Renewable forecast risk and its impacts on market prices: The German case

Philip Schnaars*

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Abstract

This paper develops a framework for renewable producers to withhold capacity from the day-ahead market in response to higher renewable output risk. The developed hypotheses are tested on a rich dataset from the German electricity market, with a novel measure of renewable forecast risk. The data does not support the presence of renewable withholding in Germany, based on the observed risk premium and day-ahead supply bids. This suggests that firms do not have access to this information or do not regard this as relevant.

1 Introduction

There are numerous aspects of the transition towards a sustainable energy system that have been investigated. These include, among others, the price impact of renewable production, firms behavior with now diversified portfolios and the balancing of forecast errors. This paper raises a related but distinct question. Do renewable firms react to risk in weather predictions?

This is a relevant issue, as the share of intermittent renewable capacities exposed to market prices is set to increase in electricity markets around the world. The market price will be increasingly driven by renewable supply and their supply decision has a significant impact on the market outcome. This will likely increase price volatility, as storage capacities are lagging behind in development.
If renewable firms face output and price risk, they should withhold capacity from the day-ahead market to avoid being short and having to cover their obligations at high prices at the next market stage. This additional market stage has been introduced to allow firms to hedge risks from forecasts. Withholding will increase the day-ahead price by lowering low-cost supply.

Electricity markets with a significant share of renewable capacity have been the subject of several papers.

*Universität Hamburg, Department of Socioeconomics. philip.schnaars@uni-hamburg.de
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Kakhbod et al. (2021) study a one-stage market with imperfect competition among strictly renewable firms that have private information. They show that firms strategically withhold renewable electricity from the market in response to higher expected supply from the other firm.
Fabra & Llobet (2020) consider a similar oligopolistic market setting, where firms exercise market power by withholding capacity if their utilization rate is high. This phenomenon disappears in a competitive environment.
These two papers show that renewable firms strategically impact the price in a one-stage market.

Acemoglu et al. (2017) extend this framework to allow for firms with diverse[1] generation portfolios, engaging in a two-stage market with unknown renewable generation in the first stage. Diversified firms reduce the merit-order effect of renewables via strategic substitution, keeping the total supply unchanged. The variance of the expectation of renewables does not enter the model.

Bessembinder & Lemmon (2002) show in their seminal paper that the day-ahead price contains a risk premium that increases with the variability of demand, as retailers hedge themselves against being short in the intraday market by increasing their day-ahead order volume. Longstaff & Wang (2004) provide empirical evidence of this effect in the PJM market, while Pietz (2009) does not find an empirical relationship between price skewness and the price premium in Germany.

These papers study settings where the price risk arises from volatility of demand. The underlying principle is very similar when considering a market with a significant share of renewable capacity. Renewable firms hedge against weather-induced price risk on the intraday market by reducing their day-ahead exposure. The residual demand curve shifts to the right, hence increasing the day-ahead price.
Obermüller (2017) identifies a variety of weather conditions and concludes that some are associated with a higher price premium in the German day-ahead price. These particular weather conditions are tied to higher forecast errors and therefore implicitly measure intraday price risk.

This paper extends the existing research by deriving a general motivation for the presence of renewable withholding and consequent risk premia that is applicable to various electricity markets and provides a different angle on price formation in power markets with a significant share of renewable capacity. This framework is then applied to the German market with unique data on renewable forecast risk and detailed information on day-ahead bidding behavior. This data is used to assess the effects of risk on the price premium and renewable withholding.

I find that renewable firms in Germany do not consider renewable output risk as important information. A higher output risk does not increase the difference between the day-ahead and the intraday price. Further, I do not find any evidence of firms withholding renewable capacity from the day-ahead market in response to riskier forecasts. This implies that firms can balance their forecast errors at reasonable prices.

[1]A diverse generation portfolio consists both of renewable and conventional capacity.

2 Theoretical Framework

The electricity market consists of two stages and renewable firms can decide at which stage to sell their output. At the day-ahead market, firms have to form expectations about the price at the subsequent market stage and about the amount of electricity they can generate at the time of delivery in order to make an optimal decision. These predictions carry a certain risk, which varies with weather conditions.

This risk resolves at the intraday stage. Forecast errors have to be balanced at this stage at the resulting price[2]. The intraday price will decrease with respect to the day-ahead price if there is additional renewable supply and vice versa. This sell pressure can either be caused by a forecast error or by renewable plant operators withholding from the day-ahead market. It is this day-ahead withholding that introduces a risk premium into the day-ahead price. In the following, I discuss the conditions under which day-ahead withholding can occur, taking the perspective of a single firm.

I assume that a risk-averse firm operates a single renewable site, has no market power[3] and knows their own forecast level as well as that of all other market participants. Furthermore, it has knowledge about the level of confidence with which their forecasted amount is produced. The higher the output risk, the higher the probability of a significant individual forecast error. The firm also has information on the variance of the other firms' forecasts. This knowledge does not entail any information about the direction of the possible forecast errors of itself and the other firms, i.e. the distributions around the predicted output are assumed to be symmetric.

The output risk of a single firm translates into price risk when the output risk of sufficiently many firms is high. In the following discussion, I consider four distinct, stylized cases and discuss how renewable firms behave under different situations.

Case A: High Output Risk, High Price Risk
The firm will have to balance its forecast error on the intraday market, where the expected price has a high variance. To avoid this price risk, renewable electricity will be withheld from the day-ahead market, introducing a risk premium in the day-ahead price.

Case B: High Output Risk, Low Price Risk
The expectation of the intraday price shows low variance. The probability that the individual forecast will be wrong is high. A firm responds to this by offering less on the day-ahead market. This single firm is too small to impact the day-ahead market price.

[2]It is possible for market participants to rely on balancing services provided by the grid operator to balance their forecast errors. However, it is generally cheaper to balance deviations actively by trading on the intraday market.

[3]The following discussion is also valid for an oligopolistic market. The single firm can then be understood as a fringe supplier without market power, similar to the design in Ito & Reguant (2016). The price risk is introduced by the output risk of at least one of the firms with market power. The German wholesale electricity market is characterized by five companies owning diverse portfolios. These portfolios made up over 70 percent of generated electricity in 2018 (Bundesnetzagentur, 2020). The cartel office concluded in their latest report that these companies bid their marginal costs and do not withhold capacity in a significant manner (Bundeskartellamt, 2011). These companies compete with each other.

Case C: Low Output Risk, High Price Risk
The market participant faces a wide range of possible intraday prices. As a result, renewable production will be withheld from the day-ahead price, which contains a risk premium from other firms withholding capacity.

Case D: Low Output Risk, Low Price Risk
The firm is indifferent between selling at the day-ahead or at the intraday market. No price effect is expected.

To summarize, the day-ahead market price contains a risk premium when sufficiently many firms face individual output risk, which then aggregates into price risk (cases A and C). The risk premium is defined as the difference between the day-ahead and the intraday price that is not caused by forecast errors.

In cases A, B and C, a (small) set of firms either experience output or price risk or a combination of both. They respond by reducing the quantity offered at the day-ahead market. When renewable firms reduce their offer, the shape of the supply curve changes, keeping everything else in the market constant.

This theoretical framework can be directly applied to the German electricity market, where firms operate price-exposed renewable capacity in a two-stage market. This capacity forms clusters depending on prevailing local weather conditions, introducing heterogeneity in the price impact of renewables.

As the market price for electricity tends not to be sufficiently high for renewable producers to recover their fixed cost, the German government pays out subsidies in one of two schemes. First, producers sell their electricity to the grid operator at a fixed price. The grid operator is then responsible for marketing that electricity at the exchange. Second, they can sell directly at the exchange, with a market premium paid out by the government that increases their revenues above the market level.

Under the first scheme, renewable producers do not care about price risk, as the relevant grid operator takes the responsibility. All expenses of the grid operator are covered by the government. Ito & Reguant (2016) report that renewable firms stopped withholding electricity after renumeration was changed to a fixed price.
The profit of a firm that is subsidized with a market premium directly depends on the market price. A profit-maximizing firm should consider this risk when making its marketing decision.

The share of the market premium model since its creation in 2012 has been steadily increasing, making up over 95 percent for both onshore and offshore wind electricity and about 25 percent of the total solar electricity produced in 2018 (Fraunhofer, 2019). The remaining production was predominantly compensated with a fixed amount. In the remainder of this paper, I consider those renewable firms that receive financial support via a market premium.

In a setting with market power and limited entry to arbitrage, strategic firms can generate a systematic price premium (Ito & Reguant, 2016). I disregard the possibility of market power. Official investigations of the bidding behavior of electricity companies did not reveal evidence in favor of firms not bidding their marginal costs (Bundeskartellamt, 2011).
As the spatial correlation of wind speed tends to be high, one can also think about the renewable generation structure as consisting of two clusters of different sizes. One is located in the north of Germany where wind speeds tend to be higher and installed capacities are high. The other group of producers is located in the south with only small installed capacities at their disposal. The firm in the north has an impact on the market price with its output decision and its individual output risk translates into price risk. The smaller firm located in the south also faces individual output risk, but the aggregate price risk depends on the risk the bigger firm in the north faces[4].
Case A refers to the case where both clusters face high output risk. Case B considers a situation where only the small cluster is exposed to high output risk. Case C expresses the situation where the northern cluster faces price risk while the southern cluster does not. In case D, both clusters can rely on confident predictions.

The following section introduces the data that is used to investigate the presumed behavior discussed above in the German electricity market.

3 Data

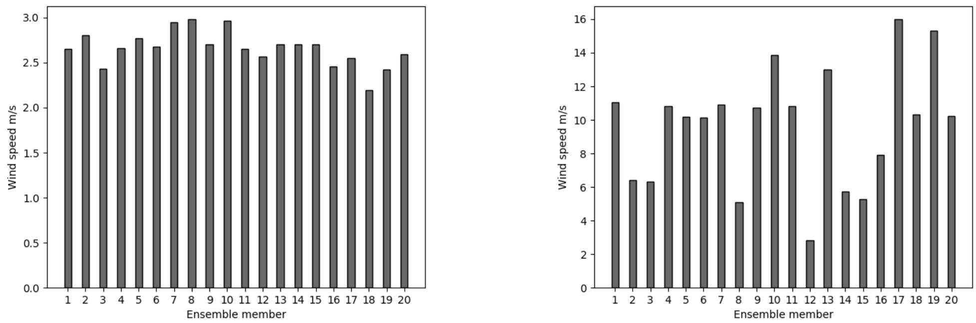
I use hourly data from January 2015 until May 16th 2018. Information on the settlement prices of the day-ahead auction and the intraday transactions as well as expected and realized demand and renewable production was provided by the German power exchange operator EEX (EEX, 2020). Prices for fuels and European Emission Allowances (EUA) are taken from EEX and Quandl (Quandl, 2020). Furthermore, detailed data on day-ahead supply and demand bids were obtained by EPEX Spot (EPEX Spot, 2020).

3.1 Measuring renewable output risk

The risk inherent in day-ahead weather predictions is not publicly available. Electricity companies either buy forecasts from a third party or run their own prediction models, both for their own as well as on the production of competitors. It is reasonable to assume that these models also provide a range of possible values, carrying the inherent risk.
To obtain a high-quality measure, I use data from the short-term ensemble prediction model COSMO-DE-EPS that was operated by the German Weather Service. This model uses information from the day before the electricity is being delivered to make predictions on the subsequent day. The weather information should therefore be very close to the data that electricity traders use. For each hour, the model predicts 20 different values. Each of those is called an ensemble member. Every ensemble member has slightly different input values, i.e. assumed weather relationships. If these ensemble

[4]When considering the risk of solar predictions, the relative cluster size are reversed to form a high capacity cluster towards the south-eastern part of Germany.

members predict dissimilar values, the risk of the prediction is relatively high and vice versa. Figure 1 illustrates the cases of a prediction with a relatively low and a relatively high risk. This risk is calculated as the standard deviation among the 20 ensemble members.



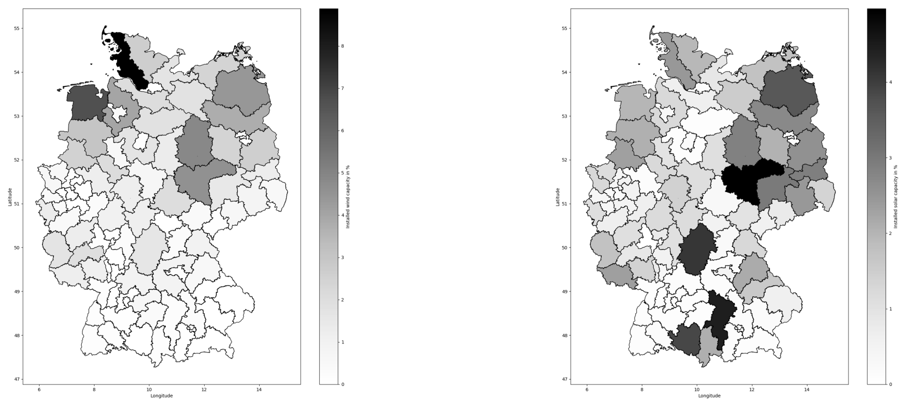
(a) Low risk

(b) High risk

Note: Wind speed projections over 20 different ensemble member for the region for an exemplary, relatively windy region in Schleswig-Holstein (postal code-region 23). Figure (a) shows hour 4-5 on 30.8.2016. Figure (b) shows hour 23-0 on 18.1.2018.

Figure 1: Risk over time

Originally, the weather data is provided on a grid of 2.5×2.5 kilometers. Averages are formed along the first two digits of the postal code. This results in 95 regions, displayed in figure 2. The capacity-weighted[5] average represents the aggregate price risk. The figure identifies regions with a potentially higher price impact due to the relatively large installed capacity, indicated by darker colors.



(a) Wind

(b) Solar

Note: Capacity shares of the respective technology are displayed. Darker colors indicate a higher share.

Figure 2: Installed capacities over regions

I will use three different risk definitions in the subsequent analysis. First, the capacity-weighted average of the standard deviation over the regions for both technologies. Second, to relate more closely to

[5]Installed capacities are taken from Marktstammdatenregister (Bundesnetzagentur, 2020).

the elaborations in section 2, I identify high price impact regions based on the cumulative distribution function of capacity[6]. The resulting continuous variables measure the risk of renewable output separately in high price impact and low price impact regions.
The third measure combines information about the price impact and the level of risk in a binary manner. Output risk in each of four regions from the second measure is considered to be high if it exceeds the respective 90th percentile[7]. This quantity describes the laid out theory closest.

3.2 Descriptive Statistics

Under the null hypothesis of renewable withholding, the day-ahead price should rise over the corresponding intraday price. This difference can be considered a risk premium and measured using both observed prices[8], as in equation 1, which will serve as the dependent variable in the subsequent regression analysis.

$$Premium = DA\_price - ID\_price \tag{1}$$

The identification of the effects of renewable risk on the price difference requires controlling for all other determining factors, such as the realized forecast errors of renewables and demand. The renewable forecast errors will not have a mean of zero in this case.
Under the alternative hypothesis, the companies expect the shocks to renewable availability to be random with a mean of zero. This implies that the expected intraday price equals the observed intraday price. Among others, Haugom & Ullrich (2012) term this the rational expectation hypothesis and use the realized intraday price to measure the risk premium.

Table 1 introduces the variables and their description. On average, the forecast errors for wind and solar are positive. This implies that the realized value is above the predicted amount. The opposite is true for demand. The predicted demand for electricity is below the actual demand. All of these means are statistically different from zero. This hints at the fact that renewable producers systematically underestimate their production day-ahead.

One might be surprised by the fact that radiation can take negative values. The weather model uses the convention to denote radiation directed towards the surface with a positive sign and radiation away from the surface with a negative sign. This ensures that the intertemporal sum will always be zero. Net radiation will be negative at night.

[6] Regions with an installed capacity over the 90th percentile are considered to have a high price impact. Qualitative results remain unchanged when this cutoff is altered.
[7] Qualitative results are not affected by choosing a different cutoff.
[8] The intraday market, unlike the day-ahead market, is continuous. I use the average of all transaction prices weighted by trading volume.

Variable	Description	mean	min	max	sd	count
premium	Price premium EUR	-0.181	-106.1	72.60	6.899	29185
windstd	Wind forecast risk	0.761	0.263	1.920	0.315	28603
radiationstd	Radiation forecast risk	19.25	0.0133	127.0	29.14	28603
windmean	Predicted wind speed m/s	5.068	1.995	11.22	1.924	28603
radiationmean	Predicted solar radiation kJ/m2	0.113	-0.00366	0.703	0.172	28603
FE_wind	Forecast error wind GWh	0.101	-12.84	22.46	1.491	29185
FE_solar	Forecast error solar GWh	0.0312	-10.88	6.605	0.728	29185
FE_load	Forecast error demand GWh	-0.675	-17.96	12.97	2.128	29185
expload	Forecasted demand GWh	55.03	28.82	75.91	9.635	29185
eua	Price EUA EUR/tCO2	6.729	3.870	15.07	2.068	29185
gas	Price Gas EUR/MWh	17.48	10.28	59.49	3.570	29185
coal	Price Coal USD/kt	69.08	43.40	96.65	16.39	29185
outcap	Fossil capacity unavailable GW	0.633	0	5.460	0.649	29185

Note: The column variable indicates the variable names that are used throughout their paper together with their description.

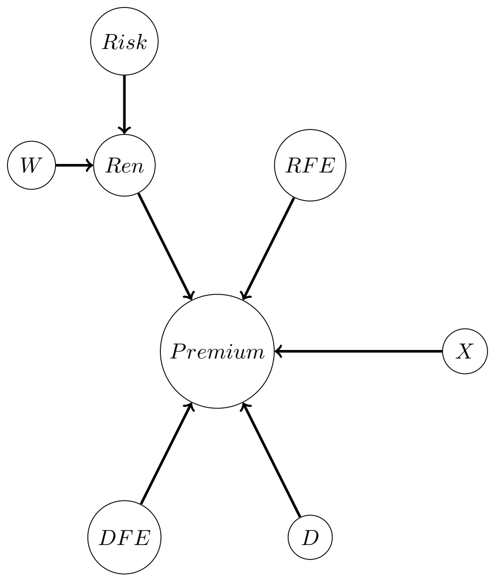
Table 1: Summary statistics

4 Results

4.1 Risk premium

The factors that explain the risk premium are depicted in the Directed Acyclic Graph (DAG) shown in figure 3. The main sources of variation in this premium are the forecast errors of renewables (*RFE*) and demand (*DFE*). Important drivers of this are also demand (*D*) and renewables (*Ren*). These control for the price level, i.e. the relevant area on the supply curve. The supply and demand curves in the day-ahead and intraday market are likely different. This was empirically shown by Knaut & Paschmann (2017) for Germany in 2015 and 2016, who find the intraday supply curve to be significantly steeper than the day-ahead supply curve. Participation constraints that, for example, arise from limited flexibility of the power plant can cause these differences.

If renewable risk (*Risk*) affects prices as suggested by Obermüller (2017) via the amount of renewables bid into the market, it should only affect the premium indirectly. The main driver of renewable generation is the weather, denoted by *W*. Additional control variables that, for example, exogenously affect the bidding of conventional power producers are included in the vector *X*.



Note: Ren: Renewables, Risk: Renewable risk, W: Weather, RFE: Realized Renewable Forecast Errors, D: Demand, DFE: Realized Demand Forecast Errors, X: control variables

Figure 3: DAG of price premium

Relationships between variables in a DAG can be taken as a causal relationship if there is no path, represented by arrows, that originates in one variable and ends in that same variable. The graph is then called acyclic. We can identify causal effects of any variable X[9] on another variable Y if it is a direct cause of Y or of any variable that then causes Y (Pearl, 2009).

In the language of graph theory, the amount of renewables *Ren* represents a collider. This is defined as a node which receives edges from two other nodes (Pearl, 2009). Controlling for a collider variable in a regression will make the formerly independent variables, here *W* and *U*, dependent on each other. In addition, it will be impossible to examine the effect of the forecast risk on the premium, if the model conditions on *R*. I will therefore disregard this variable in the subsequent regressions and condition on the risk *U* and the weather *W*. This setup allows me to identify the causal effect of renewable uncertainty on the premium.

I estimate the following models to assess the effect of renewable forecast risk on the price difference, where $\boldsymbol{X}$ captures fuel prices, outage capacity, lagged dependent terms and hourly fixed effects:

$$premium_t = \alpha_0 + \alpha_1 windstd_t + \alpha_2 radiationstd_t + \alpha_3 windmean_t + \alpha_4 radiationmean_t + \\ \alpha_5 FE\_wind_t + \alpha_6 FE\_solar_t + \alpha_7 expload_t + \alpha_8 FE\_load_t + \boldsymbol{\delta}_1 \boldsymbol{X}_t + \epsilon_t \quad (2)$$

[9]This does not refer to the vector of explanatory variables depicted in figure 3.

$$
\begin{aligned}
premium_t = \beta_0 + \beta_1 windstd\_high_t + \beta_2 windstd\_low_t + \beta_3 radiationstd\_high_t \\
+\beta_4 radiationstd\_low_t + \beta_5 windmean_t + \beta_6 radiationmean_t + \\
\beta_7 FE\_wind_t + \beta_8 FE\_solar_t + \beta_9 expload_t + \beta_{10} FE\_load_t + \boldsymbol{\delta}_2 \boldsymbol{X}_t + \eta_t
\end{aligned} \tag{3}
$$

$$
\begin{aligned}
premium_t = \gamma_0 + \gamma_1 windstd\_high\_high_t + \gamma_2 windstd\_low\_high_t + \\
\gamma_3 radiationstd\_high\_high_t + \gamma_4 radiationstd\_low\_high_t + \gamma_5 windmean_t + \\
\gamma_6 radiationmean_t + \gamma_7 FE\_wind_t + \gamma_8 FE\_solar_t + \\
\gamma_9 expload_t + \gamma_{10} FE\_load_t + \boldsymbol{\delta}_3 \boldsymbol{X}_t + u_t
\end{aligned} \tag{4}
$$

All variables are stationary except for *eua* and *coal*, based on unit root tests displayed in table A.4. Henceforth, these two variables will be treated in their first differences in order to achieve the same level of integration among the covariates.

Table xx shows first order autocorrelation coefficients. An explanatory variable x_t that is correlated over time will be correlated with the error term u_t if it has an influence on the serially correlated dependent variable y_t. Including lagged terms of the dependent variable will alleviate this problem if the error term becomes white noise.
In this application, it is sufficient to include two lagged terms of the dependent variable as covariates to render the residuals white noise, i.e. to specify a dynamically complete model.

	(2)	(3)	(4)
windstd	-0.21		
	[-0.43 ; 0.01]		
radiationstd	0.00		
	[-0.00 ; 0.00]		
windstd_high		0.05	
		[-0.28 ; 0.37]	
windstd_low		-0.42	
		[-0.83 ; -0.01]	
radiationstd_high		0.00	
		[-0.00 ; 0.01]	
radiationstd_low		-0.00	
		[-0.01 ; 0.00]	
windstd_high_high			-0.01
			[-0.24 ; 0.22]
windstd_low_high			-0.16
			[-0.37 ; 0.05]
radiationstd_high_high			-0.01
			[-0.30 ; 0.28]
radiationstd_low_high			0.01
			[-0.27 ; 0.28]
windmean	-0.02	-0.02	-0.02
	[-0.06 ; 0.03]	[-0.07 ; 0.02]	[-0.06 ; 0.03]
radiationmean	-0.14	-0.19	-0.12
	[-0.91 ; 0.63]	[-0.96 ; 0.58]	[-0.82 ; 0.58]
FE_wind	-0.42	-0.42	-0.42
	[-0.49 ; -0.35]	[-0.49 ; -0.35]	[-0.49 ; -0.35]
FE_solar	-0.62	-0.61	-0.60
	[-0.72 ; -0.51]	[-0.72 ; -0.51]	[-0.70 ; -0.50]
FE_load	0.07	0.07	0.07
	[0.04 ; 0.10]	[0.04 ; 0.10]	[0.04 ; 0.10]
expload	-0.00	0.00	0.00
	[-0.01 ; 0.01]	[-0.01 ; 0.01]	[-0.01 ; 0.01]
eua	-0.09	-0.04	-0.10
	[-2.77 ; 2.58]	[-2.77 ; 2.68]	[-2.76 ; 2.55]
coal	-0.15	-0.21	-0.11
	[-0.69 ; 0.39]	[-0.77 ; 0.36]	[-0.64 ; 0.42]
gas	-0.03	-0.03	-0.03
	[-0.04 ; -0.01]	[-0.04 ; -0.01]	[-0.04 ; -0.01]
outcap	-0.15	-0.16	-0.15
	[-0.25 ; -0.06]	[-0.25 ; -0.07]	[-0.24 ; -0.06]
l premium	0.87	0.87	0.87
	[0.82 ; 0.93]	[0.81 ; 0.93]	[0.82 ; 0.93]
l2 premium	-0.07	-0.07	-0.07
	[-0.12 ; -0.02]	[-0.12 ; -0.02]	[-0.12 ; -0.03]
Constant	1.03	1.10	0.83
	[0.44 ; 1.63]	[0.50 ; 1.70]	[0.23 ; 1.42]
Observations	26,997	26,414	28,029
Cumby-Huizinga AR(1) p	0.89	0.91	0.94

Note: The dependent variable is *premium*. 99 percent confidence intervals in brackets. The underlying standard errors are robust to heteroskedasticity and autocorrelation up to 14 lags. Column titles refer to the equation that is estimated. The coefficients of hourly fixed effects are not displayed. The variables *eua* and *coal* in first differences. The p-value of the Cumby-Huizinga test for first order autocorrelation is reported.

Table 2: Effects of risk on the price premium

The regression estimates do not support the presence of an effect of renewable forecast risk on the price premium at the 99 % significance level, irrespective of the specification of risk.

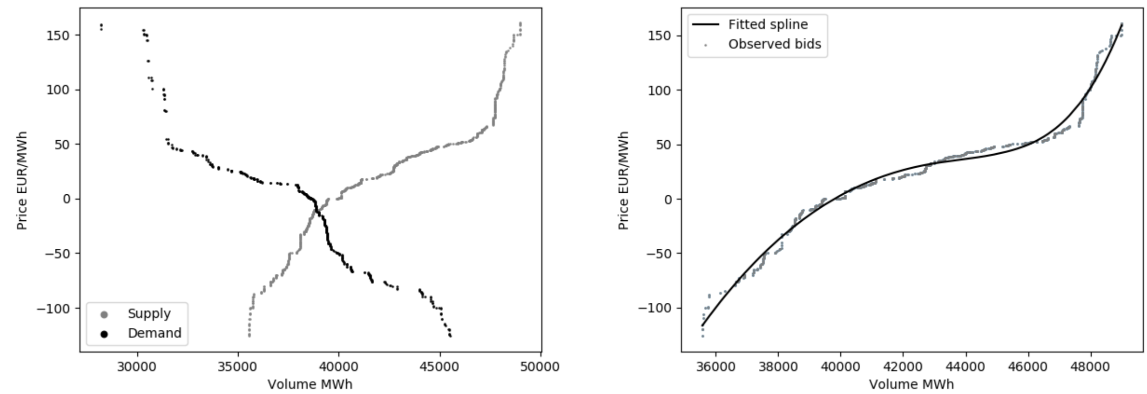
The main drivers of the price difference are the forecast errors of both demand and the renewable technologies. The estimated coefficients and their levels of statistical significance are robust over the specifications. Forecast errors for solar have a stronger price effect than wind forecast errors. This was also found by Obermüller (2017). This could be due to the forecast errors happening primarily at different times during the day. Solar forecast errors tend to happen at times of higher demand where the marginal power plant is different than at night. In the case of a negative forecast error the additional electricity will be provided by a power plant on a different part of the supply curve, where it might have a different slope.

Furthermore, the level of the price, as indicated by *expload*, does not matter for the premium. This suggests that the supply curves are sufficiently comparable to allow for similar prices across the observed range of demand. The estimated confidence intervals of *windspeed* and *radiation* further support this claim.
It is possible that the price premium does not respond to changes in renewable risk, because market participants adjust their bidding behavior accordingly.

4.2 Withholding in the day-ahead bids

To further assess the presence of withholding in response to higher renewable output risk, I analyze the bids in the day-ahead auction. This data does not allow me to disentangle the bids by technology, as the bids are aggregated to form price-quantity pairs. This makes it impossible to directly assess the offered renewable quantity. I derive a data-driven solution utilizing information about the shape of the supply curve.

If renewable producers, ceteris paribus, reduce the amount they offer in the day-ahead market, the shape of the supply curve should change. I assume that operators bid their marginal costs, at least in the relevant range of the data. In particular, renewables should offer their electricity at a price close to zero. Given a certain demand, the point on the supply curve where the market clears should shift towards the more convex part when bid renewable volumes decrease, i.e. the second derivative of the supply function should increase. The left panel in figure 4 shows the observed bids on 7.4.2018 at 12am. This hour was randomly chosen for illustration. Less supply from renewables will, ceteris paribus, shift the market clearing point to a higher point in the supply curve, where both the first and second derivative are higher.



(a) Supply and demand

(b) Supply with fitted spline

Note: The left panel shows observed supply and demand bids for delivery on 7.4.2018 12am. The right panel displays the supply bids and the fitted spline function.

Figure 4: Day-ahead bids and fitted spline

The bid data is restricted to the minimum and maximum day-ahead clearing price observed over the sample period[10]. The bids outside this range are not relevant for the question at hand and will distort the fitting process.

An appropriate procedure to obtain a continuous function from discrete and potentially noisy data is a smoothing spline (Craven & Wahba, 1978). In this case, a cubic spline interpolation is fitted to every observed set of auction bids. The number of cubic functions fitted to the data is determined by equally placed knots, i.e. "anchor points" in the data between which a function will be fitted. The number of knots is determined by a smoothing parameter, which is chosen using generalized cross-validation to avoid overfitting[11]. Cross-validation refers to randomly splitting the data into k folds. One fold is left validating the model, the test data, while the model is fitted using $k-1$ folds, the training data. In this case, the most common approach with $k=5$ is chosen. When the model fits perfectly to the training data, it will usually not perform well on the previously unseen test data. The model accuracy has to be decreased on the training data in order to perform better on the test data. This process is repeated for each of the k folds.

The right panel of 4 shows the result of the above procedure. The smoothing spline interpolation captures the information in the underlying data well without modeling the noise and provides a continuous and twice-differentiable function. For each of the fitted splines, the first and second derivatives[12] are determined. I use the curvature as the dependent variable.

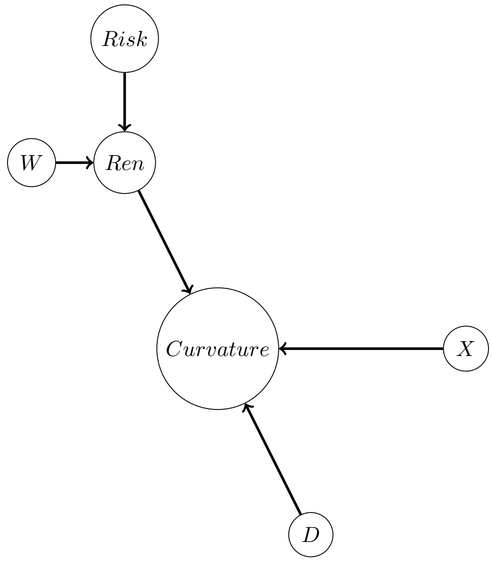
The identification strategy remains similar to the analysis of the price premium. At the day-ahead market, the forecast errors are not yet realized, therefore will not have a direct impact on the offered

[10] Over the sample period, the hourly day-ahead market cleared at prices between -130 EUR/MWh and 163 EUR/MWh. Bids outside of this range stem mostly from must-run conditions or at prohibitive prices.

[11] Not using a cross-validation approach in this context commonly leads to a prediction accuracy of 100 %. The model therefore also captures the noise in the data.

[12] The calculated values are multiplied by 10^6 to enhance readability of coefficients.

quantity.



Note: Ren: Renewables, Risk: Renewable risk, W: Weather D: Demand, X: control variables

Figure 5: DAG of curvature

The following equations will be estimated by OLS to identify the effect of renewable risk on the shape of the supply curve and the offered renewable amount.

$$\begin{aligned} curvature_t = \kappa_0 + \kappa_1 windstd_t + \kappa_2 radiationstd_t + \kappa_3 windmean_t + \kappa_4 radiationmean_t + \\ \kappa_5 expload_t + \boldsymbol{\delta}_4 \boldsymbol{X}_t + \epsilon_t \end{aligned} \quad (5)$$

$$\begin{aligned} curvature_t = \zeta_0 + \zeta_1 windstd\_high_t + \zeta_2 windstd\_low_t + \zeta_3 radiationstd\_high_t \\ + \zeta_4 radiationstd\_low_t + \zeta_5 windmean_t + \zeta_6 radiationmean_t + \\ + \zeta_9 expload_t + \boldsymbol{\delta}_5 \boldsymbol{X}_t + \eta_t \end{aligned} \quad (6)$$

$$\begin{aligned} curvature_t = \theta_0 + \theta_1 windstd\_high\_high_t + \theta_2 windstd\_low\_high_t + \\ \theta_3 radiationstd\_high\_high_t + \theta_4 radiationstd\_low\_high_t + \theta_5 windmean_t + \\ \theta_6 radiationmean_t + \\ \theta_7 expload_t + \theta_8 FE\_load_t + \boldsymbol{\delta}_6 \boldsymbol{X}_t + u_t \end{aligned} \quad (7)$$

Maybe it is a good idea to put the graph of the forecast-error adjusted price premia (which can be negative), after the initial regression, where we learn that there is no risk premium. in order to focus on buy/sell pressure, it makes sense to clean the graph as much as possible.

	(5)	(6)	(7)
windstd	-0.31		
	[-0.67 ; 0.06]		
radiationstd	-0.00		
	[-0.01 ; 0.01]		
windstd_high		-0.48	
		[-0.98 ; 0.02]	
windstd_low		0.17	
		[-0.45 ; 0.80]	
radiationstd_high		-0.00	
		[-0.02 ; 0.01]	
radiationstd_low		0.00	
		[-0.01 ; 0.02]	
windstd_high_high			-0.25
			[-0.61 ; 0.10]
windstd_low_high			-0.05
			[-0.38 ; 0.28]
radiationstd_high_high			-0.21
			[-0.79 ; 0.37]
radiationstd_low_high			0.23
			[-0.36 ; 0.82]
windmean	-0.39	-0.39	-0.39
	[-0.46 ; -0.32]	[-0.46 ; -0.32]	[-0.46 ; -0.33]
radiationmean	-0.01	-0.01	-0.01
	[-0.01 ; -0.00]	[-0.01 ; -0.00]	[-0.01 ; -0.00]
expload	0.00	0.00	0.00
	[0.00 ; 0.00]	[0.00 ; 0.00]	[0.00 ; 0.00]
eua	0.88	0.76	1.05
	[-1.76 ; 3.52]	[-1.96 ; 3.48]	[-1.58 ; 3.68]
coal	-0.08	-0.02	-0.12
	[-0.59 ; 0.42]	[-0.54 ; 0.49]	[-0.62 ; 0.39]
gas	-0.06	-0.06	-0.06
	[-0.09 ; -0.02]	[-0.09 ; -0.02]	[-0.09 ; -0.02]
outcap	0.00	0.00	0.00
	[-0.00 ; 0.00]	[-0.00 ; 0.00]	[-0.00 ; 0.00]
l curvature	0.26	0.26	0.26
	[0.23 ; 0.29]	[0.23 ; 0.29]	[0.23 ; 0.29]
l2 curvature	0.12	0.12	0.12
	[0.09 ; 0.14]	[0.09 ; 0.14]	[0.09 ; 0.14]
Constant	-3.61	-3.58	-3.69
	[-4.62 ; -2.60]	[-4.61 ; -2.55]	[-4.69 ; -2.69]
Observations	25,709	25,144	26,712
Cumby-Huizinga AR(1) p	0.59	0.65	0.58

Note: The dependent variable is *curvature*. 99 percent confidence intervals in brackets. The underlying standard errors are robust to heteroskedasticity and autocorrelation up to 14 lags. Column titles refer to the equation that is estimated. The coefficients of hourly fixed effects are not displayed. The variables *eua* and *coal* in first differences. The p-value of the Cumby-Huizinga test for first order autocorrelation is reported.

Table 3: Effects of risk on shape of the supply curve

The estimates presented in table 3 strengthen the previous results. Based on this analysis, renewable uncertainty does not seem affect the amount of renewables offered at the market. As expected, the wind speed and solar radiation decreases the curvature, i.e. moves the market-clearing point to the left of the curve. This is the merit-order effect. Increasing demand, as indicated by the coefficient of *expload*, moves the intersection of supply and demand curve to the right.

Overall, the empirical analysis does not reveal an effect of renewable risk on either the price premium or the offered renewable quantity.

5 Discussion & Conclusion

This paper estimates the impacts of day-ahead risk in generation from renewable sources on the risk premium in the day-ahead price. Using a detailed model-based measure for this risk, the analysis shows that renewable output risk does not increase the risk premium, irrespective of the potential price impact of this risk.
To review whether this implies that there is no strategic withholding in the market, detailed auction data is used. The evidence from this data does not deliver support to this hypothesis. Renewable risk does not have an effect on the shape of the supply curve. The data does not support a withholding effect.

A large share of renewable capacity is operated by firms that also own dispatchable capacity. It is possible that companies with diverse generation portfolios strategically substitute renewable quantity by conventional power, as suggested by Acemoglu et al. (2017). The total quantity offered will not change in response to renewable risk. However, there should be a price effect, as the marginal costs of conventional power are generally larger than those of renewables. This either implies that these firms do not offer their available renewable capacity at marginal costs or there is no strategic substitution.

When firms do not consider fundamental information such as their output risk, their behavior and subsequently the market outcome can be information inefficient. If that is the case, renewable firms should incorporate this information to achieve a more efficient market outcome.
If the firms have knowledge about their output risk, the results suggest that they can be relatively assured that they can balance their forecast errors at reasonable prices in the intraday market.

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Appendix

A Tables

Variable	Augmented Dickey-Fuller	Phillips-Perron
premium	-20.858	-46.908
windstd	-9.458	-17.872
radiationstd	-2.868	-16.367
windmean	-12.070	-15.433
radiationmean	-0.938	-15.641
FE_wind	-14.816	-32.793
FE_solar	-19.809	-28.373
FE_load	-17.042	-26.518
expload	-17.622	-17.334
eua	2.875	1.682
gas	-6.756	-5.016
coal	-0.326	-0.313
outcap	-19.663	-36.035
curvature	-11.804	-146.118

Note: The lag length was chosen with Schwerts criterion (Schwert, 2002), resulting in 49 lags. The 1% critical value is -3.430 for both tests. All variables are stationary, except for *coal* and *eua*. The ADF test statistic does not correct for heteroskedasticity, while the PP accounts for the presence of changing variance. Therefore I consider *radiationmean* as stationary.

Table A.4: Unit root tests