Renewables intermittency versus power (in)flexibility: new insights from tail-index estimates

Ronald Huisman[a], Evangelos Kyritsis[b], Cristian Stet[c]

[a]*Erasmus School of Economics at the Erasmus University Rotterdam, Rotterdam, The Netherlands, +31 10 408 8925, rhuisman@ese.eur.nl*
[b]*Department of Business and Management Science, Norwegian School of Economics, Bergen, Norway, +47 55 95 9953, evangelos.kyritsis@nhh.no*
[c]*Corresponding author. Erasmus School of Economics at the Erasmus University Rotterdam, Rotterdam, The Netherlands, +31 61 653 6077, stet@ese.eur.nl*

Abstract

Power prices are well known to have a fat-tailed probability distribution function. These fat tails represent the probability of sudden high and low prices that occur as a result of sudden changes in supply, partly due to intermittent renewable power generation, and/or in demand due to inelastic short-term demand and the absence of sufficient storage capacity.

In addition to the consensus view in the literature, that the level of intermittent renewable power supply has an effect on power prices and volatility, we show that the level of wind and solar supply has an effect on the fatness of the tail of empirical power price distributions. The more wind and solar supply, the fatter the tails of the left side of the distribution function and the thinner the tails on the right side.

From our empirical findings on the tail asymmetry in the distribution of electricity prices, we conclude that the power system has higher need for downward than for upward power system flexibility during times with high share of intermittent renewable energy in the power system and the opposite during times with low share of intermittent renewable energy in the power system. A better understanding of the need for power system flexibility is the first step before actually adopting new measures and designing/updating the energy policy in

the market.

Keywords: Intermittent supply, fat tails, renewables, flexibility, power prices.

1. Introduction

Electricity markets have experienced important structural changes over the past few decades. During this period of time, many countries liberalised their electricity sector and set the path to the creation of competitive power markets. On top of that, these markets changed because of the ever increasing share of intermittent renewable energy generation (wind and solar) in the power generation mix. The shift towards an increasing share of intermittent power generation has a significant impact on power prices and increases the need for flexibility in the power supply. A better understanding of the impact that intermittent generation has on electricity prices can help both managers and policy makers in taking better long- and short- term decisions in operating in and respectively designing electricity markets in terms of increased power system flexibility.

Focusing on the German power market Kyritsis et al. (2017) show that both solar and wind power influence the probability distribution function of power prices by inducing a merit order effect being that power prices decline when the share of renewables in the power system increases. Würzburg et al. (2013) present a list of 20 articles (of which 9 focus on the German electricity prices) that all show this same result.[1] Kyritsis et al. (2017), Tveten et al. (2013) and Ketterer (2014) went further by examining how changes in intermittent renewable supply affect the volatility of power prices. Kyritsis et al. (2017) show that wind and solar have a different impact on the volatility of electricity prices: wind power generation increases volatility and the probability of spikes occurring in the electricity prices; solar power generation decreases the electricity price volatility and probability of having electricity price spikes. The same

[1] More recent papers that yield the same conclusion are among others Dillig et al. (2016), Ketterer (2014), Tveten et al. (2013) and Paraschiv et al. (2014).

relation between wind and volatility of electricity prices was exhibited in Ketterer (2014) and between solar and volatility of electricity prices in Tveten et al. (2013).

The clear view from the literature is that power prices decline as a result of an increase in renewable intermittent supply and that the volatility of power prices changes as a result of changes in solar and wind supply. This view motivated us to further examine the impact of intermittent supply on the probability distribution function of power prices. We question whether increasing the share of intermittent supply might also affect the tails of power price distribution functions, since tails of electricity prices are closely related to power system flexibility which is the key challenge towards the integration of large-scale renewable energy sources.

In the literature so far there is not a consensus view on the relation between wind and solar supply and the tails of the power price distribution functions. Evidence comes from papers that marginally touch on the link between extreme electricity prices and intermittent supply. For instance Paraschiv et al. (2014) do not find conclusive evidence for the case of solar supply but, their results show that upward price spikes occur mostly when wind supply is low. LeBaron and Samanta (2005) show, by comparing the tail fatness of empirical power distribution functions between emerging and developed economies, that one of the factors that influences the distribution of electricity prices is the difference is the level of penetration of intermittent energy generators. Lindstrom and Regland (2012) study five European electricity markets and use a regime switching model and find a positive relation between the frequency of extreme price events and the share of renewables used in power production suggesting that renewable supply increases the tail fatness of the electricity prices. In contrast Paraschiv et al. (2015) find, by applying an AR-GARCH model on EPEX day-ahead market data, that heaviness of tails is reduced between 2008 and 2014. Even if the authors do not make a strong claim, they suggest that their results might be influenced by an increasing share of renewables (specifically wind) in the generation mix.

As Kyritsis et al. (2017) demonstrate the difference between the impact of wind and solar supply on volatility, we question whether their result would also hold for the tail fatness of power distribution functions. This paper contributes to the literature by extending Kyritsis et al. (2017). We examine, using their data and methodology, the impact that the penetration of intermittent renewables in the German power supply mix has on the tails of German electricity prices empirical distribution functions. Understanding this further completes the picture of how changes in the intermittent renewable supply affect changes in the power price distribution function.

The following parts of the paper are structured as follows. Section 2 presents the methodology and the data that we used. Section 3 introduces the results of the analysis and provides a discussion on the implication of the results. Section 4 concludes the article.

2. Methodology and data

As stated previously, our goal is to extend Kyritsis et al. (2017) by examining how wind and solar supply not only affect the standard deviation (volatility) of the empirical power price distribution, but also the tails. Due to price inelastic demand and non storability, power prices exhibit mean reversion, high volatility and frequent upward and downward price spikes. As a consequence the price distribution function of power prices is non-normal and exhibits fat tails. This is shown by for example Byström (2005), Chan and Philip Gray (2006), Walls and Zhang (2005), Huisman and Huurman (2003), and Herrera and González (2014) who apply extreme value theory (EVT) to investigate the behaviour of extreme electricity prices. None of the aforementioned papers focus on a direct link between the probability and magnitude of extreme prices and the fundamentals of the electricity markets (generation mix, storability, expected demand, available supply etc.). Paraschiv et al. (2014) is one of the papers that calls for giving more importance to fundamentals when analysing electricity prices suggesting that stochastic models often include too simplistic assumptions. With our paper we endeavor to examine the relationship between the probability and magnitude of extreme electricity prices and wind and solar supply using EVT. In addition we argue that changes in intermittent renewable supply might have a different effect on the right side of the (empirical) electricity price distribution than on the left side. In the literature there is yet mixed evidence for this tail fatness asymmetry, with no general consensus among researchers. Frestad et al. (2010) do not find enough evidence to suggest tail fatness asymmetry in the Nordic Electricity Swap Market. On the opposite, the results of González-Pedraz et al. (2014) suggest that positive price spikes are more frequent in electricity prices than drops, thus indicating tail asymmetry.

We follow Kyritsis et al. (2017) and use the same data as they use. It consists of German day-ahead spot electricity prices from 1st of January 2010 to 30th of June 2015. This timeframe consists of a period of rapid and large-scale integration of renewables, period for which we know that wind and solar supply explain changes in electricity price standard deviation. The German power market is an interesting case, not only due to the large share of intermittent renewables, but also due to its large share of inflexible base-load power generation. This is in contrary to other countries with more flexible power generation, such as Norway with it vast available hydropower supply.

From this data we create samples containing the average daily prices, average prices during off-peak hours and average prices during peak hours. For the average daily price we use Phelix Day Base data that measures the daily prices based on the average of over the 24 hourly prices of the day; for peak hour prices we use the Phelix Day Peak prices that are based on the average hourly prices for the hours 9-20; the off-peak hour prices are calculated based on the average prices for the 21-8 hours. Through this separation between peak and off-peak hours, it is possible to observe the magnitude of the impact of wind and solar penetration on the German electricity prices when demand is high and when demand is low.

To separate between different levels of penetration of wind and solar in the total electricity generated, we follow the methodology of Kyritsis et al. (2017) and Nicolosi (2010) using actual power generation data for the total, wind and solar output. However, their sampling method creates too many categories and too small samples to draw conclusions from. Therefore we adjust their sampling method to create equally sized sub-samples, which are large enough to measure the tail-index estimtes from.[2]

To differentiate between left and right tail of the distribution of electricity prices, we place the values below the median into the left tail observations and the values above the median into the right tail observations.

Table 1, Table 2 and Table 3 present the wind, solar and intermittent sub-samples and the number of observations in them. The intermittent subsamples are formed by adding together the wind and solar outputs. By examining the left and right tails of the empirical distribution function using the samples as shown in the tables mentione before, we are able to observe the impact of wind and solar power for different levels of wind and solar penetration and the impact of demand on the tails. For instance, the sub-sample with low wind penetration (low wind; between 0.4% and 4.9% share in production) has 334 observations for measuring the left tail. By comparing the tail index estimates for the different samples we can observe the difference in the tail index for periods with low and high wind penetration, low and high solar penetration and low and high intermittent penetration in combination with low (off-peak) and high (peak) de-

[2]Using the sampling method of Kyritsis et al. (2017) initially we obtained similar qualitative results as that we discuss later.

mand. Additionally, we can observe at each level of wind, solar or intermittent output penetration level the tail index differences between the right and the left tail of electricity distribution functions.

Table 1: Number of observations by wind output level

Wind in total system		All hours			Peak hours			Offpeak hours		
		Left	Both	Right	Left	Both	Right	Left	Both	Right
Low Wind	0.4-4.9%	334	669	334	334	669	334	334	669	334
Med Wind	4.9-11.1%	334	669	334	334	669	334	334	669	334
High Wind	11.2-50.6%	334	669	334	334	669	334	334	669	334

Table 2: Number of observations by solar output level

Solar in total system		All hours			Peak hours			Offpeak hours		
		Left	Both	Right	Left	Both	Right	Left	Both	Right
Low Solar	0-2.2%	334	669	334	334	669	334	333	669	334
Med Solar	2.2-6.7%	334	669	334	334	669	334	334	669	334
High Solar	6.7-20.9%	333	669	334	334	669	334	334	669	334

Table 3: Number of observations by intermittent output level

Intermittent in total system		All hours			Peak hours			Offpeak hours		
		Left	Both	Right	Left	Both	Right	Left	Both	Right
Low Intermittent	0.5-10.5%	334	669	334	334	669	334	334	669	333
Med Intermittent	10.5-17.4%	333	669	334	334	669	334	334	669	334
High Intermittent	17.4-52.2%	334	669	333	334	669	334	334	669	334

To observe the fatness of the tails, we calculate the tail index. Fat-tailed distributions are probability distributions whose tails do not exhibit exponential decay such as the normal distribution. Instead they have fatter tails. A fat-tailed distribution is a distribution for which the probability density function follows the power law $x^{-1/\gamma}$ for large observations of x. The parameter γ is the tail-index. The higher γ is, the fatter the tail, i.e. the slower the probability density function decays to zero. This definition is good for the purpose of this paper, but for a more general discussion we refer to for instance Huisman et al. (2001) and to Paraschiv et al. (2015) which are more recent and applied studies to power prices. The tail-index is a measure of tail fatness.

To estimate the tail index we use the methodology suggested by Huisman et al. (2001). They present a variation of the Hill tail index estimator that is more robust when used with small samples. Since our set of observations per sample is relatively small we believe that the Huisman et al. (2001) methodology is appropriate. As with the Hill estimator, the Huisman et al. (2001) estimator requires the researchers to determine where the tails of the empirical distribution functions start. We rely on Paraschiv et al. (2015) which offers an in depth investigation on the thresholds to be used for German electricity prices. They show that tail index stays relatively stable between selecting the biggest/smallest 10% and 15% of the observations. Besides the 10% and 15% thresholds, we also investigate the tail index at 20% threshold driven by the small sample used.

3. Results

Table 4 presents the tail index estimates for the different wind penetration sub-samples at the right tail, left tail and also at both tails combined. Moreover, in this table it can be observed the t-values for the difference between the right tail and the left tail of electricity price distribution function. For instance the top left estimate in Table 4 of 0.08 represents the tail-index estimate for the left tail of the empirical distribution function when there is a low penetration of wind supply when we assume that 10% of all observations in the sub-sample are tail observations. When we compare this estimate with the tail-index estimate for the right tail of the empirical distribution function at low wind penetration and 10% considered threshold, being 0.29, we can see that the right tail is statistically significantly fatter than the left one (t-value of -20.67). In contrast, when we look at the high wind penetration samples, the opposite result is observed: the left tail of the distribution function (tail-index estimate of 0.42) is significantly fatter than the right one (tail-index estimate of 0.04) (t-value of 53.53).

Table 4: Difference in left vs. right tail index estimate by wind output level

Wind category	Selected threshold	All hours Left	All hours Both	All hours Right	Peak hours Left	Peak hours Both	Peak hours Right	Offpeak hours Left	Offpeak hours Both	Offpeak hours Right
Low Wind (0.4-4.9%)	tail at 10%	0,08	0,13	0,29	0,04	0,15	0,29	0,06	0,11	0,12
	se at 10%	0,010	0,001	0,000	0,011	0,000	0,000	0,006	0,016	0,003
	(t-statistic)		*(-20,67***)*			*(-21,33***)*			*(-10,1***)*	
	tail at 15%	0,09	0,2	0,27	0,08	0,17	0,31	0,11	0,14	0,13
	se at 15%	0,042	0,003	0,002	0,013	0,008	0,001	0,012	0,018	0,024
	(t-statistic)		*(-4,25***)*			*(-17,76***)*			*(-0,95)*	
	tail at 20%	0,15	0,22	0,27	0,12	0,18	0,29	0,14	0,14	0,11
	se at 20%	0,008	0,059	0,008	0,036	0,023	0,006	0,016	0,010	0,014
	(t-statistic)		*(-10,29***)*			*(-4,56***)*			*(1,16)*	
Med Wind (4.9-11.1%)	tail at 10%	0,13	0,23	0,32	0,13	0,22	0,35	0,11	0,15	0,21
	se at 10%	0,002	0,000	0,000	0,002	0,000	0,000	0,008	0,001	0,000
	(t-statistic)		*(-114,35***)*			*(-124,06***)*			*(-12,29***)*	
	tail at 15%	0,13	0,18	0,26	0,08	0,19	0,35	0,11	0,14	0,16
	se at 15%	0,021	0,006	0,002	0,007	0,004	0,001	0,046	0,038	0,041
	(t-statistic)		*(-5,99***)*			*(-39,93***)*			*(-0,73)*	
	tail at 20%	0,11	0,17	0,25	0,08	0,19	0,33	0,14	0,12	0,15
	se at 20%	0,007	0,022	0,012	0,010	0,014	0,004	0,019	0,242	0,037
	(t-statistic)		*(-10,83***)*			*(-24,21***)*			*(-0,41)*	
High Wind (11.2-50.6%)	tail at 10%	0,42	0,37	0,04	0,31	0,26	0,08	0,64	0,47	0,03
	se at 10%	0,000	0,000	0,007	0,000	0,000	0,014	0,000	0,000	0,008
	(t-statistic)		*(53,54***)*			*(15,79***)*			*(77,16***)*	
	tail at 15%	0,37	0,29	0,02	0,26	0,22	0,09	0,53	0,36	0,05
	se at 15%	0,001	0,001	0,009	0,002	0,002	0,007	0,001	0,001	0,010
	(t-statistic)		*(36,82***)*			*(26,12***)*			*(46,06***)*	
	tail at 20%	0,35	0,25	0,03	0,24	0,21	0,07	0,47	0,32	0,06
	se at 20%	0,003	0,009	0,011	0,018	0,029	0,015	0,002	0,003	0,011
	(t-statistic)		*(28,34***)*			*(7,1***)*			*(35,49***)*	

*Significant at p***<0,01, p**<0,05, p*<0,1; tail = tail index estimate; se = standard errors*

Table 5 shows the differences between tail-index estimates for the high and low wind penetration sub-samples at the right tail, left tail and also at both tails combined. The results show that the tail-index estimates for the sub-samples with high wind penetration are statistically significantly different from the estimates for the low wind penetration sub-samples both when we look at the left tail and at the right tail of electricity price distribution. If we take the a similar example as above, looking at estimates for the left tail for all hours, we can see that the tail-index estimate for the high wind sub-sample (0.42) is higher than the one calculated for the low wind sub-sample (0.08) at 10% tail observations threshold. The difference between the two estimates between these estimates is significant with a t-value of 32.48.

Table 5: Difference in high vs low wind output tail index at left and right tail

Selected tail	Selected threshold	All hours		Peak hours		Offpeak hours	
		High	Low	High	Low	High	Low
Left tail	tail at 10%	0,42	0,08	0,31	0,04	0,64	0,06
	se at 10%	0,000	0,010	0,000	0,011	0,000	0,006
	(t-statistic)	*(32,48***)*		*(23,37***)*		*(96,26***)*	
	tail at 15%	0,37	0,09	0,26	0,08	0,53	0,11
	se at 15%	0,001	0,042	0,002	0,013	0,001	0,012
	(t-statistic)	*(6,69***)*		*(14,16***)*		*(35,8***)*	
	tail at 20%	0,35	0,15	0,24	0,12	0,47	0,14
	se at 20%	0,003	0,008	0,018	0,036	0,002	0,016
	(t-statistic)	*(23,67***)*		*(2,89***)*		*(21,04***)*	
Both tails	tail at 10%	0,37	0,13	0,26	0,15	0,47	0,11
	se at 10%	0,000	0,001	0,000	0,000	0,000	0,016
	(t-statistic)	*(199,28***)*		*(227,88***)*		*(23,23***)*	
	tail at 15%	0,29	0,20	0,22	0,17	0,36	0,14
	se at 15%	0,001	0,003	0,002	0,008	0,001	0,018
	(t-statistic)	*(29,16***)*		*(5,81***)*		*(12,66***)*	
	tail at 20%	0,25	0,22	0,21	0,18	0,32	0,14
	se at 20%	0,009	0,059	0,029	0,023	0,003	0,010
	(t-statistic)	*(0,5)*		*(0,6)*		*(17,13***)*	
Right tail	tail at 10%	0,04	0,29	0,08	0,29	0,03	0,12
	se at 10%	0,007	0,000	0,014	0,000	0,008	0,003
	(t-statistic)	*(-35,87***)*		*(-14,15***)*		*(-11,1***)*	
	tail at 15%	0,02	0,27	0,09	0,31	0,05	0,13
	se at 15%	0,009	0,002	0,007	0,001	0,010	0,024
	(t-statistic)	*(-25,73***)*		*(-33,16***)*		*(-3,03***)*	
	tail at 20%	0,03	0,27	0,07	0,29	0,06	0,11
	se at 20%	0,011	0,008	0,015	0,006	0,011	0,014
	(t-statistic)	*(-17,63***)*		*(-13,5***)*			*(-2,99***)*

*Significant at p***<0,01, p**<0,05, p*<0,1; tail = tail index estimate; se = standard errors*

From these results exhibited in Table 4 and Table 5 we can see that the left tail of the electricity price distribution becomes fatter (higher tail-index estimates) and that the right the tail of the electricity price distribution becomes thinner (lower tail-index estimates) when the share of wind in the production mix increases. These results hold regardless of the number of tail observations chosen (being either 10, 15 or 20%).[3] We observe this effect when we look at all hours, peak hours and off-peak hours but, the magnitude of the effect is different in each case.

The highest impact of wind on the left tail of the electricity price distribution happens in the off-peak hours when demand is on average low. In such times, high inflow of wind in the power systems appears to increase greatly the probability of having low extreme prices. This can be explained by lack of flexibility to ramp down production from the marginal producers (coal power plants). In peak hours, the level of wind output also seems to increase the left tail fatness but with a much lower impact. A plausible explanation for this effect is the fact that during peak hours, on average, demand is high and also the marginal producers (gas power plants) are more flexible to cut their production levels. Clearly wind penetration influences the left tail of the empirical distribution function of power prices.

On the right tail, the level of wind output has the opposite effect on the tail fatness of the electricity prices. The more wind is supplied, the thinner the right tail of the electricity prices. On the right tail, the effect is more pronounced in the peak hours where the absence of wind increases significantly the tail-index estimates and, consequently, the probability of having high extreme electricity prices. This result means that the absence of wind in periods of high demand (peak hours) is impacting much more the marginal price than in periods with low demand (offpeak hours). This phenomenon can be explained by the fact

[3]Plotting Hill estimates for thresholds up to 30% of the observations indicate similar results

that while the absence of wind in peak hours triggers the activation of costly marginal cost gas producers, the lack of wind in offpeak hours can be replaced with other lower cost coal or cheaper gas idle available producers.

Table 6: Difference in left vs. right tail index estimate by solar output level

Solar category	Selected threshold	All hours Left	All hours Both	All hours Right	Peak hours Left	Peak hours Both	Peak hours Right	Offpeak hours Left	Offpeak hours Both	Offpeak hours Right
Low Solar (0-2.2%)	tail at 10%	0,23	0,20	0,24	n.a.	0,10	0,19	0,38	0,32	0,20
	se at 10%	0,000	0,000	0,000	n.a.	0,000	0,000	0,000	0,000	0,000
	(t-statistic)		*(-31,62***)*			*n.a.*			*(454,31***)*	
	tail at 15%	0,21	0,25	0,26	0,09	0,17	0,24	0,36	0,32	0,18
	se at 15%	0,004	0,001	0,002	0,012	0,025	0,002	0,001	0,001	0,012
	(t-statistic)		*(-11,63***)*			*(-12,97***)*			*(14,56***)*	
	tail at 20%	0,25	0,26	0,24	0,17	0,22	0,26	0,32	0,31	0,17
	se at 20%	0,015	0,006	0,022	0,022	0,022	0,010	0,004	0,003	0,028
	(t-statistic)		*(0,33)*			*(-3,49***)*			*(5,19***)*	
Med Solar (2.2-6.7%)	tail at 10%	0,27	0,30	0,31	0,08	0,22	0,33	0,44	0,34	0,17
	se at 10%	0,000	0,000	0,000	0,050	0,000	0,000	0,000	0,000	0,000
	(t-statistic)		*(-124,64***)*			*(-5,16***)*			*(482,25***)*	
	tail at 15%	0,25	0,32	0,26	0,11	0,25	0,32	0,35	0,36	0,17
	se at 15%	0,002	0,001	0,002	0,081	0,001	0,001	0,001	0,001	0,042
	(t-statistic)		*(-5,18***)*			*(-2,56**)*			*(4,28***)*	
	tail at 20%	0,28	0,32	0,22	0,15	0,24	0,29	0,34	0,36	0,14
	se at 20%	0,006	0,003	0,080	0,019	0,011	0,006	0,003	0,002	0,028
	(t-statistic)		*(0,74)*			*(-6,8***)*			*(7,45***)*	
High Solar (6.7-20.9%)	tail at 10%	0,24	0,19	0,10	0,33	0,23	0,12	0,11	0,08	0,04
	se at 10%	0,000	0,000	0,080	0,000	0,000	0,004	0,008	0,011	0,010
	(t-statistic)		*(1,77*)*			*(47,78***)*			*(5,92***)*	
	tail at 15%	0,23	0,20	0,18	0,28	0,22	0,15	0,14	0,11	0,10
	se at 15%	0,002	0,002	0,013	0,001	0,002	0,185	0,040	0,006	0,018
	(t-statistic)		*(3,63***)*			*(0,68)*			*(1,01)*	
	tail at 20%	0,21	0,21	0,19	0,26	0,22	0,16	0,18	0,13	0,11
	se at 20%	0,011	0,144	0,038	0,010	0,040	0,027	0,012	0,020	0,010
	(t-statistic)		*(0,66)*			*(3,39***)*			*(4,87***)*	

*Significant at p***<0,01, p**<0,05, p*<0,1; tail = tail index estimate; se = standard errors*

Overall, the impact of wind output on electricity prices is higher on the left tail than on the right tail of electricity distribution function. This can be explained as before through the fact that there is more flexibility in the system to increase production than to decrease production by coal plants. We like to mention that these results are robust across the three selected tail thresholds 10%, 15% and 20% showing the fact that there is not much sensitivity towards the selected threshold. The patterns indicated above, are present at each of the three selected tail observations thresholds.

Table 7: Difference in high vs low solar output tail index at left and right tail

Selected tail	Selected threshold	All hours		Peak hours		Offpeak hours	
		High	Low	High	Low	High	Low
Left tail	tail at 10%	0,24	0,23	0,33	n.a.	0,11	0,38
	se at 10%	0,000	0,000	0,000	n.a.	0,008	0,000
	(t-statistic)	*(31,78***)*		*n.a.*		*(-34,02***)*	
	tail at 15%	0,23	0,21	0,28	0,09	0,14	0,36
	se at 15%	0,002	0,004	0,001	0,012	0,040	0,001
	(t-statistic)	*(4,38***)*		*(15,8***)*		*(-5,47***)*	
	tail at 20%	0,21	0,25	0,26	0,17	0,18	0,32
	se at 20%	0,011	0,015	0,010	0,022	0,012	0,004
	(t-statistic)	*(-1,67*)*		*(3,44***)*		*(-10,79***)*	
Both tails	tail at 10%	0,19	0,20	0,23	0,10	0,08	0,32
	se at 10%	0,000	0,000	0,000	0,007	0,011	0,000
	(t-statistic)	*(-42,35***)*		*(18,56***)*		*(-22,35***)*	
	tail at 15%	0,20	0,25	0,22	0,17	0,11	0,32
	se at 15%	0,002	0,001	0,002	0,025	0,006	0,001
	(t-statistic)	*(-17,26***)*		*(2,32**)*		*(-32,53***)*	
	tail at 20%	0,21	0,26	0,22	0,22	0,13	0,31
	se at 20%	0,144	0,006	0,040	0,022	0,020	0,003
	(t-statistic)	*(-0,36)*		*(0,1)*		*(-9,11***)*	
Right tail	tail at 10%	0,10	0,24	0,12	0,19	0,04	0,20
	se at 10%	0,080	0,000	0,004	0,000	0,010	0,000
	(t-statistic)	*(-1,76*)*		*(-16,51***)*		*(-16,09***)*	
	tail at 15%	0,18	0,26	0,15	0,24	0,10	0,18
	se at 15%	0,013	0,002	0,185	0,002	0,018	0,012
	(t-statistic)	*(-5,92***)*		*(-0,5)*		*(-3,5***)*	
	tail at 20%	0,19	0,24	0,16	0,26	0,11	0,17
	se at 20%	0,038	0,022	0,027	0,010	0,010	0,028
	(t-statistic)	*(-1,09)*		*(-3,42***)*		*(-2,21**)*	

*Significant at p***<0,01, p**<0,05, p*<0,1; tail = tail index estimate; se = standard errors*

Table 6 and Table 7 show the tail-index estimates for the different solar penetration sub-samples. The results here are most reliable for peak hours as there is much less sunshine during off-peak hours (which includes the night hours). During peak hours, the pattern that we observe for solar output in relation to tail fatness is the same as when we look into the wind output. On the left tail, the more solar output we have in the system the fatter the tail and, on the right tail the opposite effect. The potential explanation behind this result is the same as for the wind.

Table 8: Difference in left vs. right tail index estimate by intermittent output

Intermittent category	Selected threshold	All hours			Peak hours			Offpeak hours		
		Left	Both	Right	Left	Both	Right	Left	Both	Right
Wind and Solar (0.5-10.5%)	tail at 10%	0,17	0,27	0,35	0,19	0,32	0,39	0,14	0,17	0,20
	se at 10%	0,000	0,000	0,000	0,000	0,000	0,000	0,001	0,000	0,000
	(t-statistic)		*(-337***)*			*(-460,17***)*			*(-54,62***)*	
	tail at 15%	0,16	0,26	0,36	0,19	0,28	0,31	0,19	0,19	0,19
	se at 15%	0,148	0,001	0,001	0,006	0,001	0,001	0,006	0,004	0,005
	(t-statistic)		*(-1,37)*			*(-19,21***)*			*(0,03)*	
	tail at 20%	0,17	0,25	0,34	0,16	0,25	0,34	0,18	0,19	0,18
	se at 20%	0,026	0,008	0,003	0,016	0,008	0,003	0,040	0,007	0,027
	(t-statistic)		*(-6,4***)*			*(-10,73***)*			*(0,11)*	
Wind and Solar (10.5-17.4%)	tail at 10%	0,09	0,10	0,09	0,05	0,05	0,06	0,11	0,05	0,03
	se at 10%	0,030	0,017	0,012	0,008	0,008	0,005	0,037	0,008	0,011
	(t-statistic)		*(-0,13)*			*(-1,59)*			*(1,95*)*	
	tail at 15%	0,11	0,10	0,11	0,11	0,11	0,11	0,13	0,08	0,03
	se at 15%	0,017	0,039	0,007	0,744	0,011	0,016	0,018	0,006	0,010
	(t-statistic)		*(0,29)*			*(0,01)*			*(4,82***)*	
	tail at 20%	0,13	0,10	0,11	0,12	0,12	0,12	0,13	0,09	0,07
	se at 20%	0,007	0,103	0,216	0,055	0,018	0,030	0,022	0,015	0,010
	(t-statistic)		*(0,08)*			*(0,05)*			*(2,56**)*	
Wind and Solar (17.4-52.2%)	tail at 10%	0,43	0,34	0,03	0,32	0,25	0,06	0,65	0,45	0,05
	se at 10%	0,000	0,000	0,008	0,000	0,000	0,014	0,000	0,000	0,062
	(t-statistic)		*(48,01***)*			*(18,58***)*			*(9,63***)*	
	tail at 15%	0,39	0,29	0,06	0,31	0,21	0,08	0,53	0,38	0,11
	se at 15%	0,001	0,001	0,009	0,001	0,002	0,007	0,001	0,001	0,022
	(t-statistic)		*(37,19***)*			*(33,03***)*			*(19,04***)*	
	tail at 20%	0,37	0,25	0,07	0,25	0,18	0,09	0,48	0,34	0,11
	se at 20%	0,003	0,008	0,010	0,014	0,019	0,008	0,002	0,002	0,007
	(t-statistic)		*(29,49***)*			*(9,85***)*			*(49,49***)*	

*Significant at p***<0,01, p**<0,05, p*<0,1; tail = tail index estimate; se = standard errors*

Table 9: Difference in high vs low intermittent output tail index at left and right tail

Selected tail	Selected threshold	All hours		Peak hours		Offpeak hours	
		High	Low	High	Low	High	Low
Left tail	tail at 10%	0,43	0,17	0,32	0,19	0,65	0,14
	se at 10%	0,000	0,000	0,000	0,000	0,000	0,001
	(t-statistic)	*(480,26***)*		*(295,76***)*		*(481,77***)*	
	tail at 15%	0,39	0,16	0,31	0,19	0,53	0,19
	se at 15%	0,001	0,148	0,001	0,006	0,001	0,006
	(t-statistic)	*(1,58)*		*(18,46***)*		*(53,79***)*	
	tail at 20%	0,37	0,17	0,25	0,16	0,48	0,18
	se at 20%	0,003	0,026	0,014	0,016	0,002	0,040
	(t-statistic)	*(7,52***)*		*(4,01***)*		*(7,46***)*	
Both tails	tail at 10%	0,34	0,27	0,25	0,32	0,45	0,17
	se at 10%	0,000	0,000	0,000	0,000	0,000	0,000
	(t-statistic)	*(355,83***)*		*(-336,56***)*		*(879,36***)*	
	tail at 15%	0,29	0,26	0,21	0,28	0,38	0,19
	se at 15%	0,001	0,001	0,002	0,001	0,001	0,004
	(t-statistic)	*(17,4***)*		*(-29,18***)*		*(49,02***)*	
	tail at 20%	0,25	0,25	0,18	0,25	0,34	0,19
	se at 20%	0,008	0,008	0,019	0,008	0,002	0,007
	(t-statistic)	*(-0,1)*		*(-3,63***)*		*(20,04***)*	
Right tail	tail at 10%	0,03	0,35	0,06	0,39	0,05	0,20
	se at 10%	0,008	0,000	0,014	0,000	0,062	0,000
	(t-statistic)	*(-38,16***)*		*(-23,93***)*		*(-2,39**)*	
	tail at 15%	0,06	0,36	0,08	0,31	0,11	0,19
	se at 15%	0,009	0,001	0,007	0,001	0,022	0,005
	(t-statistic)	*(-33,61***)*		*(-33,72***)*		*(-3,64***)*	
	tail at 20%	0,07	0,34	0,09	0,34	0,11	0,18
	se at 20%	0,010	0,003	0,008	0,003	0,007	0,027
	(t-statistic)	*(-26,18***)*		*(-27,75***)*		*(-2,48**)*	

*Significant at p***<0,01, p**<0,05, p*<0,1; tail = tail index estimate; se = standard errors*

Table 8 and Table 9 show the tail-index estimates for the combined wind and solar samples. The aforementioned results show that both solar and wind outputs have the same impact on the tails of the distribution functions of electricity prices in Germany. This indicates that solar and wind effect on tail-index estimates is complementary. Creating intermittent output sub-samples helps us obtaining a much more clear picture on how wind and solar output impacts the tail-index estimates of electricity prices. In Table 8 and Table 9 we can observe clearly the same patterns as before: the tail-index of the left tail increases with the share of intermittent renewables in the system and the right tail-index decreases respectively. These results hold at each level analyzed (all hours, peak hours and offpeak hours).

For the high and low intermittent sub-samples, the results are very similar to the ones obtained for the wind output. This outcome is not surprising since wind output (between 0.4 and 50.6% of total power generation) is generally much higher than the solar output (between 0 and 20.9% of total power generation) and, therefore, has a higher influence on the results. Besides reconfirming the results from the wind sub-samples and solar sub-samples, the intermittent sub-samples gives us more insights on the transition from a fatter right tail than left tail to a thinner right tail then left tail with the increasing intermittent output. For the combined intermittent sub-samples, it can be noticed in Table 8 that for all hours and peak hours, when there is a medium level of intermittent supply in the German power system, both left and right tails tend to be very thin and not significantly different from each other. In offpeak hours with medium intermittent output, the left tail already becomes significantly fatter than the right tail. This result indicates that at a level of intermittent supply between 10.5 to 17.4% in the German power system, the left tail tends to become fatter than the right one during offpeak hours. Results also indicate that during peak hours a higher level of intermittent output is needed in order to generate a fatter left tail than right tail of the distribution functions of the German electricity prices compared to the output level needed in the offpeak hours for having the same effect. This results can be again explained by the differences between (in)flexibility in the power system during peak and offpeak hours.

4. Conclusion

In addition to the consensus view in the literature that the level of intermittent renewable power supply has an effect on power prices and volatility, we show that the level of wind and solar supply has an effect on the fatness of the tails of empirical power price distributions. The more wind and solar supply, the fatter the tails of the left side of the distribution function and the thinner the tails on the right side.

New policy measures in the power markets are currently under investigation with the view to increase power system flexibility, this time also from the demand side through flexible consumers (see for example Kubli et al. (2018)). It is, however, of crucial importance to first investigate how fundamental factors such as intermittent renewables, which already constitute a significant part of the supply mix in Germany, challenge flexibility, and how exactly this varies over time or different market conditions. Answers to these questions are provided through empirical evidence in this study. For instance, from our empirical finding on the tail asymmetry in the distribution of electricity prices, we conclude that: 1) the power system has higher need for downward (ramping down) than for upward (ramping up) power system flexibility during times with high share of intermittent renewable energy in the power system, particularly during off-peak hours for the case of wind and during peak hours for the case of solar, and 2) the opposite (increased need for upward (ramping up) flexibility) during times with low share of intermittent renewable energy in the power system, particularly during peak hours and especially for the case of solar. A better understanding of the need for power system flexibility is the first step before actually adopting new measures and designing/updating the energy policy in the market.

References

Byström, H. N. E., 2005. Extreme value theory and extremely large electricity price changes. International Review of Economics and Finance 14 (1), 41–55.

Chan, K. F., Philip Gray, 2006. Using extreme value theory to measure value-at-risk for daily electricity spot prices. International Journal of Forecasting 22, 283–300.

Dillig, M., Jung, M., Karl, J., 2016. The impact of renewables on electricity prices in Germany - An estimation based on historic spot prices in the years 2011-2013. Renewable and Sustainable Energy Reviews 57, 7–15.

Frestad, D., Benth, F. E., Koekebakker, S., 2010. Modeling term structure dynamics in the Nordic electricity swap market. Energy Journal 31 (2), 53–86.

González-Pedraz, C., Moreno, M., Peña, J. I., 2014. Tail risk in energy portfolios. Energy Economics 46, 422–434.

Herrera, R., González, N., 2014. The modeling and forecasting of extreme events in electricity spot markets. International Journal of Forecasting 30 (3), 477–490.

Huisman, R., Huurman, C., 2003. Fat Tails in Power Prices. Erasmus Research Institute of Management Report Series.

Huisman, R., Koedijk, K. G., Kool, C. J. M., Palm, F., 2001. Tail-index estimates in small samples. Journal of Business and Economic Statistics 19 (2), 208–216.

Ketterer, J. C., 2014. The impact of wind power generation on the electricity price in Germany. Energy Economics 44, 270–280.

Kubli, M., Loock, M., Wüstenhagen, R., 2018. The flexible prosumer: Measuring the willingness to co-create distributed flexibility. Energy Policy 114, 540–548.

Kyritsis, E., Andersson, J., Serletis, A., 2017. Electricity prices, large-scale renewable integration, and policy implications. Energy Policy 101, 550–560.

LeBaron, B., Samanta, R., 2005. Extreme value theory and fat tails in equity markets. Society for Computational Economics.

Lindstrom, E., Regland, F., 2012. Modeling extreme dependence between European electricity markets. Energy Economics 34 (4), 899–904.

Nicolosi, M., 2010. Wind power integration and power system flexibility-An empirical analysis of extreme events in Germany under the new negative price regime. Energy Policy 38 (11), 7257–7268.

Paraschiv, F., Erni, D., Pietsch, R., 2014. The impact of renewable energies on EEX day-ahead electricity prices. Energy Policy 73, 196–210.

Paraschiv, F., Hadzi-Mishev, R., Keles, D., 2015. Extreme Value Theory for Heavy-Tails in Electricity Prices. Journal of Energy Markets 33, 1–22.

Tveten, Å. G., Bolkesjø, T. F., Martinsen, T., Hvarnes, H., 2013. Solar feed-in tariffs and the merit order effect: A study of the German electricity market. Energy Policy 61, 761–770.

Walls, W., Zhang, W., 2005. Using extreme value theory to model electricity price risk with an application to the Alberta power market. Energy, Exploration & Exploitation 23 (5), 375–403.

Würzburg, K., Labandeira, X., Linares, P., 2013. Renewable generation and electricity prices: Taking stock and new evidence for Germany and Austria. Energy Economics 40, S159–S171.