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How renewable production depresses electricity prices: Evidence from the German market[☆]

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ABSTRACT

The urgency of climate change has led several countries to develop renewable energy in order to reduce CO_2 emissions, through the means of various subsidies. In the electricity sector, one drawback of such policies is the negative impact on electricity prices, known as the merit-order effect. This paper aims at assessing how intermittent renewable production depresses electricity prices in Germany, which has experienced a significant increase of its renewable capacity over the last two decades. To do so, we use a two-regime Markov switching model, that enables to disentangle the impact of wind and solar generation, depending on the price being high or low. We find as expected that renewable production induces a negative marginal effect, which is stronger in regimes of relatively high prices. In addition, we show that both wind and solar productions have a significant impact on the distribution of prices, and in particular on the frequency and expected duration of each regime. This has implications in terms of market design, security of supply, and support mechanisms for renewables.

1. Introduction

The development of renewable energy sources (RES) is often justified by the need to address global warming, through the reduction of green-house gases emissions, and is also led by the will to reach energy independence in fossil and fissile fuel-dependent countries. In the electricity sector, main RES are wind power and solar photovoltaic (PV). These technologies are spreading throughout the world and Europe, which has announced RES targets for the next decades: 20% in the final energy consumption by 2020 and 27% by 2030. To reach these goals, renewables often need to be subsidised, as they would generally not be competitive otherwise on the wholesale market.[1] In addition to the aforementioned goals, the subsidisation of these energies aims at internalising the “learning effect”, i.e. the decrease of their cost along with their development. This is a positive externality that is by definition not taken into account by the market, and which would lead to too few investments in these technologies if not accounted for.

However, the development of electric RES challenges the current design of electricity markets. Indeed, they were originally designed to reflect the short-term production cost of electricity via the system marginal price, i.e. the marginal cost of the last unit needed to meet the demand. While marginal costs were traditionally driven by fuel costs such as coal, gas, oil, or uranium; wind and photovoltaic have on the contrary (almost) no marginal cost. Therefore, they tend to lower prices when they are producing, which is commonly known as the “merit-order effect” (Sensfuß et al., 2008). In addition, wind and solar energies are intermittent (or variable), albeit with seasonal patterns, while electricity prices are highly seasonal, with seasonality being driven mainly by demand at the daily, weekly and yearly time scales. Hence, RES generation is likely to have a different impact on electricity prices, depending on the state of the supply-demand equilibrium. Additionally, renewable production is expected to affect electricity also globally, and in particular its distribution, which is only partly captured by the analysis of the merit-order effect.

This article addresses these issues for the German day-ahead market by developing a two-regime Markov switching (MS) model. In particular, we are able to disentangle the merit-order effect in function of the price level, while keeping temporal coherence of the time series.

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[1] However, distributed renewable generation such as rooftop solar PV is becoming more and more profitable for end-users, as their levelized cost of electricity (LCOE) can in some places be lower than the retail tariff they are faced with (grid parity). Such consumers, often called “prosumers”, do not need to be subsidised by public funds (even though it is sometimes the case), but they can benefit from cross-subsidies via the distribution network tariff.

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Furthermore, we allow for time-varying probabilities (inhomogeneous model), in order to capture the impact of RES on the switching mechanism from "high" to "low" prices, and hence on the proportion and duration of each regime.

Studying the merit-order effect in Germany is quite relevant, as the country has had a huge development of wind and solar PV over the past two decades (RAP, 2015). Furthermore, since more than 40% of the electricity production in Germany (and Austria) is traded on the EEX day-ahead spot market, the related price is a relatively good indicator of the electricity supply-demand equilibrium. Hence, for these several reasons, the choice of Germany seems quite appropriate.

The remainder of the article is structured as follows. In Section 2, we briefly explain the mechanism behind the merit-order effect as well as other consequences of renewable production on electricity prices. In Section 3, we provide a review of the literature on the impact of RES production on electricity prices as well as on MS models applied to electricity prices and we explain which gap we aim at filling with this paper. Then, Section 4 briefly describes the data we used. Section 5 then presents the modelling strategy, and empirical results are presented and discussed in Section 6. Finally, Section 7 concludes the article by providing the main findings and policy implications.

2. Theoretical analysis

In this section, we use basic microeconomic tools to illustrate how the merit-order effect arises and why it is differentiated depending on the price level. We explain also how renewable production is likely to impact the distribution of prices more globally.

Graphically, we can see that if at the equilibrium the inverse supply curve[2] is locally steep, the impact is expected to be higher than when it is locally flat. In Germany, on average the steepness of the inverse supply curve increases with load, i.e. it is convex (except in the negative-price zone). It may not be the case elsewhere, but for example Karakatsani and Bunn (2008), show that in the British market the aggregate supply function is also convex. Fig. 1 illustrates this case by showing the variation of the merit-order effect with the load level.

Formally, this can be seen in the following way: if $D: p \mapsto D(p)$ (with $(D' < 0)$ and $S: p \mapsto S(p)$ (with $S' > 0$) are the expressions of the instantaneous demand and supply functions, the impact on the price of an infinitesimal shock of supply (e.g. RES production) or demand would be at the first order (proof in Appendix A):

$$\frac{\partial p}{\partial Load} = \frac{-1}{\frac{\partial D}{\partial p} - \frac{\partial S}{\partial p}} = -\frac{\partial p}{\partial RES} > 0 \tag{1}$$

In reality, supply and demand are piecewise constant functions, as they are the result of a bidding process. Hence they have zero derivatives except in points of discontinuity where they are non-differentiable. Nevertheless, it is convenient to assume differentiability as it gives the right insight, and in the case of rather small increments it is a good approximation. From Eq. (1), it is clear that the higher the slope of the inverse supply function S^{-1}, the lower the slope of S (equal to its inverse), and thus the higher the marginal (merit-order) effect. Note also that on average the impact of wind, solar and load has no reason to be the same, as all variables and the supply and demand functions vary over time. In addition to this marginal effect, RES production is expected to have a more global impact on electricity prices, in particular on its conditional or unconditional distributions. For example, we could expect prices to be "low" more often, especially if complementary sites can be used for RES installations. Also, conditional volatility is expected to be higher in periods of "high" prices (because of the same slope argument), while unconditional volatility can be lower or higher, depending on how much more "low" prices (with lower conditional volatility) there are.

[2] The inverse supply function S^{-1} gives the price p in function of the supply quantity q. The inverse supply curve is thus defined by $p = S^{-1}(q)$.

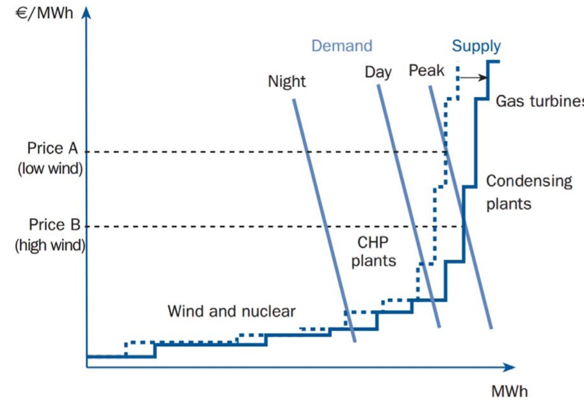

Fig. 1. Differences in the merit-order effect (source: Risø DTU).

3. Literature review

3.1. Impact of renewable production on electricity prices

The impact of subsidised renewable generation on electricity prices and its distributional implications have been widely discussed empirically and theoretically, e.g. by Meyer and Luther (2004), Munksgaard and Morthorst (2008), Gonzalo Sáenz de et al. (2008), Sensfuß et al. (2008), Cutler et al. (2011), Tveten et al. (2013), Cludius et al. (2014), Kallabis et al. (2016) and Bublitz et al. (2017). In this topic, the use of time series econometrics to study the market impact of RES production is more recent and very abundant as well. Many of them used ARMA-GARCH models, such as Woo et al. (2011) in Texas, Liu and Shi (2013) for the ISO-New England market, Ketterer (2014) in Germany or Karanfil and Li (2017) for the Danish intraday market, just to cite a few ones. All these analyses found a significant negative impact of RES generation on electricity prices and a positive one on conditional volatility (when modelled). However, the measured effect is necessarily averaged over the whole time series due to the used methods. Additionally, these studies mainly describe the merit-order effect, but do not tell how renewable production affects the proportion and duration of the price levels, which can be an issue for the profitability of plants relying on episodes of high prices.

Nevertheless, some authors have used other models in order to capture variability in the merit-order effect and additional properties. For example, Jónsson et al. (2010) quantify the impact of wind forecast on electricity prices for each hour of the day using a non-parametric approach. They also analyse the distributional impacts on the price under several scenarios, and show in particular that the unconditional volatility decreases with wind penetration. Unfortunately, they do not model the underlying mechanisms. In a different fashion, Paraschiv et al. (2014) estimate the impact of RES generation (and other variables) on electricity prices in Germany for each hour of the day, using time-varying coefficients. In particular, they show that the impact of wind (resp. solar) energy is more important during afternoon, evening and night hours (resp. noon peak hours).

However, electricity prices are expected to become less and less deterministic as the share of renewable generation increases and demand-response and storage become more available. This fact calls for a more flexible approach, which should be based on the level of prices rather than on predefined periods (hours, days, etc.). In this spirit, Keles et al. (2013) show that the wind power feed-in has a distinct impact on prices depending on the load and residual load levels (and hence implicitly on the price level) for each hour and day type. Their analysis is performed using linear regressions on ascending 2-MW load clusters, which are then used in a simulation of electricity prices. Unfortunately,

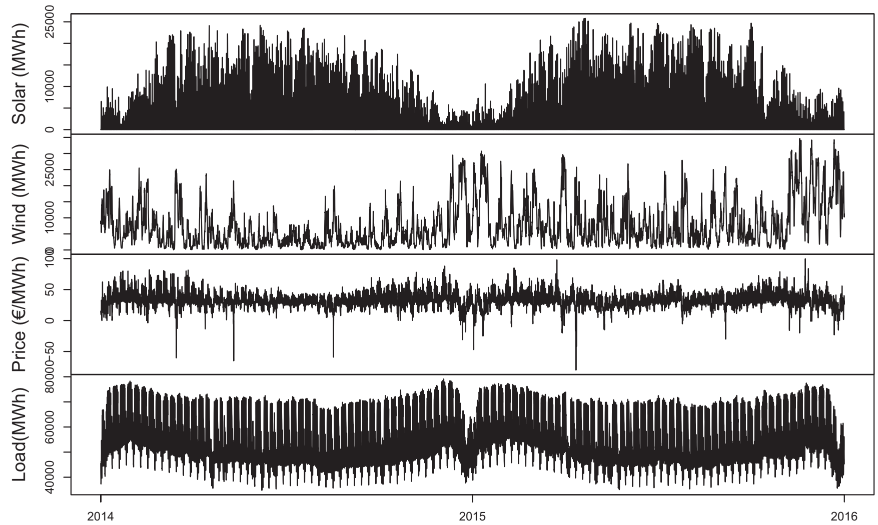

Fig. 2. Final data.

their modelling does not take into account the temporal connection between the load clusters, nor discusses the impact on the price distribution.

3.2. Markov switching models and applications to electricity prices

The general literature on Markov switching models is also wide: Goldfeld and Quandt (1973) and Hamilton (1990, 1989) for a first introduction to MS models, Cai (1994); Hamilton and Susmel (1994) and Gray (1996) for MS-(G)ARCH models, and Hamilton (1996) for testing MS models). Finally, one can also see Krolzig (1997) for MS-VAR, and Kim et al. (2008) concerning endogenous switching.

Since electricity cannot be stored at a wholesale scale, electricity prices are highly volatile, with the existence of both positive and negative price peaks, heavy tails, jumps, etc. Hence, first MS models applied to electricity were for prices "alone", as they were able to capture these peculiarities (Deng, 1998; Ethier and Mount, 1998; Huisman and Mahieu, 2003; Janczura and Weron, 2010). On different topics, Haldrup et al. (2010) and Haldrup and Nielsen (2006) show that Nordic electricity prices present long-memory and regime-switching behaviours, and Cifter (2013) exhibits two distinct volatility regimes using a MS-GARCH model. Other authors have studied the impact of exogenous variables on the conditional mean (Zachmann, 2013), on transition probabilities of inhomogeneous MS models (Mount et al., 2006; Huisman, 2008), or both (Kanamura and Kazuhiko, 2008). Finally, Veraart (2016) models the impact of wind production on electricity prices using a regime-switching Lévy semi-stationary process, with regimes depending on the wind penetration index.

3.3. Contribution of the paper to the literature

In the end, we believe that a MS model is an appropriate tool to answer our research question. Indeed, as mentioned above, it has already be shown that electricity prices present Markovian regime changes. In addition, MS models estimate time-varying coefficients, while keeping the temporal integrity of the time series, instead of dividing them in distinct series, that would for instance depend on the price level or on the hour of the day. Indeed, we will show in Section 5 that after applying an appropriate transformation to the price time series, we can identify two distinct regimes, of respectively "high" and "low" prices. This feature is very suitable for regime-switching models as they can give mixture distributions. The estimation then shows that the regimes are serially correlated, hence justifying the Markovian switching mechanism. Furthermore, the autocorrelation and conditional autoregressive heteroskedasticity observed in electricity prices can also be captured (Krolzig, 1997). Finally, the chosen MS model allows us also to quantify some distributional impacts of RES production through the modelling of transition probabilities, which we link to the proportion and duration of the price regimes and hence on the distribution of prices.

Table 1
Pearson correlation coefficients between the variables.

	Wind	Price	Load
Solar	− 0.157	− 0.039	0.331
Wind		− 0.424	0.037
Price			0.674

Table 2
Descriptive statistics of the electricity price.

	Min	Q1	Median	Mean	Q3
Price (€/MWh)	− 79.9	25.4	31.1	32.2	40.0
	Max	S.D.	C.V.[a]	Skewness	Kurtosis
Price (€/MWh)	99.8	12.7	0.39	− 0.3	6.2

[a] Coefficient of variation: C. V. =S. D./ Mean.

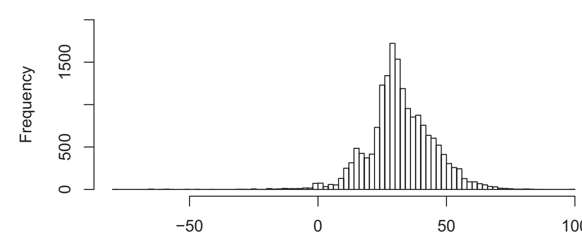

Fig. 3. Histogram of price (/MWh).

4. Data

4.1. Overview of the data and first correlations

Our data is originally composed of four time series for the period 2014–2015, that come from various sources:

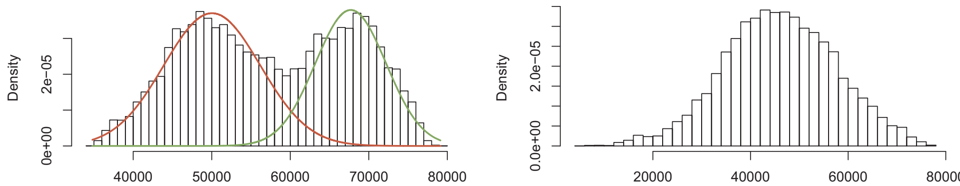

Fig. 4. Histogram and estimated mixture model densities of load (left), and histogram of residual load (right), in MWh.

Table 3
Descriptive statistics of load and residual load.

	Min	Q1	Median	Mean	Q3
Load (MW)	34, 801	48, 825	57, 237	57, 616	66, 891
Residual load (MW)	5, 903	38, 214	45, 845	45, 939.9	53, 905
	Max	S.D.	C.V.	Skewness	Kurtosis
Load (MW)	79, 120	10, 332	0.18	− 0.02	1.8
Residual load (MW)	77, 898	11, 425	0.25	− 0.1	2.9

- hourly day-ahead electricity spot prices, obtained from EEX-Powernext;
- solar and wind electricity generation,[3] obtained from the four German TSOs (TenneT, Amprion, 50Hertz, Transnet BW) websites, at the 15 min time step;
- hourly electricity load (from ENTSO-E website).

We summed the RES generation data of the TSOs and aggregated it to the hourly time step, in order to obtain 17,520 values for each variable. Fig. 2 represents the corresponding final time series, and Table 1 shows the correlation coefficients between the variables.

As one would expect, solar energy has a strong yearly seasonality, with much more production during summer, while wind energy has a relatively opposite seasonality, and they are indeed negatively correlated. Obviously, solar generation follows also a daily pattern (day/night), which is not observed for wind. The electricity demand is very cyclical as well, with annual and daily patterns, the latter being probably the reason for the positive correlation with solar production. We also find these patterns in the price series, which is highly and positively correlated with load, negatively with wind, and almost not correlated with solar generation. The seasonality of these price and load time series will be more thoroughly discussed in Section 4.4. Finally, although the electricity consumption is higher in winter, essentially because of heating and lighting, there is a huge decrease in demand (and hence in price) during the Christmas holidays, because of a drop in the industrial activity (Do et al., 2016).

4.2. Price statistics

Since we are interested in modelling the electricity prices, we need to take a deep look at the price time series, which is the goal of this subsection. Table 2 below present the main descriptive statistics of the price time series. First of all, we notice that the price is quite volatile, has heavy tails and is slightly skewed, which are common features of electricity prices, and can be the result of a regime-switching mechanism (Krolzig, 1997). As already seen in Fig. 2, there are negative prices (190 occurrences, i.e. a little more than 1% of the total), and high positive spikes as well. These well-known specificities of electricity prices are mostly due to the fact that electricity is (almost) non storable. Hence, demand must be met by production at all time, while conventional plants have flexibility constraints (limited ramp up/down in particular). Any change in demand and/or generation will then have an immediate impact on the price, that reflects the supply-demand equilibrium. The histogram (Fig. 3 below), the normal QQ-plot (Fig. 17, Appendix B) and the boxplot (Fig. 18, Appendix B) illustrate the previous analysis and show strong evidence of non-normality, which is confirmed by a Jarque-Bera test (($p - \text{value} < 2.2.\ 10^{-16}$).

It is also interesting to look at the “complete” histogram in Fig. 19 (Appendix B). Indeed, we can see that there are some isolated spikes, for example near zero, that probably correspond to marginal prices of some specific units and in particular RES. A closer look around zero shows that there is in fact a range of prices from approximately −0.10 to 0.10/MWh (Fig. 20 in Appendix B).

Finally, we make sure that the price time series is stationary by performing two unit root tests: augmented Dickey-Fuller, Phillips-Perron; and the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) stationarity test (Appendix B, Table 8). All these tests show that the price time series is stationary.

4.3. Load-related statistics

If we now look at the histogram of load (Fig. 4, left), we see that there appears to be two modes, with respectively “high” and “low” demand. When studying relations between price, RES production and demand, it is frequent to consider the residual demand, i.e. demand minus RES generation. The histogram of the residual load is visible on Fig. 4 right. We clearly see that the “high-demand mode” has disappeared, which could be explained by the high correlation between demand and solar production due to their daily seasonality. The descriptive statistics of the load and residual load are shown in Table 3. We see that although the residual demand is still not Gaussian, it is more volatile (due to the volatility of the wind and solar outputs), and has slighlty heavier tails. It is also interesting to note that although RES production strongly contribute to off-peak load reduction (-28.9 GW), it only generates a 1.2 GW decrease of peak demand.

Furthermore, residual load (net demand) has a correlation coefficient with price of 0.88, which makes it a “better” candidate for the model than gross demand ($\rho = 0.67$). Similarly, it is often convenient to study the relative share of RES production, as suggested by Jónsson et al. (2010). In our case, they have higher correlation coefficients with price (−0.56 for wind and −0.095 for solar) than RES generation itself, but also with residual load (−0.62 and −0.18). This could possibly lead to high variance inflation factors, but as we will see in Section 6, the obtained coefficients are significant and stable.

4.4. Price and load seasonality

Electricity prices are highly seasonal, mainly because of the demand seasonality. To illustrate this, the left graph on Fig. 5 below shows the power spectra (or periodograms) of the price and residual load time series. These enable to detect the dominant frequencies (or equivalently, periods) in the series. We find that the price and residual load have identical periods, i.e. 12 h, 24 h, 168 h (a week) in particular, which was expected. Furthermore, the right graph on Fig. 5 represents the squared coherency spectrum, which is the amplitude of the cross-correlation function. It shows which percentage of the variance is

[3] As suggested by Jónsson et al. (2010), the day-ahead forecast would be a better candidate than the actual energy output, since production decisions are taken on the basis of forecasts. However the forecast data provided by the TSOs was incomplete, and many actors have they own forecast, which may differ from the one made by the TSOs. Finally, using real production instead of forecast values should not dramatically change the value of the coefficients, but rather the goodness of fit.

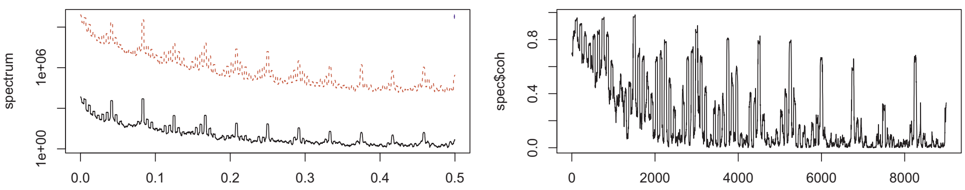

Fig. 5. Smoothed log-periodograms of price (black, bottom curve, left) and residual load (red, top curve, left) and squared coherency spectrum (right) (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.).

shared by the two variables at each frequency.[4] This analysis confirms that the seasonality of electricity prices is mainly driven by the (residual) demand.

This seasonality affects the distributions of price and (residual) load, but our analysis strongly suggests that these variations will be correlated, given the very high correlation between the price and the residual load, both in the temporal and frequency domains. Thus, it seems sufficient to control for this seasonality using the residual load as a covariate in the model. In particular, we seek to keep the model as parsimonious as possible, as MS models can prove very difficult to estimate. Indeed, having too many regressors can lead to non-convergence or local convergence (i.e. wrong estimates). Furthermore, differentiating the model for each season and type day would require dividing the series accordingly and hence break the temporal integrity, which we wish to avoid as the series present some autocorrelation, that the MS model takes (at least partly) into account.

5. Methodology

In this section, we first present the transformation that we apply on the price time series, before exposing the model itself.

5.1. Variable transformation

It is quite common in time series analysis to perform a logarithmic (or sometimes a Box-Cox) transformation. Indeed, the logarithmic transformation has several interesting properties, from reducing the weight of extreme values (and more generally reducing non-normality). It also enables to interpret coefficients of regressions as elasticities, or to interpret first differences of the transformed data as rate of returns.

However, we cannot take the logarithm of the price, because of negative prices (1% of the total). This could be artificially prevented by adding an offset value to the series so that it would be strictly positive, enabling then to use the log transformation, as suggested by Sewalt and Jong (2003). If the offset was low enough compared to the mean, it would produce little distortion, but in our case, the price goes as low as -79.9/MWh, for a mean of 32.2/MWh and a maximum of 99.8/MWh. Hence, adding 80/MWh to prices and taking the logarithm would then highly "compress" high prices together while maybe giving "too much" importance to negative prices.

Furthermore, we want to be able to distinguish the merit-order effect depending on the level of prices, while keeping a unique and coherent time series. It is rather obvious that the previously exposed methodology will not help us identify price regimes, as prices will be "stacked" together. Thus, in order to enhance regime identification while taking into account negative prices and reducing the importance of extreme values, we use an inverse hyperbolic sine transformation. This transformation was originally described by Johnson (1949) and more recently used by Schneider (2012) for electricity prices. This transformation is achieved by applying the inverse of the hyperbolic sine function, which is defined by the following expression, with offset and scale parameters $\xi, \lambda \in \mathbb{R}$:

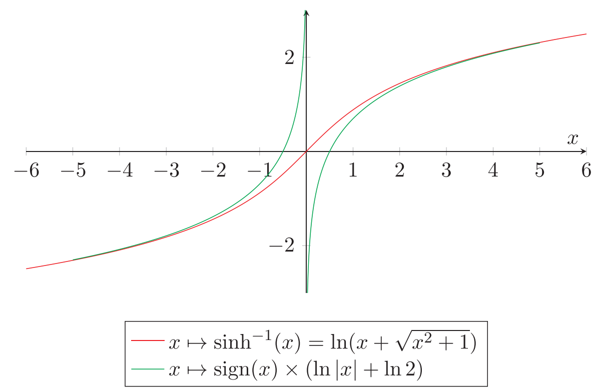

Fig. 6. Inverse hyperbolic sine (red) and symmetric logarithm (green) functions (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.).

$$\forall\ x \in \mathbb{R} \quad f(x, \xi, \lambda) = \sinh^{-1}\left(\frac{x-\xi}{\lambda}\right) = \ln\left[\frac{x-\xi}{\lambda} + \sqrt{\left(\frac{x-\xi}{\lambda}\right)^2 + 1}\right] \tag{2}$$

The behaviour of this function is logarithmic when $|x| \to \infty$ and linear when $x \to \xi$:

$$f(x, \xi, \lambda) \underset{x \to \xi}{\sim} \frac{x-\xi}{\lambda} \tag{3}$$

$$f(x, \xi, \lambda) \underset{|x| \to +\infty}{\sim} \text{sign}(x) \times \ln\left(\frac{2|x|}{\lambda}\right) = \text{sign}(x) \times \left[\ln\left(\frac{|x|}{\lambda}\right) + \ln 2\right] \tag{4}$$

Hence,the logarithmic behaviour of the function will "compress" the extreme values, while its linear behaviour will on the contrary "expand" intermediate values, hopefully leading to the desired distribution. Fig. 6 below represents the inverse hyperbolic sine function with $\xi = 0$ and $\lambda = 1$ in red, and in green the symmetric logarithmic function (with position factor $\ln 2$) and its symmetric with respect to the origin.

There are many ways to choose the values for λ and ξ. For example, one could use the values that give the most normal mixture distribution, or that is best fit by the model. In particular, the choice of ξ will strongly condition the range of each regime. However, for the sake of simplicity, we simply decided to take the mean value of the price for ξ. This choice enables us to separate the two regimes quite clearly, and gives them a relatively similar importance as the mean is quite close to the median. Additionally, we chose $\lambda = 1$ €/MWh for simplicity reasons also. As expected, the histogram of the transformed price (Fig. 7) lets appear two distinct modes, that could not be seen in the original histogram. We can highlight the bimodality of the distribution by trying to fit it as a mixture of two normal distributions. This gives the red and green densities in Fig. 7: the two modes are well identified, but are not Gaussian (they have no reason to be, nor is it required by the model). However, extreme values are indeed reduced for each regime.

5.2. Model

Now that we have described and transformed the data, we develop an econometric model to quantitatively evaluate the impact of RES generation on electricity prices. We consider a discrete-time ($t \in \mathbb{N}$),

[4] On this graph the frequency is obtained by dividing the abscissa by the number of observations, i.e. 17,520. The period is then the inverse of the frequency, as on the left figure. The smallest period is 2 h as we are dealing with hourly data. Hence the maximum frequency is 0.5 h^{-1}.

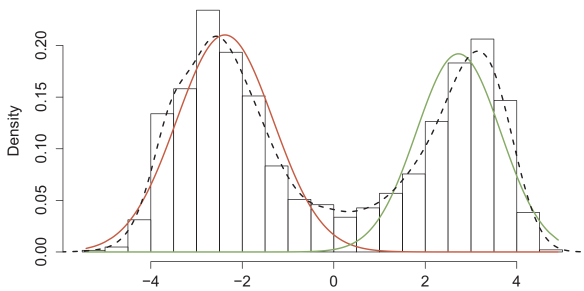

Fig. 7. Histogram, estimated mixture model densities and kernel density (dashed) of the transformed price.

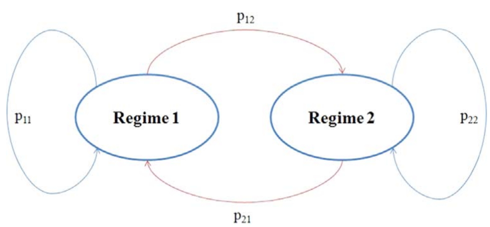

Fig. 8. Graph representing the Markov chain process.

two-regime MS model, in which the coefficients of the covariates and the variance of the residuals depend on the value of a latent unobserved state (or regime) variable $S \in \{1; 2\}$. The state variable is a Markov chain, i.e. the probability of switching from a regime is Markovian (it only depends on its current state, and not its past):

$$\forall \; t \in \mathbb{N} \quad \mathbb{P}(S_t = j | S_{t-1} = i, S_{t-2}, \ldots, S_0) = \mathbb{P}(S_t = j | S_{t-1} = i) = p_{ij}(t) \tag{5}$$

as visually described in Fig. 8. We denote by P the stochastic matrix associated with the process:

$$\forall \; t \in \mathbb{N} \quad P(t) = \begin{pmatrix} p_{11}(t) & p_{12}(t) \\ p_{21}(t) & p_{22}(t) \end{pmatrix} \quad \text{with:} \quad \forall \; i \in \{1, 2\} \quad p_{i1} + p_{i2} = 1 \tag{6}$$

Then, we have by recurrence that: $\mathbb{P}(S_{t+k} = j | S_{t-1} = i) = (P(t) \times \ldots \times P(t+k))_{(i,j)}$. Furthermore, the underlying Markov chain is supposed to be ergodic, i.e. irreducible (it is possible to switch from a state to another with positive probability) and if all its states are ergodic (i.e. aperiodic and recurrent). We also allow the Markov chain to be inhomogeneous, with probabilities of transition varying over time. A simple and widely spread specification for inhomogeneous MS models is to have the probabilities being described by a logistic function of external regressors.[5] In our case, we want probabilities to vary with wind and solar penetration indices. Finally, the model to estimate is given by Eqs. (7)–(9) below (note that all the parameters of the model are estimated together via maximum likelihood):

$$\forall \; t \in \mathbb{N} \quad Price_t^* = \beta_0(t) + \beta_1(t)\frac{Wind_t}{Load_t}\beta_2(t)\frac{Solar_t}{Load_t} + \beta_3(t)RLoad_t + \varepsilon_t \tag{7}$$

where $RLoad = Load - Wind - Solar$ is the residual load, $Price^*$ is the transformed price, and:

$$\forall \; t \in \mathbb{N} \begin{cases} \beta(t) = \beta^{(1)} \times \mathbb{1}(S_t = 1) + \beta^{(2)} \times \mathbb{1}(S_t = 2) \in \mathbb{R}^4 \\ \varepsilon_t \rightsquigarrow \mathcal{N}(0, (\sigma_1)^2 \times \mathbb{1}(S_t = 1) + (\sigma_2)^2 \times \mathbb{1}(S_t = 2)) \end{cases} \tag{8}$$

[5] It would also be possible to use another specification, for example a probit one as in Kim et al. (2008), but we think that a logit specification allows to interpret the coefficients more easily, and should not fundamentally change the results, as it is usually the case for discrete choice models.

Table 4
Coefficient estimates.

Variable	Coefficient	Std. Error	z-Statistic	p-value
Regime 1				
Intercept	− 7.171284	0.056058	− 127.9269	0.0000
Wind/Load	1.271735	0.064171	19.81791	0.0000
Solar/Load	1.530959	0.064736	23.64942	0.0000
RLoad	0.000114	$1.19e-6$	95.71098	0.0000
σ_1	0.581968	0.006004	96.93304	0.0000
Regime 2				
Intercept	− 3.416402	0.089319	− 38.24955	0.0000
Wind/Load	1.569330	0.135748	11.56058	0.0000
Solar/Load	2.242196	0.126642	17.70505	0.0000
RLoad	0.000106	$1.40e-6$	75.80216	0.0000
σ_2	0.695252	0.008222	84.56472	0.0000
Transition Matrix Parameters				
$\alpha_0^{(1)}$	1.109705	0.059471	18.65958	0.0000
$\alpha_1^{(1)}$	5.306012	0.345166	15.37235	0.0000
$\alpha_2^{(1)}$	4.464573	0.414828	10.76247	0.0000
$\alpha_0^{(2)}$	− 2.762521	0.069484	− 39.75780	0.0000
$\alpha_1^{(2)}$	6.971012	0.392717	17.75075	0.0000
$\alpha_2^{(2)}$	1.483876	0.441446	3.361400	0.0008

Table 5
Time-varying transition probabilities and expected durations.

Time-varying transition probabilities $p_{ij}(t)$:			
		1	2
Mean	1	0.876859	0.123141
	2	0.182783	0.817217
		1	2
Std. Dev.	1	0.060346	0.060346
	2	0.150465	0.150465
Time-varying expected durations:			
		Regime 1	Regime 2
Mean		12.64588	8.048185
Std. Dev.		13.72816	3.877061

$$\forall \; t \in \mathbb{N} \quad \text{logit}(p_{i1}(t)) = \ln\left(\frac{p_{i1}(t)}{1 - p_{i1}(t)}\right) = \alpha_0^{(i)} + \alpha_1^{(i)}\frac{Wind_t}{Load_t} + \alpha_2^{(i)}\frac{Solar_t}{Load_t} \tag{9}$$

$$\Leftrightarrow \quad p_{i1}(t) = \frac{1}{1 + \exp\left(-\alpha_0^{(i)} - \alpha_1^{(i)}\frac{Wind_t}{Load_t} - \alpha_2^{(i)}\frac{Solar_t}{Load_t}\right)} \tag{10}$$

$$\Leftrightarrow \quad p_{i2}(t) = 1 - p_{i1}(t) = \frac{1}{1 + \exp\left(\alpha_0^{(i)} + \alpha_1^{(i)}\frac{Wind_t}{Load_t} + \alpha_2^{(i)}\frac{Solar_t}{Load_t}\right)} \tag{11}$$

It is also possible to compute the expected duration of each state. This is done numerically for an inhomogeneous model, while for an homogeneous models the expected duration of regime $i \in \{1, 2\}$ has the following closed-form expression:

$$\mathbb{E}\tau_i = \sum_{k=1}^{+\infty} k\mathbb{P}(\tau_i = k) = \sum_{k=1}^{+\infty} kp_{ij}p_{ii}^{k-1} = \frac{1}{p_{ij}} = \frac{1}{1 - p_{ii}} \tag{12}$$

For an homogeneous ergodic Markov chain, one can also compute the stationary distribution $\pi = (\pi_1, \pi_2)$, with $\pi_1 + \pi_2 = 1$, which by definition is the probability distribution of states that does not change in time. These probabilities can be interpreted as the mean proportion of (or the unconditional probability of being in) each regime:

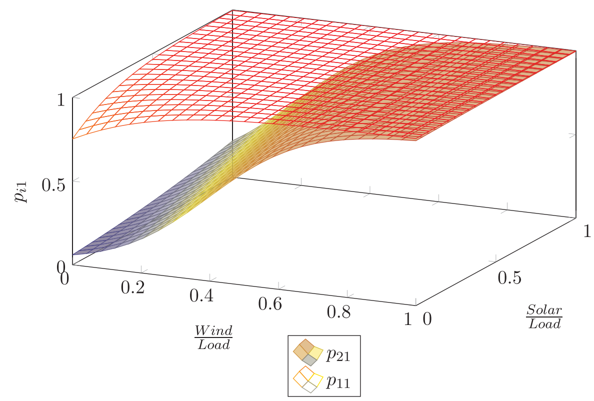

Fig. 9. Probabilities of transition.

$$\pi P = \pi \Leftrightarrow \pi_1 = 1 - \pi_2 = \frac{p_{21}}{p_{12} + p_{21}} = \frac{\mathbb{E}\tau_1}{\mathbb{E}\tau_1 + \mathbb{E}\tau_2} \tag{13}$$

An ergodic Markov chains has a unique stationary distribution, and if it is homogeneous it is also the equilibrium (or limiting) distribution, i.e. it is reached asymptotically:

$$\lim_{n \to +\infty} P^n \underset{not.}{=} P^\infty = \begin{pmatrix} \pi_1 & \pi_2 \\ \pi_1 & \pi_2 \end{pmatrix} \tag{14}$$

For an inhomogeneous Markov chain these values have usually no closed-form expressions, but can nevertheless be estimated numerically, which is done with the estimation.

6. Results and discussion

Let us now present the estimation results, before discussing more in depth the interpretation of the regimes in a second subsection. Then, we will derive (average) marginal effects from the model, as the interpretation of the coefficients is not straightforward. Lastly, we will examine the impact on the structure of the regimes, and in particular their expected duration.

6.1. Estimation results

The estimation results are presented in Tables 4 and 5 below. All coefficients are highly significant and significantly different from a regime to another (Wald tests were performed to test this). It is surprising at first sight that the coefficients associated with the relative shares of wind and solar productions are positive. However, we will show in Section 6.3 that we can indeed deduce negative marginal effects of wind and solar productions. This is due to the fact that these productions are also present in the residual load variable.[6]

Furthermore, we conducted several robustness checks. Indeed, the possible multicollinearity between the three covariates could lead the estimates to be either non-significant or numerically unstable (Belsley et al., 2005). The estimation results show that the coefficients are statistically significant, which rules out the first issue. Regarding numerical stability, we have realised 50 additional estimations after adding noise to the data. We also estimated the model after removing the first and last four days from the sample (192 h in total, i.e. roughly 1% of the whole sample). We found that in all cases the estimates were little affected by these operations, and we thus consider that multicollinearity is not an issue here.

Concerning the transition matrix parameters, $\alpha_1^{(i)}$ and $\alpha_2^{(i)}$ are both positive, i.e. the probability of staying in or switching to regime 1 (resp. regime 2) is an increasing (resp. decreasing) function of the relative shares of wind and solar productions. Fig. 9 shows the evolution of the modelled probabilities of transition with the relative shares of wind and solar. This graph reveals two particular features: firstly, the influence of the wind energy output is much stronger than the influence of the solar one; secondly, the impact on p_{11} (and hence on p_{12}) is quite limited, compared to the impact on p_{21} (and p_{22}).

Table 5 below shows that the mean probabilities of transition are also significant, hence justifying the switching mechanism. Additionally, we showed using Wald tests that p_{11} and p_{21} (and thus also p_{12} and p_{22}) were significantly different from one another. This proves that the switching mechanism is indeed Markovian, at the opposite of a "simple" switching model, for which the probability of being in a given regime would be unconditional (i.e. $p_{11} = p_{21}$ and $p_{22} = p_{12}$).

Finally, let us comment the time-varying expected durations: although regime 1 is on average 4.6 h longer than regime 2, it is also much more variable. Also, one should not be surprised that the sum of the mean expected durations does not equal 24 h. In particular, this means that there can be more than one regime change during a single day.

6.2. Regime visualisation

In this subsection, we now associate the regimes with the levels of prices and other variables. Fortunately, the estimation procedure computes for each time step the probability of being in each regime. In fact three kind of probabilities are computed by the algorithm:

- one-step probabilities: $\mathbb{P}(S_t = i | S_{t-1})$;
- filtered probabilities: $\mathbb{P}(S_t = i | S_{t-1}, ..., S_1)$;
- smoothed probabilities: $\mathbb{P}(S_t = i | \{St\}_{t \in [\![1;T]\!]})$.

Filtered or smoothed probabilities are often used to attribute the regimes to each time step. We will use smoothed probabilities, but there is almost no difference with the filtered probabilities in the regime attribution. In practice, the probabilities are very close to 1 or 0, so that the choice between a regime or another is unambiguous.

6.2.1. Dynamic visualisation

A very common and useful way to visualise the switching process is shown in Fig. 10 below. From this short sample (first week of September 2014), we clearly see that as expected, the regimes are associated to a price mode: prices are higher in regime 2 than in regime 1. Also, these regimes seem to be quite correlated to the hours of the day. This is normal since prices are strongly seasonal, as already explained in Section 4.4. However, there are some exceptions, that the MS model is able to take into account, as we can see in this example. We find this week to be rather representative, as it presents the usual daily and weekly seasonalities of electricity demand and prices while showing the influence of the variable RES production on prices. Also, as can be seen later in Figs. 11 and 12, there difference in the attribution of the regimes is much more driven by the type of day than by the season.

These graphs contain a lot of information, and hence need to be analysed. First of all, we notice the very regular pattern followed by the load, with a peak at 11 a.m. and very low demand during the night and the weekend. During the first two days, wind and solar production is rather low, and the regimes seem to be driven by load only: regime 2 coincides with high demand and high prices, from 6 a.m. to 10 p.m., so roughly during daytime. On Wednesday and Thursday however, wind and solar generation increases. This incurs a change in regime with a decrease in price, respectively from 12 p.m. to 5 p.m. and 3 p.m. On Friday, the wind energy output is rather low, but solar production reaches its week peak at 1 p.m., and there is a slight and quick change of regime ($\mathbb{P}(S = 1) = 0.66$). Finally, the load decrease during the weekend, associated with a still strong solar generation, keeps the prices low.

[6] We could have chosen a specification whose coefficients could be more easily interpreted, but the chosen modelling was the only one with lowest information criteria and residual variance, which converged, and which was able to distinguish the two regimes properly.

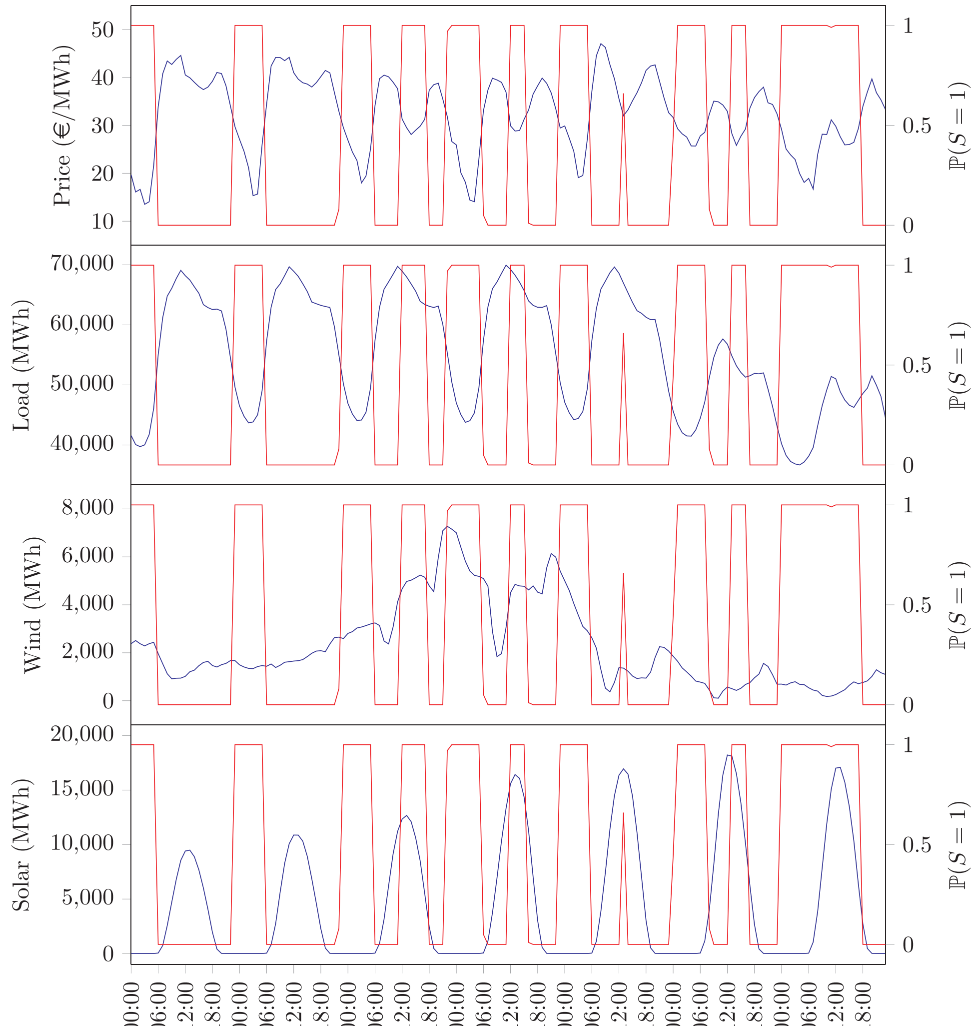

Fig. 10. Price, gross demand, wind and solar productions (blue, left axis) and probability of being in regime 1 (red, right axis), first week of September 2014 (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.).

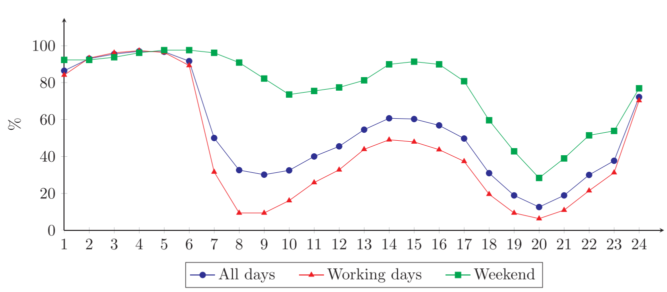

Fig. 11. Mean frequencies of occurrence of regime 1 for each hour of the day, for working days and weekends.

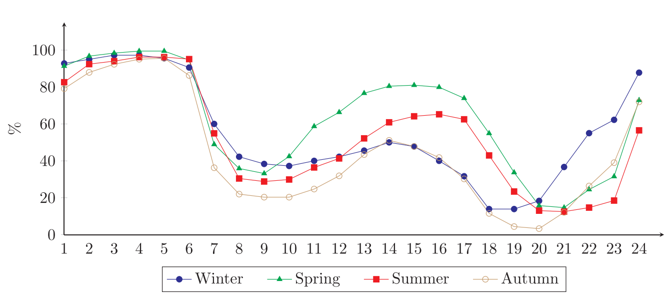

Fig. 12. Mean frequencies of occurrence of regime 1 for each hour of the day, per season.

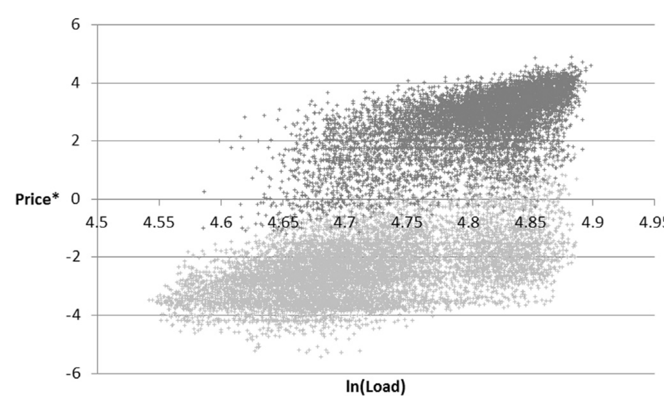

Fig. 13. Transformed price vs. logarithm of load for the two regimes (light grey: regime 1, dark grey: regime 2).

6.2.2. Seasonality analysis of the regimes

Let us now look at the frequency of occurrence of regime 1 for each hour, per type of day[7] (Fig. 11) and season[8] (Fig. 12). We observe as

[7] We do not consider holidays in this analysis, but we believe that it would not change the results much, and that the pattern would be rather similar to the one observed for weekends.

[8] For simplicity, we considered that winter was running from December to February, spring from March to May, etc.

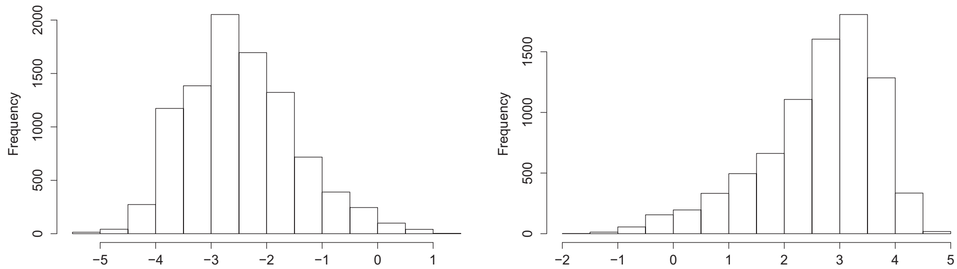

Fig. 14. Histograms of the transformed price for regime 1 (left) and 2 (right).

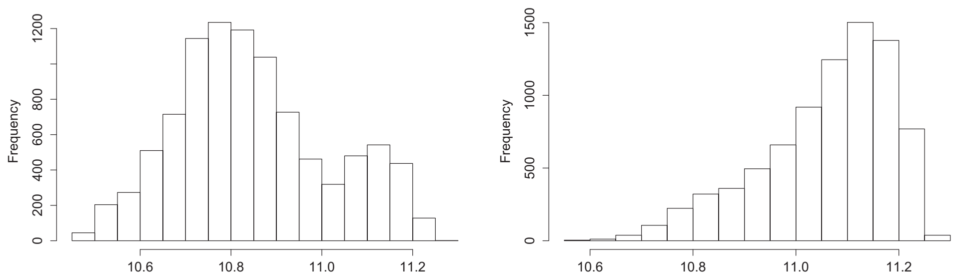

Fig. 15. Histograms of the logarithm of load for regime 1 (left) and 2 (right).

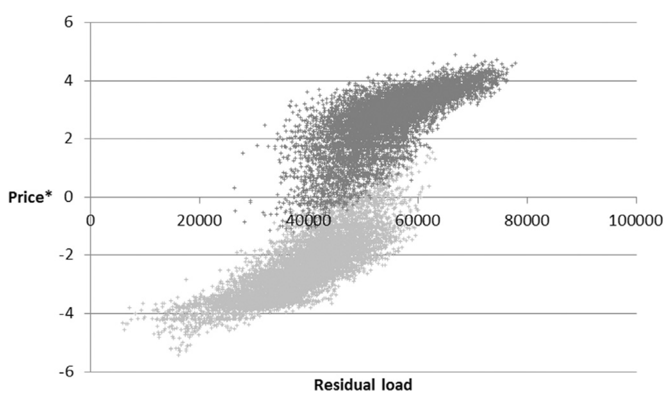

Fig. 16. Transformed price vs. residual load in regime 1 (light grey) and 2 (dark grey).

Table 6
Average marginal effect for each regime.

	Regime 1			Regime 2		
	Mean	S.D.	C.V.	Mean	S.D.	C.V.
$\frac{\partial Price}{\partial Wind}$ ((€/MWh)/(GW))	− 0.77	0.73	0.94	− 1.0	0.79	0.79
$\frac{\partial Price}{\partial Solar}$ ((€/MWh)/(GW))	− 0.73	0.68	0.94	− 0.96	0.76	0.79
$\frac{\partial Price}{\partial Load}$ ((€/MWh)/(GW))	0.93	0.84	0.90	1.18	0.92	0.78

expected that night hours are mainly during the low-price regime (1), for all types of day and seasons. The morning peak hours (8–10 a.m.) are more associated to high prices (regime 2), but only for working days. Evening peak hours (6–8 p.m.) are associated with high prices for all types of days (but less during week-ends), and particularly in autumn (Fig. 13).

During working days, the middle of the day is less associated with a specific regime, except during spring in which prices are relatively lower. Indeed, although the type of day seems to be the main driver for the level of prices, the frequency of occurrence of regime 1 differs a lot among months, reaching 88.7% at 1–2 p.m. in March while it is of only 41.7% in November. This confirms the fact that the model is indeed able to take the seasonality into account, while staying non-deterministic and hence more flexible.

6.2.3. Comparison of price and load regimes

We can also visualise the regimes thanks to 2D plots such as figure ??: (transformed) price vs. (logarithm of) load. On this graph the two regimes are easily identifiable. Also, this partly confirms what we saw previously in Fig. 10, i.e. that price regimes are highly correlated with load regimes. When looking at the histograms of the transformed price for each regime (Fig. 14), we find that the two modes correspond to the previously identified ones in Fig. 7.

However, we can see from the Price-Load graph that there exists a region for which the demand is high, while the price remains low. This is confirmed by taking a look at the histograms of load for each regime (Fig. 15): during regime 1 there is a (relatively small) proportion of "high" demand, whereas only a high-demand mode is present in regime 2.

Finally, if we plot the transformed price versus the residual demand (Fig. 16), this region disappears, and the relationship between the transformed price and the residual load appears to be rather linear within each regime, hence comforting the choice of the transformation and of the residual demand as covariate.

6.3. Effect on prices

6.3.1. Average marginal effects

Interpreting the coefficients can be difficult, since the price has been transformed and because we use wind and solar penetration indices as well as residual load. In particular, the coefficients associated with wind and solar productions are positive, which would mean at first look that they increase the price. However, when taking into account the effect of RES through the residual load coefficient we should find a negative effect. Hence, it is interesting to derive an expression for the average marginal effects (slopes), that would tell how much the decrease in price is when RES production and load increase. We do not compute elasticities, because they would be very high when prices approach zero, and would change sign whenever the price does. For clarity reasons, we put in Appendix C the computations and the formal expressions of the average marginal effects (Eqs. (26)–(28)), while we show the results here (Table 6)[9].

As expected, we find negative average marginal effects for RES generation, and a positive one for load, for each time step. Then on average, an increase of 1 GW of wind will decrease the price in regime 1 (resp. 2) by 0.77€/MWh (resp. 1€/MW h). The influence of solar is slightly weaker, as an extra gigawatt hour lowers the price of 0.73€/MWh in period 1, and 0.96€/MWh in regime 2. On the contrary, if the demand increases by 1 GW in regime 1 (resp. 2), the price increases on average by 0.93€/MWh (resp. 1.18€/MWh). Moreover, we performed Welch *t*-tests on the obtained coefficients to test whether their means are significantly different from one another (from a regime to another and for each variable within each regime), which seems to be the case.

Even though we cannot rigorously conclude about the statistical significance of the average marginal effects, many elements are consistent with the fact the effect is negative. Indeed, the time series computed from Eqs. (26)–(27)) are fully negative, and the estimated coefficients of the model are indeed statistically significant. Furthermore, we estimated a model using RES productions in level instead of their relative shares, which produced statistically significant negative marginal effects on the transformed price[10].

This analysis confirms the existence of different merit-order effects in high-price and low-price regimes. However, these slopes have very high coefficients of variation, which means that inside each regime the marginal effect can vary a lot. Nevertheless, these high variations are partly due to the reverse transformation that is needed to compute those slopes, and the estimated coefficients (β) are on the contrary very well determined, with rather low standard deviations. It is thus important to remember that these marginal effects are not equivalent to the model, which considers a non-linear transformation of the price, but only illustrate it in a linear framework. Additionally, when trying to estimate the MS model for the non-transformed price, we fail to disentangle the two regimes, which confirms the usefulness of the price transformation. Yet, the existence of different marginal effects for high and low prices confirms that the inverse supply curves are on average convex, as explained in the introduction. Similarly, the volatility was found to be higher in regime 2 than in regime 1, which is consistent with this hypothesis.

6.3.2. Non-marginal effects

Although the average marginal effects are of huge interest, they are only valid inside each regime, i.e. when there is no switching. Indeed, when there is a regime change, marginal effects are not defined since the coefficients change. In particular, the predicted change of the transformed price conditionally on the previous period is:

$$\mathbb{E}[\Delta Price^*|S_{t-1}=i] = p_{ii}\left[\beta_1^{(i)}\Delta\left(\frac{Wind}{Load}\right)+\beta_2^{(i)}\Delta\left(\frac{Solar}{Load}\right)+\beta_3^{(i)}\Delta RLoad\right] + p_{ij}\left[\Delta\beta_0+\Delta\left(\beta_1\frac{Wind}{Load}\right)+\Delta\left(\beta_2\frac{Solar}{Load}\right) + \Delta(\beta_3 RLoad)\right] \tag{15}$$

We recognise in this expression a weighted average of a regime-*i* term and a regime-*j* switching term. The first term is the equivalent of the marginal effect, which is computed for an infinitesimal change of the covariates. This cannot be done with the second term, because of the switching coefficients. To have an idea of the importance of the switching term, the mean price in regime 1 is 23.5€/MWh, while it is 42.6€/MWh in regime 2, i.e. approximately the first and third quartiles Q1 and Q3.

Table 7
Odds ratios of the logit model for the transition probabilities.

Variable	(1)	(2)
e^{α_0}	3.033463	0.06313241
$e^{\alpha_1/100}$	1.054493	1.072197
$e^{\alpha_2/100}$	1.045657	1.014949

6.4. Impact on the regimes

6.4.1. Odds ratios

Also of interest is the interpretation of the coefficients of the time-varying probabilities. We have already analysed the effect of the RES penetration indices on the probabilities through the sign of the coefficients, but we would also like to assess the impact more quantitatively. The first and natural idea is to look at odds ratios (e^{α}), which would tell how the odds of switching or staying in a regime vary with the shares of renewable production. This is given in Table 7 below:

From this table we can see for example that an increase of one percentage point of the relative share of wind energy output would increase the odds of staying in regime 1 by 5.4% while increasing the odds of switching from regime 2 to regime 1 by 7.2%. Similarly, an increase of one percentage point of the relative share of solar production would increase the odds of staying in regime 1 by 4.6% while increasing the odds of switching from regime 2 to regime 1 by 1.5%. These odds ratios show again that solar generation has a smaller impact than wind generation, especially when it comes to switching from high to low prices.

6.4.2. Impacts on regime durations

In addition, we would like to refer to more understandable variables than probabilities of transition, e.g. the expected duration of each regime $\mathbb{E}\tau_i$, or the stationary distribution π, as defined at the end of Section 5. We have presented closed-form expressions for these variables in the homogeneous case, that are no longer valid in the inhomogeneous one. However, deriving closed-form expressions for marginal effects on these variables in the inhomogeneous case can give an idea of the magnitude of the impact, even though it is not mathematically rigorous. Since the expression of the stationary distribution involves both $\alpha^{(i)}$ coefficients, we will focus on the expected durations only. Also, we will only derive the impact of RES production (similar expressions can be derived for the load). We show in Appendix C the following results:

$$\left\langle \frac{\frac{\partial(\mathbb{E}\tau_1-1)}{\mathbb{E}\tau_1-1}}{\partial Wind}\right\rangle \simeq \frac{\alpha_1^{(1)}}{\langle Load\rangle} \simeq 9.2\%.\ \mathrm{GW}^{-1} \quad \left\langle \frac{\frac{\partial(\mathbb{E}\tau_2-1)}{\mathbb{E}\tau_2-1}}{\partial Wind}\right\rangle \simeq \frac{-\alpha_1^{(2)}}{\langle Load\rangle} \simeq -12\%.\ \mathrm{GW}^{-1} \tag{16}$$

$$\left\langle \frac{\frac{\partial(\mathbb{E}\tau_1-1)}{\mathbb{E}\tau_1-1}}{\partial Solar}\right\rangle \simeq \frac{\alpha_2^{(1)}}{\langle Load\rangle} \simeq 7.7\%.\ \mathrm{GW}^{-1} \quad \left\langle \frac{\frac{\partial(\mathbb{E}\tau_2-1)}{\mathbb{E}\tau_2-1}}{\partial Solar}\right\rangle \simeq \frac{-\alpha_2^{(2)}}{\langle Load\rangle} \simeq -2.6\%.\ \mathrm{GW}^{-1} \tag{17}$$

Hence, $\frac{\alpha_1^{(i)}}{\langle Load\rangle}$ and $\frac{\alpha_2^{(i)}}{\langle Load\rangle}$ can be interpreted as the (absolute values of the) semi-elasticities of $\mathbb{E}\tau_i - 1$ with respect to wind and solar productions, respectively. The fact that $\mathbb{E}\tau - 1$ is considered instead of simply $\mathbb{E}\tau$ is due to the mathematical derivation of the expressions, but it also reminds us that the expected duration of a regime cannot be lower than

[9] The standard deviations are computed directly from the time series generated by Eqs. (26)–(28).

[10] Unfortunately, this model could not converge when using time-varying probabilities, which is why we did not use it.

1, as long as it exists (it can nevertheless be very rare, which corresponds to a marginal stationary distribution close to zero). Furthermore, as $\mathbb{E}\tau$ is the expected duration of a regime conditionally on being in this regime, one could interpret $\mathbb{E}\tau - 1$ as the mean "remaining time" in the regime, as the current period is taken into account in the definition of $\mathbb{E}\tau$.

On average, when there is an additional GW of wind (resp. solar), $\mathbb{E}\tau_1 - 1$ increases by 9.2% (resp. 7.7%), while $\mathbb{E}\tau_2 - 1$ decreases by 12% (resp. 2.6%). As a reminder, the computed mean expected durations where $\mathbb{E}\tau_1 = 12.6$h and $\mathbb{E}\tau_2 = 8.04$h. The computed semi-elasticities are quite high (in absolute value), and it must be remembered that they are only approximate mean values. However, this confirms that RES generation not only affect electricity prices marginally, but also more globally, through the expected duration of each regime, but also their frequency (not derived here).

In the long run, with very high shares of renewable production, these estimates have no reason to stay valid. In particular, the price structure is expected to change, with on average lower prices and less episodes of high prices. With time, regime 2 as defined here is likely to shrink or disappear, while regime 1 will become more and more predominant. In fact, recall that the regimes have more or less been "predefined", as we chose the mean price as location parameter for the inverse hyperbolic sine transformation. Hence, as the mean is expected to decrease as well, a new transformation would have to be defined at some point. One could also think of including a dynamic modelling of the mean itself, but this would most certainly prove very difficult to achieve.

7. Conclusions and policy implications

We have assessed the impact of wind and photovoltaic productions on electricity prices, taking into account the intermittency of these power generating units. For this purpose, we developed a two-state Markov switching model that we estimated using data from the German market. We exhibited two regimes, of "low" (1) and a "high" (2) prices, which present intra and inter-regime temporal correlation. Within each regime, the marginal impact of RES production is shown to be negative, and significantly different from a regime to another. These results are in line with standard electricity markets theory: the higher the prices, the higher the merit-order effect, and the higher the volatility as well. This is due to the fact that (inverse) supply curves are on average convex, as peak power plants have a relatively high marginal cost but usually provide little capacity compared to base power plants. Also, while marginal effects are only valid inside each regime (i.e. when there is no switching), we show that is also a non-marginal switching effect, which is influenced by renewable generation through their impact on the transition probabilities. Indeed RES production, and especially the wind one, leads to more frequent and longer low-price episodes. As a consequence, although the regimes are partly deterministic (due to the strong seasonality of demand), there are many exceptions, i.e. episodes of low prices with high demand. From the estimation of the transition probabilities, we derived odds ratios as well as approximations of semi-elasticities for the expected remaining duration of each regime. These values confirm and help quantify the overall impact of RES production on the structure of prices.

Although we have only considered the effect of RES generation on electricity prices, there is necessarily an impact on the other units of production and on cross-border flows. Hence, we can also expect to have a differentiated effect on the conventional units, depending on the merit-order and on which plant is marginal. However, a more thorough analysis would be needed to numerically evaluate this impact. For example, using a different methodology, Graf and Marcantonini (2016) used panel data in Italy to show that RES generation effectively reduces CO_2 emissions while increasing the average plant emission factor. Furthermore, although we have only shown that the volatility is higher during the high-price regime, intermittent RES production might influence it as well. This could be done for example using MS-GARCH modelling.

Finally, the policy implications of these results are diverse, but the first related issues are security of supply and support schemes for renewables. Indeed, since we expect RES production to decrease prices on average, we might also expect fewer episodes of very high prices. Unfortunately, these are essential to the profitability of peak power plants, who in turn suffer from "missing money". This well known "failure" of the energy-only market has led several countries to adopt capacity remuneration mechanisms (CRMs), such as capacity payments, capacity obligations, or strategic reserves.

Yet this issue concerns other production facilities as well. In particular, renewables are expected to become competitive on energy markets (at least on the retail market, which is already the case today in some places). However competitiveness might not ensure profitability on the wholesale market, if prices become too low. Indeed, it might then be necessary to keep subsidising RES for longer than expected, while some conventional power plants could have to be subsidised as well, for example through CRMs,[11] if they are valuable to the system as secure capacity. Indeed, it is often considered that security of supply is a public good, which can then be subsidised if it is not produced in sufficient quantity by the market (market failure), for example if prices are too low, or high enough on average but with very few occurrences of very high prices, i.e. with a lot of uncertainty. In the long run, electricity markets and support mechanisms would have to be redesigned to take into account all these specificities. Hopefully, dynamic retail pricing and electricity storage might help gain overall efficiency, but it is still uncertain whether they will be available soon and deliver their promises or not. In any case, it is necessary to start addressing the problem by thinking about future market design. In this context, this paper contributes to understanding the market impact of load and renewable production, by highlighting the nonlinear relationship between electricity prices and these particular determinants. Consequently, policy makers will have to take into account these increasing interactions when designing future electricity markets.

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Appendix A. Marginal shock on supply or demand: theory

Let us denote $D: p \mapsto D(p)$ (with $(D' < 0)$ and $S: p \mapsto S(p)$ (with $S' > 0)$ the demand and supply functions for a certain time step, and let us derive

[11] Note that CRMs are not necessarily subsidies, and that other means of subsidies could be used in the present case.

the expression of the marginal effect on price for an infinitesimal change in supply $dRES$ or demand $dLoad$. At the equilibrium, price and quantity are jointly determined by equating supply and demand: $Q = D(p) = S(p)$. Suppose that there is a change in supply so that the equilibrium quantity writes $Q = S(p, s)$, and/or a change in demand so that $Q = D(p, d)$. Hence, as $Q = D(p, d) = S(p, s)$, when s and d change, p does too so that the equation continues to hold. We can then write the price as function of s and d: $p = p(s, d)$; and the equilibrium equation becomes: $D(p(s, d), d) = S(p(s, d), s)$. Differentiating then yields:

$$\frac{\partial D}{\partial p}\left(\frac{\partial p}{\partial s}\mathrm{d}s + \frac{\partial p}{\partial d}\mathrm{d}d\right) + \frac{\partial D}{\partial d}\mathrm{d}d = \frac{\partial S}{\partial p}\left(\frac{\partial p}{\partial s}\mathrm{d}s + \frac{\partial p}{\partial d}\mathrm{d}d\right) + \frac{\partial S}{\partial s}\mathrm{d}s \tag{18}$$

For an additive change in supply only we simply have $S(p, s) = S(p) + s$ and $D(p, d) = D(p)$, so that:

$$\frac{\partial D}{\partial p}\frac{\partial p}{\partial s} = \frac{\partial S}{\partial p}\frac{\partial p}{\partial s} + 1 \tag{19}$$

Rearranging and replacing s by RES gives:

$$\frac{\partial p}{\partial RES} = \frac{1}{\frac{\partial D}{\partial p} - \frac{\partial S}{\partial p}} < 0 \tag{20}$$

Finally, considering an additive change in demand only we have $D(p, d) = D(p) + d$ and $S(p, s) = S(p)$. Replacing d by $Load$ then gives Eq. (1):

$$\frac{\partial p}{\partial Load} = \frac{-1}{\frac{\partial D}{\partial p} - \frac{\partial S}{\partial p}} = -\frac{\partial p}{\partial RES} > 0 \tag{21}$$

Table 8
Unit root and stationarity tests for the price time series.

Null Hypothesis: PRICE has a unit root			
Exogenous: Constant			
Lag Length: 28 (Automatic - based on SIC, maxlag = 43)			
		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		− 17.13532	0.0000
Test critical values:	1% level	− 3.430552	
	5% level	− 2.861513	
	10% level	− 2.566797	
*MacKinnon (1996) one-sided p-values.			
Null Hypothesis: PRICE has a unit root			
Exogenous: Constant			
Bandwidth: 19 (Newey-West automatic) using Bartlett kernel			
		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		− 24.45028	0.0000
Test critical values:	1% level	− 3.430551	
	5% level	− 2.861513	
	10% level	− 2.566797	
*MacKinnon (1996) one-sided p-values.			
Null Hypothesis: PRICE is stationary			
Exogenous: Constant, Linear Trend			
Bandwidth: 86 (Newey-West automatic) using Bartlett kernel			
			LM-Stat.
Kwiatkowski-Phillips-Schmidt-Shin test statistic			0.109461
Asymptotic critical values*:	1% level		0.216000
	5% level		0.146000
	10% level		0.119000
*Kwiatkowski-Phillips-Schmidt-Shin (1992, Table 1)			

Appendix B. Price statistics

Figs. 17–20.

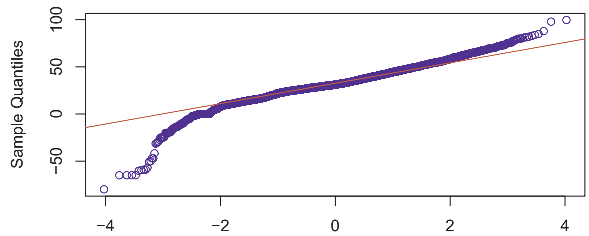

Fig. 17. Normal QQ-plot.

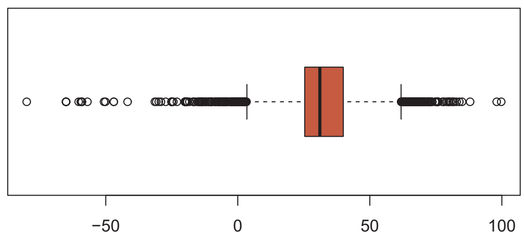

Fig. 18. Box-plot.

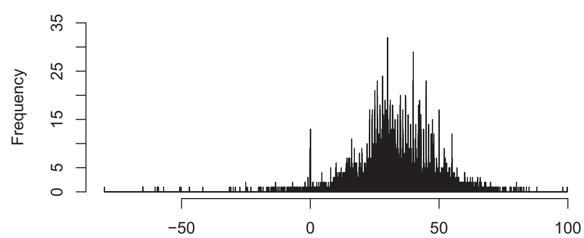

Fig. 19. "Complete" histogram.

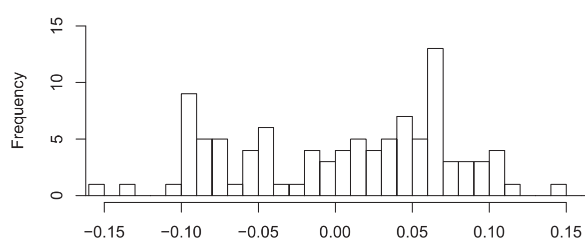

Fig. 20. Histogram around 0/MWh.

Appendix C. Mathematical expressions of the marginal effects

C.1. Marginal effects on price

We show here how to derive the expression for the marginal effects in each regime. For simplicity of presentation, we use the centred variable $X = Price - \langle Price \rangle$ (where $\langle \cdot \rangle$ is the temporal mean operator), we denote by $W = \frac{Wind}{Load}$ and $S = \frac{Solar}{Load}$ the relative shares of wind and solar productions, and we drop the index t. As the derivative of $x \mapsto \sinh^{-1} x$ is $x \mapsto (x^2+1)^{-1/2}$, we have the following computations[12]:

$$\sinh^{-1} X = \beta_0 + \beta_1 W + \beta_2 S + \beta_3 RLoad \tag{22}$$

$$\Rightarrow \quad \frac{\mathrm{d}Price}{\sqrt{X^2+1}} = \beta_1 \mathrm{d}W + \beta_2 \mathrm{d}S + \beta_3 \mathrm{d}RLoad \tag{23}$$

$$= \beta_1 \left(\frac{\mathrm{d}Wind}{Load} - \frac{Wind}{Load}\frac{\mathrm{d}Load}{Load} \right) + \beta_2 \left(\frac{\mathrm{d}Solar}{Load} - \frac{Solar}{Load}\frac{\mathrm{d}Load}{Load} \right) \tag{24}$$

[12] For simplification, we omit the error term and the regime indices: we consider in fact the expectation of X conditional on a regime and on the covariates.

$$+ \beta_3(\mathrm{d}Load - \mathrm{d}Wind - \mathrm{d}Solar) \tag{25}$$

All other variables held constant, we obtain the following expressions for the marginal effects due to wind and solar productions and load:

$$\frac{\partial Price}{\partial Wind} = \sqrt{X^2+1}\left(\frac{\beta_1}{Load} - \beta_3\right) \tag{26}$$

$$\frac{\partial Price}{\partial Solar} = \sqrt{X^2+1}\left(\frac{\beta_2}{Load} - \beta_3\right) \tag{27}$$

$$\frac{\partial Price}{\partial Load} = \sqrt{X^2+1}\left(\beta_3 - \beta_1\frac{Wind}{Load^2} - \beta_2\frac{Solar}{Load^2}\right) \tag{28}$$

Finally, we compute these marginal effects for each time step and take temporal their mean and standard deviation, as shown in Table 6[13].

C.2. Marginal effects on expected duration

As stated in Section 6, the marginal effects computed below are not mathematically rigorous, since we use formulas for expected duration and stationary distribution that are only valid for homogeneous Markov chains. Nevertheless we hope that it will give an idea of the magnitude of the marginal effects. First, let us recall the aforementioned formulas:

$$\mathbb{E}\tau_i = \frac{1}{p_{ij}} = \frac{1}{1-p_{ii}} \quad \text{and} \quad \pi_1 = 1-\pi_2 = \frac{p_{21}}{p_{12}+p_{21}} \tag{29}$$

We inject the expression of the time-varying probabilities in the equation giving the expected durations, using W and S as before for the sake of simplicity:

$$p_{i1} = \frac{1}{1+\exp(-\alpha_0^{(i)} - \alpha_1^{(i)}W - \alpha_2^{(i)}S)} \quad \text{and} \quad p_{i2} = \frac{1}{1+\exp(\alpha_0^{(i)} + \alpha_1^{(i)}W + \alpha_2^{(i)}S)} \tag{30}$$

so that we have for the expected durations:

$$\mathbb{E}\tau_1 = 1 + \exp(\alpha_0^{(1)} + \alpha_1^{(1)}W + \alpha_2^{(1)}S) \tag{31}$$

$$\Rightarrow \quad \mathrm{d}\mathbb{E}\tau_1 = \alpha_1^{(1)}\exp(\alpha_0^{(1)} + \alpha_1^{(1)}W + \alpha_2^{(1)}S)\mathrm{d}W + \alpha_2^{(1)}\exp(\alpha_0^{(1)} + \alpha_1^{(1)}W + \alpha_2^{(1)}S)\mathrm{d}S \tag{32}$$

$$\Rightarrow \quad \frac{\mathrm{d}(\mathbb{E}\tau_1 - 1)}{\mathbb{E}\tau_1 - 1} = \alpha_1^{(1)}\mathrm{d}W + \alpha_2^{(1)}\mathrm{d}S \tag{33}$$

$$= \alpha_1^{(1)}\left(\frac{\mathrm{d}Wind}{Load} - \frac{Wind}{Load}\frac{\mathrm{d}Load}{Load}\right) + \alpha_2^{(1)}\left(\frac{\mathrm{d}Solar}{Load} - \frac{Solar}{Load}\frac{\mathrm{d}Load}{Load}\right) \tag{34}$$

and

$$\mathbb{E}\tau_2 = 1 + \exp(-\alpha_0^{(2)} - \alpha_1^{(2)}W - \alpha_2^{(2)}S) \tag{35}$$

$$\Rightarrow \quad \mathrm{d}\mathbb{E}\tau_2 = -\alpha_1^{(2)}\exp(-\alpha_0^{(2)} - \alpha_1^{(2)}W - \alpha_2^{(2)}S)\mathrm{d}W - \alpha_2^{(2)}\exp(-\alpha_0^{(1)} - \alpha_1^{(2)}W - \alpha_2^{(2)}S)\mathrm{d}S \tag{36}$$

$$\Rightarrow \quad \frac{\mathrm{d}(\mathbb{E}\tau_2 - 1)}{\mathbb{E}\tau_2 - 1} = -\alpha_1^{(2)}\mathrm{d}W - \alpha_2^{(2)}\mathrm{d}S \tag{37}$$

$$= -\alpha_1^{(2)}\left(\frac{\mathrm{d}Wind}{Load} - \frac{Wind}{Load}\frac{\mathrm{d}Load}{Load}\right) - \alpha_2^{(2)}\left(\frac{\mathrm{d}Solar}{Load} - \frac{Solar}{Load}\frac{\mathrm{d}Load}{Load}\right) \tag{38}$$

Finally, all other variables held constant, we can isolate the marginal effects and take their temporal mean:

$$\left\langle \frac{\frac{\partial(\mathbb{E}\tau_1 - 1)}{\mathbb{E}\tau_1 - 1}}{\partial Wind} \right\rangle = \frac{\alpha_1^{(1)}}{\langle Load\rangle} \quad \left\langle \frac{\frac{\partial(\mathbb{E}\tau_2 - 1)}{\mathbb{E}\tau_2 - 1}}{\partial Wind} \right\rangle = \frac{-\alpha_1^{(2)}}{\langle Load\rangle} \tag{39}$$

$$\left\langle \frac{\frac{\partial(\mathbb{E}\tau_1 - 1)}{\mathbb{E}\tau_1 - 1}}{\partial Solar} \right\rangle = \frac{\alpha_2^{(1)}}{\langle Load\rangle} \quad \left\langle \frac{\frac{\partial(\mathbb{E}\tau_2 - 1)}{\mathbb{E}\tau_2 - 1}}{\partial Solar} \right\rangle = \frac{-\alpha_2^{(2)}}{\langle Load\rangle} \tag{40}$$

[13] The standard deviations are computed directly from the time series generated by Eqs. (26)–(28).

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