The risk mark-up of intermittent renewable supply in German electricity forward markets☆

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Abstract

Renewable energy such as wind or solar power currently contributes a large share to the total German electricity supply as a result of the German energy transition. This paper presents an empirical analysis of how power shocks resulting from intermittent renewables affect the forecast error of the forward premium in German electricity markets. We contribute to the existing literature by investigating determinants of forward premiums, thereby focusing on wind and on solar power. We find positive monthly wind shock effects on forecast errors, i.e. a specific risk-mark up on forward prices. The findings underline the need to introduce wind power futures at the European Energy Exchange to reduce the risk mark-up for participants in forward markets. No daily wind shock and solar shock effects are found. Possible explanations are almost perfect approximations of the expected spot price. This is also in line with the EEX strategy, which is not creating wind power futures for contracts with maturities of days. The wind shock effect on monthly peak load premiums is larger than on base load premiums. This should be due to higher differences in marginal costs at the right of the merit order curve.

Keywords:
Electricity Market, Forward Premiums, Intermittent Renewables, Least Squares
JEL Classification: Q42, Q41, C22, C51

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1. Introduction

This paper presents an empirical analysis of the effect of intermittent renewable supply (mainly wind) on the forecast error of forward premiums (see section 2) in German electricity markets. In recent years, there has been a rise in the level of renewable generating capacity in Germany. This is partly the result of the German energy transition (launched by the government's feed-in law of 1991 and formulated in further detail in the Renewable Energy Act (EEG) of 2000). Renewable energy sources such as wind power currently contribute a large share to total German electricity supply. In december 2017, renewables accounted for 33.1% of the total German electricity supply. The most important renewable energy source was wind power, with a 48.6% share of the total supply of renewables. Solar (18.4%) and hydro (9.1%) made up smaller but significant shares (BDEW (2017)). A priority feed-in for renewables exists.

Spot prices depend negatively on wind and solar power. This refers to the merit order effect (cf. Jensen and Skytte (2002), Fischer (2010), Würzburg et al. (2013) and Cludius et al. (2014)).

We therefore argue that important renewable power variables should be taken into account when analyzing forward premiums and its forecast error in German electricity markets. We contribute to the existing literature by empirically investigating German electricity markets. We focus on intermittent wind and solar power because there is very little research on the effects of these potentially important variables. In particular, to our knowledge there are no empirical studies that investigate German electricity markets, despite the high share of renewable feed-in. As in Botterud et al. (2010) our aim is not to present a new theory for forward premiums: instead, we want to empirically analyze the extent to which wind and solar power can explain the forecast error of the forward premium.

Electricity wholesale markets are characterized by a need to match demand and supply precisely at every point in time, despite supply and demand shocks. In addition, short-term demand is very price-inelastic because most consumers have no flexible contracts, and power cannot be economically stored (cf. Bessembinder and Lemmon (2002)). Financial risk management by such means as long-term contracts is, therefore, an important tool for reducing price risks when facing such volatile markets. The European Energy Exchange (EEX), one of the largest European power exchanges, uses such contracts in forward markets to determine electricity forward prices for specific time periods in the future to hedge against risks of future day-ahead spot prices. The difference between forward and spot prices at the time to delivery is the forward premium. Forward premiums are important for both sides, i.e. supply and demand, of electricity markets. For example, important players such as conventional generators profit from forward contracts in case of decreasing spot prices at some future date (as a result of rising renewable feed-in for example). On the other hand, important players such as companies with high demand for power profit from forward contracts in case of rising spot prices at some future date (because of decreasing renewables due to weather dependency for example). Market sizes of German forward markets investigated in this paper show their importance (see Appendix A and Appendix B).

In this paper, we report significant positive wind shock effects on both monthly and daily ex-post forward premiums. The wind shock shifts the supply curve to the right due to the merit order effect at the time when the spot price is realized. The spot price should fall as a result. Furthermore, it should fall below the current forward price because the unexpected future wind shock cannot be accurately taken into account in the forward price. Therefore, these effects are also effects on the forecast error of the ex-ante premium. They can be seen as a risk mark-up on forward prices resulting from intermittent wind feed-in and related increased spot price volatility. The EEX has introduced a new wind power future. This is a new market instrument designed to provide market participants with the opportunity to hedge specifically against price and quantity risks of wind power generation. The findings we report here underscore the importance of this EEX strategy because the wind power future might then reduce this risk mark-up for participants in forward markets as further discussed in sections 4.1 and 6. The wind shock effect on daily ex-post forward premiums is substantially lower, i.e., near zero. Substantially reducing the maturity of the forward contract to the very near future is likely to result in almost perfect approximations of the expected spot price at the time when the forward contract is determined. This should lead to forward premiums as well as wind shock effects on the forward premium near zero. The same argument might hold for finding no significant solar shock effect on daily premiums. The wind shock effect on monthly peak load premiums is larger than on base load premiums. Intuitively, at peak load times, there is a higher demand for power. Thus, more power supply (normally with gas as the back-up generation type) is needed, leading to a higher equilibrium spot price. If there is then an unexpected wind shock at peak load times, the spot price might fall further below the current forward price due to higher differences in marginal costs at the right of the merit order curve. There should be then also a higher risk mark-up on forward prices.

This paper is structured as follows. Section 2 presents past research on forward premiums and its forecast errors. Section 3 presents the chosen estimation approach and gives an overview of the data and regression variables. In section 4, estimation results are presented. Section 5 shows some robustness checks. Section 6 concludes.

2. Literature review

Electricity is not economically storable and is a flow rather than a stock. Thus, classic cost-of-carry approaches for spot and forward markets, which date back to Kaldor (1939), are not applicable (cf. Bessembinder and Lemmon (2002)). Equilibrium approaches are used instead to model the relationship between spot and forward prices (dating back to Keynes (1930)) when market agents build expectations about future spot prices (cf. Redl et al. (2009)). Agents with the need to hedge spot price uncertainty treat the forward price as being determined as the expected future spot price plus an ex-ante premium. This premium is, unfortunately, unobservable. Thus, empirical research often looks instead at the ex-post forward premium, which is the difference between the forward price and the ex-post spot price at the time to delivery. The relation between the two premiums is the following:

$$\begin{aligned} forward_{t,t+k} - spot_{t+k} &= forward_{t,t+k} - E_t[spot_{t+k}] + E_t[spot_{t+k}] - spot_{t+k} \\ &= forward_{t,t+k} - E_t[spot_{t+k}] + \epsilon_t. \end{aligned} \tag{1}$$

The forward price, determined at time t contracting delivery for time $t+k$ (k is the contract maturity), minus the realized spot price at time $t+k$, i.e. the spot price at time to delivery, is the ex-post premium. It is equal to the difference between the forward price and the expectation of the spot price at time $t+k$ (called "future spot price" in the remainder of this paper) made at time t plus the difference between the expected future spot price and the realized spot price. The first difference is the ex-ante premium. The ex-post premium is a consistent estimator of the ex-ante premium if the error distribution has zero mean (cf. Redl and Bunn (2013)). The second difference is the error term ϵ_t. It refers to price shocks between t and $t+k$ (which may occur due, for example, to price-inelastic short-term demand). ϵ_t is also the forecast error of the ex-ante premium (cf. Redl and Bunn (2013)), i.e. the difference between the ex-post and the ex-ante premium. As forward market participants at time t cannot observe intermittent renewable supply such as wind power between t and $t + k$ such renewable supply would estimate a specific component of the forecast error of the ex-ante premium, i.e. a risk mark-up on forward contracts due to renewable supply as stated in section 1, and further discussed in sections 4.1 and 6.

One way to model equilibria in forward markets is to create a two-stage game where Cournot producers behave more competitively in the spot market due to forward commitments they have made in an oligopolistic environment (cf. Allaz and Vila (1993)). Further model assumptions are risk neutrality of agents and no arbitrage (leading to a zero ex-ante premium). In Ritz (2016), the model of Allaz and Vila (1993) was expanded to incorporate intermittent renewable generation and provide solutions also for more than two strategic players. However, results of this game theory approach differ when the two-stage assumption is relaxed. Therefore, the results are ambiguous (cf. Redl and Bunn (2013)). Furthermore, Bessembinder and Lemmon (2002) stated that the no-arbitrage condition might not hold when the good under investigation is non-storable electricity.

This leads to the other approach to equilibrium modeling of forward markets. Bessembinder and Lemmon (2002) created an equilibrium model with risk-averse utility maximizing agents by applying a competitive marginal-cost-based approach (producers equate their marginal revenues to their marginal costs) for specific electricity forward and spot markets. However, a weakness of this model is that demand is an exogenous random variable and not derived by the model itself. One solution that has been proposed in the literature is to endogenously determine the ex-ante premium as a linear function of the expected variance (negative effect) and expected skewness (positive effect) of spot prices, and a large body of empirical literature has sought to verify this result. The stated moments of the spot price distribution can be seen as measures of risk management of the market participants. When participants believe that future spot prices will be unusually high (i.e., expect a high skewness), they will determine contracts with higher forward prices, such that the forward premium goes up (cf. Weron and Zator (2014)). On the other hand, when market participants believe that future spot prices will vary widely (i.e., expect higher risk and a high variance), forward prices and, therefore, forward premiums will decrease. Peura and Bunn (2016) developed a model of spot and forward markets combining the hedging aspects of Bessembinder and Lemmon (2002) and the strategic aspects of Allaz and Vila (1993). They also analyze the impact of intermittent wind on these markets. Gersema and Wozabal (2017) extended the model of Bessembinder and Lemmon (2002) by including wind power futures. Using a simulation, they found that market actors benefit from these futures due to specific hedging against wind power risks.

Many empirical analyzes have found different results when attempting to verify the derived functional relationship between the forward premium and the stated spot price distribution moments of Bessembinder and Lemmon (2002) (BL-relation). Empirical results vary across markets and chosen timescales for the premium. Furthermore, depending on the market, other drivers have been identified as important and forecast errors have been also considered. For example, Botterud et al. (2010) analyzed weekly risk premiums (negation of forward premiums) in the most mature hydro-dominated electricity market in the world (Nord Pool). They could not confirm the BL-relation, but found that variables referring to hydro power are further important drivers of the risk premium. At Nord Pool, hydro power (with marginal costs equal or close to zero) contributes the largest share to total electricity supply, which stands in contrast to the marginal-cost-based approach of Bessembinder and Lemmon (2002). Weron and Zator (2014) found a different effect of water reservoir levels on the risk premium as in Botterud et al. (2010) when revisiting the empirical research of forward and spot markets at Nord Pool due to potential empirical pitfalls (see section 5). They still could not confirm the BL-relation. Woo et al. (2015) found a positive effect of wind power on hourly forward premiums when analyzing Californian day-ahead and real-time electricity markets of the United States (US). In Woo et al. (2016), merit order effects are found and further analyzed in these markets. Redl et al. (2009) analyzed monthly forward premiums in German markets (among others) managed by the EEX. They could not confirm the negative effect of the variance of spot prices, but the positive effect of the skewness of spot prices on the forward premium. Moreover, in addition to drivers regarding risk assessment, they included drivers that refer to supply and demand in order to control for related shocks influencing spot prices. Redl and Bunn

(2013) expanded this research to analyze these premiums using a multi-factor model, and found other important drivers in these markets, such as forward premiums of gas production and a variable combining supply and demand shocks called the margin shock in order to estimate forecast errors. They found a positive effect of skewness and of a volatility factor of spot prices on the forward premium (the latter stands in contrast to the result reported by Bessembinder and Lemmon (2002)). Forward premiums in EEX markets were also analyzed by, for example, Diko et al. (2006), Kolos and Ronn (2008) and Benth et al. (2008).

3. Estimating forward premiums

German electricity markets have become even more volatile as the feed-in of high fluctuating renewables has increased. We find here that forward premiums significantly differ from zero (see Appendix A and Appendix B), which indicates that the no-arbitrage condition (cf. section 2) does not hold in current German electricity forward markets. Therefore, the BL-relation of Bessembinder and Lemmon (2002) explaining the forward premium and its forecast error is used as a starting point for estimation, with moments of the spot price distribution as explanatory variables to control for risk assessment. However, these drivers should only be able to explain premiums in recent German electricity markets to a limited extent, because marginal costs of renewables such as wind or solar power are also near or equal to zero and therefore stand in contrast to a marginal-cost-based approach. Thus, drivers of supply and demand (with a focus on wind power) are included to control for their related shocks. The variables are chosen according to the multi-factor analysis of premiums in Redl and Bunn (2013) because they empirically investigate determinants of ex-post forward premiums in German electricity forward and spot markets in a detailed way (without focusing on renewable power). The BL-relation explaining the forward premium is a linear function. Therefore, effects on the ex-post forward premium are estimated using ordinary least squares (OLS).

A detailed presentation of the data and discussion about regression variables and econometric preliminary analyzes such as stationarity tests are given in Appendix A and Appendix B. We use time series of monthly as well as of daily forward contracts of EEX German electricity markets to analyze month-ahead as well as day-ahead premiums. There exist many monthly as well as daily contracts, and both are therefore relevant to investigate. Furthermore, we want to investigate whether there is a significant difference in the wind shock effects on the forecast error of the forward premium when the maturity time shrinks from a monthly to a daily timescale.

We use time series of last several years (May 2009 to December 2015 for monthly data and November 2012 to December 2015 for daily data): This is a period in which renewables came to play an important role in German electricity markets as a result of the energy transition. Solar shock effects can only be investigated for daily premiums due to data availability from January 2011 on (see Appendix A and Appendix B). We further consider premiums including both base and peak load prices in order to analyze whether there are different renewable shock effects at peak load times.

4. Results

4.1. Month-ahead premium

The following general equation is estimated:

$$
\begin{aligned}
premium_{t,t+1} &= \beta_0 + \beta_1 spot_t + \beta_2 spot\_std.dev._t + \beta_3 spot\_skewness_t \\
&+ \beta_4 spot\_kurtosis_t + \beta_5 margin\_wind_t + \beta_6 margin\_wind\_shock_t \\
&+ \beta_7 margin\_hydro_t + \beta_8 margin\_hydro\_shock_t + \beta_9 basis_t \\
&+ \sum_{i=2}^{4} \gamma_i quarter_{i,t} + \sum_{j=2}^{7} \delta_j year_{j,t} + \epsilon_t, \qquad (2)
\end{aligned}
$$

where *premium* is the one month ex-post forward premium, *spot* the current spot price mean variable, *spot_std.dev.* the current spot price standard deviation variable, *spot_skewness* the current spot price skewness variable, *spot_kurtosis* the current spot price kurtosis variable, *margin_wind* the wind margin variable which is wind feed-in divided by total load at the current month t observable by forward market participants, *margin_wind_shock* its one month future shock which is wind feed-in divided by total load one month in the future not observable by forward market participants, *margin_hydro* the hydro margin variable which is hydro feed-in divided by total load at the current month t observable by forward market participants,

$margin\_hydro\_shock$ its one month future shock which is hydro feed-in divided by total load one month in the future not observable by forward market participants, and $basis$ the basis variable which is the difference between the forward and the current spot price. The sum of $quarter_i$ and $year_j$ are quarterly and yearly time dummies.

Table 1 shows regression results for both base and peak load month-ahead premiums. For regressing the base load premium the information criterion of Akaike (1974) (AIC) is minimized when using the mean and the kurtosis of the spot price, wind and hydro margin shocks and the basis as explanatory variables.[2] The very high correlation between spot price skewness and kurtosis should not lead to multicollinearity.[3] The skewness variable is insignificant in both base and peak regressions with and without including spot kurtosis and, therefore, the insignificance is not due to omitted variable bias. Moreover, multicollinearity should be not the case because spot skewness is also insignificant when spot kurtosis is omitted. Thus, regressions without spot skewness are considered instead for interpretation.

The positive effect of the wind margin shock on the base load forward premium can be interpreted in line with the argument in Redl and Bunn (2013) regarding misjudgments of future supply, i.e. as an effect on the forecast

[2]The AIC is additionally used because regression models with different drivers explaining the premium can be seen as competing models as in Redl and Bunn (2013).

[3]Following Verbeek (2008) multicollinearity might be a problem if the modulus of a cross-correlation between explanatory variables (cf. Table A.4 in Appendix A) exceeds 0.8.

VARIABLES	premium	premium	premium	premium_peak	premium_peak	premium_peak
spot	0.00699***	0.00786***	0.00586**	0.00596**	0.00697**	0.00439
	(0.00211)	(0.00242)	(0.00276)	(0.00294)	(0.00309)	(0.00318)
spot_std.dev.	0.00194	0.00277	0.00272	0.00466	0.00581*	0.00575*
	(0.00242)	(0.00326)	(0.00269)	(0.00291)	(0.00313)	(0.00302)
spot_kurtosis	0.00120***		0.00206***	0.00146**		0.00266**
	(0.000228)		(0.000648)	(0.000630)		(0.00114)
margin_wind	-0.481	-0.545	-0.504	-0.413	-0.499	-0.446
	(0.338)	(0.333)	(0.350)	(0.399)	(0.412)	(0.398)
margin_wind_shock	1.416***	1.454***	1.361***	1.702***	1.746***	1.626***
	(0.197)	(0.233)	(0.180)	(0.339)	(0.351)	(0.343)
margin_hydro	-1.663	-2.048	-1.720	-0.163	-0.665	-0.242
	(1.380)	(1.347)	(1.588)	(2.294)	(2.357)	(2.284)
margin_hydro_shock	6.809***	7.042***	6.739***	4.063*	4.357**	3.966*
	(1.180)	(1.163)	(1.246)	(2.118)	(2.177)	(2.109)
basis	0.00717***	0.00708***	0.00813***	0.00575*	0.00573	0.00709**
	(0.00243)	(0.00214)	(0.00207)	(0.00330)	(0.00353)	(0.00346)
spot_skewness		-0.0101	0.0149		-0.0114	0.0208
		(0.00853)	(0.0121)		(0.00939)	(0.0166)
Constant	-0.591***	-0.609***	-0.554***	-0.328*	-0.347*	-0.276
	(0.118)	(0.108)	(0.138)	(0.170)	(0.178)	(0.175)
Quarterly dummies	Yes	Yes	Yes	Yes	Yes	Yes
Yearly dummies	Yes	Yes	Yes	Yes	Yes	Yes
F(p-value)	0.000	0.000	0.000	0.000	0.000	0.000
R-squared	0.601	0.579	0.608	0.621	0.598	0.631
Adj. R-squared	0.49	0.461	0.491	0.516	0.486	0.52
Observations	79	79	79	79	79	79

Standard errors of Newey and West (1987) in parentheses in base load regressions in order to control for autocorrelated residuals.
The test of Breusch (1978) and Godfrey (1978) for residual autocorrelation is used.
Non-robust standard errors in parentheses in peak load regressions.
Test results for no autocorrelated residuals are available from the author upon request.
*** p<0.01, ** p<0.05, * p<0.1.

Table 1: Drivers of the month-ahead base and peak load premium

error of the ex-ante premium. The effect refers to a wind shock and not to a load shock as will be shown in the robustness checks. The wind shock (a specific supply-type shock) included in the wind margin shock shifts the supply curve to the right due to the merit order effect at the time when the spot price is realized. Because of this, the spot price should fall. Furthermore, the spot price should fall below the forward price determined one month before because the unexpected wind shock one month ahead cannot be taken into account in the forward price accurately. This effect can be interpreted as a risk mark-up on forward prices resulting from higher intermittent wind feed-in and related increased spot price volatility. It reveals a specific component of the difference between the ex-post and ex-ante premium regarding wind power shocks. The data suggests that if there is a wind margin shock of 1

%, the premium increases on average by around 6 % which also shows the importance of unexpected wind in forward markets.

The positive sign of this effect is in line with the one in Woo et al. (2015). It is also in line with Woo et al. (2016), who also identified that forward premiums depend on wind forecast errors. Parts of the wind shock variable in this paper should be attributed to these forecast errors. Considering the theoretical model of Ritz (2016), the forward price falls in any case if there is an increase in intermittent renewable power. This increase leads to a displacement of power production in the spot market (merit order effect) and to lower incentives to make forward commitments (forward-contracting effect). The spot price falls only when renewable penetration is sufficiently high, i.e., when the merit order effect outweighs the forward-contracting effect leading to a rising ex-ante premium. Even if the estimated effect in this paper is not comparable and some model assumptions in Ritz (2016) such as the no-arbitrage condition are likely to be violated this large penetration might be (on average) the case in the investigated German electricity markets. In the model of Peura and Bunn (2016), where a no-arbitrage assumption is not included, ex-ante premiums are also likely to increase due to a wind increase when expected wind power is high and the renewable subsidy scheme is a feed-in tariff.

Spot price volatility, one theoretical effect on the forward premium according to Bessembinder and Lemmon (2002), is not significant. The effect of the spot price kurtosis as a higher distribution moment and the basis effect is positive and significant and, therefore, in line with arguments of Redl and Bunn (2013). These effects are discussed in Appendix A. In addition, there is a positive significant effect of the current spot price mean on the forward premium. Intuitively, forward prices should take into account the current spot price when trying to anticipate expected future spot prices. Therefore, the forward premium should rise when the current spot price rises.

Regarding the month-ahead peak load premium, the AIC is minimized when using the same explanatory variables and in addition the standard deviation of the spot price. However, the standard deviation is an insignificant driver when considering the regression without spot skewness.

Again, there are positive wind margin shock effects on the peak load forward premium. The wind margin shock effect on the peak load premium is slightly larger than on the base load premium. At peak load times, there is a higher demand for power. Thus, more power supply (normally with gas as the back-up generation type) is needed, leading to a higher equilibrium spot price. If there is an unexpected wind shock at peak load times, the future spot price might fall further below the forward price due to higher differences in marginal generation costs at the right of the merit order curve. Therefore, there should be a larger risk mark-up on forward prices. The other control effects are more or less the same as in the base load regression.

When comparing the empirical results reported by Redl and Bunn (2013) for EEX markets, the peak regression fit considering the R-squared of around 0.6 in this paper is relatively high (0.25 in Redl and Bunn (2013)). In this paper, there is also a significant positive basis effect. The skewness effect is insignificant. This stands in contrast to the effect for peak load reported by Redl and Bunn (2013), who found no significant spot price kurtosis effects but a significant spot price volatility effect for base load premiums. These differences may be due to the much lower renewable power feed-in during the earlier time period from November 2003 to December 2009. In this paper, forward premiums are probably not explained by margin effects of the current month, in contrast to the results reported in Redl and Bunn (2013) (see also section 5). However, the latter defined the margin as the share of total supply in the total load. Besides the argument of the different time period, there should be no problem taking current wind power production into account in the forward contract determined in the same month and, therefore, no effect on the forward premium.

4.2. Day-ahead premium

For both base- and peak load premiums the AIC is minimized when using only spot price standard deviation, wind shock, and solar margin as explanatory variables in the regression.

The following general equation is estimated:

$$
\begin{aligned}
premium_{t,t+1} &= \beta_0 + \beta_1 spot_t + \beta_2 spot\_std.dev._t + \beta_3 spot\_skewness_t \\
&+ \beta_4 spot\_kurtosis_t + \beta_5 margin\_wind_t + \beta_6 margin\_wind\_shock_t \\
&+ \beta_7 margin\_solar_t + \beta_8 margin\_solar\_shock_t + \beta_9 basis_t \\
&+ \sum_{i=2}^{7} \gamma_i week_{i,t} + \sum_{j=2}^{12} \delta_j month_{j,t} + \sum_{k=2}^{4} \eta_k year_{k,t} + \epsilon_t,
\end{aligned} \tag{3}
$$

where *premium* is the one day ex-post forward premium, *spot* the current spot price mean variable, *spot_std.dev.* the current spot price standard deviation variable, *spot_skewness* the current spot price skewness variable, *spot_kurtosis* the current spot price kurtosis variable, *margin_wind* the wind margin variable which is wind feed-in divided by total load at the current day t observable by forward market participants, *margin_wind_shock* its one day future shock which is wind feed-in divided by total load one day in the future not observable by forward market participants, *margin_solar* the solar margin variable which is solar feed-in divided by total load at the current day t observable by forward market participants, *margin_solar_shock* its one day future shock which is solar feed-in divided by total load one day in the future not observable by forward market participants, and *basis* the basis variable which is the difference between the forward and the current spot price. The sum of $week_i$, $month_j$ and $year_k$ are weekly, monthly and yearly time dummies.

Table 2 shows the regression results when all drivers are included as well as when only choosing the variables suggested by minimized AIC. The very high correlation between solar margin and its shock (cf. table B.7 in Appendix B) should not lead to multicollinearity because the solar margin shock is insignificant in all regressions, whether with or without solar margin (see also section 4.1). Thus, only regressions omitting the solar margin shock are considered for interpretation.

VARIABLES	premium	premium	premium	premium	premium	premium	premium_peak	premium_peak	premium_peak	premium_peak	premium_peak	premium_peak
spot	-1.14e-06	-7.24e-07	-9.73e-07				2.62e-07	1.46e-07	3.34e-07			
	(1.07e-06)	(1.06e-06)	(1.08e-06)				(9.08e-07)	(8.80e-07)	(8.98e-07)			
spot_std.dev.	2.68e-06*	2.61e-06*	2.61e-06*	1.73e-06	1.98e-06*	1.70e-06	1.61e-06	1.57e-06	1.58e-06	1.89e-06	1.72e-06	1.87e-06
	(1.44e-06)	(1.45e-06)	(1.46e-06)	(1.14e-06)	(1.12e-06)	(1.14e-06)	(1.46e-06)	(1.47e-06)	(1.46e-06)	(1.31e-06)	(1.30e-06)	(1.31e-06)
spot_skewness	1.41e-06	-2.09e-06	1.12e-06				-7.67e-06	-5.37e-06	-7.80e-06			
	(7.87e-06)	(7.63e-06)	(7.90e-06)				(6.86e-06)	(6.81e-06)	(6.92e-06)			
spot_kurtosis	-4.64e-06	-4.27e-06	-4.62e-06				1.36e-06	1.11e-06	1.37e-06			
	(3.33e-06)	(3.33e-06)	(3.39e-06)				(4.02e-06)	(3.97e-06)	(4.02e-06)			
margin_wind	-1.68e-05	2.07e-05	-2.71e-05				3.44e-05	-6.31e-06	2.98e-05			
	(8.87e-05)	(8.94e-05)	(8.95e-05)				(8.41e-05)	(8.30e-05)	(8.43e-05)			
margin_wind_shock	6.00e-05	5.28e-05	8.29e-05	9.79e-05**	0.000101**	0.000102**	8.40e-05	0.000117	9.42e-05	0.000104**	0.000106**	0.000105**
	(7.58e-05)	(7.98e-05)	(7.82e-05)	(4.85e-05)	(4.86e-05)	(4.86e-05)	(8.00e-05)	(7.99e-05)	(7.92e-05)	(4.18e-05)	(4.21e-05)	(4.21e-05)
margin_solar	-0.000242		-0.000330*	-0.000212		-0.000313*	0.000288*		0.000249	0.000209		0.000172
	(0.000166)		(0.000192)	(0.000148)		(0.000180)	(0.000166)		(0.000203)	(0.000151)		(0.000200)
basis	-3.10e-07	-3.60e-07	-1.30e-08				-1.86e-07	2.07e-07	-5.52e-08			
	(9.88e-07)	(1.04e-06)	(1.02e-06)				(1.01e-06)	(9.62e-07)	(9.41e-07)			
margin_solar_shock		1.33e-05	0.000169		2.53e-05	0.000189		0.000192	7.46e-05		0.000158	6.82e-05
		(0.000137)	(0.000162)		(0.000128)	(0.000160)		(0.000161)	(0.000199)		(0.000155)	(0.000206)
Constant	2.21e-05	-4.29e-06	1.36e-05	-3.31e-05	-3.82e-05	-3.26e-05	-6.60e-05	-5.62e-05	-6.98e-05	-4.77e-05*	-4.45e-05	-4.75e-05*
	(5.06e-05)	(4.90e-05)	(5.07e-05)	(2.61e-05)	(2.63e-05)	(2.60e-05)	(5.22e-05)	(4.95e-05)	(5.13e-05)	(2.79e-05)	(2.74e-05)	(2.79e-05)
Weekly dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Monthly dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Yearly dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F(p-value)	0.6152	0.718	0.584	0.4799	0.6485	0.4254	0.0126	0.0168	0.0181	0.0052	0.004	0.0061
R-squared	0.031	0.029	0.033	0.028	0.025	0.029	0.038	0.036	0.038	0.036	0.035	0.036
Adj. R-squared	-0.002	-0.005	-0.002	0.001	-0.002	0.001	0.005	0.003	0.004	0.009	0.008	0.009
Observations	778	778	778	778	778	778	778	778	778	778	778	778

Standard errors of Newey and West (1987) in parentheses in order to control for autocorrelated and heteroskedastic residuals.
The test of Breusch (1978) and Godfrey (1978) for residual autocorrelation is used.
*** p<0.01, ** p<0.05, * p<0.1.

Table 2: Drivers of the day-ahead base load and peak load premium

Most of the effects are not significant in any regression. For base load, only spot price standard deviation and the wind margin shock (also suggested by AIC) are significant in several regressions (wind margin shock only when omitting variables not suggested by AIC). No significant solar shock is found, as stated above. Both significant effects are positive. The argument for a positive wind margin shock is the same as for month-ahead premiums. The positive spot price standard deviation effect as a volatility effect stands in contrast to the results of Bessembinder and Lemmon (2002), as stated in section 2, but is in line with Redl and Bunn (2013) as stated in Appendix A. Due to the convexity of the merit order, shocks creating high volatility and skewness are similar and should have similar signs. However, there is no significant skewness effect on day-ahead premiums.

For peak load, only the wind margin shock and solar margin are significant (again wind margin shock only when omitting variables not suggested by AIC). The wind margin shock effect is still positive. The solar margin effect is only slightly significant in one peak load regression, and the positive sign is contrary to Redl and Bunn (2013) and counter-intuitive.

For both base and peak load, all effects are in principle zero, even if they are significant. For base load, even the null of the F-test that all explanatory variables are mutually zero cannot be rejected. Reducing the maturity of the forward contract substantially from one month to one day is likely to lead to almost perfect approximations of the expected spot price at the time when the day-ahead forward contract is determined (see also Appendix B). This should lead to forward premiums as well as effects on the forward premium very close to zero, although Wald-test results shown in Appendix B present significant non-zero day-ahead premium means.

5. Robustness Checks

Table C.9 in Appendix C shows effects on month-ahead base and peak load premiums when the margin variables for wind and hydro power are included separately and related margin shock variables are omitted. For both base and peak load, the wind margin shock, if included, is significant in all regressions. Comparing the different base and peak load regressions separately, the effects are very similar. The wind margin variable is not significant in any regression when the wind margin shock variable is not included. This indicates that the effect of the wind margin shock variable indeed refers to unobservable wind power shocks occurring at the delivery date and not to other unspecified shocks also captured by this variable.

Regarding hydro power, in the base load regressions, the hydro margin variable is significant when the margin shock variable is omitted. It turns into an insignificant driver when the margin shock variable is included as well. Therefore, in contrast to wind power, there may be unspecified shocks in the hydro margin shock variable that do not refer to hydro shocks. Thus, interpretation of the hydro margin shock variable is not clear.

The spot price kurtosis as well as the spot price mean effect are significant and similar in all base and peak regressions. The standard deviation effect is insignificant in the regressions. The basis effect is insignificant in several regressions. This might be due to omitting wind or hydro margin shocks.

Table C.10 in Appendix C shows regression results for day-ahead premiums when the wind margin variable is included separately and together with its shock. All insignificant drivers, as stated in section 4.2, are omitted. The coefficient signs have not changed. Spot price standard deviation is insignificant in most regressions. The wind margin variable turns from significance to insignificance when its shock is included as well. Thus, the wind margin shock variable might not only capture wind shocks but other unspecified shocks as well. However, day-ahead premiums near zero should lead to effects on them near zero at all. For base load again the null of the F-test that all explanatory variables are mutually zero cannot be rejected.

Table C.11 in Appendix C shows regression results for month-ahead base- and peak load premiums when the margin and margin shock variables due to wind and hydro power are decomposed into single wind, hydro, and load and their shocks. Wind and hydro shocks are still positive significant effects on base- and peak load premiums (again the wind shock effect is larger on the peak load premium), but the load shock itself is insignificant in all regressions. The driver of the wind margin shock variable is indeed the wind shock. The hydro margin shock should be interpreted with caution as stated above. Margin variables are still insignificant.

Table C.12 in Appendix C shows related regression results for the day-ahead premiums. Again only the variables likely to be significant are included and, therefore, solar is also omitted. The wind shock effect is positive and significant, but the load shock is insignificant in both regressions. Therefore, the wind margin shock might be again driven by the wind shock. Wind itself is insignificant in both regressions, but load itself is significant for the peak premium (with a counter intuitive sign, cf. Redl and Bunn (2013)). The effects are again in principle zero, which is likely due to day-ahead forward premiums very close to zero. Again, for base load, the null of the F-test that all drivers are mutually zero cannot be rejected.

Weron and Zator (2014) stated that there may be simultaneity problems if the current spot price is included on the right-hand side of the regressions because the forward price on the left-hand side might influence the current spot price. However, the forward premium as the dependent variable is defined as the difference between two different random variables (current forward and future spot price). Moreover, the future spot price is constructed as the mean of all hourly random spot prices in the future month. Finally this difference is divided by the future spot price (cf. Appendix A and Appendix B). Therefore, this constructed random variable, the forward premium, should not be the same stochastic process as the single current spot price. Thus, simultaneity is unlikely the case. This is also clearly shown by t-test results of significantly no equal means of premiums and spot prices (cf. table C.13 in Appendix C).[4] Including the basis on the right hand side should also be no problem, since the premium should also not be the same stochastic process as the difference between current forward and spot price. According again to Weron and Zator (2014), significance test results after OLS estimations may be biased due to autocorrelated conditional heteroskedastic (ARCH) resid-

[4]Regressions when omitting the spot price as an explanatory variable are additionally conducted. The results are very similar (available from the author upon request).

uals. Table C.14 in Appendix C shows related test results for month- and, respectively, day-ahead premiums after applying the LM-test of Engle (1982) for ARCH residuals. The null of no ARCH residuals cannot be rejected for month-ahead premiums or for the day-ahead base load premium. For the day-ahead peak load premium, there may be ARCH residuals. However, the significance level of 9.1 % for rejecting the null is high.[5] Moreover, as stated above, day-ahead premiums and related effects on them are in principle zero.

6. Conclusion

The main aim in this paper has been to empirically analyze the effect of intermittent renewable supply on ex-post forward premiums and forecast errors of ex-ante premiums in German electricity markets. Significant positive wind shock effects on both month-ahead and day-ahead ex-post forward premiums are found for German electricity markets using OLS. The effects are in line with empirical studies on other countries as well as with results from theoretical studies that consider a feed-in tariff and/or high renewable penetration, even if the theoretical effects on ex-ante premiums are not directly comparable. Control effects reported here are also in line with past literature. The wind shock as a specific supply-type shock shifts the supply curve to the right due to the merit order effect at the time when the spot price is realized. Therefore, ex-post forward premiums should rise. The wind

[5]In Weron and Zator (2014) test results and significance levels are not presented.

shock effect on day-ahead forward premiums is substantially lower, i.e., close to zero. Shrinking the maturity of the forward contract substantially to the very near future leads likely to almost perfect approximations of the expected spot price at the time when the forward contract is determined. This should lead to forward premiums as well as effects on the forward premium near zero. No significant solar shock effect on daily premiums is found. The wind shock effect on month-ahead peak load premiums is larger than on base load. This should be due to higher differences in marginal costs at the right of the merit order curve and, therefore, to a larger spot price decrease.

A rise in ex-post forward premiums can be interpreted as a risk mark-up on forward prices resulting from higher intermittent wind feed-in, as stated in section 4.1, when market participants use "standard" forward contracts, but no specific wind power futures. The EEX has introduced a new wind power future (see section 1) and clearly states that this future is a "hedging instrument against wind induced power price volatility".[6][7] Therefore, a "standard" forward contract is likely not precisely the instrument to deal with all kinds of risk. The findings in this paper underline the need to create a new instrument dealing with risks of wind power for month-ahead forward contracts in order

[6]`https://www.eex.com/en/products/energiewende-products/wind-power-futures`

[7]EEX wind power futures can be seen as specific weather derivatives. Using an underlying index referring to the average demand covered by wind power over the contract maturity (based on German meteorological service data) future prices (similar to those of "standard" forward contracts) for contracts with different maturities are derived, but now focusing only on power delivery covered by wind power.

to reduce the risk mark-up found in this paper for participants in forward markets as much as possible. Participants such as conventional producers should then get a better insurance against price risks when using wind power futures instead of using only a "standard" forward contract.[8] However, such an instrument might not be necessary for day-ahead contracts because in principle no effects and therefore also no wind shock effects on day-ahead premiums are found. This is at least partly in line with the EEX strategy, which is creating such an instrument for contracts with maturities of weeks, months, quarters, or years, but not days.

There may be also solar shock effects on month-ahead premiums. However, in the present paper, that analysis has not been possible due to data availability. This might be a fruitful area for further research. Other control variables as in Redl and Bunn (2013) such as forward premium for gas are not included due to lack of data, which further research could also account for. Dynamic behavior of wind and solar power influencing spot prices (cf. Paschen (2016)) could also be taken into account in future analyzes of forward premiums.

[8] In addition Cap and Floor futures for German intraday markets were also introduced as instruments to hedge specifically "against positive or negative price spikes on the intraday market resulting from the growing share of renewables" at EEX (see `https://www.eex.com/en/products/energiewende-products/german-intraday-cap-futures`) which are also important for market participants such as conventional producers.

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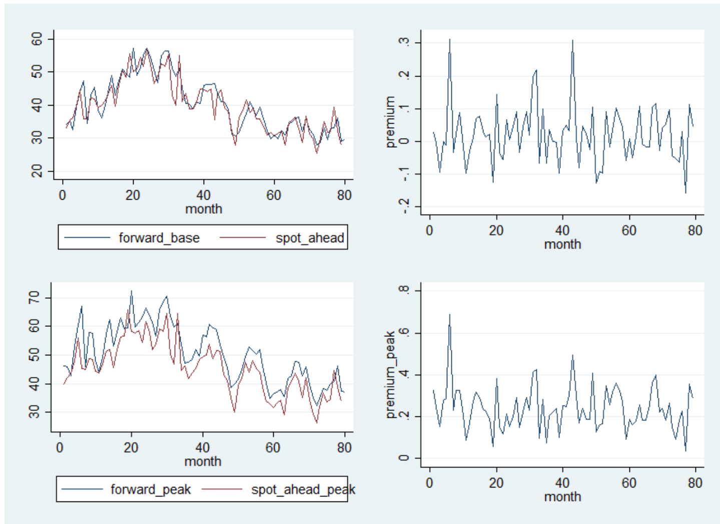
Appendix A. Monthly data

The time period from May 2009 to December 2015 includes 80 monthly observations.[9] For monthly base contracts yearly average quantities worth 3.9 billion € , and 560 million € for monthly peak contracts were traded. Contracts including all hours of the day seem to be much more important. We use Phelix one-month forward prices of the contracts made on the last trading day in every month for the following month. When using monthly data, forecast errors referring to month-ahead premiums should be as low as possible (cf. Redl et al. (2009)). The last trading day is chosen in order to use the best expectation of the spot price of the next month of market participants as in Redl and Bunn (2013). Spot prices are average monthly prices of hourly time series of day-ahead spot prices traded at the EEX.[10] The variable to be explained, both for base and peak load,[11] is the relative ex-post forward premium, which is the ex-post forward premium defined in

[9] The number of monthly observations is not very high. However, it should be high enough to conduct econometric analyzes (cf. Redl and Bunn (2013) where the number of monthly observations is even lower).

[10] Data source for monthly Physical Electricity Index (Phelix) future and spot prices for the market area of Germany and Austria is EEX (`http://www.eex.com/de/`). For the investigated time period, many monthly forward contracts with different monthly maturities are set every day. We use forward settlement prices (€/MWh) of the last trading day for the next month in every month. Original spot prices are day-ahead settlement prices (€/MWh) for each hour of the next day.

[11] For base load, the underlying for daily forward prices are daily averages of hourly day-ahead spot prices (Phelix Day Base). For peak load, the underlying are daily averages of hourly day-ahead peak spot prices (Phelix Day Peak) considering only peak hours from 8:00 am to 8:00 pm of the next day.



Y-axis: Forward, spot prices (€/MWh) and relative premiums (base (upper graphics) and peak load (lower graphics)).

Figure A.1: Monthly time series forward, one month future spot prices and forward premiums

section 2 divided by the realized future spot price:

$$premium_{t,t+1} = \frac{forward_{t,t+1} - spot_{t+1}}{spot_{t+1}},$$
$$premium\_peak_{t,t+1} = \frac{forward\_peak_{t,t+1} - spot\_peak_{t+1}}{spot\_peak_{t+1}}. \tag{A.1}$$

Figure A.1 shows time series of forward prices, realized one month future spot prices (*spot_ahead*), and forward premiums. Starting in May 2009, both base and peak load spot prices increase over time up to the end of 2010. From the beginning of 2011 on, they decrease, which should be due to the merit order effect resulting from renewables. The time series also clearly indicate seasonal behavior, with higher prices in months with higher demand (autumn and winter). The behavior of spot prices over time is relatively well anticipated by the forward prices. Peak load prices are higher than base load prices due to higher demand at peak hours of the day. For peak load, forward prices overestimate spot prices more than for base load, and there is no underestimation. Therefore, the peak load forward premium is higher than for base load and is always positive. For base load, there are also months of underestimating the spot price, resulting in negative premiums. In contrast to Redl and Bunn (2013), time fixed effects modeled as quarterly and yearly time dummies are included in the regressions to capture seasonal behavior in the price series as well as in several following explanatory variables.[12]

Table A.3 presents descriptive statistics of both base and peak forward premiums, forward and realized future spot prices, and of potential explanatory variables. Both premium means are positive, mean and standard deviation of the peak premium are higher than those of the base premium as in Redl and Bunn (2013). This clearly indicates the existence of non-zero premiums and, therefore, the invalidity of the no-arbitrage condition in German markets, as discussed in section 3. Furthermore, non-zero premium means are significant (cf. again table A.3). For base premiums, forward prices are on average traded lower above spot prices on the last monthly trading day, but for peak premiums substantially higher. For both premiums there is less volatility than in Redl and Bunn (2013).

[12]Seasonality in the price series may be transferred to the premiums, the variables to be explained.

Variable	Obs	Mean	Std. Dev.	Min	Max	Test (p-value)
premium	79	.021	.086	-.159	.313	.0368
premium_peak	79	.24	.105	.035	.687	.000
forward_base	79	40.562	8.108	27.8	57.25	-
spot_ahead	79	39.833	7.704	25.358	56.831	-
forward_peak	79	50.662	9.971	32.31	72.25	-
spot_ahead_peak	79	45.326	9.136	26.161	65.791	-
spot (€/MWh)	79	39.873	7.649	25.358	56.831	-
spot_std.dev. (€/MWh)	79	14.139	4.558	6.311	38.719	-
spot_skewness	79	-.537	1.364	-8.422	2.057	-
spot_kurtosis	79	7.94	18.097	2.07	156.359	-
margin_wind	79	.092	.038	.037	.233	-
margin_hydro	79	.043	.007	.03	.066	-
basis (€/MWh)	79	.689	3.635	-9.803	11.292	-

Wald test (cf. Judge et al. (1985)) in last column with null hypothesis: Variable has zero mean.
Wind and hydro margin shocks are omitted because the series are one month future series of the margin variables, cf. equation A.2.

Table A.3: Descriptive statistics of monthly variables

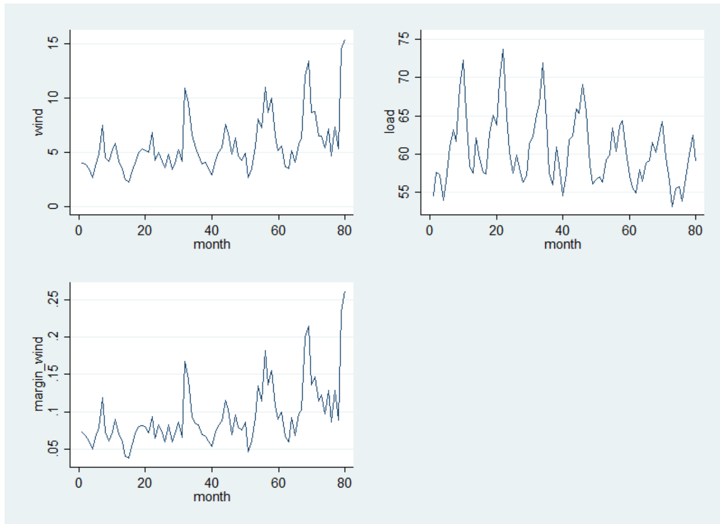
One explanatory variable is the wind margin, which is wind power divided by total load. Such a combined variable is used to control for both supply and demand (cf. Redl and Bunn (2013)). The difference is that supply looks only at the specific renewable type of wind generation to analyze the effect of wind supply alone on forward premiums. Current values of this variable in the same month when the forward contract is set are observable by market participants. However, wind and load shocks occurring in $t+1$ are not, which is captured in the one future month margin variable, the other variable of interest. These shocks are, therefore, effects on the forecast error of the ex-ante premium. To be specific, the wind margin shock is the wind margin one month in the future. In addition,[13] hydro margin (hydro power divided

[13]Data source for wind, hydro power, and load is the European Network of Transmission System Operators for Electricity (ENTSO-E) (`http://www.entsoe.eu/`). Load is average German total demand for power (GW) per month, including domestic load, net exports (exports minus imports, all electricity trades between respective countries), and network losses. Wind and hydro are average German wind power and, respectively, hydro power feed-in (GW) per month. In hydro, all types of hydro power available for German power generation are included.

by load) and its shock are further variables referring to a specific renewable supply type using this combined approach:

$$\begin{aligned} margin\_wind_t = \frac{wind_t}{load_t},\ margin\_wind\_shock_t = \frac{wind_{t+1}}{load_{t+1}}, \\ margin\_hydro_t = \frac{hydro_t}{load_t},\ margin\_hydro\_shock_t = \frac{hydro_{t+1}}{load_{t+1}}. \end{aligned} \tag{A.2}$$

According to Redl and Bunn (2013) these variables stand for fundamental and shock effects on forward premiums (focusing on specific supply types). Due to robustness checks, wind, hydro and load series are taken into account separately (see section 5). Other important variables in this context should be margin variables referring to intermittent solar power. However, not enough observations are available on a monthly timescale (data available starting in January 2011). Considering table A.3, wind power covers on average about 10% of total load, hydro about 4%. Volatility for wind is relatively high due to its inherent intermittency in contrast to hydro power, which in principle is constant. Figure A.2 presents time series of wind, load, and the wind margin. In both wind and load series, the same seasonal behavior is observable as in the price series indicating again that time dummies should be used in the regressions. Load and wind is higher in autumn and winter months. In the load series, there might also be yearly cyclical behavior. Wind power is rising over time due a higher focus on renewables in Germany and the priority feed-in and, therefore, relevant to investigate as stated in section 3. The behavior



Y-axis: Wind power (GW), load (GW) (upper graphics), wind margin (lower graphic).

Figure A.2: Monthly time series wind power, load and wind margin

of wind is in principle transferred to the wind margin (so that there should be no problem when analyzing wind margin instead of wind).

Further explanatory control variables are moments of the spot price distribution (also of higher order): Mean, standard deviation, skewness and kurtosis of hourly spot prices in every current month (notation: *spot* for the mean and *spot_moment* for the others). Standard deviation as a volatility factor and skewness are already included in the model of Bessembinder and Lemmon (2002) as drivers on the forward premium, as stated in section 2. Except for the mean, these variables refer to behavioral effects on forward premiums as reported in Redl and Bunn (2013). The authors argue that the spot price kurtosis on the premium should also have a positive effect due to increasing interest in fat tails and aversion to extreme outcomes of spot prices when assuming adaptive price expectations of market participants. In addition, the authors argue that the volatility effect could also be positive because, due to the merit order convexity, shocks creating high skewness and volatility could have the same signs. Table A.3 shows descriptive statistics of spot price controls. Monthly equilibrium spot price is about 40 €/MWh on average with a high standard deviation. Spot standard deviation and kurtosis are relatively high on average; kurtosis also has a high standard deviation. Spot skewness is very low, but negative on average.

A further control variable is the *basis*, the difference between current forward (last trading day) and spot (monthly average) prices, referring to dynamic effects on forward premiums as in Redl and Bunn (2013). When forming expectations about month-ahead spot prices, market agents may adapt these expectations to recent spot price averages. The effect of the basis on the forward premium should therefore be positive. Forward prices are on average traded above current spot prices on the last trading day of the current month, as shown in table A.3, but there is also moderate standard deviation. Table A.4 shows cross-correlations between explanatory variables.

All variables are tested for stationarity using the augmented unit root test of Dickey and Fuller (1979). All variables are found to be stationary and, therefore, their levels are used. The process under the null is assumed to be an autoregressive process of order 1 (AR(1)). By graphical inspection, it is not clear which test equation to choose. Therefore, different test equations are used and test decisions with a majority are selected. The time series

Variables	spot	spot_std.dev.	spot_skewness	spot_kurtosis	margin_wind	margin_wind_shock	margin_hydro	margin_hydro_shock	wind	wind_shock	hydro	hydro_shock	load	load_shock	basis
spot	1.000														
spot_std.dev.	0.100	1.000													
spot_skewness	0.109	-0.462	1.000												
spot_kurtosis	-0.025	0.523	-0.832	1.000											
margin_wind	-0.415	0.184	0.029	-0.029	1.000										
margin_wind_shock	-0.187	0.112	0.146	0.002	0.643	1.000									
margin_hydro	-0.619	-0.155	-0.014	-0.104	-0.020	-0.090	1.000								
margin_hydro_shock	-0.510	-0.218	0.157	-0.148	0.058	-0.010	0.723	1.000							
wind	-0.338	0.236	0.035	-0.026	0.989	0.637	-0.105	-0.015	1.000						
wind_shock	-0.117	0.173	0.127	0.015	0.643	0.989	-0.163	-0.093	0.651	1.000					
hydro	-0.528	0.016	0.013	-0.124	0.060	-0.026	0.913	0.665	0.028	-0.068	1.000				
hydro_shock	-0.393	-0.048	0.158	-0.145	0.151	0.068	0.596	0.913	0.115	0.038	0.643	1.000			
load	0.418	0.365	0.048	0.010	0.150	0.138	-0.563	-0.400	0.291	0.231	-0.186	-0.142	1.000		
load_shock	0.411	0.428	-0.108	0.091	0.150	0.144	-0.522	-0.551	0.254	0.283	-0.285	-0.171	0.688	1.000	
basis	-0.111	0.150	-0.444	0.158	0.040	-0.193	0.139	-0.255	0.024	-0.154	0.096	-0.200	-0.161	0.220	1.000

Table A.4: Cross-correlations of explanatory monthly variables

of wind and wind margin indicate trends. However, test results indicate stationarity in levels for wind power and wind margin, especially when a trend is included. Thus, these variables are selected to be stationary (cf. table A.5).

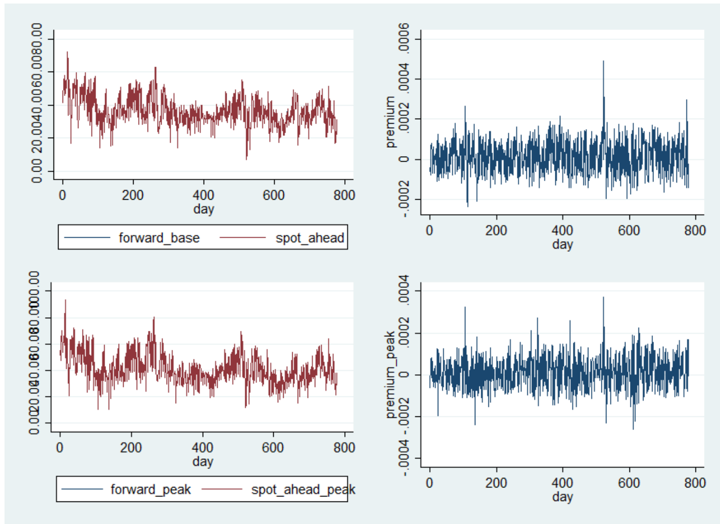
Variables	no constant, no trend	constant, no trend	constant, trend
premium	$< .01$	2.620e-14	1.460e-13
premium_peak	$.01 < p < .05$	8.410e-12	1.137e-10
spot	$> .1$	.00267823	.00567495
spot_std.dev.	$.01 < p < .05$	5.796e-09	1.682e-07
spot_skewness	$< .01$	1.011e-12	2.107e-12
spot_kurtosis	$< .01$	2.690e-12	9.000e-12
margin_wind	$> .1$	.00245314	.00451365
margin_hydro	$> .1$	.00019365	.00479535
wind	$> .1$	.00168411	.00954781
hydro	$> .1$	.00004289	.00147819
load	$> .1$	.00010081	.00584689
basis	$< .01$	2.331e-15	1.672e-15
MacKinnon approximate p-values.			
Null hypothesis: Variable has a unit root.			
Test equations include trend, constant or none.			

Table A.5: Augmented Dickey-Fuller test for unit roots for monthly time series

Appendix B. Daily data

The time period is November 22, 2012 to December 30, 2015, including 778 daily observations. For daily base contracts yearly average quantities worth 43 million € , and 22 million € for daily peak contracts were traded. Comparing with monthly contracts it seems that hedging against prices at much later future dates is much more important due to higher uncertainty. We use Phelix one-day forward prices made one trading day before the following day. At EEX, day-ahead forward contracts have the shortest maturity. Besides following the argument that this keeps corresponding forecast errors as low as possible, we want to compare month-ahead premiums with premiums when the maturity of the forward contract is as short as possible. At the EEX, forward contracts with maturities of one day are a relatively new financial tool. These contracts were introduced at the end of 2012 (data available starting on November 22, 2012).[14] Therefore, the time period as a whole is about 3 years shorter for these data than for the data on month-ahead premiums. However, renewable feed-in has been present in Germany especially in the last few years and, thus, this time period is also relevant. Spot prices are the daily indices (Phelix Day Base, Phelix Day Peak), the average base and peak daily prices of hourly time series of day-ahead spot prices traded

[14]Day-ahead forward contracts existed before 2012 at the Over-The-Counter (OTC) market. However, this paper focuses on non-bilateral contracts.



Y-axis: Forward, spot prices (€/MWh) and relative premiums (base (upper graphics) and peak load (lower graphics)).

Figure B.3: Daily time series forward, one day future spot prices and forward premiums

at the EEX.[15] Dependent variable is the relative ex-post forward premium as in Appendix A, now using daily data:

$$premium_{t,t+1} = \frac{forward_{t,t+1} - spot_{t+1}}{spot_{t+1}},$$
$$premium\_peak_{t,t+1} = \frac{forward\_peak_{t,t+1} - spot\_peak_{t+1}}{spot\_peak_{t+1}}. \tag{B.1}$$

Figure B.3 shows time series of forward prices, future spot prices (*spot_ahead*), and forward premiums. Decreasing prices due to the merit order effect in that time period are also present, as well as seasonal behavior (cf. Appendix A).

[15]Data source for Phelix future and spot prices is again EEX, as in Appendix A. We use forward settlement prices (€/MWh) for the next day at (only) every trading day. Original spot prices are day-ahead settlement prices (€/MWh) for each hour of the next day.

In addition, weekly behavior might also be observable. By graphical inspection of the price series, no difference in the forward and realized future spot prices is observable, resulting in forward premiums very close to zero. It seems that approximations of one-day future spot prices are nearly perfect. However, as shown in table B.6, Wald test results indicate that the premiums are significantly different from zero. Therefore, analyses of day-ahead premiums are considered in this paper as well, despite premiums near zero. Time fixed effects modeled as weekly, monthly, and yearly time dummies are included in the OLS regressions in order to capture seasonal behavior in daily price series as well as in several subsequent daily explanatory variables. Table B.6 shows descriptive statistics of the premiums, forward and future spot prices, and of explanatory variables. Descriptive moments and statistics of the premiums are zero.

Variable	Obs	Mean	Std. Dev.	Min	Max	Test (p-value)
premium	778	0	0	0	0	0
premium_peak	778	0	0	0	0	0
forward_base	778	36.761	9.071	6.78	72.07	-
spot_ahead	778	36.761	9.071	6.78	72.069	-
forward_peak	778	41.545	11.958	10.33	93.19	-
spot_ahead_peak	778	41.545	11.958	10.327	93.192	-
spot	778	38.383	8.521	4.453	72.069	-
spot_std.dev.	778	10.506	3.781	3.094	29.102	-
spot_skewness	778	.012	.611	-1.837	2.861	-
spot_kurtosis	778	2.295	.982	1.192	12.233	-
margin_wind	778	.107	.09	.006	.476	-
margin_solar	778	.063	.044	.001	.183	-
basis	778	-1.621	6.556	-29.669	23.313	-

Wald test (cf. Judge et al. (1985)) in last column with null hypothesis: Variable has zero mean.
Wind and solar margin shocks are omitted because the series are one day future series of the margin variables, cf. equation B.2.

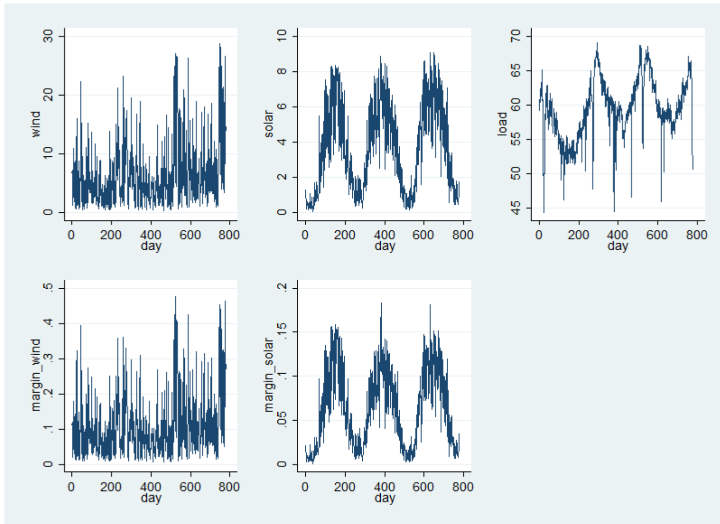
Table B.6: Descriptive statistics of daily variables

Explanatory variables are again the margin variables and their shocks (main explanatory variables, cf. Appendix A) for daily data. Production types are now wind and solar:[16]

$$
\begin{aligned}
margin\_wind_t = \frac{wind_t}{load_t},\ margin\_wind\_shock_t = \frac{wind_{t+1}}{load_{t+1}},\\
margin\_solar_t = \frac{solar_t}{load_t},\ margin\_solar\_shock_t = \frac{solar_{t+1}}{load_{t+1}}.
\end{aligned} \tag{B.2}
$$

Margin shocks are now the margin variables one day in the future. German solar data is available starting in January 2011 as stated in Appendix A. Therefore, enough observations to conduct regressions are available when using daily data. Separate wind, solar, and load series are analyzed in section 5. Hydro data are not available on a daily timescale. Considering table B.6, wind power covers on average about 10% of total load also for this time period on a daily timescale. Solar covers about 6%. Volatility for wind is now higher compared to monthly data due to also intermittent feed-in on different days. Solar power also deviates from the mean to a relatively large extent due to its intermittency, but only amounts to half of wind volatility. Figure B.4 shows daily time series of wind, wind margin, solar, solar margin, and load. Again, wind and load is higher in the autumn and winter months. Solar is, in contrast, higher in spring and summer due to more days of solar power

[16] For wind and solar data sources are the German transmission system operators (http://www.amprion.net,http://www.tennettso.de,http://www.50hertz.com/de,http://www.transnetbw.de). Original data is average German power feed-in (MW) per 15 minutes. Few days are omitted due to data gaps on specific days from specific sources. Data is transformed into average power feed-in (GW) per day. For load data, the source is again ENTSO-E (http://www.entsoe.eu/). Original load is average German total demand (cf. Appendix A) for power (MW) per hour. Data is transformed into average demand (GW) per day.



Y-axis: Wind power (GW), solar power (GW), load (GW) (upper graphics), wind margin, solar margin (lower graphics).

Figure B.4: Daily time series wind power, solar power, load, wind margin and solar margin

available in those months. Rising wind power over time is again observable. Solar power is relatively constant. In daily load, there might also be a cyclical weekly behavior in addition to possible yearly cyclical behavior present. The behavior of wind and solar are transferred to the margin variables.

Control variables referring to the spot price distribution are the same as for monthly data: Mean, standard deviation, skewness, and kurtosis of hourly spot prices, but now on every current day. Considering descriptive statistics as shown in table B.6, for this time period, the daily equilibrium spot price is about 38 €/MWh, also with a high standard deviation compared to the monthly spot price. Average spot standard deviation is still high, in contrast to average kurtosis, compared to their monthly averages. Their daily average standard deviations are much lower, especially the one for kurtosis. Daily average spot skewness is very low, but now positive.

Finally, the basis control variable, the difference between current day-ahead forward and spot (daily average) prices, is included. Day-ahead forward prices are on average traded below current spot prices on the current trading day in contrast to prices on a monthly timescale as presented above, but the standard deviation on a daily timescale is twice as high (cf. table B.6).

Table B.7 shows cross-correlations between explanatory variables. Table B.8 shows stationarity tests (see Appendix A). All variables are found to be stationary and, therefore, their levels are used.

Variables	spot	spot_std.dev.	spot_skewness	spot_kurtosis	margin_wind	margin_wind_shock	margin_solar	margin_solar_shock	wind	wind_shock	solar	solar_shock	load	load_shock	basis
spot	1.000														
spot_std.dev.	0.484	1.000													
spot_skewness	0.087	0.031	1.000												
spot_kurtosis	-0.083	0.215	0.575	1.000											
margin_wind	-0.624	0.054	-0.121	0.101	1.000										
margin_wind_shock	-0.419	-0.018	-0.038	0.024	0.690	1.000									
margin_solar	-0.309	-0.520	0.086	0.008	-0.272	-0.231	1.000								
margin_solar_shock	-0.293	-0.506	0.036	-0.006	-0.255	-0.257	0.889	1.000							
wind	-0.604	0.051	-0.103	0.098	0.993	0.693	-0.300	-0.283	1.000						
wind_shock	-0.402	0.003	-0.031	0.029	0.694	0.987	-0.265	-0.295	0.709	1.000					
solar	-0.316	-0.526	0.117	0.026	-0.266	-0.226	0.994	0.882	-0.290	-0.256	1.000				
solar_shock	-0.302	-0.501	0.054	0.016	-0.247	-0.260	0.885	0.986	-0.270	-0.285	0.887	1.000			
load	0.150	0.156	0.189	0.035	0.116	0.129	-0.527	-0.514	0.207	0.221	-0.458	-0.451	1.000		
load_shock	0.131	0.234	0.096	0.064	0.082	0.032	-0.391	-0.457	0.147	0.156	-0.345	-0.338	0.737	1.000	
basis	-0.298	0.055	-0.091	0.094	0.284	-0.272	0.006	-0.078	0.280	-0.226	0.009	-0.017	0.022	0.378	1.000

Table B.7: Cross-correlations of explanatory daily variables

Variables	no constant, no trend	constant, no trend	constant, trend
premium	$< .01$	0	0
premium_peak	$< .01$	0	0
spot	$.01 < p < .05$	0	4.411e-20
spot_std.dev.	$< .01$	0	0
spot_skewness	$< .01$	0	0
spot_kurtosis	$< .01$	0	1.188e-22
margin_wind	$< .01$	0	6.745e-22
margin_solar	$< .01$	9.204e-14	1.041e-09
wind	$< .01$	0	1.123e-21
solar	$< .01$	4.630e-14	5.442e-10
load	$> .1$	9.202e-11	3.028e-08
basis	$< .01$	0	0
MacKinnon approximate p-values.			
Null hypothesis: Variable has a unit root.			
Test equations include trend, constant or none.			

Table B.8: Augmented Dickey-Fuller test for unit roots for daily time series

Appendix C. Additional tables: Robustness checks

VARIABLES	premium	premium	premium	premium_peak	premium_peak	premium_peak
spot	0.00699***	0.00784***	0.00678***	0.00596**	0.00699**	0.00584*
	(0.00211)	(0.00261)	(0.00249)	(0.00294)	(0.00346)	(0.00300)
spot_std.dev.	0.00194	0.00143	0.000803	0.00466	0.00405	0.00398
	(0.00242)	(0.00209)	(0.00294)	(0.00291)	(0.00343)	(0.00295)
spot_kurtosis	0.00120***	0.00121***	0.00138***	0.00146**	0.00147*	0.00157**
	(0.000228)	(0.000305)	(0.000273)	(0.000630)	(0.000742)	(0.000640)
margin_wind	-0.481	-0.0167	-0.249	-0.413	0.145	-0.275
	(0.338)	(0.371)	(0.282)	(0.399)	(0.452)	(0.401)
margin_wind_shock	1.416***		1.386***	1.702***		1.685***
	(0.197)		(0.229)	(0.339)		(0.346)
margin_hydro	-1.663	-2.307	2.733*	-0.163	-0.938	2.460
	(1.380)	(1.513)	(1.541)	(2.294)	(2.699)	(1.881)
margin_hydro_shock	6.809***	6.573***		4.063*	3.780	
	(1.180)	(1.247)		(2.118)	(2.496)	
basis	0.00717***	0.00524**	0.00244	0.00575*	0.00342	0.00293
	(0.00243)	(0.00235)	(0.00250)	(0.00330)	(0.00386)	(0.00302)
Constant	-0.591***	-0.526***	-0.493***	-0.328*	-0.249	-0.269
	(0.118)	(0.148)	(0.122)	(0.170)	(0.200)	(0.171)
Quarterly dummies	Yes	Yes	Yes	Yes	Yes	Yes
Yearly dummies	Yes	Yes	Yes	Yes	Yes	Yes
F(p-value)	0.000	0.000	0.000	0.000	0.000	0.000
R-squared	0.601	0.44	0.505	0.621	0.465	0.598
Adj. R-squared	0.49	0.295	0.378	0.518	0.327	0.495
Observations	79	79	79	79	79	79

Standard errors of Newey and West (1987) in parentheses in base load regressions in order to control for autocorrelated residuals.
The test of Breusch (1978) and Godfrey (1978) for residual autocorrelation is used.
Non-robust standard errors in parentheses in peak load regressions.
Test results for no autocorrelated residuals are available from the author upon request.
*** p<0.01, ** p<0.05, * p<0.1.

Table C.9: OLS month-ahead base and peak load regressions, margin variables with and without shocks

VARIABLES	premium	premium	premium_peak	premium_peak
spot_std.dev.	1.76e-06	1.95e-06*	1.40e-06	1.65e-06
	(1.12e-06)	(1.10e-06)	(1.28e-06)	(1.30e-06)
margin_wind	8.78e-05*	4.27e-05	6.49e-05*	4.09e-06
	(5.28e-05)	(5.30e-05)	(3.82e-05)	(4.68e-05)
margin_wind_shock		7.34e-05		9.88e-05*
		(4.60e-05)		(5.21e-05)
Constant	-3.66e-05	-3.97e-05	-3.89e-05	-4.31e-05
	(2.74e-05)	(2.69e-05)	(2.77e-05)	(2.77e-05)
Weekly dummies	Yes	Yes	Yes	Yes
Monthly dummies	Yes	Yes	Yes	Yes
Yearly dummies	Yes	Yes	Yes	Yes
F(p-value)	0.6111	0.6293	0.0087	0.0044
R-squared	0.026	0.023	0.033	0.027
Adj. R-squared	-0.001	-0.003	0.006	0.002
Observations	778	778	778	778

Standard errors of Newey and West (1987) in parentheses in order to control for autocorrelated and heteroskedastic residuals.
The test of Breusch (1978) and Godfrey (1978) for residual autocorrelation is used.
*** p<0.01, ** p<0.05, * p<0.1.

Table C.10: OLS day-ahead base and peak load regressions, wind margin variable with and without shocks

VARIABLES	premium	premium_peak
spot	0.00586**	0.00420
	(0.00222)	(0.00295)
spot_std.dev.	0.00222	0.00478
	(0.00223)	(0.00301)
spot_kurtosis	0.00127***	0.00159**
	(0.000235)	(0.000630)
wind	-0.00846	-0.00711
	(0.00553)	(0.00631)
wind_shock	0.0232***	0.0277***
	(0.00293)	(0.00541)
hydro	-0.0288	-0.00218
	(0.0214)	(0.0388)
hydro_shock	0.123***	0.0827**
	(0.0249)	(0.0358)
load	-0.00188	-0.00501
	(0.00313)	(0.00486)
load_shock	-0.00278	0.00134
	(0.00228)	(0.00360)
basis	0.00518**	0.00228
	(0.00248)	(0.00373)
Constant	-0.281	-0.0675
	(0.247)	(0.321)
Quarterly dummies	Yes	Yes
Yearly dummies	Yes	Yes
F(p-value)	0.000	0.000
R-squared	0.618	0.652
Adj. R-squared	0.495	0.541
Observations	79	79

Standard errors of Newey and West (1987) in parentheses in base load regressions in order to control for autocorrelated residuals.
The test of Breusch (1978) and Godfrey (1978) for residual autocorrelation is used.
Non-robust standard errors in parentheses in peak load regressions.
Test results for no autocorrelated residuals are available from the author upon request.
*** p<0.01, ** p<0.05, * p<0.1.

Table C.11: Single wind, hydro and load shocks on month-ahead base and peak load premium

VARIABLES	premium	premium_peak
spot_std.dev.	2.37e-06**	1.89e-06
	(1.15e-06)	(1.27e-06)
wind	3.07e-07	-1.39e-07
	(8.39e-07)	(7.56e-07)
wind_shock	1.31e-06*	1.61e-06*
	(7.66e-07)	(8.41e-07)
load	-7.78e-07	-3.41e-06*
	(2.32e-06)	(1.83e-06)
load_shock	-2.72e-06	1.28e-06
	(2.37e-06)	(2.18e-06)
Constant	0.000171	7.87e-05
	(0.000120)	(7.73e-05)
weekly dummies	Yes	Yes
monthly dummies	Yes	Yes
Yearly dummies	Yes	Yes
F(p-value)	0.611	0.0017
R-squared	0.035	0.038
Adj. R-squared	0.006	0.009
Observations	778	778

Standard errors of Newey and West (1987) in parentheses in order to control for autocorrelated and heteroskedastic residuals.
The test of Breusch (1978) and Godfrey (1978) for residual autocorrelation is used.
*** p<0.01, ** p<0.05, * p<0.1.

Table C.12: Single wind and load shocks on day-ahead base and peak load premium

month-ahead	base load	peak load
Test statistic	-45.996909	-45.741273
p-value	8.338e-59	1.260e-58
day-ahead	base load	peak load
Test statistic	-125.64291	-125.64292
p-value	0	0

Two sided t-test for premium mean and spot price mean equality.
Null hypothesis: Means are equal.
Test statistic is student's t.
Equal variances are not assumed.

Table C.13: Two sided t-test for premium mean and spot price mean equality

month-ahead	base load	peak load
Test statistic	.022	.045
p-value	.8831	.8314
day-ahead	base load	peak load
Test statistic	2.33	2.855
p-value	.1269	.0911

Engle LM-test for ARCH residuals after month- and day-ahead base and peak load regressions (see section 4).
Null hypothesis: No ARCH residuals.
Test statistic asymptotically chi-squared.

Table C.14: Engle LM-test for ARCH residuals