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What comes down must go up: Why fluctuating renewable energy does not necessarily increase electricity spot price variance in Europe

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ABSTRACT

The increase in the share of wind and solar energy has led to higher variance in electricity production. We summarize why this does not necessarily result in a higher variance in electricity spot prices but—depending on the shape of the supply curve and variance of the renewable production—can lead to lower price variance. Extending the approach of Wozabal et al. (2016), panel model and single country regression results for seven out of nine analyzed European countries confirm a U-shaped relationship between the share of renewable electricity production and price variance. While the minimum price variance for most countries is found to be between a 10% and 40% renewable electricity production share, price variance is higher for lower and higher shares. The availability of export and import capacities, flexible power plants, and hydro (pump) storage is more important for a country's ability to balance price variance than the level and variance of the renewable infeed itself. Several countries (e.g., Denmark) show how these factors can foster successful integration of high shares of renewables. The finding that the price variance decreases before it rises again in many European countries calls for policies to secure investments in flexibility options, such as grid expansion, storage facilities, flexible power plants, and demand-side management, in the period of low price variance when market-based solutions might fail and eventually lead to situations where electricity system stability is at risk.

1. Introduction

There has been significant growth in renewable electricity generation throughout Europe over the past decade. In 2019, 12.1% of gross electricity consumption was covered by wind energy and 4.4% by solar energy in the European Union (EU),[1] doubling its wind and solar electricity generation between 2012 and 2019 (Eurostat, 2021). The majority of newly added electricity generating technologies, such as wind and solar, have fundamentally different production patterns than conventional power plants since the production of these newly added technologies is highly fluctuating and nondispatchable. This paper analyzes how this generation behavior in renewable energy influences spot price variance in Europe.

On the one hand, electricity price variance is seen as one of the main triggers for investments in flexibility options, such as storage facilities, flexible power plants, and demand-side management (DSM) (Varghese and Sioshansi, 2020). With the share of fluctuating, renewable electricity generation in the grid becoming larger, the establishment of flexibility options ensuring supply security continues to gain in importance and is a central determinant of the success of the transformation and decarbonization of the electricity sector. However, the competitiveness of these technologies depends mainly on the spread between low and high electricity prices, as their business model incentivizes buying electricity at times of low prices and selling at times of high prices. A high price variance in the current market setting is a major precondition for investments in electricity storage facilities and infrastructures, which increase the flexibility of the demand side of the market. On the other hand, electricity spot price variance is a measure of the system's ability to react to changes in demand and supply levels.

Understanding electricity price variance is important for at least two reasons. First, storage and other flexibility options are exactly those needed to balance fluctuating generation and to enable the integration of large shares of wind and solar photovoltaics (PV) (Panos et al., 2019). Increased shares of renewable electricity generation are expected to lead

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to higher price fluctuations that could then make investments in flexibility options more competitive. Nevertheless, as long as the relationship between the intermittent renewable electricity (IRE) infeed and price variance is unclear, the investment-driving mechanisms of these market-based incentives are rather questionable.

Second, extreme prices are avoided mainly for political reasons. Electricity consumers in the EU should be protected from excessive price fluctuations and extremely high prices, which could occur from time to time. Thus, policy-makers and investors alike are interested in understanding the mechanisms driving price variance in a time of increasing renewable electricity generation in European electricity markets.

This paper analyzes two major factors driving price variance: the shape of the supply function and the distribution of the residual load (i.e., the electricity demand reduced by intermittent renewable generation) in an electricity market. It adds new evidence to the controversy regarding how electricity spot price variance is influenced by different levels of wind and solar penetration in Europe. The question of primary interest is as follows: Does a higher share of renewable generation in the electricity grid necessarily lead to higher price variance in Europe?

Electricity spot prices are determined by demand and supply levels and are able to react quickly to changes on both sides. The increased share of IRE generation, such as wind and solar, has led to remarkable changes in European electricity spot markets. There has been a consensus in the literature that IRE infeed has a price-reducing effect on electricity spot prices, known as the merit order effect (see, e.g., Bublitz et al. (2017), Clò et al. (2015), Cludius et al. (2014), Di Cosmo and Malaguzzi Valeri (2012), Dillig et al. (2016), , Jónsson et al. (2010), Ketterer (2014), Martinez-Anido et al. (2016)Neubarth et al. (2006), Nicholson et al. (2010), Nicolosi (2010), Praktiknjo and Erdmann (2016), Welisch et al. (2016), and Zipp (2017)).

Since IRE generation reduces the spot price and shows fluctuating characteristics, one could conclude that spot price fluctuations increase in the same way with increasing IRE generation. However, while the literature is largely unanimous concerning the reducing effect of IRE generation on spot price levels, the question of spot price variance triggers different opinions. Some studies argue that price variance is dependent on the type and amount of IRE generation and can even reduce price variability (see, e.g., Tveten et al. (2013) and Wozabal et al. (2016)). Others see a higher share of renewable energy as definitely linked to increased price variance (see, e.g., Ketterer (2014), Klinge Jacobsen and Zvingilaite (2010), or Woo et al. (2011)). Most of the studies that have been conducted thus far focus on single countries or single technologies.

This paper primarily adds to the literature by explaining how the—at first glance—contradictory findings from the literature relate to each other. Second, building on the work of Wozabal et al. (2016), we assess the impact of IRE on electricity spot price variance in a conceptual and empirical model. Third, to the best of our knowledge, this is the first time such empirical analysis has been applied to nine European countries. We can therefore compare effects and patterns for a broad range of different countries, which allows us to show the possible impacts of the availability of different flexibility options, such as flexible power plants and export/import capacities. In fact, our analysis covers 78% of wind generation and 79% of solar generation in the current EU's electricity market (Eurostat, 2021).[2]

2. State of the art in explaining the influence of renewable electricity on price variance

While the literature is more or less univocal regarding the price dampening effect of renewables on the electricity market, i.e., the merit order effect, the findings regarding their influence on price variance are much more diverse.

Several papers support the hypothesis that increased renewable electricity generation increases price variance. Ketterer (2014) looks at the German market using a generalized autoregressive conditional heteroscedasticity (GARCH) model and finds that wind generation increases price variance, whereas load decreases it. Woo et al. (2011) analyze historical spot prices in Texas in a linear regression model. They conclude that increased wind energy generation leads to increased price variance in that geographic area. A higher fluctuation of prices as a result of increased renewable generation is presented by Klinge Jacobsen and Zvingilaite (2010) in their analysis of the market in Denmark. However, they also state that an increase in renewable generation lowers peak price frequency. Milstein and Tishler (2011) construct a two-stage game for electricity producers (with the possibility of building up IRE generation), finding that intermittent renewable generation can increase price volatility. In their study for Ghana, Adom et al. (2017) find that increased shares of IRE increase electricity price variance in the short and long run. The UK market in 2020 is modeled by Green and Vasilakos (2010), who evaluate monthly price distributions in a numerical supply function equilibrium model using wind generation as input (using real-world wind data and information on existing and planned wind farms) and including factors, such as the variation in the wind production, demand, and the competitiveness of the market. Based on their analysis, they expect increasing price volatility in the UK electricity market in the future. Martinez-Anido et al. (2016) model the power system in New England and find that electricity price volatility increases with wind penetration. Additionally, they identify a stronger effect of wind generation on short-term volatility than on longer term volatility (a 5-min instead of an hourly time resolution).

The papers mentioned above conclude that increased intermittent renewable electricity generation leads to increased price volatility. However, other papers do not support that hypothesis in general. Wozabal et al. (2016) show that increasing shares of IRE can increase or decrease electricity price variance. Their argument is supported by the analysis of the Austrian-German market zone for the years 2007–2013. Jónsson et al. (2010) show in their study for Denmark that an increased share of forecasted wind generation in the total load even lowers intraday price variance. They find that the probability of extremely high prices is reduced for high wind shares, which translates into a reduction in price volatility. Another example is the analysis of Tveten et al. (2013), who look at historical data and conclude that PV generation in Germany reduced price variance between 2009 and 2011. A possible explanation for this phenomenon is the fact that times of high PV production usually coincide with times of low power prices. PV plants and other renewable technologies with low short-term marginal costs push plants, such as natural gas plants, out of the merit order; therefore, peak prices are less frequent at those times. Möbius and Müsgens (2015) state that increasing shares of IRE can increase and decrease price variance. They analyze the effect of an increasing share of wind on price variance not in an empirical model but through a full-cost approach using an investment and dispatch model. They find that in a stylized electricity system with three generation technologies, at low shares of wind generation, additional wind decreases electricity price variance, whereas at higher shares, price variance increases with additional wind. In this general setting, they conclude that curtailment and ramping constraints of conventional power plants are the main reasons for this pattern. Rintamäki et al. (2017) show that wind energy has a lessening effect on daily price volatility in Denmark, while it increases daily price volatility in Germany and weekly price volatility in both countries.

Most of the studies that have been conducted thus far focus on single countries or single technologies. One reason why the analysis of price variance is more diverse than that dealing with price levels is that there are several definitions for price variance or variability. Possible definitions found in the literature are, e.g., the range of observable prices, the frequency of price spikes, volatility (standard deviation of logarithm of past returns or derived from options), or price variance (Wozabal et al., 2016). The choice of conceptual models, time horizon, and empirical

[2] Renewable shares in EU28's electricity generation for the year 2019.

estimation additionally contributes to divergences in the results.

Our conceptual model builds on the two basic factors (shape of the supply curve and variance of IRE) influencing significant price variance (Green and Vasilakos, 2010). Our study is more general than most of the literature discussed above. We apply our analysis to very different European countries and include two different sources of IRE (wind and solar).[3] The analysis of multiple countries enables us to identify in a statistically sound way the impact of factors that show little variation within a single country, e.g., the share of flexible generation capacities in the power mix and transmission lines allowing for balancing of the IRE infeed.

3. Methodology

3.1. Conceptual model

The studies presented above identify IRE production (wind and solar), the variance of IRE production, demand, prices of primary energy sources, temperature, the competitiveness of the market, weather fluctuations in wind or solar radiation, or daylight hours as drivers of electricity price variance. Green and Vasilakos (2010) argue that significant price variance is dependent on two major factors: 1) sufficient changes in renewable infeed, i.e., the distribution of residual load, and 2) the relationship between net demand for thermal generation and price, i.e., the supply function covering the residual load. Möbius and Müsgens (2015) state that the generation capacity mix that determines the merit order has an impact on electricity price variance, and they see the need for an analysis closer to an empirical-market setting. Wozabal et al. (2016) reformulate the findings of Green and Vasilakos (2010) and Möbius and Müsgens (2015) and identify two pivotal factors impacting electricity prices in Germany: the shape of the supply function and the distribution of the residual load in an electricity market. Fig. 1 shows their conceptual model, which is based on a standard static market model with a given inelastic demand for electricity. We use this model as a basis for our analysis of the influence of IRE generation on price variance in nine European countries.

The x-axis shows the residual load, defined as $X = Q - I$, where Q is the aggregate electricity demand (i.e., load) and I is IRE production (i.e., wind and solar). The intersection of the residual load X and the black, static supply curve S (aggregate marginal cost function without IRE) determines the electricity spot price. The concave-convex shape of the supply curve was found to approximate the real supply curve best (see Fanone et al. (2013), He et al. (2013), and Wozabal et al. (2016)). The low and even negative prices toward the left end of the supply curve are a consequence of the dispatch decision of conventional power plants, which accept very low prices rather than switch off their plants due to ramping constraints. The blue and red distributions located above the x-axis represent the stochastically varying residual loads, whereas the densities of the stochastic prices are located to the right of the y-axis. The distribution of the residual load creates the price distributions according to the slope of the static supply curve in a given time frame. In flat areas of the curve, fluctuating renewable infeed (i.e., alternating residual load levels) causes smaller price changes than in areas with a steeper slope.

In Fig. 1a and Fig. 1b, two time frames with different levels of IRE infeed are compared. In Fig. 1a, one time frame with high prices (red) is compared with a time frame with lower prices (blue). The distribution of the residual load stays the same for both cases. When the increasing IRE share shifts the residual load to the left, two effects can be observed. First, the price level decreases; i.e., the merit order effect of renewables occurs. Second, the intersection with the black static supply curve moves to a flatter area, which indicates that the same distribution of residual load creates a different, narrower price distribution and leads to a decreasing price variance in that case.

In Fig. 1b, the intersection shifts to the flat area of the supply curve as well, but its residual load distribution also changes (e.g., because the share of IRE has a higher variance than the non-IRE increases). We observe two opposing effects in addition to the decreasing price level here. On the one hand, the shift from a steep to a flat area of the supply curve causes a decrease in price variance, as already seen before. On the other hand, the change from a narrow to a broader residual load distribution broadens the price distribution and therefore increases the price variance. In sum, depending on the relative size of those two effects, an increased share of renewable production can either increase or decrease price variance in this conceptual model. Panel c in Fig. 1 shows the price variance as a function of the mean *residual load X* for a given distribution of the residual load. For low and high residual loads, high variance can be observed, whereas for a medium residual load, lower price variance occurs.

In this conceptual model, DSM, storage, and the export and import to or from other electricity markets change the residual load and, therefore, have an impact on the point where the supply curve intersects with the load curve (see again Fig. 1). At low prices, the residual load is increased (shifting to the right on the supply curve), and at high prices, the residual load is reduced (shifting to the left on the supply curve). This indicates that the flat, middle part of the supply curve determines the price more often, resulting in lower price variance in such a system than in a system without storage and export/import.

The formal description of the model can be found in the Appendix.

3.2. Empirical model

In the empirical model, we consider two renewable electricity technologies as IRE: wind and solar. All other renewable sources, such as hydropower or geothermal energy, are assigned to conventional sources. This is the prevalent choice in the literature cited above because of the high share of wind and solar in renewable generation and their characteristic intermittent, nondispatchable production patterns. Other renewable energy technologies (e.g., hydropower or biomass plants) are dispatchable to a greater extent and, therefore, do not rely on highly fluctuating resources.

Using regression models, we test whether the variance of the electricity price is caused by the variance of the IRE and how this is related to the shape of the supply function for several countries in Europe. The explained variable in the regression is price variance per day. As a measure of variance, we use the variance of past prices, which is the most straightforward definition typically used in economics. Volatility, instead, is a concept from finance, and price ranges or spikes require decisions about the appropriate thresholds to use, which can be difficult to choose in cross-country comparisons.

To test the influence of the shape of the supply function and the variance of electricity generation on price variance, we model shape and variance as additive terms. The shape is modeled with a linear and a squared term of the daily mean residual load to allow for a U-shaped relation between the residual load and price variance (see Fig. 1c).

Our Basic Model (based on Wozabal et al. (2016)) is specified as

$$Var(Price)_{it} = \alpha + R_{it}\,\beta' + K_{it}\,\gamma' + \theta_t + \rho_t + C_i\,\delta' + u_{it}, \tag{1}$$

where α is the intercept and R_{it} is an *Nx3* matrix containing the variables of interest for all N observations: residual load ("*Residual Load*"), residual load squared ("*Residual Load*^{2}"), and variance of residual load ("*Residual Load var*") for country i at Day t. The vector β' contains the respective coefficients. K_{it} is a matrix containing the control variables natural gas price and three months lagged natural gas price, θ_t is an *Nx6* matrix containing day-fixed effects, and ρ_t is an *Nx11* matrix containing month-fixed effects. C_i is an *Nx3* matrix containing variables constant over time: export/import capacities, the share of oil and gas power plants in installed capacities, and the share of hydro (pump) storage

[3] Earlier stages of this methodological approach were presented in Schöniger (2018).

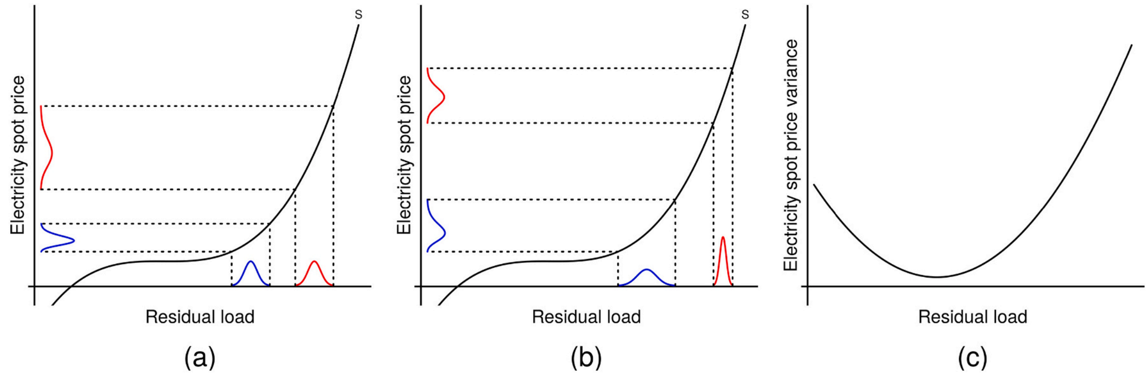

Fig. 1. The two pivotal influencing factors on electricity price variance—shape of the supply curve (illustrated in Panel (a)) and distribution of the residual load (illustrated in Panel (b)). Panel (c) shows the price variance for the supply curve in Panels (a) and (b) at a given distribution of residual load.
Source: Illustration based on Wozabal et al. (2016).

plants in installed capacities. Finally, u_{it} is an error term that consists of a time-constant part ν_i and an idiosyncratic part ϵ_{it} such that $u_{it} = \nu_i + \epsilon_{it}$.

The explanatory variable "*Residual Load var*" in the Basic Model in Eq. (1) is determined not only by the variance of IRE but also by any other shifts in the residual load. To identify the influence of IRE variance, an alternative specification is to divide residual load X into its two components: load Q and IRE production I. The squared term X results then in

$$X^2 = (Q - I)^2 = Q^2 - 2QI - I^2 \tag{2}$$

and for the variance

$$\mathrm{Var}(X) = \mathrm{Var}(Q - I) = \mathrm{Var}(Q) - 2\mathrm{Cov}(Q, I) + \mathrm{Var}(I) \tag{3}$$

This results in the Extended Model:

$$Var(Price)_{it} = \alpha + M_{it}\,\beta' + K_{it}\,\gamma' + \theta_t + \rho_t + C_i\,\delta' + u_{it}, \tag{4}$$

where M_{it} is an *Nx8* matrix containing the variables of interest: load ("*Load*"), load squared ("*Load*^{2}"), intermittent renewable electricity production ("*IRE*"), intermittent production squared ("*IRE*^{2}"), variance of load ("*Load var*"), variance of intermittent renewable electricity production ("*IRE var*"), covariance between intermittent renewable production and load ("*IRE Load cov*"), and an interaction term of load and intermittent renewable production ("*Load * IRE*").

Further splitting IRE into electricity generated from wind and solar results in the Wind & Solar Model

$$Var(Price)_{it} = \alpha + W_{it}\,\beta' + K_{it}\,\gamma' + \theta_t + \rho_t + C_i\,\delta' + u_{it} \tag{5}$$

where W_{it} is an *Nx12* matrix containing load ("*Load*"), load squared ("*Load*^{2}"), wind ("*Wind*"), wind squared ("*Wind*^{2}"), Solar ("*Solar*"), Solar ("*Solar*^{2}"), variance of load ("*Load var*"), variance of IRE ("*IRE var*"), covariance IRE and load ("*IRE Load cov*"), and the corresponding interaction terms ("*Load * wind*", "*Load * Solar*", "*Wind * Solar*").

The countries included in the analysis vary substantially in the total load. We, therefore, transform all explanatory variables to relative values (except for dummies): We first calculate the country-specific maximum average load (i.e., the maximum of the daily loads of a country). We then express load, residual load, IRE, and wind and solar generation as a percentage of this maximum load (i.e., a value of 15 for wind means that wind on that day was 15% of the maximum load of this country). Based on these relative values, we then derive squared terms, variances, and covariances. The explained variable "*Price var*" is left unchanged because it is the absolute value of the price variance, which is of concern for consumers or investors.

The exogeneity of our variables of interest (i.e., no correlation of explanatory variables with the error term (u_t)) is necessary for the estimated coefficients to be interpreted as causal effects. The variance of wind and solar (and therefore also the variance of IRE and the residual load) is determined by the weather, making it unlikely that there are unobserved time-varying confounders influencing IRE and the price variance of a country. For load and residual load to be exogenous, it must also be assumed that there are no unobserved confounding variables between the variance of price and residual load. Industries (or households) might consider price variance when deciding how much electricity to consume. Our weekday- and month-fixed effects control for reoccurring patterns of price variance. These time-fixed effects thus likely control for most unobserved time-varying confounders related to electricity demand.

To address the potential influence of (unobservable) time-constant variables that differ across countries, we analyze the three models (Basic, Extended, and Wind & Solar Model) in four different ways. The first approach (pooled model) is pooling data from all countries and running a linear regression with the relative variables (as defined in the paragraph above). In the second approach (fixed effects model), we also use relative variables from all countries but transform all variables by subtracting the country-specific mean; e.g., $\ddot{x}_{it} = x_{it} - N_i^{-1}\sum_{it}^{N_i} x_{it}$, where N_i is the number of observations of country i. In the third approach (first difference model), we transform all relative variables by subtracting the observation from the previous day; e.g., $\Delta x_{it} = x_{it} - x_{it-1}$, which means losing the first observation of each country. The fourth approach is analyzing all countries separately without transforming the variables (this can be done with relative or absolute variables leading to different coefficients but identical standard errors). See, e.g., Wooldridge (2010), for a detailed treatment of the four approaches.

The advantage of the pooled model (our first approach) lies in being able to include observed time-constant variables C_i explicitly. The disadvantage is that unobserved time-constant variables (ν_i) cannot be included. This will result in biased estimated coefficients if the unobserved variables are correlated with explanatory variables. The fixed effects (second approach) and the first difference (third approach) models solve this problem by allowing us to control for unobserved time-constant effects. Due to the transformations of variables, all time-constant variables are swept out (the intercept (α), observed (C_i), and unobserved (ν_i) time-constant variables). The identification of the causal effect of linear terms thus hinges on variation over time only.[4] The interpretation of the estimated coefficients of the fixed effects and the first difference model is still the effect of the untransformed relative variable on the price variance (i.e., as in Eqs. (1), (4), and (5)) even

[4] For squared terms, the identification is slightly more complex, since cross-section variation still matters to the extent that when squaring the variables before demeaning or differencing them, the original level still matters (and not just differences over time); see McIntosh and Schlenker (2006) for details.

though the estimation has been run with transformed relative variables. The $R^{2,}$ however, is typically much lower because it is reported in terms of the transformed relative variables.

A fixed effects estimator can be subject to spurious regression if the variables have unit roots (i.e., if they follow a random walk). We, therefore, check our variables for unit roots using the Maddala and Wu panel unit root test procedure (Croissant and Millo, 2018; Maddala and Wu, 1999). We find that none of our variables except the (lagged) gas price have a unit root (see Appendix Table A.10). Given that we do not face the problem of spurious regression, we report fixed effects and first difference models.[5] To address serial correlation, we use White standard errors clustered by countries for the fixed effects estimator (Croissant and Millo, 2018; White, 1980) and Newey West standard errors for the first difference estimator (Croissant and Millo, 2018; Newey and West, 1987). We do likewise for all joint significance tests.

While time-constant country-specific variables cannot be included in the fixed effects and first difference models, their interaction terms can. We, therefore, estimate an additional set of models where we interact the variables of interest (R_{it}, M_{it}, and W_{it}) with the time-constant observable variables C_i.

The appeal of fixed effects and first difference models is the ability to control for unobserved time-constant heterogeneity. However, pooling countries means that the estimated coefficients are weighted averages across all countries. For example, the estimated effect of a 1% point increase in load is the weighted average across all countries (i.e., a weighted average of the effect of the shape of different merit order curves on price variance). While this is interesting in itself, a complementary approach is analyzing countries separately. We run all models (Basic, Extended, and Wind & Solar Model) for all countries.

In the fixed effects and first difference models, we can control for confounders constant over the observational period, but in the single country models, we cannot. Most prominently, flexibility options, such as DSM, storage facilities, and transmission capacity to neighboring electricity markets, are mostly constant for the time period we observe. The availability of those flexibility options is expected to result in a lower influence of the shape of the supply curve on the price variance. This will contribute to differences between the estimated coefficients of the countries analyzed. Standard errors of the single country models (and joint significance tests) are heteroscedasticity and autocorrelation consistent (HAC) since Durbin-Watson tests suggest significant autocorrelation of residuals. The modeling is conducted in MATLAB R2019b (MathWorks, 2019) and R 3.6.3 (R Core Team, 2020).

3.3. Data

The analysis is based on data for 2015–2019 and covers nine countries[6] with the highest share of wind and solar generation in the EU during the period considered (Eurostat, 2021). These countries had a share of wind and solar generation in their overall electricity generation of at least 12% in the considered period 2015–2019.

Most variables (load, residual load, IRE, etc.) are originally available at an hourly resolution and enter the models at a daily resolution. This resolution is appropriate for two reasons. First, it is long enough that varying the IRE infeed can have an effect on the spot price. If we only looked at an hourly time window, certain factors, e.g., changes in the weather conditions and consequently changes in the IRE infeed, could not be appropriately captured. Second, a lower time resolution would lead to a loss of information since IRE production would become too aggregated.

The explained variable in the regressions is the daily spot price variance. Therefore, the day-ahead spot prices [Euro/MWh] are first standardized to an hourly resolution for all countries, and then, the variance per day is computed from these 24 observations. The daily values of the explanatory variables are derived from the day-ahead load [GW] and the day-ahead generation forecast for wind and solar [GW] (all from (ENTSO-E, 2021)). The natural gas price considered is the Dutch TTF day-ahead spot price [Euro/MWh] and was standardized to have a zero mean and a standard deviation of 1 for data availability reasons (EEX, 2022; Intercontinental Exchange, 2022; Trading Hub Europe, 2022). Export and import capacities are modeled values from the national transmission operators for 2020 (ENTSO-E, 2019). However, since transmission capacity build-up is an inert process and this share is relatively constant for all countries, the value for 2020 is seen as an acceptable proxy for the considered period of 2015–2019 as well. Electricity generation capacities are annual values and derived from ENTSO-E (2021).

There are some particularities regarding the price data for several countries: German data were aggregated with data from Austria and Luxembourg (referred to as “Austria/Germany” in the following) since these countries formed one market zone until September 30, 2018. In the regression model for Germany, we added a market split dummy to account for the structural change and used the data for Germany-Luxembourg after the split since it is the larger part of the market zone and accounts for the majority of wind and solar generation. Where necessary, national currencies were transformed into euros using historical exchange rates (ÖNB, 2021). Exchange rates are available only for working days; therefore, the figures used for the days in between were interpolated between the two framing days available. Load and price data for some countries are divided into different bidding zones. For Denmark, Sweden, and Italy, the respective weighted average values were considered. Some installed generation capacities were missing for Austria-Germany in 2015, so these technologies have been assumed to have the same installed capacities as in 2016. For the UK, only the bidding zone “GB” was considered because of insufficient data for the Irish part of the zone.

3.4. Descriptive statistics

Table 1 presents the descriptive statistics for all countries analyzed for 2015–2019. The values are means calculated from the hourly primary data; the price is the day-ahead price; price variance is the daily price variance.

Mean electricity day-ahead prices range between 33.2 Euro/MWh in Denmark and more than 54 Euro/MWh in Greece and GB. The German-Austrian market zone is the largest zone, with an average hourly load of 60.9 GW. The highest relative share of IRE is found in Denmark, with an average hourly share of 45% of the load produced by IRE. In terms of absolute numbers, Austria/Germany produced the highest amount of IRE, with an average IRE generation of 15.9 GW in 2015–2019. The daily price variance is exceptionally high in GB (363.01 $(\text{Euro/MWh})^2$). This is on account of a few days in the second half of 2016, where five days show a daily price variance of more than 20,000 $(\text{Euro/MWh})^2$; without these five days, the mean price variance would be 216.08 $(\text{Euro/MWh})^2$. The panel model presented in the next section is based on

[5] The choice of fixed effects vs. first difference hinges on the assumption about the idiosyncratic errors ϵ_{it}. The fixed effects estimator is more efficient if the ϵ_{it} are serially uncorrelated, while the first difference estimator is more efficient if the ϵ_{it} follow a random walk. Applying a test proposed by Wooldridge (Croissant and Millo, 2018; Wooldridge, 2010), we reject the hypothesis of no serial correlation of the differenced errors for the first difference model and reject the hypothesis of no serial correlation in the original errors for the fixed effects model. We find these results for all three model variants estimated (Basic, Extended, and Wind & Solar Model). Since in this case, these tests provide no guidance, we report results for fixed effects and first difference estimators. The results of the test are available from the authors and as part of the code and data supplementary material.

[6] Originally, the ten countries with the highest IRE share were chosen but Ireland could not be analyzed because of insufficient electricity price data (ENTSO-E, 2021). Luxembourg and Austria were not among these countries with the highest share of IRE but are included in the analysis as part of the common market zone together with Germany.

Table 1
Descriptive statistics for all countries examined for 2015–2019. Means of hourly electricity spot price, electricity load, and IRE generation (separated into wind onshore, wind offshore, and solar). The calculated means and IRE share in the load are based on hourly values.

Mean values	Price	Daily price variance	Load	IRE	IRE share	Wind onshore	Wind offshore	Solar
Unit	Euro/MWh	$(\text{Euro/MWh})^2$	GW	GW		GW	GW	GW
Austria/Germany	35.44	97.90	60.9	15.9	26.14%	9.7	1.8	4.4
Denmark	33.20	64.29	3.8	1.7	44.68%	1.0	0.5	0.1
GB	54.01	363.01	33.9	6.4	18.87%	3.1	2.2	1.1
Greece	54.73	81.15	5.9	0.9	15.91%	0.6	–	0.4
Italy	52.34	98.50	33.4	3.8	11.45%	1.7	–	2.1
Portugal	49.54	43.70	5.7	1.5	25.88%	1.4	–	0.1
Romania	42.89	187.33	6.8	1.0	14.18%	0.8	–	0.1
Spain	49.43	47.86	28.7	7.1	24.65%	5.6	–	1.5
Sweden	33.21	42.02	15.7	1.9	12.02%	1.9	–	–

Source: ENTSO-E (2021).

Table 2
Share of flexible power plants in installed capacities for all countries examined, means for 2015–2019. Export/import capacities for 2020 compared to the maximal load observed in 2015–2019. When different, the mean of export and import capacity was taken.

	Hydro (pump) storage capacities	Oil & gas	Export/import capacities
	% of all installed generation capacities		% of max. load in 2015–2019
Austria/Germany	6.7%	17.7%	11.7%
Denmark	–	23.2%	138.9%
GB	3.1%	32.8%	10.4%
Greece	18.0%	30.6%	34.5%
Italy	11.7%	42.8%	18.9%
Portugal	19.6%	24.8%	54.0%
Romania	17.0%	20.6%	25.7%
Spain	23.3%	29.7%	18.6%
Sweden	41.3%	–	42.7%

Source: Generation capacities and load (ENTSO-E, 2021); Ex−/import capacities (ENTSO-E, 2019).

all countries other than GB, which we excluded due to the exceptionally high price variance in 2016.[7] Table 2 shows the share of flexible production capacities—as an approximation, oil and gas plants were considered here[8]—hydro (pump) storage capacities, and transmission capabilities to other countries. All these variables differ considerably between countries.

To render the variables comparable, the countries are additionally analyzed in relative terms. Table 3 contains the statistics of the relative variables of the whole panel without GB.

4. Results and discussion

4.1. Results of the panel model

Table 4 shows the estimated coefficients and hypothesis tests of the fixed effects model for the Basic, Extended, and Wind & Solar Models. The explanatory variables are measured in relative terms (between 0 and 100, except for the gas price). The estimates are based on all 14,266 observations of eight countries (GB is excluded due to the exceptionally high price variance, see above). As is typical for fixed effects models with cross-section observations, the R^2 is rather small since

Table 3
Summary statistics for relative variables (i.e., in percentag of maximum load), excluding Great Britain.

	Mean	1st Qu.	Median	3rd Qu.	NAs
Residual Load	58.41	50.63	60.04	68.58	302
Residual Load^2	3631.09	2563.83	3605.14	4703.54	302
Residual Load var	118.61	51.68	82.40	141.50	331
Load	75.26	68.03	76.59	82.54	30
Load^2	5777.06	4627.58	5866.55	6813.00	30
IRE	16.82	8.19	12.71	20.77	277
IRE^2	458.99	67.12	161.65	431.45	277
Wind	13.75	4.89	9.36	17.28	237
Wind^2	374.17	23.93	87.54	298.71	237
Solar	3.03	0.94	2.17	4.95	204
Solar^2	16.31	0.89	4.69	24.49	204
Load var	117.33	57.77	103.31	160.72	46
IRE var	48.71	9.46	26.72	60.53	291
IRE Load cov	23.46	−0.17	18.39	45.25	331

it measures the share of explained variance over total variance after demeaning. The results for the pooled models and first difference models are comparable in conclusions and are shown in the Appendix (see Table A.1 - Table A.3).

4.1.1. Basic Model

The results of the Basic Model, which only includes the terms of the residual load, are displayed in the first column of Table 4. All coefficients are statistically significant (p value <0.05).

The results show that the residual load has a convex quadratic influence on the price variance, as anticipated in the conceptual model (see Fig. 1), since the coefficients of *Residual Load* (−5.19) and *Residual Load*^{2} (0.05) are statistically significant (jointly and individually). According to Table 3, the third quartile of the residual load is 68.58% residual load. At this point, a decrease of 10%-points in residual load causes the price variance to decrease by 17.38 $(\text{Euro/MWh})^2$. At the median, a decrease of 10%-points in the residual load reduces the price variance by 8.84 $(\text{Euro/MWh})^2$, and at the first quartile, it increases the price variance by 0.57 $(\text{Euro/MWh})^2$. This is as expected due to the U-shaped relationship between price variance and the residual load. The minimum price variance is estimated to be reached if the residual load is 51.2% of the load (or when the IRE is 48.8% of the load). The variance of the residual load increases the price variance as expected and has a marginal effect of 0.19. At the mean of the variance of the residual load ($118.61\%^2$), the effect on the price variance is thus 22.54 $(\text{Euro/MWh})^2$. At the third quartile ($141.50\%^2$), the effect is 26.89 $(\text{Euro/MWh})^2$. Thus, at Q3 of the residual load, the shape-induced effect from a 10% reduction in the residual load (17.38 $(\text{Euro/MWh})^2$) partly compensates for the effect from the residual load variance (26.89 $(\text{Euro/MWh})^2$). At Q1 of the residual load, this is not the case.

[7] Estimated coefficients and standard errors are similar when GB is included, but the R^2 is very small. The results are available from the authors and can be generated easily from the code in the supplementary material.

[8] Other power plants are also able to provide dispatchable power; however, oil & gas technology was taken because of their flexible generation characteristics and high share in historic power plant fleets. Nevertheless, other decarbonized flexible power plants will be needed in the future.

Table 4
Regression results for the fixed effects panel model for the Basic, Extended, and Wind & Solar Models.

	Model					
	Basic		Extended		Wind & Solar	
Residual Load	−5.19	(0.000)				
Residual Load^2	0.05	(0.000)				
Residual Load var.	0.19	(0.000)				
Load			−20.47	(0.000)	−18.06	(0.000)
Load^2			0.17	(0.000)	0.16	(0.000)
IRE			13.47	(0.000)		
IRE^2			0.02	(0.000)		
Wind					9.69	(0.000)
Wind^2					0.03	(0.000)
Solar					32.55	(0.000)
Solar^2					0.75	(0.007)
Load var.			0.08	(0.235)	0.12	(0.050)
IRE var.			0.11	(0.000)	0.09	(0.000)
IRE Load cov			−0.43	(0.000)	−0.41	(0.000)
Load*IRE			−0.18	(0.000)		
Load*Wind					−0.15	(0.000)
Load*Solar					−0.64	(0.000)
Wind*Solar					0.65	(0.000)
Gas Price	15.82	(0.000)	14.63	(0.000)	14.67	(0.000)
Lagged Gas Price	−8.02	(0.017)	−6.96	(0.034)	−6.76	(0.036)
Observations	14,266		14,266		14,266	
R^2	0.088		0.102		0.113	
Joint Significances:						
Residual Load and Residual Load^2	47.03	(0.000)				
Load, Load^2			45.85	(0.000)	37.36	(0.000)
IRE, IRE^2			12.71	(0.000)		
Load, Load^2, IRE, IRE^2			78.53	(0.000)		
Load var., IRE var., IRE Load cov, Load*IRE			209.63	(0.000)		
Wind, Wind^2, Load*Wind, Wind*Solar					91.52	(0.000)
Solar, Solar^2, Load*Solar, Wind*Solar					65.09	(0.000)
Load, Load^2, Wind, Wind^2, Solar, Solar^2, Load*Wind, Load*Solar, IRE Load cov					292.42	(0.000)
Load var., IRE var.					31.66	(0.000)

Note: p values in parenthesis based on clustered standard errors. Joint significances report the F statistics with p values in parenthesis. Dummies for weekdays and months are included in all models but not shown.

4.1.2. *Extended Model*

In the Extended Model, the influence of the residual load is divided into its two components, namely, *Load* and *IRE* production. The results confirm the hypothesis from the conceptual model that the shape of the residual load, i.e., the distributions of the load and IRE production, influence price variance: *Load, Load^2, IRE, IRE^2* and *Load*IRE* are all individually statistically significant. Fig. 2 illustrates the effects of load and IRE on the price variance (shifted to start at zero) by setting all variables except load, IRE, and the interaction term to their means (or zero for the time dummies). The price variance is highest at low levels of load combined with high levels of IRE (low prices). Similarly, the price variance is relatively high at high levels of load combined with low levels of IRE (high prices). These peaks are driven by the negative interaction term of load and IRE. Consequently, we find a U-shaped effect of load only at a low level of IRE, and we find a U-shaped effect of IRE only at high levels of load. Thus, the interaction term is key to understanding whether a U-shape is found.

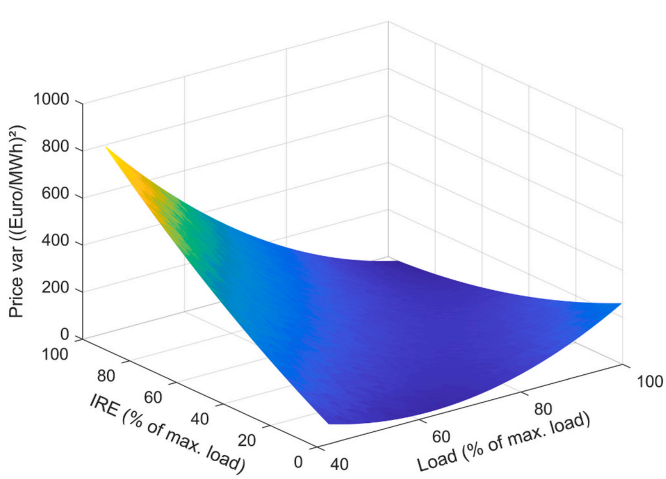

Fig. 2. Impact of load and IRE on electricity price variance based on fixed effects estimates. Load and IRE are depicted in % of maximal load.

The effect of the variance of the load and the variance of IRE are jointly statistically significant, while the marginal effect of IRE (0.11) is also individually significant. The covariance (−0.43) of IRE and load, in contrast, has a negative effect on price variance since a higher load increases and a higher IRE infeed decreases the price level. If load and IRE vary jointly within a day, this reduces price variance. This is similar to the negative interaction term (−0.18), which measures the effect between days.

4.1.3. *Wind & Solar Model*

The Wind & Solar Model was introduced to analyze the impact of wind and solar generation on price variance separately. From Table 4 (Column 3), it can be seen that the estimated coefficients are very similar to those from the Extended Model (Column 2) for variables other than the wind-related and solar-related variables. We, therefore, discuss a variant of the Wind & Solar Model that includes interactions with shares of flexible electricity generation and export/import capacities (see Appendix). Using the figures shown below, the model in the Appendix allows for the analysis of the influence of flexible power plants and export/import on price variance. The shapes of wind and solar are statistically significant, as are the interaction terms of the flexible generation and export/import capacities (see Table A.6 in the Appendix). To interpret the sign and magnitude of the coefficients, the results are depicted in

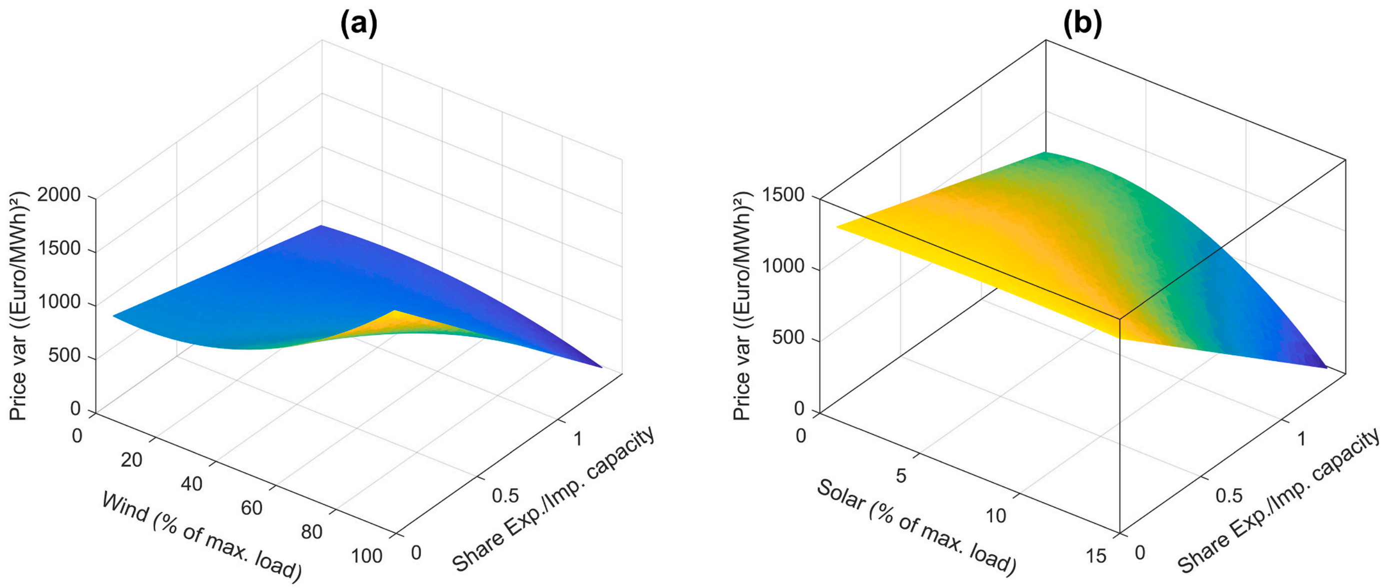

Fig. 3. Impact of wind (Panel (a)) and solar generation (Panel (b)) and export/import capacity on electricity price variance based on fixed effects estimates. Wind and solar generation are depicted in % of maximal load. Transmission capacity is depicted as share of maximal load.

Fig. 3.

We observe a U-shaped impact of wind infeed on the electricity price variance, which is not observable for solar generation. However, much higher shares of wind infeed (up to 93.9%) than solar infeed (up to 14.1%) are present in the analyzed data sample covering the years 2015–2019, making the effect of solar much harder to elicit. The share of transmission capacities allowing the countries to balance the IRE infeed through exports/imports has a much higher impact on the price variance than the IRE infeed itself: The better a country is interconnected to its neighboring markets, the lower the effect of IRE infeed on the price variance. The same effect can be observed for the share of flexible power plants in the system (see Fig. 4): The higher the capabilities of flexible power plants (Panel (a)) and hydro (pump) storage (Panel (b)) are, the less distinct the impact of the IRE infeed on price variance. The higher the share of wind in the system is, the higher—the more important—the impact of export/import capacity (see Fig. 3, Panel (a)) and flexible power plants (see Fig. 4, Panel (a)), as shown by the steeper slope of the dependency. The effect of the availability of those flexibility options has a greater impact than the level and variance of IRE generation for the observed wind and solar shares. Figures for all possible combinations of flexibility options and technology types can be found in the Appendix (see Fig. A.1).

These results show that flexible generation capacity and interconnections with neighboring markets are able to balance IRE infeed very well so that its impact on price variance is kept at a low level.

4.2. Country-specific results

The analysis of multiple countries in Europe allows us to derive country-specific findings subject to different electricity systems. All explanatory variables are expressed in relative terms (i.e., as % of maximum load) to render them comparable between countries (results for the absolute variables lead to the same conclusions and can be found in the Appendix; see Table A.7 - Table A.9).

4.2.1. Basic Model

Table 5 shows the results of the Basic Model for individual countries.

The results show that for the majority of countries analyzed—Austria/Germany, Denmark, GB, Greece, Italy, Romania, and Sweden—the hypothesis of a convex quadratic influence of the residual load on the price variance can be supported (see negative coefficient of *Residual Load*, positive coefficient of *Residual Load*^{2}, and joint significance); i.e., the price variance is higher for low and high average residual loads. The coefficients for Portugal and Spain are (jointly) significant, but the signs are different, resulting in an inverse U-shape or a flat line (see Fig. 5), suggesting that there is limited influence of the shape in these two countries. Furthermore, the variance of the residual load—which is significant for eight out of nine countries in the Basic Model—can be said to increase price variance significantly in Europe. Hence, both the shift to steep parts of the supply curve due to low or high residual load and the distribution of the residual load itself have a significant influence on the price variance in the majority of the countries under study.

Based on the regression results of the Basic Model, we can depict the partial effect of the residual load on price variance by calculating the amount of residual load that leads to the minimal price variance in each country (see Fig. 5). The variance of the residual load is fixed at its daily mean for the years 2015–2019 for each country. This means that on the deployment path toward more IRE in the electricity system, the countries move from the right to the left. For Austria/Germany, Greece, Italy, Romania, and Sweden, we find that the minimal price variance is reached when IRE covers approximately 10–40% of the average load level for 2015–2019. Assuming that IRE production will increase, this result implies that the point of minimal price variance for these countries was reached in the later years of the period considered or lies in the future. For Denmark, we can see a very weak dependence of the price variance on the residual load level. As explained above, Portugal and Spain show a different pattern.[9]

The variance of the residual load increases the electricity spot price variance in all countries. However, there are differences in the extent to which a country is impacted by a fluctuating residual load. Fig. 6 shows the coefficient of the variance of the residual load from the country regression models (see Table 5) with respect to the dependence of the residual load variance on their share of flexible power plants and export/import capacities in the system (see Table 2).

The Iberian and the Nordic countries show the lowest impact of fluctuating residual load on electricity price variance. It becomes obvious that with increasing shares of flexible power plants or import/export capacities, the impact of a fluctuating residual load on the price

[9] The influence of Denmark, Portugal and Spain likely causes the minimum of the panel model (48.8%) to be comparably high.

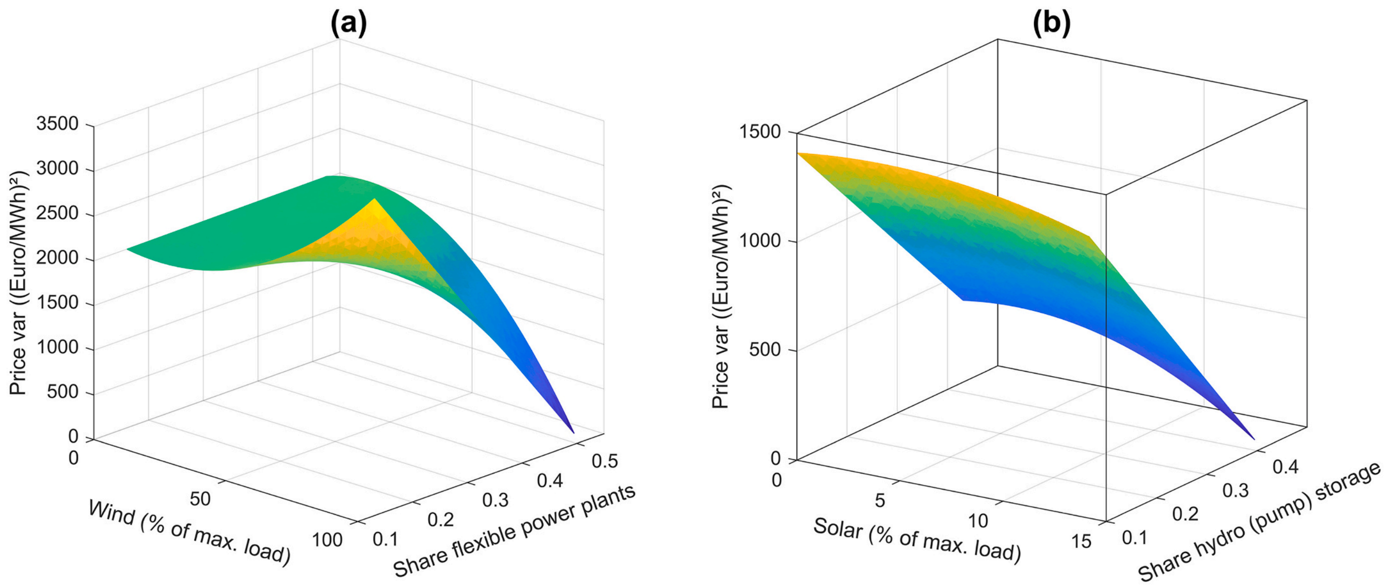

Fig. 4. Impact of wind generation and flexible power plants (oil and gas, Panel (a)), and solar generation and hydro (pump) storage (Panel (b)) on electricity price variance based on fixed effects estimates. Wind and solar generation are depicted in % of maximal load. Flexible generation and hydro (pump) storage capacities are depicted as share of overall generation capacity.

variance decreases.

Spain and Portugal present a different picture than the other countries, with a very flat dependence of the price variance on IRE generation (see Fig. 5). One reason could be that Portugal and Spain have the highest share of hydro (pump) storage capacity after Sweden (see Table 2). Additionally, Spain has a high share of (flexible) gas power plants. Since augmenting their interconnection capacities in 2014, these two national electricity markets remain closely coupled, which offers the advantages of spatial arbitrage without trading barriers, resulting in improved geographical allocation of generation. Pereira da Silva and Horta (2019) find that the sensitivity of price volatility to wind generation decreased sharply after market coupling. Pereira et al. (2017) also found that the high share of hydro power balancing options helps Spain to reduce electricity price volatility. These flexibility options may partly explain the flat curve for these two countries.

Denmark shows a very low impact of a fluctuating residual load on price variance (see Fig. 7) but reflects almost no share of flexible power plants (see Fig. 6). However, the highest share of export/impact capacity, i.e., balancing opportunities with neighboring countries—and other specifics of the power system that are not covered by our regression—lead to a low impact of a fluctuating residual load. Denmark has the highest share of IRE of all the countries examined (see Table 1) and may have gained experience integrating large amounts of IRE production into the electricity system so that the build-up of IRE capacities no longer has an impact on price variance.

Since the Nordic countries were among the first ones to liberalize their markets, compared with other countries, they may have more mature liberalized markets and may thus be better able to handle the factors influencing price variance. Additionally, flexibility due to large hydroreservoirs is exceptionally high in Sweden. In 2015–2019, 41% of the installed generation capacity was hydrostorage plants (ENTSO-E, 2021), which offer a greatly enhanced ability to balance fluctuations from wind generation. The results indicate that for its current level of IRE production, Sweden has well-suited capabilities for achieving low levels of price variance. However, with increasing shares, this may change (see the steep increase of price variance in Fig. 5). One aspect that was not explicitly analyzed in our regression is the demand side response. The Nordic countries show high shares of electric heating and energy-intensive industries, which result in a particularly high flexible load per inhabitant (Bergaentzlé et al., 2020; Kirkerud et al., 2021), giving those countries additional options to balance electricity demand more effectively.

Unobserved variables may account for why the price variance of GB is not well explained (see low R^2 in Table 5). Specifically, there are a few exceptionally high daily price variance values (up to 100,000 (Euro/MWh)^2) in the second half of 2016 (see Section 3.4) that add substantial noise to the data. On these days, intraday price hikes were caused by fundamental changes (e.g., foreign exchange movements and fuel commodity price increases) after the referendum vote to leave the EU and a general tightness of capacity margins (severed by a shutdown of French nuclear reactors and damage to international transmission lines) during that time (Ward and Unwin, 2017). Gissey et al. (2018) found that following these events, gas was subject to more price setting in GB than in other major European electricity markets (2–2.5 times greater than in Spain and Italy and almost 5 times greater than in Germany). The price hikes in the second half of 2016 are thus most likely unrelated to IRE production and the load and should not bias our estimates. Additional reasons for the differing results in GB may be that it was one of the first countries to introduce Contracts for Difference in their national renewable support strategy (UK Public General Acts, 2013), as well as being a capacity market and among the assessed countries having by far the largest share of offshore wind in their generation mix (see Table 1), which is less intermittent than onshore wind (Stehly and Beiter, 2019).

4.2.2. Extended Model

In the Extended Model, the effects of the 1) shape of the supply curve and 2) the variance of the residual load are divided into several components.

The shape of the supply curve (measured by the joint significance of *Load, Load^2, IRE, IRE^2, IRE Load cov, and Load*IRE*) has a significant impact on the price variance in seven out of nine countries in the Extended Model (see Table 6). Similarly to the results from the Basic Model, the variance of the residual load (measured by the joint significance of *Load var and IRE var*) is significant in all countries except GB. The covariance of IRE and load (*IRE Load cov*) is significant for eight out of nine countries. All countries show a significantly negative influence of this covariance on price variance (GB is significant only at the 10% level). The interaction term *Load * IRE* shows a significantly negative impact on price variance for five out of nine countries. The Extended Model shows the important role of the interaction between load and IRE:

Table 5
Regression results for individual countries in the Basic Model.

	Basic Model																	
	Austria/Germany		Denmark		GB		Greece		Italy		Portugal		Romania		Spain		Sweden	
Intercept	929.12	(0.000)	87.29	(0.000)	42.27	(0.982)	930.14	(0.007)	565.57	(0.000)	74.82	(0.000)	393.38	(0.170)	106.19	(0.000)	1036.15	(0.015)
Residual Load	−30.19	(0.000)	−3.22	(0.000)	−39.09	(0.504)	−31.81	(0.004)	−18.60	(0.000)	1.01	(0.055)	−10.22	(0.214)	−0.57	(0.574)	−41.60	(0.011)
Residual Load^2	0.25	(0.000)	0.05	(0.000)	0.59	(0.190)	0.27	(0.004)	0.15	(0.000)	−0.01	(0.002)	0.11	(0.119)	−0.01	(0.152)	0.39	(0.010)
Residual Load var.	0.95	(0.000)	0.12	(0.000)	1.69	(0.089)	1.08	(0.001)	0.62	(0.000)	0.08	(0.000)	1.25	(0.000)	0.52	(0.000)	0.48	(0.005)
Gas Price	28.91	(0.000)	13.30	(0.017)	−115.76	(0.466)	25.54	(0.058)	10.81	(0.026)	5.74	(0.006)	25.85	(0.055)	6.07	(0.018)	11.20	(0.558)
Lagged Gas Price	−11.50	(0.043)	6.36	(0.233)	−44.10	(0.599)	−34.68	(0.044)	−1.80	(0.762)	−0.18	(0.943)	−8.53	(0.561)	−0.87	(0.762)	−10.52	(0.431)
Market split dummy	3.16	(0.795)																
Observations	1785		1818		1820		1786		1779		1698		1815		1826		1759	
R^2	0.43		0.19		0.03		0.11		0.26		0.40		0.26		0.54		0.17	
Joint significance of Residual Load and Residual Load^2	25.39	(0.000)	15.82	(0.000)	3.98	(0.019)	4.27	(0.014)	13.99	(0.000)	26.39	(0.000)	4.85	(0.008)	52.72	(0.000)	4.08	(0.017)

Note: p values in parenthesis based on HAC robust standard errors. Joint significances report the F statistics with p values in parenthesis. Dummies for weekdays and months are included in all models but not shown.

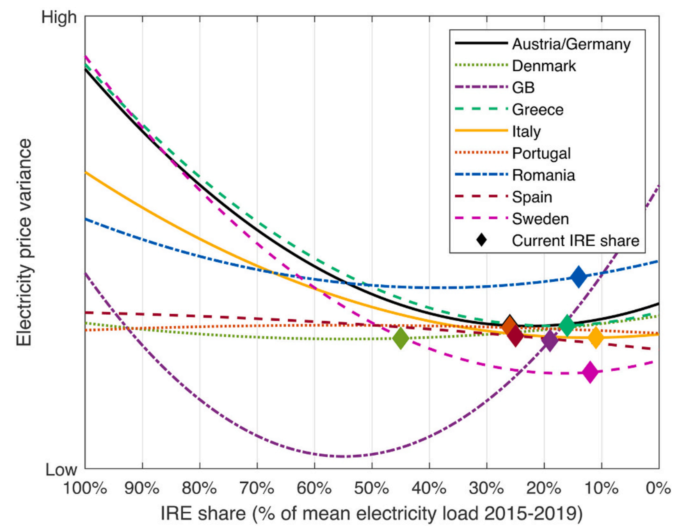

Fig. 5. Electricity price variance depending on the share of IRE in the electricity load (mean of the load 2015–2019) for several European countries. The current IRE share depicted is the average IRE infeed during the study period 2015–2019.

the higher the timewise correlation of load and electricity generation is, the lower the price variance.

4.2.3. *Wind & Solar Model*

The countries analyzed also show peculiarities in how wind and solar infeed impacts price variance. The countries differ greatly in terms of infeed levels: Wind infeed is highest in Denmark at certain times (up to 93.9% of the maximal load) and solar infeed in the Austrian-German market zone (up to 14.1% of the maximal load). These differences are reflected in Table 7, which shows the estimated coefficients for the Wind & Solar Model: Wind is found to have a jointly significant influence on price variance in all countries other than GB and Romania. Solar, on the other hand, is found to have a jointly significant effect only in Austria/Germany, Portugal, and Romania. Sweden has negligible solar production, and the influence of solar is therefore not available in the data.

Fig. 7 shows the effect of the percentage of wind and solar production on the fitted values of price variance for all countries except Sweden (where no solar data are available), Spain, and Portugal (which had an inverse U-shape for the residual curve). For better comparison, the price variance is shifted to zero at the origin. For the countries shown, high wind and high solar infeed at the same time lead to the highest price variance in all countries except for Romania. In the Austrian-German market zone, GB, and Greece, solar infeed increases price levels at high wind infeed, whereas solar production reduces price variance at low wind infeed. In times of high wind production, prices are often already low and defined by the steep part on the left end of the supply curve. The solar infeed in these hours pushes prices even lower and increases price variance. However, when there is no wind infeed, increasing solar production is able to reduce otherwise high electricity prices and push residual demand from the steep right part to the flatter part of the supply curve in the middle: Then, it decreases price variance. The combination of low wind and low solar infeed leading to increased price variance (and confirming the U-shaped impact of IRE infeed) is especially distinct for Greece but can also be observed in the Austrian-German market zone, Denmark, GB, and Italy. In Denmark, price variance is mainly impacted by wind infeed, while solar infeed shows very little effect.

5. Conclusion and policy implications

This paper addresses the question of how intermittent renewable

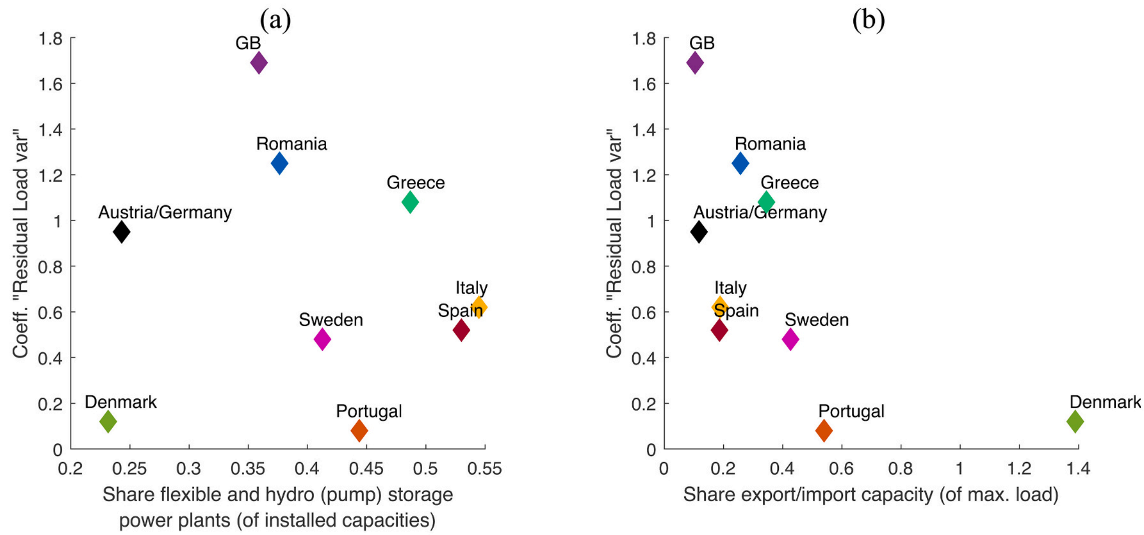

Fig. 6. The coefficient of the variance of the residual load for all analyzed countries with respect to the dependence of the variance on their share of flexible power plants and (pump) hydro storage capacities (Panel (a)) and export/import capacities (Panel (b)). Capacities are based on Table 2. Flexible power plants include oil and gas capacities. Flexible and hydro (pump) storage power plants are depicted as share of overall generation capacity. Transmission capacity is depicted as share of maximal load.

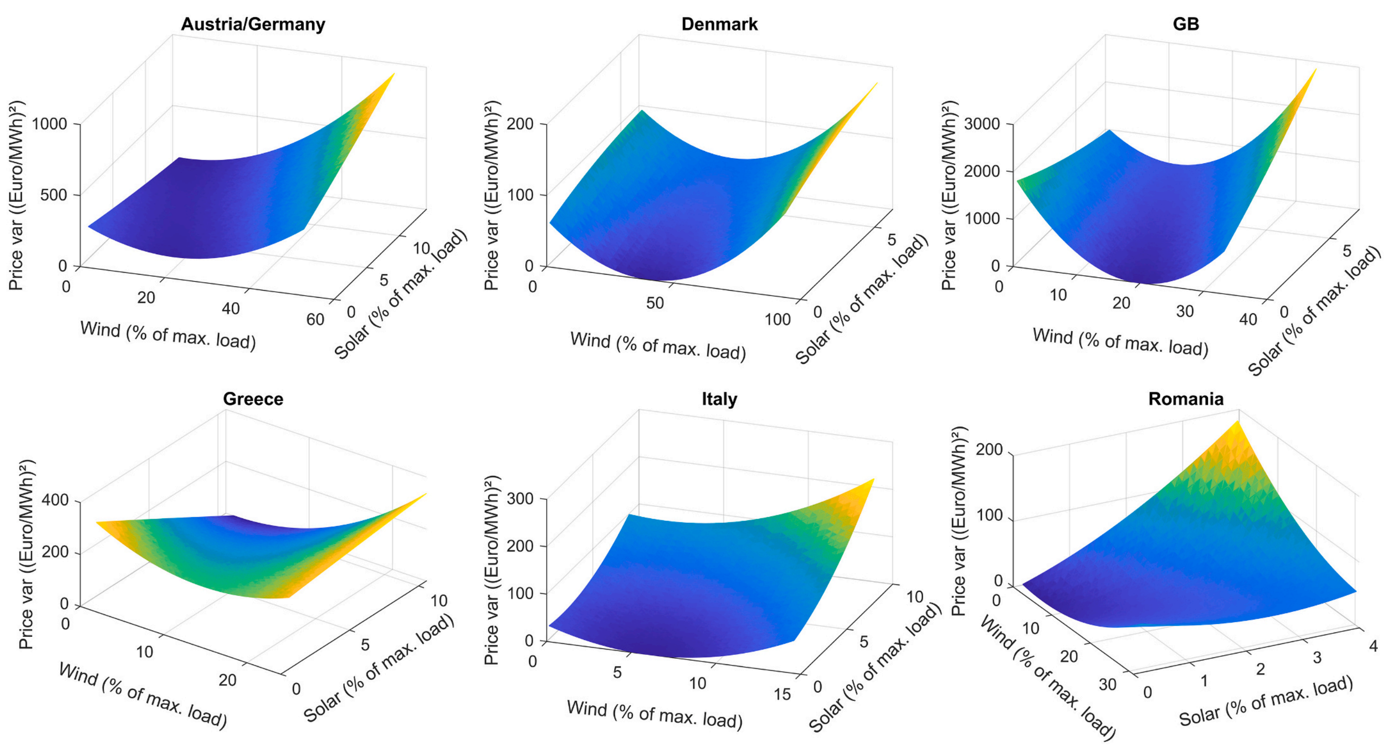

Fig. 7. Electricity price variance depending on the share of wind and solar in the electricity load for several European countries. Wind and solar generation are depicted in % of maximal load.

electricity (IRE) generation influences electricity spot price variance in Europe and what flexibility options help different countries cope with IRE infeed. Our analysis covers nine[10] countries, encompassing 78% of the wind generation and 79% of the solar generation in the current EU's electricity market (Eurostat, 2021). The more the residual load (i.e., load minus IRE production) fluctuates, the higher the price variance. This can be confirmed for eight out of nine countries. Furthermore, our analysis confirms that in seven out of nine countries analyzed, low and high residual load levels lead to higher price variance than moderate levels. This indicates—depending on the current deployment level of IRE in a country—that an increased share of IRE does not necessarily increase price variance but can even lower it. These results confirm previous analyses (e.g., by Wozabal et al. (2016)) for the first time for a wide range of countries. The minimum price variance is found to be between 10% and 40% of the IRE share for the countries that adhere to the described pattern. For these countries, given the increasing shares of IRE

[10] Austria/Germany/Luxembourg were analyzed as one country because of the common market zone.

Table 6
Regression results for individual countries in the Extended Model.

	Extended Model																	
	Austria/Germany		Denmark		GB		Greece		Italy		Portugal		Romania		Spain		Sweden	
Intercept	390.19	(0.154)	281.04	(0.316)	−3259.20	(0.406)	146.77	(0.789)	455.01	(0.004)	210.63	(0.026)	602.84	(0.287)	11.68	(0.924)	1324.78	(0.018)
Load	−13.39	(0.075)	−9.75	(0.232)	78.95	(0.529)	−12.26	(0.420)	−15.57	(0.002)	−2.45	(0.304)	−20.98	(0.170)	2.00	(0.555)	−49.69	(0.013)
Load^2	0.15	(0.013)	0.12	(0.054)	−0.29	(0.742)	0.16	(0.143)	0.14	(0.001)	0.01	(0.340)	0.21	(0.072)	−0.03	(0.196)	0.44	(0.010)
IRE	21.85	(0.000)	3.02	(0.076)	−118.73	(0.478)	39.29	(0.008)	15.23	(0.023)	−0.94	(0.314)	−4.04	(0.659)	−0.26	(0.879)	22.21	(0.063)
IRE^2	0.33	(0.000)	0.04	(0.000)	4.95	(0.103)	0.68	(0.040)	0.63	(0.063)	−0.01	(0.056)	0.15	(0.150)	0.00	(0.969)	0.67	(0.013)
Load var.	0.41	(0.119)	−0.53	(0.000)	3.57	(0.151)	1.26	(0.000)	0.46	(0.000)	−0.13	(0.002)	0.26	(0.734)	0.62	(0.000)	0.17	(0.808)
IRE var.	1.32	(0.000)	0.10	(0.000)	5.88	(0.062)	0.70	(0.035)	1.12	(0.000)	0.05	(0.028)	1.44	(0.000)	0.61	(0.000)	−0.41	(0.451)
IRE Load cov	−1.95	(0.000)	−0.27	(0.000)	−3.30	(0.068)	−2.10	(0.013)	−1.51	(0.000)	−0.20	(0.000)	−2.22	(0.000)	−1.02	(0.000)	−1.52	(0.000)
Load*IRE	−0.46	(0.000)	−0.08	(0.001)	−1.01	(0.362)	−0.79	(0.000)	−0.36	(0.002)	0.03	(0.020)	−0.02	(0.878)	0.03	(0.186)	−0.54	(0.034)
Gas Price	23.06	(0.000)	11.49	(0.013)	−126.10	(0.451)	23.21	(0.072)	11.03	(0.024)	5.72	(0.002)	14.47	(0.245)	6.41	(0.012)	8.94	(0.615)
Lagged Gas Price	−11.31	(0.021)	6.20	(0.197)	−55.74	(0.496)	−34.94	(0.044)	−3.26	(0.602)	2.70	(0.234)	−4.82	(0.732)	−0.90	(0.747)	−8.41	(0.493)
Market split dummy	−3.87	(0.787)																
Observations	1785		1818		1820		1786		1779		1698		1815		1826		1759	
R^2	0.43		0.23		0.04		0.11		0.27		0.42		0.28		0.54		0.18	
Joint Significances:																		
Load, Load^2	6.17	(0.002)	18.26	(0.000)	2.89	(0.056)	4.03	(0.018)	6.12	(0.002)	0.58	(0.560)	3.56	(0.029)	8.20	(0.000)	3.71	(0.025)
IRE, IRE^2	20.19	(0.000)	23.65	(0.000)	3.24	(0.039)	7.55	(0.001)	5.41	(0.005)	2.78	(0.062)	1.04	(0.354)	0.02	(0.984)	3.11	(0.045)
Load, Load^2, IRE, IRE^2, IRE Load cov, Load*IRE	11.27	(0.000)	16.30	(0.000)	2.07	(0.082)	4.89	(0.001)	4.77	(0.001)	1.75	(0.136)	4.87	(0.001)	6.87	(0.000)	3.25	(0.011)
Load var., IRE var.	26.92	(0.000)	36.02	(0.000)	1.08	(0.364)	5.14	(0.000)	17.95	(0.000)	24.41	(0.000)	18.38	(0.000)	59.63	(0.000)	7.54	(0.000)

Note: p values in parenthesis based on HAC robust standard errors. Joint significances report the F statistics with p values in parenthesis. Dummies for weekdays and months are included in all models but not shown.

beyond this minimum in the future, increased price variance can be expected. However, there are measures that dampen this effect, as shown by countries such as Denmark that already have a high share of IRE but where this nevertheless has a low impact on price variance.

Lower price variance in the medium to long run is reached by different flexibility options that help to balance fluctuating IRE by 1) reducing the variance of the IRE infeed itself or 2) changing the shape of the supply curve—i.e., by export or import capacities. These flexibility options include storage ((pump) hydropower, batteries, thermal storage technologies, or hydrogen), transmission capacities, and demand-side management (DSM) in households, the commercial sector, and industry. In the longer term, the quality of forecasting IRE generation will also gain importance in dealing with the variability of IRE production since despite the relative forecast error decreasing with increasing IRE shares, absolute errors still play an important role. Increased short-term trading is also a possible means of balancing price variances, which is a development that is observable in European electricity spot markets (Koch and Hirth, 2019).

Furthermore, we find that the effect of wind and solar infeed on spot price variance is relatively low compared to the impact of certain electricity system characteristics of a country. More specifically, the availability of flexible power plants and export/import capacities are more important factors for a country's ability to balance IRE infeed than the extent and the variance of the IRE production itself. Since the extension of transmission capacities is a very inert process, countries should foster this early on in their IRE deployment.

The comparison of multiple countries shows the lowest impact of IRE infeed on price variance in the Iberian and Nordic countries. They all are characterized by either high shares of flexible power plants, hydro (pump) storage, or transmission capacities to the neighboring countries. Denmark, which has the highest share of IRE (41%[11]) among the countries analyzed, shows how these factors can support the successful integration of intermittent renewables in a power system, and our results suggest that these factors make a difference. For the support of IRE uptake, it is most important to minimize the price risk for IRE producers (Egli, 2020). Therefore, in many European countries, IRE generators still receive incentives to generate electricity even if the spot price levels are negative for up to six hours. Denmark was one of the first countries to scrap this rule for new wind offshore generation (González and Kitzing, 2019), which means that generators will avoid generation as soon as there are negative prices indicating a surplus of renewable generation and pushing demand toward the steep part of the supply curve to the left.

Our regression models cannot fully explain the price variance because factors, such as supply shortages, policy shifts and remuneration schemes, are not explicitly covered. Such factors—even if not the focus of our analysis—can also have a great impact on price variance. We show for the case of GB that exceptionally high price variance over a few days due to the electricity supply shortages in 2016 caused a tremendous increase in the average price variance.[12]

While electricity spot price variance is not problematic in itself, a low variance is an indicator of an electricity system's desired ability to react on time to demand- or supply-side fluctuations. On the other hand, many flexibility options used for balancing, such as storage or DSM, exactly depend on these price fluctuations since their business case is based on arbitrage between low and high electricity price levels. Similarly to DSM and storage solutions, some conventional power plants are dependent on intermittently rare but very high price peaks in the current market setting so that they can compensate for long periods of low power prices due to increased IRE production. Our finding that increasing IRE can even lower price variance in a wide range of countries, therefore, has

[11] Average IRE share in hourly load in 2015–2019.

[12] Since the causes for these supply shortages were uncorrelated to IRE production and load, the exogeneity of our variables of interest is maintained.

Table 7
Regression results for individual countries in the Wind & Solar Model.

	Wind & Solar Model																	
	Austria/Germany		Denmark		GB		Greece		Italy		Portugal		Romania		Spain		Sweden	
Intercept	134.88	(0.660)	551.56	(0.162)	−3537.62	(0.404)	−438.20	(0.427)	490.72	(0.006)	146.13	(0.205)	1789.49	(0.021)	66.47	(0.559)	1324.78	(0.018)
Load	−6.91	(0.372)	−16.41	(0.122)	85.46	(0.525)	−6.03	(0.654)	−15.77	(0.002)	−1.07	(0.690)	−48.56	(0.016)	1.18	(0.710)	−49.69	(0.013)
Load^2	0.11	(0.059)	0.15	(0.037)	−0.33	(0.728)	0.20	(0.079)	0.13	(0.001)	0.01	(0.548)	0.36	(0.011)	−0.03	(0.206)	0.44	(0.010)
Wind	20.05	(0.000)	3.22	(0.108)	−132.15	(0.505)	33.00	(0.012)	17.58	(0.010)	−0.89	(0.392)	3.89	(0.728)	0.07	(0.966)	22.21	(0.063)
Wind^2	0.33	(0.000)	0.04	(0.000)	4.95	(0.111)	0.65	(0.080)	0.96	(0.002)	−0.01	(0.030)	0.11	(0.310)	−0.01	(0.657)	0.67	(0.013)
Solar	38.71	(0.000)	−18.98	(0.510)	−59.64	(0.894)	170.64	(0.032)	−2.85	(0.886)	11.11	(0.620)	−245.91	(0.015)	−12.77	(0.108)		
Solar^2	0.19	(0.561)	−0.67	(0.673)	6.55	(0.840)	−0.04	(0.990)	1.40	(0.187)	−0.37	(0.902)	5.16	(0.706)	0.19	(0.625)		
Load var.	0.45	(0.094)	−0.44	(0.000)	3.65	(0.135)	0.79	(0.010)	0.56	(0.000)	−0.12	(0.003)	0.34	(0.620)	0.61	(0.000)	0.17	(0.808)
IRE var.	1.24	(0.000)	0.10	(0.000)	3.93	(0.149)	1.31	(0.025)	0.59	(0.159)	0.05	(0.064)	1.29	(0.001)	0.64	(0.000)	−0.41	(0.451)
IRE Load cov	−1.89	(0.000)	−0.27	(0.000)	−3.25	(0.061)	−1.71	(0.030)	−1.85	(0.000)	−0.22	(0.000)	−2.49	(0.000)	−1.03	(0.000)	−1.52	(0.000)
Load*Wind	−0.44	(0.000)	−0.08	(0.002)	−0.87	(0.536)	−0.73	(0.000)	−0.41	(0.001)	0.02	(0.044)	−0.06	(0.596)	0.03	(0.140)	−0.54	(0.034)
Load*Solar	−0.68	(0.000)	0.37	(0.288)	−1.46	(0.614)	−2.84	(0.029)	−0.02	(0.949)	−0.36	(0.162)	3.53	(0.021)	0.16	(0.039)		
Wind*Solar	0.87	(0.000)	0.04	(0.711)	11.59	(0.270)	1.63	(0.158)	0.85	(0.333)	0.17	(0.318)	−1.71	(0.353)	−0.12	(0.257)		
Gas Price	25.10	(0.000)	11.83	(0.010)	−127.47	(0.453)	21.84	(0.081)	11.97	(0.015)	4.81	(0.010)	17.93	(0.154)	6.08	(0.019)	8.94	(0.615)
Lagged Gas Price	−11.88	(0.021)	5.94	(0.219)	−53.07	(0.516)	−36.06	(0.037)	−3.75	(0.543)	2.27	(0.305)	−9.42	(0.519)	−0.78	(0.777)	−8.41	(0.493)
Market split dummy	−7.38	(0.594)																
Observations	1785		1818		1820		1786		1779		1698		1815		1826		1759	
R^2	0.44		0.23		0.04		0.12		0.28		0.44		0.30		0.55		0.18	
Joint Significances:																		
Wind, Wind^2, Load*Wind, Wind*Solar	11.59	(0.000)	11.90	(0.000)	1.67	(0.154)	5.17	(0.000)	8.35	(0.000)	10.82	(0.000)	0.98	(0.415)	33.71	(0.000)	2257.78	(0.000)
Solar, Solar^2, Load*Solar, Wind*Solar	5.96	(0.000)	1.59	(0.173)	1.16	(0.324)	1.61	(0.170)	1.06	(0.374)	8.42	(0.000)	2.40	(0.048)	1.45	(0.215)		
Load, Load^2, Wind, Wind^2, Solar, Solar^2, Load*Wind, Load*Solar, IRE Load cov	21.44	(0.000)	16.53	(0.000)	1.02	(0.420)	3.94	(0.000)	14.38	(0.000)	15.73	(0.000)	19.51	(0.000)	33.06	(0.000)	8359.11	(0.000)
Load var., IRE var.	24.76	(0.000)	43.99	(0.000)	1.44	(0.238)	8.87	(0.000)	18.86	(0.000)	6.84	(0.001)	6.41	(0.002)	56.00	(0.000)	0.72	(0.489)

Note: p values in parenthesis based on HAC robust standard errors. Joint significances report the F statistics with p values in parenthesis. Dummies for weekdays and months are included in all models but not shown.

important market and policy implications. The empirical analysis shows that a large volume of IRE increases price variance. However, we see that along the deployment path of rising IRE shares in a market, price variance may even be lowered by IRE. This indicates that during the current phase of moderate amounts of IRE, the market alone cannot provide incentives for sufficient investments in flexibility facilities. Since most of the countries analyzed are still expected to see lower price variance with increasing IRE share (see Fig. 5), price variance alone cannot be the driver for these investments. The findings call for policies to secure investments in flexibility options, such as grid expansion, storage facilities, flexible power plants, and DSM, in the period of low price variance when market-based solutions might fail and eventually lead to situations where grid stability is at risk. Targeted policies for increased flexibility options are necessary to tackle this issue. Waterson (2017), e.g., argues that market reforms are necessary for storage concepts to function competitively. However, concrete policy plans and measures for this kind of support are difficult to find in the plans of European countries (Thonig et al., 2020). Therefore, it is important that further studies quantify how price variance changes investment decisions in generation capacities, as well as storage, transmission, and DSM, in the medium to long term. Policy action to support investments in supply and demand management must be taken while price variance is temporarily low.

Another major conclusion of this study is that the covariance and interplay of IRE and demand are important drivers in decreasing price variance. This implies that IRE technologies, whose production tends to coincide with times of peak load, as well as technologies that complement each other's generation patterns, decrease price variance. Continuous deployment and integration of different technologies, therefore, help to stabilize the electricity system because they show partly compensating effects. One policy implication of this is that targeted technology-specific support to reach a balanced technology mix has advantages over technology-neutral, least-cost policies, which might result in a strong concurrence of IRE infeed (del Río, 2017). The variance of the IRE infeed is mainly determined by the availability of the natural resource (i.e., solar radiation or wind). However, policy design impacts the way IRE plants operate. For example, feed-in premiums or contracts-for-difference that force IRE producers to market their electricity themselves instead of fixed feed-in tariffs give incentives to consider market signals and shift generation to times of higher prices, hence usually times of higher demand or lower IRE infeed. Schmidt et al. (2013) show that under a feed-in premium, wind generators are incentivized to consider the covariance between renewable production and demand as well as between different wind power locations for their power plant design. However, this is of course only possible to a limited extent. A feed-in premium puts more risk on the IRE producer and should preferably be deployed at the later stage of the IRE deployment path of a country (maximization of the value of electricity) when the integration of high shares of IRE is a major concern; however, the feed-in premium is a well-proven means of achieving fast, high-volume deployment at an earlier stage (maximization of produced energy) (del Río and Kiefer, 2021). Our finding that price variance even decreases for moderate levels of IRE infeed supports this strategy for IRE support.

Our study examines how targeted policy design, integration of flexibility options, such as transmission capabilities, flexible generation assets, storage, and DSM, and improved short-term trading can reduce price variance in the long term and draws a hopeful conclusion that taking these measures can foster the successful integration of IRE.

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Availability of data

All data and code underlying the findings reported in this paper can be found under supplementary material; the analysis and all figures are fully reproducible (a readme file is included).

Declaration of Competing Interest

None.

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Appendix A. Formal description of the conceptual model

Based on Wozabal et al. (2016), the supply covering the residual load can be described by a differentiable function as

$$\mathrm{k}(\mathrm{X}) = a + b\mathrm{X} + c\mathrm{X}^2 + d\mathrm{X}^3 \tag{A.1}$$

where k denotes the total costs per energy unit, X is the residual supply, and a, b, c and d are the respective coefficients. Given a certain level of residual load, the change in costs (or marginal costs) is

$$\frac{\mathrm{dk}(\mathrm{X})}{\mathrm{dX}} = b + 2cX + 3d\,\mathrm{X}^2 \tag{A.2}$$

Assuming an inelastic (i.e., vertical) residual load, the change in price is the derivative of the cost function

$$\frac{\mathrm{dk}(\mathrm{X})}{\mathrm{dX}} = \frac{\mathrm{dp}(\mathrm{X})}{\mathrm{dX}} \tag{A.3}$$

where p is the spot price of electricity. This derivative, which differs depending on the level of X (and the parameters), describes the part of the price variance influenced by the shape of the supply curve. Price variance is also caused by the variance in X, which can be the result of the variance of IRE production or of the variance of the load itself. For the special case in which the variance of X is not "broader" after an increase in IRE than before the increase, Wozabal et al. (2016) formally show that the variance of the price decreases. In the general case, the change in the variance of the price depends in a nontrivial way on the interaction between the shape of the supply function and the distribution of the residual load. There is no straightforward economic interpretation of this interaction, but a Taylor approximation can be used to describe the interaction of supply function shape and the variance of the residual load (Wozabal et al., 2016).

Approximating the supply function from Eq. (A.1) by a first-order Taylor approximation around $E(X) = \mu$ yields

$$k(X) = a + b\mu + c\mu^2 + d\mu^3 + \left(b + 2c\mu + 3d\mu^2\right)(X - \mu) \tag{A.4}$$

By applying the variance operator on both sides and taking into account that μ is a constant, we obtain

$$Var(k(X)) = \left(b + 2c\mu + 3d\mu^2\right)^2 Var(X) \tag{A.5}$$

and

$$Var(k(X)) = \left(\frac{dk(\mu)}{dX}\right)^2 Var(X). \tag{A.6}$$

The variance of the price is approximated by the square slope of the supply function (which equals the marginal cost function) evaluated at the mean of the residual load times the variance of the residual load. This confirms the intuition from the figures that the shape of the supply function and the variance of the residual load determine the variance of the electricity price.

Appendix B. Detailed results

Table A.1
Panel model results for the Basic Model.

	Basic Model					
	Pooled		Fixed effects		First difference	
(Intercept)	341.92	(0.000)			0.01	(0.991)
Residual Load	−5.41	(0.000)	−5.19	(0.000)	−3.92	(0.000)
Residual Load^2	0.06	(0.000)	0.05	(0.000)	0.04	(0.000)
Residual Load var.	0.13	(0.000)	0.19	(0.000)	0.22	(0.000)
Gas Price	15.44	(0.001)	15.82	(0.000)	−14.17	(0.146)
Lagged Gas Price	−7.54	(0.095)	−8.02	(0.017)	−0.34	(0.848)
Share oil gas	−137.98	(0.000)				
Share hydro storage	−217.72	(0.000)				
Share export import	−81.85	(0.000)				
Observations	14,266		14,266		14,258	
R^2	0.106		0.088		0.047	
Joint significance of Residual Load and Residual Load^2	15.31	(0.000)	47.03	(0.000)	36.23	(0.000)

Note: p values in parenthesis based on HAC robust (Pooled), clustered (FE), and Newey West (FD) standard errors. Joint significances report the F statistics with p values in parenthesis. Dummies for weekdays and months are included in all models but not shown.

Table A.2
Panel model results for the Extended Model.

	Extended Model					
	Pooled		Fixed effects		First difference	
(Intercept)	836.90	(0.000)			0.01	(0.991)
Load	−18.12	(0.000)	−20.47	(0.000)	−12.63	(0.000)
Load^2	0.15	(0.000)	0.17	(0.000)	0.11	(0.000)
IRE	9.57	(0.000)	13.47	(0.000)	8.16	(0.000)
IRE^2	0.06	(0.000)	0.02	(0.000)	0.02	(0.000)
Load var.	−0.17	(0.053)	0.08	(0.235)	0.14	(0.005)
IRE var.	0.11	(0.000)	0.11	(0.000)	0.12	(0.000)
IRE Load cov	−0.46	(0.000)	−0.43	(0.000)	−0.50	(0.000)
Load*IRE	−0.17	(0.000)	−0.18	(0.000)	−0.12	(0.000)
Gas Price	16.17	(0.001)	14.63	(0.000)	−14.66	(0.135)
Lagged Gas Price	−7.41	(0.087)	−6.96	(0.034)	−0.28	(0.877)
Share oil gas	−52.04	(0.048)				
Share hydro storage	−301.49	(0.000)				
Share export import	−70.62	(0.000)				
Observations	14,266		14,266		14,258	
R^2	0.123		0.102		0.052	
Joint Significances						
Load, Load^2	10.01	(0.000)	45.85	(0.000)	16.13	(0.000)
IRE, IRE^2	42.41	(0.000)	12.71	(0.000)	13.76	(0.000)
Load, Load^2, IRE, IRE^2	14.06	(0.000)	78.53	(0.000)	28.69	(0.000)
Load var., IRE var., IRE Load cov, Load*IRE	38.62	(0.000)	209.63	(0.000)	220.73	(0.000)

Note: p values in parenthesis based on HAC robust (Pooled), clustered (FE), and Newey West (FD) standard errors. Joint significances report the F statistics with p values in parenthesis. Dummies for weekdays and months are included in all models but not shown.

Table A.3
Panel model results for the Wind & Solar Model.

	Wind & Solar Model					
	Pooled		Fixed effects		First difference	
(Intercept)	702.45	(0.000)			0.02	(0.976)
Load	−15.37	(0.000)	−18.06	(0.000)	−7.40	(0.015)
Load^2	0.14	(0.000)	0.16	(0.000)	0.08	(0.001)
Load var.	−0.12	(0.166)	0.12	(0.050)	0.14	(0.004)
IRE var.	0.13	(0.000)	0.09	(0.000)	0.10	(0.000)
IRE Load cov	−0.34	(0.000)	−0.41	(0.000)	−0.47	(0.000)
Wind	6.70	(0.001)	9.69	(0.000)	5.89	(0.000)
Wind^2	0.06	(0.000)	0.03	(0.000)	0.02	(0.000)
Solar	27.54	(0.005)	32.55	(0.000)	39.56	(0.000)
Solar^2	0.98	(0.005)	0.75	(0.007)	0.79	(0.027)
Load*Wind	−0.15	(0.000)	−0.15	(0.000)	−0.10	(0.000)
Load*Solar	−0.71	(0.000)	−0.64	(0.000)	−0.67	(0.000)
Wind*Solar	0.66	(0.000)	0.65	(0.000)	0.55	(0.000)
Gas Price	15.98	(0.001)	14.67	(0.000)	−15.45	(0.109)
Lagged Gas Price	−6.91	(0.105)	−6.76	(0.036)	−0.28	(0.872)
Share oil gas	17.21	(0.614)				
Share hydro storage	−319.56	(0.000)				
Share export import	−92.18	(0.000)				
Observations	14,266		14,266		14,258	
R^2	0.139		0.113		0.060	
Joint Significances						
Load, Load^2	10.94	(0.000)	37.36	(0.000)	23.79	(0.000)
Wind, Wind^2, Load*Wind, Wind*Solar	17.57	(0.000)	91.52	(0.000)	51.27	(0.000)
Solar, Solar^2, Load*Solar, Wind*Solar	21.43	(0.000)	65.09	(0.000)	67.92	(0.000)
Load, Load^2, Wind, Wind^2, Solar, Solar^2, Load*Wind, Load*Solar, IRE Load cov	26.23	(0.000)	292.42	(0.000)	273.95	(0.000)
Load var., IRE var.	28.20	(0.000)	31.66	(0.000)	35.62	(0.000)

Note: p values in parenthesis based on HAC robust (Pooled), clustered (FE), and Newey West (FD) standard errors. Joint significances report the F statistics with p values in parenthesis. Dummies for weekdays and months are included in all models but not shown.

Table A.4
Panel model results with all interaction terms for the Basic Model.

	Basic Model					
	Pooled		Fixed effects		First difference	
(Intercept)	1485.08	(0.000)			−0.01	(0.994)
Residual Load	−52.35	(0.000)	−52.77	(0.000)	−49.88	(0.000)
Residual Load^2	0.48	(0.000)	0.45	(0.000)	0.41	(0.000)
Residual Load var.	1.22	(0.000)	1.60	(0.000)	1.81	(0.000)
Gas Price	15.70	(0.000)	16.42	(0.000)	−15.48	(0.104)
Lagged Gas Price	−7.06	(0.098)	−7.81	(0.012)	−1.12	(0.521)
Share oil gas*Load	101.50	(0.002)	98.51	(0.001)	101.49	(0.000)
Share oil gas*Load^2	−0.94	(0.001)	−0.88	(0.001)	−0.94	(0.000)
Share oil gas*Load var.	−0.76	(0.131)	−1.18	(0.004)	−1.40	(0.002)
Share hydro storage*Load	37.20	(0.243)	31.68	(0.280)	43.56	(0.101)
Share hydro storage*Load^2	−0.34	(0.248)	−0.26	(0.336)	−0.31	(0.205)
Share hydro storage*Load var.	−2.87	(0.000)	−3.13	(0.000)	−3.66	(0.000)
Share export import*Load	18.82	(0.000)	19.59	(0.000)	17.44	(0.000)
Share export import*Load^2	−0.16	(0.000)	−0.15	(0.000)	−0.12	(0.003)
Share export import*Load var.	−0.69	(0.000)	−0.89	(0.000)	−1.00	(0.000)
Share oil gas	−2626.84	(0.003)				
Share hydro storage	−958.91	(0.255)				
Share export import	−542.67	(0.000)				
Observations	14,266		14,266		14,258	
R^2	0.150		0.151		0.103	
Joint Significances						
Residual Load, Residual Load^2	11.05	(0.000)	162.49	(0.000)	144.36	(0.000)
Share oil gas interactions	5.64	(0.000)	32.88	(0.000)	68.75	(0.000)
Share hydro storage interactions	24.67	(0.000)	83.61	(0.000)	87.30	(0.000)
Share export import interactions	38.83	(0.000)	147.56	(0.000)	152.86	(0.000)

Note: p values in parenthesis based on HAC robust (Pooled), clustered (FE), and Newey West (FD) standard errors. Joint significances report the F statistics with p values in parenthesis. Dummies for weekdays and months are included in all models but not shown.

Table A.5
Panel model results with all interaction terms for the Extended Model.

	Extended Model					
	Pooled		Fixed effects		First difference	
(Intercept)	−231.79	(0.701)			0.00	(0.996)
Load	4.28	(0.815)	−34.27	(0.012)	−6.08	(0.613)
Load^2	0.09	(0.511)	0.34	(0.001)	0.11	(0.210)
IRE	11.58	(0.275)	39.41	(0.000)	19.08	(0.096)
IRE^2	0.73	(0.000)	0.55	(0.000)	0.70	(0.000)
Load var.	−0.41	(0.268)	1.26	(0.000)	1.61	(0.000)
IRE var.	2.27	(0.000)	2.56	(0.000)	2.51	(0.000)
IRE Load cov	−3.40	(0.000)	−3.06	(0.000)	−3.72	(0.000)
Load*IRE	−0.62	(0.000)	−0.82	(0.000)	−0.62	(0.000)
Gas Price	15.64	(0.000)	14.78	(0.000)	−15.63	(0.096)
Lagged Gas Price	−7.12	(0.088)	−7.03	(0.021)	−1.06	(0.543)
Share oil gas*Load	16.98	(0.679)	78.86	(0.016)	35.99	(0.226)
Share oil gas*Load^2	−0.32	(0.325)	−0.72	(0.008)	−0.46	(0.072)
Share oil gas*IRE	2.48	(0.942)	−39.38	(0.185)	−22.28	(0.400)
Share oil gas*IRE^2	−1.28	(0.007)	−1.11	(0.012)	−1.68	(0.000)
Share oil gas*Load var.	1.97	(0.008)	−0.89	(0.087)	−0.93	(0.168)
Share oil gas*IRE var.	−2.21	(0.013)	−2.97	(0.000)	−3.28	(0.000)
Share oil gas*IRE Load cov	2.12	(0.102)	1.70	(0.118)	2.96	(0.027)
Share oil gas*(Load*IRE)	0.80	(0.185)	1.26	(0.021)	1.26	(0.006)
Share hydro storage*Load	−94.54	(0.048)	−19.98	(0.629)	−53.88	(0.165)
Share hydro storage*Load^2	0.54	(0.160)	0.06	(0.856)	0.41	(0.213)
Share hydro storage*IRE	17.87	(0.604)	−26.10	(0.397)	4.29	(0.879)
Share hydro storage*IRE^2	−0.96	(0.008)	−0.61	(0.048)	−0.78	(0.007)
Share hydro storage*Load var.	−1.04	(0.158)	−2.63	(0.000)	−4.46	(0.000)
Share hydro storage*IRE var.	−5.37	(0.000)	−5.86	(0.000)	−4.71	(0.000)
Share hydro storage*IRE Load cov	7.19	(0.000)	6.14	(0.000)	7.39	(0.000)
Share hydro storage*(Load*IRE)	0.44	(0.450)	0.72	(0.172)	0.41	(0.358)
Share export import*Load	−12.08	(0.280)	8.45	(0.359)	−3.48	(0.670)
Share export import*Load^2	0.05	(0.549)	−0.08	(0.249)	0.04	(0.565)
Share export import*IRE	−7.53	(0.179)	−20.78	(0.000)	−9.35	(0.073)
Share export import*IRE^2	−0.28	(0.000)	−0.18	(0.001)	−0.20	(0.000)
Share export import*Load var.	−0.29	(0.060)	−0.91	(0.000)	−1.13	(0.000)
Share export import*IRE var.	−1.20	(0.000)	−1.27	(0.000)	−1.21	(0.000)
Share export import*IRE Load cov	1.97	(0.000)	1.79	(0.000)	1.99	(0.000)
Share export import*(Load*IRE)	0.26	(0.004)	0.34	(0.000)	0.20	(0.014)
Share oil gas	−190.35	(0.882)				
Share hydro storage	3256.18	(0.026)				
Share export import	483.58	(0.188)				
Observations	14,266		14,266		14,258	
R^2	0.172		0.157		0.106	
Joint Significances						
Load, Load^2	6.90	(0.000)	82.11	(0.000)	34.85	(0.000)
IRE, IRE^2	13.36	(0.000)	149.72	(0.000)	74.53	(0.000)
Load, Load^2, IRE, IRE^2	7.81	(0.000)	172.57	(0.000)	94.61	(0.000)
Load var., IRE var., IRE Load cov, Load*IRE	14.09	(0.000)	411.61	(0.000)	411.91	(0.000)
Share oil gas interactions	4.42	(0.000)	54.20	(0.000)	67.98	(0.000)
Share hydro storage interactions	15.36	(0.000)	98.29	(0.000)	96.01	(0.000)
Share export import interactions	14.09	(0.000)	163.56	(0.000)	185.64	(0.000)

Note: p values in parenthesis based on HAC robust (Pooled), clustered (FE), and Newey West (FD) standard errors. Joint significances report the F statistics with p values in parenthesis. Dummies for weekdays and months are included in all models but not shown.

Table A.6
Panel model results with all interaction terms for the Wind & Solar Model.

	Wind & Solar Model					
	Pooled		Fixed effects		First difference	
(Intercept)	−575.07	(0.330)			0.01	(0.993)
Load	15.99	(0.351)	−12.84	(0.340)	10.98	(0.404)
Load^2	0.00	(0.993)	0.22	(0.024)	0.02	(0.870)
Load var.	0.06	(0.872)	1.24	(0.000)	1.66	(0.000)
IRE var.	2.11	(0.000)	2.32	(0.000)	2.61	(0.000)
IRE Load cov	−2.85	(0.000)	−3.21	(0.000)	−3.44	(0.000)
Wind	12.43	(0.236)	41.17	(0.000)	20.71	(0.055)
Wind^2	0.67	(0.000)	0.63	(0.000)	0.73	(0.000)
Solar	−7.62	(0.782)	113.18	(0.000)	95.89	(0.001)
Solar^2	2.70	(0.029)	−0.77	(0.417)	−2.12	(0.043)
Load*Wind	−0.62	(0.000)	−0.86	(0.000)	−0.66	(0.000)
Load*Solar	−0.94	(0.019)	−1.46	(0.000)	−1.34	(0.000)

(*continued on next page*)

Table A.6 (*continued*)

Wind & Solar Model						
	Pooled		Fixed effects		First difference	
Wind*Solar	1.93	(0.001)	1.38	(0.005)	1.82	(0.000)
Gas Price	15.57	(0.000)	14.57	(0.000)	−16.20	(0.084)
Lagged Gas Price	−6.96	(0.094)	−6.98	(0.021)	−1.07	(0.529)
Share oil gas*Load	−11.00	(0.769)	41.10	(0.190)	−3.97	(0.892)
Share oil gas*Load^2	−0.12	(0.710)	−0.51	(0.050)	−0.23	(0.341)
Share oil gas*Wind	−20.24	(0.554)	−46.77	(0.119)	−32.27	(0.215)
Share oil gas*Wind^2	−1.33	(0.010)	−1.54	(0.002)	−1.91	(0.000)
Share oil gas*Solar	−135.74	(0.255)	−212.19	(0.051)	−332.25	(0.001)
Share oil gas*Solar^2	7.20	(0.272)	6.78	(0.220)	4.51	(0.360)
Share oil gas*Load var.	1.30	(0.074)	−0.91	(0.079)	−1.14	(0.096)
Share oil gas*IRE var.	−1.51	(0.269)	−3.08	(0.019)	−4.07	(0.000)
Share oil gas*IRE Load cov	1.48	(0.305)	1.79	(0.148)	1.60	(0.298)
Share oil gas*(Load*Wind)	1.08	(0.086)	1.45	(0.011)	1.45	(0.002)
Share oil gas*(Load*Solar)	2.29	(0.219)	2.80	(0.078)	5.41	(0.000)
Share oil gas*(Wind*Solar)	−1.22	(0.698)	−5.89	(0.028)	−6.77	(0.003)
Share hydro storage*Load	−113.12	(0.022)	−59.41	(0.171)	−96.22	(0.021)
Share hydro storage*Load^2	0.71	(0.069)	0.27	(0.428)	0.69	(0.050)
Share hydro storage*Wind	15.39	(0.637)	−31.23	(0.296)	−1.87	(0.945)
Share hydro storage*Wind^2	−0.75	(0.039)	−0.55	(0.081)	−0.72	(0.012)
Share hydro storage*Solar	427.96	(0.000)	−34.62	(0.801)	162.45	(0.208)
Share hydro storage*Solar^2	−20.76	(0.009)	−4.47	(0.530)	10.87	(0.097)
Share hydro storage*Load var.	−2.33	(0.001)	−2.69	(0.000)	−4.26	(0.000)
Share hydro storage*IRE var.	−5.41	(0.000)	−4.66	(0.000)	−4.39	(0.000)
Share hydro storage*IRE Load cov	6.52	(0.000)	7.01	(0.000)	7.73	(0.000)
Share hydro storage*(Load*Wind)	0.41	(0.455)	0.72	(0.158)	0.46	(0.287)
Share hydro storage*(Load*Solar)	−2.91	(0.088)	−0.03	(0.983)	−4.03	(0.015)
Share hydro storage*(Wind*Solar)	−3.88	(0.098)	3.30	(0.141)	2.41	(0.185)
Share export import*Load	−22.46	(0.040)	−2.30	(0.810)	−8.41	(0.361)
Share export import*Load^2	0.12	(0.131)	−0.02	(0.782)	0.06	(0.360)
Share export import*Wind	−3.11	(0.568)	−20.77	(0.000)	−9.29	(0.064)
Share export import*Wind^2	−0.23	(0.000)	−0.17	(0.002)	−0.18	(0.001)
Share export import*Solar	19.16	(0.413)	−24.05	(0.323)	−13.85	(0.569)
Share export import*Solar^2	−4.20	(0.004)	−4.31	(0.003)	0.72	(0.586)
Share export import*Load var.	−0.38	(0.008)	−0.87	(0.000)	−1.12	(0.000)
Share export import*IRE var.	−1.19	(0.000)	−1.08	(0.000)	−1.15	(0.000)
Share export import*IRE Load cov	1.64	(0.000)	1.85	(0.000)	2.02	(0.000)
Share export import*(Load*Wind)	0.21	(0.016)	0.33	(0.000)	0.20	(0.012)
Share export import*(Load*Solar)	0.60	(0.079)	0.58	(0.062)	0.05	(0.864)
Share export import*(Wind*Solar)	−1.22	(0.000)	0.09	(0.765)	−0.07	(0.792)
Share oil gas	744.97	(0.529)				
Share hydro storage	3756.20	(0.018)				
Share export import	770.31	(0.039)				
Observations	14,266		14,266		14,258	
R^2	0.183		0.162		0.109	
Joint Significances						
Load, Load^2	5.48	(0.000)	80.12	(0.000)	42.94	(0.000)
Wind, Wind^2, Load*Wind, Wind*Solar	7.72	(0.000)	227.82	(0.000)	152.13	(0.000)
Solar, Solar^2, Load*Solar, Wind*Solar	5.52	(0.000)	57.83	(0.000)	37.20	(0.000)
Load, Load^2, Wind, Wind^2, Solar, Solar^2, Load*Wind, Load*Solar, IRE Load cov	12.37	(0.000)	613.77	(0.000)	575.18	(0.000)
Load var., IRE var.	21.46	(0.000)	130.84	(0.000)	118.88	(0.000)
Share oil gas interactions	3.22	(0.000)	51.67	(0.000)	57.64	(0.000)
Share hydro storage interactions	11.47	(0.000)	123.08	(0.000)	184.19	(0.000)
Share export import interactions	9.86	(0.000)	161.19	(0.000)	165.38	(0.000)

Note: p values in parenthesis based on HAC robust (Pooled), clustered (FE), and Newey West (FD) standard errors. Joint significances report the F statistics with p values in parenthesis. Dummies for weekdays and months are included in all models but not shown.

Table A.7
Basic model results for individual countries, explanatory variables measured in absolute values.

	Basic Model								
	Austria/Germany	Denmark	GB	Greece	Italy	Portugal	Romania	Spain	Sweden
Intercept	929.12 (0.000)	87.29 (0.000)	42.27 (0.982)	930.14 (0.007)	565.57 (0.000)	74.82 (0.000)	393.38 (0.170)	106.19 (0.000)	1036.15 (0.015)
Residual Load	−38.66 (0.000)	−66.25 (0.000)	−84.70 (0.504)	−385.06 (0.004)	−40.06 (0.000)	14.10 (0.055)	−116.81 (0.214)	−1.61 (0.574)	−171.45 (0.011)
Residual Load^2	0.41 (0.000)	19.37 (0.000)	2.77 (0.190)	40.06 (0.004)	0.69 (0.000)	−2.82 (0.002)	14.01 (0.119)	−0.10 (0.152)	6.55 (0.010)
Residual Load var.	1.56 (0.000)	49.34 (0.000)	7.91 (0.089)	158.71 (0.001)	2.88 (0.000)	14.84 (0.000)	162.83 (0.000)	4.19 (0.000)	8.15 (0.005)
Gas Price	28.91 (0.000)	13.30 (0.017)	−115.76 (0.466)	25.54 (0.058)	10.81 (0.026)	5.74 (0.006)	25.85 (0.055)	6.07 (0.018)	11.20 (0.558)
Lagged Gas Price	−11.50 (0.043)	6.36 (0.233)	−44.10 (0.599)	−34.68 (0.044)	−1.80 (0.762)	−0.18 (0.943)	−8.53 (0.561)	−0.87 (0.762)	−10.52 (0.431)
Market split dummy	3.16 (0.795)								
Observations	1785	1818	1820	1786	1779	1698	1815	1826	1759
R^2	0.43	0.19	0.03	0.11	0.26	0.40	0.26	0.54	0.17
Joint significance of Residual Load and Residual Load^2	25.39 (0.000)	15.82 (0.000)	3.98 (0.019)	4.27 (0.014)	13.99 (0.000)	26.39 (0.000)	4.85 (0.008)	52.72 (0.000)	4.08 (0.017)

Note: p values in parenthesis based on HAC robust standard errors. Joint significances report the F statistics with p values in parenthesis. Dummies for weekdays and months are included in all models but not shown.

Table A.8
Extended model results for individual countries, explanatory variables measured in absolute values.

	Extended Model								
	Austria/Germany	Denmark	GB	Greece	Italy	Portugal	Romania	Spain	Sweden
Intercept	390.19 (0.154)	281.04 (0.316)	−3259.20 (0.406)	146.77 (0.789)	455.01 (0.004)	210.63 (0.026)	602.84 (0.287)	11.68 (0.924)	1324.78 (0.018)
Load	−17.15 (0.075)	−200.64 (0.232)	171.08 (0.529)	−148.42 (0.420)	−33.54 (0.002)	−34.37 (0.304)	−239.91 (0.170)	5.70 (0.555)	−204.79 (0.013)
Load^2	0.24 (0.013)	49.27 (0.054)	−1.35 (0.742)	23.43 (0.143)	0.66 (0.001)	2.90 (0.340)	27.83 (0.072)	−0.26 (0.196)	7.49 (0.010)
IRE	27.99 (0.000)	62.02 (0.076)	−257.30 (0.478)	475.61 (0.008)	32.81 (0.023)	−13.20 (0.314)	−46.22 (0.659)	−0.75 (0.879)	91.53 (0.063)
IRE^2	0.54 (0.000)	17.54 (0.000)	23.26 (0.103)	100.10 (0.040)	2.92 (0.063)	−2.35 (0.056)	20.20 (0.150)	−0.01 (0.969)	11.45 (0.013)
Load var.	0.67 (0.119)	−226.16 (0.000)	16.75 (0.151)	184.69 (0.000)	2.16 (0.000)	−26.31 (0.002)	34.02 (0.734)	5.00 (0.000)	2.85 (0.808)
IRE var.	2.16 (0.000)	41.51 (0.000)	27.59 (0.062)	103.19 (0.035)	5.22 (0.000)	10.75 (0.028)	188.85 (0.000)	4.97 (0.000)	−7.00 (0.451)
IRE Load cov	−3.21 (0.000)	−112.61 (0.000)	−15.49 (0.068)	−307.41 (0.013)	−7.02 (0.000)	−40.19 (0.000)	−290.18 (0.000)	−8.29 (0.000)	−25.74 (0.000)
Load*IRE	−0.75 (0.000)	−35.09 (0.001)	−4.74 (0.362)	−116.05 (0.000)	−1.67 (0.002)	5.27 (0.020)	−2.33 (0.878)	0.22 (0.186)	−9.18 (0.034)
Gas Price	23.06 (0.000)	11.49 (0.013)	−126.10 (0.451)	23.21 (0.072)	11.03 (0.024)	5.72 (0.002)	14.47 (0.245)	6.41 (0.012)	8.94 (0.615)
Lagged Gas Price	−11.31 (0.021)	6.20 (0.197)	−55.74 (0.496)	−34.94 (0.044)	−3.26 (0.602)	2.70 (0.234)	−4.82 (0.732)	−0.90 (0.747)	−8.41 (0.493)
Market split dummy	−3.87 (0.787)								
Observations	1785	1818	1820	1786	1779	1698	1815	1826	1759
R^2	0.43	0.23	0.04	0.11	0.27	0.42	0.28	0.54	0.18
Joint Significances									
Load, Load^2	6.17 (0.002)	18.26 (0.000)	2.89 (0.056)	4.03 (0.018)	6.12 (0.002)	0.58 (0.560)	3.56 (0.029)	8.20 (0.000)	3.71 (0.025)
IRE, IRE^2	20.19 (0.000)	23.65 (0.000)	3.24 (0.039)	7.55 (0.001)	5.41 (0.005)	2.78 (0.062)	1.04 (0.354)	0.02 (0.984)	3.11 (0.045)
Load, Load^2, IRE, IRE^2, IRE Load cov, Load*IRE	11.27 (0.000)	16.30 (0.000)	2.07 (0.082)	4.89 (0.001)	4.77 (0.001)	1.75 (0.136)	4.87 (0.001)	6.87 (0.000)	3.25 (0.011)
Load var., IRE var.	26.92 (0.000)	36.02 (0.000)	1.08 (0.364)	5.14 (0.000)	17.95 (0.000)	24.41 (0.000)	18.38 (0.000)	59.63 (0.000)	7.54 (0.000)

Note: p values in parenthesis based on HAC robust standard errors. Joint significances report the F statistics with p values in parenthesis. Dummies for weekdays and months are included in all models but not shown.

Table A.9
Wind & Solar Model results for individual countries, explanatory variables measured in absolute values.

	Wind & Solar Model								
	Austria/ Germany	Denmark	GB	Greece	Italy	Portugal	Romania	Spain	Sweden
Intercept	134.88 (0.660)	551.56 (0.162)	−3537.62 (0.404)	−438.20 (0.427)	490.72 (0.006)	146.13 (0.205)	1789.49 (0.021)	66.47 (0.559)	1324.78 (0.018)
Load	−8.85 (0.372)	−337.58 (0.122)	185.19 (0.525)	−73.05 (0.654)	−33.98 (0.002)	−14.99 (0.690)	−555.22 (0.016)	3.37 (0.710)	−204.79 (0.013)
$Load^2$	0.17 (0.059)	64.46 (0.037)	−1.55 (0.728)	29.20 (0.079)	0.62 (0.001)	1.91 (0.548)	47.37 (0.011)	−0.24 (0.206)	7.49 (0.010)
Wind	25.68 (0.000)	66.29 (0.108)	−286.37 (0.505)	399.52 (0.012)	37.87 (0.010)	−12.52 (0.392)	44.49 (0.728)	0.21 (0.966)	91.53 (0.063)
$Wind^2$	0.54 (0.000)	17.27 (0.000)	23.27 (0.111)	95.87 (0.080)	4.44 (0.002)	−2.83 (0.030)	14.85 (0.310)	−0.06 (0.657)	11.45 (0.013)
Solar	49.57 (0.000)	−390.47 (0.510)	−129.25 (0.894)	2065.65 (0.032)	−6.14 (0.886)	155.72 (0.620)	−2811.50 (0.015)	−36.34 (0.108)	
$Solar^2$	0.31 (0.561)	−285.28 (0.673)	30.74 (0.840)	−5.21 (0.990)	6.49 (0.187)	−73.17 (0.902)	674.02 (0.706)	1.53 (0.625)	
Load var.	0.74 (0.094)	−184.89 (0.000)	17.14 (0.135)	116.06 (0.010)	2.62 (0.000)	−23.67 (0.003)	44.14 (0.620)	4.96 (0.000)	2.85 (0.808)
IRE var.	2.04 (0.000)	42.74 (0.000)	18.44 (0.149)	191.97 (0.025)	2.73 (0.159)	9.10 (0.064)	168.51 (0.001)	5.15 (0.000)	−7.00 (0.451)
IRE Load cov	−3.10 (0.000)	−112.30 (0.000)	−15.28 (0.061)	−250.39 (0.030)	−8.60 (0.000)	−42.35 (0.000)	−325.24 (0.000)	−8.36 (0.000)	−25.74 (0.000)
Load*Wind	−0.73 (0.000)	−35.50 (0.002)	−4.08 (0.536)	−106.57 (0.000)	−1.89 (0.001)	4.72 (0.044)	−8.30 (0.596)	0.25 (0.140)	−9.18 (0.034)
Load*Solar	−1.11 (0.000)	155.28 (0.288)	−6.87 (0.614)	−416.50 (0.029)	−0.08 (0.949)	−71.02 (0.162)	462.04 (0.021)	1.33 (0.039)	
Wind*Solar	1.42 (0.000)	18.08 (0.711)	54.41 (0.270)	238.35 (0.158)	3.94 (0.333)	33.20 (0.318)	−223.83 (0.353)	−0.93 (0.257)	
Gas Price	25.10 (0.000)	11.83 (0.010)	−127.47 (0.453)	21.84 (0.081)	11.97 (0.015)	4.81 (0.010)	17.93 (0.154)	6.08 (0.019)	8.94 (0.615)
Lagged Gas Price	−11.88 (0.021)	5.94 (0.219)	−53.07 (0.516)	−36.06 (0.037)	−3.75 (0.543)	2.27 (0.305)	−9.42 (0.519)	−0.78 (0.777)	−8.41 (0.493)
Market split dummy	−7.38 (0.594)								
Observations	1785	1818	1820	1786	1779	1698	1815	1826	1759
R^2	0.44	0.23	0.04	0.12	0.28	0.44	0.30	0.55	0.18
Joint Significances									
Wind, $Wind^2$, Load*Wind, Wind*Solar	11.59 (0.000)	11.90 (0.000)	1.67 (0.154)	5.17 (0.000)	8.35 (0.000)	10.82 (0.000)	0.98 (0.415)	33.71 (0.000)	133.42 (0.000)
Solar, $Solar^2$, Load*Solar, Wind*Solar	5.96 (0.000)	1.59 (0.173)	1.16 (0.324)	1.61 (0.170)	1.06 (0.374)	8.42 (0.000)	2.40 (0.048)	1.45 (0.215)	
Load, $Load^2$, Wind, $Wind^2$, Solar, $Solar^2$, Load*Wind, Load*Solar, IRE Load cov	21.44 (0.000)	16.53 (0.000)	1.02 (0.420)	3.94 (0.000)	14.38 (0.000)	15.73 (0.000)	19.51 (0.000)	33.06 (0.000)	324.45 (0.000)
Load var., IRE var.	24.76 (0.000)	43.99 (0.000)	1.44 (0.238)	8.87 (0.000)	18.86 (0.000)	6.84 (0.001)	6.41 (0.002)	56.00 (0.000)	0.71 (0.493)

Note: p values in parenthesis based on HAC robust standard errors. Joint significances report the F statistics with p values in parenthesis. Dummies for weekdays and months are included in all models but not shown.

Table A.10
Panel unit root tests as described in Maddala and Wu (1999). P values in parentheses (alternative hypothesis: stationarity).

	Exogenous variables		Individual intercepts and trends	
	Individual intercepts			
Price var.	518.11	(0.000)	470.99	(0.000)
Residual Load	495.03	(0.000)	447.97	(0.000)
Residual Load^2	490.83	(0.000)	442.21	(0.000)
Residual Load var.	256.70	(0.000)	217.04	(0.000)
Gas Price	30.94	(0.014)	16.26	(0.435)
Lagged Gas Price	26.26	(0.050)	12.97	(0.675)
Load	229.33	(0.000)	197.16	(0.000)
Load^2	232.34	(0.000)	199.40	(0.000)
IRE	675.00	(0.000)	617.97	(0.000)
IRE^2	715.79	(0.000)	624.82	(0.000)
Load var.	192.28	(0.000)	172.87	(0.000)
IRE var.	526.09	(0.000)	472.35	(0.000)
IRE Load cov	381.74	(0.000)	312.42	(0.000)
Load*IRE	556.88	(0.000)	504.28	(0.000)
Wind	590.80	(0.000)	547.98	(0.000)
Wind^2	613.04	(0.000)	570.17	(0.000)
Load*Wind	518.96	(0.000)	478.30	(0.000)
Solar	68.05	(0.000)	46.28	(0.000)
Solar^2	72.92	(0.000)	51.48	(0.000)
Load*Solar	82.54	(0.000)	59.79	(0.000)
Wind*Solar	398.05	(0.000)	366.38	(0.000)

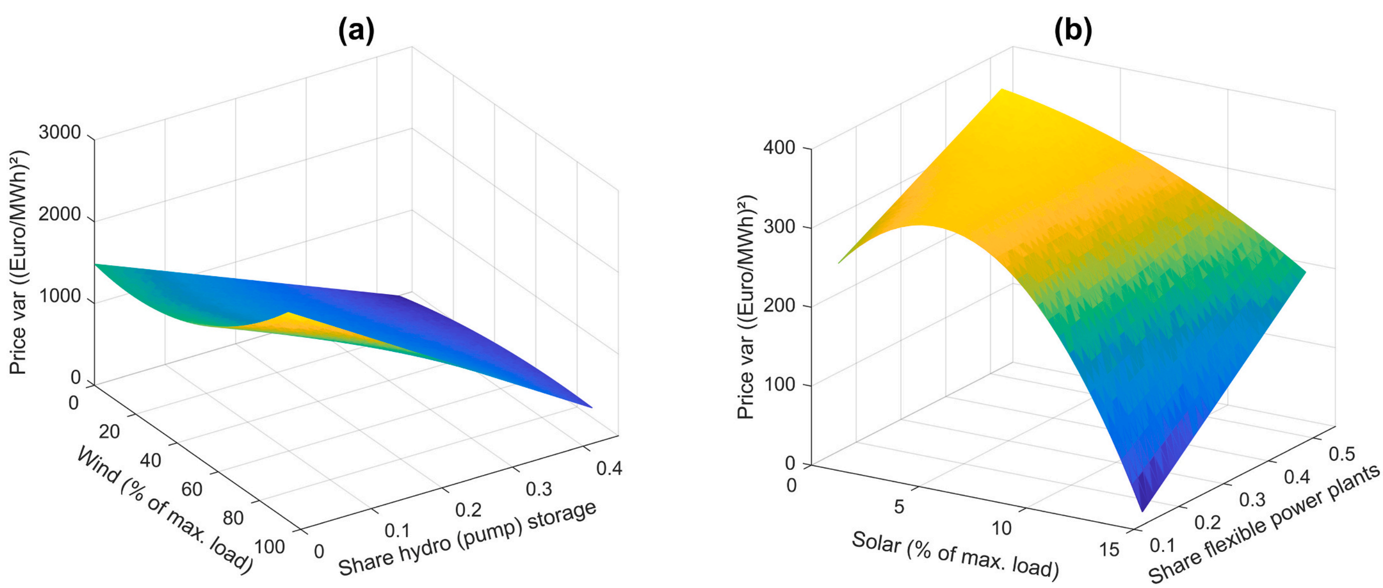

Fig. A.1. Impact of wind generation and hydro (pump) storage (Panel (a)) and solar generation and flexible power plants (oil and gas, Panel (b)) on electricity price variance based on fixed effects estimates. Wind and solar generation are depicted in % of maximal load. Hydro (pump) storage and flexible generation capacities are depicted as share of overall generation capacity.
Note: The unexpected positive effect of flexible power plants on the price variance (see Panel (b)) is caused by a statistical artifact: The insignificant coefficient of "Share oil gas * Load" has a magnitude of 40.10 (see Table A.6). In the first difference model, the respective coefficient is −3.97, and the figure shows a negative effect of flexible power plants on the price variance (see the figures included in the supplementary online material).

Appendix C. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.eneco.2022.106069.

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