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Do generation diversity and renewables mitigate price shocks? Empirical evidence from the 2022 European energy crisis

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HIGHLIGHTS

- We find no evidence that generation diversity moderated the 2022 price shocks.
- Pre-crisis self-sufficiency shows no robust association with price outcomes.
- Larger reservoir hydro shares are associated with lower average price increases.
- Higher VRE shares are linked to increased day-to-day variability but not price levels.
- Zonal supply-security metrics may overstate price resilience in interconnected markets.

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ABSTRACT

Generation diversity, renewable energy supply, and self-sufficiency are commonly cited hedges against supply disruptions and price risk in electricity markets, yet empirical validation of their effectiveness remains limited. The 2022 European energy crisis exposed electricity markets to severe price shocks driven by curtailed Russian gas imports. We use this natural experiment to test whether these factors mitigated the price shocks across 38 European bidding zones. Using robust linear regression models, we relate pre-crisis system characteristics (generation diversity, renewable integration, and self-sufficiency in electricity supply) to changes in average prices, extreme prices, and price variability. We find no evidence that greater generation diversity or self-sufficiency moderated price shocks during the crisis, challenging assumptions about their protective value. Larger reservoir hydro shares are the only robust predictor of smaller price increases, though we cannot fully separate the role of hydro reservoir's flexibility and low cost from that of the partial market isolation. Variable renewable energy shares do not systematically lower either average or extreme price changes, but are associated with larger increases in day-to-day price variability. Natural gas shares show a directionally positive but imprecise association with price outcomes. The results suggest that under market coupling and marginal pricing, crisis-driven shocks transmit across bidding zones, limiting the explanatory power of zonal supply security indicators. Accordingly, assessments of price resilience should place greater emphasis on regional market dependencies rather than zonal generation structure alone.

1. Introduction

In 2022, Europe experienced its most severe energy crisis in decades, drawing comparisons to the oil shocks of 1973 [1]. By August, electricity prices in the EU soared to a historic high of €700/MWh, largely driven by an exceptionally high natural gas price of €341/MWh [2,3]. The sharp rise in prices was driven by Russia's invasion of Ukraine and the resulting curtailment of gas imports, while widespread French nuclear outages amplified the pressure on electricity markets [4]. The crisis had repercussions across society, with rising energy prices significantly affecting consumers, especially low-income households. In Germany, for example, approximately 600,000 households were at risk of falling

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Bidding zone abbreviations

AT Austria
BE Belgium
BG Bulgaria
CH Switzerland
CZ Czech Republic
DE-LU Germany-Luxembourg
DK1, DK2 Denmark
EE Estonia
FI Finland
FR France
GR Greece
HU Hungary
HR Croatia
IE Ireland
IT-N Italy North
IT-CN Italy Central-North
IT-CS Italy Central-South
IT-S Italy South
IT-Sic Italy Sicily
IT-Sar Italy Sardinia
LT Lithuania
LV Latvia
NL Netherlands
NO1, NO2, NO3, NO4, NO5 Norway
PL Poland
RO Romania
RS Serbia
SE1, SE2, SE3, SE4 Sweden
SI Slovenia
SK Slovakia

below the poverty threshold [5]. Meanwhile, energy-intensive industries faced significant increases in production costs [6].

Diversification is widely recognized as a “no-regret” strategy for hedging against supply risks, as it enables the redirection of energy flows when normal supply routes are disrupted [7–9]. While the concept initially focused on the diversification of imported fuels, particularly oil [10], it has since evolved to encompass the broader energy supply, including diversity in technologies, suppliers, and infrastructure [11]. Numerous studies have applied diversity indicators such as the Shannon–Wiener Index and the Herfindahl-Hirschman Index to measure energy supply diversity as a component of energy security [12–14], and a small subset has tried to explore the relationship between diversification and electricity prices [15–17].

Alongside diversification, import dependence plays a key role in energy security assessments [9,15]. In electricity systems, structural reliance on imports is viewed as a vulnerability factor that can amplify exposure to external price shocks [16,18]. This concern is particularly relevant during synchronized regional crises, when cross-border supply relief is limited [16]. However, empirical evidence on how structural trade orientation affects price outcomes during such events remains limited [17].

A common view among experts is that lower energy prices are an important goal of energy security, and that greater diversification of energy sources, enhanced self-sufficiency, and increased deployment of renewable energy sources all contribute to achieving this goal [15]. Still, Molyneaux et al. [17] conducted an empirical analysis in this vein of U.S. states during the oil price shocks (1973–1982) and demand shock (2003–2012), and found that greater diversity and electricity trade orientation had no apparent effect on electricity prices.

The role of renewables is equally unresolved. Simon and Anadon [19], through simulating the future system, claimed that the European electricity system aligned with 2030 wind and solar deployment targets could reduce the impact of natural gas price shocks on electricity prices by up to 40% compared to the 2024 system. In contrast, Bajo-Buenestado et al. [20] empirically estimated that countries with larger shares of intermittent renewables are more vulnerable to price spikes during gas price shocks, possibly due to their reliance on complementary natural gas generation.

This study examines how pre-crisis system characteristics of 38 European bidding zones affected electricity price outcomes during the 2022 energy crisis. This analysis contributes to the relatively limited body of empirical research on the topic of energy security and price resilience, where it examines whether commonly used energy security indicators are informative for understanding the impact of supply shocks on price outcomes in liberalized electricity markets. Specifically, we test whether generation diversity, renewable integration, and trade orientation mitigated price shocks. Insights from this study could support the development of more robust indicators for assessing energy security in the power sector.

2. Method

We analyze 38 European bidding zones (BZs) to examine how pre-crisis system characteristics shaped wholesale electricity price outcomes during the 2022 energy crisis. We distinguish between two aspects of system structure: generation-related structure and electricity trade orientation. Trade orientation is measured by the Proportion Export-Import (PEI) index. The generation-related structure is captured using either diversity indices (Shannon–Wiener, Stirling) or generation shares (variable renewables, reservoir hydro, natural gas). We then assess how these indicators relate to observed electricity price changes during the crisis using statistical modeling. We consider three price outcome variables: the change in annual average price (ΔAverage Price), the change in the 95th percentile of average daily prices (ΔP95), and the change in the coefficient of variation of average daily prices (ΔCV). Combining three representations of generation structure with the three price outcome variables yields nine model specifications, as summarized in Table 1. Descriptive statistics for all variables are reported in the Supplementary Information (SI Section 5). Spain and Portugal are excluded due to the wholesale gas price cap implemented in June 2022, which materially altered price dynamics [21,22] (see SI Section 3 for policy details).

Table 1
Overview of model specifications.

Model ID	Dependent Variable	Independent Variables
Diversity (Shannon-Wiener)		
Model 1	Δ Average Price	SWI, PEI
Model 2	Δ P95	SWI, PEI
Model 3	Δ CV	SWI, PEI
Diversity (Stirling Index)		
Model 4	Δ Average Price	Stirling Index, PEI
Model 5	Δ P95	Stirling Index, PEI
Model 6	Δ CV	Stirling Index, PEI
Generation Shares		
Model 7	Δ Average Price	Share Reservoir Hydro, Share VRE, Share Gas, PEI
Model 8	Δ P95	Share Reservoir Hydro, Share VRE, Share Gas, PEI
Model 9	Δ CV	Share Reservoir Hydro, Share VRE, Share Gas, PEI

Notes: Models 1–9 are the main specifications. SWI = Shannon-Wiener Index; PEI = Proportion Export-Import.

2.1. Dependent variables

To evaluate the BZs' price performance, we use three complementary metrics that capture distinct dimensions of wholesale prices during the crisis (2022) relative to a pre-crisis benchmark (2017–2019):

1. ΔAverage Price (average price-level shift),
2. $\Delta P95$ (change in extreme prices; $P95$ is the 95th percentile of average daily prices),
3. ΔCV (change in within-year price variability; $CV = \sigma/\mu$, of average daily prices).

For all three metrics, smaller values indicate better price performance.

2.1.1. Change in annual average price (Δ*Average Price*)

The first price metric measures the change in average electricity prices, in absolute terms, from the pre-crisis baseline. Unlike other studies that focus solely on price levels [17,20,23], our approach adjusts for each BZ's average pre-crisis price, so that our metrics capture crisis-induced changes rather than general price differences between systems.

The price increase could also be measured as a percentage change. However, this measure is too sensitive to past performance, as historically cheap systems can have large percentage increases while the magnitude of the price change remains relatively small.

The average annual price increase for a given BZ is calculated as:

$$\Delta\text{Average Price} = \overline{P}_{2022} - \overline{P}_{2017\text{–}2019} \quad [\text{€/MWh}]$$

where:

- $\overline{P}_{2022}$ is the load-weighted average day-ahead wholesale electricity price in 2022.
- $\overline{P}_{2017\text{–}2019}$ is the load-weighted average day-ahead wholesale electricity price during the reference period.

Load-weighting ensures that prices are scaled by the corresponding electricity demand in each hour, so that periods with higher consumption contribute proportionally to the average price. The load-weighted average price in year y is defined as:

$$\overline{P}_y = \frac{\sum_{t\in y} p_t \cdot L_t}{\sum_{t\in y} L_t},$$

where p_t denotes the day-ahead price and L_t the system load in hour t.

Day-ahead wholesale electricity prices are sourced from ENTSO-E [24]. For countrywide BZs, we use the Ember database, which provides an ENTSO-E–based price series that is already harmonized (in euros and with quarter-hourly values resampled to hourly) [25]. For sub-national BZs, we use ENTSO-E day-ahead prices directly, as these are already available in euros at hourly resolution. All load time series are retrieved from ENTSO-E.

2.1.2. Change in the 95th percentile ($\Delta P95$)

To capture exposure to extreme price conditions, we measure the change in P95, the 95th percentile of the distribution of daily average prices within each year. A positive ΔP95 indicates that the daily price level exceeded on 5% of days has increased, i.e., a rightward shift in the upper tail of the price distribution. We use daily rather than hourly prices to focus on prolonged episodes of elevated prices. The sustained high-cost pressure on households can increase the risk of bill defaults [26], and electricity-intensive industries may be forced to curtail production [6]. We define the dependent variable as:

$$\Delta P95 = P95_{2022} - \overline{P95}_{2017\text{–}2019} \quad [\text{€/MWh}],$$

where:

- $P95_{2022}$ is the 95th percentile of the daily average price distribution in 2022.
- $\overline{P95}_{2017\text{–}2019}$ is the average yearly 95th percentile calculated separately for 2017, 2018, and 2019.

2.1.3. Change in coefficient of variation (ΔCV)

For measuring intra-annual price variability, we make two key methodological choices. First, we compute the variability from daily average prices. This filters out intra-daily swings that tend to average out at the annual level, while capturing the day-to-day unpredictability. This inability to predict day-to-day costs can impose economic costs on both households and firms. Higher market uncertainty is empirically linked to weaker business investment [27], and sector-specific models find that energy price uncertainty lowers output and capital expenditure [28]. Second, we normalize by the annual mean to ensure scale invariance, preventing higher absolute prices from inflating the measure. This mean-adjusted variability, known as the coefficient of variation (CV), better supports comparison across different systems. Let $p_{d,y}$ be the daily average day-ahead price on day d in year y, with mean μ_y and standard deviation σ_y. We use the following formula:

$$\Delta CV = CV_{2022} - \overline{CV}_{2017\text{–}2019} \quad [\text{unitless}],$$

where:

- $CV_y = \sigma_y/\mu_y$.
- $\overline{CV}_{2017\text{–}2019}$ is the average over the reference period.

2.2. Independent variables

The independent variables are designed to reflect the pre-crisis system characteristics of each BZ's electricity system. A summary of the independent variables and their expected interplay with the price outcomes is shown in Table 2.

2.2.1. Adjusted capacity mix

To represent an electricity system's supply side, a common starting point is to look at generation shares [29–31]. Yet, a BZ's generation mix

Table 2
Independent variables used in the statistical model and expected interplay with price.

Variable	Definition	Interplay with price			
		ΔPrice	ΔP_{95}	ΔCV	**Hypothesis**
SWI	Shannon–Wiener (Diversity) Index	–	–	–	Risk-spreading across generation sources
Stirling Index	Diversity Index	–	–	–	Risk-spreading across generation sources
PEI > 0	Pre-crisis trade orientation (net exporter)	–	–	–	Self-sufficient; reduced supply scarcity risk
PEI < 0	Pre-crisis trade orientation (net importer)	+	+	+	Import-dependent, increased supply shock-exposure
Share Reservoir Hydro	Share of dispatchable reservoir hydropower	–	–	–	Cheap, flexible; dampens price shocks
Share VRE	Share of variable renewables (wind–solar–run-of-river)	–	–	+	Fuel-free, domestic; intermittency raises variability
Share Gas	Share of natural gas	+	+	±	Gas-crisis; variability channel unclear
IC_{95}	Interconnection Capacity Index	±	±	±	No directional hypothesis

Notes: Signs indicate expected correlations with price changes. ΔAverage Price is the annual average price change; $\Delta P95$ is the change in the 95th percentile; ΔCV is the change in the coefficient of variation.

in 2022 was shaped by the unique conditions of the energy crisis, which makes it unsuitable for our purposes, as it is not an independent representation of the electricity system. An alternative approach would be to use installed capacities. However, raw installed capacities overstate the energy contribution of variable renewable energy technologies, because they typically operate well below their nameplate capacity [32].

To overcome these issues, we introduce the Adjusted Capacity Mix (ACM). The ACM scales installed capacities with historical CFs, providing a representative measure of the typical energy contribution of each technology. The ACM offers two key advantages: (i) it incorporates capacity additions up to the onset of the crisis, ensuring the metric reflects the system as it stood in 2022; (ii) it constructs a representative, structural generation profile based on historical, pre-crisis utilization rates. This represents the structural generation configuration for each system, which isolates it from any specific operational strategies or policies implemented during the crisis.

To calculate the ACM, we scale the installed capacities of each BZ by the country-specific CF for each technology, representing average utilization under pre-crisis operating conditions:

$$\mathrm{ACM}_{bz,i} = \mathrm{Cap}_{bz,i} \times \mathrm{CF}_{c,i},$$

where $\mathrm{Cap}_{bz,i}$ is the installed capacity of technology i in zone bz, and $\mathrm{CF}_{c,i}$ is its historical, country-specific CF. The adjusted generation share of technology i in zone bz is then defined as:

$$\hat{s}^{\mathrm{ACM}}_{bz,i} = \frac{\mathrm{ACM}_{bz,i}}{\sum_j \mathrm{ACM}_{bz,j}}.$$

For solar and wind, we use a 5-year average (2017–2021) capacity-weighted CFs from IRENA [33] to smooth out interannual weather variability. For the remaining generation types, we rely on 2019 data from ENTSO-E [24], as 2019 provides the most recent "normal" year prior to the disruptions of the COVID-19 pandemic and the 2022 energy crisis. We apply multi-year averaging only to solar and wind, since reliable CF data are available across multiple years, whereas ENTSO-E data are less complete over the time span. The concept of ACM is illustrated through the example of Poland in Fig. 1, which shows the difference between ACM, installed capacity, and realized generation in 2022.

2.2.2. Shannon-wiener index (SWI)

Diversification of energy supply is often emphasized as a lever for mitigating supply risks [7,9,34]. Furthermore, it is frequently framed as a potential hedge against price risk amid volatile energy prices [35,36]. We therefore hypothesize that greater generation diversity supports price performance across all price outcomes. Diversity is typically assessed through indices that account for the variety (number of distinct generation sources) and balance (evenness of their contributions) [8,11]. The Shannon–Wiener Index (SWI), a diversity measure commonly used in energy policy and energy system analysis [11,37,38], captures these two dimensions and is defined as:

Table 3
Generation categories used in the analysis.

Generation types		
Fossil Brown coal (lignite)	Reservoir Hydropower	Biomass
Fossil Hard Coal	Run-of-river and Pondage	Waste
Fossil Gas	Onshore Wind	Geothermal
Oil	Offshore Wind	Marine
Fossil Peat	Solar	Other Renewables
Nuclear		Other

$$SWI = -\sum_{i=1}^{N} p_i \ln(p_i),$$

where p_i denotes the ACM share of technology i. A higher SWI reflects a more diverse energy portfolio in terms of variety and balance. Table 3 shows all generation technologies included in our study. While the technologies are granular enough to capture differences in fuel inputs across generation types, we do not examine diversity of fuel sources themselves for a specific generation type, such as import routes or supplier concentration. Instead, the analysis focuses on diversity within the electricity generation portfolio.

2.2.3. Stirling index

The SWI assumes that all energy sources are equally dissimilar in qualitative characteristics. For example, it treats gas and coal as just as distinct as coal and wind, despite wind being non-dispatchable, and having a near-zero marginal cost, whereas oil and gas are fuel-driven and dispatchable. To address this shortcoming, Stirling [34,39] introduces a third dimension of diversity: *disparity*. Disparity refers to the degree of qualitative dissimilarity between energy sources. This approach allows the index to capture not only the number of sources and their even distribution, but also reflects how functionally different they are from one another. For example, a portfolio consisting of equal parts coal and gas would yield lower disparity than one combining coal and wind, as the former shares similar thermal and operational characteristics.

The general form of the Stirling Index is:

$$\text{Stirling Index} = \sum_{i=1}^{N}\sum_{j=1}^{N} p_i p_j d_{ij},$$

where p_i and p_j denote the ACM share of technology i and j, and d_{ij} denotes the dissimilarity between them. We use two characteristics of the generation sources to assess system diversity: fuel cost (C) and dispatchability (D). The dissimilarity coefficient d_{ij} is calculated as the Euclidean distance between normalized attribute values:

$$d_{ij} = \sqrt{(D_i - D_j)^2 + (C_i - C_j)^2}.$$

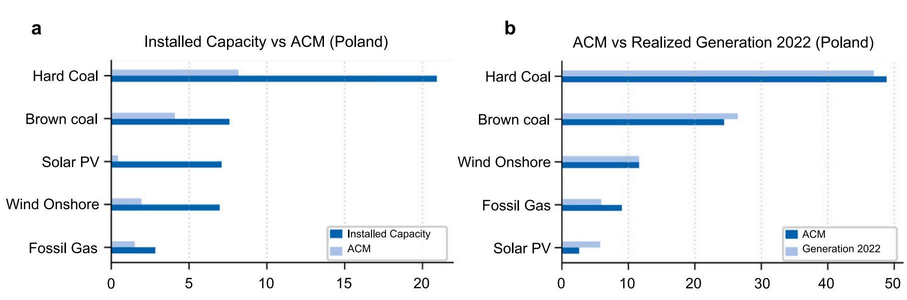

Fig. 1. Poland technology mix compared using: (a) installed capacity vs. ACM in absolute terms, only technologies with ≥ 2% of total installed capacity are included; (b) ACM vs. realized generation in 2022, only technologies contributing ≥ 2% of 2022 generation are included.

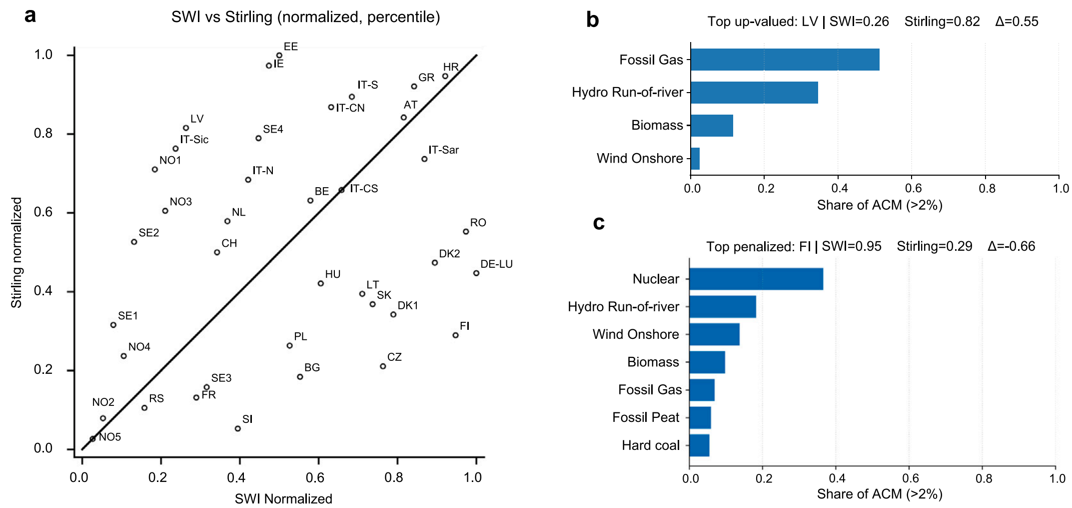

Fig. 2. Shannon–Wiener Index (SWI) vs. Stirling (percentile-normalized). (a) Scatter of BZs using percentile-normalized SWI (x) and Stirling (y), with a 1:1 line marking agreement. Points above the diagonal are up-valued by Stirling relative to SWI, and points below are down-valued. (b) Generation-mix (ACM shares) for the most up-valued zone (Latvia), and (c) the most down-valued zone (Finland), alongside their normalized SWI and Stirling values.

We select fuel cost and dispatchability as disparity attributes, since they are important differentiators between generation technologies in terms of their operational roles. Fuel costs are an important factor when determining dispatch order in competitive markets, Cludius et al. [40], and dispatchability reflects a technology's ability to provide power on demand and support system flexibility [41,42]. Fig. 2 compares the percentile-normalized Stirling and SWI indices across all BZs, illustrating how the two measures differ in how they value diversity.

2.2.4. Proportion of export-import (PEI)

Import dependence and self-sufficiency are widely recognized metrics for assessing supply security and resilience in energy systems [9,15]. We apply this logic to the electricity sector, using the proportion export-import (PEI) index, which quantifies the degree to which a BZ was import-dependent or export-oriented prior to the crisis. This formulation, adapted from Molyneaux [17], divides the net electricity trade balance by either consumption (for importers) or generation (for exporters). Using net trade values excludes electricity that merely transits through a BZ, and the different denominators ensure that the index ranges from -1 (all consumption is imported) to $+1$ (all generation is exported).

We hypothesize that a BZ's pre-crisis trade orientation is linked to crisis-period price outcomes. More import-dependent zones (PEI closer to –1) might operate with a structural generation deficit and rely on external supply to meet demand. During a regional supply crisis, this reliance exposes them to high-priced imports, making them more vulnerable to price shocks. By contrast, net-exporting zones (PEI closer to $+1$) tend to be self-sufficient in generation capacity, and will therefore face a lower risk of supply scarcity, which provides a buffer against scarcity-driven price spikes. The PEI is defined as:

$$PEI = \begin{cases} -\dfrac{\mathit{Net\ Import}}{\mathit{Total\ Consumption}}, & \text{if } \mathit{Net\ Import} > 0 \quad \text{(net importer)}, \\ \dfrac{\mathit{Net\ Export}}{\mathit{Total\ Generation}}, & \text{if } \mathit{Net\ Export} > 0 \quad \text{(net exporter)}, \\ 0, & \text{if Exports} = \text{Imports} \end{cases}$$

The PEI is calculated for all BZs from 2017 to 2019 using data from ENTSO-E [24] and the European Commission's Eurostat electricity statistics [43]. For countrywide BZs, we use reported net trade data from Eurostat. For sub-national BZs, we construct annual net trade as the difference between gross generation and load, with data from ENTSO-E [24].

2.2.5. Share of adjusted capacity mix: variable renewable energy, reservoir hydro, gas

In the final set of model specifications (Models 7–9, Table 1), we replace the composite diversity indices with selected ACM components (VRE, reservoir hydro, and gas). This approach provides a more direct link from specific generation types to price performance than composite indices such as the SWI, enabling us to isolate their distinct impacts. We include VRE as its intermittency can raise short-term price variability [42], while domestic, fuel-free VRE generation is often regarded as a hedge against fuel price shocks and supply disruptions [19,30,44]. Reservoir hydropower combines low operating costs with storage-backed dispatchability, supplying intertemporal flexibility that can dampen price spikes and support price stability [41]. Natural gas is included because it frequently sets the marginal price in European wholesale markets, exceeding 80% of hours in 2021 in several countries, and the surge in gas prices was a principal driver of wholesale electricity prices in 2022 [45].

2.2.6. Interconnection capacity index (IC_{95})

The indicators introduced so far characterize each BZ's internal supply structure (generation diversity, self-sufficiency and generation shares). Neither captures the physical trade capacity of the BZs, which determines the extent to which a zone can engage in bilateral trade (large bilateral trade volumes can average to zero in PEI). We therefore introduce an interconnection-capacity indicator (IC_{95}) as a complementary, infrastructure-based metric. Whereas PEI reflects the net trade balance in the pre-crisis years, IC_{95} reflects how much cross-border exchange capacity is available relative to zonal demand. We approximate the effective transmission capacity of each cross-border corridor as the 95th percentile of observed hourly physical flows, and normalize the sum of these corridor capacities by mean annual load:

$$\mathrm{IC}_{95,i} = \frac{\sum_{j \in N_i} \max\big(P_{95}(f_{ij}),\ P_{95}(f_{ji})\big)}{\bar{L}_i},$$

where N_i is the set of BZs directly adjacent to i, $P_{95}(f_{ij})$ is the 95th percentile of hourly physical flows from i to j, and $\bar{L}_i$ is mean annual load. This flow-based proxy is adapted from Stiewe et al. [46] and reflects that transmission capacity is not a fixed technical parameter, but varies over time according to operational and physical constraints. The use of the 95th percentile provides a measure of effective transmission capacity while reducing the influence of rare high flow events. Hourly trade flow data for 2021 are obtained from ENTSO-E [24].

To test whether cross-border exchange capacity modifies our results, we re-estimate Models 1–9 with IC_{95} added as an additional regressor, reporting these specifications in Table 6. We treat this as a separate analysis, as IC_{95} is partly distinct from the energy security indicators previously defined, being derived from literature on price formation under market integration [46], and because adding a fifth regressor to Models 7–9 approaches the degrees-of-freedom limits at $N = 38$. Higher IC_{95} can in principle work in either direction – greater capacity to import cheap electricity can displace more expensive zonal generation types, or increase exposure to imported price shocks – so we do not impose a directional hypothesis.

2.2.7. Changes in load and gas price

We explore the potential impact of demand and fuel-related drivers to assess whether observed differences in electricity price performance might be explained by variations in consumption patterns or gas prices. Indicators are created for gas prices (2020–2022) and load changes (2019–2022). Each indicator is matched to the price metric used in the specific regression. For example, if the specification targets average price change, we assess the corresponding change in load and gas price. Spot price data for gas are sourced from the European Energy Exchange [47]. Day-ahead load data are sourced from ENTSO-E [24]. BZs without a gas hub are assigned values from their nearest trading hub, based on regional groupings in the 2022 European Gas Hub map [48].

However, we observe limited cross-sectional variability, particularly regarding gas prices (see Table S3). Consequently, given the limited sample size ($N = 38$), we exclude gas and load indicators from the primary model specifications to mitigate the risk of overfitting. Estimates including the gas and load variables are reported in Table S8, where we find that their inclusion does not substantially alter the main results.

2.3. Statistical analysis

To quantify the effects of independent variables on the three price metrics, we estimate robust linear models (RLM) for all BZs, employing Tukey's biweight to downweight observations with large residuals, thereby reducing the influence of potential outliers [49,50]. Standard errors are computed using a finite-sample corrected covariance estimator [50]. This correction (denoted as 'H3' in the *statsmodels* library) supports inference given our limited sample size ($N = 38$). To evaluate model performance, we calculate a weighted pseudo coefficient of determination (R_w^2). This metric incorporates the robust weights assigned by the robust estimator and provides a measure of fit that focuses on the core data distribution while discounting outliers.

Separate regressions are run for each price metric to capture distinct mechanisms driving price levels, extremes, and variability. Because we evaluate multiple model specifications, we interpret results based on consistency of sign and magnitude across related models, rather than relying on individual p-values. We assess multicollinearity using variance inflation factors (VIF) reported in Tables S5 and S6, where diagnostic values indicate acceptable levels across model specifications. Modeling and diagnostics are performed in Python using scikit-learn for pre-processing and statsmodels for estimation, significance testing, and confidence interval computation with H3 adjustments [51,52]. Finally, given the cross-sectional nature of the models, the estimated coefficients should be interpreted as conditional associations rather than causal effects.

2.4. Sensitivity analysis: leave-one-out & omitted variables

A concern is whether our results are sensitive to inclusion of specific zones or regional clusters. Systematic regional exclusion, e.g., the Nordic zones dominated by hydropower, would reduce our sample to $N = 32$ or fewer and substantially compress the variation in our key explanatory variables. For reservoir hydropower share in particular, removing the Nordic zones removes most of the upper range of the variable's distribution, making the coefficient unidentified rather than testing whether the effect is robust.

We therefore adopt a leave-one-out (LOO) sensitivity analysis as the primary diagnostic for identifying unstable estimates and data points with disproportionate influence. For each main specification, we re-estimate the model 38 times, dropping one zone at each iteration, and report the resulting distribution of coefficient estimates for the independent variables (SI Section 4.6). This provides an assessment of how sensitive the results are to the exclusion of any single zone while preserving the degrees of freedom needed for stable estimation. The LOO approach is well-suited to small samples [53] and provides more interpretable diagnostic information than full exclusions of different regions.

Similarly, our small sample size limits the number of predictors that can be included before too many degrees of freedom are lost. We therefore test variables that could plausibly introduce omitted variable bias by adding them one at a time to our main models. We define and evaluate reserve margin, storage capacity ratio, and disaggregate VRE into wind and solar shares (SI Section 4.5). As a final temporal robustness check, we test whether our results are sensitive to the choice of reference period and target year. First, we extend the baseline period from 2017 to 2019 to 2016–2019 and re-estimate Models 1–9 (Table S15). Second, we repeat the analysis using an additional dependent variable for the target year 2023 while retaining the original baseline period (Table S16). Since 2023 retained elevated, though lower, gas prices relative to the pre-crisis period [2], this provides a second observation point to test whether the patterns identified in 2022 are specific to that single crisis year or hold under related, but partially stabilized, conditions.

3. Results

3.1. Spatial patterns

We first examine spatial patterns of key variables. Mapping the variables allows us to identify regional clusters and preliminary correlations between system characteristics and price outcomes, providing context for the regression analysis that follows. Fig. 3 illustrates the spatial distribution of the SWI (Panel a), reservoir hydro shares (Panel b), and annual average price increases (Panel c), and Fig. 4 displays the spatial distributions of trade orientation (PEI), VRE, and natural gas shares. The spatial distributions for all variables are provided in Figure S2.

Fig. 3(c) shows a north–south gradient in the magnitude of price increases. The most severe price shocks are observed in Southern Europe, peaking in Italy, with the intensity diminishing northward toward the Nordic region. Comparing this price gradient with Fig. 3(a) reveals a counter-intuitive overlap: regions with the lowest generation diversity (SE1, SE2, NO3, NO4) coincide with the lowest average price increases. Fig. 3(b) provides a plausible explanation for the price-diversity pattern, showing an overlap between zones with low diversity, high shares of reservoir hydro, and the lowest price increases.

Fig. 4(a) (PEI) shows no distinct continent-wide pattern, though localized trends are visible, such as a north-to-south export gradient in the Nordics and a south-to-north export flow in Italy. VRE shares, in Fig. 4(b), exhibit a scattered distribution across the continent rather than a clear geographic cluster.

Gas intensity, in Fig. 4(c), is most pronounced in Italy, while the rest of the continent is largely characterized by shares below 20%. Comparing the gas shares with the change in average price (Fig. 3(c)) reveals that zones with low domestic gas dependence, such as Switzerland (CH), experienced price shocks comparable to their gas-intensive neighbors like Italy. This indicates that gas-induced price shocks likely spread through cross-border trade.

3.2. Robust linear models

The results of the RLMs are reported in Table 4.

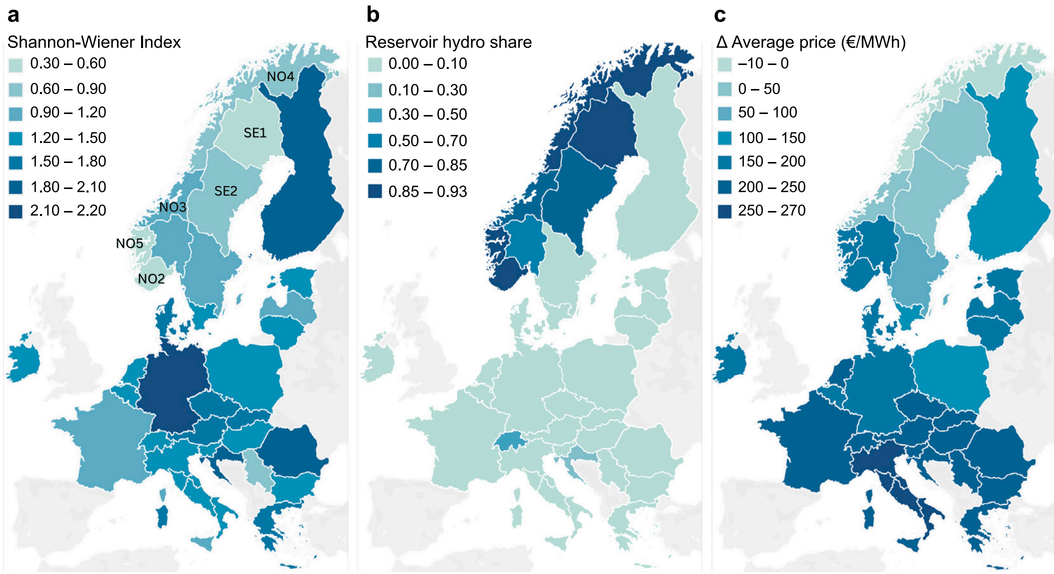

Fig. 3. Spatial distribution of key variables overlaid on a map of Europe. (a) generation diversity (Shannon-Wiener Index), (b) share of reservoir hydro, and (c) change in annual average electricity price (€/MWh).

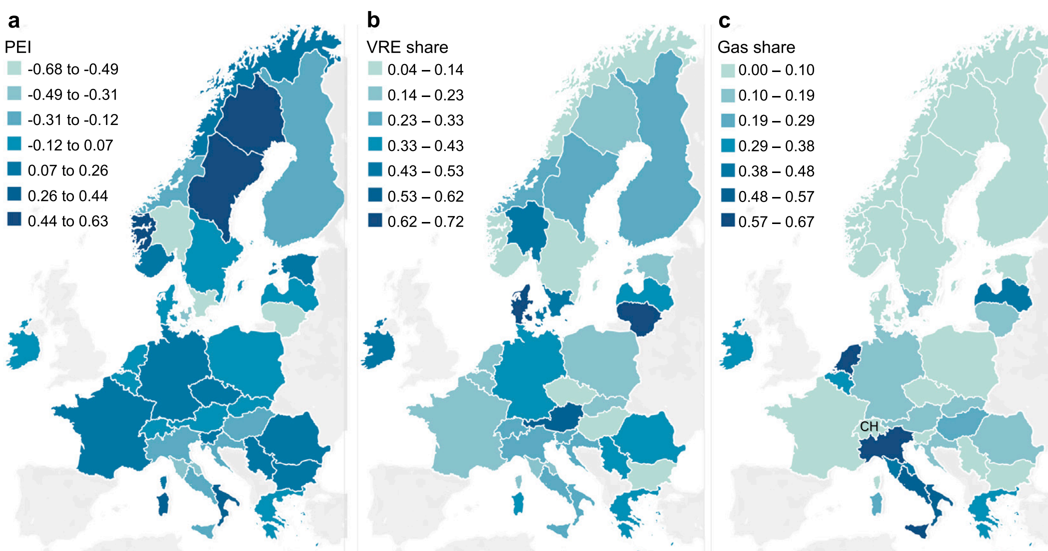

Fig. 4. Spatial distribution of system characteristics overlaid on a map of Europe. (a) Pre-crisis trade orientation (PEI), (b) share of variable renewable energy (VRE), and (c) share of natural gas generation.

Greater generation diversity (SWI) is significantly associated with larger average price increases (Model 1, $p = 0.045$). This aligns with the visual patterns in Fig. 3 and suggests that more diverse generation portfolios did not provide protection against the 2022 price shocks. Moreover, when the Stirling Index is used in Model 4, the association between diversity and average price increases loses significance. Additionally, neither diversity index significantly predicts changes in extreme prices (Models 2 and 5) or price variability (Models 3 and 6), with fit statistics for these models indicating negligible predictive value. Overall, Models 1–6 demonstrate that the diversity-based specifications have modest to low predictive power ($R^2_w = 0.05$–0.18) across all three price outcomes, with the SWI–ΔAverage Price coefficient as the only statistically significant association.

Models 7–9 provide a different angle by explicitly accounting for specific generation types. Model 7 achieves the highest explanatory power among the main specifications ($R^2_w = 0.48$). Here, we observe that larger reservoir hydro shares are significantly correlated with smaller increases in average electricity prices ($p = 0.012$). The estimated effect is notable: a one-percentage-point increase in a BZ's reservoir hydro share is associated with a 1.29 €/MWh smaller increase in its average annual price. This confirms Fig. 3's spatial patterns, which show that reservoir-hydro-dominated zones in the northern Nordics (SE1, SE2, NO3, NO4) experienced modest price increases. The dominance of a single generation type also leads to low diversity in these regions. This suggests that reservoir hydro may confound the SWI-price relationship, in which low diversity appears to be correlated with lower price increases, which we test below in Section 3.2.1. Neither VRE nor natural gas shares show a robust association with the average or extreme price outcomes. However, the gas share coefficient in Model 7 ($\beta = +99$, $p = 0.058$) is only marginally insignificant, with a large positive estimate.

Table 4
Robust linear model estimates for price outcomes (Models 1–9).

	Δ Average Price			Δ P95			Δ CV		
Variable	Coef	SE	P-val	Coef	SE	P-val	Coef	SE	P-val
	Model 1			**Model 2**			**Model 3**		
SWI	60.72	30.28	**0.045**	30.39	29.31	0.300	−0.09	0.06	0.129
PEI	−14.71	42.51	0.729	−33.26	48.53	0.493	−0.15	0.08	0.063
R^2_w	(0.18)			(0.08)			(0.16)		
	Model 4			**Model 5**			**Model 6**		
Stirling Index	96.25	82.78	0.245	−2.69	94.44	0.977	−0.26	0.19	0.169
PEI	−13.40	56.10	0.811	−51.88	55.95	0.354	−0.17	0.09	0.065
R^2_w	(0.06)			(0.05)			(0.15)		
	Model 7			**Model 8**			**Model 9**		
Share Reservoir Hydro	−129.40	51.21	**0.012**	−122.05	110.10	0.268	0.22	0.09	**0.022**
Share VRE	−37.90	63.97	0.554	−21.83	82.65	0.792	0.24	0.10	**0.024**
Share Gas	99.25	52.27	0.058	76.62	64.38	0.234	−0.03	0.09	0.781
PEI	−2.03	37.43	0.957	−26.69	46.86	0.569	−0.09	0.08	0.216
R^2_w	(0.48)			(0.31)			(0.37)		
Observations per model = 38									

Notes: Estimates from robust linear models (Tukey's biweight) with finite-sample corrected standard errors. Bold indicates $p < 0.05$. SWI = Shannon-Wiener Index; PEI = Proportion Export-Import; VRE = Variable Renewable Energy. R^2_w denotes the weighted pseudo coefficient of determination.

Table 5
Reservoir hydro as a confounding factor (Model 10).

	Δ Average Price		
Variable	Coef	SE	P-val
	Model 10		
Share Reservoir Hydro	−155.34	65.04	**0.017**
SWI	2.06	34.91	0.953
PEI	−0.21	37.90	0.996
R^2_w	(0.42)		

Notes: Estimates from a robust linear model (Tukey's biweight) with finite-sample corrected standard errors. Bold indicates $p < 0.05$. SWI = Shannon-Wiener Index; PEI = Proportion Export-Import. Observations N = 38. R^2_w denotes the weighted pseudo coefficient of determination.

Both higher VRE shares ($p = 0.024$) and higher reservoir hydro shares ($p = 0.022$) were significantly linked to greater increases in price variability in Model 9 ($R^2_w = 0.37$). Finally, across all models (1-9), a BZ's pre-crisis trade orientation (PEI) showed no significant effect on any of the price metrics.

3.2.1. *The confounding effect of reservoir hydro*

Both the SWI and reservoir hydro are associated with changes in average prices. To test whether the SWI effect persists once reservoir hydro shares are accounted for, we extend Model 1 with share reservoir hydro (Table 5). In this specification, the explanatory power increases substantially, with the R^2_w rising from 0.18 to 0.42, and the relationships shift drastically: the SWI coefficient drops to near-zero and loses its statistical significance ($p = 0.953$), while the reservoir hydro remains significant ($p = 0.017$). This suggests that reservoir hydro acts as a confounder in the SWI–price relationship. We conduct additional tests to assess whether controlling for nuclear or coal shares affects the SWI estimate, but find no evidence of confounding (Table S17).

3.3. *Interconnection capacity as a complementary predictor*

The diversity, trade-orientation, and generation-share indicators in Models 1–9 all characterize zonal supply structure. To account for bilateral trade potential, we re-estimate Models 1–9 with IC_{95} added as an additional regressor (Table 6).

In the diversity-index-based Models 1c–6c, IC_{95} is negatively and significantly associated with both ΔAverage Price (Model 1c; Model 4c) and ΔP95 (Model 2c; Model 5c), and positively associated with ΔCV in Model 3c. Adding IC_{95} substantially improves model fit, with R^2_w rising from 0.18 to 0.42 in Model 1c and from 0.06 to 0.44 in Model 4c. Notably, the previously significant SWI–ΔAverage Price association (Model 1c) loses significance once IC_{95} is included.

In Models 7c, IC_{95} and reservoir hydro share attenuate each other, rendering neither variable statistically significant. Only in Model 9c (ΔCV) do both variables remain individually significant. In our sample, the zones with the largest reservoir hydro shares are largely the same zones with the highest IC_{95} values, which limits the joint specification's ability to partition the effect between the two. A shift is noted for the gas-share coefficient in Model 7c that is now marginally significant ($p = 0.049$) with the point estimate essentially unchanged.

Taken together, IC95 adds explanatory power in the diversity-based specifications, but its effect cannot be cleanly separated from reservoir hydro share in our cross-sectional sample due to moderate collinearity and their shared geographic concentration. The Pearson correlation between IC95 and reservoir hydro share is approximately $r = 0.4$, reflecting how the northern Nordic bidding zones combine both high reservoir-hydro shares and high interconnection capacity values, though variance inflation factors remain below conventional thresholds across all specifications (Tables S6–S7). The leave-one-out analysis (Section 3.4) indicates that reservoir hydro carries the primary explanatory signal, while IC_{95} partly acts as a proxy when reservoir hydro is omitted.

3.4. *Leave-one-out analysis*

We assess sensitivity to individual zones by re-estimating each specification 38 times, excluding one zone in each iteration. For each coefficient, we report the share of iterations that preserve the sign of the full-sample coefficient estimate (Sign%) and the zone whose exclusion produces the largest change in the estimate. Results for Models 1–10 are reported in Table S12, and the corresponding IC_{95} specifications in Table S13.

Every coefficient that is significant in the full sample retains its sign in all 38 iterations. The reservoir hydropower coefficient is most strongly influenced by the northern Nordic bidding zones, particularly NO5 in Model 7 and SE2 in Model 10. SE2 also accounts for most of the variation in IC_{95} across the diversity specifications. Coefficient magnitudes vary more substantially in Models 7c–9c, where both reservoir hydropower

Table 6
Robust linear model estimates for price outcomes including interconnection capacity index (Models 1c–9c, complementary specification).

Variable	Δ Average Price			Δ P95			Δ CV		
	Coef	SE	P-val	Coef	SE	P-val	Coef	SE	P-val
	Model 1c			**Model 2c**			**Model 3c**		
SWI	24.38	23.46	0.299	11.93	27.45	0.664	−0.05	0.06	0.439
PEI	−13.71	28.65	0.632	−42.49	34.42	0.217	−0.04	0.09	0.678
IC_{95}	−26.93	7.79	**0.001**	−27.64	10.67	**0.010**	0.12	0.04	**0.001**
R^2_w	(0.42)			(0.33)			(0.58)		
	Model 4c			**Model 5c**			**Model 6c**		
Stirling Index	109.22	74.67	0.144	17.46	90.32	0.847	−0.25	0.18	0.168
PEI	−2.19	30.39	0.943	−43.62	37.11	0.240	−0.06	0.09	0.488
IC_{95}	−31.74	7.66	**0.000**	−29.40	10.08	**0.004**	0.13	0.04	**0.000**
R^2_w	(0.44)			(0.33)			(0.58)		
	Model 7c			**Model 8c**			**Model 9c**		
Share Reservoir Hydro	−87.39	82.91	0.292	−86.24	119.74	0.471	0.18	0.08	**0.019**
Share VRE	−20.05	57.78	0.729	−1.54	78.71	0.984	0.20	0.07	**0.005**
Share Gas	93.41	47.50	**0.049**	74.09	61.92	0.232	0.01	0.07	0.844
PEI	3.19	34.45	0.926	−19.99	43.77	0.648	−0.07	0.06	0.247
IC_{95}	−14.88	12.52	0.235	−14.41	18.72	0.442	0.06	0.02	**0.005**
R^2_w	(0.50)			(0.33)			(0.64)		
Observations per model = 38									

Notes: Estimates from robust linear models (Tukey's biweight) with finite-sample corrected standard errors. Bold indicates $p < 0.05$. SWI = Shannon-Wiener Index; PEI = Proportion Export-Import; VRE = Variable Renewable Energy; IC_{95} = Interconnection Capacity Index. R^2_w denotes the weighted pseudo coefficient of determination.

share and IC_{95} are included. Although both coefficients retain their sign throughout the leave-one-out analysis, their ranges widen considerably. This pattern reflects the identification issue discussed in Section 3.3, as the highest values of both variables are concentrated in the same Nordic zones. Because SE2 emerges as a disproportionately influential zone, we re-estimate the specifications with SE2 excluded (Table S14). Reservoir hydro remains statistically significant in the baseline specification, whereas the IC_{95} coefficient in the ΔAverage Price and ΔP95 specifications becomes insignificant and decreases by roughly half in magnitude. This further supports the interpretation that reservoir hydro carries the primary explanatory signal, while IC_{95} partly acts as a proxy when reservoir hydro is not explicitly included.

Variables that are not statistically significant in the full sample, including PEI and the Stirling Index, frequently change their coefficient estimate signs across iterations. This behavior is consistent with effects that are indistinguishable from zero rather than being driven by specific zones.

3.5. Temporal robustness & omitted variables

Re-estimating all main specifications against an extended 2016–2019 baseline yields coefficient signs, magnitudes, and significance levels broadly consistent with the 2017–2019 results (Table S15). Reservoir hydro share remains the only robust predictor of lower average price increases, and the diversity indices remain weak predictors across all three outcome metrics.

Extending the analysis to 2023, the same broad pattern persists. Reservoir hydro share is associated with smaller price increases, and VRE share retains its positive association with ΔCV (Table S16). The diversity indices attain conventional significance for several 2023 outcomes; however, all but one of these estimates carry a positive sign, thus associating greater diversity with larger, not lower, price increases. We refrain from interpreting the 2023 estimates further given the absence of a pre-registered hypothesis, but the stable reservoir-hydro and VRE coefficients, together with the unchanged diversity signs, indicate that the structural patterns identified for 2022 are not specific to that single crisis year.

We also test variables that could plausibly introduce omitted variable bias. Adding reserve margin or storage capacity leaves the main results essentially unchanged, and neither variable is itself statistically significant in any specification (Tables S9–S10). Finally, we re-estimate Models 7–9 with VRE disaggregated into separate wind and solar shares (Table S11). In our sample, solar capacity is concentrated in the high priced southern zones and wind in the more moderately affected northern zones (Figure S5), so both shares overlap with the north–south gradient of the price shock itself (Fig. 3). The wind and solar coefficients are therefore not cleanly separable from zonal location in this setting. The solar coefficient illustrates this point. It is large and positive (Model 7S, $\beta \approx +568$), which is implausible for a near-zero-marginal-cost technology and better interpreted as solar share capturing southern location effects. The same geographic gradient appears in wind with the opposite sign, so the negative and significant wind coefficient (Model 7W, $\beta \approx -32$) cannot be reliably separated from its concentration in northern zones. We therefore decline to interpret either coefficient as a technology effect and retain the aggregated VRE share.

4. Discussion

Diversity and price performance

By analyzing the price performance of 38 bidding zones (BZs) across Europe, we find no evidence that greater diversity in the generation mix mitigated the electricity price shocks of 2022. Studies using composite energy security indicators typically link diverse generation portfolios to lower market and operational risks [54] and lower overall energy risk scores [55]. Similarly, conceptual studies often frame diversity as a hedge against supply risks under uncertain future conditions [7,34,56]. In our setting, however, we find no evidence that these suggested benefits carry over to favorable price outcomes. Prior empirical evidence points in the same direction. Molyneaux et al. [17] found a positive association between diversity and U.S. state electricity prices from 2003 to 2012, which disappeared once fuel shares were accounted for. While Molyneaux et al. studied price levels over a decade, and we focus on a single acute event in 2022, both results indicate that generation-mix diversity is, at best, a null factor for electricity price outcomes.

Why does diversity appear not to mitigate the price shocks?

Two mechanisms of the European electricity market explain this result. First, cross-border trade drives regional price convergence [57]. When transmission is congested, trade tends to narrow price differentials, and during unconstrained hours, connected BZs effectively merge into a single price area, aligning prices regardless of supply differences. Second, marginal pricing anchors the wholesale price to the cost of the most expensive unit needed to meet demand [58]. In 2022, this marginal unit was predominantly natural gas, which set the price in 55% of hours despite contributing only 19% of generation [57].

Consequently, for a diverse portfolio to lower a BZ's prices during a gas crisis, two conditions must be met: (1) the low-cost portfolio must be capable of displacing any zonal gas-fired unit from the margin, and (2) generate a low-cost surplus sufficient to saturate interconnectors (causing congestion and price separation), or generate sufficient low-cost surplus to displace all the gas-fired units in the neighboring regions when it is not congested. Our results show that diverse systems did not systematically outperform less diverse ones on any measured price outcome, consistent with the interpretation that these conditions were not systematically met.

The role of import dependence

If generation diversity failed to shield markets from price shocks, how about trade-orientation? We hypothesized that net importers would be more exposed, while net exporters would be shielded by their structural surplus. Our results, however, show no systematic relationship between pre-crisis trade orientation and price outcomes. This illustrates a dual dynamic of the European interconnected market. While interconnection supports resource adequacy for deficit zones, it creates a channel for price contagion, causing both surplus and deficit zones to converge toward the same price [57]. For example, Lithuania consistently imports over 60% of its demand, and Norway's NO5 exports over 40%, yet both experienced price increases near the sample mean (see Fig. 3(c); Fig. 4(a)). Molyneaux et al. [17] similarly found no systematic relationship between trade orientation and average electricity prices during the U.S. demand shock of 2003–2012. While their setting features heterogeneous state-level market rules, and we study BZs under more uniform market conditions, the message remains consistent: trade orientation does not explain price outcomes under system-stress conditions.

Finally, transmission capacity was largely intact during the crisis, meaning cross-border flows could still provide relief and likely prevented the most extreme domestic scarcity outcomes in deficit zones. Results from Models 1c–9c further indicate that interconnection capacity (IC_{95}) shows a stronger association with price outcomes than PEI. This suggests that, during the crisis, the scale of bilateral market coupling may have been more consequential than the net direction of electricity trade itself.

Reservoir hydro and interconnection capacity

Larger reservoir hydro shares are robustly associated with smaller average price increases, holding in both Model 7 and the extended Model 10 (Table 4; Table 5). One interpretation is that the intertemporal flexibility of reservoir hydro can reduce exposure to high prices by enabling low-cost energy to be shifted across time, in line with our original hypothesis. At the same time, the leave-one-out analysis and the spatial patterns in Fig. 3 suggest the effect is primarily driven by the northern Nordic zones. These zones are distinct because they combine large reservoir hydro shares with limited interconnection to continental markets. Moving them into a Switzerland-type setting, with strong coupling to gas-exposed neighbors, would likely have produced substantially higher price outcomes despite the same underlying generation mix. To illustrate, despite having among the largest reservoir-hydro shares in our sample, the southern Norwegian BZs (NO2 and NO5) saw annual average price increases more comparable to those in continental Europe (Fig. 3).

As identified in the leave-one-out analysis, the IC_{95} estimate is largely contingent on one zone (SE2), falling to insignificance once SE2 is excluded while reservoir hydro remains significant. We therefore do not interpret IC_{95} as an independent moderator of changes in average or extreme prices, but rather as a proxy for the omitted reservoir-hydro signal. Of the available interpretations, we therefore find the combination of reservoir hydro and partial market isolation the most plausible explanation for the price-moderating pattern.

Reconciling the gas-share finding

The absence of a statistically significant association between gas generation shares and price outcomes in the main Models 7–9 may appear counterintuitive, given that the 2022 crisis was driven by surging gas prices. However, the gas-share coefficient in Model 7 is positive and sizable ($\beta = +99$, $p = 0.058$), and clears conventional significance once the interconnection capacity (IC_{95}) is included (Model 7c, $p = 0.049$). The directional effect aligns with prior expectations across both specifications; what is absent is statistical precision. Two mechanisms explain why the gas share indicator can be a noisy predictor.

First, what matters for price exposure is not how dependent a zone is on gas-fired generation, but how frequently gas-fired generators are the marginal, price-setting units. A zone generating 40% of its electricity from gas is not necessarily less exposed than one generating 60%, if gas clears the market in a similar share of hours in both. A linear specification assuming that higher gas shares always imply higher price exposure is therefore inherently noisy. Second, under market coupling, a neighboring zone's gas-fired unit can set the regional marginal price regardless of the zonal fuel mix. When transmission is unconstrained, zones effectively merge into a single price area, further weakening the link between zonal gas share and gas driven price exposure. Both mechanisms are visible in the spatial patterns: Switzerland and France, with negligible domestic gas generation, experienced price increases comparable to gas-intensive Italy (Figs. 3c and 4c).

These dynamics explain why gas share, as a structural pre-crisis indicator, does not clearly differentiate zonal price outcomes, while remaining broadly consistent with the expected directional effect.

The absent price moderation of variable renewables

Higher VRE shares show no robust association with changes in average or extreme prices in our models. This pattern can be explained by how VRE interacts with the marginal price-setting unit. While inframarginal wind and solar lower the residual load met by other units, they do not lower the wholesale price in the hours when gas remains marginal – and in 2022 gas set the price in the majority of hours despite supplying less than a fifth of generation [57]. A zone's VRE share therefore lowered its prices only in the comparatively rare hours when VRE output was high enough to push gas off the margin entirely. This result is consistent with current European system configurations, where intermittent wind and solar generation are balanced largely by gas-fired generation [57,59]. Under these conditions, high VRE zones remain exposed to gas price volatility during low-wind and low-solar periods rather than insulated from it. Simulations of future European power systems suggest that high shares of VRE, when complemented by storage, demand-side flexibility, and grid expansion, could effectively displace gas at the margin and thereby reduce exposure to gas price shocks [19]. However, these mechanisms were likely not sufficiently established yet in 2022 for the hedging value of renewables to be realized.

Daily price variability

Our results show no systematic link between the change in average daily price variability and trade orientation, gas dependence, or generation diversity. We do, however, find that zones with higher reservoir hydro shares and a higher share of VRE tend to see larger increases in daily price swings. Looking at the 2022 daily price time series of two reservoir-hydro-dominated zones (NO3 and NO4), with the highest scores on the variability metric, we see long runs of stable, low-cost days, punctuated by occasional, short price spikes (see Figure S3). In such cases, the high ΔCV metric reflects episodic spikes rather than persistent day-to-day instability. For VRE, the interpretation is different. When systems rely largely on intermittent generation, the price range varies from very low in hours of abundant VRE output to the gas-based marginal price when VRE output is low (see DK1 and LT; Figure S3). In periods of high gas prices, this amplifies day-to-day price swings, as wholesale prices move with both the weather and gas market conditions. Thus, our volatility measure highlights two very different experiences of high variability: reservoir systems with mostly calm prices but occasional price spikes, and VRE-heavy systems with more frequent, day-to-day price swings.

One observation, though not decisive, favors the gas-complementary interpretation over a purely intrinsic intermittency explanation. In the pre-crisis 2017–2019 reference period, high-VRE-share zones did not exhibit systematically elevated day-to-day variability compared with low-VRE zones (Figure S4). The relationship is in fact weakly negative, although overall VRE penetration was lower during that period. If VRE intermittency mechanically translated into price volatility, one would expect at least a weak positive baseline relationship. The absence of such a pattern at baseline is therefore more consistent with a mechanism in which VRE effects are mediated by interactions with the marginal price-setting technology, rather than reflecting an intrinsic volatility effect of VRE itself. However, cleanly separating the two channels would require either hourly merit-order data within zones or a sample contrasting VRE-heavy zones with and without gas-fired balancing capacity.

4.1. Limitations & future research

Our analysis has several limitations. First, our analysis relies on a sample of 38 BZs, which has limited statistical power. Second, we only examine linear relationships; non-linear relationships or threshold effects may therefore remain undetected within the scope of our model. Third, our findings apply specifically to a single synchronized fuel-price shock under operative European market coupling, and may not generalize to qualitatively different shock types such as droughts, extreme weather events, or large unit failures. Finally, while we exclude two bidding zones subject to direct price-altering policies during the crisis (the Iberian zones), other policy measures introduced during the crisis, such as retail price subsidies, windfall taxes, and demand reduction targets, might contribute to residual variation in our models, though these policies are difficult to quantify cross-sectionally. Future work should test the indicators examined here against different shock types necessary to determine whether the diversity null is specific to fuel-price shocks under market coupling or reflects a more general feature of liberalized electricity markets. Most importantly, given the disconnect between zonal physical supply structure and price outcomes documented here, supply-security indicators should be extended to explicitly account for cross-border interconnections and marginal price dynamics, rather than focusing on zonal or national generation portfolios alone.

5. Conclusion

Our results add nuance to the assumption that generation diversity, renewable energy deployment, and self-sufficiency protect electricity markets from price shocks during fuel supply disruptions. Across 38 bidding zones, we find limited evidence that these pre-crisis structural characteristics account for cross-zone variation in wholesale price outcomes during the 2022 energy crisis. Specifically:

1. We find no evidence that greater generation diversity mitigated the price shock.
2. Neither structural import dependence nor export orientation shows a robust association with price performance.
3. Reservoir hydro share is the only robust predictor of smaller price increases, though we cannot separate the contribution of reservoir hydro's flexibility and low-cost characteristics from that of partial market isolation in our sample.
4. Larger shares of variable renewables are associated with amplified day-to-day price variability, without systematically lowering average or extreme prices – plausibly reflecting high-VRE systems' reliance on gas-fired balancing.
5. Gas generation shares show a directionally positive but imprecise association with price outcomes, consistent with spillover across coupled markets diluting the zonal gas-share signal.

These results are specific to a synchronized fuel-price shock under European market coupling, and we are cautious about generalizing them to different shock types or system configurations. Within this setting, our findings nonetheless provide empirical evidence that commonly used energy security indicators did not deliver the price-moderating effect their conceptual framing predicts. The broader implication is that, in interconnected markets with marginal pricing, regional market dynamics can dominate the influence of zonal supply characteristics. Future assessments should therefore explicitly account for these market mechanisms rather than optimizing portfolios according to zonal supply metrics. Otherwise, policymakers risk pursuing system configurations for price benefits they cannot deliver.

Glossary

BZ (Bidding Zone) A geographic electricity market area with a single wholesale day-ahead price.

Day-ahead price The wholesale electricity price is formed in the day-ahead market.

Load-weighted average price Annual average electricity price weighted by hourly electricity demand, so high-load hours contribute more.

Marginal pricing Electricity market pricing mechanism where the marginal generating unit sets the market-clearing price.

Market coupling Cross-border electricity market integration where interconnection and trade link prices between zones.

ΔAverage Price Crisis-induced change in annual average day-ahead price, defined as $P_{2022} - P_{2017\text{–}2019}$ (€/MWh).

ΔP95 Change in the 95th percentile of daily average prices (extreme price indicator), from 2017–2019 to 2022 (€/MWh).

ΔCV (Coefficient of Variation) Change in relative price variability measured as $CV = \sigma/\mu$ (unitless), from 2017–2019 to 2022.

ACM (Adjusted Capacity Mix) A structural generation mix indicator where installed capacities are scaled by historical capacity factors to approximate typical energy contributions by technology.

CF (Capacity factor) Average utilization rate of a generating technology over time.

SWI (Shannon–Wiener Index) A diversity metric capturing variety and balance of technology shares in the adjusted capacity mix.

Stirling Index A diversity metric that combines variety, balance, and disparity (functional differences between technologies).

Disparity The degree of functional difference between technologies, used as a component in the Stirling Index.

Dispatchability The ability of a technology to supply electricity on demand (i.e., controllability of output).

PEI (Proportion Export–Import Index) A pre-crisis trade-orientation indicator ranging from −1 (all consumption imported) to +1 (all generation exported).

VRE (Variable Renewable Energy) Renewable generation with variable availability, including solar, wind, and run-of-river (and pondage).

Reservoir hydro Dispatchable hydropower with storage capability, allowing shifting of generation over time.

Run-of-river (and pondage) Hydropower with limited or no storage; generation largely follows river inflows.

IC95 Cross-zonal interconnection capacity in 2021 normalized by average annual load.

RLM (Robust Linear Model) Regression approach designed to reduce sensitivity to outliers.

Tukey's biweight A robust weighting function used to down-weight outliers in robust regression.

R^2_w **(Weighted pseudo-R^2)** A model fit metric adapted for robust regression, accounting for robustness weights.

VIF (Variance Inflation Factor) A diagnostic measure for multicollinearity among regression predictors.

CRediT authorship contribution statement

Marcus Edman: Writing – original draft, Visualization, Software, Methodology, Formal analysis, Data curation. **Yodefia Rahmad:** Writing – original draft, Supervision, Methodology, Formal analysis. **Xiaoming Kan:** Writing – original draft, Supervision, Methodology, Formal analysis, Conceptualization. **Emanuel Carlsson:** Writing – review & editing, Methodology, Formal analysis, Data curation. **Fredrik Hedenus:** Writing – review & editing, Supervision, Methodology, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data for this article can be found online at doi:10.1016/j.apenergy.2026.128304.

Data availability

All data are publicly available, with the exception of the natural gas spot price time series, which is proprietary. Code and data to reproduce the main results are available in a public repository: https://github.com/marcusedman/edman2026-replication.

References

[1] Schramm L. Some differences, many similarities: comparing Europe's responses to the 1973 oil crisis and the 2022 gas crisis. Eur Polit Sci Rev 2024;16(1):56–71. https://doi.org/10.1017/S1755773923000255

[2] Trading Economics. EU natural gas TTF; 2025 https://tradingeconomics.com/commodity/eu-natural-gas [Accessed 25 June 2025].

[3] EPEX. Market data [dataset]. https://www.epexspot.com/en/market-data [Accessed 15 December 2025]. (n.d.).

[4] Alderman L. As Europe quits Russian gas, half of France's nuclear plants are offline. The New York Times; 2022 https://www.nytimes.com/2022/11/15/business/nuclear-power-france.html [Accessed 10 November 2025].

[5] Praktiknjo AJ. Kurzstudie: Auswirkungen steigender energiepreise auf einkommen und energieverbräuche der privaten haushalte. Tech. rep. RWTH Aachen University; 2022. https://doi.org/10.18154/RWTH-2022-03085

[6] International Energy Agency. What is behind soaring energy prices and what happens next? 2021 https://www.iea.org/commentaries/what-is-behind-soaring-energy-prices-and-what-happens-next [Accessed 8 September 2025].

[7] Cherp A, Jewell J. The three perspectives on energy security: intellectual history, disciplinary roots and the potential for integration. Curr Opin Environ Sustain 2011;3(4):202–12. https://doi.org/10.1016/j.cosust.2011.07.001

[8] Skea J. Valuing diversity in energy supply. Energy Policy 2010;38(7):3608–21. https://doi.org/10.1016/j.enpol.2010.02.038

[9] Kruyt B, Van Vuuren DP, de Vries HJ, Groenenberg H. Indicators for energy security. Energy Policy 2009;37(6):2166–81. https://doi.org/10.1016/j.enpol.2009.02.006

[10] Yergin D. Ensuring energy security. Foreign Aff 2006;69–82. https://doi.org/10.2307/20031912

[11] Stirling A. Multicriteria diversity analysis: a novel heuristic framework for appraising energy portfolios. Energy Policy 2010;38(4):1622–34. https://doi.org/10.1016/j.enpol.2009.02.023

[12] Chalvatzis KJ, Ioannidis A. Energy supply security in the EU: benchmarking diversity and dependence of primary energy. Appl Energy 2017;207:465–76, Transformative Innovations for a Sustainable Future – Part II. https://doi.org/10.1016/j.apenergy.2017.07.010

[13] Park H, Bae S. Quantitative assessment of energy supply security: Korea case study. Sustainability 2021;13(4):1854. https://doi.org/10.3390/su13041854

[14] Ioannidis A, Chalvatzis KJ, Li X, Notton G, Stephanides P. The case for Islands' energy vulnerability: electricity supply diversity in 44 global Islands. Renew Energy 2019;143:440–52. https://doi.org/10.1016/j.renene.2019.04.155

[15] Ren J, Sovacool BK. Quantifying, measuring, and strategizing energy security: determining the most meaningful dimensions and metrics. Energy 2014;76:838–49. https://doi.org/10.1016/j.energy.2014.08.083

[16] Molyneaux L, Wagner L, Froome C, Foster J. Resilience and electricity systems: a comparative analysis. Energy Policy 2012;47:188–201. https://doi.org/10.1016/j.enpol.2012.04.057

[17] Molyneaux L, Brown C, Wagner LD, Foster J. Measuring resilience in electricity generation: an empirical analysis. Working Paper Energy Economics and Management Group, School of Economics, University of Queensland; 2016. https://mpra.ub.uni-muenchen.de/72884/.

[18] Siskos E, Burgherr P. Multicriteria decision support for the evaluation of electricity supply resilience: exploration of interacting criteria. Eur J Oper Res 2022;298(2):611–26. https://doi.org/10.1016/j.ejor.2021.07.026

[19] Navia Simon D, Diaz Anadon L. Power price stability and the insurance value of renewable technologies. Nat Energy 2025;10(3):329–41. https://doi.org/10.1038/s41560-025-01704-0

[20] Bajo-Buenestado R, Bento AM, Kaffine D, Marmarelis ZE. Decarbonization and electricity price vulnerability. Nat Sustain 2025;8(2):170–81. https://doi.org/10.1038/s41893-024-01502-8

[21] Gumbau A. The 'Iberian exception': a success story? 2022 https://www.energymonitor.ai/policy/market-design/the-iberian-exception-a-success-story/?cf-view&cf-closed [Accessed 24 October 2025].

[22] Escribano G, Fachada J, Arbeloa IU, Gouveia AF. After the energy crisis: policy responses in the Iberian peninsula; 2025. https://www.brookings.edu/articles/after-the-energy-crisis-policy-responses-in-the-iberian-peninsula/.

[23] Ang'u C, Muthama NJ, Oludhe C, Chitedze I. The role of diversity, reserve margin and system structure on retail electricity tariffs in Kenya. Heliyon 2020;6(8). https://doi.org/10.1016/j.heliyon.2020.e04626

[24] ENTSO-E. ENTSO-E transparency platform [dataset]. https://transparency.entsoe.eu/. Access via ENTSO-E Transparency Platform API [Accessed 15 December 2025]. (n.d.).

[25] Ember. European wholesale electricity price data – hourly CSV[dataset]. https://ember-energy.org/data/european-wholesale-electricity-price-data/ [Accessed 10 January 2026]. (n.d.).

[26] Guan Y, Yan J, Shan Y, Zhou Y, Hang Y, Li R, Liu Y, Liu B, Nie Q, Bruckner B, et al. Burden of the global energy price crisis on households. Nat Energy 2023;8(3):304–16. https://doi.org/10.1038/s41560-023-01209-8

[27] Organisation for Economic Co-operation and Development (OECD). Reigniting investment for more resilient growth. Tech. rep. OECD Publishing; 2025. https://doi.org/10.1787/83363382-en

[28] Punzi MT. The impact of energy price uncertainty on macroeconomic variables. Energy Policy 2019;129:1306–19. https://doi.org/10.1016/j.enpol.2019.03.015

[29] International Energy Agency (IEA). Share of power generation by source; 2020 https://www.iea.org/data-and-statistics/charts/share-of-power-generation-by-source [Accessed 20 January 2026].

[30] International Energy Agency. Renewables 2022: analysis and forecast to 2027. Tech. rep. International Energy Agency, Paris; 2022 https://www.iea.org/reports/renewables-2022 [Accessed 15 December 2025].

[31] Ember. Global electricity review 2024; 2024 https://ember-energy.org/latest-insights/global-electricity-review-2024/ [Accessed 15 November 2025].

[32] Moraes Jr L, Bussar C, Stöcker P, Jacqué K, Chang M, Sauer DU. Comparison of long-term wind and photovoltaic power capacity factor datasets with open-license. Appl Energy 2018;225:209–20. https://doi.org/10.1016/j.apenergy.2018.04.109

[33] International Renewable Energy Agency (IRENA). IRENASTAT online data query tool [dataset]. https://pxweb.irena.org/pxweb/en/IRENASTAT/ [Accessed 10 December 2025]. (n.d.).

[34] Stirling A. On the economics and analysis of diversity. Science Policy Research Unit (SPRU), Electronic Working Papers Series, Paper 1998 https://www.researchgate.net/profile/Andy-Stirling/publication/247036152_On_the_Economics_and_Analysis_of_Diversity/links/00463539acc9aa0a0e000000/On-the-Economics-and-Analysis-of-Diversity.pdf [Accessed 8 December 2025]. 28 1–156.

[35] Cunha J, Ferreira PV. Designing electricity generation portfolios using the mean-variance approach. Int J Sustain Energy Plan Manag 2015;4:17–30. https://doi.org/10.5278/ijsepm.2014.4.3

[36] Chuang MC, Ma HW. Energy security and improvements in the function of diversity indices—Taiwan energy supply structure case study. Renew Sustain Energy Rev 2013;24:9–20. https://doi.org/10.1016/j.rser.2013.03.021

[37] Asia Pacific Energy Research Centre (APERC). Quest for energy security in the 21st century: resources and constraints. Asia Pacific Energy Research Centre, Tokyo, Japan; 2007. https://aperc.or.jp/file/2010/9/26/APERC_2007_A_Quest_for_Energy_Security.pdf.

[38] Ranjan A, Hughes L. Energy security and the diversity of energy flows in an energy system. Energy 2014;73:137–44. https://doi.org/10.1016/j.energy.2014.05.108

[39] Stirling A. Diversity and ignorance in electricity supply investment: addressing the solution rather than the problem. Energy Policy 1994;22(3):195–216. https://doi.org/10.1016/0301-4215(94)90159-7

[40] Cludius J, Hermann H, Matthes FC, Graichen V. The merit order effect of wind and photovoltaic electricity generation in Germany 2008–2016: estimation and distributional implications. Energy Econ 2014;44:302–13. https://doi.org/10.1016/j.eneco.2014.04.020

[41] Newbery D. Shifting demand and supply over time and space to Manage intermittent generation: the economics of electrical storage. Energy Policy 2018;113:711–20. https://doi.org/10.1016/j.enpol.2017.11.044

[42] Wozabal D, Graf C, Hirschmann D. The effect of intermittent renewables on the electricity price variance. OR Spectr 2016;38(3):687–709. https://doi.org/10.1007/s00291-015-0395-x
[43] Eurostat. Simplified energy balances (nrg_bal_s) [dataset], Eurostat data [Accessed 15 December 2025]. (n.d.). https://doi.org/10.2908/NRG_BAL_S
[44] International Energy Agency. World energy outlook 2022. Tech. rep. International Energy Agency, Paris; 2022 https://www.iea.org/reports/world-energy-outlook-2022 [Accessed 15 December 2025].
[45] Zakeri B, Staffell I, Dodds PE, Grubb M, Ekins P, Jääskeläinen J, Cross S, Helin K, Castagneto Gissey G. The role of natural gas in setting electricity prices in Europe. Energy Rep 2023;10:2778–92. https://doi.org/10.1016/j.egyr.2023.09.069
[46] Stiewe C, Xu AL, Eicke A, Hirth L. Cross-border cannibalization: spillover effects of wind and solar energy on interconnected European electricity markets. Energy Econ 2025;143:108251. https://doi.org/10.1016/j.eneco.2025.108251
[47] European Energy Exchange (EEX). European natural gas spot market data [dataset]. https://www.eex.com/en/market-data/natural-gas [Accessed 4 November 2025]. (n.d.).
[48] European Gas Hub. European gas hubs: still relevant? 2023 https://europeangashub.com/report-presentation/european-gas-hubs-still-relevant [Accessed 10 November 2025].
[49] Beaton AE, Tukey JW. The fitting of power series, meaning polynomials, illustrated on band-spectroscopic data. Technometrics 1974;16(2):147–85. https://doi.org/10.1080/00401706.1974.10489171
[50] Huber PJ. Robust statistics, Wiley Series in Probability and Mathematical Statistics. New York: John Wiley & Sons; 1981. https://doi.org/10.1002/0471725250
[51] Pedregosa F, Varoquaux G, Gramfort A, Michel V, Thirion B, Grisel O, Blondel M, Prettenhofer P, Weiss R, Dubourg V, Vanderplas J, Passos A, Cournapeau D, Brucher M, Perrot M, Duchesnay É. Scikit-Learn: machine learning in Python. J Mach Learn Res 2011;12:2825–30. http://jmlr.org/papers/v12/pedregosa11a.html.
[52] Seabold S, Perktold J. Statsmodels: econometric and statistical modeling with Python. In: van der Walt S, Millman J, editors. Proceedings of the 9th Python in science conference (SciPy 2010). Austin, Texas, USA; 2010. p. 92–6. https://conference.scipy.org/proceedings/scipy2010/.
[53] Belotti F, Peracchi F. Fast leave-one-out methods for inference, model selection, and diagnostic checking. Stata J 2020;20(4):971–83. https://doi.org/10.1177/1536867X20976312
[54] Cooray A, Shahbaz M, Kuziboev B, Çatık AN. Mitigating energy risk through energy sources diversification. J Environ Manag 2025;380:124955. https://doi.org/10.1016/j.jenvman.2025.124955
[55] Fan Y, Chang T, Ranjbar O. Energy security and energy mix diversification nexus in the OECD countries. Econ Anal Policy 2024;84:2071–85. https://doi.org/10.1016/j.eap.2024.11.012
[56] Costello K. Diversity of generation technologies: implications for decision-making and public policy. Electr J 2007;20(5):10–21. https://doi.org/10.1016/j.tej.2007.04.006
[57] Gasparella A, Koolen D, Zucker A. The merit order and price-setting dynamics in European electricity markets. Scientific analysis or review, Anticipation and foresight European Commission, Petten (The Netherlands); 2023 https://publications.jrc.ec.europa.eu/repository/handle/JRC134300 [Accessed 12 January 2026].
[58] European Commission. Electricity market design. https://energy.ec.europa.eu/topics/markets-and-consumers/electricity-market-design_en [Accessed 10 January 2026]. (n.d.).
[59] Eurelectric. Decarbonisation speedways: final report. Tech. rep. Eurelectric, Brussels; 2023 https://www.eurelectric.org/wp-content/uploads/2024/06/extended-full-report_decarbonisation-speedways.pdf [Accessed 20 September 2025].