When Prices Slow Down: Renewable Energy, Climate Deviations, and Mean Reversion

Abstract We investigate how the increasing penetration of variable renewable energy sources (VREs) influences the speed at which electricity spot prices revert to equilibrium following weather-driven shocks. Using German spot electricity prices and temperature data, we estimate a continuous-time jump–diffusion model with stochastic mean reversion and exploit the Fukushima accident as a quasi-natural experiment. Our findings show that, in the post-Fukushima period, climate deviations substantially slowed mean reversion, lowered the risk premium, and increased expected shortfall, thereby amplifying exposure to extreme price outcomes. These results suggest that while the expansion of VREs advances decarbonization, it may simultaneously intensify market tail risks unless supported by complementary flexibility measures such as capacity mechanisms and cross-border integration.

Keywords: Spot prices; Variable Renewable Energy; Jump-Diffusion

JEL codes: C58, C22, G13

1. Introduction

Over the past decades, governments worldwide have promoted and subsidized the adoption of variable renewable energy sources (VREs) as part of their strategy to mitigate climate change (see (López Prol and Schill, 2021), (Liu et al., 2023), (Xiong and Dai, 2023)). Beyond financial incentives, institutional reforms have also played a central role. A prominent example is Germany's feed-in tariff system, under which VRE producers are guaranteed a fixed payment for 21 years (Frondel et al., 2022). These measures have fostered a rapid expansion of renewable capacity and transformed the structure of power markets.

These developments have stimulated a growing literature on the implications of VRE integration for electricity markets. One line of research investigates the optimal level of renewables in the generation mix, emphasizing the role of intermittency as a key limiting factor (see (Hirth, 2015); (de Faria et al., 2022); (Petersen et al., 2024)). Another strand analyzes how VRE penetration affects the statistical properties of day-ahead electricity prices, including mean

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levels (see (Gelabert et al., 2011) and (Grossi et al., 2017)), volatility (see (Ballester and Furió, 2015) and (Schöniger and Morawetz, 2022)), and tail behavior (see (Fanone et al., 2013) and (Huisman and Stet, 2022)).

Despite these contributions, an important question remains largely unexplored: how VRE expansion affects the speed of mean reversion in spot electricity prices following weather-driven shocks. In other words, when climate conditions deviate from long-term patterns, how quickly do prices revert to equilibrium? Understanding this dynamic is crucial, since slower mean reversion amplifies exposure to persistent price distortions and may exacerbate risks for market participants and system operators.

To address this gap, we develop a continuous-time jump–diffusion model with stochastic mean reversion that incorporates the direct influence of weather conditions on price dynamics. This framework allows us to capture key empirical features of electricity spot prices—seasonality, abrupt jumps, and state-dependent persistence—while explicitly linking them to climate deviations. Our empirical strategy exploits the Fukushima nuclear accident as a quasi-natural experiment, following (Grossi et al., 2017). The disaster triggered an exogenous supply shock by accelerating the phase-out of German nuclear power plants and simultaneously intensifying investment in renewable capacity (see (Renn and Marshall, 2016); (Bundestag, 2011); (Winter, 2013)).

We show that the policy responses of the German government to the Fukushima accident increased risk in the German electricity market by altering the speed of mean reversion and, consequently, the distribution of price outcomes. In particular, we compute the expected shortfall under different climate scenarios using parameters estimated from our model. This analysis highlights that while VRE expansion is indispensable for decarbonization, it also heightens exposure to extreme prices unless accompanied by adequate flexibility measures, such as capacity mechanisms and cross-border integration.

The remainder of the paper is structured as follows. Section 2 reviews the literature on the impact of VREs on electricity markets. Section 3 presents the theoretical model. Section 4 outlines the empirical strategy, and Section 5 describes the dataset. Section 6 reports the main results. Section 7 provides the expected shortfall analysis. Section 8 concludes with policy implications.

2. Literature review

(Arndt et al., 2019) and (López Prol and Schill, 2021) argue that many countries have promoted the integration of variable renewable energy sources (VREs) into their electricity supply because of their potential to reduce CO_2 emissions and their low marginal costs. Yet the deployment of VREs poses challenges: these sources are highly sensitive to weather conditions and may fail to meet demand during periods of high consumption (see (Hirth, 2015)).

One strand of the literature focuses on determining the optimal mix of energy sources in the electricity matrix—specifically, the appropriate capacity of VREs and their impact on wholesale prices, availability, and profitability. According to (Hirth, 2015), this research typically relies on economic models solved with numerical methods, which often face a trade-off between geographic scope and temporal or spatial resolution. Empirical contributions—including (Fripp and Wiser, 2008), (Joskow, 2011), (Milstein and Tishler, 2011), (Hirth, 2015), (de Faria et al., 2022), and (Petersen et al., 2024)—show that intermittency significantly limits VRE adoption. A key limitation of these studies, however, is that they tend to abstract from positive and negative externalities, such as pollution and energy security, when evaluating the optimal capacity of different sources ((Borenstein, 2012); see also (Green and Vasilakos, 2010), (Borenstein and Bushnell, 2015)).

A second line of inquiry examines the impact of VRE integration on the distribution of electricity prices. Several studies analyze the merit-order effect—that is, whether higher VRE penetration depresses expected spot prices.[1] For instance, (Gelabert et al., 2011) show that greater VRE participation in Spain reduces spot prices regardless of demand conditions, though they do not control for net imports or simultaneity between supply and demand. Similarly, (Cludius et al., 2014) find price-reducing effects in Germany, but highlight that benefits are unevenly distributed: under the Renewable Energy Sources Act (EEG), energy-intensive industries receive lower rates than other consumers.

Other work extends this line of research. (Grossi et al., 2017), exploiting the Fukushima accident as a quasi-natural experiment, show that an increase in the share of intermittent energy significantly alters German and Austrian power prices. Using IV-GMM estimation, they demonstrate robustness to supply curve specifications and cross-border shocks, but do not explicitly account for price spikes (see (Lucia and Schwartz, 2002)). More recently, (Tselika et al., 2024) analyze the Danish and Swedish markets using an asymmetric fixed-effects panel model, finding that a decrease in VRE supply leads to a greater price increase than the price reduction resulting from an increase in VRE supply, although this effect can be mitigated by greater transmission capacity.

Beyond mean levels, a large body of research investigates whether VREs amplify volatility and extreme price outcomes. Evidence from (Jacobsen and Zvingilaite, 2010), (Ketterer, 2014), and (Ballester and Furió, 2015) suggests

[1] See (Jensen and Skytte, 2002) for a microeconomic model of the merit-order effect.

that VRE penetration raises price volatility in Denmark, Germany, and Spain, respectively. In contrast, (Wozabal et al., 2016) find opposing results, showing that volatility effects are context-dependent. Building on this, (Schöniger and Morawetz, 2022) demonstrate that variance depends on the slope of the supply curve: spot price volatility may increase or decrease depending on residual demand. Their panel evidence from nine European countries suggests a U-shaped relationship between VRE penetration and price variance, moderated by interconnection capacity and plant flexibility.

Finally, studies employing a range of econometric approaches—including Markov-switching models ((Lindström and Regland, 2012)), fractal autoregressive processes ((Fanone et al., 2013)), continuous-time diffusion models ((Ballester and Furió, 2015)), and panel quantile regressions ((Huisman and Stet, 2022))—find that VREs heighten the frequency of extreme price events. Collectively, this research establishes that VREs affect the mean, variance, and tails of the electricity price distribution. Yet no study to date has examined how VRE integration influences the speed of mean reversion—that is, the ability of spot prices to return to equilibrium following transitory, weather-driven shocks. This is the gap our study addresses.

3. Proposed model

Some of the previous studies discussed in Section 2 fail to account for key stylized facts of spot electricity prices—such as pronounced seasonality, mean reversion, abrupt price spikes, and volatility clustering (see (Lucia and Schwartz, 2002), (Knittel and Roberts, 2005), (Escribano et al., 2011)). While a few contributions have modeled subsets of these features, they typically do so in isolation—for example, focusing on mean reversion without accounting for volatility clustering, or capturing spikes while ignoring seasonal patterns. Neglecting the joint presence of these stylized facts can lead to misspecified dynamics, inefficient estimates of risk premia, and understated tail risk. To address this gap, we propose a unified model—formally specified in Equations (1)–(4)—that explicitly incorporates all of these characteristics, thereby providing a more reliable framework for inference on both risk premia and market tail risk.

Let P_t denote the electricity spot price at time t. We model P_t as the product of a deterministic component, S_t, and a stochastic component, X_t:

$$P_t = \frac{S_t}{(1 - X_t)} \tag{1}$$

The deterministic factor S_t captures the cyclical behavior of electricity supply and demand over the year and can be interpreted as the equilibrium price. The stochastic factor X_t governs deviations from this equilibrium, with uncertainty arising from short-term shocks. Its dynamics are described by Equations (2)-(4):

$$dX_t = \mu(X_t;Z_t)dt + \sigma(X_t)dW_t + G_t dN_t, \tag{2}$$

$$\mu(X_t;Z_t) = \alpha(Z_t) + \beta(Z_t)(X_t - \omega) - \gamma(X_t - \omega), \tag{3}$$

$$\sigma(X_t) = \sqrt{\xi_0^2 + \xi_1^2 X_t^2}, \tag{4}$$

where Z_t is a vector of strictly exogenous random variables at time t, dW_t denotes a Brownian motion, and G_t is an i.i.d. Gaussian random variable with mean μ_J and standard deviation σ_J that governs the jump sizes. The process dN_t captures the spikes observed in the data, with its dynamics specified in Equations (5) and (6). Furthermore, dW_t and dN_t are mutually independent, and γ, ω, ξ_0, and ξ_1 are constants.

$$P(dN_{i,t} = 1) = \lambda dt, \tag{5}$$

$$P(dN_{i,t} > 1) = o(dt), \tag{6}$$

where the functions $\alpha(\cdot)$ and $\beta(\cdot)$ describe how exogenous variables affect the risk premium and the speed of mean reversion, respectively. Similar specifications are used by (Benth and Meyer-Brandis, 2009) and (Hinderks et al., 2020), who show that external factors such as weather forecasts, CO_2 emissions, and demand conditions influence the risk premium of spot and forward electricity prices. The advantage of our specification is that it allows us to quantify how these variables change the incentives for taking short or long positions in electricity contracts.

The model also includes a jump component with intensity parameter λ, which generates the spikes observed in electricity prices. According to (Knittel and Roberts, 2005), such spikes often arise from congestion in transmission lines. The function $\sigma(X_t)$ is specified to capture volatility persistence.

Finally, the sign of $\beta(\cdot)$ reveals whether exogenous factors accelerate or decelerate the return of spot prices to equilibrium after a shock. Given the inelastic nature of electricity demand (see (Escribano et al., 2011)), the mean-reversion speed can be interpreted as an indicator of supply rigidity, with higher values reflecting a greater ability of suppliers to adjust output in response to changing market conditions. When suppliers are able to provide additional electricity as needed, prices converge more rapidly toward their equilibrium level, which is precisely what a higher mean-reversion speed captures.

4. Empirical strategy

In order to achieve the objectives of this work, we establish as our spot price as the price of day-ahead delivery electricity contracts for Germany like (Paschen, 2016). Moreover, we use temperature as a proxy for climate conditions because not only it is related with demand ((Grossi et al., 2017)) but also is important for VRE as it impacts solar radiation and wind speed (see (Van den Besselaar et al., 2015) and (Fei et al., 2023)).

We follow (Janczura and Weron, 2010) and (Benth et al., 2012) and divide the estimation procedure into two stages. In the first step, we seasonally adjust spot prices and temperature using equation (7):

$$S_t^Y = c^Y + f^Y t + g^Y \cos\left(\psi_0^Y + 2\pi \frac{t}{365}\right) + h^Y \cos\left(\psi_1^Y + 4\pi \frac{t}{365}\right), \quad (7)$$

where c^Y, f^Y, ψ_0^Y, and ψ_1^Y are parameters estimated for the variable Y. To simplify notation, we use P and TM to denote spot electricity prices and temperature, respectively.

It is worth noting that c^P and f^P represent, respectively, the fixed and long-run trend components of power production costs, while ψ_0^P and ψ_1^P capture the seasonal price patterns driven by annual fluctuations in electricity demand and supply. Consequently, S_t^P represents the long-run component of the spot price at time t.

Similarly, c^{TM} and f^{TM} denote the average temperature level and its long-term trend, which may reflect phenomena such as global warming. The parameters ψ_0^{TM} and ψ_1^{TM} describe the seasonal temperature cycle.

We estimate the parameters c^Y, f^Y, ψ_0^Y, and ψ_1^Y using nonlinear least squares implemented in the stats package in R (R Core Team, 2025). It is also worth mentioning that (Benth et al., 2012) and (Blanco et al., 2018) use a similar specification to deseasonalize German spot price levels.

Once the parameters of Equation (7) are obtained, we compute the predicted values for the deterministic series. The next step is to extract the stochastic component using the following Equation (8).

$$\hat{X}_t = \frac{P_t - \hat{S}_t^p}{P_t} \tag{8}$$

Finally, we estimate climate deviation using Equation (9). This variable captures temperature shocks that may increase energy demand. Our measure is closely related to that of (Chen et al., 2023), who use cooling and heating degree days to quantify temperature departures and the resulting demand shocks.

$$\hat{CV}_t = \frac{Tmp_t - \hat{S}_t^{TM}}{100Tmp_t}, \text{ where} \tag{9}$$

Tmp_t is temperature measured at time t. It is important to note that we standardize by $100Tmp_t$, so our climate deviation estimator is scale invariant and to deal with an estimation problem that is explained below.

In the second phase of our estimation strategy, we specify, respectively, functions $\alpha(z_t)$ and $\beta(z_t)$ with Equations (10) and (11). The main intuition behind these is that we estimate the influence of Fukushima accident through two channels: the risk premium and supply constraint channels.

$$\alpha(Z_t) = \phi_0|CV_t| + \phi_1 D_t + \phi_2 D_t|CV_t| \tag{10}$$

$$\beta(Z_t) = \phi_3|CV_t| + \phi_4 D_t|CV_t|, \text{ where} \tag{11}$$

Z_t is a vector of exogenous variables whoseelements are D_t and CV_t. D_t is a dummy variable that always value 1 for all $t > t^F$, where t^F is the date that Fukushima accident happenned and 0 otherwise.

Through the risk premium channel, we examine how the Fukushima accident may have altered trading incentives for day-ahead electricity delivery contracts. The signs of the coefficients ϕ_1 and ϕ_2 indicate how these incentives changed: positive values suggest that traders face stronger incentives to buy power spot contracts, whereas negative values imply that economic agents earn higher returns from shorting day-ahead delivery contracts compared with the pre-Fukushima period. The intuition is that, because some power plants were shut down, the probability of sharp upward price movements increased. As a result, economic agents would demand higher compensation for providing hedging services, thereby affecting the structure of the risk premium.

Additionally, it is worth mentioning that $\alpha(z_t)$ may be interpreted as the structural component of spot prices as in (Hinderks et al., 2020). Alternativelly, it also may be interpreted as the information premium proposed by (Benth and Meyer-Brandis, 2009).

The supply constraint channel evaluates the rate at which electricity prices adjust back to equilibrium after market disruptions. Because electricity demand remains largely inelastic (see (Escribano et al., 2011)), supply-side responses must bear the primary responsibility for restoring market balance. Our analysis focuses on whether alterations to the energy matrix affected this adjustment process by examining coefficient ϕ_4: when positive, it signals that price corrections have become more sluggish in response to shocks; when negative, it indicates that equilibrium convergence occurs more swiftly.

Building on the stochastic specification introduced in the previous paragraphs, we now turn to the estimation of its parameters. We employ the density-matching method proposed by (Ait-Sahalia, 1996) and (Fernandes, 2006), which relies on the stationary conditional density of the process. This approach offers several advantages. Unlike the generalized method of moments (GMM) of (Hansen, 1982), it does not require selecting a set of moments that correctly identifies the model. Moreover, it avoids the strong assumption—implicit in maximum likelihood—that the model is fully well specified, while still allowing us to formally test the null hypothesis of correct specification.

To implement this method, we make use of the conditional density function given in Equation (12) (see equation 7.8 in (Cont and Tankov, 2004)), following the general structure of (Ball and Torous, 1985). However, instead of relying on the transitional density as in their approach, we follow (Creedy and Martin, 1994) and (Fernandes, 2006) and use the stationary conditional density to represent the data-generating process. This choice is particularly suitable for our context. First, the stationary density admits a closed-form analytical expression, which facilitates the estimation procedure. Second, it provides a clear economic interpretation. The stationary density describes the long-run equilibrium pattern of the stochastic component x_t of spot prices. The exogenous variables z_t determine how x_t fluctuates around this equilibrium by shaping the conditions under which the process evolves. In our specific case, the uncertainty represented by x_t is influenced by climate conditions (CV_t) and by the policy decisions implemented after the Fukushima accident (D_t).

In this setting, $f(x_t \mid z_t, \theta)$ should be interpreted as the stationary density of the diffusion component augmented by the jump component. In other words, it corresponds to the stationary equilibrium density of the process, perturbed by the occurrence of rare events.

$$f(x_t \mid z_t, \theta) = e^{\eta}\left((1-\lambda\Delta t) f^{EQ}(x_t \mid z_t, \theta) + \lambda \Delta t \int_{-\infty}^{\infty} f^{EQ}(x_t - y \mid z_t, \theta) g(y)\, dy\right), \tag{12}$$

where $g(\cdot)$ is the density of a normal ditribution with mean μ_J and standard deviation σ_J, $\Delta t = \frac{1}{365}$, θ is a vector with parameters of Equations (2)-(4) and 10-11, e^{η} is a normalization component and $f^{EQ}(\cdot|z_t, \theta)$ is the stationary conditional density. To derive the analytical expression for $f^{EQ}(\cdot \mid z_t, \theta)$, we solve the Kolmogorov forward equation for the model[2] in Equation (13), which corresponds to the jump-free version of the specification introduced in Section 3, thus on our model jumps are disturbances that depart stochastic component from its long term behavior.

$$dX_t = \mu(X_t; Z_t)dt + \sigma(X_t)dW_t \tag{13}$$

$$f^{EQ}(x|z_t, \theta) = e^{\int \frac{2\mu(s;z_t) - \frac{d}{ds}\sigma^2(s)}{\sigma^2(s)} ds} \tag{14}$$

When we plug in Equation (14) the drift and diffusion components described by expressions (3) and (4) and solve the integral we get Equation (15). It is worth mentioning that this density is a special case of the generalized Student t distribution with two variables and time varying parameters (check section II from (Lye, 1998)).

$$f^{EQ}(x_t \mid z_t, \theta) = (\xi_0^2 + \xi_1^2 x_t^2)^{\frac{\xi_1^2 + \beta(z_t) - \gamma}{\xi_1^2}} \exp\left(\frac{(\omega(2\gamma - 2\beta(z_t)) + 2\alpha(z_t)) \tan^{-1}\left(\frac{\xi_1 x_t}{\xi_0}\right)}{\xi_0 \xi_1} + \eta\right) \tag{15}$$

When we analyze Equation (15), we notice that if $\xi_1^2 + \beta(z_t) - \gamma > 0$, then $f(x_t|z_t, \theta)$ would diverge when it was integrated from $-\infty$ to ∞, thus in order

[2] Check Appendix B for details.

to deal with this situation we divide the difference between the temperature and its expected value by 100 on Equation (9).

Moreover, it is also important to highlight that while $\alpha(z_t)$ influence only the skewness of the distribution, $\beta(z_t)$ affect both the skewness and heaviness of the distribution (see (Lye and Martin, 1993) and (Lye, 1998)).

Consequently, our model can reproduce some of the empirical findings associated with the introduction of renewable power sources in a country energy matrix. For example, it could describe the merit-order effect[3] if ω, ϕ_1, $\phi_2 < 0$, and $\gamma > 0, \phi_4 > 0$ and ϕ_0 and ϕ_3 are negligible, then stochastic component will present negative skewness, so it will be more likely to observe lower prices.

Additionally, our model can also capture the increase the likelihood of extreme prices with the expansion of renewable energy sources on the power supply because the greater the value of ϕ_4, the higher is the probability of observing higher values on spot prices. According to (Hagfors et al., 2016), this phenomenon happens because renewable energy sources are intermittent, thus production may not match demand and then electricity prices increase.

We now turn to the second component of Equation (12). Since this term does not admit a closed-form expression, we follow the approximation strategy proposed by (Cont and Tankov, 2003) and (Chib et al., 2009). Specifically, we apply a Taylor expansion around μ_J to approximate $f^{EQ}(x_t - y \mid z_t, \theta)$. This approach ensures that the resulting expression depends solely on the jump parameters μ_J and σ_J, leading directly to the approximation in Equation (16).

$$\int_{-\infty}^{\infty} f^{EQ}(x_t - y|z_t,\theta)g(y)dy = f^{EQ}(x_t - \mu_J|z_t,\theta) + \frac{\sigma_J^2}{2}\frac{d^2 f^{EQ}(x_t - \mu_J|z_t,\theta)}{dy^2} \tag{16}$$

With this approximation in place, we now have all the necessary components to construct the likelihood function and estimate the parameters in θ by solving expression (17). Once these estimates are obtained, we compute confidence intervals and standard errors using the bootstrap procedure described in (Fernandes, 2006).

$$\min_{\theta} \frac{\Sigma_{t=1}^{T}(f(x_t|z_t,\theta) - \hat{f}(x_t|z_t,\theta))^2}{T}, \text{ where} \tag{17}$$

[3](López Prol and Schill, 2021) defines merit-order effect as the decrease of wholesale power prices with an increase of supply renewable energy sources.

$\hat{f}(x_t|z_t,\theta)$ is the density non parametric density estimator. In this work, we follow (Ait-Sahalia, 1996) and (Fernandes, 2006) and use gaussian kernel and Silverman's rule of thumb (see (Sheather, 2004)) to calculate $\hat{f}(x_t|z_t,\theta)$.

5. Data

We conduct our empirical analysis using German day-ahead electricity prices traded on the European Power Exchange (EPEX Spot) from 12/03/2009 to 10/03/2013, available at Workspace, as well as daily maximum temperatures from Germany and from countries that traded electricity with Germany during the same period. These temperature data are reported by the European Climate Assessment & Dataset project[4]. Specifically, we collect maximum daily temperatures from Austria, Belgium, the Czech Republic, Denmark, France, the Netherlands, and Switzerland, which together account for 97.21% of all cross-border electricity flows[5] between 2009 and 2013.

We choose to work with maximum daily temperature because, as explained by (Klein Tank, 2007), it is measured over a 24-hour period, thereby reflecting weather conditions on the day when the day-ahead electricity contract is traded. Moreover, we compute the average of the maximum daily temperatures across the selected countries to obtain a representative measure of the temperature in the region affecting the German electricity market. Hereafter, we refer to this variable simply as temperature and it takes the role of TMP_t on our model.

Figure 1 depicts the evolution of daily temperature over the sample period. As expected, it exhibits a seasonal pattern that aligns with the European climate cycle: temperatures increase from January to August and subsequently decline.

Visual inspection of Figure 1 does not suggest that the temperature series is weakly stationary. To formally assess this, we conduct Augmented Dickey-Fuller (ADF) and Kwiatkowski-Phillips-Schmidt–Shin (KPSS) tests. The results, reported in Table 1, confirm that, at the 5% significance level, the temperature series is not weakly stationary.

Additionally, the series displays asymmetry between positive and negative temperature values. That is, temperatures tend to reach higher positive values than negative ones and remain mostly in the positive range. This indicates that extreme hot and cold conditions do not occur with the same frequency or intensity.

In contrast, the dynamics of German electricity spot prices shown in Figure 2 do not exhibit a seasonal pattern corresponding to weather cycles. This is

[4] See https://www.ecad.eu/.
[5] See https://www-genesis.destatis.de/datenbank/online/, using code 43312 – 0002.

likely due to the fact that energy consumption is largely driven by industrial and commercial users, whose demand remains relatively stable throughout the year, as well as by the actions of transmission operators who regulate power supply in the grid.

Nonetheless, from 2009 to 2011, electricity spot prices follow an upward trend, partially driven by the economic recovery following Global Financial Crisis (GFC), which, according to (Cludius et al., 2014), had caused a notable decline in prices during 2009. Another contributing factor may have been the rise in coal prices spurred by Chinese demand ((IEA, 2011)), since coal represents a significant portion of Germany's energy mix (see Figure 2 in (Würzburg et al., 2013)).

From 2011 to 2013, day-ahead electricity prices exhibit a downward trend, which may be attributed to the merit-order effect ((Cludius et al., 2014)), enhanced market integration ((Bublitz et al., 2017)), declining coal and natural gas prices ((IEA, 2013); (Liu et al., 2020)), or a structural break in the distribution of spot prices. These developments suggest that German electricity prices may not be weakly stationary.

We formally assess this by applying ADF and KPSS tests, the results of which are reported in Table 1. As expected, both tests reject the null hypothesis of stationarity at the 5% significance level for electricity prices.

Figure 2 also reveals sharp discontinuities, potentially indicating the occurrence of rare events. (Lucia and Schwartz, 2002) and (Escribano et al., 2011) suggest that such price spikes result from sudden surges in electricity demand, while (Grossi et al., 2017) attributes them to congestion in transmission lines.

Finally, it is worth noting that spot electricity prices occasionally dropped below zero, which occurs when energy supply exceeds demand. Empirical evidence from (Fanone et al., 2013), (Prokhorov and Dreisbach, 2022), and (Frondel et al., 2022) suggests that, in the German electricity market, subsidies for variable renewable energy (VRE) are a major factor contributing to this phenomenon[6].

[6](Fanone et al., 2013) also argue that negative electricity prices may arise from limited production flexibility among power generators.

Figure 1
This plot represents the evolution of daily temperature from 12/03/2009 to 10/03/2013. The temperature series corresponds to the average maximum daily temperature measured across Austria, Belgium, the Czech Republic, Denmark, France, Germany, the Netherlands, and Switzerland.

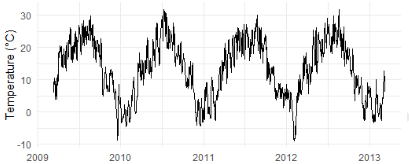

Figure 2
This plot represents the evolution of daily electricity spot prices in Germany from 12/03/2009 to 10/03/2013. The series corresponds to the daily spot market prices for the German electricity market over the full sample period.

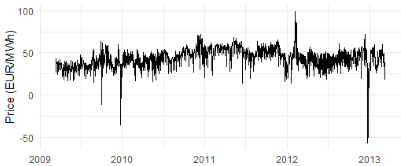

Table 1 reports the descriptive statistics for the variables under analysis. The first observation is that both time series exhibit high volatility over the sample period. However, when examining the coefficient of variation—which adjusts for the scale effect of the standard deviation—we find that temperature displays greater relative dispersion. This suggests that not all weather-related shocks are transmitted to wholesale electricity prices, providing evidence that system operators actively manage supply to buffer the impact of climatic fluctuations.

In the same period, electricity spot prices exhibit negative skewness, which may indicate that Germany experienced power oversupply during this timeframe. This outcome could be attributed to government subsidies for variable renewable energy (VRE) or to declining coal prices, as discussed above.

Comparing the kurtosis and range estimates of the two series reveals that the distribution of spot prices has heavier tails than that of temperature. A plausible explanation is that electricity prices are subject to additional types of shocks, such as transmission line congestion ((Grossi et al., 2017)).

Table 1
This table reports descriptive statistics of daily electricity spot prices (P_t) from Germany and daily temperature (Tmp_t) from 12/03/2009 to 10/03/2013. Temperature corresponds to the average maximum daily temperature in degrees Celsius across Austria, Belgium, the Czech Republic, Denmark, France, Germany, the Netherlands, and Switzerland. *, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.**

Stat	P_t	Tmp_t
Mean	43.911	13.386
Median	44.815	14.091
Std-Dev	11.293	8.874
Coeff. Var	0.257	0.663
Skew.	-1.196	-0.221
Kurt.	11.899	2.070
Min.	-56.870	-8.911
Max.	98.980	31.792
ADF Stat	-1.131	-1.551
KPSS Stat	1.860***	0.273***

Figure 3 displays the daily variation in temperature over the sample period. In contrast to Figure 1, no discernible seasonal pattern emerges, nor is there an apparent asymmetry between positive and negative values. This irregularity suggests that changes in weather conditions—and, by extension, fluctuations in power supply and demand—can occur unpredictably throughout the year and in either direction.

A visual inspection of the daily temperature changes shown in Figure 4 further suggests that their distribution may exhibit heavier tails than that of the temperature levels. The presence of sharp discontinuities supports the hypothesis of a fat-tailed distribution, potentially reflecting a higher incidence of extreme deviations.

Figure 4 illustrates the evolution of daily variations in spot electricity prices. The most immediate observation is the absence of any regular pattern—there is no clear deterministic trend or seasonal component. This behavior is consistent with the notion of weak-form market efficiency. Nonetheless, the presence of price spikes suggests that the market is influenced by rare or extreme events, in line with the empirical findings of (Lucia and Schwartz, 2002), (Knittel and Roberts, 2005), and (Escribano et al., 2011).

However, a visual inspection of Figure 4 does not reveal any clear seasonal clustering of these spikes. This contrasts with the results of (Knittel and Roberts, 2005) and (Escribano et al., 2011), who document a higher concentration of price spikes during specific times of the year. A possible explanation for this discrepancy is that Germany's access to cross-border electricity imports allows it to compensate for domestic supply shortages triggered by weather-induced demand surges.

Figure 3
This plot represents the evolution of daily temperature variation from 13/03/2009 to 10/03/2013. Temperature corresponds to the average maximum daily temperature in degrees Celsius across Austria, Belgium, the Czech Republic, Denmark, France, Germany, the Netherlands, and Switzerland.

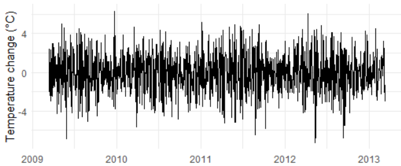

Figure 4
This plot represents the evolution of daily electricity spot price variation in Germany from 13/03/2009 to 10/03/2013. The series shows the day-to-day changes in the German electricity spot market over the sample period.

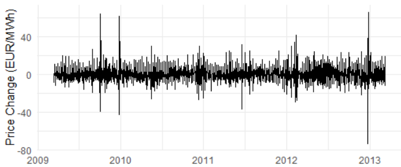

Table 2 presents descriptive statistics for the daily changes in the variables under study. The results indicate that temperature variations during the sample period exhibited high volatility. Moreover, both the ADF and KPSS tests suggest that the daily change in temperature is weakly stationary at the 5% significance level.

Additionally, the estimated kurtosis of daily temperature variation exceeds 3, implying a departure from normality and the presence of heavy tails in the distribution. This further suggests that the distribution of temperature changes have heavier tails than that of the temperature levels.

The statistics reported in Table 2 also reveal that first difference of German electricity prices share some characteristics with the spot price levels, such as elevated volatility and high kurtosis. However, in contrast to the spot price level, the variation in electricity prices exhibits positive skewness over the sample period. As noted by (Bessembinder and Lemmon, 2002) and (Knittel and Roberts, 2005), this asymmetry may be a consequence of convexity of cost function.

Moreover, ADF and KPSS test results indicate that at a 5% level of significance, day-ahead electricity price variations are weakly stationary. Consequently, we do not have any evidence that a change on power supply matrix caused a change on the unconditional mean, variance and autcorrelation structure of the daily variations but it does not exclude the possibility that a change on the mean-reversion speed happenned.

Table 2

Descriptive statistics (pre-Fukushima): This table reports descriptive statistics of daily electricity spot price variations (ΔP_t) from Germany and daily temperature changes (ΔTmp_t) from 13/03/2009 to 10/03/2013. Temperature corresponds to the average maximum daily temperature in degrees Celsius across Austria, Belgium, the Czech Republic, Denmark, France, Germany, the Netherlands, and Switzerland. *, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.**

Stat	ΔP_t	ΔTmp_t
Mean	-0.003	0.000
Median	-0.920	0.008
Std-Dev	9.222	1.990
Coeff. Var	-2701.895	8121.690
Skew.	0.583	-0.092
Kurt.	11.316	3.146
Min.	-73.470	-7.269
Max.	66.220	6.326
ADF Stat	-20.489***	-15.460***
KPSS Stat	0.006	0.032

Finally, on tables 3-6, we report descriptive statiscs before and after Fukushima accident. As we can see, statistical features of our data remained largely the same but it is noteworthy that kurtosis of spot price level increased after Fukushima accident, while its skewness became lower, which is compatible with higher participation of VREs on power supply.

Table 3
Descriptive statistics (pre-Fukushima): This table reports descriptive statistics of daily electricity spot prices (P_t) from Germany and daily temperature changes (Tmp_t) from 12/03/2009 to 10/03/2011. Temperature corresponds to the average maximum daily temperature in degrees Celsius across Austria, Belgium, the Czech Republic, Denmark, France, Germany, the Netherlands, and Switzerland. *, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.**

Stat	P_t	Tmp_t
Mean	41.714	12.977
Median	41.560	13.972
Std-Dev	10.452	9.054
Coeff. Var	0.251	0.698
Skew.	-0.704	-0.168
Kurt.	7.455	2.017
Min.	-35.570	-8.714
Max.	72.060	31.792
ADF Stat	-0.401	-1.099
KPSS Stat	4.864***	1.086***

Table 4
Descriptive statistics (post-Fukushima): This table reports descriptive statistics of daily electricity spot prices (P_t) from Germany and daily temperature (Tmp_t) from 11/03/2011 to 10/03/2013. Temperature corresponds to the average maximum daily temperature in degrees Celsius across Austria, Belgium, the Czech Republic, Denmark, France, Germany, the Netherlands, and Switzerland. *, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.**

Stat	P_t	Tmp_t
Mean	46.103	13.794
Median	47.740	14.532
Std-Dev	11.676	8.677
Coeff. Var.	0.253	0.629
Skew.	-1.771	-0.271
Kurt.	16.622	2.132
Min.	-56.870	-8.911
Max.	98.980	31.684
ADF Stat	-1.142	-1.159
KPSS Stat	2.411***	1.734***

Table 5
Descriptive statistics (post-Fukushima): This table reports descriptive statistics of daily electricity spot price variations (ΔP_t) from Germany and daily temperature changes (ΔTmp_t) from 13/03/2009 to 10/03/2011. Temperature corresponds to the average maximum daily temperature across Austria, Belgium, the Czech Republic, Denmark, France, Germany, the Netherlands, and Switzerland. *, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.**

Stat	ΔP_t	ΔTmp_t
Mean	0.016	0.004
Median	-0.855	-0.005
Std-Dev	8.708	1.945
Coeff. Var.	548.410	452.169
Skew.	1.031	-0.084
Kurt.	11.612	2.977
Min.	-42.780	-6.896
Max.	64.090	6.326
ADF Stat	-12.710***	-11.297***
KPSS Stat	0.010	0.058

Table 6
Descriptive statistics (post-Fukushima): This table reports descriptive statistics of daily electricity spot price variations (ΔP_t) from Germany and daily temperature changes (ΔTmp_t) from 13/03/2011 to 10/03/2013. Temperature corresponds to the average maximum daily temperature across Austria, Belgium, the Czech Republic, Denmark, France, Germany, the Netherlands, and Switzerland. *, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.**

Stat	ΔP_t	ΔTmp_t
Mean	-0.021	-0.006
Median	-0.995	0.033
Std-Dev	9.720	2.035
Coeff. Var.	-459.851	-351.429
Skew.	0.257	-0.095
Kurt.	10.890	3.274
Min.	-73.470	-7.269
Max.	66.220	6.086
ADF Stat	-7.572***	-14.399***
KPSS Stat	0.021	0.027

6. Results

In this section we report results of estimating parameters of model described by Equations (1) - (7), (10) and (11) using empirical strategy described on section 4. Tables 8 and 7 report estimates for parameters of deterministic component of temperature and German day-ahead electricity prices respectively. Their results are largely in line with unit root tests results showed on section 5, that is, at a 5% level of significance both variables not only presented a trend but also a seasonal component in the sampled period.

Table 7
Seasonal component parameter estimation results (full sample): This table reports the estimated parameters of equation 7 using daily temperature data from 12/03/2009 to 10/03/2013. Temperature corresponds to the average maximum daily temperature across Austria, Belgium, the Czech Republic, Denmark, France, Germany, the Netherlands, and Switzerland. *, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.**

Par	Estimate	Std. Error	Test Stat.
$\hat{c}^P$	12.250***	0.541	22.647
$\hat{f}^P$	0.001**	0.000	2.143
$\hat{g}^P$	-11.380***	0.139	-82.081
$\hat{h}^P$	0.212***	0.012	17.474
$\hat{\psi}_0^P$	-1.246***	0.137	-9.085
$\hat{\psi}_1^P$	0.055	0.110	0.502

Table 8
Deterministic component parameter estimation results (full sample): This table reports the estimated parameters of equation 7 using German day-ahead electricity prices from 12/03/2009 to 10/03/2013. *, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.**

Par	Estimate	Std. Error	Test Stat.
$\hat{c}^{TM}$	32.066***	1.604	19.987
$\hat{f}^{TM}$	0.005***	0.001	7.505
$\hat{g}^{TM}$	1.551***	0.413	3.755
$\hat{h}^{TM}$	-0.744***	0.262	-2.836
$\hat{\psi}_0^{TM}$	-1.499***	0.407	-3.685
$\hat{\psi}_1^{TM}$	0.048	0.271	0.176

We test the hypothesis that our model is well specified using test proposed by (Fernandes, 2006). The main idea behind it is that if the model is well specified, then the standardized difference between stationary density and its non-parametric specifications[7] should be small. Table 9 reports specification test results and it shows that at a 5% level of significance our model is well specified.

[7] Check section 4.1 of (Fernandes, 2006) for further details.

Table 9
This table reports the model specification test results proposed by (Fernandes, 2006). The bootstrap p-value is computed using 200 repetitions. *, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.**

Test Stat.	Asymptotic p-value	Bootstrap p-value
-1.808	0.071*	0.065*

Finally, on table 10 we report parameter estimates for the model described on sections 3 and 4. It shows that at 5% level of significance $\hat{\phi}_4$ is differente from 0 and positive, thus confirming our hypothesis that an increase of VREs on power supply reduces mean speed reversion, that is, supply adjust more slowly whenever climate deviate from its long term behavior.

Moreover, our estimates also provide evidence of a reduction in the premium for climate deviation. At the 5% significance level, $\hat{\phi}_2$ is statistically different from 0 and negative. In addition, the sum of $\hat{\phi}_0$ and $\hat{\phi}_2$ is negative, implying that the *average risk premium* associated with climate deviation becomes negative.

This result suggests that, after the Fukushima accident, economic agents had an increased incentive to offer day-ahead electricity contracts, that is, to hedge against price volatility. The shutdown of nuclear power plants reduced available power supply, making it more expensive to provide energy when temperatures moved further away from their average levels, whether hotter or colder.

Estimates of our model parameters indicate that we are able to capture key stylized features of spot electricity prices, particularly mean reversion and the leverage effect (see (Knittel and Roberts, 2005), (Escribano et al., 2011) and (Benth et al., 2012)). As shown in Table 10, $\hat{\gamma}$ is positive and statistically different from zero at the 5% significance level. This implies that, even in the absence of deviations in climate conditions from their usual patterns, the stochastic component of the process converges toward its equilibrium value. In contrast, the estimate of $\hat{\omega}$ may not be statistically different from zero at the 5% level, suggesting that the process instead converges to the deterministic component of spot electricity prices.

Turning to the leverage effect, both ξ_0 and ξ_1 are statistically different from zero at the 5% significance level. This indicates that the model successfully captures the inverse leverage effect documented by (Knittel and Roberts, 2005), which arises from the convexity of power plants' cost functions. The results also suggest that shocks exert a stronger influence when the level of uncertainty is high.

Evidence regarding the jump component is less clear-cut. Although the estimated jump intensity $\hat{\lambda}$ is significant at the 5% level, the estimate of jump volatility is not: the confidence intervals for $\hat{\sigma}_J$ with $B = 200$ include zero. A reasonable interpretation is that the relatively short sample limits the precision of the jump-parameter estimates, contributing to these inconclusive results.

Table 10
This table reports the parameter estimates for the model described in Sections 3 and 4. The standard errors and the 95% confidence intervals for the parameter estimates are computed using B artificial samples generated through the bootstrap algorithm described in (Fernandes, 2006).

Par	Estimate	Std. Error (B=99)	CI (B=99)	Std. Error (B=200)	CI (B=200)
$\hat{\omega}$	-0.695	0.499	[-1.282, 0.886]	0.403	[-0.786, 0.702]
$\hat{\gamma}$	24.705	3.677	[15.021, 27.696]	3.972	[12.280, 27.330]
$\hat{\phi}_0$	3.319	1.420	[2.725, 7.252]	1.244	[2.732, 6.972]
$\hat{\phi}_1$	0.974	1.600	[-4.055, 1.987]	1.511	[-3.391, 2.522]
$\hat{\phi}_2$	-5.959	0.844	[-7.282, -3.880]	0.954	[-7.319, -3.665]
$\hat{\phi}_3$	-23.303	2.114	[-24.779, -16.222]	2.270	[-24.975, -16.093]
$\hat{\phi}_4$	26.547	2.451	[24.049, 33.549]	2.444	[23.708, 32.221]
$\hat{\xi}_0$	2.686	0.665	[1.025, 3.510]	0.559	[1.015, 3.107]
$\hat{\xi}_1$	4.920	2.863	[1.367, 11.425]	2.570	[1.267, 10.204]
$\hat{\eta}$	-0.814	0.699	[-2.933, -0.074]	0.712	[-3.035, -0.152]
$\hat{\mu}_J$	0.422	1.097	[-3.480, 0.555]	1.092	[-3.784, 0.555]
$\hat{\lambda}$	12.264	3.567	[4.892, 20.057]	4.622	[5.838, 21.946]
$\hat{\sigma}_J$	6.517	3.369	[0.921, 13.657]	4.271	[-1.395, 16.005]

7. Policy implications

This section presents the expected shortfall of the stochastic component, computed using the parameter estimates from Section 6 and reported in Table

11. Expected shortfall is a risk measure that represents the expected gain or loss of a random variable once a specified threshold has been exceeded ((Bartels and Ziegelmann, 2016)). At the 95% confidence level, the expected shortfall increases across different levels of climate deviations, indicating a higher risk of extreme spot price events in day-ahead electricity markets.

This increase in risk is not attributable to higher volatility. Rather, it is driven by changes in the distributional tail behavior, as governed by the parameter $\beta(z_t)$. As discussed in Section 4 and originally shown by (Creedy and Martin, 1993), a lower mean reversion speed (i.e., a smaller β) results in fatter tails, increasing the probability of extreme realizations. Thus, when climate conditions diverge from historical patterns, the likelihood of experiencing particularly high spot prices grows.

These results point to a substantial shift in the risk profile of electricity contracts, associated with the German government's decisions to phase out nuclear power and accelerate the deployment of variable renewable energy (VRE) sources. By altering the structure of generation capacity without ensuring adequate backup or storage, these policy choices have amplified exposure to tail risk in the market.

Table 11
This table reports the expected shortfall of $1/(1-X_t)$ at the 95% confidence level, calculated using quantiles of the absolute level of climate deviation in our sample. The pre-Fukushima and post-Fukushima expected shortfall values (ES) were computed by setting respectively $D_t = 0$ and $D_t = 1$ in Equation 16.

Quantile	$\|CV_t\|$	Pre-Fukushima ES	Post-Fukushima ES
10%	0.035	0.096	2.275
25%	0.096	0.096	2.287
50%	0.207	0.096	2.311
75%	0.476	0.095	2.380
90%	1.323	0.091	2.894

These findings suggest that governments face a trade-off: accelerating pollution reductions by shutting down conventional power plants can also expose the energy sector to greater volatility. This heightened uncertainty may weaken firms' ability to invest and increase their risk of bankruptcy. To limit these effects, governments should carefully design and coordinate the decommissioning of fossil fuel-based generators.

In addition, expanding cross-border transmission infrastructure could mitigate localized risks through electricity imports. However, this strategy requires that countries be at asynchronous stages in their energy transitions, making regional coordination an essential component of successful policy design.

8. Concluding remarks

This study examines whether increased participation of VREs in power supply alters spot price responses to transitory shocks. We employ the same quasi-natural experiment framework used by (Grossi et al., 2017), leveraging the Fukushima accident as an exogenous shock. To conduct this analysis, we propose a stochastic differential equation (SDE) model that captures the common characteristics of day-ahead electricity prices, including seasonality, mean reversion, and volatility persistence (see (Lucia and Schwartz, 2002), (Knittel and Roberts, 2005) and (Escribano et al., 2011)).

Our empirical analysis provides evidence that following the Fukushima accident, temperature deviations from long-term patterns resulted in reduced mean reversion speed in electricity prices. This finding indicates that power supply systems became less responsive to demand fluctuations caused by temperature variations from normal patterns. Additionally, our results demonstrate a reduction in the risk premium associated with climate deviations, though it remained positive after the accident, suggesting that economic agents retained incentives to maintain long positions in spot markets.

Furthermore, our estimates indicate heightened risk in day-ahead electricity contracts, reflected in higher expected shortfall values across different levels of climate deviation. Because power companies have the ability to pass through their additional costs to end consumers, this increased risk ultimately raises the potential cost burden on households. These findings highlight the importance of careful policy design during the transition to renewable energy systems. Without adequate safeguards, consumers may face even higher prices during periods of elevated demand—either because VREs cannot fully meet consumption needs or because increased volatility raises retailers' costs, which are then passed through to consumers, as shown by (Mirza and Bergland, 2012) and (Correa-Giraldo et al., 2021).

Conflict of interest The authors declare no conflict of interest.

Artificial Intelligence This research utilized AI tools to assist in data analysis, manuscript drafting, and figure generation. All AI-generated content was critically reviewed and validated by the authors to ensure accuracy and alignment with the scientific integrity of the study.

Data availability All data used in this study are available from the corresponding author upon reasonable request.

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