demand of energy and the non-storability of energy lead to occasions in which frictions occur between supply and demand. Frictions are caused by the non-controllable variability of solar and wind energy generation, which depend on weather conditions (Kyritsis et al., 2017). As a result, extremely high and extremely low electricity prices became more common. Extremely low prices could result from oversupply, while extremely high prices could result from undersupply, both challenging flexibility from conventional power plants to meet demand by scaling down or ramping-up their generation. Extreme electricity prices increased the importance of modelling the tails of the electricity price distribution for participants on the energy market. A number of previous studies analysed German energy prices and their relation with solar and wind energy generation (e.g. Kyritsis et al., 2017; Hagfors et al., 2016; Paraschiv et al., 2014), but tail behaviour of electricity spot prices and causes of extreme price movements are currently not well understood. Especially in markets with a large share of intermittent renewable energy and with negative price occurrences, literature on the prediction of extreme electricity price behaviour is lacking (Kyritsis et al, 2017). This paper tries to fill this gap by investigating the effect of the supply of wind and solar energy on the tails of electricity prices in Germany, a country in which sustainable energy accounts for a large share of the total energy supply.

1.1 Previous Research

Kyritsis et al. (2017) conducted research on the effect of intermittent renewable power generation on electricity price formation in Germany by using univariate GARCH-in-Mean models for electricity prices. In their research, they underlined the importance of investigating the effect of wind and solar energy separately. They found that solar power generation reduces the volatility of electricity prices by scaling down the use of peak-load power plants, while wind power generation increases the volatility of electricity prices by challenging electricity market flexibility. The volatility measure does not provide an indication on the direction of the positive and the negative spikes of electricity prices. Besides the high volatility and large price spikes that electricity prices show compared to other financial assets, electricity prices are also characterized by a skewed distribution, volatility clustering, and seasonality (Hagfors et al., 2016a). As the research of Kyritsis et al. (2017) does not provide a distinction between the left tail and the right tail of the price distribution, it is likely that the non-normal behaviour of electricity prices is not fully understood and that the understanding can be improved.

Hagfors et al. (2016b) developed logit models using fundamental variables to estimate the probability of extreme prices and they found wind and photovoltaic power to impact the probability of negative prices as well as positive spikes. Their findings revealed substantial differences in how negative and positive price spikes are affected. They found positive spikes to be related to high demand, low supply, and high price on the previous day, while they found negative prices to be related to low demand in combination with high wind power generation. The investigation of the effect of wind and solar energy generation in particular revealed the importance of wind power in relation to negative prices, especially during night-time hours, while solar power only affects negative prices occasionally, especially during day-time hours. Differences in fundamental drivers regarding the probability of negative prices and positive spikes emphasize the importance to investigate the impact of solar and wind power generation on the magnitude of negative and positive price spikes separately, while taking into account demand.

The increased complexity of the market structure that resulted from the introduction of renewables and the non-linear relationships of electricity prices towards fundamental drivers make it hard to model pricing behaviour. Bunn, Andresen and Westgaard (2017) introduced quantile regression as a mean to forecast the value-at-risk of electricity prices. Their study was a methodological comparison of different methods to model electricity prices, and they underlined the benefits of quantile regression compared to benchmarks of

GARCH, as used by Kyritsis et al. (2017). The non-normal behaviour of electricity prices makes a semi-parametric technique more appealing, as it does not require assumptions on the distribution of the residuals and as the tails can be estimated with distinct regressions. Hagfors et al. (2016a; 2016c) did apply quantile regression models on both UK and German day-ahead electricity prices in order to model quantile dependencies. However, they did not include renewable energy as an explanatory variable when modelling UK electricity prices because this did not yet play a substantial role in the UK during the timespan of their data. They investigated the effect of wind and solar electricity generation on German electricity prices, but this research is very preliminary and no special attention is paid to the tails of the price distribution. Better presentation and interpretation of the results regarding the tails is therefore needed to draw conclusions on the tail dependencies and to provide insight into price expectations and value at risk properties.

1.2 Addition to Previous Research

Electricity price formations are complicated, non-linear relationships to fundamental variables and electricity prices behave highly different compared to prices of other financial assets such as regular stocks (Hagfors et al., 2016a). Sensitivity of electricity prices towards solar and wind power generation in the lowest and the highest quantiles provides insights on the confidence interval and properties of price risk. These properties of price risk, as represented by the predictive distribution rather than expected values, have previously not been fully analysed. As a result of the intermittency in the supply of renewable energy and the inelastic demand on the short run, I expect wind and solar energy generation, depending on the demand, to have different effects on extremely high and extremely low prices. This prediction is in line with the findings of Hagfors et al. (2016b) and would lead to an asymmetrical change in the distribution of electricity prices. To test this expectation, I will model the tails of price distributions rather than formulating central expectations, which is more common in the estimation of price behaviour of other financial assets. A change in volatility, as found by Kyritsis et al. (2017), does not reveal how the left tail and the right tail are affected individually. The volatility measure rather gives an overall indication of the variation in electricity prices in both the left tail and the right tail. This research adds to the understanding of tail behaviour in electricity prices by measuring the effect of solar and wind energy on the left and the right tail of the price distribution separately using quantile regression analysis. This regression technique can be used for value at risk calculations and is therefore useful for assessing price risk for consumers, suppliers, traders, risk managers and regulators (Hagfors et al., 2016c).

In conclusion, this paper tries to extend the perspective of Kyritsis et al. (2017) by looking at the upper and lower bound of the confidence interval separately rather than the volatility measure of electricity prices. This allows to recognise a different effect of wind and solar energy generation on the tails of electricity prices, given the differential effects found by Hagfors et al. (2016b) of solar and wind energy on positive and negative price spikes during different times of the day. Besides, this paper will expand the findings of Hagfors et al. (2016c) by going more into detail and by providing better understanding of quantile regression results on the distribution of German day-ahead electricity prices. To do so, I will investigate whether wind energy generation and solar energy generation as a share of total energy consumption, referred to as solar and wind energy penetration in the remainder of this paper, affect the bandwidth of the confidence interval during peak hours and off-peak hours. Moreover, I will examine how this effect applies to the left tail and the right tail of the confidence interval differently. This research will, therefore, combine and complement the established literature on the effect of renewable energy sources on day-ahead electricity prices, as well as the literature on the occurrence of extreme electricity prices on the day-ahead market. The ultimate aim is to provide a more comprehensive understanding for market participants and policy makers, such that an efficient energy market with increased levels of renewable energy penetration and decreased levels of CO_2 emissions can be reached. This could follow from reduced flexibility requirements (Kyritsis et al., 2017) through, for example, improved demand response and further development of energy storage (e.g. in terms of batteries). The latter could serve the long-term objectives of the full replacement of conventional power supply with renewable power supply. Improved insights in electricity prices could enhance investment in batteries by an increased understanding of the benefits of energy storage and corresponding trading strategies.

1.3 Research Questions

The resulting research question of this paper is as follows:

What is the effect of the share of wind and solar energy penetration on ***(a)*** *the left tail (q5) and* ***(b)*** *the right tail (q95) of the German electricity price distribution, and* ***(c)*** *what is the corresponding effect on the bandwidth of the 90% confidence interval?*

This research question will be answered for peak hours as well as for off-peak hours electricity prices. As mentioned, electricity price formations are complicated, non-linear relationships to fundamental variables. To get a better understanding of the underlying dynamics that drive electricity prices, several secondary questions will first be answered related to the German energy system, the supply and demand of electricity, and the current knowledge on the effects of wind and solar energy generation on electricity prices. The resulting secondary questions are as follows:

1. *How did the German electricity market develop?*
2. *How does the German energy mix look like?*
3. *How does the supply of electricity relate to electricity prices?*
4. *How does demand for electricity relate to electricity prices?*
5. *How do solar and wind energy generation affect peculiarities (seasonality, positive and negative price spikes in specific) in electricity prices?*

These questions will help in formulating hypotheses on the effect of wind and solar energy penetration on the left and the right tail of peak and off-peak electricity prices.

The structure of this paper is as follows. *Chapter 2* includes a theoretical framework that will provide a better understanding of electricity price formation and the corresponding effect of solar and wind power generation in Germany by answering the secondary questions. Thereafter, hypotheses related to the research question are formulated in *Chapter 3*. *Chapter 4* discusses the methodology and the data used and *Chapter 5* provides the corresponding results. The paper ends with a conclusion and discussion in *Chapter 6*.

Chapter 2: Theoretical Framework

This chapter provides insights into the developments in the German electricity market, discusses the main drivers of electricity prices (i.e. supply and demand), and discusses how solar and wind energy generation relate to electricity prices. The aim is to underpin the reasoning behind the hypotheses that will follow in *Chapter 3* on the expected effect of wind and solar energy penetration on the tails of the distribution of German day-ahead electricity prices in peak hours and off-peak hours.

2.1 Developments in the German Electricity Market

2.1.1. Deregulation

In 2005, a new set up regulatory authority facilitated independent electricity suppliers to use the grid. In 2009, incentive regulation (referred to as *Anreizregulierung)* was introduced to improve efficiency. Hereby, costs to use the grid were decreased and competition among network operators was increased (Mautz, 2010). The deregulation caused a shift in the way prices were formulated. Before the deregulation, a public utility commission set prices to ensure financial solvency of the firms (Kyritsis et al., 2017). Price variation was therefore limited. The increased competition led to a substantial increase in electricity price variation. The increase in price variation resulted from the market-clearing price being set on the German day-ahead power exchange, the EPEX spot market. Power producers bid certain amounts of power for a certain price while buyers bid how much power they are willing to buy at a certain price. This happens at noon every day for all hours of the following day (Genoese, Genoese & Wietschel, 2010). A distinction is made between peak-hours and off-peak hours, as there is an obvious difference in supply and demand dynamics between those hours. Peak hours reflect hours with high demand, whereas off-peak hours reflect hours with low demand. The bids are put in order and this leads to a supply curve and a demand curve. The market operator sets the market-clearing price at the level where expected supply meets expected demand. This price is paid to all successful bids. Supply and demand need to be balanced to create a stable power system, as electricity cannot be stored efficiently on a large scale. . The supply curve, which is non-linear and convex, is also referred to as the merit-order curve. Demand is inelastic on the short-run, so prices are highly dependent on the supply curve The dynamics of the merit-order supply curve and demand in on-peak hours and off-peak hours will be further elaborated on in *section 2.2.* Next to demand and supply, day-ahead prices are also influenced by lagged prices because prices have the tendency to follow yesterday's price, a form of behavioral adaptation (Hagfors et al., 2016a).

The deregulation in the electricity market allowed for another development to take place in the meantime: the introduction of renewables, which was triggered by environmental and socio-political considerations (Mautz, 2010). This development started to play a large role with the introduction of the *Energiewende*, the German energy transition.

2.1.2. The Energiewende

In March 2011, the *Energiewende* was introduced in Germany. As a result of this aggressive policy in the energy transition, Germany became the European leader in terms of renewable energy. This transition concerns both the phasing out of nuclear energy and the penetration of renewable energy in the energy system. The ultimate goals of the German policy concern all electricity generation to come from renewable energy sources, increased efficiency, and to decrease CO2 emissions and other greenhouse gasses (Renn & Marshall, 2016). To realise the increase in renewable energy generation, a support scheme was introduced which included, among others, fixed feed-in tariffs for renewables accompanied by a take-off obligation and a priority dispatch for renewables (Kyritsis et al., 2017). The support scheme increased investments in renewable energy projects and, thereby, the capacity for renewable energy generation. This shifted the merit-order supply curve to the right, leading to decreased electricity prices. Moreover, the intermittency and unpredictability of renewable energy supply also increased the variation in electricity prices. Current knowledge on the peculiar relationship between renewable energy penetration and electricity prices is further discussed in *section 2.3.* The strong growth in renewables makes Germany an interesting country to investigate the role of solar and wind energy generation on the distribution of electricity prices. The developments in the energy mix in Germany that resulted from the *Energiewende* are discussed in the subsequent section.

2.1.3. The German energy mix

In the period between 2010 and 2015, coal fired plants had the highest share in the production mix of Germany. Nuclear production has been decreasing at a fast pace, from 22.2 percent of total production in 2010 to 14.1 percent in 2015. In the meantime, the share of renewable energy production has almost doubled, from 16.6 percent of total production in 2010 to 30.1 percent of total production in 2015. This continued to increase to even 39 percent in 2018. Hereby, renewable energy became the primary source of electricity production in Germany. The increase in renewable energy is mainly attributable to wind and solar energy. Wind energy plays the biggest role in terms of renewables with 13.5 percent in 2015, followed by biomass, which accounted for 6.8 percent and solar photovoltaic, which accounted for 5.9 percent. In 2018, the share of wind increased even further to 21.0 percent and the share of solar increased to 7.8 percent (AG Energiebalanzen, 2018). The increasing importance of wind and solar energy as a share of total energy production in Germany leads to an increased interest in understanding their dynamics with electricity prices.

In line with data investigated by Kyritsis et al. (2017), data will be investigated for the period between 2010 and 2015. Table 1 is set up to provide an overview of the share of energy generation of different energy sources in Germany during these years. From Table 1, it can be observed that the share of renewables increased substantially, while the share of nuclear power decreased substantially. This is in line with the goals of the *Energiewende,* This trend is continued in the following years up till 2019 and given the policy objectives, it is expected that the role of renewables will continue to increase further in the near future. This expectation seems achievable given the increase of 52% and 16% in installed capacities of wind and solar plants respectively between 2015 and 2019 (ENTSOE Transparency Platform, 2019). This continuation emphasizes the importance for policy makers and participants in the electricity market to gain better insights into the extreme prices resulting from solar and wind energy penetration. It is important to be aware that increased capacity could lead to increased undersupply at times when solar and wind power plants do not generate or increased oversupply at times when solar and wind energy generate in excessive quantities. Consequently, increased flexibility or decreased flexibility requirements in the system's design are required in order to achieve the ultimate policy objective in which efficiency can be sustained while the total energy production originates from renewables. A forecasting model on extreme electricity prices could help market participants and policy makers with realizing this objective, for example through an increased understanding in how batteries can be used to balance supply and demand.

Table 1. Share of electricity production in Germany per power plant

	2010	2011	2012	2013	2014	2015
Hard coal	18.5	18.3	18.5	19.9	18.9	18.1
Lignite	23	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	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 energy	16.6	20.2	22.8	23.9	25.9	30.1
Solar	*1.8*	*3.2*	*4.2*	*4.9*	*5.7*	*5.9*
Wind	*6*	*8*	*8*	*8.1*	*9.1*	*13.5*

Source: AG Energiebalanzen 2018

2.2 Supply and Demand for Electricity

As previously mentioned, the day-ahead market-clearing price is derived at the intersection of the supply (or merit-order) curve and the demand curve. It concerns the day-ahead price, so the supply and demand mentioned in this section refer to day-ahead expectations of supply and demand. *Section 2.2.1* provides a better understanding of the underlying dynamics of the merit-order supply curve and *section 2.2.2* provides an enhanced understanding of the electricity demand. A distinction is made between on-peak hours and off-peak hours.

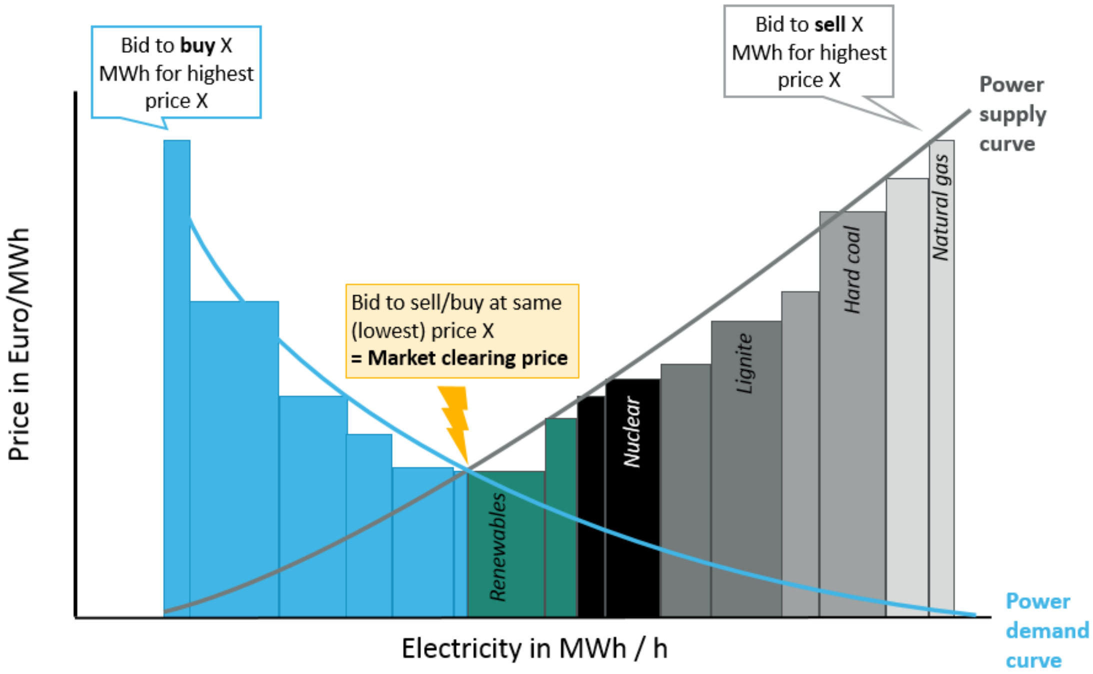
2.2.1. Merit-order supply curve

This section will provide a comprehensive understanding of the merit-order supply curve in Germany, which is the main driver of the variation in electricity prices given the inelastic short-term demand. The electricity supply curve is a merit-order curve where each plant's spot on the curve represents the cost and capacity of the plant. This results in a non-linear, convex supply curve. Different energy sources have different characteristics and costs. Power plants at the start of the merit order have the lowest marginal costs and will be exploited until the demand exceeds their capacity. This is repeated until the demand curve crosses the supply curve, and this intersection represents the day-ahead price and the corresponding energy mix (Clò, Cataldi & Zoppoli, 2015). Differences in the costs of different plants are mainly caused by the technology and fuels used in the production. The plants with the lowest marginal costs enter at the left side of the curve, whereas the plants with the highest marginal costs enter at the right side of the curve (Sensfuß, Ragwitz and Genoese, 2008). Renewable energy sources have the lowest marginal costs as these sources have zero or even negative marginal costs resulting from the support scheme (Kyritsis et al., 2017). Therefore, they position at the left end of the curve. Thereafter, the costs of nuclear are lowest, followed by the costs of coal and thereafter the costs of natural gas. These plants produce at approximately 10, 15 and 40 euros per MWh respectively (Paraschiv, Erni & Pietsch, 2014). As a result, natural gas enters on the right end of the curve, which is fired up to cover peaks in demand.

The structure of the merit-order supply curve is shown in Figure 1A. The expensive sources on the right side of the curve are more flexible than the sources on the left side that cover the base-load. Base-load power plants fueled by coal have less flexibility and produce energy constantly, while peak-load plants that use gas are way more flexible and only produce when additional energy is needed, mainly during peak-demand in the evening. These flexible power plants can also set higher prices resulting from increased market power. Renewables show a quite different pattern: solar panels produce between sunrise and sunset, while wind turbines produce when there is wind. This is contrary to conventional generators that determine output through economic incentives and current demand (Kyritsis et al., 2017).

Before the deregulation and the transition in the German energy market, the curve only consisted of nuclear and coal power plants covering the base load, until natural gas; the most expensive peak-load units covering peak load. The increased share of renewables displaced part of the large-scale base-load plants when actively producing (Hagfors et al., 2016b). Renewable energy sources play a particular role in the supply curve, as they are not concerned with marginal costs and are characterized by an intermittent nature. Given the inelastic demand curve, the generation of renewable electricity decreases electricity prices by shifting the merit-order supply curve to the right, referred to as the merit-order effect. A lower electricity price follows, as well as increased complexity of the electricity market dynamics through the increased need for flexibility (Kyritsis et al, 2017). Flexibility in this case refers to the ability to efficiently cover fluctuating electricity demand given the energy mix in place.

Figure 1A. Merit-order supply curve



Source: Clean Energy Wire 2018

The magnitude of the merit-order effect depends on several factors: the level of demand, the slope of the merit-order curve (which depends on fuel prices, efficiencies of power plants and market power), and the renewable electricity generation. Renewable electricity generation is intermittent: variability is non-controllable and generation is unpredictable resulting from unpredictability of weather. The non-controllable variability affects day-ahead prices. Generation is determined by weather conditions and this could lead to situations in which renewable power plants are unavailable at times of increased demand or situations in which renewable power plants generate a substantial amount of energy irrespective of a low demand level. As a result, conventional power plants are required to adjust to this intermittency and cover the time-varying electricity demand by providing flexibility. One of the possible consequences concerns the occurrence of negative prices, an effect of opportunity costs for shutting down being higher than the price that conventional power plants need to pay to get rid of their energy supply. Another possible consequence concerns positive price spikes, when additional plants higher on the merit-order curve (e.g. natural gas) with high market power need to be fired up to bridge the time with insufficient solar and wind in-feed to cover demand (Paraschiv et al., 2014). The exact dynamics behind negative and positive price spikes are discussed in more detail in *section 2.3.2*.

The predictability of demand during peak hours and off-peak hours leads to a distinction in the use of power plants between off-peak hours and peak hours. Different suppliers operate at different times of the day and this leads to differences in the flexibility and capacity during on-peak and off-peak hours. During off-peak hours, base-load plants like coal or nuclear are mainly operating, and these plants have high opportunity costs for shutting-down or ramping-up. As a result, flexibility during off-peak hours is lower than flexibility during peak-hours in terms of shutting-down. As a result of differences in flexibility, it is expected that renewable energy in-feed has different implications on electricity prices during peak hours and off-peak hours.

2.2.2. Demand

The merit-order supply curve is the main driver of variation in electricity prices, as demand is inelastic in the short-run. This inelastic nature results from the necessity of electricity for households, the manufacturing, and the service industry; consumers accept any price when they need electricity. Nevertheless, consumers' demand does play an important role in the determination of the prices, as oversupply is more likely in times of low demand and undersupply is more likely in times of high demand. The level of demand influences the effect of solar and wind energy penetration substantially by determining the position of the intersection with the merit-order supply curve. The daily pattern of the national demand follows a regular and predictable pattern (Boßmann and Staffell, 2015), in which seasonal behavior and historical figures can be used in making predictions. Weather conditions and the time of the day are the main predictors (McSharry Bouwman & Bloemhof, 2005). A distinction is made during hours of high demand, referred to as peak hours, and hours of low demand, referred to as off-peak hours. Peak hours cover the period between 9 in the morning and 8 in the evening, and off-peak hours cover the remaining hours (Kyritsis et al., 2017). The high demand during peak hours results from activity among households, the service sector, and industries. During the night, weekends, and holidays, demand is lower as a result of the service sector and the industrial activity being partly switched off. Besides the relationship between time of activity and demand, there is also a relationship between the temperature and demand. Demand could, for example, turn out high when low temperatures and bad weather forecasts occur, as this goes hand in hand with the need for heating.

The expectation of the demand of energy, and more particularly the residual demand, is an important driver in the day-ahead price. The integration of renewables increased variability of residual demand (Kyritsis et al., 2017). The residual demand concerns the level of demand that renewables cannot meet and must be served by conventional power plants, determining the marginal technology that sets the electricity price based on its production cost. On the one hand, an increase in demand above normal levels implies firing up additional plants higher on the merit order curve, which pushes prices up. This can be visualized by shifting the blue demand line, shown in Figure 1A, to the right. A low demand level, on the other hand, increases the probability of oversupply.

In conclusion, the merit-order effect provides some intuition in how extreme prices are affected by wind and solar energy generation when considering demand. The convexity of the curve shows that an increase in renewable energy generation decreases prices much stronger when demand and prices are high, as it replaces those flexible power plants that have high market power and high marginal costs. When renewable energy supply cannot meet increased levels of demand, extremely positive price spikes could occur as a result of this market power and high marginal costs of the flexible power plants that situate at the right end of the supply curve. Differences in the effect between high and low demand periods is for example in line with the findings of De Lagarde and Lantz (2018), who found that the decreasing effect of renewable production on German electricity prices through the merit-order effect is more important during high-price periods. This relates to the fact that peak plants have relatively high marginal costs but low capacity compared to base-load power plants. In contrast, base-load power plants have low flexibility in terms of scaling down, which easily leads to oversupply as a result of renewable energy in-feed in times of low demand. A likely consequence of high wind in-feed during low demand concerns negative price spikes. The merit-order effect plays an important role in the expected effect of wind and solar energy penetration on extreme electricity prices and should, therefore, be considered and well-understood to develop hypotheses regarding the research questions.

2.3 Characteristics of Electricity Prices in Relation to Renewable Energy

Electricity prices behave highly abnormal as a result of the complex and nonlinear relationship with fundamental drivers. Properties of electricity prices are substantially different from those of other financial assets (Fleten et al., 2013). Electricity prices are characterized by high volatility, volatility clustering, seasonality, large price spikes, a skewed distribution, and the occurrence of negative prices. Differences between electricity prices and other financial assets result from the inelastic demand in the short-run, the lack of efficient storability on a sufficient scale, and the intermittency of renewable energy caused through wind and solar conditions (Hagfors et al., 2016b). The intermittency of renewable energy sources is challenging from a risk management perspective (Hagfors et al., 2016b). As a result of the continuous nature in which energy is sold and consumed, shocks in either supply or demand directly affect electricity prices. Given the intuition of the merit-order supply curve and the corresponding demand, spikes can occur from extreme load fluctuations (e.g. caused by extreme weather conditions or during holidays) and extreme supply fluctuations (e.g. through high wind and solar generation outages). This section will elaborate on how the peculiarities of day-ahead electricity prices are related to wind and solar energy generation in order to get a better understanding of how they will likely influence the tails of electricity prices.

2.3.1. Seasonality

Seasonality is one of the peculiarities that can be recognized in electricity prices. Seasonality refers to a predictable fluctuation or pattern that recurs or repeats over a one-year period. It can have a big impact in trading and it is, therefore, important to consider when modeling electricity prices. Seasonality in electricity prices results from the fact that electricity is a flow commodity that needs to be consumed immediately. As stated in *section 2.2.2,* demand is highly dependent of weather conditions and the time of the day, which causes seasonality in demand patterns. The same holds for the supply of both solar and wind energy. Wind energy generation is more common during evening hours and night hours (Hagfors et al. 2016b; Paraschiv et al. 2014). At the same time, demand is low during these hours. As a result, extremely low or negative prices are more common during the nighttime when there is high wind energy generation. Solar energy generation, by contrast, shows more similarities with patterns in electricity demand: high during day hours and low during night hours

(Kyritsis et al., 2017). This leads to lower electricity prices during the day. Oversupply is unlikely to be a result of solar electricity generation because of the similarities in demand and sunshine. These seasonal patterns can be underpinned by the findings of previous research. Hagfors et al. (2016b) found the role of wind power to be particularly important in the probability of negative price spikes during the night hours while they found the role of solar power to be related to negative spikes only highly occasionally during daytime hours. Paraschiv et al. (2014) performed research on the effect of wind and solar electricity on German day-ahead prices and they found highly variable effects of wind energy on electricity prices, especially during night. For solar, they found a more constant effect that is strongest around noon. This is in line with the reasoning that wind power generation shows a higher level of intermittency than solar power generation. The findings of Kyritsis et al. (2017) showed decreased volatility as a result of solar power in-feed during on-peak hours, but increased volatility as a result of wind power in-feed during off-peak hours. These findings confirm that seasonality patterns of the underlying drivers of electricity prices (i.e. supply and demand) are transmitted into seasonality in electricity prices, suggesting that positive and negative price spikes can be predicted given the level of wind and solar energy penetration and demand.

2.3.2. Negative and positive price spikes

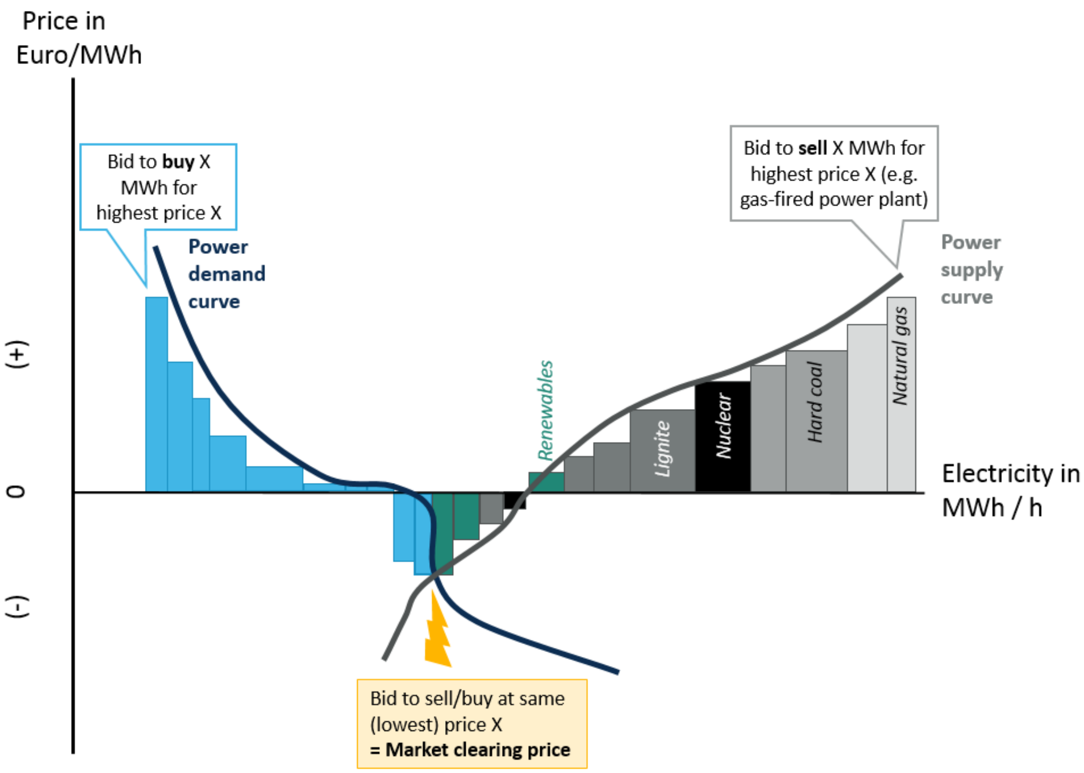
The main risk of trading on the energy market relates to extreme tail price occurrences (Hafgors et al., 2016b). The increase in renewable energy sources was accompanied by increased occurrence of extreme price spikes, providing a considerable challenge in achieving policy objectives and in achieving energy risk management. Given these developments, understanding the behavior of electricity prices in the tail as a result of wind and solar in-feed became more important than forecasting the expected price for participants in the energy market. As already mentioned in the introduction, Hagfors et al. (2016b) conducted research on fundamental drivers that influence the probability of extreme price occurrences in the German day-ahead electricity market and they found substantial differences in the drivers of extreme high and extreme low prices. Before I proceed with formulating hypotheses on tail dependencies of wind and solar energy generation, established literature on extreme prices is discussed in more detail in this section.

Negative price spikes

Negative prices have been allowed at the EPEX since the first of September 2008 to ensure market clearing in situations of oversupply (Genoese et al., 2010) and they represent limited system's flexibility (Kyritsis et al, 2017). Negative prices mainly occur during night hours when demand and flexibility of the system are low, and they are caused to a large extent by high wind energy generation, which leads to excess electricity supply (Paraschiv et al., 2014). Hagfors et al. (2016b) found similar results: 65% of negative prices occur during night hours and there is a clear link between extreme wind in-feed, low demand and negative prices.

The EEG regime requires the system operators to accept the delivery of power from independent producers of wind- and solar-based electricity into the grid. This could occasionally force base-load power plants, such as coal plants, to shut down when demand is low and wind in-feed is high. Opportunity costs for shutting down and starting up when wind in-feed falls again are high for big generating conventional plants (Hagfors et al., 2016b). These plants might, therefore, prefer to pay negative prices to avoid ramp-downs and to continue their revenues when opportunity costs and start-up costs are higher than the negative prices they need to bid (Keles et al., 2011). In the case that prices fall just below 0, conventional plants are willing to pay a small fee for not shutting down for a few hours, to avoid start-up and ramping costs. Figure 1B visualizes how negative electricity prices follow from the merit-order supply curve and its intersection with demand.

Figure 1B. The occurrence of negative electricity prices



Source: Clean Energy Wire 2018

Positive price spikes

The link of renewable energy generation with upward spikes is less obvious. They only occur during day-time hours, and almost all of them during the weekdays rather than the weekend days (Paraschiv et al., 2014). This period is characterized by high demand. Hagfors et al. (2016b) found that positive spikes occur when demand is high, supply is low, and when yesterday's prices were high, mainly during the morning and afternoon peak hours.

The convex merit-order supply curve suggests that upward spikes occur when demand takes higher levels than the in-feed of renewable energy and base-load plants fired up by coal (or nuclear) can meet, which is more likely during the day than during the night. As a consequence, more expensive power plants are required to meet the unmet demand in times of scarcity, and as a result of high market power during scarcity for those with available capacity, prices can increase well above the marginal costs of these flexible power plants. This contributes to occasions in which prices are extremely high (Bunn et al., 2016).

Understanding the mechanisms that drive extreme negative and positive prices in day-ahead electricity prices is crucial for managing risk and market design (Hagfors et al., 2016c).

Previous findings on extreme German electricity prices can be well used in formulating hypotheses of the effect of wind and solar energy penetration to the left tail and the right tail and the resulting confidence interval of electricity prices.

Chapter 3: Hypotheses Development

In this chapter, I will set up hypotheses with the aim to provide directions in answering the research question by looking at both the role of supply and demand in the price distribution of day-ahead electricity prices. Hypotheses on the 90% confidence interval, the left tail, and the right tail will be formulated. In this research, the supply side is analysed from the perspective of renewable energy in terms of wind and solar energy penetration. As a distinction is made in electricity prices between peak hours and off-peak hours, I will hypothesize on differences in on-peak and off-peak hours as well.

Due to the non-linear properties of the merit-order curve, it is likely that day-ahead electricity prices have different sensitivities to renewable energy penetration across the left tail and the right tail of the price distribution. Moreover, the differences in intermittency of solar and wind energy generation in relation to demand suggest that the confidence interval is affected differently by solar and wind energy penetration during peak-hours and off-peak hours. Previous findings not only provide evidence for different effects between solar and wind energy generation on positive and negative electricity price spikes in the day-ahead market, but also for differences in the effects on electricity prices between off-peak hours and on-peak hours and differences between high and low expected demand. As peak and off-peak hours already reflect hours with high demand and low demand respectively, only a distinction is made between peak and off-peak hours in the development of the hypotheses. Table 2 is set up to provide an overview of the expectations based on these different perspectives that need to be considered. This table is used to come up with main hypotheses for the effects of wind and solar energy penetration on the left tail and the right tail of the 90% confidence interval. The rationale behind the expectations provided in Table 2 is briefly elaborated on in *section 3.1* and *3.2.*

Table 2: Intuition for hypotheses

	Left tail (q5)		**Right tail (q95)**		**Effect on confidence interval (90%)**	
	Off-peak	*On-peak*	*Off-peak*	*On-peak*	*Off-peak*	*On-peak*
Solar	No impact	Slight decrease	Moderate decrease	Strong decrease	Decreases	Decreases
Wind	Strong decrease	Moderate decrease	Moderate decrease	Strong decrease	Increases	Decreases

Note: the effect of wind is expected to be stronger in all cases as a result of higher intermittency and capacity compared to solar (the size of the effects should be interpreted separately for solar and wind as the relative difference between the left tail and right tail).

3.1 The effect of solar energy penetration

From Table 2 it can be observed that solar energy penetration is expected to decrease the right tail of day-head electricity prices substantially by shifting the merit-order supply curve to the right, with more extreme effects during on-peak hours resulting from the convexity of the supply curve. At the same time, solar energy penetration is expected to decrease the left tail only slightly during on-peak hours. This expectation follows from the findings of Hagfors et al. (2016b), which indicate that solar energy affects the probability of negative spikes only occasionally during daytime hours. This results from the fact that solar energy generation shows similar patterns as for demand such that oversupply during off-peak hours does not occur as a result of solar energy penetration.

Building on this theory, it is expected that solar power generation decreases the 90% confidence interval, which mainly results from a stronger decrease in the right tail of the price distribution compared to the left tail of the price distribution. A decrease in the confidence interval seems to be in line with the decreased volatility in electricity prices resulting from solar energy generation as found by Kyritsis et al. (2017). This results in the following hypothesis:

H1: *Solar power penetration decreases the confidence interval through a stronger decrease in the right tail of the price distribution compared to the left tail of the price distribution during peak hours as well as during off-peak hours.*

3.2 The effect of wind energy penetration

Table 2 reveals different expectations of the effects of solar energy penetration and wind energy penetration on the tails. This results from the higher intermittent variability of wind energy generation and the lower resemblance with the demand pattern compared to solar energy generation. A more extreme negative effect is expected on the left tail, and this effect is stronger during off-peak hours. Nevertheless, negative prices could still occur during high demand as a result of excessive levels of wind energy generation. These expectations follow from the previous findings of, among others, Hagfors et al. (2016b). They found a strong relation between wind power and negative prices, mainly during night-time hours. It is expected that the right tail of the distribution is also affected negatively through the shift of the merit-order effect, which is expected to be stronger during on-peak hours compared to off-peak hours due to the convexity of the supply curve.

The decreasing effect on the right tail is expected to be less extreme than the decreasing effect of wind energy generation on the left tail during off-peak hours. This leads to an expected increase in the 90% confidence interval during off-peak hours, resulting from a stronger decrease in the left tail compared to the right tail. This increase seems to be in line with the increased volatility resulting from wind energy generation as found by Kyritsis et al. (2017). In contrast, a stronger decrease is expected in the right tail compared to the left tail during on-peak hours, which leads to an expected decrease in the 90% confidence interval. These expectations result in the following hypothesis:

H2: *Wind power penetration* ***(a)*** *increases the confidence interval during off-peak hours through a stronger decrease in the left tail of the price distribution compared to the right tail of the price distribution, and* ***(b)*** *decreases the confidence interval during peak hours through a stronger decrease in the right tail of the price distribution compared to the left tail of the price distribution*

The developed hypotheses are used to test expectations on different effects of solar and wind power penetration on the left and the right tail of electricity prices.

Chapter 4: Research Methods

3.1 Methodology

3.1.1. Quantile regression models

As already introduced in *section 1.1*, Bunn et al. (2017) proposed quantile regression as the best way to model the distribution of electricity prices and value-at-risk. Quantile regression offers a semi-parametric formulation of the predictive distribution, such that the quantiles of the distribution can be estimated with distinct regressions. The quantile regression lines will pass through different quantiles of the distributions, instead of through the average of the data set as in OLS regression. In these models, no assumptions are made about the distribution of the residuals. The highly non-normal behaviour of electricity prices makes this semi-parametric regression technique appealing, as it captures, among others, the non-normal specification effects of spikes and time-varying volatility (Bunn et al., 2017).

A set of regression functions is computed, corresponding to the 5^{th}, the 50^{th} and the 95^{th} quantile of the conditional distribution of the price. The 5^{th} and the 95^{th} quantile offer comprehensive view on how solar and wind energy penetration affect electricity prices in the lowest and the highest price range and on the corresponding 90% confidence interval. The median quantile is also modelled to provide some intuition on differences between the effects on the median and the tails. Different coefficients are estimated for fundamental factors at these different quantiles. From a risk perspective, this enables to estimate tail dependencies more accurately and it provides insight into the value-at-risk properties. This improves the understanding of electricity prices, compared to the volatility measure found by Kyritsis et al. (2017). Policy makers and market participants can use the quantile regression results to develop expectations on the tails and the corresponding range of electricity prices for different forecasts on wind and solar energy penetration.

3.1.2. Model specification

This section describes specifications of the model and some assumptions made. Price formation, and hence risk, varies systematically throughout the day. Different models are commonly being specified for peak-hours and off-peak hours to reflect the dynamics of load and the various technologies setting the marginal price (Hagfors et al., 2016a). The models will be applied for average EPEX prices, on-peak EPEX prices, and off-peak EPEX prices as dependent variables. Distinguishing between peak prices and off-peak prices separately allows for a distinction in the sensitivity between these price formulations on the confidence interval. Significant differences in the effect on the right and the left tail between peak hours and off-peak hours provide insights into price expectations and risk management during different hours of the day.

Explanatory variables considered in the models are the share of solar energy penetration, the share of wind energy penetration, lagged price, load, and a possible interaction between the share of solar and wind with load. Interaction terms are considered as it might occur that, in some cases, the effect of wind and solar energy penetration on extremely low or extremely high prices is reinforced or weakened through the level of demand.

The significance in the effects of solar and wind energy penetration are expected to be different across both the left tail and the right tail and across peak-hours and off-peak hours. For example, solar energy penetration is not expected to provide a significant effect on the left tail during off-peak hours. To allow for these different dynamics, most insignificant variables are excluded from the model until all variables show a significant effect on day-ahead electricity prices. The resulting models capture the right explanatory variables, improving the explanatory power of the models. In case all variables show a significant effect, the following quantile regression model is specified:

Letting q ∈ (0,1) represent the different quantiles, 5%, 50% and 95%, then:

$$Q_q(p_{i,t}) = a_i^q + \beta_{i,1}^q PRICE_{i,t-1} + \beta_{i,2}^q \, LOAD + \beta_{i,3}^q \, SHARE\_SOLAR + \beta_{i,4}^q \, SHARE\_WIND + \beta_{i,5}^q \, SHARE\_SOLAR * LOAD + \beta_{i,6}^q \, SHARE\_WIND * LOAD$$

Where *i* = 1, 2, 3 represents EPEX, EPEX on-peak and EPEX off-peak

STATA is used to model the quantile regressions, in which 9 (3 x 3) models are estimated as a result of three different price specifications and three different quantiles. If certain variables do not show significant results in the combination of a specific quantile (e.g. 5%) and a specific price specification (e.g. off-peak), these variables are excluded one by one from the above specification until all variables show a significant effect.

Considering that the dependent variables in the models concern day-ahead electricity prices, expected day-ahead supply and expected day-ahead demand would lead to the most reliable results as these drive day-ahead electricity prices. However, objective measures of both expected day-ahead supply of wind and solar energy generation and day-ahead demand are lacking. Possible measures are the system operator’s forecast on expected demand and weather forecasts for expected wind and solar energy generation (e.g. used by Hagfors et al., 2016c), but these measures are still subjective and subject to possible forecasting errors. Another possibility concerns the use of actual levels of supply and demand as a measure of day-ahead expectations (e.g. used by Kyritsis et al., 2017). Total electricity generation can be used as a measure of demand given the instantaneous nature of electricity consumption, and actual wind and solar energy generation can be used as a measure of expected day-ahead generation. Given the nowadays highly accurate weather forecasts in place and given the ability to use seasonal patterns to draw forecasts on, I make the assumption that actual levels can be used as a measure of forecasted levels. Moreover, I make the assumption that there are no systematic errors between expected day-ahead levels and actual levels. This is in line with the reasoning of Kyritsis et al. (2017) and this allows for a clean comparison with their results.

Negative prices are included in the analysis, because I am especially interested in the tails of the price distributions and negative prices situate in the left tail. Besides, previous findings revealed evidence for a strong relation between negative prices and wind energy generation (e.g. Hagfors et al., 2016b), which emphasizes the importance of inclusion of negative prices. Therefore, levels are used rather than logarithmic formations to improve modelling of the lower extreme prices, consistent with Kyritsis et al. (2017) and Hagfors et al. (2017c).

3.1.2. Sensitivity analysis

The second step of this research concerns sensitivity analysis by using the quantile regression results of the first step. The analysis will show how different levels of solar and wind penetration combined with different levels of demand influence the confidence interval, the left tail, and the right tail of the electricity prices. The share of solar and wind will range between low and high values that occur in the dataset. Demand will be measured on three levels: low, average and high load. Market participants and policy makers can use this to predict price distributions for a range of scenarios with different levels of demand and solar and wind generation. This provides a better insight on how market participants can reduce risk and make better trading and bidding strategies through solar and wind forecasts. Moreover, policy makers can use these predictions to detect what kind of policy measures are needed to reach an efficient and sustainable energy system in the long-term.

3.2 Data

3.2.1. Data collection

The methodology described in the previous section is applied to the dataset of Kyritsis et al. (2017). The data covers the period between the 1st of January 2010 and the 30th of June 2015. This time span is used to allow for a clean comparison with the research of Kyritsis et al. (2017). Despite the fact that this period is slightly out-dated, renewable energy already became highly important during this period. Therefore, this time span is sufficient to investigate dynamics in the distribution of electricity prices related to renewable energy penetration. The EPEX price relates to the average day-ahead prices calculated by summing up all prices for each hour of the day, divided by the 24 hours a day consists of. The same holds for on-peak EPEX prices and the off-peak EPEX prices, but calculated separately for the peak hours (9am – 8pm) and the off-peak hours (8pm – 9am) respectively. The data on electricity prices and wind and solar energy generation is collected from the European Energy Exchange (EEX). The data on total load is collected from the European Network of Transmission System Operators for Electricity (ENTSOE).

3.2.2. Data description

Before I proceed with the results related to the quantile regression models and the sensitivity analyses, I will first provide descriptive statistics of the data. Table 3 provides a description of the variables and Table 4 provides summary statistics. The summary statistics reveal extreme minimum and maximum values. In line with expectations, off-peak prices show lower values with more extreme minimum values, whereas on-peak prices show higher values with more extreme maximum values. The level of skewness and kurtosis are also provided, as these measures can be used to judge the probability of prices falling in the tails of the probability distribution. Skewness makes a distinction between the extreme values in the right tail and the left tail and kurtosis is a measurement of extreme values in either tail.

Table 3: Variable description

Variable	Description
epex	Day-specific average day-ahead electricity price over the hourly prices per 24 hours of that day. Collected from: EEX
epexon	Day-specific average day-ahead electricity price over the peak hours (9am – 8pm) of that day. Collected from: EEX
epexoff	Day-specific average day-ahead electricity price of the off-peak hours (8pm – 9am) of that day. Collected from: EEX
solar	Actual solar electricity generation per day in MWh. Used as an indication for the day-ahead solar electricity generation forecast. Collected from: EEX
wind	Actual wind electricity generation per day in MWh. Used as an indication for the day-ahead wind electricity generation forecast. Collected from: EEX
load	Actual total electricity generation per day in MWh. Used as an indication for the day-ahead electricity demand forecast. Collected from: ENTSOE
share_solar	Daily solar penetration: solar electricity generation as a share of load
share_wind	Daily wind energy penetration: wind electricity generation as a share of load

Table 4: Summary statistics

Variable	Mean	Std. Dev.	Min	Max	Skewness	Kurtosis
epex	40.7098	12.14406	-56.87	98.98	-0.637	6.558
epexon	46.01762	14.51608	-18.99	129.94	-0.113	4.155
epexoff	35.40321	11.13048	-124.68	68.03	-2.878	37.184
solar	67090.68	52857.64	86.73	218297.8	0.673	2.433
wind	131069.3	110880.6	5449.85	661556.8	1.652	6.169
load	1326660	164759.1	900507	1704961	-0.390	2.399
share_solar	5.257367	4.305629	.0058242	20.88324	0.787	2.761
share_wind	9.957438	8.395836	.4473335	50.6218	1.635	6.069

The electricity prices show high levels of skewness and kurtosis, with higher levels for off-peak electricity prices compared to on-peak electricity prices. The skewness levels are negative for all price formulations; all distributions are skewed to the left. This is visualized in the histograms shown in Figures 2 – 4. The extreme price spikes and the fat tails that relate to the skewed distribution and the high kurtosis make price forecasting and assessment of the risk of extreme prices on the electricity market challenging.

Figure 2. Histogram average daily electricity prices (EPEX)

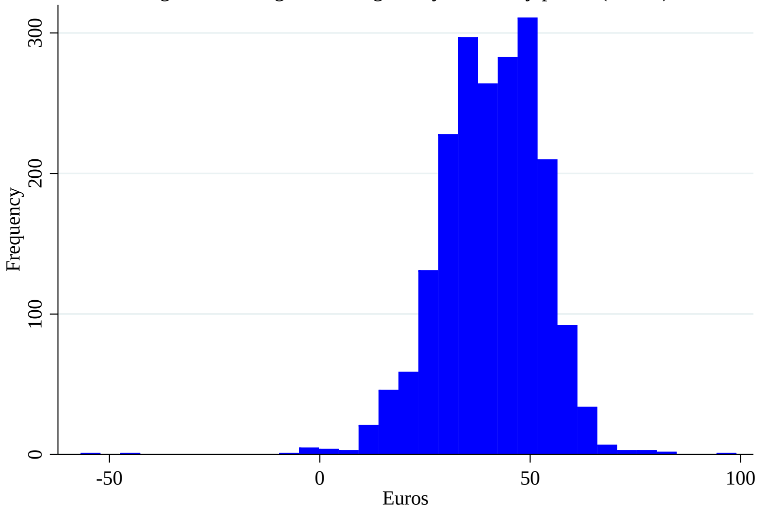


Figure 3. Histogram average daily on-peak electricity prices (EPEXON)

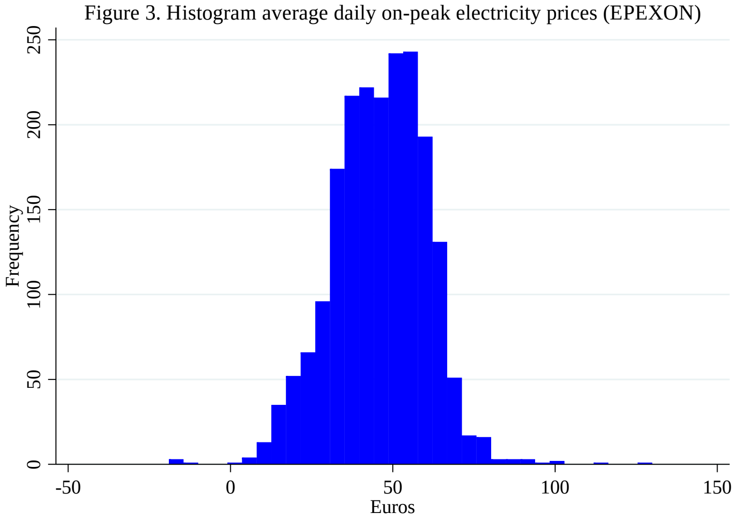
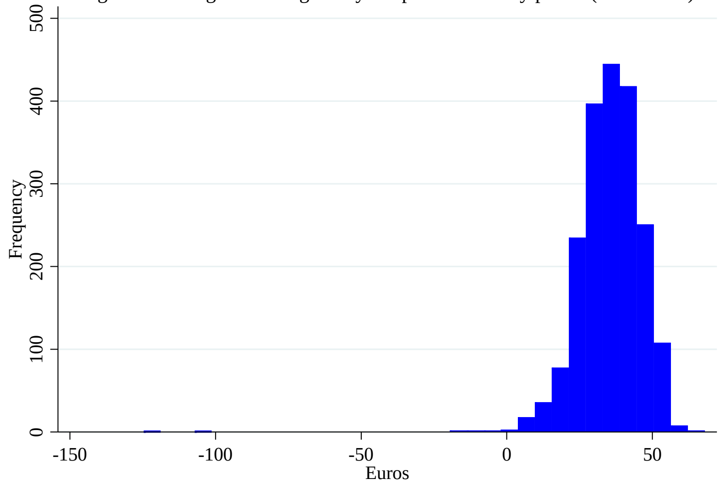


Figure 4. Histogram average daily off-peak electricity prices (EPEXOFF)



To provide some intuition on the development of electricity prices through the years, Figures 5 – 7 are set up with a distinction for all-hours, peak hours, and off-peak hours over the years 2010 to 2015. The figures show a rough pattern in which electricity prices decrease during the first half of the year and increase during the last half of the year, which became more obvious as of 2013. Besides seasonality, the figures show high volatility, extreme price spikes in both positive and negative direction, mean-reverting behaviour, and volatility clustering. This confirms the non-normal behaviour of electricity prices. Another remarkable observation concerns the slightly decreasing trend in electricity prices. This is likely to be the result of the merit-order effect that followed from the increased shares of renewable energy generation.

Figure 5. Average daily electricity price (EPEX)

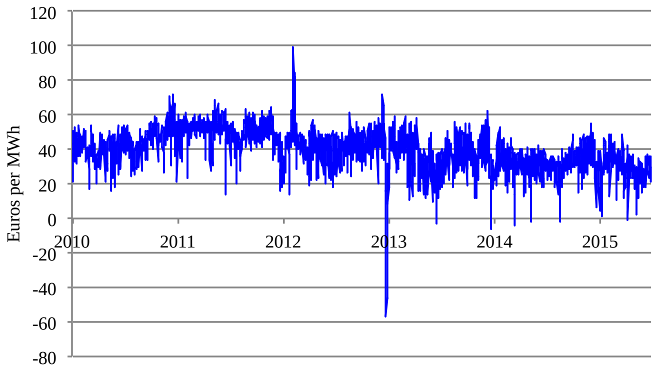


Figure 6. Average daily electricity price (EPEXON)

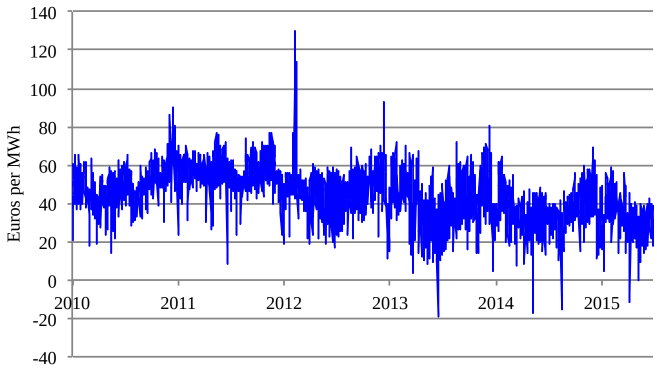
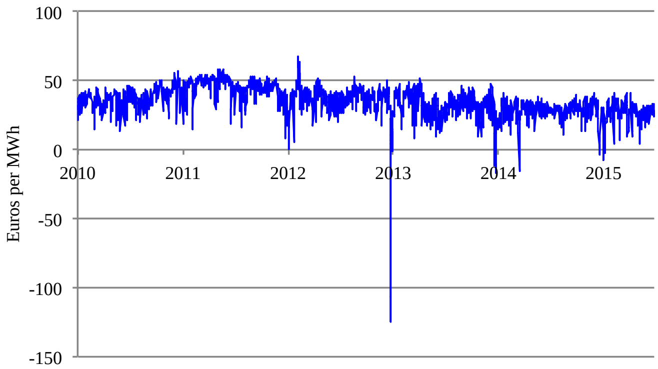


Figure 7. Average daily electricity price (EPEXOFF)



Figures 8 – 10 show the generation of total energy (load), wind energy, and solar energy separately. Similar to the patterns of electricity prices provided in Figures 5 – 7, these figures also show obvious seasonal patterns. This is a logical consequence of weather conditions, affecting both the demand for electricity and the generation of wind and solar energy. Seasonality is most obvious for total electricity generation and solar electricity generation. Note that the patterns move in the opposite direction. Solar energy generation increases during the first half of the year and decreases during the second half of the year. Total load decreases during the first half of the year and increases during the second half of the year. The pattern of wind energy generation is less obvious, which is a likely consequence from the higher level of intermittency of wind energy generation compared to solar energy generation during the year. Nevertheless, the pattern does show a decreasing trend during the first half of the year (i.e. fewer positive price spikes) and an increasing trend during the second half of the year (i.e. more positive price spikes). This shows similarities to the demand pattern.

Overall, as expected from the German energy transition, an increase is observed in both wind and solar energy generation. From the vertical axis of Figures 9 and 10, it can be observed that wind energy generation reaches substantially higher maximum values than solar energy generation. In 2015, for example, solar energy generation reaches maxima of around 200,000 MWh of electricity, while wind energy generation reaches maxima of around 650,000 MWh of electricity. This is a logical consequence of the higher capacity of wind power compared to solar power and results from the fact that solar power generation only takes place during sun hours, while wind power generation could occur all hours. Total load ranges between approximately 900,000 and 1,700,000 MWh during this period and a slight increase can be observed after 2013.

An interesting characteristic of solar and wind energy concerns the level of intermittency. The high level of intermittent variability of both solar and wind energy generation can be recognized by the many spikes in both the positive and negative direction that occur in Figures 9 and 10. This intermittent nature is strongest for wind energy generation, which leads to higher variability in wind energy generation compared to solar energy generation.

Figure 8. Total electricity generation (load)

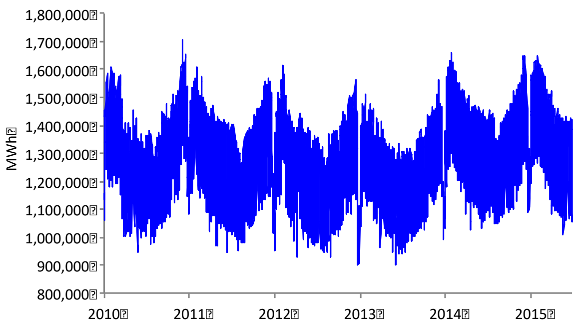


Figure 9. Solar electricity generation

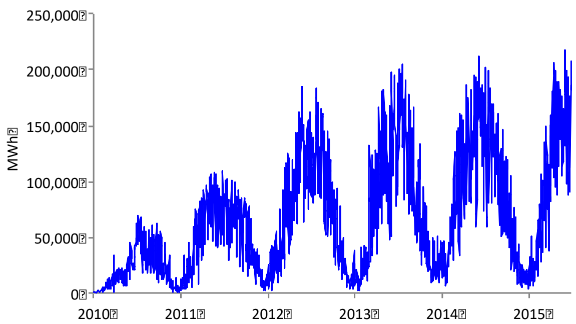
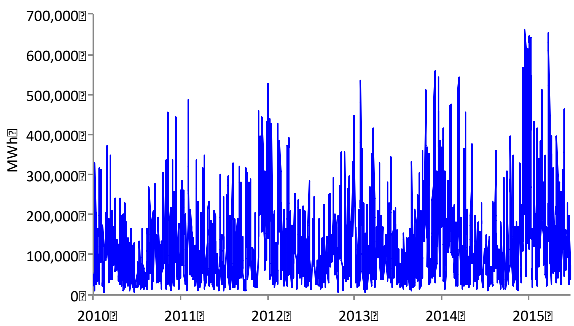


Figure 10. Wind electricity generation



Figures 11 and 12 show solar and wind energy generation as a share of total energy generation, as the share of solar and wind energy penetration are used as explanatory variables in the quantile regression models. The patterns remain similar to those of solar and wind energy generation. The values range between 0 and approximately 20% for the share of solar and 50% for the share of wind.

Figure 11. Solar electricity penetration

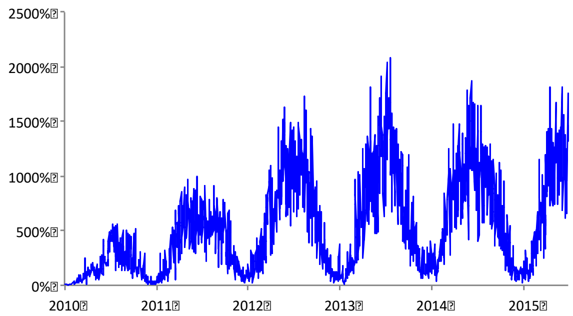
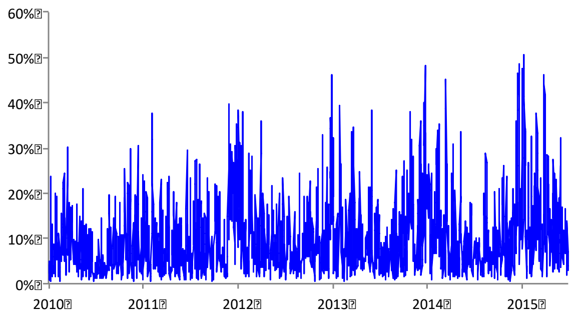


Figure 12. Wind electricity penetration



The seasonal patterns found in off-peak and on-peak electricity prices (Figures 6 and 7) and solar and wind electricity penetration (Figures 11 and 12) are compared. From these patterns, it seems plausible that solar electricity generation decreases the occurrence of positive price spikes during on-peak electricity prices as a result of high penetration levels. This can be recognized by the decreasing on-peak electricity prices during the first half of the year, in which solar energy generation increases. Positive spikes are less common during this period, which suggests a decrease in the right tail of electricity prices as a result of solar energy generation. Negative price spikes, by contrast, occur more often for on-peak prices during this period. These negative spikes could, for example, result from oversupply caused by both high solar and high wind energy penetration during day-time hours.

During times in which positive spikes are most common in wind energy generation, negative spikes in off-peak electricity prices are also more common, suggesting wind energy penetration to decrease the left tail of off-peak electricity prices. This mainly occurs at the beginning and the end of the year.

Note that this reasoning is only suggestive and does not proof any causal relation between price spikes and solar and wind energy penetration. Moreover, no distinction can be made between the effects of wind and solar energy penetration on electricity prices from the figures. Further investigation is needed on the relation between wind and solar energy penetration and the tails of the price distribution to test whether this reasoning is correct. The results in the subsequent section aim to do so.

Chapter 5: Results

This chapter is divided into two parts, similar to the steps discussed in the methodology. First, the quantile regression results are provided and briefly discussed. The inclusion of interaction terms in the models makes it difficult to directly understand the exact effect of solar and wind penetration on the electricity prices from the regression results. The second part therefore aims to visualize how the effects apply to the left tail and the right tail of the distribution with sensitivity analysis on different shares of wind and solar penetration and demand for all-hours, on-peak and off-peak electricity prices separately. In the remainder of this paper, the effect of "wind" and "solar" are used now and then as abbreviation for the effect of "the share of wind energy penetration" and "the share of solar energy penetration".

5.1 Quantile Regression Results

Table 3 provides the results of the quantile regression models. Part 1 of the table reflects the results related to all-hours electricity prices (EPEX), part 2 reflects the results related to the on-peak electricity prices (EPEXON), and part 3 reflects the results related to the off-peak electricity prices (EPEXOFF). Results are provided for the 5th quantile, the median quantile and the 95th quantile, reflected in the left, the middle and the right columns of the graph respectively. First, some common observations are discussed. Subsequently, the results are interpreted for the different formulations of electricity prices separately, focusing on the effects found in the 5th quantile, referred to as the left tail, and the effects found in the 95th quantile, referred to as the right tail.[1]

[1] The median quantile is shown to provide some intuition on differences in the effect on the median compared to the tails. However, no further attention is devoted to the interpretation of the median quantile as this research focuses on the confidence interval that results from the tails of the price distribution. Consequently, results in the median quantile are not discussed in this paper

Table 3: Quantile Regression Results

	5%	P>|t|	50%	P>|t|	95%	P>|t|
1. EPEX						
epex_lagged	0.5164341	0.000	0.551823	0.000	0.3705084	0.000
share_solar	-1.238144	0.002	-1.30892	0.000	-0.2835319	0.005
share_wind	-1.334928	0.000	-0.4830645	0.000	0.6619046	0.048
load	1.28E-05	0.000	1.77E-05	0.000	3.55E-05	0.000
share_solar#load	7.24E-07	0.021	6.96E-07	0.003		
share_wind#load	5.57E-07	0.000			-8.67E-07	0.001
_cons	1.403754	0.732	1.329329	*0.570*	-4.757883	0.387
Psuedo R-squared	0.6011		0.5033		0.4089	
2. EPEXON						
epexon_lagged	0.3942542	0.000	0.4285879	0.000	0.2184417	0.000
share_solar	-0.7226978	0.000	-1.824737	0.000	-0.676405	0.000
share_wind	-0.6625568	0.000		0.000	1.171291	0.000
load	2.73E-05	0.000	0.00003	0.000	5.30E-05	0.000
share_solar#load			8.35E-07	0.019		
share_wind#load			-4.08E-07		-1.38E-06	0.000
_cons	-9.538768	0.000	-4.533694	0.490	-11.32858	0.017
Psuedo R-squared	0.5462		0.4679		0.4020	
3. EPEXOFF						
epexoff_lagged	0.66448	0.000	0.6684705	0.000	0.4955514	0.000
share_solar		0.000	-0.9363851	0.000	-1.536854	0.001
share_wind	-1.162967		-0.6265795	0.000		0.000
load	1.40E-05	0.000	8.31E-06	0.000	9.96E-06	0.005
share_solar#load			6.16E-07	0.001	1.02E-06	0.000
share_wind#load	4.35E-07	0.003	1.93E-07	0.039	-2.51E-07	0.000
_cons	-8.361096	0.004	4.957214	0.042	17.64183	0.000
Psuedo R-squared	0.6140		0.5177		0.4053	

Note. * = $p \leq .05$; ** = $p \leq .01$; *** = $p \leq .001$. Variables that did not show significant results in certain price specifications and quantiles were excluded from the quantile regression model, leading to some empty cells in the table

Common observations of the effects on electricity prices concern positive coefficients for the lagged electricity price of the previous day and positive coefficients for total load. This implies that yesterday's prices and demand increase electricity prices in all three quantiles, both during on-peak and off-peak hours. The significant coefficients found for the share of solar and the share of wind energy penetration show negative coefficients in most cases. Only the share of wind energy penetration shows positive coefficients on the 95^{th} quantile for all hours and on-peak electricity prices. However, when taking into account the interaction term, the effect of wind becomes negative for all possible levels of load. This reveals that, in line with expectations, both solar and wind energy penetration negatively affect electricity prices in all cases where they show a significant effect.

The values of the Pseudo R-squared are highest for the models of the 5th quantile, followed by the median quantile and lowest for the models of the 95th quantile. This suggests that the predictive power of the models is highest on the left tail of the electricity prices.

Significance tests show that, except for one, all the coefficients found for the explanatory variables *share_solar*, *share_wind* and their interaction terms with *load* are significantly different between the 5th and 95th quantile.[2] The only exception concerns *share_solar* for on-peak prices. I hereby make the assumption that these explanatory variables are all independent from each other. In Table 1 of the Appendix, the results of the significance tests can be found. The fact that significant differences are found between the 5th and the 95th quantile implies different effects of wind and solar energy penetration on the left tail and the right tail of the electricity price distribution. Different effects found in the tails affect the left bound and the right bound of the 90% confidence interval differently. This adds to the understanding of Kyritsis et al. (2017) on the volatility of the electricity price distribution. The differences found in the regression results between the left tail and the right tail as well as between all-hours, on-peak, and off-peak electricity prices are discussed in more detail in the subsequent sections.

5.1.1. All-hours electricity prices (EPEX)

The results show that both the effect of the share of solar and wind on the left tail of all-hours electricity prices depend on their interaction term with load. The negative coefficients for *share_solar* and *share_wind* are offset by the positive coefficients of their interaction term with *load.* This implies that the effects of solar and wind energy penetration on the left tail of the price distribution become less negative when demand increases. The negative effect of wind energy penetration in combination with the interaction term with load is more extreme than the negative effect of solar energy penetration in combination with the interaction term with load.

The right tail of the distribution is negatively affected by solar. The interaction term with load does not provide significant results, thus the effect of solar does not depend on the level of demand. This could be due to the fact that when solar energy is generated, increased

[2] Note that if only a significant effect is found in either the 5th or the 95th quantile, a significant different is per definition in place

levels of demand are also in place so it does always decrease the right tail of electricity prices by shifting the merit order curve to the right. The left tail, by contrast, is only affected negatively by solar when demand is low. At high demand levels, the negative effect is offset. A positive coefficient is found for *share_wind* on the right tail, but this positive effect is offset by the negative coefficient of the interaction between *share_wind* and *load* at all possible levels of load. The effect of wind on the right tail is dependent on demand. This might relate to the fact that wind energy generation is more intermittent than solar energy generation and shows less similarity with the demand pattern.

All explanatory variables related to *share_solar* and *share_wind* show significant different results between the left tail and the right tail, which implies an asymmetrical effect on the distribution of electricity prices. How the effects of different levels of solar and wind energy penetration exactly influence the tails and the confidence interval is elaborated on in more detail in the sensitivity analysis in *section 5.2.1*.

5.1.2. On-peak electricity prices (EPEXON)

This section discusses the regression results for average on-peak electricity prices. Again, a negative effect is found for both solar energy penetration and wind energy penetration on the left tail of on-peak electricity prices. For on-peak electricity prices, however, this effect does not depend on the level of demand, as there are no significant effects found for the interaction terms of both *share_wind* and *share_solar* with *load*. The share of solar and the share of wind therefore decrease the left tail of on-peak electricity prices independent of the level of demand.

The right tail of the electricity prices is affected in a similar way by solar energy penetration. The effect does not depend on the level of demand, which could result from the similarities between demand and solar energy generation patterns during on-peak hours. Wind energy penetration shows a positive coefficient on the right tail but this positive effect is, again, offset through the interaction term between *share_wind* and *load*. In conclusion, wind energy penetration decreases the left tail of on-peak electricity prices independent of demand, while it decreases the right tail of on-peak electricity prices more heavily when demand is high (which is most likely during on-peak hours) but less heavily when demand is low. This leads to different effects of wind energy penetration on the confidence interval of on-peak electricity prices at different levels of demand.

Note that the coefficients found for *share_solar* are not significantly different from each other in the 5th and the 95th quantile. This suggests that solar energy penetration does not significantly increase or decrease the 90% confidence interval for on-peak electricity prices, but only shifts the price distribution to the left. The effects found for *share_wind* are significantly different from each other, affecting the confidence interval differently through the left and the right tail. The effects of solar and wind on the left tail and the right tail and the corresponding confidence intervals are visualized and elaborated on in the sensitivity analysis in *section 5.2.2.*

5.1.3. Off-peak electricity prices (EPEXOFF)

The regression results for average off-peak electricity prices are discussed. In the left tail, *share_solar* does not show a significant effect on off-peak electricity prices. This is a logical consequence from the fact that solar energy penetration does not take high levels during off-peak electricity prices, which makes it unlikely that it affects low prices through oversupply. Consequently, the left tail of the off-peak electricity price distribution is not affected by *share_solar*. Wind energy penetration does, as expected, show a highly negative coefficient on the left tail of the off-peak electricity prices. This negative effect is partly offset when demand takes higher levels, as can be seen from the positive coefficient of the interaction term. Nevertheless, the effect of wind energy penetration remains negative at all levels of *load* that occur in the dataset.

A significant negative effect is found in the right tail for solar energy penetration and a significant positive effect is found for the interaction term between *share_solar* and *load*. The effect of *share_solar* on the right tail of electricity prices is dependent on the level of demand. It is likely that this results from the few hours in which solar energy could generate during off-peak hours (e.g. in the early morning or late evening hours during summer). As a result, changes in the confidence interval that follow from solar take place only in the right tail of the price distribution. Wind energy penetration only shows a significant effect for the interaction term with load. The negative coefficient shows that, when both demand and the share of wind energy penetration are high, the right tail of the price distribution is decreased more heavily. This reveals that the effect of wind on the right tail is dependent on demand during off-peak hours. Note, however, that off-peak hours reflect relatively low levels of demand.

The coefficients found for *share_solar* and *share_wind* show significantly different results between the left tail and the right tail, which implies an asymmetrical effect on the distribution of electricity prices. The consequences of the different effects found for wind and solar on the right and left tail of off-peak electricity prices are visualized and elaborated on further in the sensitivity analysis in *section 5.2.3.*

5.2 Sensitivity Analysis

It is challenging to interpret the exact effect of wind and energy penetration on the distribution of electricity prices from the regression results because of the different model specifications and the inclusion of interaction terms. As a result, the coefficients cannot be compared to each other directly across different quantiles and different price specifications. This section will provide a better intuition and visualization of the sensitivity of the left and the right tail of the electricity price distribution for different levels of demand. The effect of 20% wind and 20% solar energy penetration will be compared separately to zero wind and solar energy penetration and the absolute difference and the relative difference are visualized for both the left tail and the right tail. This gives insight into how the 90% confidence interval is affected by high values of wind and solar energy penetration. The sensitivity analysis is performed on all hours, on-peak and off-peak electricity prices and will be discussed separately in the subsequent sections.

In this analysis, a distinction is made between average load, minimum load and maximum load that occur in the dataset as a measurement of demand. The low demand level is therefore set at 900,507 MWh, the moderate demand level at 1,326,660 MWH and the high demand level at 1,704,961 MWh. Note that peak-hours already reflect increased levels of demand, while off-peak hours reflect decreased levels of demand. I therefore assume that during peak-hours, demand mainly ranges between average and high demand, while demand mainly ranges between average and low demand during off-peak hours. As a result, the low demand level is not likely during on-peak hours, while the high demand level is not likely during off-peak hours. All demand levels are visualized for each price specification to provide better intuition, but expected values related to low levels during on-peak hours and high levels during off-peak hours should be interpreted with caution. Yesterday's price is set at the average electricity price of the dataset. This is €41 for all hours, €46 for on-peak and €35 for off-peak electricity prices.

Moreover, figures are set up to visualize and interpret the effect of different levels of solar and wind energy penetration on the electricity prices, ranging between the minimum and the maximum shares that occur in the dataset. Table 4 demonstrates that the share of solar ranges between approximately 0 and 20% while the share of wind ranges between approximately 0 and 50%. These ranges are, therefore, used in setting up graphs that reflect the development of the price distribution (i.e. the left tail and the right tail) and the corresponding confidence interval. The same input for yesterday's prices and load is used as in the sensitivity analysis described above and again a distinction is made between all hours, on-peak, and off-peak electricity prices. The fact that the quantile regression models provide substantially distinct results for the models of on-peak and off-peak specifications of electricity prices leads to an increased interest in the sensitivity analysis on on-peak and off-peak electricity prices separately. This allows for a better understanding of tail behavior and improved possibilities in risk assessment during different periods of the day.

5.2.1. All-hours electricity prices (EPEX)

<u>*Solar energy penetration*</u>

Table 4 provides the results of the sensitivity analysis described above on all-hours electricity prices (EPEX). The findings indicate that, given an average load, the left tail of the distribution decreases by 14% when the share of solar energy generation changes from 0 to 20%, while the right tail of the distribution decreases by only 10%. As a result, the 90% confidence interval decreases by the relatively stronger decrease in the left tail than in the right tail. In case of maximum load or high levels of demand, the left tail of the distribution is hardly affected while the right tail of the distribution is decreased by 8%. This leads to an even stronger decrease in the 90% confidence interval. In contrast, in case of minimum load or low levels of demand, the confidence level increases as a result of solar energy generation. This results from a considerably stronger increase of 35% in the left tail, compared to a decrease of 13% in the right tail.

The graphs in Figure 13 show the development of the 5^{th} and the 95^{th} quantile of all-hours electricity prices given average, minimum, and maximum load. The 90% confidence interval that results from the 5^{th} and the 95^{th} quantile electricity prices is visualized in Figure 14. The graphs on the left-hand side of Figure 13 show that the right tail decreases with an approximately similar slope at different levels of load. The left tail decreases at a highly similar rate as the right tail at average load, which leads to no major changes in the width of the confidence interval as a result of solar, as can be seen in Figure 14. When load takes lower values, it can be observed that the left tail decreases at a faster pace with solar energy penetration and this increases the confidence interval, as visualized in Figure 14. When load takes higher values, the slope becomes flatter and the left tail of electricity prices becomes less affected by solar energy penetration. This results in a more narrow confidence interval, as can be seen in Figure 14. In conclusion, the effect of solar energy penetration on the confidence interval of all-hours electricity prices is highly dependent on demand. These differences predominantly result from different effects of solar energy penetration on the left tail of the price distribution.

Wind energy penetration

Table 4 shows that at average load, the left tail of the electricity prices is decreased by 31% when 20% wind penetration is in place compared to zero wind energy penetration. In contrast: the right tail is only decreased by 17%. This causes an increase in the 90% confidence interval. At minimum load, the decrease in the left tail is even stronger while the decrease in the right tail is substantially smaller. This causes the confidence interval to increase more heavily. At maximum load, the relative decrease in the left tail becomes smaller than the relative decrease in the right tail, with 18% and 23% respectively. This decreases the confidence interval.

The graphs on the right-hand side of Figure 13 visualize the development of the left tail and the right tail of all-hours electricity prices given different levels of wind energy penetration at average load, minimum load, and maximum load. The graphs reveal highly different patterns that demonstrate that the effect of wind energy penetration depends on the level of demand in both the left tail and the right tail of the distribution. This leads to a decrease in the confidence interval during times of average and low demand, while the confidence interval is decreased during times of high demand. This is also visualized in the right-hand graph in Figure 14. In conclusion, wind energy penetration affects the confidence interval through both the left tail and the right tail of the all-hours electricity price distribution.

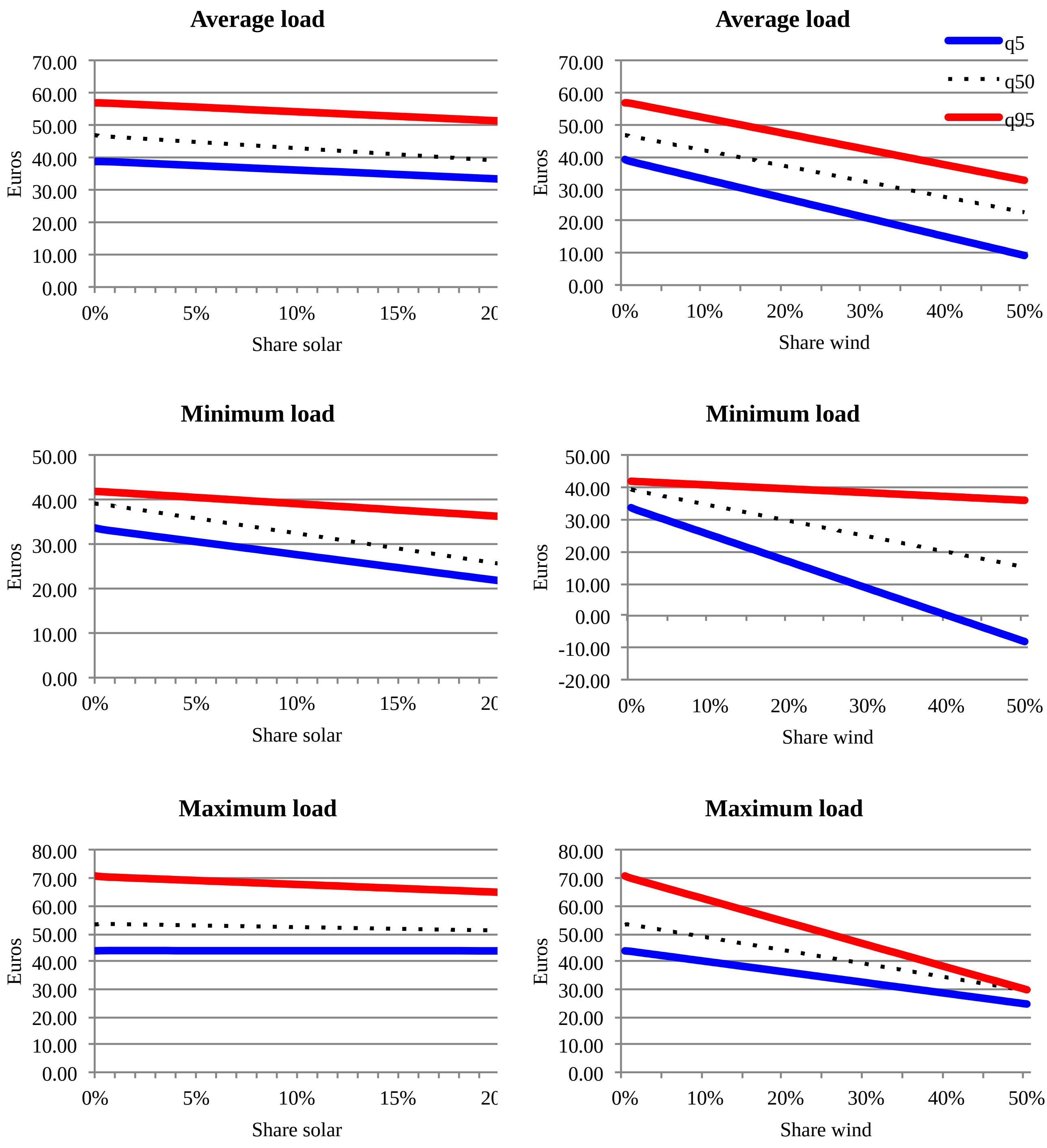
Table 4. Sensitivity of the different quantiles of all-hours electricity prices (EPEX) to solar or wind energy penetration

	Share solar	Share wind	q5	Δ	%Δ	q95	Δ	%Δ	q95-q5
Average load	0	0	€ 39.04			€ 57.16			€ 18.12
	20%	0	€ 33.49	-€ 5.55	-14%	€ 51.49	-€ 5.67	-10%	€ 18.00
	0	20%	€ 27.12	-€ 11.92	-31%	€ 47.39	-€ 9.77	-17%	€ 20.27
Minimum load	0	0	€ 33.59			€ 42.03			€ 8.44
	20%	0	€ 21.86	-€ 11.72	-35%	€ 36.36	-€ 5.67	-13%	€ 14.50
	0	20%	€ 16.92	-€ 16.67	-50%	€ 39.65	-€ 2.38	-6%	€ 22.73
Maximum load	0	0	€ 43.88			€ 70.59			€ 26.70
	20%	0	€ 43.81	-€ 0.08	0%	€ 64.92	-€ 5.67	-8%	€ 21.11
	0	20%	€ 36.18	-€ 7.71	-18%	€ 54.26	- € 16.33	-23%	€ 18.08

Note: Δ = The absolute difference in electricity price in q5 or q95 between 20% solar and 20% wind energy penetration separately and zero wind and solar energy penetration

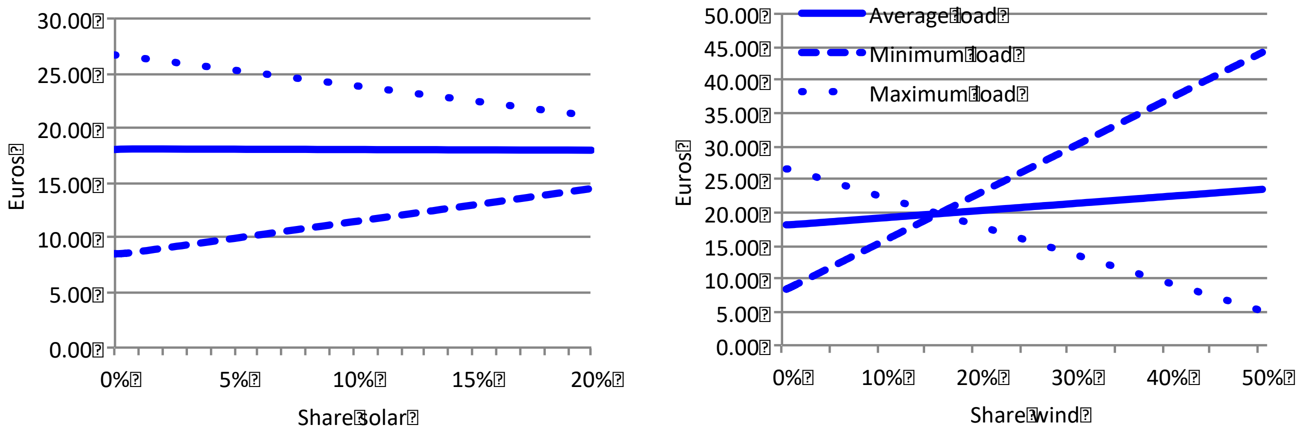
%Δ = The relative difference in electricity price in q5 or q95 between 20% solar and 20% wind energy penetration separately and zero wind and solar energy penetration.

Figure 13. Left and right tail of all-hours electricity prices (EPEX) for different levels of wind and solar energy penetration and load



Note. Yesterday's prices are set at the average level of the dataset, the share of wind is zero for the graphs on the left hand side and the share of solar is zero for the graphs on the right hand side

Figure 14. 90% Confidence interval (q95-q5) of all-hours electricity prices (EPEX) for different levels of solar and wind energy penetration and load



In conclusion, the effect of solar energy generation on the right tail of the average daily electricity price distribution is independent of demand and the right tail decreases at a relatively similar rate (exactly similar in absolute terms) at different levels of demand. The effect on the left tail of the all-hours price distribution depends on the level of demand. A stronger decrease is found at times of low demand while the negative effect diminishes at times of high demand. It can, therefore, be concluded that the effect of the share of solar energy penetration on the 90% confidence interval is highly dependent on demand and that the left tail of the distribution mainly affects this difference. The effect of wind energy generation depends on load for both the left tail and the right tail of the distribution. The confidence interval increases when there is low or average demand while the confidence interval decreases when there is high demand. This results from both the left tail and the right tail of the distribution.

These findings result from a combination of off-peak hours and on-peak hours. The next sections will emphasize the effects on the tails of electricity prices related to on-peak and off-peak periods separately.

5.2.2. On-peak electricity prices (EPEXON)

Table 5 illustrates the sensitivity analysis for on-peak electricity prices (EPEXON) and Figures 15 and 16 visualize the sensitivity of the left tail and the right tail and the corresponding confidence interval of on-peak electricity prices to different levels of solar and wind energy penetration. Note that the occurrence of minimum load is unlikely during on-peak hours. Nevertheless, it is used to offer an improved understanding of the influence of load on the effects of solar and wind on prices.

Solar energy penetration

Table 5 reveals that the absolute decrease in both the left and the right tail of electricity prices is constant for the different levels of load. In the left tail, a decrease of €14.45 is found and in the right tail, a decrease of €13.53. The relative decrease shows different percentages as an outcome of dissimilarities in the initial prices, which result from the different loads when there is zero solar and wind energy penetration. The relative change rising from solar energy penetration is higher at low initial price levels that are related to low demand and becomes smaller at higher levels of demand or load. Note that the regression coefficients found were not significantly different from each other in the 5^{th} and the 95^{th} quantile, such that no conclusions can be drawn on the effect of solar on the width of the 90% confidence interval.

The graphs on the left-hand side of Figure 15 show that the decreasing slopes of the 5^{th} and the 95^{th} quantile resulting from solar are relatively similar. As a result, the width of the 90% confidence interval of on-peak electricity prices remains relatively stable at different levels of the share of solar energy penetration. This can be observed from the flat lines in the left graph in Figure 16.

Wind energy penetration

Table 5 shows that 20% share of wind energy generation decreases the left tail of the on-peak electricity prices similarly, with €13.25, in absolute terms given different levels of load. The effect of 20% share of wind compared to zero shares of solar and wind energy penetration on the right tail does depend on load. At maximum load, a much stronger decrease of 27% is found, while only a decrease of 19% is found at times of average load and 3% at times of minimum load. This results in different effects on the 90% confidence interval at different levels of demand.

The graphs on the right-hand side of Figure 15 illustrate that the slopes of the left and the right tail move in different directions when comparing the graphs of different loads. At maximum load, the decrease in the left tail becomes flatter while the decrease in the right tail becomes steeper. This results in a decreasing confidence interval when the share of wind increases. At average load, the slopes are relatively similar, which leads to a stable width of the confidence interval. Assuming that load usually ranges between average and maximum load during on-peak hours, a decline or rather stable width of the confidence interval results from wind energy penetration in most situations.

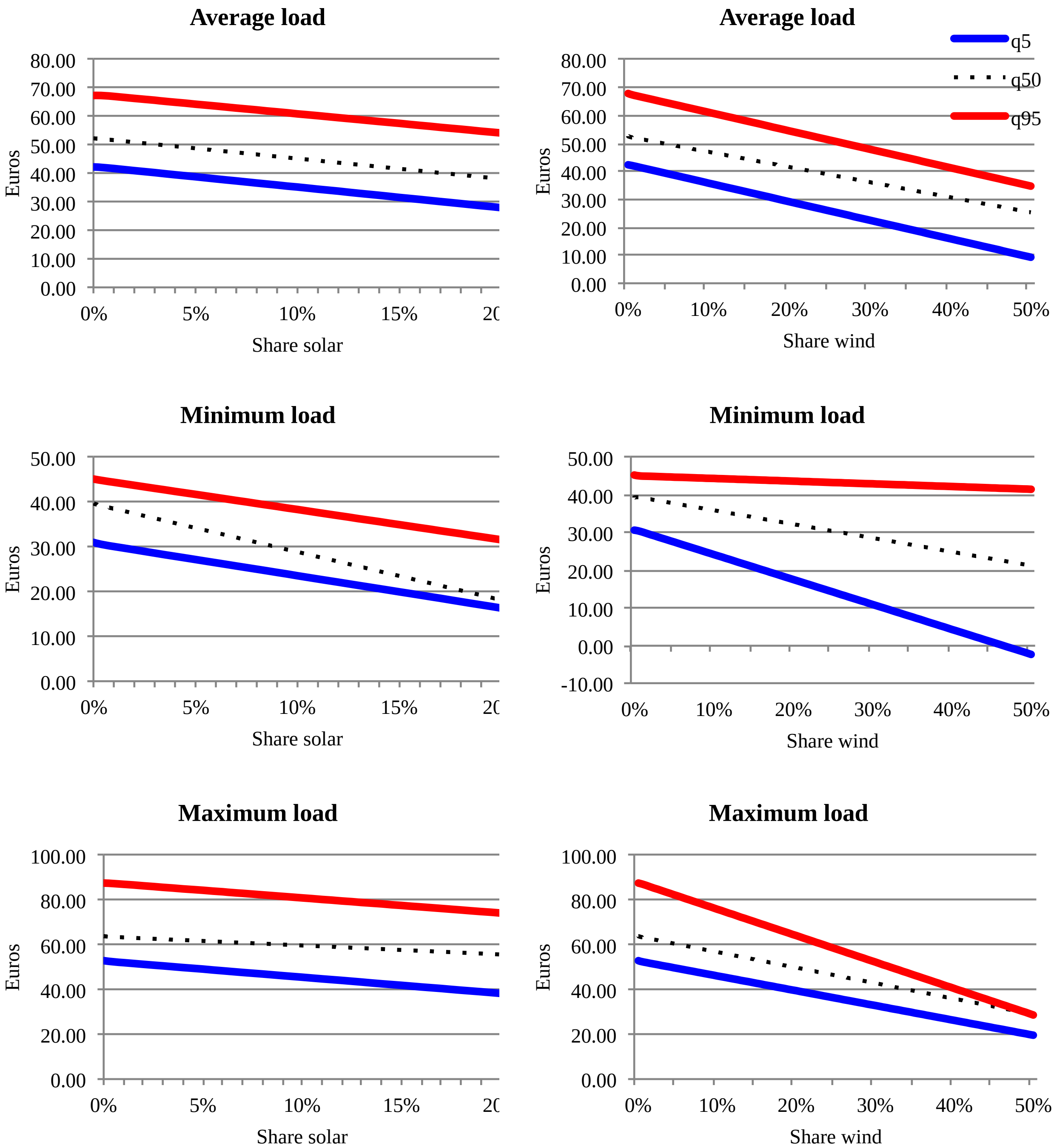
Table 5. Sensitivity of the different quantiles of on-peak electricity prices (EPEXON) to solar or wind energy penetration

	Share solar	Share wind	q5	Δ	%Δ	q95	Δ	%Δ	q95-q5
Average load	0	0	€ 42.45			€ 67.72			€ 25.27
	20%	0	€ 28.00	-€ 14.45	-34%	€ 54.19	-€ 13.53	-20%	€ 26.20
	0	20%	€ 29.20	-€ 13.25	-31%	€ 54.53	-€ 13.19	-19%	€ 25.33
Minimum load	0	0	€ 30.82			€ 45.14			€ 14.32
	20%	0	€ 16.36	-€ 14.45	-47%	€ 31.61	-€ 13.53	-30%	€ 15.25
	0	20%	€ 17.56	-€ 13.25	-43%	€ 43.71	-€ 1.43	-3%	€ 26.14
Maximum load	0	0	€ 52.78			€ 87.77			€ 35.00
	20%	0	€ 38.32	-€ 14.45	-13%	€ 74.24	-€ 13.53	-15%	€ 35.92
	0	20%	€ 39.53	-€ 13.25	-22%	€ 64.14	-€ 23.63	-27%	€ 24.62

Note: Δ = The absolute difference in electricity price in q5 or q95 between 20% solar and 20% wind energy penetration seperately and zero wind and solar energy penetration

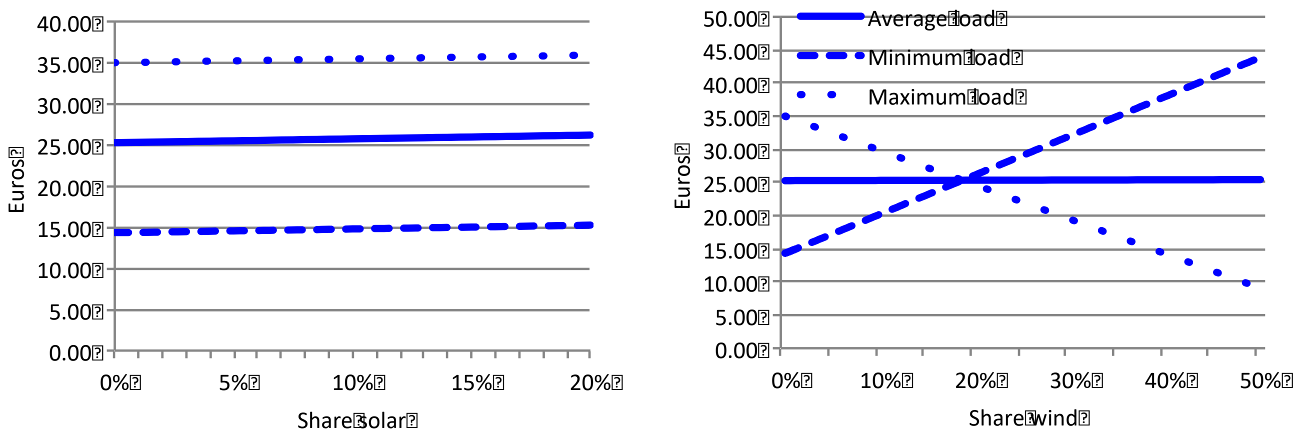
%Δ = The relative difference in electricity price in q5 or q95 between 20% solar and 20% wind energy penetration separately and zero wind and solar energy penetration

Figure 15. Left and right tail of on-peak electricity prices (EPEXON) for different levels of wind and solar energy penetration and load



Note. Yesterday's prices are set at the average level of the dataset, the share of wind is zero for the graphs on the left hand side and the share of solar is zero for the graphs on the right hand side

Figure 16. 90% Confidence interval (q95-q5) of on-peak electricity prices (EPEXON) for different levels of solar and wind energy penetration and load



In conclusion, during on-peak hours, the share of solar energy generation does not affect the width of the confidence interval, as the effects found on the left tail and the right tail are not significantly different from each other. The effect of the share of wind energy generation is highly dependent on the level of demand, both in terms of the left tail and the right tail. When demand is low, the width of the confidence interval increases as a result of an increase in the share of wind energy penetration. When demand is high, the width of the confidence interval decreases as a result of an increase in the share of wind energy penetration. At average load, the left tail and the right tail are affected approximately similar, which results in the width of the confidence interval staying unchanged. It is likely that during on-peak hours, demand ranges between average load and maximum load. Therefore, wind is likely to make the confidence interval narrower during on-peak hours by a stronger increase in the right tail compared to the left tail.

5.2.3. Off-peak electricity prices (EPEXOFF)

Table 6 provides the sensitivity analysis for off-peak electricity prices and Figures 17 and 18 visualize the sensitivity of the left tail and the right tail and the corresponding confidence interval of off-peak electricity prices to different levels of solar and wind energy penetration. Note that during off-peak hours, it is unlikely that demand takes high levels and, hence, the occurrence of maximum load is unlikely. Nevertheless, all levels are again used to develop an enhanced understanding of the influence of load on the effects of solar and wind on prices.

Solar energy penetration

A significant effect for the share of solar energy penetration in the quantile regressions on the left tail of off-peak electricity prices is absent. As a consequence, there is no difference found in the left tail of off-peak electricity prices from 20% solar energy penetration. Changes in the confidence interval as a result of solar can, therefore, only originate from changes in the right tail. A decrease is found, which takes higher levels at times of low demand. At 20% solar energy penetration, a relative increase of 27% is found. At average load, this relative decrease takes a value of 7%. Note that Table 6 shows an increase in price from 20% solar at maximum load. This is not realistic, given the fact that solar energy generation shifts the merit order supply curve to the right. As it is unlikely that the maximum load and high solar power generation occur during off-peak hours, this positive effect can be ignored.

The graphs on the left-hand side of Figure 19 demonstrate that the right tail of the off-peak electricity price distribution decreases at times of general load when the share of solar increases. This decrease becomes more apparent at times of minimum load. In conclusion, solar energy generation decreases the confidence interval when demand ranges between average and low load levels. This is visualized in the graphs on the left side of Figures 17 and 18.

Wind energy penetration

Table 6 reveals a substantial decrease in the left tail of electricity prices resulting from a 20% share of wind energy penetration compared to zero wind energy penetration. The relative decrease is more extreme at minimum load and less extreme at maximum load. The 20% share of wind energy penetration also decreases the right tail, but this decrease is weaker in absolute as well as in relative terms. At average load, the decrease in the left tail is 32% while the decrease in the right tail is only 13%. At minimum load, the decrease in the left tail is even 50% and the right tail is only 10%. This leads to an increase in the confidence interval. The increase becomes weaker at higher levels of demand.

The graphs on the right-hand side of Figure 17 reveal that especially the left tail (q5) is highly dependent on the level of load. A stronger decrease is found in the left tail compared to the right tail at times of average load and this difference becomes even greater at times of minimum load. At times of maximum load, the slopes of the left tail and the right tail become highly similar, which leads to no effects on the width of the confidence interval. These effects on the 90% confidence interval are visualized in Figure 18. Note, again, that maximum load is not likely at times of off-peak prices. Therefore, it can be concluded that wind energy penetration increases the confidence interval in most cases during off-peak hours, mainly through the strong decrease in the left tail of the off-peak price distribution compared to the right tail.

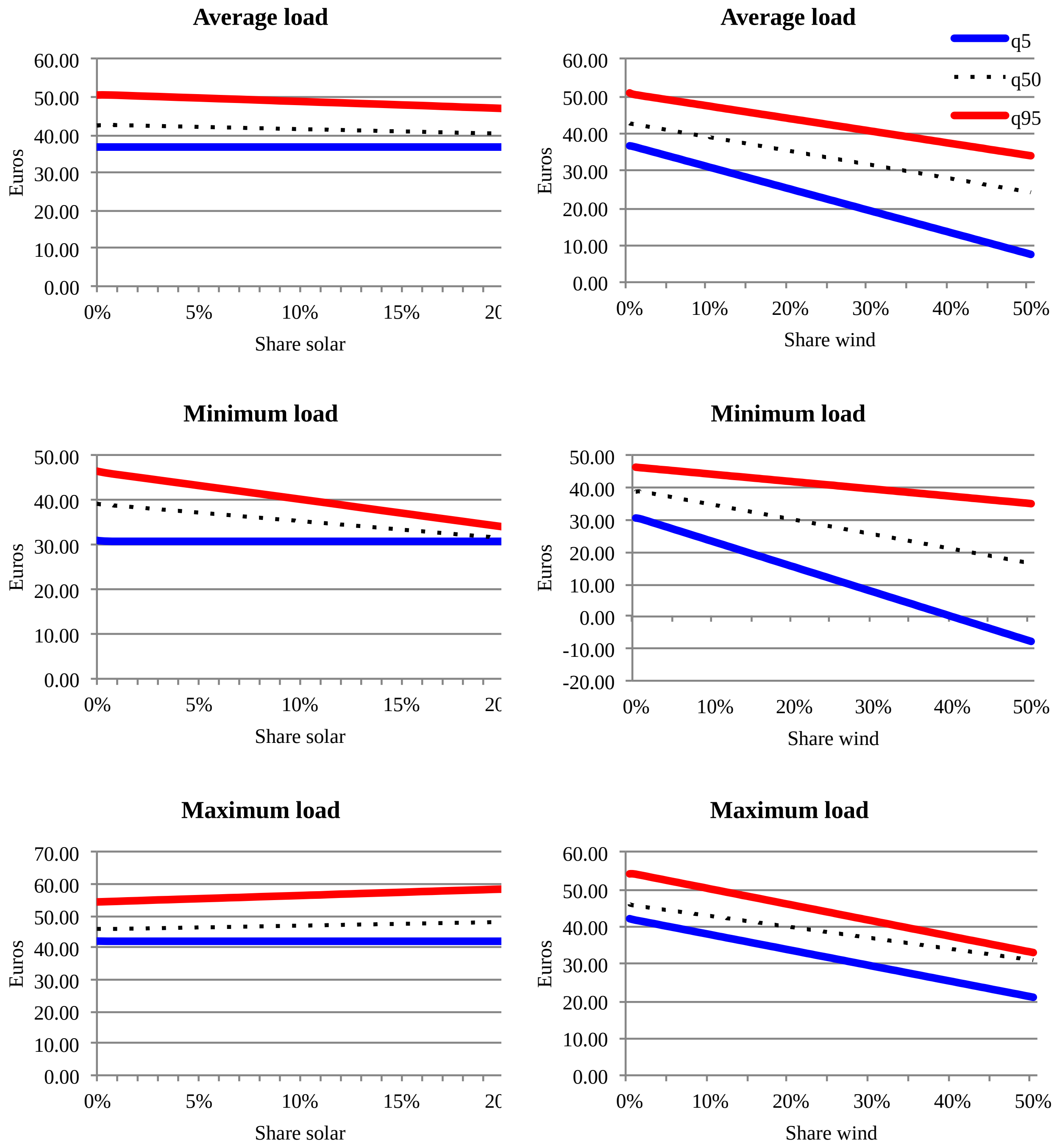
Table 6. Sensitivity of the different quantiles of off-peak electricity prices (EPEXOFF) to solar or wind energy penetration

	Share solar	Share wind	q5	Δ	%Δ	q95	Δ	%Δ	q95-q5
Average load	0	0	€ 36.79			€ 50.68			€ 13.89
	20%	0	€ 36.79	€ 0.00	0%	€ 47.00	-€3.67	-7%	€ 10.21
	0	20%	€ 25.07	-€ 11.72	-32%	€ 44.02	-€6.66	-13%	€ 18.94
Minimum load	0	0	€ 30.83			€ 46.43			€ 15.61
	20%	0	€ 30.83	€ 0.00	0%	€ 34.07	-€12.37	-27%	€ 3.24
	0	20%	€ 15.40	-€ 15.42	-50%	€ 41.91	-€4.52	-10%	€ 26.51
Maximum load	0	0	€ 42.09			€54.45			€ 12.36
	20%	0	€ 42.09	€ 0.00	0%	€58.49	€4.04	7%	€ 16.40
	0	20%	€ 33.66	-€ 8.43	-20%	€45.89	-€8.56	-16%	€ 12.23

Note: Δ = The absolute difference in electricity price in q5 or q95 between 20% solar and 20% wind energy penetration seperately and zero wind and solar energy penetration

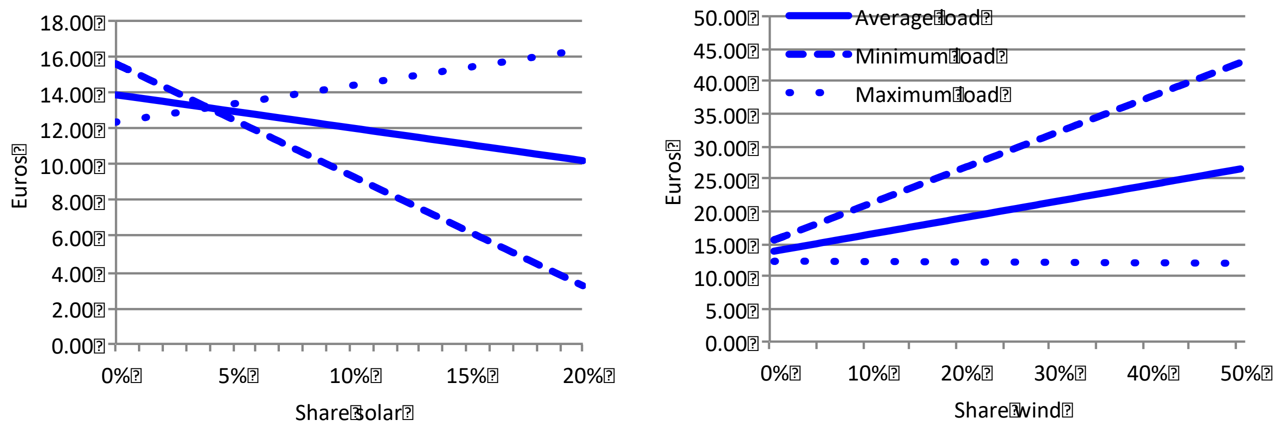
%Δ = The relative difference in electricity price in q5 or q95 between 20% solar and 20% wind energy penetration separately and zero wind and solar energy penetration

Figure 17. Left and right tail of off-peak electricity prices (EPEXOFF) for different levels of wind and solar energy penetration and load



Note. Yesterday's prices are set at the average level of the dataset, the share of wind is zero for the graphs on the left hand side and the share of solar is zero for the graphs on the right hand side

Figure 18. 90% Confidence interval (q95-q5) of off-peak electricity prices (EPEXOFF) for different levels of solar and wind energy penetration and load



In conclusion, during off-peak hours, solar energy penetration does only affect the right tail of the price distribution. As a result, a decrease is found in the 90% confidence interval of the off-peak price distribution resulting from increased shares of solar energy penetration when load ranges between average and minimum levels. Wind energy penetration shows a much stronger effect on the left tail of the price distribution, especially at times of low demand. The right tail of the price distribution is also decreased, but not as extreme as the left tail of the price distribution. As a consequence, wind energy penetration increases the confidence interval of off-peak electricity prices mainly through its effects on the left tail of the price distribution.

Chapter 6: Conclusion and Discussion

Uncertainty of electricity prices increased as a result of deregulation and the transition towards renewables on the German energy market. With the energy transition, the role of renewable energy generation became of greater importance. Moreover, German policy objectives aim at a future energy market where 100% of the supply will originate from renewables (Renn & Marshall, 2016; Hohmeyer & Bohm, 2015). The highly intermittent nature of solar and wind energy generation and the instantaneous nature of electricity consumption reinforced the non-normal behavior of electricity prices (e.g. extreme price spikes and seasonality) and, therefore, a better understanding of the tail behavior of electricity prices in relation to solar and wind energy penetration is desired. Kyritsis et al. (2017) found increased levels of volatility in electricity prices as a result of wind energy generation and decreased levels of volatility as a result of solar energy generation. Hagfors et al. (2016b) found different effects of wind and solar power generation on the probability of positive and negative price spikes at different periods of the day. Previous research did not provide distinctive estimations on the effect of wind and solar energy penetration on particularly the left tail and the right tail of the electricity price distribution. This research fills this gap in the literature by estimating the effect of solar and wind energy penetration in the German electricity market on the distribution of electricity prices by looking at the tails of the distribution rather than at the average. Quantile regression, introduced by Bunn et al. (2017), is used to model the non-normal behavior of electricity prices. This technique allows measurement of the tails with distinct regressions without making assumptions on the distribution of the residuals. Quantile regression is applied to the 5^{th} quantile and the 95^{th} quantile and these results are used to estimate the tails of electricity prices at different levels of wind and solar energy penetration. These insights improve the estimation of electricity prices and corresponding risk assessment for participants on the German energy market and can ultimately help policy makers to improve efficiency and sustainability in the energy market. A distinction is made between off-peak and peak hours, as there are structural differences in the dynamics of supply and demand across these different periods.

This chapter starts with linking the main findings to the hypotheses formulated in *Chapter 3*. Thereafter, implications of the findings of this research in terms of price estimation and risk assessment as well as policy implications are discussed. Lastly, limitations and directions for further research are provided.

6.1 Main findings

The results reveal substantial differences in the effect of wind and solar energy penetration on on-peak and off-peak electricity prices. As on-peak and off-peak price specifications are more specific and electricity prices are set separately for each hour of the subsequent day, it is useful for market participants to make a distinction between on-peak and off-peak and consider the differences found in their risk assessment. Therefore, I will focus on the effects of on-peak and off-peak electricity prices in the conclusion rather than on all-hours electricity prices.

6.1.1. The effect of solar energy penetration

The results reveal a clear distinction between the effects of solar on on-peak and off-peak hours. During on-peak hours, the left tail and the right tail are both decreased through the share of solar energy penetration. However, no significant difference is found between the effects on the left tail and the right tail, which leads to the width of the confidence interval staying relatively unchanged through solar energy penetration. This implies only a shift in the confidence interval to the left as a result of increased levels of solar energy penetration. During off-peak hours, on the other hand, the share of solar energy penetration only shows a significant, negative effect on the right tail. This decrease becomes stronger at lower levels of demand, which leads to a decrease in the confidence interval of off-peak electricity prices through increasing shares of solar energy penetration. When demand ranges between average load and maximum load, the confidence interval increases as a result of an increasing share of solar energy penetration. Note that high levels of demand are not likely during off-peak hours and, therefore, the width of the confidence interval is decreased in most cases during off-peak hours.

These findings are slightly different from the expectations in the first hypothesis (see *H1* in *section 3.2)*. The decrease in the confidence interval resulting from the effect on the right tail during off-peak hours was expected. However, the decreased confidence interval was also expected to be in place during on-peak hours, as Kyritsis et al. (2017) argued that solar energy generation decreased volatility by scaling down peak-load power plants[3]. This adds to the understanding that despite the decrease found in volatility by Kyritsis et al. (2017), the bandwidth of the confidence interval remains relatively unchanged at different levels of solar energy penetration during on-peak hours. My results show that during on-peak hours, the share of solar energy generation only shifts the confidence interval to the left but does not influence the width of the 90% confidence interval. The effect during off-peak hours is in agreement with *H1*, which expected to find no effect on the left tail because oversupply is unlikely during off-peak hours. The share of solar energy generation decreases the right tail of the confidence interval, while the left tail remains unchanged and this leads to a decrease in the width of the confidence interval. The decreased bandwidth resulting from the right tail implies a lower risk of extreme positive price spikes during off-peak hours resulting from solar energy penetration.

6.1.2. The effect of wind energy penetration

Considering the results of on-peak and off-peak hours separately, this study reveals different dynamics for wind energy penetration as well. During on-peak hours, a decrease in the 90% confidence interval mainly results from the effects on the right tail when demand ranges

[3] Note that the volatility measure and measures of the 5th and the 95th quantile are fundamentally different from each other, so it is not necessarily the case that increased volatility leads to an increased bandwidth of the confidence interval. The expectation of a decreased width of the confidence interval resulting from decreased volatility found by Kyritsis et al. (2017) was only suggestive

between average and high levels, which is likely during on-peak hours. The effect on the left tail is independent from the level of demand during on-peak hours. Consequently, the confidence interval is decreased through the stronger decreasing effect in the right tail compared to the left tail. Only when demand ranges between average and low levels, which is unlikely during on-peak hours, the confidence interval increases. During off-peak hours, the effect of wind energy penetration on the left tail seems to be more dependent on load than the effect on the right tail. The 90% confidence interval increases as a result of wind energy penetration when demand ranges between average and low levels, which is likely during off-peak hours. This is caused by the stronger decrease in the left tail compared to the decrease in the right tail. Even when demand ranges between average and maximum load (which is unlikely during off-peak hours), the 90% confidence interval does not decrease but rather increase or remain similar.

These findings are in line with the second hypothesis (see *H2* in *section 3.2*). An increase in the confidence interval was expected to be a result of the left tail during off-peak hours at low demand. This seems to be consistent with the finding of Kyritsis et al. (2017), who found increased volatility as a result of increased levels of solar energy generation during off-peak hours[4]. The fact that the decrease found in the left tail is the main influence of an increased confidence interval leads to an increased risk of extreme negative price spikes during off-peak hours. Note that this increased confidence interval only applies to off-peak hours. According to my findings, the confidence interval decreases as a result of wind energy penetration during on-peak hours when there are sufficient levels of demand, mainly resulting from a decrease in the right tail. This suggests a lower risk of extreme negative price spikes during on-peak hours compared to off-peak hours. The risk of extreme positive price spikes as a result of wind energy penetration is also higher during off-peak hours compared to on-peak hours.

6.2 Implications

The findings of this research provide novel and improved insights into tail behavior of electricity prices that result from different levels of renewable energy penetration. The results provide opportunities for improved electricity price predictions and risk assessment. Besides, policy makers can use these insights to assess necessary policy measures in order to achieve an efficient and sustainable energy market. This section discusses the implications in more

[4] Note, again, that volatility and measurements of the quantiles are fundamentally different measures. I would suggest a lower width if volatility is decreased, but this is only suggestive

detail by providing some intuition in how the findings can be utilized by participants on the energy market and how the findings can benefit policy objectives.

6.2.1. Improved risk assessment and price estimations

The extreme short-term volatility of energy prices in a deregulated market with high levels of solar and wind energy penetration increases the need for risk assessment for large consumer, suppliers and traders on the energy market (Dahlgren, Lie & Lawarree, 2003). Suppliers, for example, must seek to deliver the required volume of power to retailers and end-users while managing risk and risk assessment should be incorporated in their bidding decisions (Yau et al., 2011). Techniques used in financial markets for risk assessment, however, cannot be used directly for the energy market because of the highly different nature of electricity compared to other commodities. Previous research provided insights on the effect of wind and solar energy generation on volatility as a measure of risk in the German market (Kyritsis et al., 2017) but this risk measure does not provide insight into the direction of price spikes.

A more revealing risk measure on the electricity market concerns value at risk (VaR). This is a method to quantify the exposure to risk of a company's portfolio and it provides the expected maximum loss over a target horizon within a given confidence interval (Yau et al., 2011). VaR, in contrast to a volatility measure, does incorporate the direction of price spikes as it only focuses on the risk of making a loss. Accurate quantile estimates, as estimated in this research, can be used for the calculation of VaR. These VaR calculations can be used to consider outcomes that could result in large losses. The main findings reveal better insights into the effects of wind and solar energy on the upper and the lower bound of the 90% confidence interval through the quantile regression results found for the 5th and the 95th quantile. The sensitivity analysis can be applied to calculate expected levels of value at risk properties given wind and solar forecasts and expected demand. This helps in making better predictions on the risks related to the energy market, while distinguishing between peak and off-peak hours. Market participants can use VaR to fine-tune their bids and reduce their exposure to risk when considering solar and wind forecasts.

Besides improved risk assessment, the quantile regression results can also be used to estimate the range in which electricity prices are expected to fall for different levels of solar and wind energy penetration during off-peak and peak hours. The left tail and the right tail of the price distribution reveal a 90% confidence interval. The novel insights into electricity price behavior in relation to renewable energy generation has implications for market participants as well as for policy makers to come up with the right policy measures to achieve objectives. The following sections *(sections 6.2.2. and 6.2.3.)* aim to provide some intuition in how the findings of this research can be applied to practice.

6.2.2. Implications for market participants

To provide intuition in how the results can be used for improvement of the risk assessment, I will provide an example of risk assessment using VaR compared to risk assessment using a volatility measure when buying electricity. Imagine a party who needs to decide on a volume and bid price to buy electricity when high wind energy generation is expected during off-peak hours, such that demand is expected to be low. Kyritsis et al. (2017) found increased volatility in electricity prices during off-peak hours. This would suggest increased risk, as it implies equal probability of extreme positive price spikes and extreme negative price spikes. When looking at the results of the quantile regression, it can be observed that the confidence interval increased as a result of a relatively stronger decrease in the left tail of the distribution compared to the right tail of the distribution.

This insight can be used for VaR calculations in which only the right tail of the price distribution is taken into account, as the left tail of the price distribution would lead to gains rather than losses. This VaR measure would lead to lower risk assessment than the volatility measure and provides more specific information on the tails of the price distribution. This information can be used for incorporating risk in bidding decisions. The same holds for suppliers on the energy market. Note that for suppliers, the left tail of the price distribution would rather cause losses when selling electricity, which in its turn would lead to higher risk assessment when using VaR compared to the volatility measure in the example as described above. This originates from the fact that negative price spikes do not harm buyers of electricity, while positive price spikes do not harm sellers of electricity. The situation described above can be set up for different situations by looking at the sensitivity analysis for different levels of wind and solar energy generation and different levels of demand.

The findings of this research are in particular interesting for traders on the energy market. Traders can use the results for price expectations and risk-assessment to time their trading activity. The quantile regression results can help with developing a trading strategy such that gains are realized while mitigating the risk of losses. An interesting issue related to trading and improved estimation of electricity prices concerns energy storage in terms of batteries, which have been introduced over the recent years, but only on a small scale. The increased insight in electricity prices could improve the potential of making gains with batteries by charging batteries during low price periods and discharging batteries during high price periods. With the right trading strategy, batteries can be used to benefit from the volatility of electricity prices. To give an example on how renewable energy generation could play a role in setting up a trading strategy, I will discuss a trading strategy during off-peak hours when high levels of wind are expected. High levels of wind energy penetration strongly decrease the left tail of the price distribution. This leads to increased benefits from charging a battery during off-peak hours when high levels of wind are in place, resulting from the left tail. At extreme levels of demand, the left tail could even turn out negative. As a result, when high wind levels are expected during the night, it is beneficial to anticipate on this by emptying a battery in such a way that it can be charged when prices turn out very low. The battery can subsequently be discharged during on-peak hours when wind is expected to fall. This reasoning can be applied to different situations by looking at the expected price ranges for different levels of wind energy penetration, solar energy penetration, and demand. In conclusion, the example shows that the increased insight on the left tail and the right tail of the price distribution could have a serious impact on the benefits of using a battery to earn money with. Increased insights might result in increased validity of investing in batteries, and this could accelerate the development and introduction of batteries on a larger scale.

Besides making profits from the volatility in electricity markets, batteries could also serve as a solution in balancing supply and demand. Another possible reaction from the increased insights could be demand response, in which large-scale electricity consumers shift consumption to periods with lower expected price ranges. These implications lead to a positive externality for policy makers, as it improves efficiency on the market. I will conclude with linking the German policy objectives to the increased insights on tail behavior and the increased interest in battery storage in specific.

6.2.3. Policy implications

German policy objectives aim at a 100% renewable energy supply (Renn & Marshall, 2016; Hohmeyer & Bohm, 2015), which is the most important contribution in the reduction of CO2 emission from a human-driven climate change. The volatile electricity feed-in, resulting from wind and solar, leads to a growing demand for positive and negative balancing power (Paulus & Borggrefe, 2010). Balancing supply and demand is necessary to guarantee a reliable supply of electricity for industry and households. The balance between the inelastic, dynamic load with increased levels of intermittent renewable energy supply is necessary to realize a more sophisticated energy network, also referred to as a smart grid (Roberts & Sandberg, 2011). According to Kyritsis et al. (2017), increased flexibility seems to be the most important factor to realize efficiency in a system with high levels of intermittent renewable energy generation. Flexibility could be increased through, for example, conventional power generation, but a reduction in requirements regarding this flexibility could serve as a more sustainable solution. Kyritsis et al. (2017) for example propose energy storage and demand response.

The results could increase awareness of policy makers in potential oversupply and undersupply for different levels of wind and solar energy generation. Following the intuition of the merit-order effect, extreme negative price spikes relate to oversupply, while extreme positive price spikes relate to undersupply. The results generate interesting insight into the directions policy makers should aim at to improve efficiency and sustainability of the energy system. They could, for instance, motivate large-scale users to consume at certain moments in which oversupply is likely. If large-scale electricity users are motivated by policy measures to use electricity at times of oversupply, this could be beneficial for both the consumer through lower electricity prices and for the system's efficiency as this would improve the balance of supply and demand. Note, however, that realizing balanced supply and demand levels through demand response is limited.

A more convenient solution concerns the development of energy storage. According to Hohmeyer and Bohm (2015), a 100% renewable energy supply requires expanded energy storage to balance the system at times of low wind and solar energy generation by using the overproduction of these sources at times of high wind and solar energy generation. Bussar et al. (2014) confirm the required storage capacity for a preferred cost-efficient energy system in Europe. Energy storage in terms of batteries is a top concern for the future, as balancing supply and demand could be simplified with small amounts of energy stored through the grid (Roberts & Sandberg, 2011). Several short-term storage technologies are in place, such as batteries of electrical vehicles, but current levels are far from sufficient. Increased large-scale developments are needed in the future to reach sufficient efficiency in the system. When the increased possibilities related to electricity price estimation stimulate further development of batteries, as discussed in *section 6.2.2.*, this could ultimately give rise to an efficient system in which 100% renewable energy penetration is in place and CO_2 emissions are decreased.

6.3 Limitations and directions for future research

The previous sections have clarified the importance of the novel findings for both theory and practice. Nonetheless, the results of this study need to be considered with caution and several limitations need to be taken into account. The main limitation of this research concerns the relatively outdated timespan of the dataset. In order to make a clean comparison with the research conducted by Kyritsis et al. (2017), a similar timespan is used, reflecting a period up to the 30th of June 2015. It is, however, vital to notice that the energy market is a fast-changing environment. In the years between 2015 and 2019, wind and solar energy penetration gained even more importance in Germany. This is expected to continue in the near future, considering the German policy objectives. Suppliers, buyers, and policy makers might have already responded to these developments in terms of flexibility or bidding behavior and this could have changed the dynamics between solar and wind energy generation and the tails of electricity prices. The fast-changing developments in the market require close control of new changes in the energy mix as well as in demand. Flexibility or the need for flexibility in the system could change substantially if, for example, large-scale electricity users change their time of consumption to off-peak hours, if large-scale electricity storage becomes more common, or if grid connections improve in the future. Major changes in the effect of renewable energy generation on the left and the right tail of electricity prices and the corresponding confidence interval could result from this. It can, therefore, be seen as a shortcoming that the data reflects a period after which additional developments in the energy market took place. Consequently, it is important to conduct this research with up-to-date data such that recent developments are not ignored in risk assessments and developing policy measures based on the quantile regression results. This enables to make more generic conclusions.

Moreover, this research is conducted on German electricity prices and underlines the importance of modeling the tails of electricity prices for risk assessments and policy measures. Although Germany was a leader in the energy transition, other countries have followed or will follow in the near future. Due to country-specific characteristics such as the energy mix, demand, policy objectives, and grid connection, the results are not transmittable to other countries. Conducting similar quantile regression models on data of other countries in which renewable energy penetration increased importance is, therefore, recommended for future research. An example is the UK, where, in the best of my knowledge, the role of renewable energy has not yet been investigated on the tails of the electricity price distribution. This could add to the understanding of the research of Hagfors et al. (2016a), who already modeled the UK electricity price distributions using quantile regression but who did not yet include renewable energy in their models.

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Appendix

Table 1. Statistical significance on the 5th and the 95th quantile

	5%		95%				
	β_1	SE(β_1)	β_2	SE(β_2)	β_1-β_2	SE(β_1-β_2)	t-statistic
1. EPEX							
share_solar	-1.238	0.403	-0.284	0.100	-0.955	0.415	-2.301
share_wind	-1.335	0.209	0.662	0.335	-1.997	0.395	-5.059
share_solar#load	0.000	0.000					
share_wind#load	0.000	0.000	0.000	0.000	0.000	0.000	4.788
2. EPEXON							
share_solar	-0.723	0.066	-0.676	0.090	-0.046	0.112	-0.415
share_wind	-0.663	0.031	1.171	0.291	-1.834	0.292	-6.273
share_solar#load							
share_wind#load			0.000	0.000			
3. EPEXOFF							
share_solar			-1.537	0.461			
share_wind	-1.163	0.197					
share_solar#load			0.000	0.005			
share_wind#load	0.000	0.000	0.000	0.000	0.000	0.000	2.740