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Step-ahead spot price densities using daily synchronously reported prices and wind forecasts

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Abstract

This paper uses non-linear methodologies to follow the synchronously reported relationship between the Nordic/Baltic electric daily spot auction prices and geographical relevant wind forecasts in MWh from early 2013 to 2020. It is a well-known market (auctions) microstructure fact that the daily wind forecasts are information available to the market before the daily auction bid deadline at 11 a.m. The main objective is therefore to establish conditional and marginal step ahead spot price density forecast using a stochastic representation of the lagged, synchronously reported and stationary spot price and wind forecast movements. Using an upward expansion path applying the Schwarz (Bayesian information criterion [BIC]) criterion and a battery of residual test statistics, an optimal maximum likelihood process density is suggested. The optimal specification reports a significant negative covariance between the daily price and wind forecast movements. Conditional on bivariate lags from the *SNP* information and using the known market information for wind forecast movements at t_1, the paper establishes one-step-ahead bivariate and marginal day-ahead spot price movement densities. The result shows that wind forecasts significantly influence the synchronously reported spot price densities (means and volatilities). The paper reports day-ahead bivariate and marginal densities for spot price movements conditional on several very plausible price and wind forecast movements. The paper suggests day-ahead spot price predictions from conditional and synchronously reported wind forecasts movements. The information should increase market participants spot market insight and consequently make spot price predictions more accurate and the confidence interval considerably narrower.

KEYWORDS

conditional densities, electricity markets, seasonality, step ahead price movements, wind forecasts

1 | INTRODUCTION

This paper studies the characteristics of the synchronously reported bivariate daily spot price and wind forecast movements for the Nordic/Baltic spot electric power market.[1] Spot prices are settled daily based on auction bids at 11 a.m. where all market participants can participate. From these auctions, supply and demand are aggregated, and 24 hourly spot prices are reported at 12.45 p.m. Wind prognosis in MW are reported synchronously with auction prices. However, wind prognosis is available before the auction deadline for spot price and volume bids at 11 a.m. The main question in this article is therefore to analyse how the synchronously reported but known wind forecasts for the auction bid at 11 a.m. influences daily auction spot prices at 00.45 p.m. Can the available synchronously reported wind forecasts be used for spot expected price plots and price predictions with confidence intervals improving the information basis for good strategic auction biddings from market participants?

At the forefront of the renewable revolution is wind power. Record volumes of wind power (onshore and offshore) are being commissioned for the coming years. Increased production and deployment of wind turbines have led to a significant reduction in their capital cost inducing substantial production at a low marginal cost impacting wind power electricity prices. Several electricity markets have seen negative electricity prices during periods of high wind power electricity production. Germany and Australia, for instance, have experienced negative electricity prices during moments in which wind and solar power combined represented a very large share of the instantaneous electricity generation mix. The Nordic/Baltic market prices are fixed based on all participants' collected daily purchase and sale requests. The system price is the balance price for the aggregated supply and demand graphs; that is, the price is fixed at market equilibrium. Wind forecasts[2] are available the same morning before 11 a.m. and available to all market participants for the implicit auction market. The daily auction arena is therefore led by the wind forecast information. Hence, the bivariate synchronously reported spot prices and wind forecasts series potentially contain information giving systematic price behaviour from the leading wind forecasts. The stochastic nature of wind and wind forecasts makes the marginal production cost structures stochastic, impacting spot prices and spot price volatility. These factors will influence competitiveness and intermittent technologies. Spot prices and wind forecasts are hourly information. The paper's use of daily data in this analysis is as follows: firstly, stationarity is required of the data, and secondly, the daily price is a reference price for the physical market and the settlement price for all derivative contracts (forward/futures including options) in the financial market. That is, speculation and hedging are not only available for physical market participants but also for participants from the Nasdaq Commodities financial electricity markets[3] (Nasdaq Commodities, 2020). Knowing that wind power is generated at nearly zero marginal costs and dispatched prior to other technologies, it leaves conventional plants competing for residual demand. Hence, the overall market spot prices are depressed when conventional plants with higher marginal costs are removed from the production profile for daily purchase and sale requests at 11 a.m. Geographical dispersion of wind generation may cause congestions in the transmission system and further lower prices in congested market areas. For spot price volatility, the stochastic wind suggests changing production profiles and therefore stochastic changes to volatility.[4] For the Nordic/Baltic auction market, the spot price and wind stochastics suggest speculation opportunities and will greatly impact business investments and public procurements. The transition to more sustainable production and uptake of climate-friendly technologies will add extra momentum to the stochastic nature of energy modelling.[5]

The study is a step ahead conditional density estimation of the synchronously reported bivariate dynamics of the system spot prices and the wind forecasts series for the Nordic/Baltic electricity auction market (one-day-ahead market). The one-step-ahead conditional density represents the stationary bivariate process. This conditional density incorporates all information about various characteristics including conditional heteroskedasticity, nonnormality, time irreversibility and other forms of non-linearities. Hence, because the conditional density completely characterizes the process, it is the fundamental statistical object of interest. The implementation uses the nonparametric time series analysis (semi-nonparametric [*SNP*]) model for the estimation of the conditional density.[6] The methodology employs an expansion in hermite functions to approximate the multidimensional conditional density. An appealing feature of this expansion is that it is a non-linear nonparametric model that directly nests the Gaussian VAR model, the semiparametric VAR model, the Gaussian ARCH model, the semiparametric ARCH model, the Gaussian generalized autoregressive conditional heteroscedasticity (GARCH) model and the semiparametric GARCH model. The unrestricted SNP expansion models are more general than any of these specific models. The leading term of the series expansion is therefore an established parametric model already known to give a reasonable approximation of the process; higher order terms (hermite functions) capture departures from this initial model (Robinson, 1983). Switches can generate simulated sample paths that can be used to compute non-linear functionals of the density by Monte Carlo integration, notably the non-linear analogues of the impulse–response mean and volatility profiles used in traditional VAR, ARCH and GARCH analysis. The SNP model is fitted using conventional maximum likelihood (ML) together with a model selection strategy that determines the appropriate order of model expansion (Schwarz, 1978). The analysis reports an extensive battery of test statistics for model misspecifications. From the optimal and bivariate spot price and wind forecast model densities, this paper investigates spot price movements conditional on synchronously reported wind forecast movements. The analysis mainly comprises three steps. First, the paper addresses seasonality and trends for mean and volatility for both spot price and wind forecast series, achieving ergodic stationarity. Second, the nonparametric *SNP* model specification establishes consistent bivariate mean and volatility specifications that can be continuously updated. Specifically, from the bivariate spot price and wind forecast densities, the model describes intercept and serial correlation for the mean, and intercept, error shocks, serial correlation, leverage and level effects for the latent volatility. The remainder of this paper therefore consists of four further sections. Section 2 gives a literature overview for electricity prices, wind forecasts and the nonparametric specification model (*SNP*). Section 3 defines the empirical data and describes a general adjustment procedure for systematic location, scale and trend effects to obtain stationary bivariate series to then estimate a strictly stationary BIC-optimal bivariate density model. Section 4 reports findings with bivariate step-ahead densities for the means, volatilities and covariance. Marginal spot price densities are reported for price and wind forecast lags (x_{t-1}) and synchronous wind forecasts. Finally, Section 5 provides a summary and conclusion.

2 | BACKGROUND AND LITERATURE REVIEW

2.1 | The electricity spot price

Several international studies have explored the characteristics and dynamics of Nordic/Baltic spot electricity price series (auction market).[7] Financial models use historical price series, and when assuming stationarity, we can extract reliable characteristics for both the mean and volatility. Spot electricity prices exhibit high volatility, strong mean reversion,[8] frequent spikes and seasonal patterns,[9] and these prices differ from region to region (Li & Flynn, 2004). Goto and Karolyi (2004) find mean-reversion effect with seasonal changes in volatilities as well as volatility clustering for electricity trading hubs in the United States, Australia and the Nordic/Baltic market. Chan and Gray (2006) find serial correlation in both the mean and volatility for several electricity markets, whereas Theodorou and Kanyanpas (2008) studied the less developed and illiquid Greek electricity market. They find mean reversion and the presence of serial correlation in both the mean and the volatility.

A considerable number of models that attempt to capture the dynamics of the electricity prices have been proposed in the literature. A class of models includes stochastic models, regime switching models, cointegration analysis, mean-reverting models and other empirical models.[10] These models fail to capture the full volatility dynamics of electricity prices as well as the interrelationship of price and volatility. Another class of models introduces univariate GARCH conditional volatility models, as well as other variations of GARCH modelling, such as EGARCH and TGARCH.[11] These models capture the price and volatility dynamics of electricity prices, as well as price shock transmissions. However, univariate models fail to capture the full dynamics that exist in the electricity market. Modelling mean and volatility interrelationships between different time series require the extension of econometric modelling to the multivariate level. The use of VAR models and multivariate GARCH (MGARCH) models extends modelling capturing inter-dynamics between series. That is, the dependence was developed between synchronous mean and volatility with respect to the past mean, volatility and shocks, of other time series. Finally, Knittel and Roberts (2001) find an inverse leverage effect for electricity prices in the United States. Other studies have found similar results.[12] For the purpose of this study, we build and extend the work of Solibakke (2002) and follow the methodology of Gallant, Rossi, and Tauchen (1993) and Gallant and Tauchen (2014). For bivariate prices and wind forecast, both the seasonality and trends are extracted, and the strictly stationary time series SNP model is estimated (Gallant & Tauchen, 2010).

2.2 | Spot prices and wind forecasts movements and bivariate volatility (and covariance)

The share of wind power in electricity generation (in MWh) has been rapidly increasing in the Nordic/Baltic market. In April 2013, wind power generation was approximately 32 k MWh, and in April 2019, approximately 80 k MWh[13]; over a 4-year period, the monthly average production has tripled. Wind power has nearly zero marginal production costs and is often subsidized (Morthorst, 2003; Skytte, 1999). Wind power generation is therefore dispatched prior to other generators, leaving residual demand to other technologies (merit order effect).[14] In summary therefore, a high level of wind generation is expected to decrease electricity spot prices, suggesting a natural negative correlation between wind generation and spot price movements. As shown by Giabardo, Zugno, Pinson, and Madsen (2009), estimated future wind power generation appears as a stochastic threshold in the supply function.

Considerably less attention has been given to wind generation and price volatility. Because wind generation originates from meteorological conditions, the supply of wind power is easily classified as exogenous impulses. For periods with shifting wind power generation, the volatility of spot electricity prices will most likely increase, dependent on the flexibility of other generators. The Nordic/Baltic market with abundant hydro resources has a natural tool to cope with undirected variations in wind output, reducing spot price volatility. The impact of wind generation on electricity prices and volatility will create speculation opportunities and of course impact investment decisions. As wind power has tripled and become more competitive, it has raised more challenges for market operators. Hence, more effort has been made in modelling the displacement of technologies brought by merit order effect and the incentives to invest in different technologies under the envisaged growth of RES[15] use. For electricity mean prices, Forrest and MacGill (2013) showed that wind penetrations in the Australian electricity market were negatively correlated with the wholesale price and had greater effects at high levels of demand. This point of view is shared by Ciarreta, Espinosa, and Pizarro-Irizar (2014) for the case of Spain, as well as by Traber and Kemfert (2011) for the case of Germany.

In the case of price volatility, Green and Vasilakos (2010), Steggals, Gross, and Heptonstall (2011), Woo, Horowitz, Moore, and Pacheco (2011), Jacobsen and Zvingilaite (2010), and Twomey and Neuhoff (2010) found that the impact on spot price stability caused by wind deployment increased price variations when electricity markets relied on a large share of intermittent generation. These research studies support the notion that fluctuations in wind output threaten overall electricity supply. In the case of Denmark West bidding area, Jònsson, Pinson, and Madsen (2010) and Jónsson, Pinson, Nielsen, Madsen, and Nielsen (2013) used non-parametric regression to show, not only a discontinuous effect on price reduction but also diminishing intraday price variations caused by wind penetration. For the Nordic/Baltic region, some additional work has focused on the implementation and integration of wind power, from the perspectives of macroeconomics (Sperling et al., 2010), geographical aggregation (Østergaard, 2008) and end-user demand responsiveness (Grohnheit, Andersen, & Larsen, 2011). Munkgaard and Morthorst (2008) recognized that risk-averse investors would be reluctant to invest in wind installation in Denmark after a high feed-in tariff scheme was replaced by a new tariff scheme aiming to smooth transition from the guaranteed price to the market price for wind producers. However, none of these studies have explicitly quantified the impacts of synchronous wind penetration on the day-ahead spot price or examined the variations in markets' signals facing wind intermittency. To the best of my knowledge, establishing a bivariate spot price and wind forecast model, despite its importance, has not been undertaken for the Nordic/Baltic region. Therefore, the current paper is to fill the gap in the literature—to conduct an econometric analysis on the day-ahead spot price performance in relation to wind deployment.

2.3 | The *SNP* methodology

Non-linear stochastic models will in our study imply conditional models and so-called ARMA-GARCH methodology. Autoregressive and moving average (ARMA) is a term applied to the structure of the conditional mean, whereas GARCH is a term applied to the structure of the conditional volatility. ARMA models can be studied in detail, for example, in Mills (1990), whereas ARCH specifications were first studied by Engle (1982) and extended by Bollerslev (1986). who specified the Generalized ARCH or GARCH. The development to GARCH from ARCH occurred mainly owing to the number of lags in the ARCH specification.[16] ARCH/GARCH specifies the volatility as a function of historic price changes and volatility. In the international finance literature, a number of studies show how results from these pioneering works have been used. See, for example, Baillie and Bollerslev (1989), Bollerslev et al. (1987, 1992), Engle et al. (1986), Engle and Ng (1993), Nelson (1991). and de Lima (1995a, 1995b)). For a comprehensive introduction to ARCH models and applications in finance, see Gouriéroux (1997). Ding, Engle, and Granger (1993) extend the symmetric GARCH model into asymmetric GARCH and the truncated GARCH (Glosten, Jagannathan, and Runkle [GJR]) is described by Glosten, Jagannathan, and Runkle (1993). ML estimates of the GARCH-in-mean model can be obtained by maximizing the likelihood function. Note, however, that the information matrix is no longer block diagonal, so that all the parameters must be estimated simultaneously. This requires an iterative solution technique,[17] also known as non-linear optimisation.

SNP stands for SemiNonParametric, to suggest that it lies halfway between parametric and nonparametric procedures. The leading term of the series expansion is an established parametric model known to give a reasonable approximation to the process; higher order terms capture departures from that model. With this structure, the SNP approach does not suffer from the curse of dimensionality to the same extent as kernels and splines. In regions where data are sparse, the leading term helps to smooth gaps between data points. Where data are plentiful, the higher order terms accommodate deviations from the leading term, and fits are comparable with the kernel estimates proposed by Robinson (1983). The theoretical foundation of the method is the hermite series expansion, which for time series data is particularly attractive based on both modelling and computational considerations. In terms of modelling, the Gaussian component of the hermite expansion makes it easy to subsume into the leading term familiar time series models, including VAR, ARCH and GARCH models (Bollerslev, 1986; Engle, 1982). These models are generally considered to give excellent first approximations in a wide variety of applications. In terms of computation, a hermite density is easy to evaluate and differentiate. Also, its moments are easy to evaluate because they correspond to higher moments of the normal, which can be computed using standard recursions. Finally, a hermite density turns out to be very practical for sampling from, which facilitates simulations.[18]

3 | EMPIRICAL DATA, DETERMINISTIC ADJUSTMENTS AND SNP PROJECTIONS

3.1 | Empirical data and deterministic adjustments[19]

The study uses daily prices of the so-called system price and daily wind forecasts for the Nordic/Baltic spot market for electric power spanning the period from January 2013 to June 2019 (approximately 2,340 bivariate price/wind observations). The daily prices are the average prices for 24-h auction (system) prices. Wind forecasts are reported daily in MWh for 24 h/day and in this study, aggregated into daily forecasts.[20] When changing to winter (summer) time, the spot price and wind forecasts for 1 h (2–3 a.m.) are lost (doubled) and are carefully handled in the two series. The raw continuous prices and wind forecasts are transformed to logarithmic forms and differenced once to obtain stationarity series. However, both the spot prices and the wind forecasts show seasonal dependencies as well as the wind forecasts being influenced by renewables, showing 2.5 times increase in wind power generation from 2013 to 2019. Only the growth in wind production makes the series for our purpose most likely nonstationary.[21] Hence, prices and wind forecasts are adjusted for systematic/deterministic effects as well as linear and squared trends in both the mean and variance to obtain ergodic stationarity. The mean and variance of the time series are kept unchanged for ease of interpretation. The two series are adjusted for systematic location and scale/trend effects (Gallant, Rossi, & Tauchen, 1992) in both returns and volatility. Let ϖ denote the variable to be adjusted. Initially, the regression to the mean equation $\varpi = x \cdot \beta + u$ is fitted, where x consists of calendar variables, which are most convenient for these time series, and contains parameters for (non)linear trends, day of week, week number dummies, calendar day separation variables and relevant subperiods (eastern, summer holidays etc.). The least square residuals $\hat{u}$ are taken from the mean equation to construct the variance equation $\ln\left(\hat{u}^2\right) = x \cdot \gamma + \varepsilon$. The x is unchanged from the mean to the variance equation. Finally, a linear transformation is used to calculate $\varpi_{adj} = a + b \cdot \left(\frac{\hat{u}}{\sqrt{e^{x \cdot \hat{\gamma}}}}\right)$ as the adjusted series,[22] where a and b are chosen so that $\frac{1}{T}\sum_{i=1}^{T}\varpi_i = \frac{1}{T}\sum_{i=1}^{T}\varpi_i$ and $\frac{1}{T-1}\cdot\sum_{i=1}^{T}(\hat{\varpi}_i - \bar{\varpi})^2 = \frac{1}{T-1}\cdot\sum_{i=1}^{T}(\hat{u}_i - \bar{u})^2$. The term $\frac{\hat{u}}{\sqrt{e^{x\hat{\gamma}}}}$ is used to adjust for the use of $\ln\left(\hat{u}^2\right)$ in the volatility equation and a and b is used for the final location and scale transformation to aid interpretation. The unit of measurement of the adjusted series is the same as that of the original series. Table 1 reports the deterministic seasonal, scale and trend effects for the two series. The spot price contains seasonal as for example day of the weeks, calendar weeks and trends, and scale effects for the mean and volatility. However, more interestingly included adjustment variables such as summer holidays, Easter and Christmas etc. do not enter the adjustment procedure (insignificant). Wind forecasts are not adjusted for the mean, but to achieve ergodic stationarity, the wind forecast volatility is adjusted for 2 weeks (marginally significant and may change/disappear during continuous updating) as well as linear and squared trends.[23] The adjustment procedures turn the two series to functions that we can estimate.[24] Figure 1 reports a bivariate scatterplot of the adjusted spot price and wind forecast movements series. A linear trend function in Figure 1 reads $y = -1.05475x + 0.00796$ with $t = -29.5$ *and* $R^2 = 27.2\%$. The large negative t statistic and an R^2 of 27.4% suggest a significant negative correlation between spot prices and wind forecasts of approximately −0.522 (that is,

TABLE 1 Seasonal characteristics of the mean and volatility (2013–2020) for the raw system Price and wind forecast daily movements.

Returns $dy = (\ln(S_t/S_{t-1})$			**Volatility $\sigma_y = \ln(\text{res}^2)$**		
Var	**Coeff**	***t* stat**	**Var**	**Coeff**	***t* stat**
INTR	−0.6853	2.3049	INTR	1.5447	10.5513
MON	13.677	23.2822	MAN	1.3287	9.7120
TUE	1.6146	2.7523	SAT	0.6071	4.4378
SAT	−7.4561	12.6954	Week_4	1.0372	3.0057
SUN	−2.2127	3.7655	Week_13	−0.7850	2.2757
Others	−5.3531	3.7891	Week_30	−1.1619	3.3686
Week_1	3.4110	1.9666	Week_31	−1.2540	3.6355
			Week_32	−0.8563	2.4824
			Week_34	−0.8643	2.5056

Wind forecast $d_W = (\ln(W_t/W_{t-1})$			**Volatility $\sigma_y = \ln(\text{res}^2)$**		
Var	**Coeff**	***t* stat**	**Var**	**Coeff**	***t* stat**
INTR	—	—	INTR	2.7750	21.4158
			Week_24	0.7404	2.3544
			TRD	−2.4912	4.1687
			TRD2	1.5291	2.6438

Note. Exogenous variables (only close to significant coefficients (10%) are reported: INTR = Constant; MON = Monday; FRI = Friday, SAT = Saturday; SUN = Sunday; Eastern H = Eastern Holidays; Other H = Other Holidays; General H = General Holidays; Weeks 1–52; Trend = linear trend; Trend SQ = Squared trend;

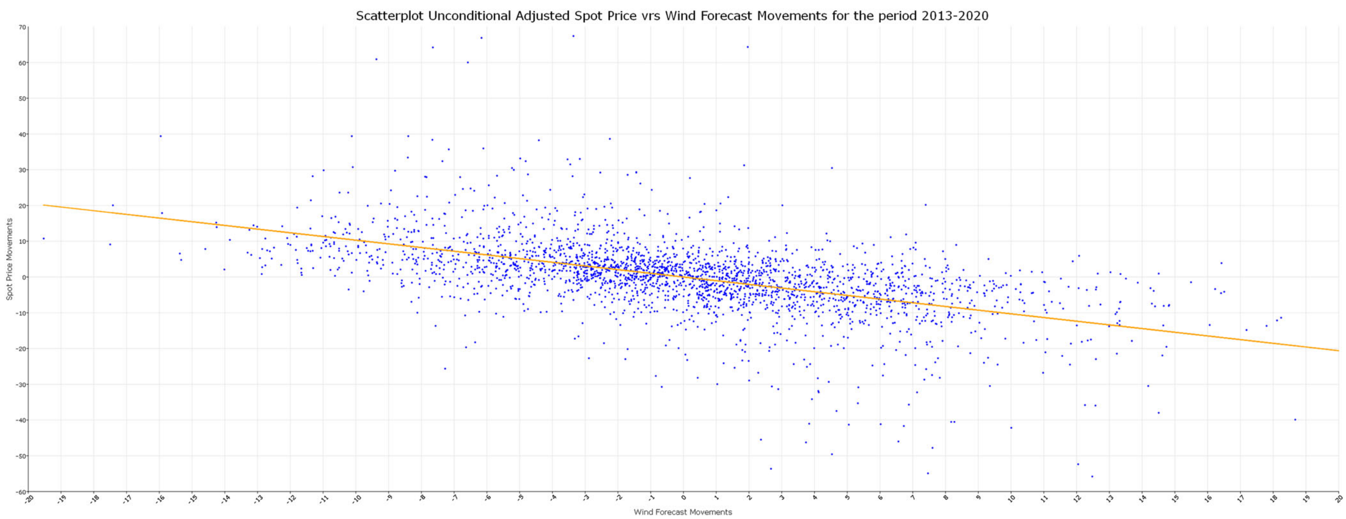

FIGURE 1 Scatterplot of adjusted spot price and wind forecast movements (2.59 *k*)

approximately √27.2% ≈52.2%). The strong unconditional mean correlation between the adjusted stationary spot price and wind forecast movements indicates an influential and systematic negative relationship, which is important for the conditional step-ahead changes.

The characteristics of the adjusted system prices and wind forecast series are reported in Table 2. For the system price movements, the mean is close to zero. The standard deviation seems high relative to other commodity markets and must be attributed to the close to nonstorable features of an electricity market dominated by hydro power production. The Cramer-von-Mises test statistic[25] confirms nonnormal series densities. Both series show serial correlation in the mean (Q)[26] and volatility (Q^2) and ARCH (Engle, 1982). The series is confirmed stationary with both the Kwiatkowski, Phillips, Schmidt and Shin (KPSS) (Kwiatkowski, Phillips, Schmidt, &

TABLE 2 Statistics for Nord Pool spot-system electricity price and logarithmic wind prognosis movements

	Mean (all/ M -(drop))	Median SD	Maximum/ minimum	Moment kurt/ skew	Quantile kurt/ skew	Quantile normal	Cramer-von Mises	Serial dependence	
								$Q(12)$	$Q2(12)$
Spot/day-ahead auction Price	−0.00343	0.40552	90.0232	19.33093	0.16975	5.5048	11.41300	70.3650	219.19
	−0.00860	11.39196	−128.1367	−1.09252	−0.07558	{0.0638}	{0.0000}	{0.0000}	{0.0000}
	BDS Z statistics ($e = 1$)				KPSS	P–P	Augmented	ARCH	RESET
	$m = 2$	$m = 3$	$m = 4$	$m = 5$	I and trend	I and trend	DF-test	(12)	(12, 6)
	9.0586	12.0101	13.3772	13.9937	0.07441	−66.01099	−36.92826	146.98888	13.38060
	{0.0000}	{0.0000}	{0.0000}	{0.0000}	{0.2218}	{0.0000}	{0.0000}	{0.0000}	{0.0374}
	Mean (all/ M -(drop))	**Median SD**	**Maximum/ minimum**	**Moment kurt/ skew**	**Quantile kurt/ skew**	**Quantile normal**	**Cramer-von Mises**	**Serial dependence**	
								$Q(12)$	$Q2(12)$
Wind day-ahead prognosis	0.00760	−0.09680	20.9627	0.25767	0.12156	2.4945	0.24684	119.036	52.11661
	0.00829	5.52783	−19.5296	0.12551	0.04647	{0.2873}	{0.0014}	{0.0000}	{0.0000}
	BDS Z statistics ($e = 1$)				KPSS	P–P	Augmented	ARCH	RESET
	$m = 2$	$m = 3$	$m = 4$	$m = 5$	I and trend	I and trend	DF test	(12)	(12, 6)
	1.2702	3.9674	5.3578	5.7620	0.03365	−180.650	−21.81397	42.85096	35.43575
	{0.2040}	{0.0001}	{0.0000}	{0.0000}	{0.3864}	{0.0001}	{0.0000}	{0.0000}	{0.0000}

Shin, 1992) and the augmented Dickey and Fuller (DF) test statistics (Dickey & Fuller, 1979). The BDS Z statistic (Brock & Deckert, 1988; Scheinkman, 1996) ($\varepsilon = 1$) suggests significant data dependence. For the wind forecasts movements, the mean is also close to zero. The wind forecasts report a high standard deviation and are highly volatile confirmed by the maximum and minimum numbers of the series. The series show nonnormal features and contain serial correlation. The KPSS and augmented DF test statistics confirm ergodic stationarity for the adjusted series. Volatility clustering and general data dependence exist but are clearly lower than for the raw and unadjusted series. Finally, for both series, the RESET (12;6) (Ramsey, 1969) suggests general specification errors.[27] Paths and distributions for the seasonal adjusted system price and wind forecast movements are reported in Figures 2 and 3.

The paths seem to be ergodic and stationary (moving randomly around zero). The kernel distributions and *QQ*-plots for the wind forecast movements seem close to normal and more normal than the spot price movements. From the kernel distribution and the *QQ*-plots, the spot price movements seem not to be normal and perhaps closer to student's t or logistics than normal. For the adjusted spot price, the movements are lower, and the distribution clearly shows a more normal distribution. However, the year 2015 was a volatile period for the spot price. The wind forecast distribution shows a decreasing volatility over time, probably due to the number of wind production sites, which have greatly increased over the period. For the adjusted wind series, the volatility is stable over the 2013–2018 period. Moreover, due to the normal density of the wind forecasts, wind derivatives for risk management in the energy market are clearly accessible.

3.2 | The density projections: Conditioning the *SNP* model

The estimation method is termed *SNP*, which stands for SNP, to suggest that it lies halfway between parametric and nonparametric procedures. To capture departures from the parametric model, higher order terms (hermite functions) are used for estimation of the conditional density. Because the conditional density completely characterizes a process, it is naturally viewed as the fundamental statistical object of interest. The leading term for the bivariate system of the spot price and the wind forecast movements series expansion is an established parametric model known to give a reasonable approximation to the process (VAR-GARCH); hermite functions[28] are higher order terms to capture departures. The SNP model is fitted using conventional *ML* together with the BIC (Schwarz, 1978) model selection strategy. The Schwarz Bayes information criterion (Schwarz, 1978) is computed

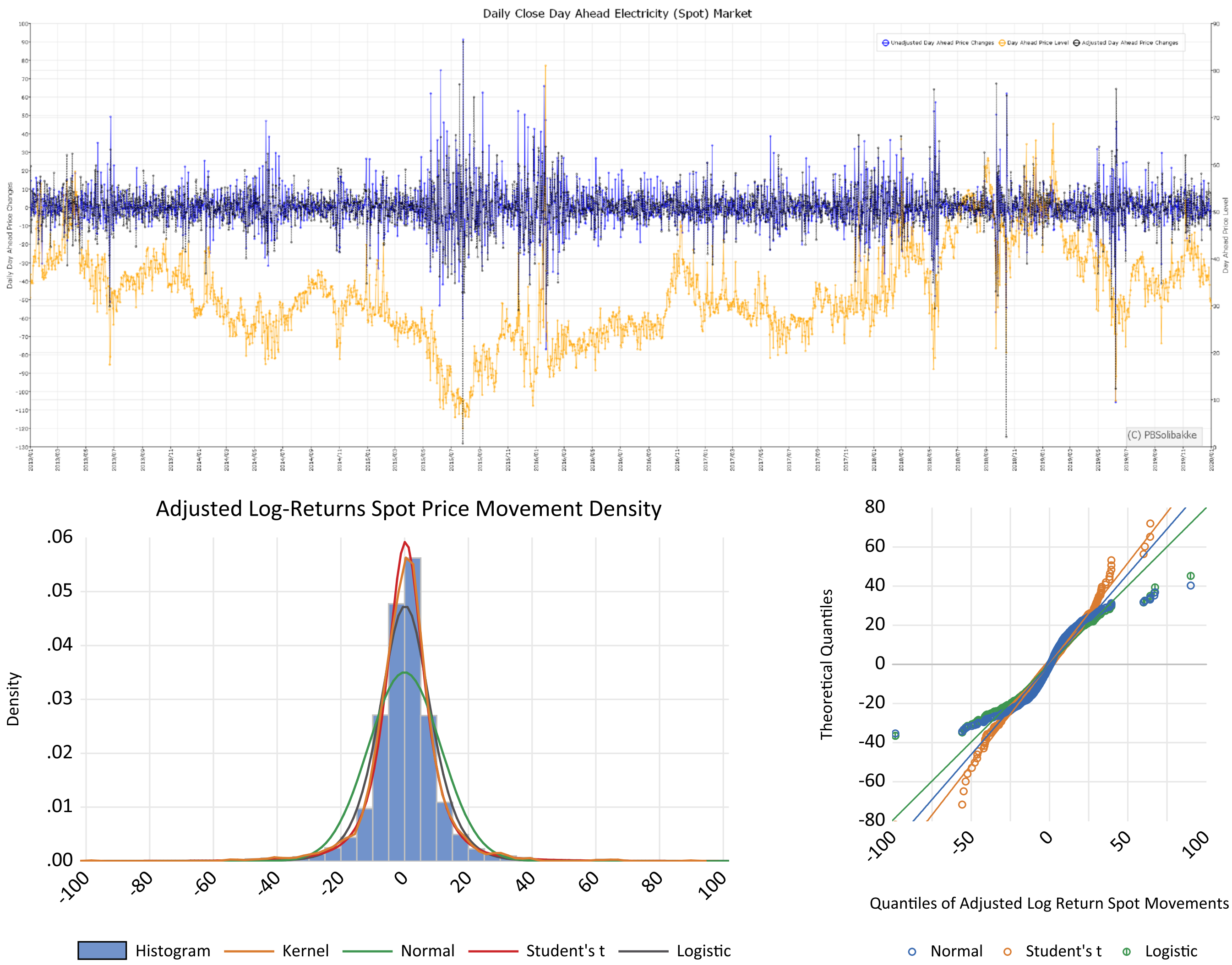

FIGURE 2 Unadjusted and adjusted spot price movements, densities and *QQ*-plots

as[29] $BIC = s_n(\hat{\theta}) + \left(\frac{1}{2}\right)\left(\frac{p_p}{n}\right)\log(n)$ with small values of the criterion preferred. The optimal estimated *SNP* model is $\hat{f}_K(\tilde{y}_t;\tilde{\omega}_t|x_{t-1},\hat{\phi})$. The optimal parameter values are (*Lu*, *Lg*, *Qtype*, *Lr*, *Ptype*, *Lv*, *Vtype*, *Lw*, *Wtype*, *Lp*, *Kz*, *max Kz*, *Iz*, *max Iz*, *Kx*, *Ix*) = (7, 1, f, 1, f, 1, f, 1, f, 1, 4, 4, 4, 0, 0, 0) meaning one intercept, seven mean lags, full ARCH, GARCH, asymmetry and level parameterization using a one lag specification, one constant term for $P(y, x)$ and four hermite polynoms with four interactions between the bivariate series.

The *ML* estimates[30] of the parameters for the SNP model specification on the adjusted bivariate time series are reported in Table 3.[31] Firstly, for the mean, the intercepts are only significant for the wind forecasts, and the serial correlations ($B[1, x]$) for almost all bivariate lags ($L = 7$) are significant. The positive drift for wind is clearly from the tremendous increase in production. The serial correlation is quite strong, up to seven lags (mostly negative dependence). Hence, the serial correlation seems to follow a weekly pattern. The negative coefficients for serial correlation suggest reversions as well as a tendency for spot prices and wind forecasts to move in opposite directions (negative comovements). That is, first positive (negative) movements 1 day suggest negative (positive) movements the next day, and second, when prices go down (up), the wind forecasts move up (down). The significant hermite polynomials suggest departure from normal distributions. The hermite functions coefficients ($a_0[1] - a_0[8]$ and $A(1,1)$ to $A(7,1)$) capture departures from the classical normally distributed model as well as coefficients for bivariate interactions ($I\_$), all BIC preferred. Table 3 reports the fully specified conditional variance coefficients for spot prices and wind forecasts. The bivariate variance coefficients show an influential correlation structure, signalling conditional heteroscedasticity as well as asymmetry (V) and level (W) effects. The largest eigenvalue of the conditional variance function P and Q companion matrix is 0.9472 suggesting a rather

TABLE 3 Bivariate SNP model for system price and wind forecasts

Bivariate mean lag structure				Hermite polynomials				Bivariate volatility equation			
Descriptor	**Theta (*f*)**	**Std. error**	***t* statistics**	**Descriptor**	**Theta (*f*)**	**Std. error**	***t* statistics**	**Descriptor**	**Theta (*f*)**	**Std. error**	***t* statistics**
$B(1, 1)$	−0.08566	0.02711	−3.15912	$a_0[1]$ 01	−0.088100	0.037090	−2.375620	$R_0[1]$	−0.01099	0.26732	−0.04111
$B(2, 1)$	−0.07452	0.02662	−2.79971	$a_0[2]$ 02	−0.103310	0.038640	−2.673430	$R_0[2]$	0.0472	0.06662	0.70847
$B(1, 2)$	−0.03662	0.02054	−1.78293	$a_0[3]$ 03	0.068520	0.015420	4.442430	$R_0[3]$	0.41671	0.05854	7.11852
$B(2, 2)$	−0.16742	0.02761	−6.06407	$a_0[4]$ 04	0.027620	0.015430	1.789910	$P(1, 1)\,f$	0.30213	0.03693	8.182
$B(1, 3)$	−0.19678	0.0241	−8.1656	$a_0[5]$ 10	0.000300	0.030950	0.009570	$P(2, 1)\,f$	0.02454	0.04954	0.49522
$B(2, 3)$	−0.12116	0.02451	−4.94372	$a_0[6]$ 20	−0.055770	0.022250	−2.506550	$P(1, 2)\,f$	−0.03601	0.03339	−1.07851
$B(1, 4)$	−0.0876	0.01883	−4.65134	$a_0[7]$ 30	−0.031270	0.013110	−2.385770	$P(2, 2)\,f$	0.11589	0.06099	1.9003
$B(2, 4)$	−0.27569	0.02522	−10.93305	$a_0[8]$ 40	0.106610	0.014210	7.500380	$Q(1, 1)\,f$	0.94536	0.01392	67.92248
$B(1, 5)$	−0.1116	0.02619	−4.26184	$A(1,1)$ 00 00	1.000000	0.000000	0.000000	$Q(2, 1)\,f$	−0.06081	0.02073	−2.93342
$B(2, 5)$	−0.0857	0.02535	−3.38087	$A(2,1)$ 11 00	0.088690	0.030350	2.922250	$Q(1, 2)\,f$	0.03061	0.02986	1.02518
$B(1, 6)$	−0.06927	0.01936	−3.57859	$A(3,1)$ 12 00	0.007040	0.012170	0.577890	$Q(2, 2)\,f$	0.80747	0.04446	18.16252
$B(2, 6)$	−0.17957	0.02536	−7.08009	$A(4,1)$ 13 00	−0.008680	0.013760	−0.631360	$V(1, 1)\,f$	−0.07647	0.12246	−0.62444
$B(1, 7)$	−0.10934	0.02412	−4.53263	$A(5,1)$ 21 00	0.016150	0.013960	1.156650	$V(2, 1)\,f$	0.12017	0.06385	1.882
$B(2, 7)$	−0.08699	0.02546	−3.41674	$A(6,1)$ 22 00	0.047760	0.014710	3.246610	$V(1, 2)\,f$	−0.08933	0.0582	−1.53472
$B(1, 8)$	−0.04989	0.02081	−2.39682					$V(2, 2)\,f$	0.40645	0.04965	8.18706
$B(2, 8)$	−0.15402	0.02552	−6.03628	Bivariate mean constants				$W(1,1)\,f$	0.46589	0.06356	7.32965
$B(1, 9)$	−0.07901	0.02403	−3.28807	Descriptor	Theta (*f*)	Std. error	*t* statistics	$W(2, 1)\,f$	−0.19548	0.04687	−4.17062
$B(2, 9)$	−0.02042	0.02467	−0.8276	$b_0[1]$	0.03976	0.04269	0.93133	$W(1, 2)\,f$	−0.2029	0.04856	−4.17829
$B(1, 10)$	−0.00458	0.02076	−0.22045	$b_0[2]$	0.16701	0.06158	2.71221	$W(2, 2)\,f$	0.06024	0.05947	1.01296
$B(2, 10)$	−0.11758	0.0251	−4.68487								
$B(1, 11)$	−0.00852	0.02236	−0.38124	SNP model specification:		71f1f14004	(detailed)				
$B(2, 11)$	−0.04396	0.0251	−1.75105	Schwarz (BIC) criterion:		2.44456564					
$B(1, 12)$	−0.07347	0.02028	−3.62268	−2 ln likelihood		2007.17349593					
$B(2, 12)$	−0.07348	0.02289	−3.21028	Largest eigenvalue of mean function matrix			0.7925280				
$B(1, 13)$	0.05547	0.0234	2.3709	Largest eigenvalue of variance function matrix			0.9471700				
$B(2, 13)$	−0.10655	0.02314	−4.60529								
$B(1, 14)$	−0.12123	0.01922	−6.30833								
$B(2, 14)$	0.01929	0.02336	0.82597								

Abbreviations: BIC, Bayesian information criterion; SNP, semi-nonparametric.

low persistence in the bivariate variance–covariance processes. The log-likelihood for the bivariate model is −1003.59.

The *SNP* projection model gives access to estimates of the conditional expectations $E(\tilde{y}_t|\tilde{y}_{t-1},...,\tilde{y}_{t-L})$ and the conditional variances $Var(\tilde{y}_t|\tilde{y}_{t-1},...,\tilde{y}_{t-L})$ (and conditional covariances[32]). Figure 4 (top) shows a two-dimensional (bivariate) plot of the conditional mean expectations, $E(\tilde{y}_t|\tilde{y}_{t-1,...,}\tilde{y}_{t-L})$, for spot prices and wind forecast movements. Figure 4 (bottom) shows a conditional scatterplot with the conditional spot changes (y) on the horizontal axes and conditional wind forecast

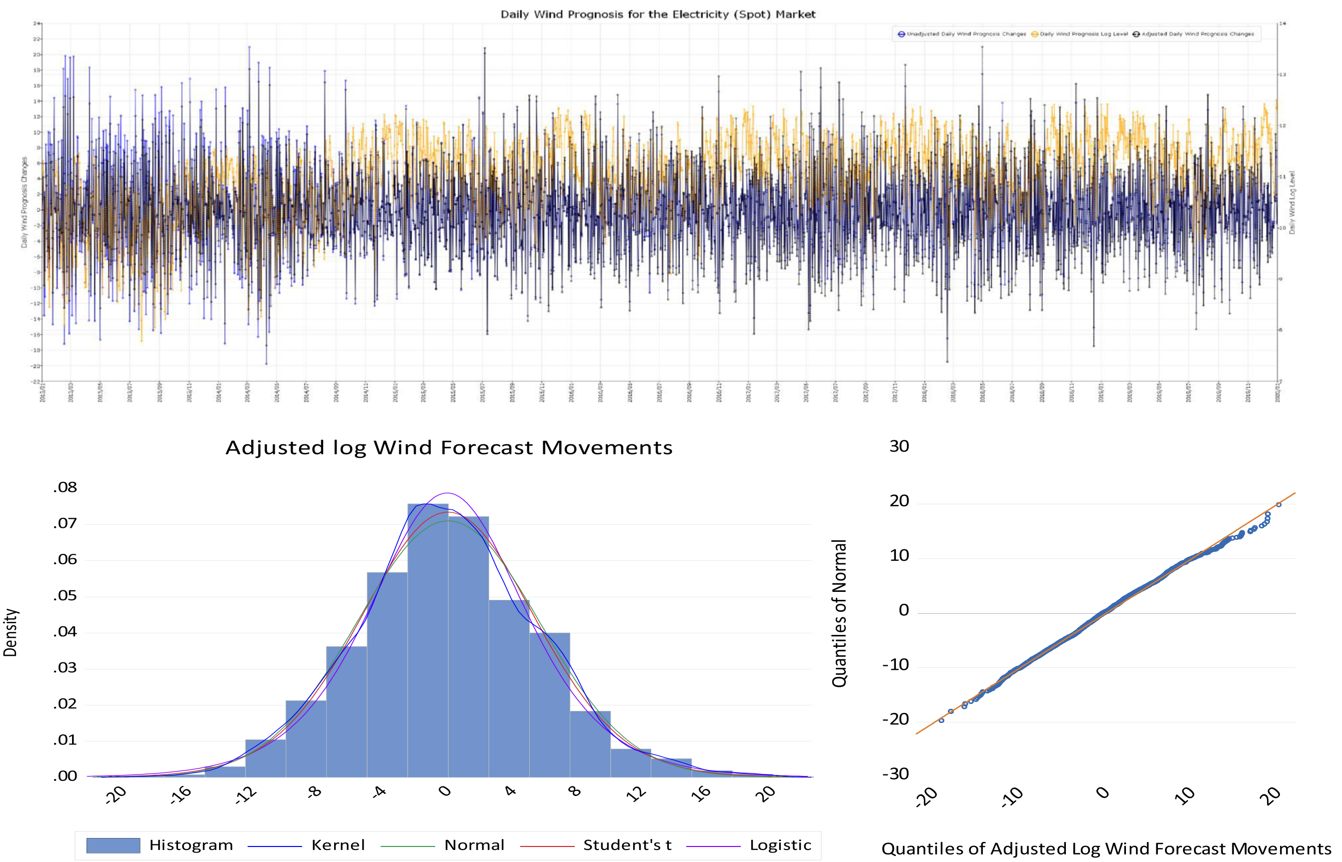

FIGURE 3 Unadjusted and adjusted wind forecast movements. Densities and *QQ*-plots for adjusted

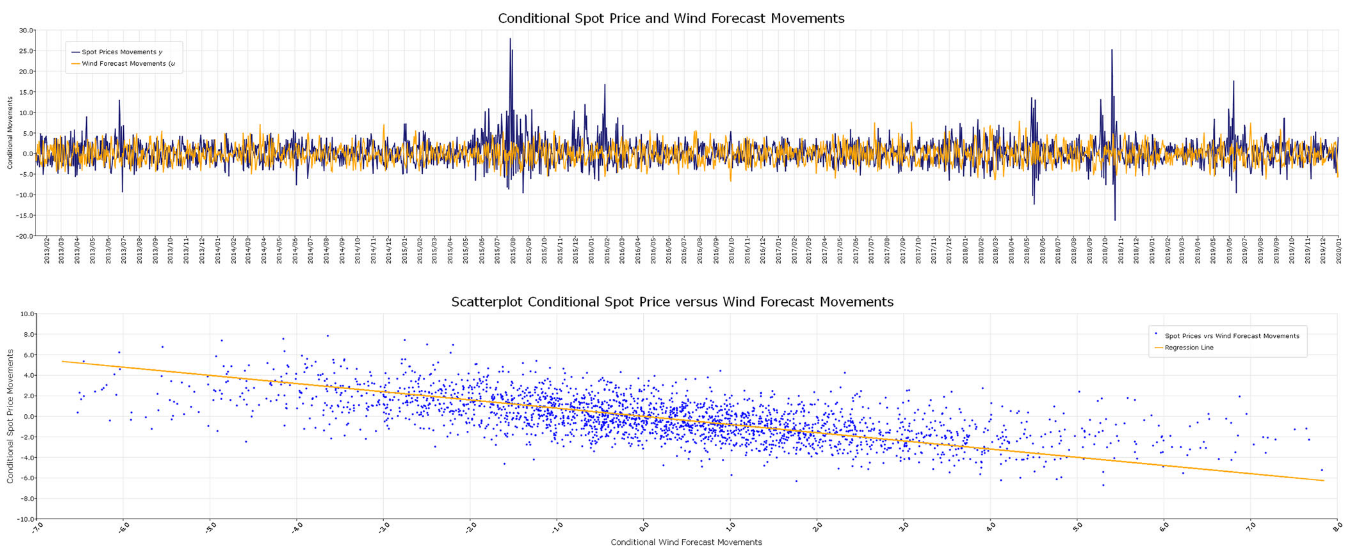

FIGURE 4 The conditional spot price and wind forecast movements (2.1 k)

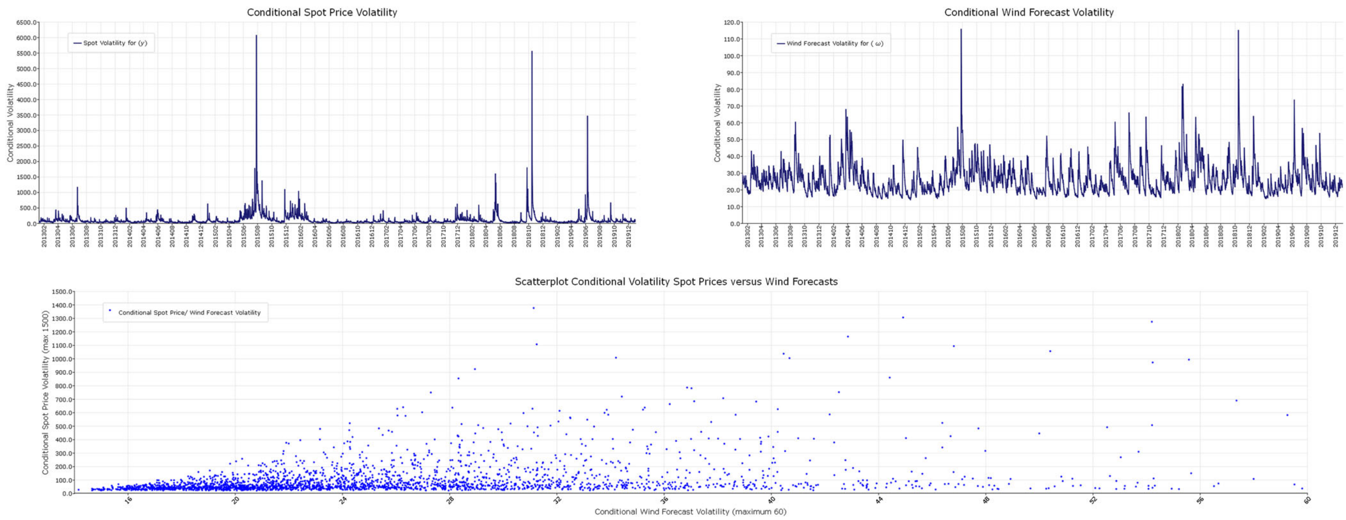

FIGURE 5 The conditional spot price and wind forecast volatility (2.5 k)

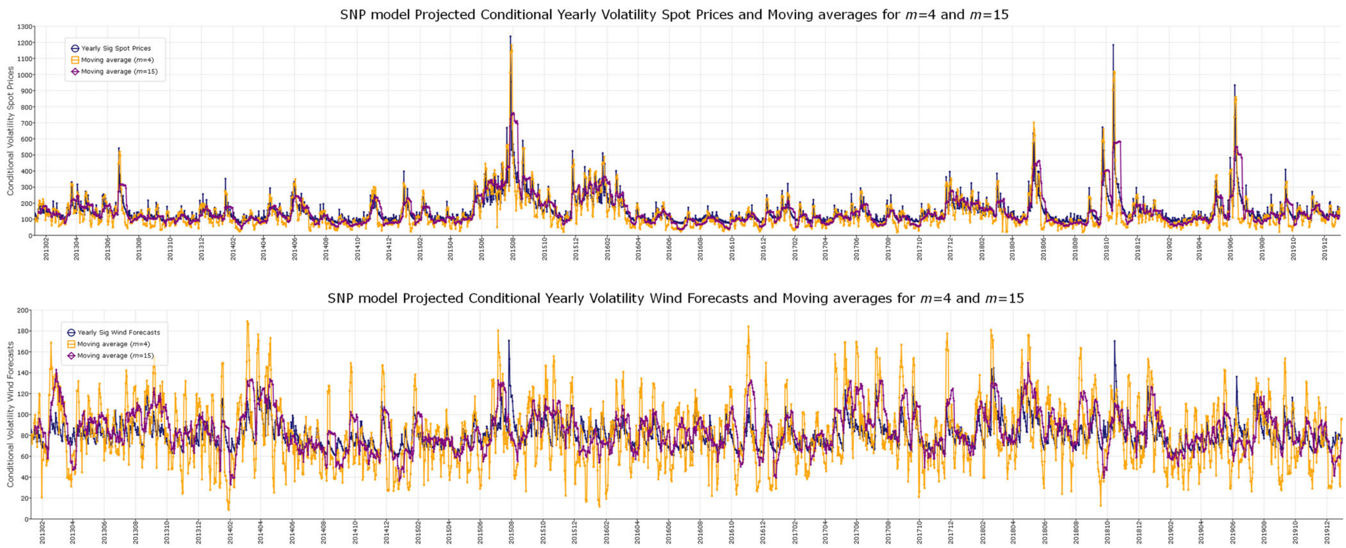

FIGURE 6 Conditional spot price and wind forecast volatility with associated moving averages (m = 4 and m = 15)

changes (ω) on the vertical axes. An ordinary regression shows a relatively strong negative relationship represented by $y = -0.7902\omega + 0.2407$; $t_\omega = -34.2$; and $R^2 = 31.5\%$. Relative to the unconditional movements plot in Figure 1, the wind forecast conditional movements report stronger influence on spot price movements than the unconditional.

Figure 5 reports the conditional variances $Var(\tilde{y}_t|\tilde{y}_{t-1,...,}\tilde{y}_{t-L})$ for spot prices and wind forecast movements (top) and a two-dimensional (bivariate) plot of the conditional variances for the bivariate movements (bottom). By looking at the axis values, the conditional variances for the conditional wind forecast movements are lower than for the spot price. However, an interesting feature is the collection of observation pairs along the wind forecasts variance axis (horizontal axis). It seems that wind forecasts in some periods can vary a lot without any changes in spot price variances (most likely for periods where the level of wind forecasts are relatively low). In fact, a medium level of wind forecast variances between 20% and 40% seems to produce the highest influence on spot price variances. However, it seems that high spikes in spot price and wind forecast variances coexist (in Figure 5, see the Dates 201508, 201810 and 201906).

Figure 6 reports the conditional volatility together with a calculation of moving averages with lags of 4 and 15 (m) for spot price (top) and wind forecast movements (bottom), respectively. From the plots, we observe that the moving average model seems more suitable for spot

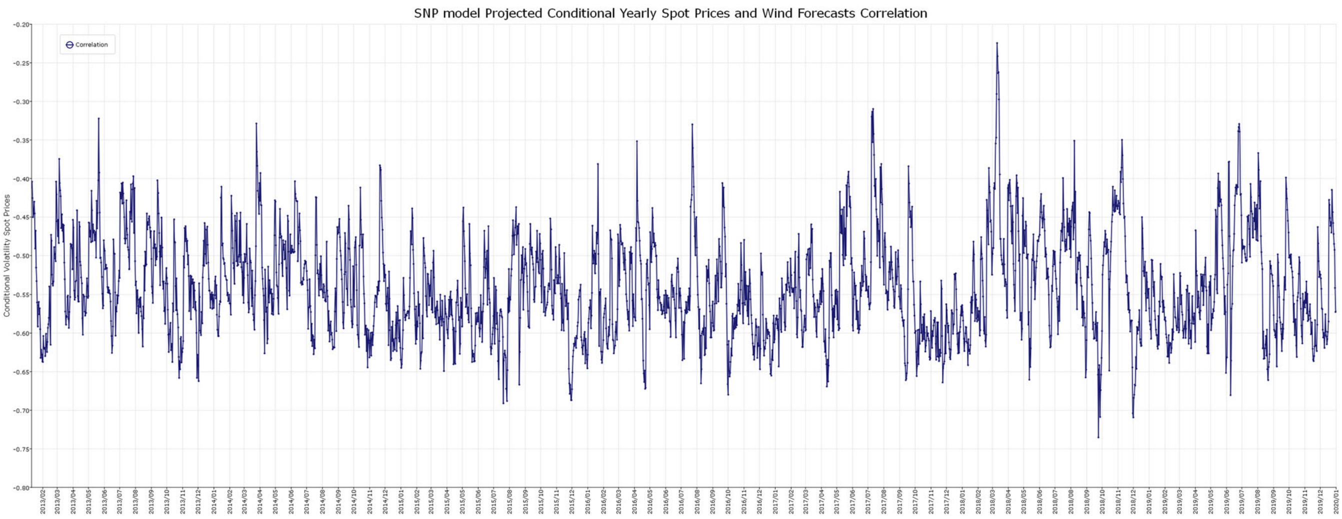

FIGURE 7 Conditional spot price and wind forecast correlations

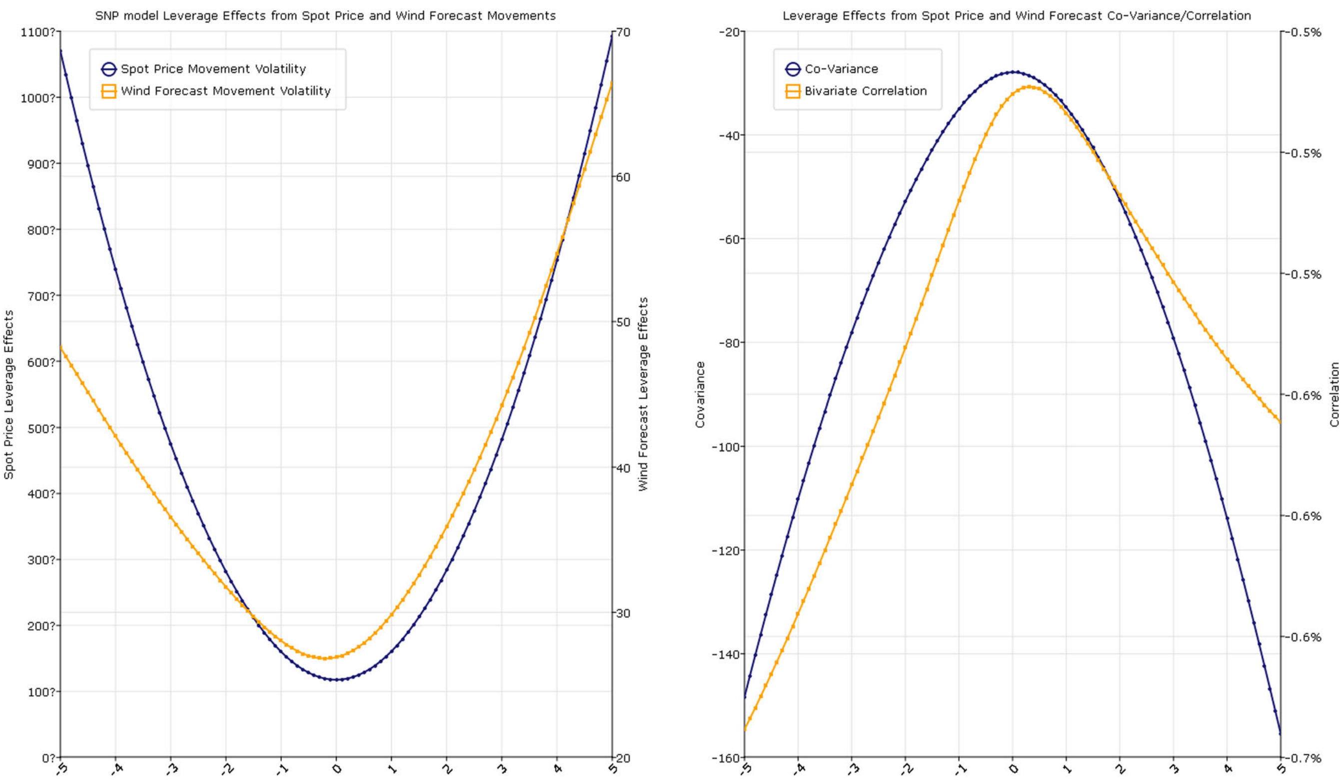

FIGURE 8 Leverage plots for spot price and wind forecast variances and covariances

price than wind forecast movements. The plots clearly indicate that the moving average series follows the spot prices more closely than they do for the wind forecasts. Furthermore, for the spot price movements, the volatile 2015 period mentioned above is clearly visible and seems partly extended into the year 2016. In contrast, the wind forecast movements show a much lower and, as expected, a more stable volatility. However, the plots suggest that the yearly spring periods may seem more turbulent. Moreover, the bivariate time series also gives access to the conditional covariances. Figure 7 reports the conditional correlation structure between spot prices and wind forecast movements. The correlation average mean is about −0.54, and it moves mainly between a daily correlation (ρ) of −0.25 and −0.75 for the whole 7-year period. Finally, Figure 8 reports leverage functions for spot price

TABLE 4 Residual statistics for spot system price and wind prognosis movements

	Mean/mode	Median/SD	Maximum/minimum	Moment kurt/skew	Quantile kurt/skew	Quantile normal	Cramer-von Mises	Serial dependence Q(12)	Q2(12)
Day-ahead auction prices	−0.00253	−0.00401	7.41835	4.03967	0.06033	0.78195	1.72430	8.7402	14.9029156073
		0.95942	−5.08017	0.51189	−0.03052	{0.6764}	{0.0000}	{0.7249}	{0.2468}
	BDS Z statistics ($e = 1$)				ARCH	RESET	Joint		
	$m = 2$	$m = 3$	$m = 4$	$m = 5$	(12)	(12;6)	Bias		
	−1.97196	−1.14503	−1.14631	−1.47460	14.70202	13.72420	8.61220		
	{0.0486}	{0.2522}	{0.2517}	{0.1403}	{0.2581}	{0.0329}	{0.0349}		
	Mean/mode	**Median/SD**	**Maximum/minimum**	**Moment kurt/skew**	**Quantile kurt/skew**	**Quantile normal**	**Cramer-von Mises**	**Serial dependence Q(12)**	**$Q2$(12)**
Wind prognosis	0.03203	0.07494	4.03793	4.87303	0.07824	1.90681	0.72628	13.6379	12.95043
		1.03755	−10.56878	−0.66670	−0.05440	{0.3854}	{0.0000}	{0.3244}	{0.3727}
	BDS Z statistics ($e = 1$)				ARCH	RESET	Joint		
	$m = 2$	$m = 3$	$m = 4$	$m = 5$	(12)	(12;6)	Bias		
	−0.11339	0.68555	0.67333	0.53754	11.84137	4.89385	2.58156		
	{0.9097}	{0.4930}	{0.5007}	{0.5909}	{0.4585}	{0.5575}	{0.4607}		

Abbreviation: ARCH, autoregressive conditional heteroscedasticity.

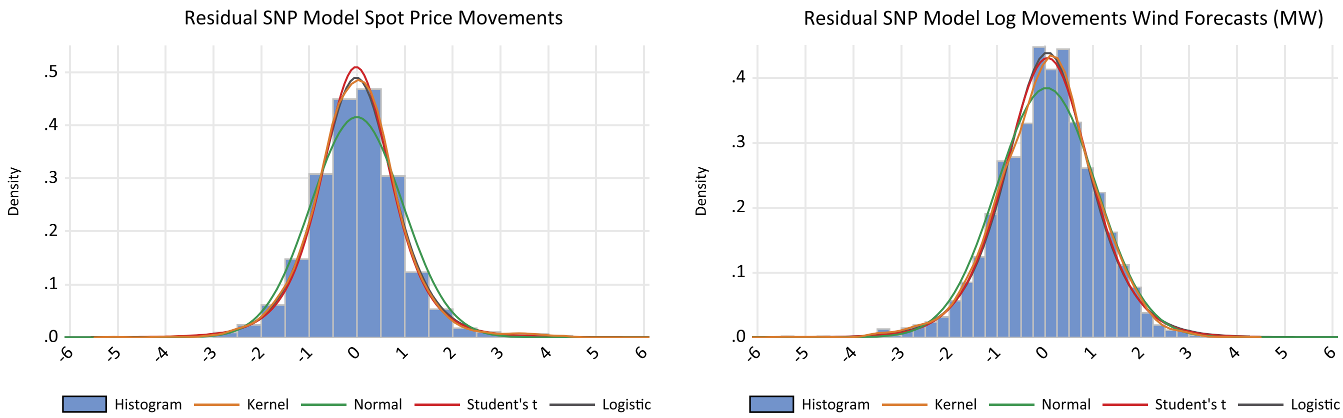

FIGURE 9 Kernel standardized residual densities for spot price and wind forecast movements from the optimal semi-nonparametric (*SNP*) model

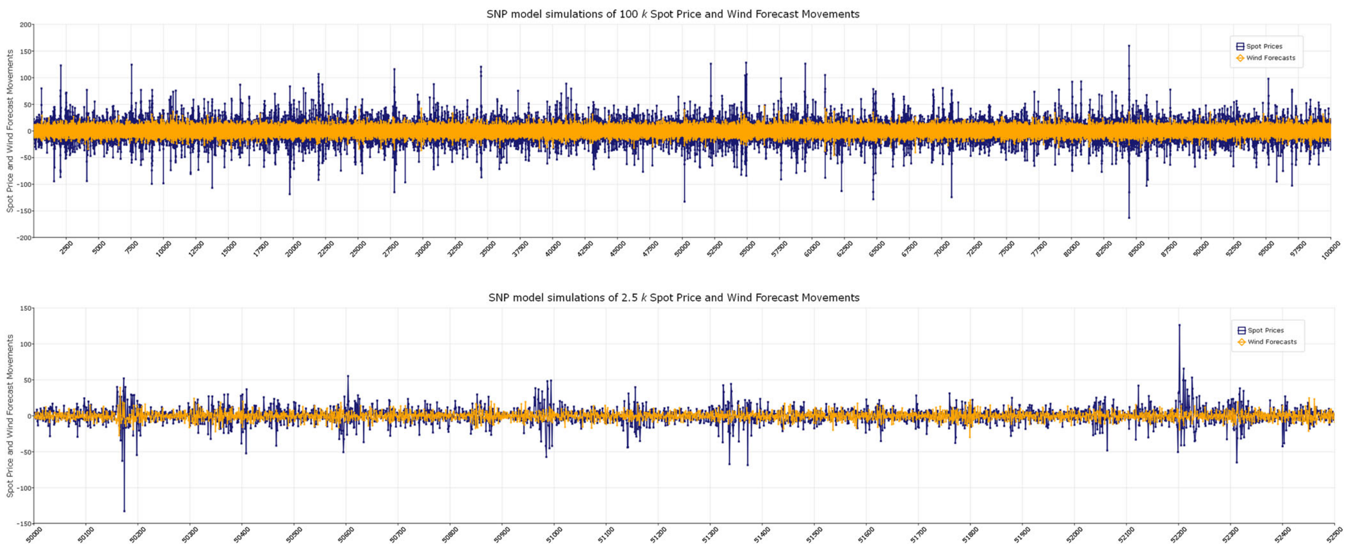

FIGURE 10 Full-sample (100 k) and subsample (2.56 k) from an optimal semi-nonparametric (*SNP*) model simulation (spot price and wind forecast movement)

and wind forecast variances. This analysis suggests that volatility from spot prices is symmetric whereas the volatility from wind forecasts shows a higher wind forecast volatility for positive wind forecast movements. There is no sign of asymmetry for the covariances. However, asymmetry is clearly visible for the spot price and wind forecast correlation. A negative correlation between spot price and wind forecast movements clearly suggests a correlation closer to a perfectly negative correlation ($\rho = -1$).

Table 4 reports a battery of misspecification statistics for the bivariate residuals. All statistics are insignificant at the 5% level except the Cramer von Mises test for normality. However, for both series, the quantile normal test is insignificant. Therefore, from Table 2, the *SNP* optimal model seems able to capture the main attributes from the bivariate adjusted series also giving us i.i.d residuals in Table 4. For both series, the mean for the standardised residuals is close to zero and the standard deviation is close to one ($N(0,1)$). The 12th order Ljung and Box (1978) statistic for the standardised residuals (Q), squared standardised residuals (Q^2), the ARCH (12), the RESET (12;6), the joint bias test statistic (Engle & Ng, 1993) and the *BDS* test are all insignificant. The specification tests therefore suggest an appropriate bivariate model specification for the adjusted spot prices and wind forecasts movements. Figure 9 shows histogram, density kernels compared with theoretical densities, for the standardized *SNP* model residuals. Figure 9 suggests that the standardised residuals are i.i.d. and not far from normally distributed.

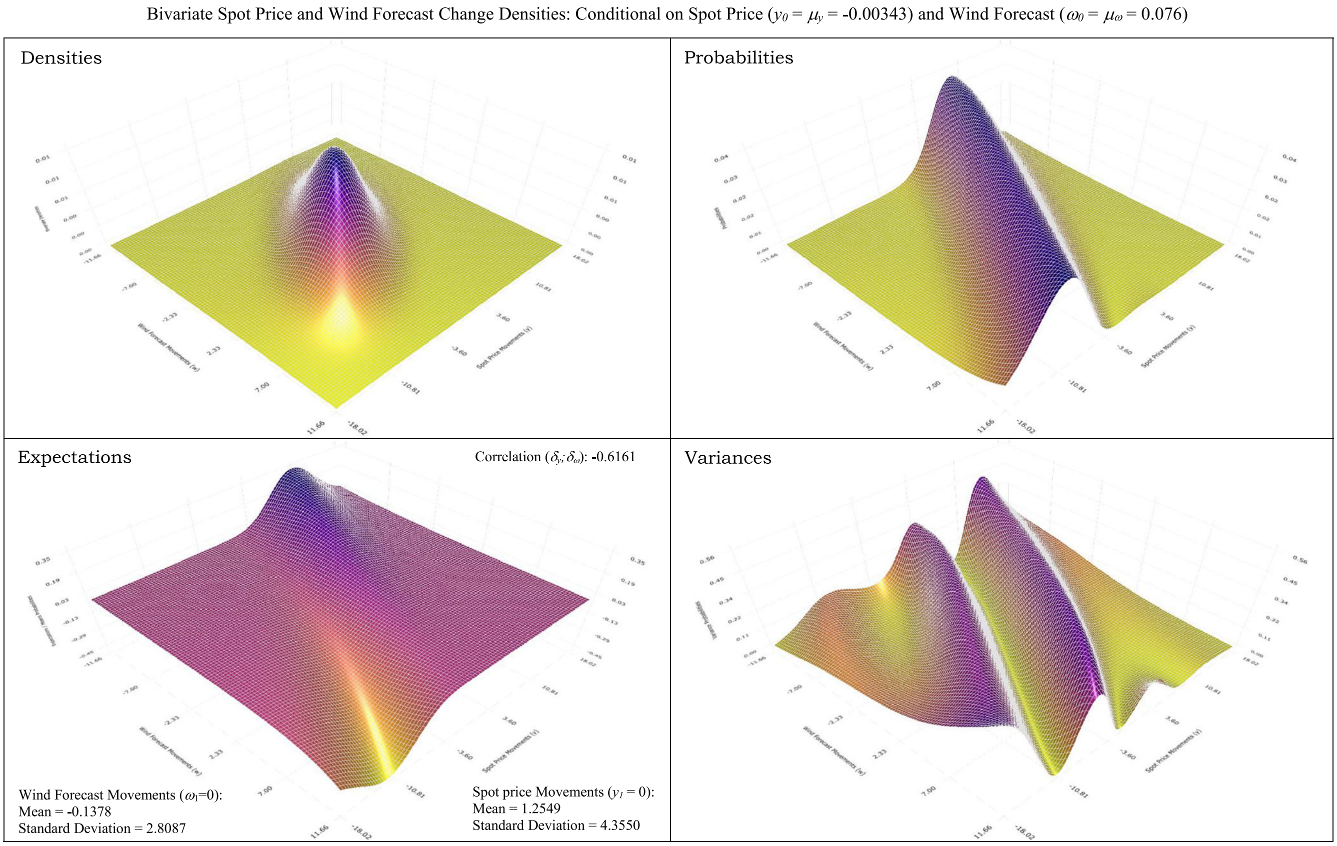

FIGURE 11 Step ahead bivariate spot price and wind forecast movement plots conditional on the unconditional means

4 | STEP-AHEAD SPOT PRICE PROJECTIONS FROM SYNCHRONOUS WIND FORECAST MOVEMENTS

Simulations in the original units of the data $\left\{\tilde{y}_t;\tilde{\omega}_t\middle|\hat{\phi}_K\right\}_{t=1}^{n}$ are available for any length (n). Changing the seed makes bootstrapping available for building confidence intervals and hypotheses testing. Figure 10 shows a one path simulation of length $n = 100\,k$ steps (top) and sublength $n = 2.5\ k$ steps (bottom). The simulation shows similar characteristics to the original 2.5 k adjusted data set (see Figure 2). However, the data set is a bit wider than the original series, but all moments match the original series. The heterogeneous characteristics of spot prices and wind forecasts movements are clearly present in the two series. The extreme behaviour of the spot price series is also clearly visible in the plot (the blue line varies from −300% to 200%). The wind forecasts show lower variance, varying between −50% and 50%. The 100-k step simulation shows an $\left(\tilde{y}_t;\tilde{\omega}_t\middle|\hat{\phi}_K\right)$ unconditional correlation of $\rho = -0.4995$, a little lower than the average correlation in Figure 4 ($\rho = -0.5092$).

The observed data set $(\tilde{y}_t,\tilde{\omega}_t)$ and the estimated *SNP* model $\hat{f}_K\left(\tilde{y}_t;\tilde{\omega}_t\middle|x_{t-1},\hat{\phi}\right)$ provide the one-step-ahead density, conditional on the values $x_{t-1} = \tilde{y}_{t-1},\tilde{y}_{t-2},...,\tilde{y}_{t-L}$ ($L = 7$). Figure 11 shows a 3D plot of the bivariate one-step-ahead density with spot price changes on the x-axis, wind forecast changes on the y-axis and the density on the z-axis. The conditional x_{t-1}values are all set to the unconditional means (−0.00342; 0.0076, respectively). Therefore, the bivariate step-ahead density plot reports mainly the density for synchronous conditional spot prices and wind forecasts movements. The density indicates clearly higher and narrower densities for negative comovement corners of the spot price and wind forecast movements. Hence, there is more mass towards the corners where the two variables move in opposite directions (the negative comovement corners). For more positive bivariate comovements, the density mass is considerably lower and wider. Market expectations are therefore the more (less) wind the lower (higher) spot prices. These comovement findings between price and wind movements are clearly already known facts for electricity market participants. However, using the step-ahead densities and condition on various plausible price and wind forecast combinations may bring new information to market participants on both the spot price movements and volatility. In other words, if we know the market microstructure (i.e., knowing that the daily wind

TABLE 5 One-step-ahead mean, standard deviation, skewness and kurtosis for reported spot prices conditional on synchronously reported lags close to the unconditional means (0) and for lagged spot price ($y_0 = \pm 10$) and wind forecast ($\omega_0 = \pm 6$) movements lags

Spot price expectations ($E(y_1 \vert x_0, \omega_1)$), standard deviations ($\sqrt{Var(y_1 \vert x_0, \omega_1)}$), maximum probability ($Max(y_1 \vert x_0, \omega_1)$) and skewness										
		Synchronously reported								
Lags/y_0	Wind (ω_1)/ω_0	−12%	−9%	−6%	−3%	0%	3%	6%	9%	12%
0%	0%	8.5338/4.3042	7.2076/4.1548	5.1167/4.1871	2.7499/4.2954	−0.0638/4.3823	−2.991/4.3621	−5.7322/4.2032	−8.6602/3.8636	−11.0341/3.7129
		10.0825/−0.9367	8.6421/−0.8135	6.8417/−0.4541	5.4013/−0.2243	−3.961/−0.1255	−5.4013/−0.0944	−7.5618/−0.0721	−9.7224/0.0389	−11.8829/0.8075
−10%	−6%	8.3651/−0.1586	7.852/0.0276	7.5896/0.1514	7.531/0.1439	7.5881/0.0368	7.7165/−0.1208	7.8732/−0.2679	8.0216/−0.3532	8.1464/−0.3303
		0/0.5812	0/0.4944	0/0.3447	0/0.3675	0/0.4693	0/0.5102	0/0.3964	0/0.1399	0/−0.1286
−10%	6%	5.921/−0.3867	5.6989/−0.1429	5.6813/−0.0053	5.7334/−0.0562	5.8346/−0.2281	5.9474/−0.3687	5.9763/−0.3592	5.9159/−0.2547	5.6402/0.5176
		0/1.1493	0/1.219	0/1.1547	0/1.1715	0/1.0393	0/0.6126	0/0.0408	0/−0.1861	0/1.0476
10%	−6%	8.7459/6.3085	7.9026/5.9976	6.1887/5.8884	3.4738/5.9036	0.5319/5.9599	−2.6325/6.0097	−6.1898/5.9857	−9.4323/5.8299	−12.5039/5.5596
		11.8863/−0.4034	10.4005/−0.1912	8.9147/0.0387	7.429/0.1089	5.9432/0.0247	−6.9336/−0.1075	−8.9146/−0.2062	−11.391/−0.1966	−13.8673/0.0112
10%	6%	7.4141/8.4994	6.8209/7.7609	4.5158/7.2826	1.6023/7.114	−1.732/7.2113	−5.4026/7.5205	−9.3473/7.8439	−13.7427/7.9133	−17.5841/7.5409
		11.6344/0.0037	11.0527/0.1767	9.3075/0.2176	7.5624/0.0739	−7.5624/−0.1626	−9.8892/−0.3137	−12.7978/−0.2473	−16.8699/0.0742	−29.086/0.5681

forecast movements are available before auction bid time at 11 a.m.), would it be possible to use this information to predict the day-ahead auction price reported daily at 00.45 p.m.? Hence, a marginal step-ahead spot price density conditional on the synchronously reported wind forecast movements is of interest to all market participants.

Using the optimal *SNP* bivariate density model and setting all lags ($L = 7$ lags) to the unconditional means (or zero), we calculate the one-step-ahead spot price (y_1) densities conditional on the synchronously reported values for wind forecast movements (ω_1), that is, conditional marginal spot price densities. The analysis is conditional on $y_0 = -10\%, \ldots, 10\%$ with a lag vector (0, 0, 0, 0, 0, 0, −10%) for $y_0 = -10\%$ and for $\omega_0 = -6\%, \ldots 6\%$ with a lag vector (0, 0, 0, 0, 0, 0, −6%) for $\omega_0 = -6\%$. Hence, we have access to a 15×13 matrix of marginal densities with associated densities, means, standard deviations, maximum probability spot prices and skewness (and kurtosis [not reported]). We report densities for y_1 and ω_1 equal to 0 and the highly plausible combinations of $y_0 = -10\%$ (10%) and $\omega_0 = -6\%$ and 6% (−6% and 6%). The reports show the densities, probabilities, expectations and variances for spot price movements (y_1) conditional on the synchronously reported but known to market participants, wind forecasts (ω_1). Conditional on $(y_0, \omega_0) = \mu_{y_0}; \mu_{\omega_0}$, Figure 11 reports the marginal spot price movement densities, probabilities, expectations and variances. Table 5 reports the mean, standard deviation, skewness and kurtosis for a set of the conditional synchronously reported wind forecasts (ω_1). For lags of spot prices (y_0) and wind forecasts (ω_0) close to zero, a synchronously reported wind forecast movement of zero ($\omega_1 = 0$), the expected spot price movements (y_1) are marginally negative −0.06, the standard deviation is $\sigma_{y_1} = 4.38$, the maximum probability is found at y_1 of −3.96, and the skewness is −0.13 (kurtosis not reported). For negative (positive) synchronously reported wind forecast movements (ω_1), the analysis reports positive (negative) expected spot prices. Interestingly, in this situation where the price and wind movement lags are close to zero, the highest absolute value with lowest standard deviation for the mean spot price is found for positive wind forecast movements. Figure 11 confirms this situation showing that when wind forecast movements report an increase, the density is almost exclusively on the left, expecting negative spot prices. However, note the density increase on the right side for positive spot prices, indicating that the positions are not without risks. Note also that the skewness follows the signs of wind forecast increases indicating larger probabilities for lower profits for recommended spot price positions.[33] Furthermore, Table 5 reports expected daily spot prices movements (y_1) for spot price lags of −10% and +10% and synchronously reported wind forecast lags of −6% and +6%, where the condition is the known wind forecasts (ω_1) −12% and +12%. As for lags close to zero, the negative correlation between prices and wind is clearly visible. The expected absolute expected price movements seem higher for positive wind movements. Conditional on positive lagged spot prices, positive wind forecasts seem to increase the negative price effect from increased wind forecasts without changing standard deviation significantly. This effect is also clearly visible from maximum probability spot price values. The skewness seems to follow the general development found for price and wind lags close to zero. Moreover, regardless of the wind forecast at ω_1, the standard deviation for spot prices at y_1 is clearly lower when the lags are negatively correlated. Moreover, when prices and wind forecasts are negatively correlated, positive wind forecast movements suggest higher negative movements in spot prices. However, this last asymmetry observation may be related to the lagged positive changes in both spot prices and wind forecasts. For example, from Table 5 (line 1) and Figures 13 and 14, where the analysis is conditional on values for y_0 and ω_0 being close to zero, a wind forecast movement of $\omega_1 = -6$ ($\omega_1 = 6$), the spot price expectation moves up with $y_1 = 5.12$ ($y_1 = -5.73$), with associated standard deviation of $\sigma_1 = 4.19$ ($\sigma_1 = 4.2$), maximum probability at $y_1 = 6.84$ ($y_1 = -7.54$), and skewness of −0.45 (−0.07). Furthermore, when the known wind forecast movements show a strong reduction $\omega_1 = -12$ (increase $\omega_1 = 12$) and continued condition close to zero $(y_0, \omega_0) = \mu_{y_0}; \mu_{\omega_0}$, the expected spot prices are expected to increase (decrease) by $y_1 = 8.53$ ($y_1 = -11.03$), with associated standard deviation of $\sigma_{y_1} = 4.30$ $(\sigma_{y_1} = 3.71)$, maximum probability at $y_1 = 10.08$ ($y_1 = -11.88$), and skewness of −0.94 (0.812). Note that wind forecast movements (ω_1) at t_1 of −12% and 12% are quite rare relative to movements of −6% and 6%.

Hence, for absolute wind forecast movements greater than 3%, the movements exceed one standard deviation, indicating a 68% change of profitable spot price positions. Figure 12 indicates absolute spot price expectations mainly higher than maximum probability. Hence, the price expectations suggest large negative tails. That is, mainly negative (positive) y_1 expected spot prices have large tails for positive (negative) expected spot prices. Hence, there are large surprises in the spot electricity market. Furthermore, the expectation densities in Figure 12 show that all expectations cover both negative as well as positive spot prices and therefore include zero spot price movements. As indicated by the standard deviation, the density shows a wide distribution showing possible values for the expected spot price movements y_1 between −18% and +18%. That is, any auction bid position will involve considerable risk conditional on the history $(y_0, \omega_0) = \mu_{y_0}; \mu_{\omega_0}$ close to zero.

The analysis now extends the historic information (lags) and uses four very plausible historic values for the synchronously reported spot price and wind forecast movements. The lagged spot price movements are $y_0 =$ −10% and 10% with associated conditional vectors (0, 0, 0, 0, 0, 0, −10%) and (0, 0, 0, 0, 0, 0, 10%), respectively, and the lagged wind forecast movements $\omega_0 = -6\%$ and 6% with associated conditional vectors (0, 0, 0, 0, 0, 0, −6%) and (0, 0, 0, 0, 0, 0, 6%), respectively. The analysis has the plausible spot price and wind forecast cases: (1) $y_0 = -10$ and $\omega_0 = -6$, (2) $y_0 = -10$ and $\omega_0 = +6$, (3) $y_0 = 10$ and $\omega_0 = -6$, and (4) $y_0 = 10$ and $\omega_0 = +6$)

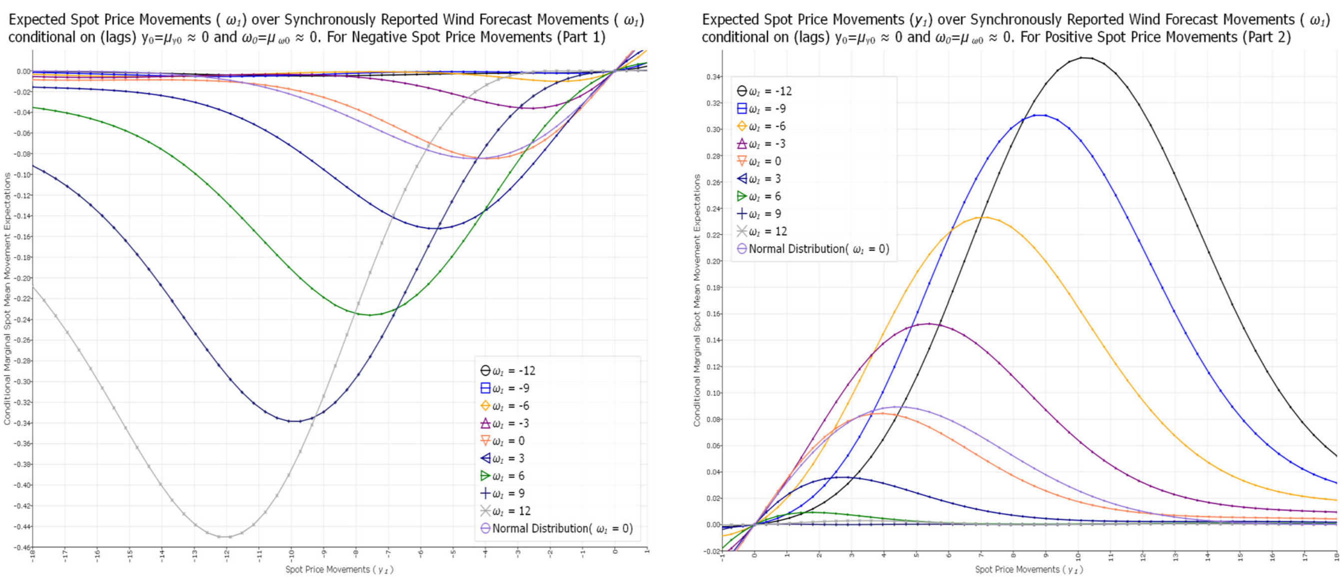

FIGURE 12 Marginal step ahead spot price densities for synchronous wind forecasts conditional on $y_0 = \mu_{y_0}$ 0 and $\omega_0 = \mu_{\omega_0} \approx 0$

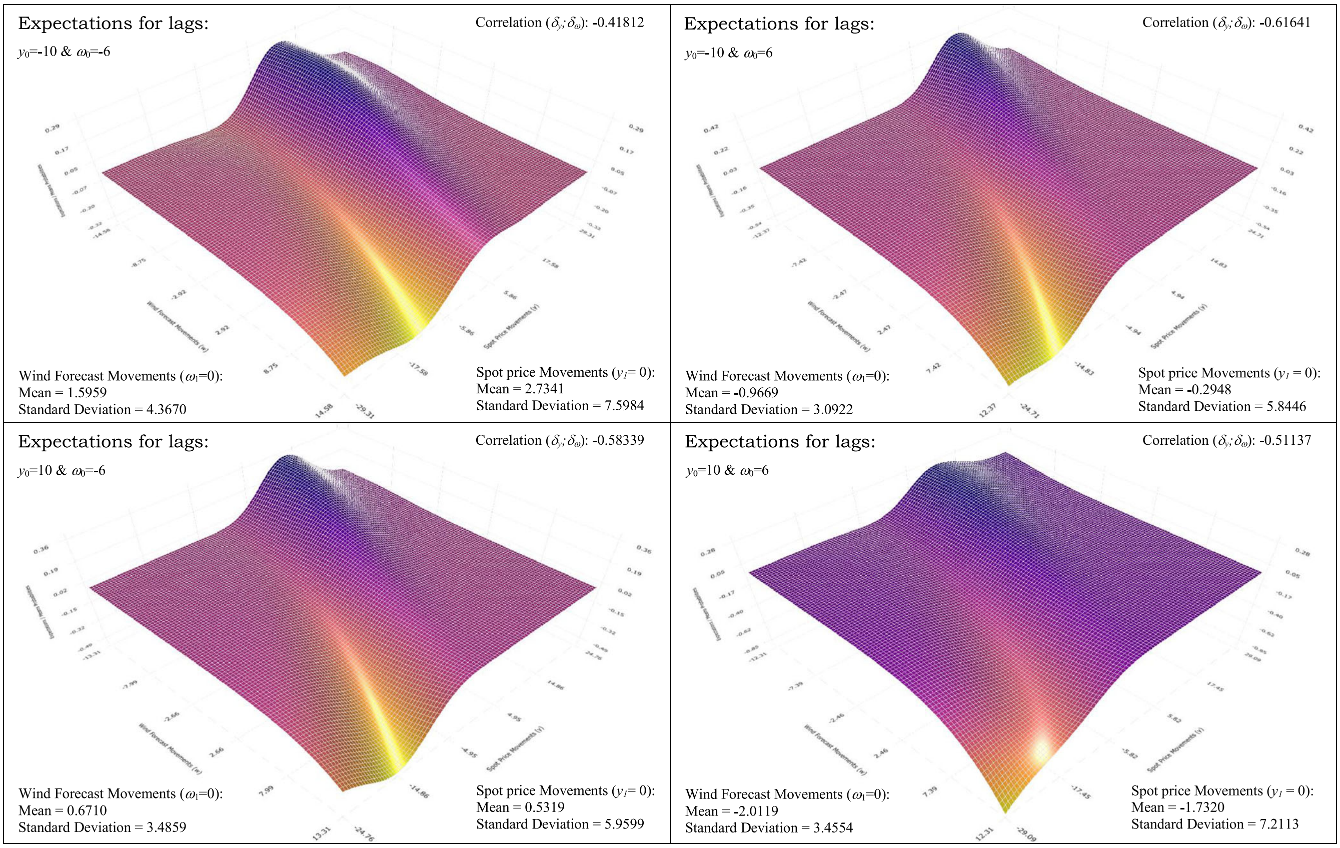

FIGURE 13 Bivariate expected spot price movement probabilities for synchronously reported spot prices and wind forecasts conditional on $y_0 = \pm 10\%$ and $\omega_0 = \pm 6\%$

Figure 13 reports bivariate spot price and wind forecast expectation plots. The four plots show similar characteristics, but looking at the z-axes, the spot price movements are higher and narrower for varying synchronously reported wind forecast movements when lagged prices and wind forecast movements show opposite signs (negative correlation). The plots report means and standard deviations. When ω_0 is negative (positive), the spot mean (y_1) is positive (negative). Moreover, when prices and forecasts behave in the normal way (negative comovements), the standard deviation is clearly lower. The bivariate plots therefore show influence from wind forecast at t_0 and t_1 for both the mean and standard deviations (risk). Furthermore, to analyse the lag differences, we apply 2D plots conditioning on the known wind forecast movements at t_1. Table 5 (Lines 2–5) reports the spot price movements mean, standard deviation, maximum spot price probability and skewness over a similar set of wind forecast movements ($\omega_1 = -12\%$, ..., $+12\%$). Hence, the analysis focuses on the known wind forecasts for the day-ahead (ω_1) before the auction bid deadline at 11 a.m.

Case 1. Figure 14 (Panel A): Lag vector is $y_0 = (0, 0, 0, 0, 0, 0, 0, -10\%)$ and $\omega_0 = (0, 0, 0, 0, 0, 0, 0, -6\%)$.

Figure 14 (Panel A) reports the marginal spot price distributions conditional on negative spot price and wind forecast movement lags for a set of synchronously reported and known wind forecasts ($\omega_1 = -12\%$, ..., 12%).[34] A wind forecast movement close to zero ($\omega_1 = 0$) means that the density for spot price movements is higher for positive than negative prices. Table 5 (Line 2) confirms this, showing a positive expected spot price movement of $y_1 = 2.73$ with an associated standard deviation of $\sigma_{y_1} = 7.6$. The spot price with maximum probability is $y_1 = 8.79$. However, as indicated by the standard deviation, the density shows a wide distribution showing possible values for the expected spot price movements y_1 between -29% and $+29\%$. The lags for Case 1 assume that spot price and wind forecasts movements are both negative (positive comovements), which contradicts the normal negative comovements ($\rho \approx -0.5$). However, the synchronously reported and known wind forecast movements clearly suggest that negative (positive) wind forecast movements are followed with positive (negative) expected spot price movements. However, the case reports a higher associated standard deviation σ_{y_1} for spot price movements indicating wider densities and higher risks (see Cases 2–4 below). For example, when the

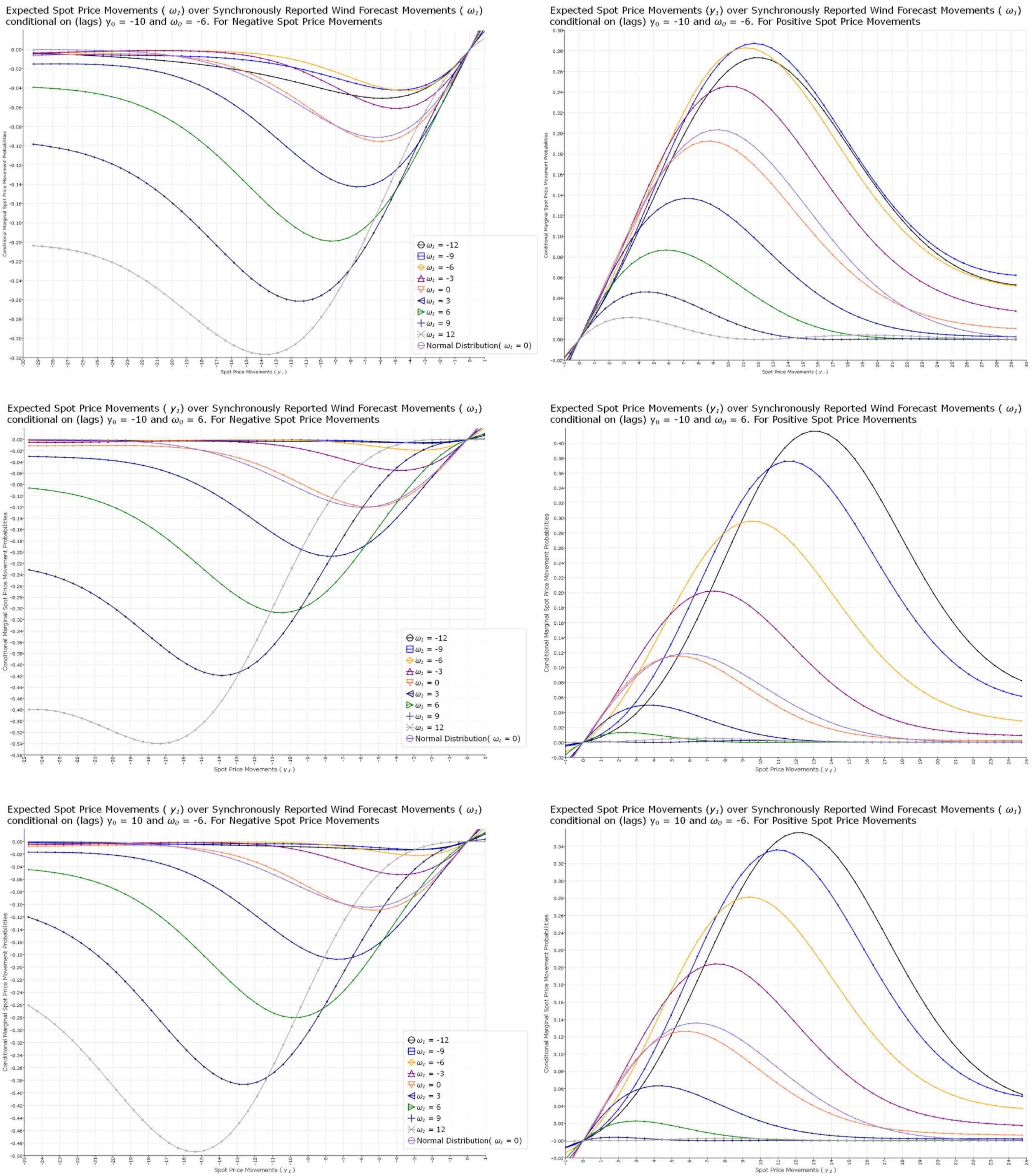

FIGURE 14 Marginal step ahead spot price densities for synchronous wind forecasts conditional on $y_0 = \pm 10$ and $w_0 = \pm 6$

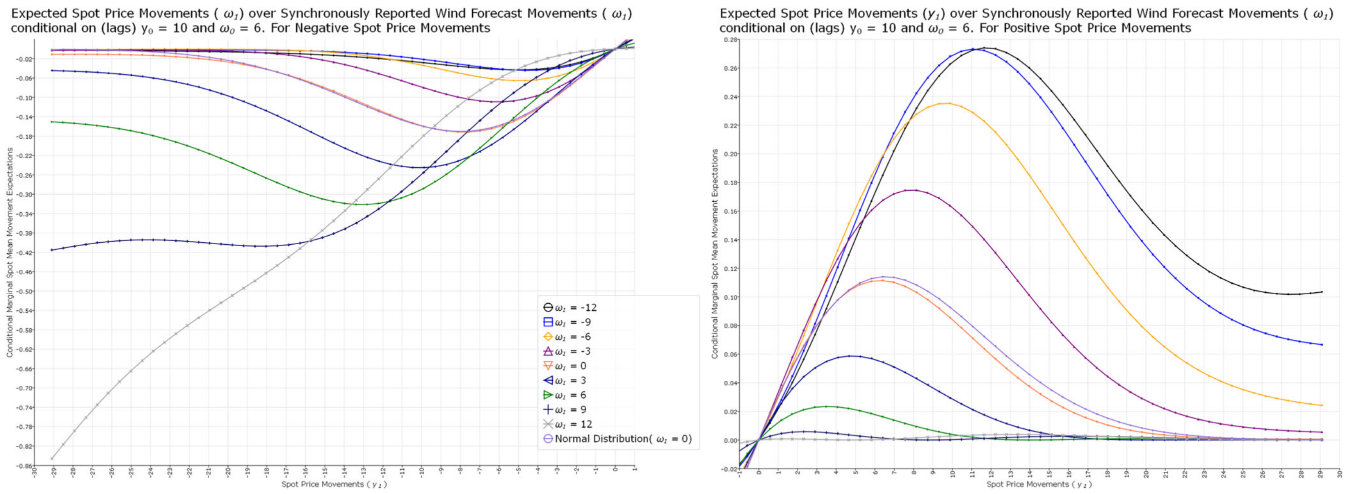

FIGURE 14 (Continued)

known wind forecast movements are −6% ($w_1 = -6$), the expected spot price movements are 6.46% ($y_1 = 6.46$) with associated standard deviation of 7.6% $\left(\sigma_{y_1} = 7.6\right)$. The spot price with maximum probability is 10.5%, and skewness is 0.16. When known wind forecast movements are 6% ($w_1 = 6$), the expected spot price movements are −2.26% ($y_1 = -2.26$) with associated standard deviation of 7.9% $\left(\sigma_{y_1} = 7.9\right)$. The spot price with maximum probability is −8.2%, and skewness is −0.28. The main observation from Table 5 and the lags $y_1 = -10\%$; $\omega_0 = -6\%$, is the higher risk without a clear spot price movement compensation. Moreover, the expected negative comovement between wind and spot price movements are extended. Finally, all the spot price densities at t_1 are positive for both negative as well as positive expected spot price movements indicating that all market positions will risk wrong market positions.

Case 2. Figure 14 (Panel B): Lag vector is y_0 = (0, 0, 0, 0, 0, 0, 0, −10%) and ω_0 = (0, 0, 0, 0, 0, 0, 0, +6%).

Figure 14 (Panel B) reports the marginal spot price distributions conditional on negative spot price and positive wind forecast movement lags for a set of synchronously reported and known wind forecasts (ω_1 = −12%, ..., 12%). A wind forecast movement close to zero ($\omega_1 = 0$) means the density for spot price movements is approximately equal for positive and negative spot price movements. Table 5 (Line 3) confirms this showing an expected spot price movement of $y_1 = -0.3$ with an associated standard deviation of 5.84. The spot price with maximum probability is $y_1 = -5.44$. However, as indicated by the standard deviation the density shows a wide distribution showing possible values for the expected spot price movements y_1 between −25% and +25%. The lags for Case 2 assume that spot price and wind forecasts movements show negative comovements ($\rho \approx -0.5$). The synchronously reported and known wind forecast movements continue to show that negative (positive) wind forecast movements are followed with positive (negative) expected spot price movements. Moreover, the case reports a lower associated standard deviation σ_{y_1} for spot price movements indicating narrower densities and lower risks (see Cases 1–4). For example, when the known wind forecast movements are −6% ($\omega_1 = -6$), the expected spot price movements are 6.5% ($y_1 = 6.5$) with associated standard deviation of 5.7% $\left(\sigma_{y_1} = 5.70\right)$. The spot price with maximum probability is 9.4%, and skewness is −0.002. When known wind forecast movements are 6% ($\omega_1 = 6$), the expected spot price movements are −7.9% ($y_1 = -7.9$) with associated standard deviation of 5.97% $\left(\sigma_{y_1} = 5.97\right)$. The spot price with maximum probability is −9.9%, and skewness is −0.35. The main observation from Table 5 and the lags $y_1 = -10\%$; $\omega_0 = 6\%$ is the lower risk. Moreover, the expected negative comovement between wind and spot price movements are extended. Finally, all the spot price densities at t_1 are positive for both negative as well as positive expected spot price movements indicating that all market position will risk wrong market positions.

Case 3. Figure 14 (Panel C): Lag vector is y_0 = (0, 0, 0, 0, 0, 0, 0, +10%) and ω_0 = (0, 0, 0, 0, 0, 0, 0, −6%).

Figure 14 (Panel A) reports the marginal spot price distributions conditional on positive spot price and negative wind forecast movement lags for a set of synchronously reported and known wind forecasts (ω_1 = −12%, ..., 12%). A wind forecast movement close to zero ($\omega_1 = 0$) means the density for spot price movements is somewhat higher for positive than negative prices. Table 5 (Line 4) confirms this, showing a positive expected spot price movement of $y_1 = 0.53$ with an associated standard deviation of $\sigma_{y_1} = 5.96$. The spot price with maximum probability is $y_1 = 5.94$. Hence, considerable distribution mass is also present for negative spot price movements, which is confirmed in Figure 14 (Panel C). Furthermore, also indicated by the standard deviation, the density shows a distribution showing possible values for the expected spot price movements y_1 between −25% and +25%. The lags for Case 3 assume that spot price and wind forecasts movements show negative comovements ($\rho \approx -0.5$). The synchronously reported and known wind forecast movements clearly show that negative (positive) wind forecast movements are followed with positive (negative) expected spot price movements. Moreover, the case reports an associated standard deviation σ_{y_1} for spot price movements indicating narrower densities and lower risks (see Cases 1–4). For example, when the known wind forecast movements are −6% ($w_1 = -6$), the expected spot price movements are 6.19% ($y_1 = 6.19$) with associated standard deviation of 5.89% $\left(\sigma_{y_1} = 5.89\right)$. The spot price with maximum probability is $y_1 = 8.91\%$, and skewness is 0.04. When known wind forecast movements are 6% ($\omega_1 = 6$), the expected spot price movements are −6.19% ($y_1 = -6.19$) with associated standard deviation of 5.99% $\left(\sigma_{y_1} = 5.99\right)$. The spot price with maximum probability is $y_1 = -9.89\%$, and the skewness is −0.2. The main observation from Table 5 and the lags $y_1 = 10\%$; $\omega_0 = -6\%$ is the lower risk from the normal negative comovements without a clear spot price movement compensation. Moreover, there is an expected negative comovement ($\rho \approx -0.5$) between the lagged wind and spot price movements. Finally, all the spot price densities at t_1 are greater than 0 for both negative as well as positive expected spot price movements indicating that all market positions will involve risks of wrong positions.

Case 4. Figure 14 (Panel D): Lag vector is $y_0 = (0, 0, 0, 0, 0, 0, 0, +10\%)$ and $\omega_0 = (0, 0, 0, 0, 0, 0, 0, +6\%)$.

Figure 14 (Panel D) reports the marginal spot price distributions conditional on positive spot price and wind forecast movement lags for a set of synchronously reported and known wind forecasts ($\omega_1 = -12\%, ..., 12\%$). A wind forecast movement close to zero ($\omega_1 = 0$) means the density for spot price movements is higher for negative than positive prices. Table 5 (Line 5) confirms showing a positive expected spot price movement of $y_1 = -1.73$ with an associated standard deviation of $\sigma_{y_1} = 7.21$. The spot price with maximum probability is $y_1 = -7.56$ indicating some distribution mass also for positive expected spot price movements. Moreover, as indicated by the standard deviation, the density shows a wide distribution suggesting possible values for the expected spot price movements y_1 between −30% and +30%. The lags for Case 4 assume that spot price and wind forecasts movements are both positive (positive comovements), which contradicts the normal negative comovement story ($\rho \approx -0.5$). However, the synchronously reported and known wind forecast movements ω_1 clearly suggest that negative (positive) wind forecast movements are followed with positive (negative) expected spot price movements. Moreover, the case reports a higher associated standard deviation σ_{y_1} for spot price movements indicating wider densities and higher risks (see Cases 1–4). For example, when the known wind forecast movements are −6% ($\omega_1 = -6$), the expected spot price movements are 4.52% ($y_1 = 4.52$) with associated standard deviation of 7.28% $\left(\sigma_{y_1} = 7.28\right)$. The spot price with maximum probability is 9.31%, and the skewness is 0.22. When known wind forecast movements are 6% ($\omega_1 = 6$), the expected spot price movements are −9.35% ($y_1 = 9.35$) with an associated standard deviation of 7.84% $\left(\sigma_{y_1} = 7.84\right)$. The spot price with maximum probability is $y_1 = -12.8\%$, and the skewness is −0.25. The main observation from Table 5 and the lags $y_1 = 10\%$; $\omega_0 = 6\%$ is a higher risk without a clear spot price movement compensation. Moreover, the expected negative comovement between wind and spot price movements are extended and not strongly influenced by positive comovement lags. However, note the strong negative expected spot price ($y_1 = -17.58\%$) when the wind forecast movements strongly increase ($\omega_1 = 12$). Finally, all the spot price densities at t_1 are positive for both negative as well as positive expected spot price movements indicating that all market positions risk wrong market positions.

5 | SPOT PRICE PREDICTION FROM SYNCHRONOUSLY REPORTED AND KNOWN WIND FORECAST MOVEMENTS

Do the spot price and wind forecast lags and cross lags ($L = 1$ lags) from the SNP model with lagged information, $y_0 = -60\%, ..., 60\%$; $\omega_0 = -20\%, ..., 20\%$, and does using the synchronously reported and known wind forecast movements, $\omega_1 = -12\%, ..., 12\%$, enable well-fitted spot price predictions (y_1) at t_1? The prediction analysis will use all available information from the structured model analysis above for the mean as well as volatility, including correlation. That is, using conditional information for lag one (t_0) for spot prices between −60% and 60% ($_0$) and wind forecasts between −20% and 20% (ω_0) together with synchronous wind forecasts at t_1 between −12% and 12% (ω_1), an expected spot price movement of mean, variance, skewness and kurtosis is estimated from known historic model

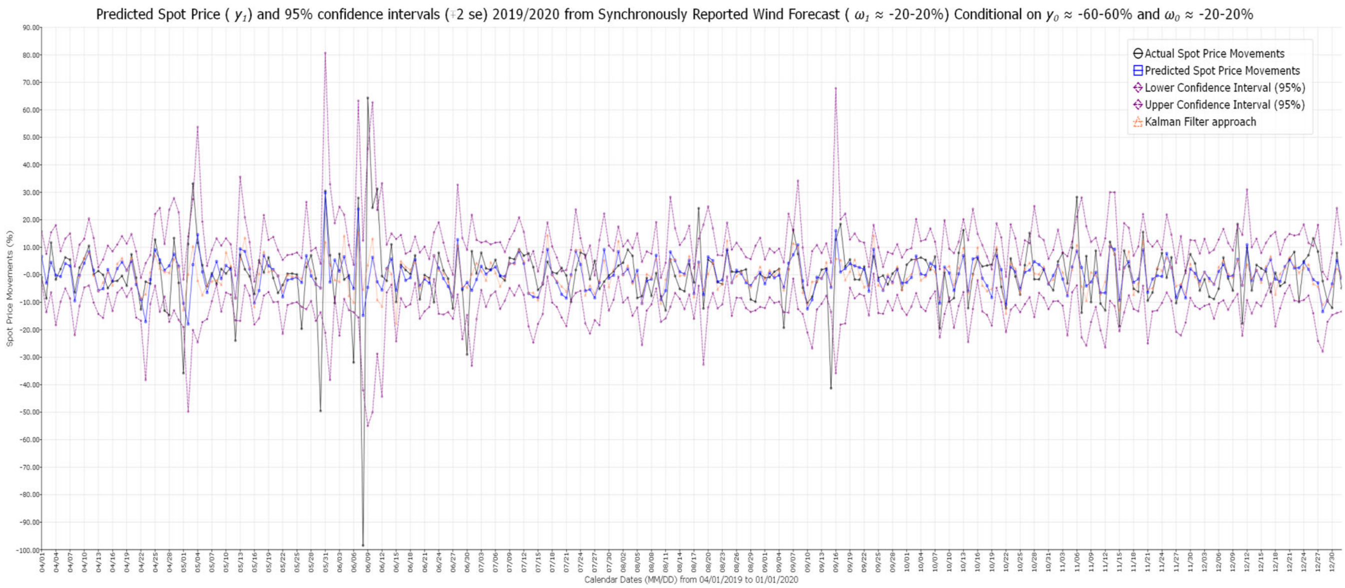

FIGURE 15 Spot price mean and 95% confidence interval predictions at t_1. Actual observations at t_1. One lag ($L = 1$) for spot price and wind forecast) movements at t_0 and synchronously reported but known wind forecast movements at t_1

information. For example, when $y_0 = -10\%$, $\omega_0 = 6\%$ and $\omega_1 = 10\%$, the spot price vector is (−12.74, 5.74, 0.08, 0.07 and −14.33). Moreover, the analysis shows that when spot price and wind forecast movements move in opposite directions (negative correlation), the densities are generally higher and narrower, indicating higher confidence for the mean expectations and narrower densities (lower risk). The one-step-ahead density predictions (static predictions) for 1 April 2019 to 1 January 2020 are reported in Figure 15 together with a Kalman filter prediction from a 100-k long *SNP* simulation, a 95% confidence interval and the actual spot price movements for the period. The actual movement observations are to a large extent inside the 95% (2 standard errors) confidence interval band of the mean predictions. The graph does not show skewness, kurtosis and the ML spot price.[35] A simple calculation is a count of the number of predictions within the confidence intervals, 244, versus the total number of predictions, 276. Hence, 88.5% of the one-step-ahead predictions are within the 95% confidence intervals. Extending the analysis with $L = 7$ lags might improve findings from these simple predictions. Moreover, a model extension from bivariate to quadruple adding for example consumption and production that are available and known prognoses before bid time at 11 a.m. might improve spot price movement predictions even further. It would be interesting to build an artificial neural network or a machine learning algorithm adding the information from lags of spot prices, wind, consumption and production forecast movements and extend the number of available lags $(-\infty \leq (y, \omega)_{t-i} \leq \infty, L = 1, \ldots, 7)$ suggesting a very large number of alternative scenarios for the spot price prediction analysis.

6 | SUMMARY AND CONCLUSIONS

We have modelled and estimated a bivariate SNP time series model[36] for the conditional mean and variance for the so-called system price and wind forecast changes in the Nordic electric power market for the period January 2013 to August 2019. The two series are adjusted for systematic seasonal, trend and scale effects for stationarity. The paper applies a bivariate SNP procedure employing expansions in hermite functions to approximate the conditional density of the bivariate spot price and wind forecast changes. The paper reports direct computation of the functionals of the fitted bivariate density. Moreover, computational accessible sample paths, which can be used to compute non-linear functionals of the density, can be obtained by Monte Carlo integration.

In summary, the article shows that the correlation between the synchronously reported spot price and wind forecasts movements is a major player for step-ahead spot price predictions. The methodology considers the relationships between the bivariate price and wind forecasts series (experimental design) in both mean and volatility. Our findings suggest that the synchronously reported but known wind forecast movements motivate day-ahead expected spot price regularities. From a *BIC* optimal model and a set of conditional wind forecast changes, the bivariate *SNP* model and all bivariate densities report negative correlation regularities suggesting potential dynamic market strategic behaviour. Moreover, the SNP model suggests that lagged price and wind movement information seems to influence the market position risks. That is, the expected spot price distributions are clearly higher and narrower when lags report negative price and wind forecast comovements. Hence, a normal comovement (negative $\rho = -0.5$) between prices and wind seems to calm down the market increasing the likelihood for prices and narrowing the distribution so reducing position risk. Moreover, the density plots in Figure 14 suggest that when lagged information shows positive comovements indicating an increase in both spot price and wind forecast movements, a further increase in wind forecasts the next day at t_1 seems to suggest an extraordinary decrease in expected spot price movements, without an associated increase in standard deviations. Hence, the systematics from the bivariate *SNP* model, the lags and the synchronously reported wind forecasts, in combinations, all suggest information to market participants, producing reliable spot price movement predictions. Because wind together with other renewables will be an increasing input factor for electricity and energy production in the future, the dynamic spot price and wind forecast comovements will contain important information for daily market positions at the Nordic/Baltic Energy Market. Building an artificial intelligence front end or a machine learning algorithm to analyse the influence of these information sets could be a very interesting future exercise for the prediction of expected spot price movements at t_1.

DATA AVAILABILITY STATEMENT

The article uses two freely available data sets. The first file '001-Electricity_Spot_prices_2013-2020.txt' contains daily system prices in Euro freely downloadable from Nordpoolgroup.com (https://www.nordpoolgroup.com/Market-data 1/#/nordic/table). The second file '002-Electricity_Wind_Forecasts_2013-2020.txt' contains daily wind forecasts from Denmark, Sweden, Estonia, Latvia and Lithuania in MwH freely downloadable from Nordpoolgroup.com (https://www.nordpoolgroup.com/Market-data 1/#/nordic/table). The Nordic/Baltic Electricity market consists of the following countries: Denmark, Estonia, Finland, Latvia, Lithuania, Norway, Sweden. The Nord Pool Group has authorized the use of the data set. The consent is given under cite agreements and that the data should not be used without authorization. The https://www.nordpoolgroup.com/Market-data 1/#/nordic/table reference gives free and direct access to spot prices and wind forecasts for the relevant period 2013–2020. The paper encloses the two daily data sets for the period 2013–2020:

1. 001-Electricity_Spot_prices_2013–2020.txt
2. 002- Electricity_Wind_Forecasts_2013–2020.txt

ENDNOTES

[1] See Solibakke, 2002.

[2] Wind forecasts are wind power prognosis in MWh for a 24-h period.

[3] The daily 'El-spot System Price' density forecasts are important information for both the physical market and the financial market. The financial market uses the daily 'El-spot System Price' as contract base for clearing. The financial Nasdaq market has around 250 members from more than 20 countries (energy producers, energy intensive industries, large consumers, distributors, funds, investment companies, banks, brokers, utility companies and financial institutions).

[4] The Nordic market is abundant in hydro production resources, making the market capable of coping with undirected wind variations.

[5] From 2013 to 2019, the wind generation in the Nordic market has grown approximately 2.5 times from 32 k MWh (April 2013) to 80 k MWh (April 2019).

[6] The estimator is consistent. See Gallant and Tauchen (1989).

[7] See, for example, Kristiansen (2014), Goto and Karolyi (2004), Bystrøm (2003) and Solibakke (2002).

[8] See, for example, Lucia & Schwartz, 2002 and Geman & Roncoroni, 2006.

[9] See Higgs and Worthington (2008), Huisman and Mahieu (2003) and Thomas, Ramiah, Mitchell, and Heaney (2011).

[10] See de Vany and Wall (1999), Higgs and Worthington (2008), Huisman and Mahieu (2003), Huisman and Kilic (2013), Haldrup and Nilsen (2006), Knittel and Roberts (2005), Li and Flynn (2004), Lindstrøm and Regland (2012), Mount, Ning and Cai (2006), Robinson (2000), Robinson and Baniak (2002), Rubin and Babcock (2011), Tashpulatov (2013) and Weron (2006, 2008).

[11] See Chan and Gray (2006), Escribano, Pena, and Villaplena (2011), Habell, Marathe, and Shawky (2004), Higgs and Worthington (2005), Koopman, Ooms, and Carnero (2007) and Solibakke (2002).

[12] See, for example, Weron (2006, 2008), Harris (2006), Geman and Roncoroni (2006), Koopman, Ooms, and Carnero (2007) and Pilipovic (2007).

[13] 32 and 80 k mean 32.000 and 80.000 MWH, respectively.

[14] An additional factor is congestion in transmission systems potentially leading to area prices (EWEA, 2010).

[15] Renewable Energy Sources (RES). The European Commission (EC) aims at raising the share of RES in energy consumption to 20% by 2020 (EC, 2009) and at least 27% by 2030 (EC, 2014).

[16] Gallant, Hsieh, and Tauchen (1997) find 18 (!) ARCH-lags for time series retrieved from the US financial market.

[17] The technique is available from version GAUSS 3.2.1.

[18] The form is

$$\sum x_{t-1} = R_0 \cdot R_0' + \sum_{i=1}^{L_g} Q_i \sum_{x_{t-1-i}} Q_i' + \sum_{i=1}^{L_r} P_i \left(y_{t-i} - \mu_{x_{t-1-i}}\right) \left(y_{t-i} - \mu_{x_{t-1-i}}\right)' P_i'$$
$$+ \sum_{i=1}^{L_v} \max\left[0, V_i\left(y_{t-i} - \mu_{x_{t-1-i}}\right)\right] \max\left[0, V_i\left(y_{t-i} - \mu_{x_{t-1-i}}\right)\right]' + \sum_{i=1}^{L_w} W_i \cdot x_{(1),t-i} \cdot x_{(1),t-i}' \cdot W_i',$$

where R_0 is an upper triangular matrix. The matrices P_i, Q_i, V_i, and W_i can be scalar, diagonal or full M by M matrices. The $\mu_{x_{t-1-i}}$ shows extraction of the time series unconditional mean for the calculation of the parameters P_i and V_i. The notation $x_{(1),t-i}$ indicates that only the first column of x_{t-i} enters the computation. The max $(0, x)$ function is applied elementwise.

[19] From Nordpoolspot Group (https://www.nordpoolgroup.com/Market-data1/#/nordic/table).

[20] Wind forecasts are wind power prognosis measured in MWh over a 24-h interval. The wind forecast information is released immediately before the spot price auction bid/ask announcement time schedule (daily 11 a.m.). The spot system price is announced approx. 00.45 p.m. same day (together with area prices for the Nordic/Baltic market). The market wind forecasts in MWh have tripled during the period 2013–2019. Some adjustment for the series may therefore be needed.

[21] In fact, the unadjusted wind forecast series report an ADF of −3 with associated t statistic of 0.12, suggesting a nonstationary series.

[22] The $\sqrt{e^{(x \cdot \hat{\gamma})}}$ *or* $e^{\left(x \cdot \hat{\gamma}/2\right)}$ is formed to adjust $\hat{u}$ in the expression ϖ_{adj} for the variance equation uses of $\ln\left(\hat{u}^2\right)$.

[23] It is important to note that the series represents wind forecasts. The 2013–2019 forecasts will acknowledge the wind production increase in this period and Weeks 24 and 28 (both with positive parameters) is both in the spring/summer season. Furthermore, the wind forecasts for the auction market are clearly adjusted for a strong non-linear increase in wind production during the 2013–2019 period. This increase suggests a nonstationary wind series.

[24] It is not possible to estimate the unadjusted series using the *SNP* methodology.

[25] The Cramer-von-Mises test statistic is a procedure to test the null that a sample comes from a population in which the variable is distributed according to a normal distribution.

[26] See Box and Jenkins (1976) and Ljung and Box (1978).

[27] The RESET test statistics is a general test for (1) omitted variables, (2) incorrect functional forms or (3) correlation between dependent variables (X) and the residuals (ε).

[28] In terms of computations, a hermite density is easy to evaluate and differentiate. Also, its moments are easy to evaluate because they correspond to higher moments of the normal (computed using standard deviations), and finally, it turns out to be very practical for sampling from simulations.

[29] The criterion rewards good fits by small $s_n\left(\hat{\theta}\right) = -\left(\frac{1}{n}\right) \sum_{t=1}^{n} \log[f(y_t | x_{t-1}, \theta)]$ and uses the term $\left(\frac{1}{2}\right)\left(\frac{p_p}{n}\right)\log(n)$ to penalize good fits obtained by means of excessively rich parameterization.

[30] Based on likelihood ratio test (*LRT*) statistics, the student t log-likelihood function is strongly preferred to a normal likelihood function.

[31] BIC optimal model: (*SNP* - 7, 1, 1, 1, 4, 0, 0, 4). That is, one intercept and seven lags in the mean, GARCH(1, 1) for the volatility, four hermite functions (K_z) to capture deviations and finally, four interactions (I_z).

[32] Note the effect of the spline transformation because the bias in the values of the conditional mean and (co)variances can be substantial without it.

[33] The camera angel for this bivariate plot is named isometric right high. Other camera angels (left, right, behind, high) are available from author upon request.

[34] All the four panels in Figure 14 include a normal density conditional on known wind forecast movements (ω_1) of zero.

[35] This information is available from author upon request.

[36] The specification is a conditional bivariate ARMA-GARCH model with full variance–covariance parametrization for the conditional variance.

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