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AUTHORS

Frank Obermüller

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Institute of Energy Economics at the University of Cologne (EWI)
www.ewi.uni-koeln.de

Institute of Energy Economics
at the University of Cologne (EWI)

Alte Wagenfabrik
Vogelsanger Straße 321a
50827 Köln
Germany

Tel.: +49 (0)221 277 29-100
Fax: +49 (0)221 277 29-400
www.ewi.uni-koeln.de

CORRESPONDING AUTHOR

Frank Obermüller
Institute of Energy Economics at the University of Cologne
frank.obermueller@hotmail.com

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Frank Obermüller[a]

[a] *Institute of Energy Economics, University of Cologne, Vogelsanger Strasse 321a, 50827 Cologne, Germany*

Abstract

With the increasing share of volatile renewable energies, weather prediction becomes more important to electricity markets. The weather-driven uncertainty of renewable forecast errors could have price increasing impacts. This research sets up an analytic model to show that the day-ahead optimal bidding under uncertain renewable production is below the expected production and thus price increasing. In a second step, the price increasing effect on forward premiums by specific weather types and their renewable production uncertainty is proved via empirical methods. Weather types are identified in which renewable production is harder to predict. The findings connect weather dependent renewable forecast uncertainty to forward premiums and support the consideration of weather types in price forecasting models.

Keywords: Forward premium, Weather type, Uncertainty, Volatile renewable production

JEL classification: D21, D22, D41, D81, P18, Q41, Q42, Q47

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Email address: frank.obermueller@hotmail.com (Frank Obermüller)

1. Introduction

Renewable energies like wind and solar are one major pillar in order to reach CO_2-emission targets in the electricity sector. The production of wind and solar energy is weather dependent and hence volatile. This volatility induces uncertainty to wholesale electricity prices. In several countries, like Germany, renewable energies have reached a significant capacity share which increases uncertainty in the electricity markets to a relevant degree. It is thus highly relevant to have insights how electricity prices are affected by wind and solar uncertainty.

Most electricity markets are organized as sequential markets, see for instance Cameron and Cramton (1999) for PJM market or Viehmann (2017) and Knaut and Paschmann (2017b) for Germany. The sequential market structure allows for risk hedging by selling or buying electricity forward. Risk hedging becomes more important under a high share of volatile wind and solar production. This weather-dependent wind and solar production can accurately be predicted to a limited time horizon, e.g. 24 hours. Thus, the relevant markets are (1) the short-term forward market, in this case the day-ahead market, and (2) the real-time market, also known as intraday-market. However, planned production and demand in the (day-ahead) forward market can deviate from the final realization in the real-time market. As a risk-neutral renewable producer, it is questionable if it is profit optimal to sell the total expected production in the day-ahead forward market. Under a non-linear convex merit order, strategic underselling could be optimal for producers to avoid re-buying forward sold quantities. The (forward) production withholding would lead to higher forward market prices. The specific problem in this paper is to identify if and to what extent wind and solar uncertainty lead to positive forward price premiums.

This essay examines the research question both theoretical and empirical. The theoretical result is based on a two-stage profit-maximizing framework under perfect competition. Renewable producers have zero marginal costs and uncertain production realization. With uncertain production and a convex, quadratic merit order curve, the optimal first-stage (i.e. forward) production is below the expected production realization. The production withholding tends to increase first stage prices and is dependent on the production's standard deviation. The empirical evaluation supports the theoretical findings within the German electricity market. The German market is considered due to its high share of wind and solar production.[1] Weather type definitions of the German Weather Service are applied to determine the forward premium effects. The weather types are also applied to classify the wind and solar uncertainty. The empirical findings confirm

[1] Wind and solar production had a share of 18.3% of Germany's gross electricity production in 2015 (cf. Bundesnetzagentur (2016)).

that weather types can be utilized to indicate forward price premiums and to classify production uncertainty. Thus, it is highly recommended to incorporate wind and solar uncertainty in price forecasting models. The results suggest that a potential classification is based on weather types.

The conducted research is based on fundamental work of Allaz (1992) as well as Bessembinder and Lemmon (2002). Allaz (1992) shows analytical that there is a general incentive within a Cournot oligopoly (with uncertain production) to sell production in forward markets. Bessembinder and Lemmon (2002) derives similar results for electricity producers under demand uncertainty. They find positive price premiums for demand uncertainty within their theoretical model and empirical support. Their scope is on a monthly granularity which was extended by the work of Longstaff and Wang (2004) to day-ahead and real-time markets. The underlying research extends the theoretical work of Bessembinder and Lemmon (2002) and the empirical analysis of Longstaff and Wang (2004) by the consideration of production uncertainty of wind and solar energy. Additionally, the underlying research focuses on perfect competition since today's electricity markets have widely reached high supplier diversity.

The major distinction of this research to existing literature is the classification of wind and solar uncertainty by weather types. To the best of my knowledge, the underlying research is the first which applies weather type classifications to derive insights on forward price premiums and price deviations. Thus, this research supports electricity market participants by new insights. First, market participants get information on the general forward premium effects by each weather type, whereas weather types can be predicted accurately several days before realization. Some weather types indicate higher forward premiums than others. The information of the weather type situation allows for an approximation of the (mean) forward premium level. Second, the increasing effect on forward premiums by wind and solar uncertainty is quantified. A reduction in uncertainty would translate to reduced forward premiums. Third, market participants can incorporate weather types in forecasting models to consider uncertainty and derive a more accurate range of their price forecasts.

The remainder of this paper is structured as follows: Section 2 provides the fundamental theoretical and empirical literature as well as background information on the weather types. The theoretical analysis and findings are stated in Section 3. It covers the analytical model settings and assumptions as well as the theoretical finding of optimal production underselling under uncertainty. The empirical analysis is presented in Section 4. This section is the core of the paper. It contains the data, the empirical model setup and the results of the hypothesis tests. Section 5 concludes the present research.

2. Background

This section provides the background for the subsequent analysis. First, the literature regarding the theory is outlined. Then, previous work on the empirical background is briefly discussed. Afterwards, weather type classifications and their utilizations are presented. Within this work, *forward premiums* are defined as the price difference between the forward market and the real-time market, which corresponds to the definitions of Bessembinder and Lemmon (2002) or Douglas and Popova (2008).

2.1. Theoretical model

Fundamental analytic work on pricing and behavior in forward markets is given by Allaz (1992) (general) and Bessembinder and Lemmon (2002) (for electricity markets). Allaz (1992) sets up a two-stage Cournot oligopoly model with a homogeneous product. He considers uncertainty of the second stage price realization. He derives his results of forward trading incentives under the assumption of oligopolistic behavior as well as a linear inverse demand function and a linear cost function. As it is shown by Knaut and Obermüller (2016) as well as Bessembinder and Lemmon (2002), a non-linear (convex) cost function is an essential prerequisite such that uncertainty leads to forward premiums. Hence, this research assumes a convex quadratic linear cost function (called merit order). The inverse demand function is inelastic as widely assumed in short-run electricity market models. Additionally, the underlying research extends the model of Allaz (1992) to perfect competition and shows that the results still hold true.

Bessembinder and Lemmon (2002) analyzes a similar two-stage model as to Allaz (1992) (forward and spot market). They show analytical and empirical evidence of the demand uncertainty effect to forward premiums. However, their focus is demand uncertainty on a monthly basis. The present research focuses on weather-dependent wind and solar production uncertainty in the short-run (day-ahead to realization). Additionally, this research focuses on perfect competition because the number of actors in electricity markets has rapidly increased since the liberalization (cf. Jamasb and Pollitt (2005) or Joskow and others (2008)). The work of Bessembinder and Lemmon (2002) is widely accepted and the model is extended in sveral ways, e.g. to consider gas storages (Douglas and Popova (2008), Bloys van Treslong and Huisman (2010)) or capacity restrictions (Cartea and Villaplana, 2008).

The underlying theoretical model is oriented on the basic work of Ito and Reguant (2016) and Knaut and Obermüller (2016). Ito and Reguant (2016) find evidence for price premiums under imperfect competition (i.e. strategic behavior) and restricted entry of arbitrage (or speculators). They set up a two-stage model and assume perfect foresight, i.e. no uncertainty. In contrast to their model assumptions, this research accounts for uncertainty under perfect competition. Evidence for price premiums is shown. Thus, this work complements the results of Ito and Reguant (2016) by the finding that uncertainty has influences on price premiums as well.

The work of Knaut and Obermüller (2016) was conducted parallel to Ito and Reguant (2016) with a similar analytical two-stage strategic bidding model. They focus on renewable producers which have in general zero marginal costs but uncertainty about their production realization. They find theoretical evidence for the incentive of strategic production withholding on the forward market to increase prices. Additionally, they find that under a linear merit order function uncertainty has no influence on the strategic bidding. Production uncertainty (e.g. of renewable producers) becomes relevant with a higher order merit order function. Bessembinder and Lemmon (2002) come to similar findings within their theoretical framework.

The present analytical model extends the model of Knaut and Obermüller (2016) by (1) perfect competition and (2) a convex quadratic merit order function. Under this model setting, uncertainty becomes a relevant price driver for profit maximization. Based on that, theoretical insights on optimal bidding under uncertainty are derived in Section 3.

2.2. Empirical evaluation

Herein before mentioned theory will be supported by empirical evidence of forward premiums. This is in line with several papers which estimate risk premiums empirically. Similar to the theoretical model of Bessembinder and Lemmon (2002), Longstaff and Wang (2004) empirically analyzed forward premiums in the day-ahead and real-time market of PJM. They find empirical evidence for forward premiums dependent on demand uncertainty. Additionally, they show that the forward premium might deviate by hour and season and could also be negative. Similar findings are confirmed by Paraschiv et al. (2015) for the German electricity market. Focus of Paraschiv et al. (2015) is on the time-varying structure of forward premiums (hourly, weekday/weekend, season). They find that risk premiums are higher during weekdays and in winter. In contrast to Paraschiv et al. (2015), the underlying research does not aim to identify or quantify hourly forward premiums. The underlying research focuses on the uncertainty classification by weather types and their effect on forward premiums.

Bunn and Chen (2013) provides an overview of different explanation approaches for drivers of forward premiums. They do not consider weather types. They state that results are to some extent ambiguous since they are strongly related on the underlying markets, competition, as well as spatial and temporal resolution. An extensive overview of further literature on risk premiums is given by Ito and Reguant (2016) and Furió and Meneu (2010). However, forward premiums are not fully explained by existing research. Recent work of Paschmann (2017) explains forward premiums to some extent by restricted possibility of trading in the real-time market instead of purely rely on hedging incentives and the merit order convexity. This indicates the necessity of further research in the field of forward premiums. Most research is focused on demand uncertainty. The present work extends the classical approaches to consider renewable (i.e. wind and solar) production uncertainty. The renewable production uncertainty becomes more relevant under the proceeding energy transition towards volatile renewable energies. Thus, it is highly relevant to consider the effects of weather-dependent uncertainty. This work incorporates weather type classifications which are described subsequently.

Throughout this paper, the focus lies on *ex-post* forward premiums. Ex-post forward premiums rely on observed price differences whereas *ex-ante* forward premiums are based estimated price realization. For a detailed discussion on ex-post and ex-ante forward premiums see Furió and Meneu (2010).

2.3. Weather classification

This research incorporates weather-dependent volatile wind and solar energies on forward premium effects. An increase in zero marginal costs renewable production has in general a price dampening effect. This effect is widely known as merit order effect and analyzed for instance in Kiesel and Paraschiv (2017), Sensfuß et al. (2008) or Hirth (2013). Besides the classical long-term merit order effect, short-term deviations have influences on real-time prices (compared to day-ahead forward prices). Positive production deviations, i.e. more production than estimated day-ahead, lead to a decrease in real-time prices. This price decreasing effect is shown exemplarily in Figure 1 for the German electricity market.

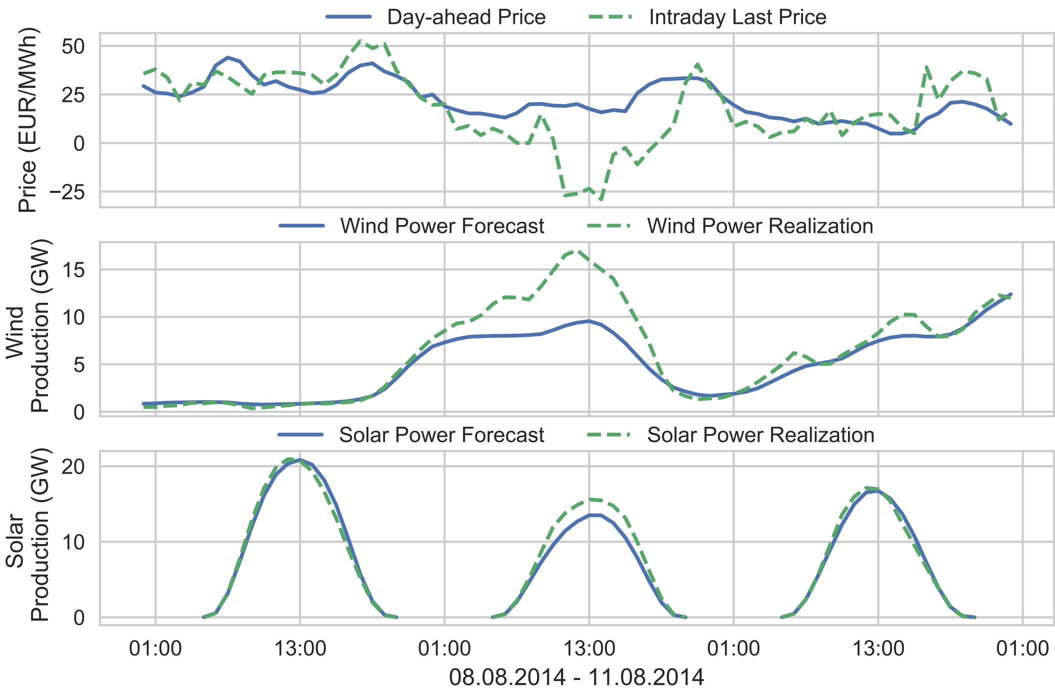


Figure 1: Forecasts and realizations for (a) electricity prices, (b) wind production and (c) solar production in Germany from 08. Aug. 2014 to 11. Aug. 2014. It shows wind and solar production forecasts and realizations in comparison to price forecasts and realizations. Realized wind production at 12:00h, 09. Aug. (center of the plot), is 16 GW and thus almost twice as high as forecasted. A simultaneous price drop to -25 EUR/MWh in intraday-prices can be observed.

The figure shows price forecasts and realizations (upper graph) in comparison to wind and solar production forecasts and realizations (two lower graphs). A remarkable drop in real-time prices can be observed at 12:00am on 09.08.2014 (horizontal center of the plot). The underestimated production realization of wind energy and to some extent solar energy seem to be a driver for the extensive price drop from +20 EUR/MWh down to -25 EUR/MWh.

For the underlying empirical analysis (Section 4), it is necessary to capture the uncertainty of wind and solar production, e.g. by clustering situations of similar uncertainty. This clustering is performed based on weather types. Other research which applies weather type classifications are for instance Lange and Waldl (2001) or Couto et al. (2015) for wind as well as Chen et al. (2011) or Shi et al. (2012) for solar. None of those research works focuses on forward price premiums. Couto et al. (2015) propose a weather clustering approach to identify and characterize weather types with high wind power ramps (i.e. strong increase in hourly wind differences). They propose that large scale weather types are a suitable clustering possibility for wind ramps. Lange and Waldl (2001) shows that the wind prediction error differ with respect to weather types. Their research is limited to two wind sites for two weather types. The applied weather type classification within this present research considers 40 different weather types to account for Germany's wind and solar prediction errors (or uncertainty). Chen et al. (2011) shows that an artificial neural network (ANN) to predict PV power production performs better if a weather type separation is applied before. They categorize as to three weather types (sunny, cloudy, rainy). Similar, Shi et al. (2012) shows that the PV power forecasting precision depends strongly on the weather type and can be improved by selection of the adequate estimation model. They differentiate between four classes (sunny, cloudy, foggy, rainy). The aforementioned research is limited to either wind or solar prediction errors. In contrast to that research, the underlying work applies weather type classifications to derive information about both wind and solar production uncertainty.

The weather types within the present research are clustered based on the 40 objective Weather Type Classifications of the German Weather Service (cf. Bissolli and Dittmann (2001)). A similar number of weather types (29) is used in James (2007) by a clustering of ERA40 re-analysis data. However, the focus of James (2007) is on the comparison between his weather type classifications and the traditional classification of Gerstengarbe et al. (2010) (which reaches back to the 1950s).

3. Theory

The theoretical findings are based on an analytical model similar to Ito and Reguant (2016), Knaut and Obermüller (2016), and Zhang et al. (2015). The model setup consists of two stages. Stage 1 is the day-ahead forward market. Stage 2 is the real-time market (or intraday market). Three groups of players interact with each other, renewable producers r, conventional producers c and the consumers:

- The *renewable producers* r have zero marginal costs of production. In stage 1, they face uncertainty of their final electricity production in stage 2. In stage 2, the uncertainty for the renewable producers resolves. The renewable players form an oligopoly. They compete in order to maximize profits with respect to production (similar to the Cournot competition). However, the focus is on a competitive outcome, which corresponds to the solution for which the number of renewable producers N tends to infinity. All renewable players are assumed to be symmetric. Note that this assumption is a simplification and can be relaxed similar to Knaut and Obermüller (2016).

- The *conventional producers* c act perfectly competitive. They have positive marginal costs (> 0) and do not deviate from bidding their marginal costs. An underbidding of their marginal costs would lead to losses whenever the electricity price is below marginal costs and production was sold. An overbidding is prohibited by the German Monopolies Commission which controls and inspects significant bidding behavior above marginal costs (Bundeskartellamt, 2011).

- The *consumers* have an electricity demand D. The demand is assumed to be inelastic in the short-run. This is a typical assumption for stylized short-run electricity market models (cf. Ito and Reguant (2016)).[2]

- All players are assumed to be risk-neutral.

The marginal cost function MC (or supply function) is assumed to be quadratic, i.e. convex and strictly monotonic increasing: $MC(q) = aq^2 + bq + c$. In some analytic electricity market models, a linear marginal costs function is assumed as simplification ($a = 0$). This is a strong simplification. As shown by Knaut and Obermüller (2016), under a linear merit order function, only the first momentum (expected production) has an impact on optimal bids. Under a quadratic (convex) merit order, the first and the second momentum (standard deviation) have an impact on optimal bids. The standard deviation can be interpreted as a measure of uncertainty. In order to capture the uncertainty effects, a more realistic quadratic merit order is used. An empirical evaluation of the order of the merit order function can be found in Appendix A. It indicates that the German merit order function can be estimated by a linear to quadratic function.

The first stage bid of the renewable producer i is denoted as q_{ir1}. For each renewable producer i, the combined first stage and second stage bids have to be equal to the total realized production Q_{ir}: $q_{ir1} + q_{ir2} = Q_{ir}$ The realized production Q_{ir} of player i in stage 2 is uncertain in stage 1 with a probability density function $f(Q_{ir})$. The uncertainty resolves in stage 2.

The aggregated first and second stage bids as well as the aggregated production of *all* renewable producers are denoted as following: $q_{r1} = \sum_i q_{ir1}$, $q_{r2} = \sum_i q_{ir2}$, $Q_r = \sum_i Q_{ir}$.

Each renewable player $i = 1, \ldots, N$ maximizes her profit function Π_{ir} under consideration of the bids of the other $(N-1)$ symmetric renewable players which results in

$$\Pi_{ir}(q_{ir1}, q_{ir2}) = p_1\left(q_{ir1}, (N-1)q_{jr1}\right) q_{ir1} + p_2\left(q_{ir1}, (N-1)q_{jr1}, q_{ir2}, (N-1)q_{jr2}\right) q_{ir2}. \tag{1}$$

Within this model setup, the following proposition holds.

Proposition 1. *Under above assumptions, the optimal amount of sold renewable production in the first*

[2] Short-run inelastic demand is a simplifying assumption for the theoretical analysis. For the German day-ahead market, Knaut and Paulus (2017) shows a demand elasticity of maximum -0.13 in certain hours. Due to recent developments of (battery) storages and demand side management, this effect is expected to grow.

stage is

$$q_{r1}^{*} = D + \frac{1}{2}\frac{b}{a} - \sqrt{\left[\left(\left(D + \frac{1}{2}\frac{b}{a}\right) - \mu\right)^{2} + \sigma^{2}\right]}. \tag{2}$$

Proof. At this point, a brief outline of the approach is given. The detailed proof can be found in Appendix B. The profit equation for one producer i is maximized. After taking the first derivative, setting it equal to zero and substituting the integrals of the distribution functions by the expectation and standard deviation, the necessary optimality conditions are derived. Then, the symmetry assumptions of the N firms are applied to derive the joint equilibrium solution. □

Equation (2) shows the competitive first stage renewables' bid. It corresponds with the expected outcome under perfect information.

Corollary 1. *Without uncertainty, the optimal first stage bid of all renewable players is* $q_{r1}^{*} = \mu$.

Proof. Without uncertainty, the production in the second stage is identic to the expected production in stage 1. Thus, no standard deviation exists. Set $\sigma = 0$ in the Equation (2). The remaining optimal bid becomes $q_{r1}^{*} = \mu$. □

In the proof of Proposition 1, two production withholding effects can be encountered. First, the potential oligopolistic behavior and second the withholding due to production uncertainty. Since the focus lies on the perfect competition case, the oligopolistic production withholding cancels out while the number of producers tend to infinity for the perfect competition case. However, Equation (B.10) in the Appendix Appendix B shows that production uncertainty leads to production withholding also for the oligopoly case. This can be found by the uncertainty-driven standard deviation σ which influences optimal oligopolistic first stage production bids. Thus, the findings can easily be transferred to oligopolies (which is not covered within this research).

The optimal first stage bid q_{ir1}^{*} of Equation (2) is dependent on σ. With higher standard deviation, the optimal bid is decreasing as stated in Proposition 2.

Proposition 2. *Under above assumptions, an increased uncertainty decreases the optimal production bid for renewable producers in the first stage.*

Proof. Take the first derivative of Equation (2) with respect to σ:

$$\frac{\partial}{\partial \sigma} q_{r1} = -\sigma \underbrace{\left(\left(\left(D + \frac{1}{2}\frac{b}{a}\right) - \mu\right)^{2} + \sigma^{2}\right)^{-1/2}}_{>0} < 0 \qquad \text{, for } \sigma \neq 0 \tag{3}$$

which is strictly negative or equal to 0. It becomes zero if and only if $\sigma = 0$, i.e. no uncertainty exists. Since the first derivative is negative, the function is decreasing in σ. □

Figure 2 visualizes the result of Proposition 2 with typical numbers inserted. The figure shows that the increase in uncertainty (i.e. increasing σ) diminishes the optimal first stage bid. The slope of the curve is

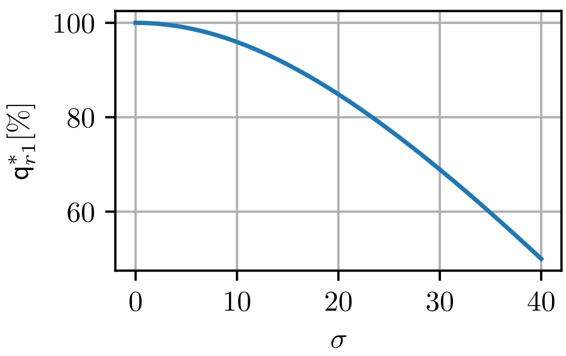


Figure 2: Impact on an increasing uncertainty via σ on the optimal first stage renewable bid q^*_{r1} relative to the expected outcome $\mathbb{E}[q_{r1}]$. The parameter to derive the figure were the aforementioned equations with $D = 70$, $\mu = 40$, $a = 0.01$, $b = 0$.

dependent on the merit order parametrization as well as the demand intersection and expected renewables' production.

The rationale for Proposition 2 is the following: The representative renewables supplier aggregates price-taking behavior of many, small renewables suppliers. Each of these suppliers does not expect that her quantity choice will affect the second period price. However, each renewable producer knows that if she produces relative little energy in stage 2, also all other renewables producers will produce little as well (assuming perfect correlation, for simplicity). Thus, she knows that whenever she is overselling (i.e., more than the expected production), she will have to buy missing quantities at a higher intraday price. Vice versa when underselling with lower intraday prices. Under a non-linear convex merit order, an overselling (i.e. selling more day-ahead than intraday produced) is more expensive than an underselling.

The behavior of conventional producers differ from the renewable producers behavior: The production ability of a conventional producer is independent of the market situation, i.e. without weather-dependence and correlation effects. Whenever the intraday market price is above her marginal costs, she will want to extend her production by one additional (marginal) unit if remaining production capacity is available. Whenever the intraday market price is below her marginal costs and she has sold production forward for at least her marginal costs, she is willing to demand one additional (marginal) unit electricity from the intraday market to fulfill her delivery responsibilities with lower costs. In all other situations (prices below marginal costs in both markets; or sold day-ahead above marginal costs and intraday-price is between marginal costs and day-ahead price), she has no incentive to deviate.

Note that the aforementioned behavior for renewable producers would not occur with a linear merit order. With a linear merit order, positive and negative price deviations would compensate each other.

This compensation requires that the merit order in the forward market and in the real-time market are identic. Knaut and Obermüller (2016) shows, that a steeper real-time market merit order would result in a stronger shift towards selling more production in the first stage (under a competitive oligopoly). Knaut and Paschmann (2017b) shows that a steeper real-time merit order can occur due to inflexible production capabilities. Overall, an optimal bid under uncertainty is below the expected production to avoid cost-intense re-buying of sold but non-realized production.

The quantity deviation in the first stage expected production (based on Proposition 1) translates to a price deviation effect. The theoretical result is stated in Proposition 3.

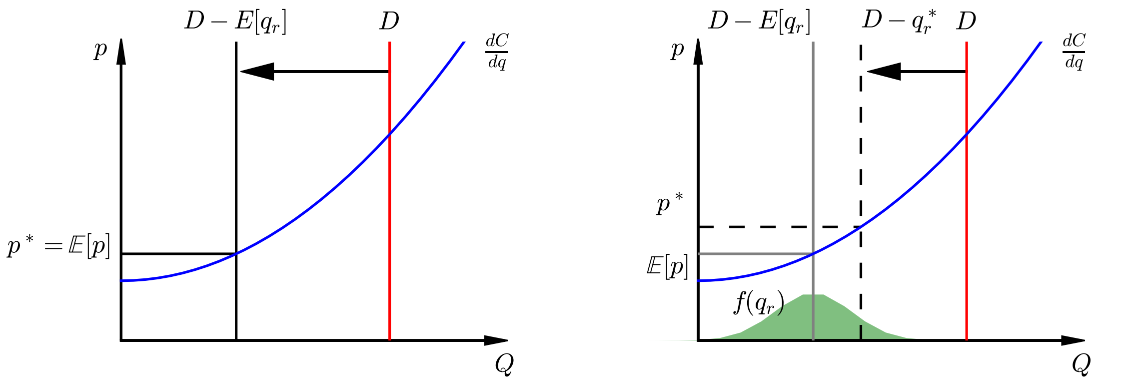
Proposition 3. *Under the above assumptions and the optimal derived first stage quantity q^*_{r1}, the corresponding first stage equilibrium price is*

$$p^*_1 = a((D-\mu)^2 + \sigma^2) + b(D-\mu) + c. \tag{4}$$

This optimal first stage wholesale price exceeds the price of trading the expected production (without uncertainty) solely by the term $a\sigma^2$.

Proof. Under the above assumptions, plug in the optimal quantity to the marginal costs function. Thus, $p^*_1 = MC(D - q^*_{r1}) = D^2a - 2Da\mu + Db + a\mu^2 + a\sigma^2 - b\mu + c = a((D-\mu)^2 + \sigma^2) + b(D-\mu) + c$. Without uncertainty, the variance σ^2 in the optimal quantity equals 0. The price delta with and without uncertainty is $a\sigma^2$ (which is positive). Thus, uncertainty increases the first stage prices. $\square$

Note that Equation (4) is the risk neutral equilibrium result. Thus, arbitrage behavior should not lead to converging day-ahead and intraday-prices. Proposition 3 shows the price increasing effect of uncertain production. Figure 3 visualizes the findings.



(a) Optimal first stage bid and price with perfect foresight. (b) Optimal first stage bid and price under uncertainty.

Figure 3: Optimal day-ahead wholesale price and residual demand under (a) perfect foresight and (b) uncertainty. D is the demand, q_r the renewable production, $f(q_r)$ a normal distribution of renewable production, p the price, dC/dq the first derivative of the cost function (i.e. the merit order). The parameter to derive the figure were $D = 70$, $\mu = 40$, $\sigma = 30$, $a = 0.01$, $b = 0$, $c = 20$. Note that neither the normal distribution nor the standard deviation of $\sigma = 30$ are realistic; they are chosen to simplify the illustration.

The uncertainty reduces the optimal first stage bid. This increases the residual demand and thus prices.

The profit optimal day-ahead price deviates from the expected day-ahead price. The plotted distribution in this figure is a normal distribution. However, the theoretical proof has no specific assumptions according to the distribution function.

The subsequent section gives empirical evidence of this price increasing effect in the German electricity markets (day-ahead to intraday). The uncertainty is measured via standard deviations within weather types.

4. Empirical evidence

This section examines the empirical evidence for the provided theoretical results of Section 3. More precisely, two hypothesis are validated:

- *Hypothesis A*: The mean level of the forward premiums can be categorized by weather types.
- *Hypothesis B*: An increased wind and solar production uncertainty leads to an increase in forward premiums.

Hypothesis A allows an ex-ante indication for higher forward premium levels in electricity markets. Simultaneously, Hypothesis A motivates the classification of uncertainty with respect to weather types. This classification is utilized in Hypothesis B. Both hypotheses are evaluated via regression models. The analysis focuses on the German/Austrian electricity market due to its comparable high share of wind and solar energy. Both electricity markets are organized as a fully coupled bidding zone.

In the subsequent, the underlying data is described firstly. Then, the effect of weather types on the mean forward premiums is tested (Hypothesis A). Afterwards, the motivation for the uncertainty classification by weather types is given which uses the standard deviation as uncertainty measure.[3] Finally, empirical tests are performed to verify the impact of higher uncertainty on forward premium increases (Hypothesis B).

4.1. Data

Four different sources provide the data for the empirical analysis. First, wind and solar forecast and realization data is derived from the EEX Transparency platform. Second, price data (day-ahead and intraday) is obtained from EPEX Spot. The ENTSO-E Transparency platform provides the load data. Fourth, the weather type classification dataset is derived from the German Weather Service (DWD). Detailed description can be found subsequently. An overview is given in Table 1. Descriptive numbers are listed in Appendix C. The analyzed timespan covers July 2015 to December 2016.

[3] As to the theory section, the standard deviation is the relevant measure. Thus, the subsequent analysis focuses on the standard deviation as the indicator for forecast uncertainty. Other indicators like the Root Mean Squared Error (RMSE) or the Mean Absolute Error (MAE) would be possible as well but include similar information. Hence, they are redundant and the focus on the standard deviation is preferred.

Data	**Source**	**Used Resolution**
Wind and Solar Production	EEX Transparency	Hourly
Day-ahead and Intraday Prices	EPEX Spot	Hourly
Load	ENTSO-e	Hourly
Weather Type Classifications	DWD	Daily

Table 1: Overview of applied data. Regional focus is the joint German/Austrian bidding zone. The timespan covers July 2015 to December 2016.

4.1.1. Wind and solar production data

The wind and solar production data is published by the EEX Transparency platform (EEX Transparency, 2017). The focus lies on the provided wind and solar data for Germany *and* Austria due to the same bidding zone. The production data is provided by the Transmission System Operators (TSOs). The data has a quarter-hourly resolution, which is aggregated within this analysis to hourly mean values for comparison reasons. In the remaining paper, the forecast error is applied which is defined as $realization - prediction$ according to Morales et al. (2013). For wind and solar production, the forecast error is normalized by the monthly installed capacity $(realization - prediction)/InstalledCapacity$. This accounts for the fact of continuously increasing capacity and ensures comparability over time. The capacity data source is the German regulator Bundesnetzagentur (`www.Bundesnetzagentur.de`). For the ease of readability, the forecast error is denoted with Δ throughout this paper. The (normalized) wind forecast error in hour h, for instance, is given by $\Delta Wind_h$.

The reported data by the TSOs is not based on exact metering for each production utility. They use extrapolations from specific metered utilities in combination with weather data; see for instance 50Hertz (2017), Amprion (2017), Tennet (2017), TransnetBW (2017) and APG (2017). The TSOs are responsible for grid stability and coordinate the market participation for a certain share of wind and solar production (especially household production). Additionally, they closely collaborate with weather forecasting institutes. Thus, the TSOs' forecasts and extrapolated realizations are the best available wind and solar production data for Germany. Nevertheless, minor biases could exist.

4.1.2. Price data

The price data is published by the EPEX Spot (EPEX SPOT, 2017). The data contains the day-ahead electricity price and the intraday electricity price. The day-ahead price can be considered as the price forecast. Additionally, the day-ahead price determines the reference point for short-run price deviations of the expected information. The price covers the joint bidding zone of the German/Austrian electricity market.

The intraday price data is the volume weighted average price of the last three hours, which is called *ID3* at EPEX Spot. The ID3-price allows to compare the day-ahead price to the final intraday price level. The average price is taken since the last accepted intraday price in the continuous intraday market might be biased due to market overreactions, open positions before gate closure and irrational trader decisions. Thus, the last bid is not necessarily a valid indicator for the fundamental price level of the intraday market. The following analysis focuses on the ID3-price. The ID3-price index is available since July 2015 which restricts the total dataset time-span.

EPEX denotes for the intraday prices that the "German and Austrian areas might be disconnected temporarily due to necessary measures done by responsible TSOs. Hence displayed values might not be common German/Austrian market data in all cases but isolated German only or isolated Austrian only market data." (EPEX SPOT, 2017). Other countries cannot participate in the intraday auction. The disruptive effects of the intraday participant restriction are investigated in Knaut and Paschmann (2017b), Knaut and Paschmann (2017a) and Paschmann (2017).

In some rare situations, price differences between the day-ahead and intraday market become exceptional large. This cannot be explained fundamentally by wind, solar or load deviations. Reasons could be for instance power plant outages or unbalanced portfolios which cause high penalties in the balancing market and lead to corresponding trader behavior. To avoid biased estimations by not fundamentally driven price differences, those observations are handled as outliers and dropped from the analysis. An observation is categorized as an outlier if the price difference exceeds three times its standard deviation. Thus the remaining data covers 99.7% of the observations. The threshold for price differences has a value of ± 37 EUR/MWh around the average day-ahead price level of 30.30 EUR/MWh in the observation period.

4.1.3. Load data

Corresponding load data for the joint bidding zone of Germany and Austria is derived by ENTSO-E. Both, a forecast and a realization value are published. The load values do not incorporate exports or imports. The current market design does not allow foreign production to participate in the intraday market (cf. Knaut and Paschmann (2017b)). Thus, it is consistent within this analysis to neglect trade in the delta comparison. In order to derive prices, instead of price differences, the foreign production needs to be considered within the day ahead market. Since the latter analysis focuses on price deltas, this is not necessary within this framework.

4.1.4. Weather type classification data

The weather type classification data is published by the German Weather Service DWD (DWD, 2017). Current weather types are published daily including forecasts for the next seven days. Detailed information as to the classification scheme can be found in Bissolli and Dittmann (2001). The objective weather type classifications are a daily categorization of the German weather situations. That means each day is categorized to one weather type. The weather types are defined according to the following criteria:

- Advection type (no prevailing direction, northwest, northeast, southwest, southeast)
- Cyclonality in 950 hPa (cyclonic, anticyclonic)
- Cyclonality in 500 hPa (cyclonic, anticyclonic)
- Humidity of the atmosphere (wet, dry)

Note that 500 hPa and 950 hPa correspond to an approximate height of 5.5 km and 0.5 km above sea level, respectively. The advection type reflects the majority of horizontal wind directions on the 750 hPa level. An advection direction is prevailing if it covers at least two thirds of the measured (weighted) wind directions (cf. Bissolli and Dittmann (2001)).

The above combinations result in 40 possible weather types. Statistics (e.g. frequency) can be found in the Appendix C.2. Data exists back to 1979. Due to price data availability reasons, the focus of this research is on the timespan from July 2015 to December 2016.

4.2. Effect of the weather types on the mean forward premium level (Hypothesis A)

This section examines Hypothesis A. The question is answered if and to what extent weather types have an effect on the mean forward premium levels. This question is analyzed by an effect coding approach which is one specific type of contrast coding. Here, the analysis provides the difference of each sub-groups' mean to the grand mean forward premium. The grand mean is defined as the mean of all observations. A general overview of contrast coding and effect coding can be found in Davis (2010) and McClendon (1994). The method dates back to former work of Overall and Spiegel (1969). In a first step, the effect of the weather types on the mean level of forward premiums is analyzed. In a second step, the criteria to define and distinguish the weather types (advection direction, cyclonality, humidity) are subject to the effect coding analysis.

4.2.1. Forward premium effects by each weather type

The analyzed effect coding model reads as following

$$ForwardPremium_h = Intercept + \sum_i \beta_i WeatherType_{i,h} + \epsilon_h \quad (5)$$

for each hourly observation h. Here, $WeatherType_{i,h}$ is a categorical dummy variable with i the weather type index 1 to 40. The weather types are defined per day and therefore matched to the corresponding hours h. For each hourly observation h, at most one dummy variable $WeatherType_i$ can be equal to one whereas all other dummies equal zero. If all dummy variables are equal to zero, the pure intercept is estimated which represents the grand mean. The ϵ_h represents the hourly error term, i.e. the difference between the estimated sub-groups' mean forward premium and the hourly observations.

The results of the effect coding how the group mean deviates from the grand mean can be found in Table 2. The overall mean is highly-significant but slightly negative over the observation period with a value of -0.14 EUR/MWh. This indicates on average lower day-ahead prices than intraday-prices. Based on the results of the theory section, this seems counterintuitive since positive day-ahead forward prices are expected. In fact, other forward premium effects could influence the overall forward premium mean. Further effects are for instance restricted participation which leads to steeper intraday merit order curves and thus higher intraday-prices (cf. Paschmann (2017)), hourly forward price deviations which could be negative (investigated by Longstaff and Wang (2004) and Viehmann (2011)), seasonal forward premium effects (Bessembinder and Lemmon, 2002), scarcity effects (low reserve margins) which could be price influencing (Bunn and Chen, 2013). If other effects outweigh the forward premium effect of production uncertainty, the overall forward premium can become negative.

The reported values of Table 2 are the deviations of the groups' mean value to the grand mean. For instance, the weather type 1 has a 1.02 EUR/MWh higher mean than the grand mean and this deviation is highly significant for the observations. The absolute mean forward premium of the Weather Type #1 is thus 0.88 EUR/MWh, derived as the delta of both aforementioned values.

In total, the mean forward premiums of 22 weather types are significantly different from the grand mean; among them 14 weather types with a significance level of 1% or below and seven weather types with a significance level between 1% and 5%. Overall, 14 of the 22 significantly deviating means of the weather types are positive whereas eight are negative deviating. Some weather types as for instance Weather Type #26 or #33 have remarkable high deviations from the grand mean of -5.07 EUR/MWh or $+2.61$ EUR/MWh, respectively. However, there is no weather type criteria such as advection direction, cyclonality or humidity

Weather Type	Wind direction	Cyclonalitity in 950 hPa	Cyclonalitity in 500 hPa	Humidity	Difference to grand mean
Overall mean					−0.140***
1	no prevailing direction	anticyclonic	anticyclonic	dry	1.015***
2	northeast	anticyclonic	anticyclonic	dry	0.391
3	southeast	anticyclonic	anticyclonic	dry	1.347**
4	southwest	anticyclonic	anticyclonic	dry	0.802***
5	northwest	anticyclonic	anticyclonic	dry	−0.942***
6	no prevailing direction	anticyclonic	anticyclonic	wet	0.664**
9	southwest	anticyclonic	anticyclonic	wet	0.488***
10	northwest	anticyclonic	anticyclonic	wet	0.366**
11	no prevailing direction	anticyclonic	cyclonic	dry	1.461***
12	northeast	anticyclonic	cyclonic	dry	0.207
14	southwest	anticyclonic	cyclonic	dry	0.904***
15	northwest	anticyclonic	cyclonic	dry	−0.024
16	no prevailing direction	anticyclonic	cyclonic	wet	2.072*
17	northeast	anticyclonic	cyclonic	wet	−3.773***
19	southwest	anticyclonic	cyclonic	wet	−0.737**
20	northwest	anticyclonic	cyclonic	wet	−0.046
21	no prevailing direction	cyclonic	anticyclonic	dry	−0.375
23	southeast	cyclonic	anticyclonic	dry	1.032**
24	southwest	cyclonic	anticyclonic	dry	−0.740
25	northwest	cyclonic	anticyclonic	dry	0.413
26	no prevailing direction	cyclonic	anticyclonic	wet	−5.076***
27	northeast	cyclonic	anticyclonic	wet	1.182
28	southeast	cyclonic	anticyclonic	wet	−1.383***
29	southwest	cyclonic	anticyclonic	wet	−1.102***
30	northwest	cyclonic	anticyclonic	wet	1.759**
31	no prevailing direction	cyclonic	cyclonic	dry	−0.170
32	northeast	cyclonic	cyclonic	dry	−0.256
33	southeast	cyclonic	cyclonic	dry	2.607***
34	southwest	cyclonic	cyclonic	dry	0.419
35	northwest	cyclonic	cyclonic	dry	1.163**
36	no prevailing direction	cyclonic	cyclonic	wet	−3.792***
37	northeast	cyclonic	cyclonic	wet	−0.312
38	southeast	cyclonic	cyclonic	wet	−1.907***
39	southwest	cyclonic	cyclonic	wet	0.718***
40	northwest	cyclonic	cyclonic	wet	−0.080

Table 2: Differences of each weather types' mean to the grand mean estimated by the effect coding approach $ForwardPremium_h = Intercept + \sum_i \beta_i WeatherType_{i,h} + \epsilon_h$. Number of observations is 13040 hourly values from July 2015 to December 2016. Significance levels denoted by * p<.1, ** p<.05, ***p<.01. Significance and estimations of the grand mean indicates the difference to a zero mean value. Note that five weather classes are omitted due to too less observations in the investigated time horizon.

which has only significant positive or negative mean deviations. Thus, no exact causality can be derived but trends of the criteria could exists. Dry weather, for instance, seems to have more often a positive significant effect whereas wet weather seems to have more often a negative significant effect. The independent effects of the separated weather type criteria are analyzed in the subsequent section.

4.2.2. Foward premium effects by the weather types' separated criteria

This section puts emphasis on the separated weather type criteria (a) advection direction, (b) cyclonality (at 950 hPa and 500 hPa) and (c) humidity. The same effect coding approach as in Equation (5) is performed in which the categorical variables are the clustered weather types' sub-criteria.

(a) Advection direction Table 3 reports the mean differences of the advection directions to the grand mean. The separated wind directions have only two significant coefficients: *Southwest wind* and *no prevailing wind direction*. Both coefficients deviate from the grand mean on a 10% significance level. For southwest wind, the mean forward premium is 0.19 EUR/MWh higher than the grand mean of −0.14 EUR/MWh. Without a prevailing wind direction, the forward premium mean is 0.25 EUR/MWh lower than the overall mean. Based on these statistics and the fact that all other wind directions show no significant contribution, the wind direction indicates limited implications on the mean forward premium.

Advection	Difference to grand mean
Grand Mean	−0.140***
Northeast	0.108
Northwest	−0.116
Southeast	0.105
Southwest	0.191*
No prevailing direction	−0.249*

Table 3: Results of the effects coding approach for the weather types' criteria *advection direction* for the model $ForwardPremium_h = Intercept + \sum_i \beta_i AdvectionDirection_{i,h} + \epsilon_h$. The estimated values indicate the difference of the criterias' mean value to the grand mean. Number of observations is 13040 hourly values from July 2015 to December 2016. Significance levels denoted by * p<.1, ** p<.05, ***p<.01. Significance and estimations of the grand mean indicates the difference to a zero mean value. Note that five weather classes are omitted due to too less observations in the investigated time horizon.

(b) Cyclonality on 950 hPa Table 4 indicates high relevance of the cyclonality on 950 hPa on the mean forward premium levels. Anticyclonic weather types increase the mean forward premium by a mean of 0.27 EUR/MWh whereas cyclonic weather types have a decreasing effect of −0.53 EUR/MWh. Both effects are highly significant at the 1% level.

Cyclonality on 950 hPa	Difference to grand mean
Grand Mean	-0.140***
Anticyclonic	0.270***
Cyclonic	-0.526***

Table 4: Results of the effects coding approach for the weather types' criteria *cyclonality on 950 hPa* for the model $ForwardPremium_h = Intercept + \sum_i \beta_i Cyclonality950hPa_{i,h} + \epsilon_h$. The estimated values indicate the difference of the criterias' mean value to the grand mean. Number of observations is 13040 hourly values from July 2015 to December 2016. Significance levels denoted by * p<.1, ** p<.05, ***p<.01. Significance and estimations of the grand mean indicates the difference to a zero mean value. Note that five weather classes are omitted due to too less observations in the investigated time horizon.

The cyclonality on 500 hPa (approximately 5.5 km above sea level) has no significant coefficients. Therefore, the higher level cyclonality cannot be confirmed to have relevant effects on the forward premium. The corresponding results can be found in Appendix E. As a reason for the non-significance, the relationship between the forward premium and the near-surface renewable production can be expected. Higher level weather conditions seem to have reduced impact for the electricity markets.

(c) Humidity The effect of the weather type criteria *humidity* on the mean forward premium level is reported in Table 5. Both, Dry and Wet, have a significantly deviating forward premium mean compared to the grand mean. Dry has a 0.25 EUR/MWh higher mean forward premium whereas Wet has a -0.27 EUR/MWh reduced mean forward premium.

	Difference to grand mean
Grand mean	-0.140***
Dry	0.254***
Wet	-0.271***

Table 5: Results of the effects coding approach for the weather types' criteria *humidity* for the model $ForwardPremium_h = Intercept + \sum_i \beta_i Humidity_{i,h} + \epsilon_h$. The estimated values indicate the difference of the criterias' mean value to the grand mean. Number of observations is 13040 hourly values from July 2015 to December 2016. Significance levels denoted by * p<.1, ** p<.05, ***p<.01. Significance and estimations of the grand mean indicates the difference to a zero mean value. Note that five weather classes are omitted due to too less observations in the investigated time horizon.

4.2.3. Discussion of the mean deviating effects of weather types on the forward premiums

The above analyses show distinguishable effects of the weather types and its sub-groups to the mean level of the forward premiums. The analysis of the separated weather type criteria (advection direction, cyclonality and humidity) allow insights on the weather-related driver of the mean forward premium. Several criteria could be identified with a significant impact on mean deviations of the forward premium. A general positive forward premium effect can be associated with southwest wind, anticyclonic weather patterns on 950 hPa, or dry weather. In contrast to this, a negative effect on forward premiums is estimated for no prevailing wind direction, cyclonic weather patterns on 950 hPa, or wet weather. However, even if these effects are significant, they do not necessarily lead to higher/lower forward premiums in each hour. Based on this analysis, the impact of weather type criteria on forward premiums can only be used as a rule of thumb. The dominating effect by a combination of sub-groups is ex-ante not clear (e.g. what is the mean forward premium effect under positive-expected anticyclonic and negative-expected wet weather?). The detailed information on each combination (i.e. each weather type) with its criteria is estimated in Table 2. In these results, the different effects of each weather type on the mean forward premiums become obvious. Several weather types have significant positive and negative implications to the mean of the forward premiums. The results can be applied by market participants such as traders to approximate the mean level of forward premiums additional to typical effects by production deltas. To derive statements for price forecasting, further investigations are necessary which could require applications in price forecasting models. However, this is not the scope of this paper and remains for further research.

The different forward premium effects by the weather types motivate the subsequent uncertainty categorization as basis for the empirical analysis in Section 4.4.

4.3. Weather classifications as a distinction of wind and solar forecast uncertainty

This subsection provides information about the wind and solar uncertainty categorization which is applied to examine Hypothesis B (forward premium increase by wind and solar uncertainty) in Section 4.4.

4.3.1. Wind and solar production levels are no sufficiently distinguishable indicators for uncertainty

For the subsequent regression analysis, the uncertainty should properly be considered. An intuitive classification could be the production level of wind and solar power. A classification based on the production level underlies the assumption of heteroscedastic errors with respect to the production level. However, the production level classification indicates low differentiation possibility. This is discussed in Appendix D. Thus, the production level classification seems not to be suitable for an adequate forecast error distinction.

4.3.2. Weather classes have deviating statistical characteristics

A potential classification scheme could be defined on weather types. This is motivated by the aforementioned analysis that weather types have distinguishable effects on forward premiums. Thus, the DWD objective weather type classifications are analyzed for potential uncertainty categorization. Details as to the weather type definitions can be found in Table C.8 whereas statistical numbers are listed in Table C.9 in the Appendix.

Certain weather types correlate with specific wind and solar forecast situations. As an example, assume anticyclonic weather constellations which are also known as high-pressure situations. Such high-pressure situations are more likely to have less clouds. Solar production is thus better predictable compared to changeable weather types. Therefore, solar production uncertainty should be lower.

Figure 4 compares the 40 objective weather type classifications with respect to the aggregated wind and solar production deviations. The production deviations are defined as the realized value minus the forecast normalized by the monthly capacity. The normalization ensures comparability of the forecast errors over the time horizon. The delta is positive if more electricity is produced than expected. It becomes obvious that

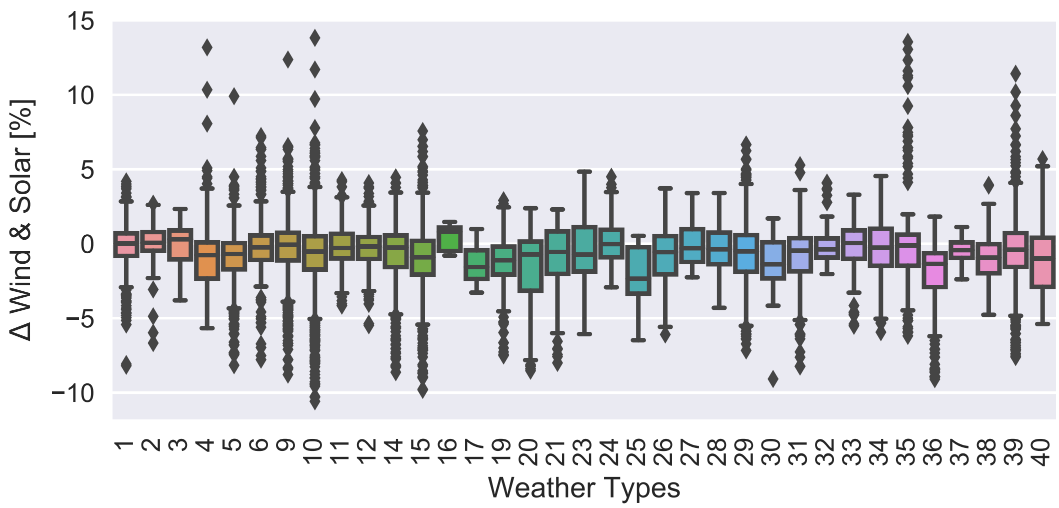


Figure 4: Aggregated wind and solar forecast errors (realization minus forecast) of each objective weather class. Production deltas are relative to the monthly installed capacity. Data covers July 2015 to December 2016.

the median, quartiles and outliers might deviate strongly between the individual classes. The distinction possibility is also true for the standard deviation as one indicator for the spread of the forecast errors. Additionally, note that weather classes have different frequencies.

4.3.3. Focus on the weather type's standard deviations

Based on the weather type classifications, the standard deviation can be calculated per weather type and be used as an indicator for expected uncertainty. Several weather types have a lower standard deviation than the average whereas some have remarkable higher standard deviations. A higher standard deviation of wind and solar forecast errors indicates that exact wind and solar production is harder to predict. Figure 5 compares the relative standard deviations of capacity-normalized wind and solar deltas for each weather type (ascending ordered). The standard deviations per weather type are relative to the grand standard deviation, i.e. of all observations. Several weather classes show a relative standard deviation below the

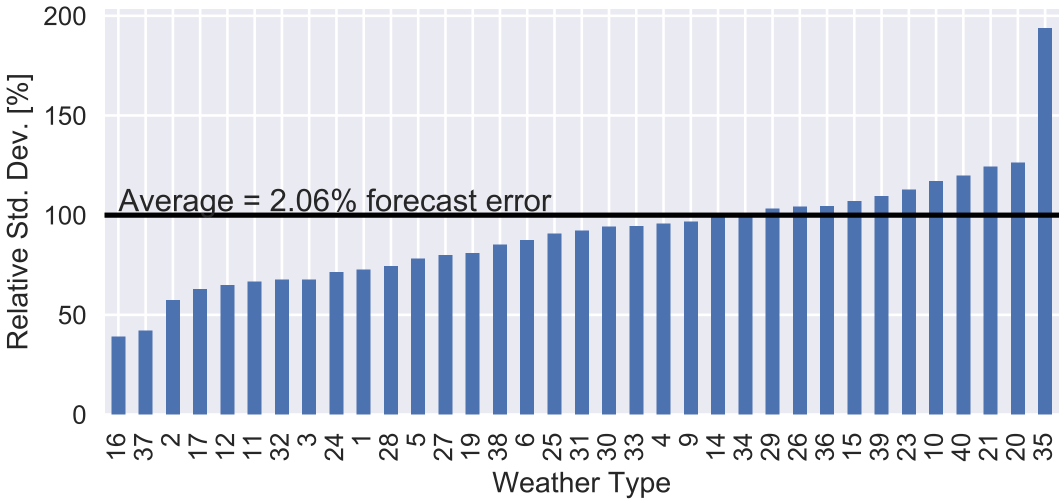


Figure 5: Relative standard deviations of the wind and solar forecast errors per weather type. The wind and solar forecasts errors are normalized by the monthly capacity. The standard deviation per weather class is relative to the standard deviation over all data (which is a forecast error of 2.06 %). Data covers July 2015 to December 2016.

average down to a minimum of 40% (i.e. absolute standard deviation of 0.82% forecast error[4]). On the other hand, weather class #35 has an exceptional high standard deviation of approximately 200% compared to the average. Class #35 defines dry cyclonic northwest wind situations which has an almost average number of occurrences. Most standard deviations are in the range between 60% and 130%. It is expected, that a higher uncertainty of the wind and solar production leads to an higher uncertainty of the forward premiums. This hypothesis is examined and supported in Appendix F. The subsequent analysis goes one step beyond. The focus is on the increasing forward price level by uncertainty instead of a solely increased (obvious) price uncertainty.

4.4. Forward price premiums rise with wind and solar production uncertainty (Hypothesis B)

This section examines empirically the Hypothesis B that an increased wind and solar production uncertainty leads to an increase in forward price premiums. Thus, empirical support is given for the price increasing effect shown analytical in Section 3. To identify the effects, three OLS regression analyses are performed denoted by *Model B1*, *Model B2* and *Model B3*. The dependent variable is the forward price premium defined as the delta between the day-ahead price to the intraday price. The results allow to detect

[4]Note that the wind and solar forecast error is the difference between realization and forecast normalized by the monthly capacity, which results as a percentage.

the overall forward premium effect. An increase in the forward premium can result by either an increased day-ahead price, a decreased intraday price or both effects simultaneously. The analysis is not suitable to determine which effect influences the forward premium. A discussion of this is provided in the latter.

4.4.1. Model description

The estimated models can be expressed as

$$\text{Model B1:} \qquad ForwardPremium_h = \alpha + \beta_1 \Delta(Wind\&Solar)_h + \beta_2 StdDev(Wind\&Solar)_h + \epsilon_h \tag{6}$$

$$\begin{aligned} \text{Model B2:} \qquad ForwardPremium_h = \alpha &+ \beta_1 \Delta Load_h + \beta_2 StdDev(Load)_h \\ &+ \beta_3 \Delta(Wind\&Solar)_h + \beta_4 StdDev(Wind\&Solar)_h + \epsilon_h \end{aligned} \tag{7}$$

$$\begin{aligned} \text{Model B3:} \qquad ForwardPremium_h = \alpha &+ \beta_1 \Delta Wind_h + \beta_2 StdDev(\Delta Wind)_h \\ &+ \mathbb{1}_{solar,h} \left(\alpha_{Solar} + \beta_3 \Delta Solar_h + \beta_4 StdDev(\Delta Solar)_h\right) + \epsilon_h \end{aligned} \tag{8}$$

where h denotes the hourly observations for the investigated timeframe from July 2015 to December 2016. Model B1 (Equation (6)) is the basic model. It estimates the price deviations dependent on the wind and solar production delta as well as the wind and solar uncertainty. The production delta is defined as *realization minus forecast*. Note that the uncertainty is defined as the standard deviation of the observations that belong to the same weather type. Since each weather type last for a complete day, the values are matched to the hourly observations. Model B2 (Equation (7)) extends the basic model by the consideration of the load deltas and the load uncertainty. An impact of load deltas to the forward price deviation can be expected (cf. Bessembinder and Lemmon (2002)). Model B3 (Equation (8)) is similar to the Basic Model B1 except that wind and solar are independent regressors. Since hours at night with 0 MWh solar forecast and solar production would bias the estimates for solar, a dummy variable is applied. The dummy variable (or indicator function) is denoted as $\mathbb{1}$ and equals 1 if not both solar forecast and production are equal to 0 MWh.

The models estimate timeseries data. Thus, it is relevant to test for stationarity, homoscedasticity and non-autocorrelation. Additionally, multi-collinearity between the variables is helpful to verify the model specification.

4.4.2. Requirements check

4.4.2.1. Low multicollinearity. No relevant high correlation occurs within the regressor variables of each analysis. The relevant correlation values between the regressors are in the range between -0.06 and 0.11. Higher correlation could occur between variables which are not simultaneously used in the same regression (e.g. a correlation of 0.86 between wind deltas as well as wind and solar deltas). The dependent variable *forward premiums* could have higher correlation to the regressors which is not critical (e.g. 0.43 to wind and solar deltas). Correlation values can be found in Appendix G.1.

4.4.2.2. Stationarity: Unit root test via Augmented Dickey-Fuller test. An Augmented Dickey Fuller test is performed as a unit root test to check for stationarity. Detailed numbers are listed in the Appendix G.2. The test statistics show that the null hypothesis of unit roots can be rejected. Thus, the timeseries is stationary or, in other words, does not have a time-dependent trend.

4.4.2.3. Heteroscedasticity and autocorrelation. White's Lagrange Multiplier Test for Heteroscedasticity rejects the null hypothesis of homoscedasticity. Additionally, the Durbin-Watson test with a value of 0.45 rejects the null hypothesis of no autocorrelation.[5] To address heteroscedasticity and autocorrelation, heteroscedastic and autocorrelation robust Newey-West standard errors are applied (Newey and West (1987)).

4.4.3. Regression results

Table 6 shows the estimated coefficients for Model B1, Model B2 and Model B3. For Model B1, both regressors are significant. The capacity-normalized delta in wind and solar production is significant at the 1% level whereas the standard deviation for wind and solar deltas per weather type is significant at the 5% level. The high significance of the wind and solar delta is expected since a lower wind and solar production than expected should lead to higher prices. This effect is also stated in other literature as for instance Kiesel and Paraschiv (2017), Sensfuß et al. (2008) or Hirth (2013). The interesting finding is the significant effect of wind and solar uncertainty on forward prices. A higher standard deviation of the wind and solar production delta per weather type leads to higher forward premiums. That indicates, in general, that the ex-ante known uncertainty is hedged to forward premiums.

Model B2 shows significant coefficients for the three regressors (a) load delta, (b) the capacity-normalized wind and solar delta and (c) the standard deviation of the capacity-normalized wind and solar delta. The standard deviation of the load delta is not significant. The non-significance of the load uncertainty is not surprising since the weather types are defined on meteorological conditions and do not necessarily reflect relevant load characteristics. Note that this does not imply, that the standard deviations of load deltas are not relevant in general. Another aggregation (e.g. load deltas dependent on season, hour or load level) may lead to significant load results, as mentioned by Bessembinder and Lemmon (2002) or Longstaff and Wang (2004). However, the load uncertainty is not the focus of this investigation and an investigation of different load uncertainty aggregations is thus neglected. The findings of the Model B2 are the following:

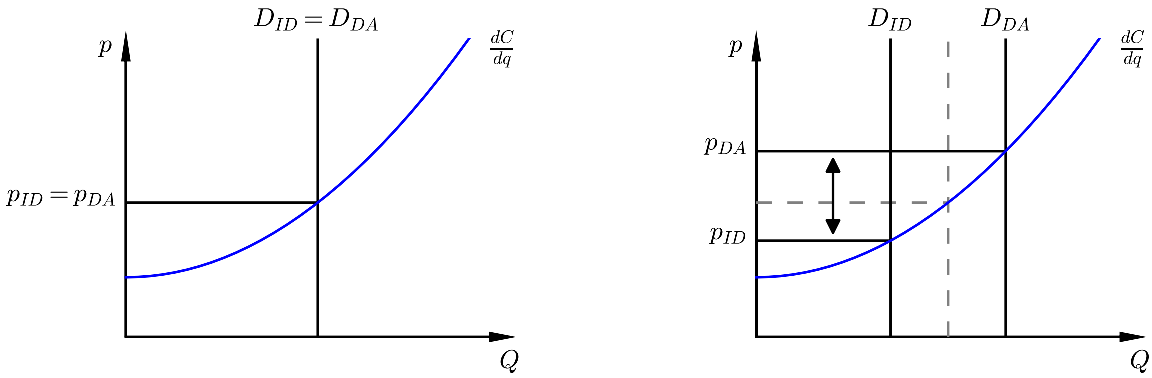
[5] No autocorrelation would require a Durbin-Watson test statistic approximately at the value of 2. Values of 0 or 4 denote perfect positive or negative auto-correlation.

$FowardPremium_h$	Model B1	Model B2	Model B3
Intercept	-0.132	-0.357	-0.075
	(0.305)	(0.377)	(0.255)
$\Delta Load_h$		-0.193***	
		(0.032)	
Std.Dev$(\Delta Load)_h$		0.177	
		(0.134)	
$\Delta Wind\&Solar_h$	1.220***	1.208***	
	(0.037)	(0.036)	
Std.Dev$(\Delta Wind\&Solar)_h$	0.393**	0.376**	
	(0.158)	(0.158)	
$\Delta Wind_h$			0.542***
			(0.020)
Std.Dev$(\Delta Wind)_h$			0.124*
			(0.070)
$\mathbb{1}_{solar,h}$			0.110
			(0.441)
$\Delta Solar_h$			0.937***
			(0.041)
Std.Dev$(\Delta Solar)_h$			0.170
			(0.221)
N	13040	13040	13038
Adj. R^2	0.166	0.171	0.174
F-statistic	557	290	269

Table 6: Regression results on the dependent variable *Forward Premium* with hourly observations. The standard deviations are calculated for each weather types and then matched to the corresponding hours. Model B1 is the basic model which considers capacity-normalized wind and solar production deltas and uncertainty. Model B2 extents Model B1 by consideration of load deltas and the load uncertainty. Model B3 separates the wind and solar data. $\mathbb{1}_{solar,h}$ is a dummy variable for solar production. Wind and solar production as well as the standard deviations are calculated with production deltas which are normalized by the monthly installed capacity to account for capacity extensions over time. Data covers July 2015 to December 2016. Standard Errors are heteroscedasticity and autocorrelation robust (HAC). Standard errors in parentheses. * p<.1, ** p<.05, ***p<.01

- An increase in the load delta (i.e. more realized load than expected) decreases the forward premium. Per GWh increased load, the price delta is estimated to decrease by 0.19 EUR/MWh.
- An increase in the capacity-normalized wind and solar delta (i.e. more realized volatile renewable production than expected) increases the forward premium. Each percent-point increased utilization of wind and solar production increases the forward price delta by 1.22 EUR/MWh. Note that the production delta is normalized by the installed capacity to account for capacity extensions.
- A higher standard deviation of the delta in wind and solar production (i.e. more uncertainty of the wind and solar forecast error) has a significant positive effect on the forward premium. It is significant at the 5% level. An increased standard deviation by 1 percent-point leads to a 0.39 EUR/MWh increase in forward premiums.

For Model B3, the combined regressors for wind and solar are disentangled. The general results of Model B1 hold true for Model B3. The separation allows additional insights on the origin of the price premium effects. A difference between the normalized wind and the solar deltas can be observed. The capacity-normalized solar deltas have a higher coefficient. This means that forward premiums are stronger increased by an unexpected additional percent-point of solar production than wind production. This finding is in line with common research for European and especially the German electricity markets. The high correlation of peak-load at noon with general high solar feed-in has a strong price reducing potential. See for instance Hirth (2013), Jägemann (2015) and Cludius et al. (2014). As to the uncertainty, only the standard deviation of wind deltas are significant (at a 10% level). The solar uncertainty is not significant at all. The positive effect of the disentangled wind uncertainty on the forward premium is 0.30 EUR/MWh. A schematic plot how uncertainty affects the forward premiums is visualized in Figure 6.



(a) Schematic day-ahead and intrady prices without uncertainty

(b) Schematic day-ahead and intrady prices with uncertainty

Figure 6: Schematic effect of uncertainty on the forward premium. The left figure (a) visualizes a situation without uncertainty (perfect foresight). Day-ahead and intraday prices are equal. Figure (b) shows the schematic impact of wind and solar production uncertainty. The forward premium is in general increased under uncertainty. p denotes prices and D denotes the demand for the day-ahead (DA) and intraday (ID) market.

The regression analysis explains effects on the forward premium whereas the forward premium is defined as the price delta. Thus, for an (absolute) increased forward premium, it is not clear whether the day-ahead price is increased, the intraday price is decreased or both effects occur. Following seems rational (even if the analysis is not suitable to provide statistical evidence): The deviations in load or wind and solar production can be assumed to be ex-ante unknown random processes in the short-run. All available ex-ante information are incorporated in the day-ahead price. Thus, short-term deviations are traded in the intraday-market which has no price effect on the earlier closed day-ahead market. These deviations should therefore influence only the intraday prices. On the other hand, the degree of uncertainty could be known ex-ante. A higher ex-ante known uncertainty level could be incorporated in the day-ahead market as well as in the intraday-market. The market selection is based on the traders' decision at which time they internalize the uncertainty. Internalization of the uncertainty in the day-ahead market would be rational in the sense of risk hedging. However, a final determination is not possible solely on these regression results. The theoretical results in Section 3 suggest to internalize uncertainty in the day-ahead forward markets. Note that these results are not differentiated as to seasons or hours. This differentiation remains for further research.

Overall, *Hypothesis B* of an increasing forward premium effect by increased production volatility can thus be confirmed based on the regression results. These findings give new insights and contributes to existing literature on forward premiums. It supports the analytic finding in Section 3 that weather-dependent production uncertainty increases the forward premium. Thus, it extends the fundamental literature which focuses on forward premium effects by demand uncertainty (e.g. Bessembinder and Lemmon (2002), Longstaff and Wang (2004)) and which identifies forward premiums with respect to different temporal resolutions (Viehmann (2011), Kiesel and Paraschiv (2017) or Furió and Meneu (2010)). The novel aspect in this research is that the weather types are almost fully decoupled of the current observation due to the long time horizon. Classical literature (e.g. Contreras et al. (2003),Conejo et al. (2005),Weron (2007)) oftenly apply autoregressive timeseries models which predict uncertainty-based price forecasts on limited past observations. Thus, the forward premium prediction is derived out of the current situation. The analysis within this paper applies a long-lasting time horizon to classify uncertainty. Hence, it can be interpreted as a classification which does not rely on the current situation. Additionally, the analysis shows that weather types are a suitable clustering method to consider wind and solar uncertainty. The effects on the forward premium are expected to increase under a higher merit order convexity as well as under a higher wind and solar production standard deviation.

4.4.4. Approximation of the economic implications

The economic implication for Germany suggests a relevant reduction in total costs if the forward premium due to wind an solar uncertainty could be reduced by 1%-point. Costs savings can be derived based on a rough approximation. For 2016, the total costs for electricity production on the day-ahead market amounts to EUR 6.625bn. This is the summation of the hourly day-ahead prices multiplied with its corresponding day-ahead volumes. The source is the EPEX Spot Market. Based on the Model B2 results, a 1%-point decrease in the wind and solar uncertainty translates to 0.376 EUR/MWh reduced forward premiums. The overall costs for 2016 with a 1%-points improved wind and solar standard deviation are EUR 6.536 bn. Therefore, the potential cost saving estimates to EUR 88m per year. The slightly higher forward premium reduction effect of Model B1 with a value of 0.393 EUR/MWh would result in total cost savings of EUR 92 million. The approximation indicates the high relevance of an forecast quality increase to reduces total system costs. Under the assumption of an inelastic consumer demand function, this represents the welfare gain of an improved forecast quality. Note that the rough approximation neglects rebound effects or interdependencies between markets (effects on intraday-markets or long-run forward markets). Additionally, the approximation assumes an equal forward premium reduction effect for each hour, which is on average true but could be higher or lower in certain situations.

5. Conclusion

Weather-dependent wind and solar production are facing an increasing share in electricity systems. This increasing share induces higher production uncertainty due to volatile characteristics by wind and solar production. This essay contributes to closing the research gap how wind and solar production uncertainty affects forward price premiums. First, theoretical evidence of an increasing forward price effect by increased uncertainty is identified. The theoretical findings show an increase in forward prices dependent on the merit order convexity and the production's standard deviation. In a second step, the theoretical findings are connected to weather type definitions and supported by empirical evidence for the German day-ahead and intraday market. The weather types have relevant impact to the forward premium levels. Additionally, the production uncertainty per weather type has an increasing effect on the forward premiums. Thus, this research contributes to understand short-term forward price premiums within electricity markets. As to the best of my knowledge, this is the first work on weather-dependent price premiums. Results support that weather types are a suitable measure for wind and solar production uncertainty. Thus, weather types should be incorporated in price forecasting methods to increase quality. An improved wind and solar forecast quality by 1%-point could additionally result in welfare gains of approximately EUR 88 million for Germany. Therefore, emphasize should be put on further weather forecast quality improvements.

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Appendix

Appendix A. On the order of the German electricity supply curve

Bessembinder and Lemmon (2002) performs his theoretical analysis with different orders of the supply curve. Note that the order reflects the highest exponent and that the supply curve is synonym with the merit order. Note additionally, that the supply curve is the first derivative of the total production costs function. Dependent on the supply curve order, the influence of the mean and skewness of the price distributions might have different effects. For instance, for higher orders (i.e. >2) of the supply curve, the forward price premium might become negative with very high standard deviations. In contrast, for linear or quadratic supply curves, the forward premium is always positive. Within the empirical evaluation, Bessembinder and Lemmon (2002) estimates the order of the supply curve via

$$Price_t = a\,(Demand_t)^{\tilde{c}} \tag{A.1}$$

$$\Leftrightarrow \qquad ln(Price_t) = a + \tilde{c}\ln(Demand_t) + \varepsilon_t, \tag{A.2}$$

where $Price_t$, is the daily average on-peak spot price, $Demand_t$ is the daily average load and a and $\tilde{c}$ the parameters to be estimated. The analysis is performed with data from PJM and CALPX electricity markets for approximately 1998 to 2000. They find empirical evidence for an average merit order convexity with a coefficient $\tilde{c} = 3.8$ for PJM and $\tilde{c} = 4.81$ for CALPX. This shows a high convexity of the merit order function. Note that Bessembinder and Lemmon (2002) estimates the order c of the Total Costs Function which first derivative reflects the order of the Marginal Cost Function $\tilde{c}$.

The estimated function in this section is similar to Equation (A.2) but with data for the German electricity market on hourly data from July 2015 to December 2016. The residual demand is applied, which is defined as total demand subtracted by wind and solar production. The estimated value for $\tilde{c}$ is 1.32 and statistical significant at a 1% level with an $Adj.R^2$ of 0.49. Different months suggest a slight deviation of the merit order function. The convexity is highest in January and December with a significant $\tilde{c}$ of 1.45 or 1.6, respectively. This effect can be explained by -in general- higher demand which utilizes power plants in the steeper right sight of the merit order. However, the estimated $\tilde{c}$ suggest a convexity between the linear and quadratic merit order function for the German electricity market for 2015 and 2016. This supports the assumption that the theoretical investigation in Section 3 is limited to the quadratic merit order function.

However, situations might occur which have higher merit order convexities, e.g. under high residual load and scarcity situations. The identification and analysis of these situations remain to further research.

Appendix B. Proof of Proposition 1

Proof. Assume the model definition as to Section 3. Assume that the expected production μ is smaller than the total demand.[6] Because all renewable producers are symmetric, the total traded renewable production of all players in stage 1 can be denoted by $q_{r1} := q_{ir1} + (N-1)q_{jr1}$ (where q_{jr1} is another symmetric renewable producer). Additionally, denote the realized production in stage 2 by $Q := NQ_i$, the expected quantity by $\mu := N\mu_{iq}$ and the standard deviation by $\sigma := N\sigma_i$.

The basic profit function of a renewable producer i in the present theoretical model framework is described in Equation (1). The following expected profit function is derived by plugging in the above formulas:

$$\begin{aligned}
\mathbb{E}[\Pi_{ir}(q_{ir1},(N-1)q_{jr1})] = & -D^2 a q_{ir1}\int f(Q_i)\,dQ_i + D^2 a\int Q_i f(Q_i)\,dQ_i + 2DNaq_{ir1}\int Q_i f(Q_i)\,dQ_i \\
& - 2DNa\int Q_i^2 f(Q_i)\,dQ_i - Dbq_{ir1}\int f(Q_i)\,dQ_i + Db\int Q_i f(Q_i)\,dQ_i \\
& - N^2 a q_{ir1}\int Q_i^2 f(Q_i)\,dQ_i + N^2 a\int Q_i^3 f(Q_i)\,dQ_i + Nbq_{ir1}\int Q_i f(Q_i)\,dQ_i \\
& - Nb\int Q_i^2 f(Q_i)\,dQ_i - cq_{ir1}\int f(Q_i)\,dQ_i + c\int Q_i f(Q_i)\,dQ_i \\
& + q_{ir1}\Big(a\left(D - q_{ir1} - q_{jr1}(N-1)\right)^2 + b\left(D - q_{ir1} - q_{jr1}(N-1)\right) + c\Big).
\end{aligned} \tag{B.1}$$

The first derivative with respect to q_{ir1} is

$$\begin{aligned}
\frac{\mathrm{d}}{\mathrm{d}q_{ir1}}\mathbb{E}[\Pi_{ir}(q_{ir1},(N-1)q_{jr1})] = & -D^2 a\int f(Q_i)\,dQ_i + 2DNa\int Q_i f(Q_i)\,dQ_i - Db\int f(Q_i)\,dQ_i \\
& - N^2 a\int Q_i^2 f(Q_i)\,dQ_i + Nb\int Q_i f(Q_i)\,dQ_i \\
& + a\left(D - q_{ir1} - q_{jr1}(N-1)\right)^2 + b\left(D - q_{ir1} - q_{jr1}(N-1)\right) \\
& - c\int f(Q_i)\,dQ_i + c + q_{ir1}\left(a\left(-2D + 2q_{ir1} + 2q_{jr1}(N-1)\right) - b\right).
\end{aligned} \tag{B.2}$$

This can be simplified by the following substitutes for the probability density function $f(Q)$:

$$\text{Distribution function has a total probability of 1:} \quad \int f(Q_i)\,dQ_i = 1 \tag{B.3}$$

$$\text{Expected value for } Q_i\text{:} \quad \int Q_i f(Q_i)\,dQ_i = \mu_i \tag{B.4}$$

$$\text{The second moment (re-ordered):} \quad \int Q_i^2 f(Q_i)\,dQ_i = \mu_i^2 + \sigma_i^2 \tag{B.5}$$

This leads to the simplified necessary condition for the profit maximizing quantity q_{ir1}^* as

$$\begin{aligned}
\frac{d}{dq_{ir1}}\mathbb{E}[\Pi_{ir}(q_{ir1},(N-1)q_{jr1})] = & -D^2 a + 2DNa\mu_i - Db - N^2 a\left(\mu_i^2 + \sigma_i^2\right) + Nb\mu_i + a\left(D - q_{ir1} - q_{jr1}(N-1)\right)^2 \\
& + b\left(D - q_{ir1} - q_{jr1}(N-1)\right) + q_{ir1}\left(a\left(-2D + 2q_{ir1} + 2q_{jr1}(N-1)\right) - b\right) \\
& \overset{!}{=} 0.
\end{aligned} \tag{B.6}$$

[6] If $\mu > D$, then the total demand can be fulfilled by renewable production such that prices close to zero or below are expected and renewable production curtailment could occur.

Now this equation can be solved for q_{ir1} which results in the profit maximizing quantity

$$q^*_{ir1} = \frac{1}{3a}\Big(2Da - 2Naq_{jr1} + 2aq_{jr1} + b + \big[4D^2a^2 - 6DNa^2\mu_i - 2DNa^2q_{jr1} + 2Da^2q_{jr1} + 4Dab + 3N^2a^2\mu_i^2 + N^2a^2q_{jr1}^2 + 3N^2a^2\sigma_i^2 - 2Na^2q_{jr1}^2 - 3Nab\mu_i - Nabq_{jr1} + a^2q_{jr1}^2 + abq_{jr1} + b^2\big]^{1/2}\Big) \tag{B.7}$$

for producers $i = 1, ..., N$. Note the square root for the square brackets. The second derivative becomes zero if and only if $q_{ir1} = \frac{1}{2N+1}(2D + \frac{b}{a})$ which can only be the case for $q_{ir1} = 0$ for perfect competition (whereas the case of perfect competition is the investigation focus).

In an equilibrium of identical players, the solutions q_{ir1} are identical as well. Thus, $q_{ir1} = q_{jr1}$ holds and can be replaced. Following is derived:

$$q_{ir1} = \frac{1}{3a}\Big(2Da - 2Naq_{ir1} + 2aq_{ir1} + b \pm \big[4D^2a^2 - 6DNa^2\mu_i - 2DNa^2q_{ir1} + 2Da^2q_{ir1} + 4Dab + 3N^2a^2\mu_i^2 + N^2a^2q_{ir1}^2 + 3N^2a^2\sigma_i^2 - 2Na^2q_{ir1}^2 - 3Nab\mu_i - Nabq_{ir1} + a^2q_{ir1}^2 + abq_{ir1} + b^2\big]^{1/2}\Big) \tag{B.8}$$

This can be solved with respect to q_{ir1} which gives

$$q^*_{ir1} = \frac{1}{2Na\,(N+2)}\Big((N+1)\,(2Da+b) + \big[4D^2N^2a^2 + 8D^2Na^2 + 4D^2a^2 - 8DN^3a^2\mu_i - 16DN^2a^2\mu_i + 4DN^2ab + 8DNab + 4Dab + 4N^4a^2\mu_i^2 + 4N^4a^2\sigma_i^2 + 8N^3a^2\mu_i^2 + 8N^3a^2\sigma_i^2 - 4N^3ab\mu_i - 8N^2ab\mu_i + N^2b^2 + 2Nb^2 + b^2\big]^{1/2}\Big) \tag{B.9}$$

Note that another possible profit optimal solution exists. This solution would have a negative bid. Thus, it is not in the feasible range of solutions and neglected. Equation (B.8) is the profit maximizing quantity q^*_{ir1} of one symmetric player i in a price-competitive oligopoly.

The optimal joint bid of all renewable producers' becomes

$$\begin{aligned} q^*_{r1} &= \sum_{i=1}^{N} q^*_{ir1} \\ &= Nq^*_{ir1} \\ &= \frac{1}{2a\,(N+2)}\Big((N+1)\,(2Da+b) - \big[4D^2N^2a^2 + 8D^2Na^2 + 4D^2a^2 - 8DN^2a^2\mu + 4DN^2ab - 16DNa^2\mu + 8DNab + 4Dab + 4N^2a^2\mu^2 \\ &\quad + 4N^2a^2\sigma^2 - 4N^2ab\mu + N^2b^2 + 8Na^2\mu^2 + 8Na^2\sigma^2 - 8Nab\mu + 2Nb^2 + b^2\big]^{1/2}\Big), \end{aligned} \tag{B.10}$$

where $\mu = N\mu_i$ and $\sigma = N\sigma_i$ since all renewable producers are assumed to be symmetric.

The focus lies on the solution under perfect competition. This is reflected via $N \to \infty$. For $N \to \infty$, Equation (B.10) becomes

$$q^*_{r1} = D + \frac{1}{2}\frac{b}{a} - \sqrt{\left[\left(\left(D + \frac{1}{2}\frac{b}{a}\right) - \mu\right)^2 + \sigma^2\right]} \tag{B.11}$$

To derive Equation (B.11) from Equation (B.10), terms with N in the denominator goes to 0 for $N \to \infty$. Additionally, if there are multiple exponents for N in one term, only the highest exponent of N is dominant for $N \to \infty$. Equation (B.11) is the optimal first stage total renewables' bid under uncertainty and the solution of the proposition. □

Appendix C. Statistics on the data

Appendix C.1. Statistics on the wind, solar, price forecasts

Table C.7 shows statistics for the price, wind and solar deviation dataset.

	Mean	Std.dev.	Min	Max
Price forecast deviation [EUR/MWh]	0.5	12.4	-138.8	253.4
Wind forecast error [GWh]	-0.4	1.5	-8.4	11.5
Solar forecast error [GWh]	-0.1	0.9	-5.8	4.7

Table C.7: Statistics on the price and wind/solar deviation dataset. Data covers July 2015 to December 2016.

A structural deviation of the mean value for the wind and solar forecast erros can be observed. A reason for the structural deviations could be the extrapolation methods of the TSOs (cf. 50Hertz (2017), Amprion (2017), Tennet (2017), TransnetBW (2017) and APG (2017)). Additionally, structural forecast overestimation could exists due to reduced efficiency (old PV modules/wind turbines), surface roughness, aerosols and air pollution and similar effects. The standard deviation of wind forecast errors is higher than for solar forecast errors.

Appendix C.2. Objective Weather Type Classification

Table C.8 shows characteristics for the forty DWD *Objective Weather Type Classifications*. Each combination of wind speed, cyclonality on 950 hPA, cyclonality on 500 hPa and humidity exists. Additionally, the frequency is shown. Table C.9 gives statistical numbers for combined wind and solar forecast errors per weather type.

No.	Wind direction	Cyclonalitity in 950 hPa	Cyclonalitity in 500 hPa	Humidity	Frequency (from 1979 to 2016)
1	no prevailing direction	anticyclonic	anticyclonic	dry	751
2	northeast	anticyclonic	anticyclonic	dry	498
3	southeast	anticyclonic	anticyclonic	dry	120
4	southwest	anticyclonic	anticyclonic	dry	640
5	northwest	anticyclonic	anticyclonic	dry	1204
6	no prevailing direction	anticyclonic	anticyclonic	wet	401
7	northeast	anticyclonic	anticyclonic	wet	80
8	southeast	anticyclonic	anticyclonic	wet	45
9	southwest	anticyclonic	anticyclonic	wet	1262
10	northwest	anticyclonic	anticyclonic	wet	1058
11	no prevailing direction	anticyclonic	cyclonic	dry	331
12	northeast	anticyclonic	cyclonic	dry	351
13	southeast	anticyclonic	cyclonic	dry	48
14	southwest	anticyclonic	cyclonic	dry	582
15	northwest	anticyclonic	cyclonic	dry	1241
16	no prevailing direction	anticyclonic	cyclonic	wet	103
17	northeast	anticyclonic	cyclonic	wet	20
18	southeast	anticyclonic	cyclonic	wet	9
19	southwest	anticyclonic	cyclonic	wet	439
20	northwest	anticyclonic	cyclonic	wet	178
21	no prevailing direction	cyclonic	anticyclonic	dry	148
22	northeast	cyclonic	anticyclonic	dry	16
23	southeast	cyclonic	anticyclonic	dry	128
24	southwest	cyclonic	anticyclonic	dry	159
25	northwest	cyclonic	anticyclonic	dry	32
26	no prevailing direction	cyclonic	anticyclonic	wet	223
27	northeast	cyclonic	anticyclonic	wet	9
28	southeast	cyclonic	anticyclonic	wet	207
29	southwest	cyclonic	anticyclonic	wet	975
30	northwest	cyclonic	anticyclonic	wet	109
31	no prevailing direction	cyclonic	cyclonic	dry	372
32	northeast	cyclonic	cyclonic	dry	55
33	southeast	cyclonic	cyclonic	dry	111
34	southwest	cyclonic	cyclonic	dry	276
35	northwest	cyclonic	cyclonic	dry	304
36	no prevailing direction	cyclonic	cyclonic	wet	251
37	northeast	cyclonic	cyclonic	wet	22
38	southeast	cyclonic	cyclonic	wet	143
39	southwest	cyclonic	cyclonic	wet	745
40	northwest	cyclonic	cyclonic	wet	173

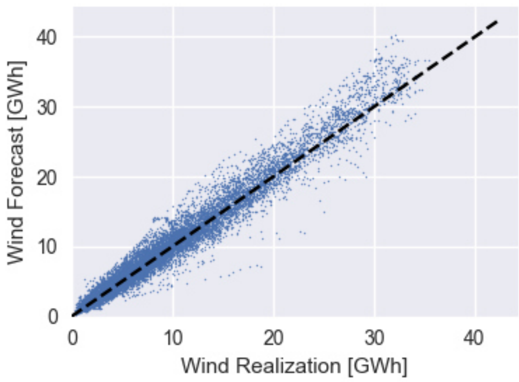
Table C.8: Objective Weather Type Classification by the German Weather Service (DWD) defined by Bissolli and Dittmann (2001). Frequency counted by daily occurrences from 1979 to 2016.

Weather type	count	mean	std	min	25%	50%	75%	max	RMSE	MAE
1	623	-0.09	1.21	-6.48	-0.68	0.01	0.58	3.45	1.22	0.88
2	264	0.09	0.96	-5.25	-0.39	0.05	0.65	2.13	0.96	0.69
3	96	0.00	1.13	-3.06	-0.84	0.24	0.74	1.92	1.12	0.90
4	648	-0.83	1.59	-4.57	-1.94	-0.63	0.08	10.62	1.79	1.31
5	1248	-0.74	1.31	-6.70	-1.41	-0.57	0.04	7.97	1.50	1.09
6	480	-0.16	1.46	-6.16	-0.88	-0.20	0.45	5.96	1.47	1.00
9	1176	-0.18	1.62	-7.00	-0.91	-0.05	0.61	9.96	1.62	1.12
10	1296	-0.61	1.94	-8.43	-1.44	-0.43	0.42	11.13	2.03	1.40
11	336	-0.13	1.12	-3.38	-0.82	-0.24	0.54	3.38	1.13	0.88
12	360	-0.22	1.07	-4.31	-0.81	-0.15	0.37	3.19	1.09	0.81
14	576	-0.52	1.66	-7.09	-1.26	-0.20	0.45	3.73	1.74	1.19
15	1008	-0.81	1.79	-7.82	-1.71	-0.74	0.15	6.54	1.97	1.47
16	24	0.33	0.66	-0.66	-0.40	0.67	0.89	1.21	0.73	0.67
17	24	-1.19	1.06	-2.68	-1.93	-1.28	-0.36	0.81	1.58	1.35
19	336	-1.02	1.33	-5.91	-1.70	-0.91	-0.16	2.35	1.67	1.30
20	216	-1.42	2.09	-6.79	-2.58	-0.60	0.12	1.94	2.52	1.71
21	120	-0.92	2.08	-6.48	-1.63	-0.45	0.66	1.87	2.27	1.61
23	144	-0.47	1.89	-4.80	-1.49	-0.60	0.93	3.99	1.94	1.56
24	168	0.15	1.19	-2.39	-0.72	-0.02	0.78	3.68	1.20	0.93
25	48	-1.67	1.53	-5.30	-2.74	-1.87	-0.18	0.41	2.25	1.76
26	168	-0.77	1.74	-4.94	-1.61	-0.45	0.42	3.10	1.89	1.39
27	24	0.04	1.36	-1.86	-1.01	-0.25	0.81	2.80	1.33	1.08
28	168	-0.30	1.27	-3.55	-1.14	-0.31	0.63	2.87	1.31	1.06
29	960	-0.49	1.70	-5.81	-1.52	-0.42	0.47	5.18	1.77	1.35
30	48	-1.04	1.56	-7.23	-1.85	-1.12	0.08	1.41	1.86	1.38
31	528	-0.65	1.52	-6.52	-1.48	-0.38	0.32	4.13	1.65	1.20
32	72	-0.06	1.17	-1.65	-0.77	-0.32	0.29	3.48	1.17	0.85
33	96	-0.19	1.62	-4.67	-0.86	0.04	0.72	2.69	1.63	1.17
34	312	-0.34	1.67	-4.81	-1.19	-0.21	0.82	3.58	1.70	1.30
35	144	0.42	3.35	-4.93	-1.21	-0.09	0.50	11.55	3.36	2.13
36	312	-1.68	1.74	-7.37	-2.34	-1.11	-0.53	1.51	2.41	1.73
37	48	-0.44	0.72	-1.98	-0.80	-0.36	0.08	0.93	0.84	0.65
38	120	-0.74	1.42	-3.93	-1.62	-0.77	-0.02	3.26	1.60	1.27
39	912	-0.33	1.84	-6.16	-1.28	-0.33	0.59	9.28	1.87	1.35
40	96	-0.87	2.01	-4.29	-2.33	-0.82	0.34	4.75	2.18	1.75
Total Data	13199	-0.52	1.67	-8.43	-1.33	-0.37	0.38	11.55	1.75	1.24

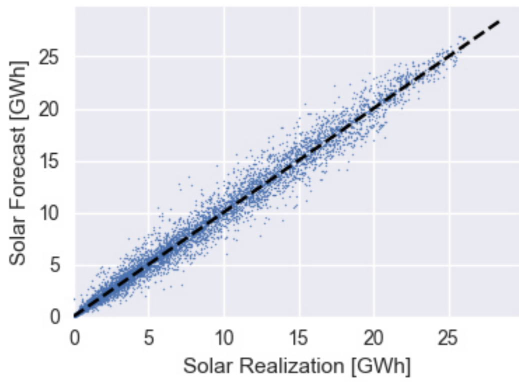
Table C.9: Statistics on the (combined) wind & solar forecast errors for the objective weather type classifications. Observations cover July 2015 to December 2016 in hourly resolution. Units are in GWh (except for count). *std* denotes the standard deviation which is incorporated as the uncertainty measure for the empirical analysis. The standard deviations deviate between 0.66 and 3.35.

Appendix D. The wind and solar production level gives insufficient information on forecast errors

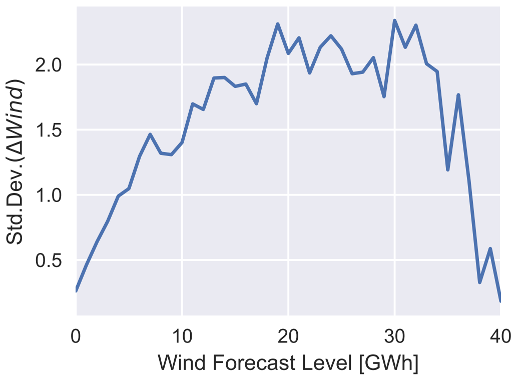
Figure D.7 addresses the question whether the wind and solar production level would be a suitable classification for forecast errors. One would expected that higher renewable production results in higher renewable forecast errors. The both upper plots of Figure D.7 show the forecast errors per hourly observation. The observations do not indicate a sufficient heteroscedastic behavior. That means, the forecast errors are not sufficiently increasing with the production level. The lower plots show the standard deviations per production level aggregated to 1 GWh clusters. It is obvious, that in a broad range of the production levels, the standard deviations have only minor gradients. The small gradients mean, that these observation have only slight differences to the surrounding classes and thus limited distinction possibility. Thus, the level of wind or solar production can be expected as no adequate estimator for forecast errors. Note that a longer dataset time period would smoothen the error but incorporates a bias effect due to different capacity levels. Lange and Heinemann (2002) report a similar finding that the production level has only limited distinction possibility.



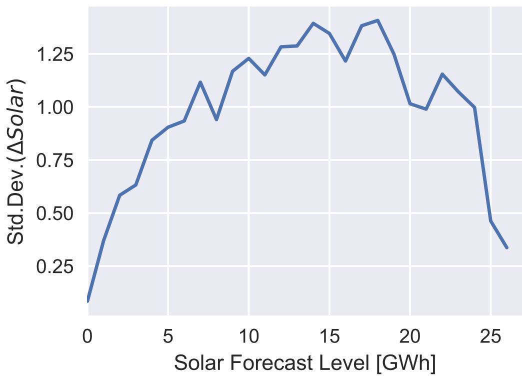
(a) Wind realization vs. wind forecast



(b) Solar realization vs. solar forecast



(c) Standard deviation of wind production clustered as to wind forecast level (1 GWh each)



(d) Standard deviation of solar production clustered as to solar forecast level (1 GWh each)

Figure D.7: Forecast errors for wind and solar dependent on forecast levels. The black dotted lines in the upper plots displays the diagonal line. Data covers July 2015 to December 2016.

Appendix E. Effect coding results for cyclonality at 500 hPa

Table E.10 reports the results of the effect coding with respect to cyclonality on 500 hPa. The effect coding estimates the deviation in the group means to the grand means. The groups are cyclonic and anticyclonic weather patterns at 500 hPa. The estimates are not significant which means, that they do not significantly deviate from the overall mean forward premium.

Cyclonality on 500 hPa	Difference to grand mean
Grand mean	-0.140***
Anticyclonic	-0.057
Cyclonic	0.078

Table E.10: Results of the effects coding approach for the weather types' criteria *cyclonality on 500 hPa* for the model $ForwardPremium_h = Intercept + \sum_i \beta_i Cyclonality500hPa_{i,h} + \epsilon_h$. The estimated values indicate the difference of the criterias' mean value to the grand mean. Number of observations is 13040 hourly values from July 2015 to December 2016. Significance levels denoted by * p<.1, ** p<.05, ***p<.01. Significance and estimations of the grand mean indicates the difference to a zero mean value. Note that five weather classes are omitted due to too less observations in the investigated time horizon.

Appendix F. Wind and solar uncertainty translates to price uncertainty

Appendix F.1. General price decreasing effect of positive production deviations

Several studies analyze the effect of an increase in renewable production on the day-ahead to intraday price differences. In general, more renewable production than forecasted would decrease the realized prices (compared to the price forecast). This is in line with the expectation (cf. Hirth (2013)). A similar trend can be observed within this dataset. It is not the focus of this research, but the dataset used shows a typical decreasing trend. The trend can be observed in Figure F.8.

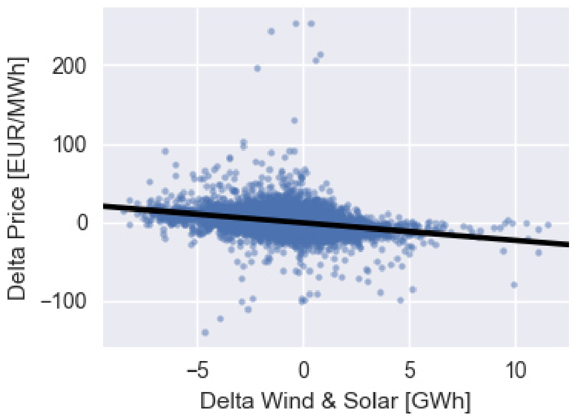


Figure F.8: Price effect of an increase in renewable production compared to forecasts (delta = realization - forecast). Price realizations are the volume weighted prices of the last three hours (ID3-prices). Observations cover July 2015 to December 2016.

An increase in wind and solar production delta (*realization minus forecast*) tend to an decrease in price delta (*intraday minus day-ahead*). A linear regression shows a price decrease of 2.22 EUR/MWh per additional GWh wind or solar production in the intraday-market. Former years (back to 2010) have higher price reduction effects than latter years. This trend can be explained by adjustment processes, learning and saturation effects.

However, in this simple linear OLS regression, several drivers are not considered. For instance, one relevant factor is the shape of the merit order, which covers e.g. information about the actual power plant fleet and outages. Another relevant factor is the residual demand level, which determines the intersection on the merit order shape and serves e.g. as an indicator for scarcity situations. Thus, the fit of the linear regression is strongly limited and has an Adj. R-squared value of 0.09.

Appendix F.2. Weather type production volatility implies forward price volatility

In this supplementary section, the hypothesis is stated that an increased production uncertainty leads to an increase in the price uncertainty. The price uncertainty is the standard deviation of the forward premiums within each weather type. The uncertainty of wind production, solar production and load is defined analogous. Note that wind and solar production are capacity-normalized to account for capacity extension over the time horizon.

Figure F.9 compares the standard deviations of the capacity-normalized wind and solar deltas (wind and solar uncertainty) to the standard deviations of the forward premiums (price uncertainty); categorized as to the weather types.

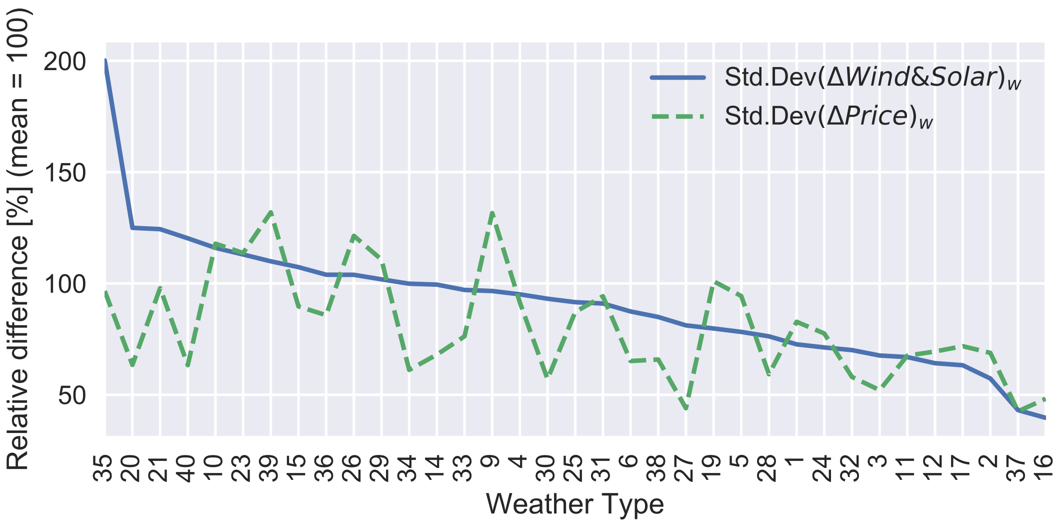


Figure F.9: Relative standard deviations of capacity-normalized wind and solar deviations as well as price deviations per weather type w. Descending sorted w.r.t. weather types' standard deviation of wind and solar deviation. Data is additionally normalized to the sample mean. Observations cover July 2015 to December 2016. The Forward premium is calculated as the delta between the day-ahead price and the volume weighted intraday price of the last three hours (ID3).

Both standard deviations have a Pearson correlation factor of 0.48, which indicates a medium correlation.

Since the wind and solar uncertainty should be independent of the price forecasts, the relationship can be interpreted as a causality. Thus, it indicates that a reduction in weather uncertainty leads in general to a certain reduction in price uncertainty.

To examine the impact of load, wind and solar uncertainty on the the forward premium uncertainty, two regression estimations are performed. In *Model C1*, the standard deviations of the forward premiums are explained by the standard deviations of the load deviation and the standard deviation of the combined wind and solar deviations (per weather type). *Model C1* can be expressed as Equation (F.1). In *Model C2* the standard deviations of the forward premiums are explained by the separated standard deviations of the (capacity-normalized) wind and the solar deltas as denoted in Equation (F.2):

$$\text{Model C1:} \qquad Std.Dev(FP)_w = \alpha + \beta_1 Std.Dev(\Delta Load)_w + \beta_2 Std.Dev(\Delta Wind\&Solar)_w + \epsilon_w \tag{F.1}$$

$$\text{Model C2:} \qquad Std.Dev(FP)_w = \alpha + \beta_1 Std.Dev(\Delta Wind)_w + \beta_2 Std.Dev(\Delta Solar)_w + \epsilon_w \tag{F.2}$$

where w states the weather type. Due to low observations (limited amount of weather types), the number of regressors need to be restricted. Thus, in Model A1, the general effect of load and volatile renewable production (i.e. combined wind and solar) are estimated. Whereas Model A2 disentangles the effect within wind and solar production and neglects load.

Table F.11 shows the regression results of the Weighted Least Squares estimation. The estimation weights are the corresponding number of observation per weather type. Note that not every weather type is represented due to occurrence in the estimated time range.

Std.Dev$(FP)_w$	Model C1	Model C2
Intercept	2.190**	3.043***
	(0.873)	(1.033)
$\Delta Load_h$	0.749**	
	(0.301)	
$\Delta Wind\&Solar_h$	1.132***	
	(0.343)	
$\Delta Wind_h$		0.556***
		(0.167)
$\Delta Solar_h$		0.468
		(0.413)
N	32	32
Adj. R^2	0.357	0.247

Table F.11: Weighted Least Squares estimation. Hourly data is aggregated to weather types. Weights are the number of observations per weather type. Note that not every weather type is represented due to occurrence in the estimated time range. Standard errors in parentheses. * p<.1, ** p<.05, ***p<.01

The estimation of Model C1 shows significant coefficients for both regressors. However, the coefficient of the standard deviation for wind and solar deviations is significant at a 1% level whereas the standard deviation of the load deviations has a broader significance level of 5%. The lowered significance level is somehow expected, since the classification is based on weather data which has limited influence on load data. The coefficient for the standard deviation of the capacity-normalized wind and solar deviations is 1.1%; the coefficient for the standard deviation of load is 0.75 GWh. Among the wind and solar deviations, the wind deviations have a significant effect whereas the solar deviations have not. This becomes obvious by the results of Model C2. Overall, the stronger the deviations with respect to wind and solar or load, the stronger fluctuates the forward premium, i.e. the day-ahead to intraday price delta. The hypothesis of an increased price volatility by increased production volatility can thus be confirmed.

Appendix G. Requirement checks for the regression analysis

Appendix G.1. No relevant correlation of regression variables

Figure G.10 shows the correlation matrix within a heatmap. No relevant high correlation occurs. The relevant correlation values between the regressors are in the range between -0.06 and 0.11. Higher correlation could occur between variables which are not simultaneously used in the same regression (e.g. a correlation of 0.86 between wind deltas as well as wind and solar deltas). The dependent variable *forward premiums* could have higher correlation to the regressors which is not critical (e.g. 0.43 to wind and solar deltas).

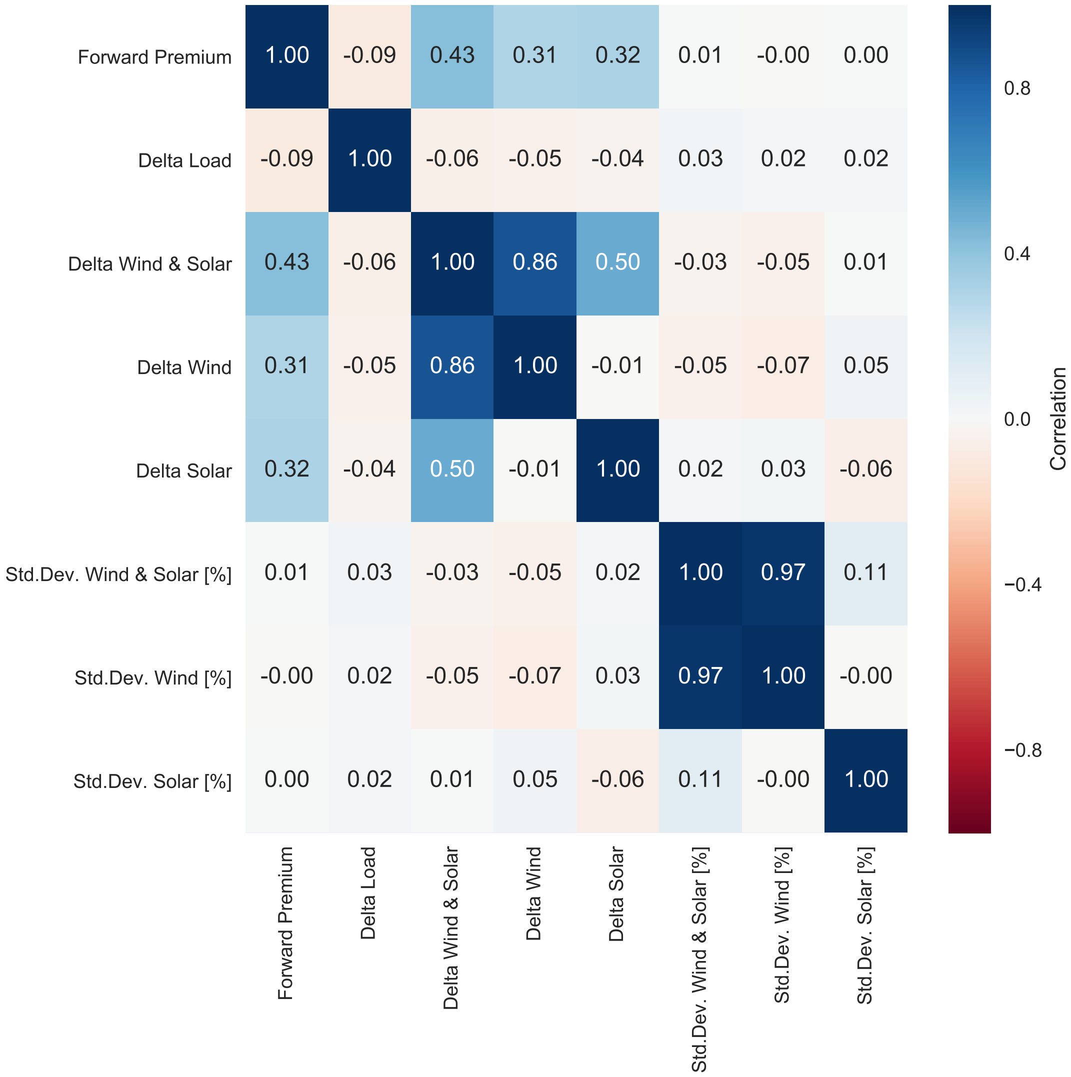


Figure G.10: Pearson correlation of the regression variables. Data covers July 2015 to December 2016.

Appendix G.2. Time series data is stationary

Table G.12 shows the statistics of the Augmented Dickey Fuller test. The null hypothesis of non-stationarity can be rejected. Thus, the data have no statistical significant time-dependent structure like a trend or seasonal effect. The time series OLS prerequisite of stationarity is fulfilled.

	Test Statistic	p-value	# lags
$\Delta Prices$	-22.96	0.00	14
$\Delta Load$	-13.71	0.00	37
$\Delta Wind$	-10.02	0.00	41
$\Delta Solar$	-12.84	0.00	27
$\Delta Wind\&Solar$	-10.50	0.00	41
StdDev($\Delta Wind$)	-11.82	0.00	24
StdDev($\Delta Solar$)	-12.22	0.00	24
Model residuals	-18.88	0.00	17

Table G.12: Test statistics for the Augmented Dickey Fuller test for unit roots (cf. Dickey and Fuller (1979)). The null hypothesis of a unit root in the respective period of observation is rejected. The test uses the Akaike Information Criterion (AIC) in order to determine the optimal lag lengths. Additional to the standard Augmented Dickey Fuller test which controls for a constant effect, the Augmented Dickey Fuller test is performed with a linear trend as well as with a linear and quadratic trend (trend and drift). Both additional tests indicate the same result, i.e. to reject the non-stationarity hypothesis at a 1% significance threshold. The *model residuals* refer to the estimation results for Equation (8).