

High to low: Price formation and bid placement at the extremes

Jilles De Blauwe^{a,*}, Thorsten Weiskopf^b, Harshit Gaur^a, Armin Ardone^b, Dogan Keles^a

^a Technical University of Denmark, Anker Engelunds Vej, Kongens Lyngby, 2800, Denmark

^b Institute for Industrial Production (IIP), Karlsruhe Institute of Technology, Hertzstraße 16, Karlsruhe, 76187, Germany

HIGHLIGHTS

- A study of strategic bidding under market tightness in high-renewable systems.
- Extreme price events emerge from both scarcity shocks and strategic behavior.
- Aggregate supply curves steepen significantly during periods of high residual load.
- Bidding volumes shift away from lower price segments and to higher price segments.
- Markup bidding may substantially increase price peaks in 2035.

ARTICLE INFO

Keywords:

Electricity spot markets
Extreme price events
Bidding patterns
Energy policy
Market design

ABSTRACT

At high penetration levels, variable renewable energy (VRE) reshapes price formation in wholesale electricity markets by increasing both oversupply and scarcity. While the fundamental mechanisms underlying extreme prices are well documented, the role of bidding behavior in amplifying price spikes under scarcity remains underexplored. This paper develops an empirical framework to characterize how aggregate bidding patterns respond to system scarcity, as proxied by residual load, and embeds the resulting behavioral rules in an agent-based market simulation to assess their implications under a future energy-transition scenario. The framework is applied to the Belgian, Dutch, and German day-ahead markets, testing it across systems with different VRE penetration levels.

The results show that aggregate supply curves become significantly steeper with residual load, while bidding volumes shift toward upper price segments. In the 2035 simulation, scarcity-induced strategic bidding increases the annual average price in Germany by 15.49% (7.38 EUR/MWh) relative to marginal-cost bidding, while the peak price rises from 153 to 561 EUR/MWh (+ 268%), with effects concentrated in a small share of scarcity hours. These results suggest that extreme price formation cannot be understood from fundamental supply conditions alone. As VRE penetration increases and the dispatchable margin becomes more constrained, scarcity-related bidding behavior can substantially amplify price extremes. Navigating these risks requires market monitoring that distinguishes efficient scarcity rents from strategic conduct, alongside careful policy design to manage the underlying structural exposure to scarcity—primarily sufficient cross-border interconnection and dispatchable capacity—without dampening the price signals needed for long-term adequacy.

1. Introduction

Since the 1990s, electricity generation in several regions has been organized into sequential markets, with the Day-Ahead Market (DAM) serving as the central trading hub, setting reference prices for the intra-day and forward markets. The Market Clearing Price (MCP) is set by the matching of supply and demand for each time interval, which occurs simultaneously across coupled zones in interconnected systems.

Because electricity demand is highly inelastic in the short run, market outcomes are driven by supply-side availability and pricing (Labandeira et al., 2017). While competitive bidding for dispatchable units is traditionally guided by marginal costs (MC) and driven by fuel inputs, the rapid penetration of Variable Renewable Energy (VRE) has introduced a “merit-order effect,” where near-zero marginal cost generation suppresses clearing prices during periods of high output (Würzburg et al., 2013). Conversely, these fundamentals can also trigger extreme prices.

* Corresponding author.

Email address: jdbl@dtu.dk (J. De Blauwe).

<https://doi.org/10.1016/j.enpol.2026.115620>

Received 19 March 2026; Received in revised form 2 September 2026; Accepted 16 September 2026

Available online 10 October 2026

0301-4215/© 2026 The Author(s). Published by Elsevier Ltd. This is an open access article under the CC BY license (<http://creativecommons.org/licenses/by/4.0/>).

Supply shocks, driven by fuel price volatility, unforeseen outages, or sharp deficits in VRE output, can push the market toward the steep tail-ends of the supply curve. During the 2021–2022 European energy crisis, high gas prices, together with low hydro availability and nuclear outages, led to unprecedented electricity prices across Europe (Zhu et al., 2024).

A growing literature examines the determinants and economic implications of such extreme price events in wholesale electricity markets. Early studies of price spikes emphasize the role of scarcity conditions and limited reserve margins in generating extreme price outcomes (Mount et al., 2006). Empirical analyses of restructured electricity markets have shown that market power can become particularly pronounced under tight system conditions, when limited supply relative to demand increases firms' ability to influence market prices (Borenstein, 2002). More recent work highlights how the expansion of variable renewable generation increases the intermittency-driven volatility of prices and can amplify extreme price events (Rintamäki et al., 2017; Paraschiv et al., 2014).

These studies have examined how structural market characteristics and system fundamentals drive extreme price realizations, but bidding behavior itself may also contribute to the magnitude of these events (Joskow and Kahn, 2002). Tight system conditions can drive generators away from competitive short-run marginal cost pricing, providing significant opportunities for strategic behavior. Firms may strategically increase markups or withhold capacity to shift the clearing price toward steeper segments of the offer curve (Borenstein et al., 2002; McRae and Wolak, 2009; Brown et al., 2023). Such behavior distorts the merit-order dispatch and increases deadweight loss as higher-cost units are called upon to replace withheld capacity (Wolfram, 1998; Fogelberg and Lazarczyk, 2019). Moreover, strategic markups exacerbate market volatility and facilitate a substantial transfer of wealth from consumers to producers (Wolak, 2003). During the 2021–2022 energy crisis, strategic behavior is estimated to have driven a significant part of the departure of observed prices from competitive benchmarks (Krzywnicka and Barner, 2025); the resulting cost increases compelled energy-intensive industrial consumers to curtail production or suspend operations entirely. The considerable downstream economic effects raise significant regulatory concerns regarding firm behavior under scarcity (Brown et al., 2023; Bundeskartellamt, 2024).

Despite an extensive literature on market power and the considerable economic importance of extreme price events, no recent study has characterized how strategic bid placement contributes to extreme price formation in high-renewable, coupled electricity markets. This paper addresses this gap by combining a comprehensive empirical analysis of historical bidding data with market simulation. Specifically, we (1) characterize the formation of extreme prices and the associated market conditions, (2) quantify how bid placement across the aggregate supply curves responds to market tightness, as measured by residual load, (3) translate these relationships into systematic bidding rules that capture strategic behavior under scarcity, and (4) embed these rules in the agent-based electricity market model PowerACE to quantify their implications for price formation in a 2035 energy-transition scenario.

The novelty of this study lies not in documenting extreme prices, which is well established, but in identifying the supply-side bidding behavior associated with their formation. Whereas Hagfors et al. (2016) model the probability of extreme prices from fundamental drivers and Ghelasi and Ziel (2026) develop a data-driven merit-order model for fundamental price forecasting, we examine how bidding behavior changes with market tightness and contributes to the magnitude of extreme prices. Krzywnicka and Barner (2025) infer strategic behavior during the 2022 German energy crisis by comparing observed prices with competitive and Nash–Cournot benchmarks, attributing the divergence to the increased profitability of infra-marginal withholding under extreme fuel prices. We complement and extend this approach by directly characterizing changes in the aggregate supply curve and individual bid placement with market tightness, using anonymized market order books rather than

a model-based counterfactual. While Ito and Reguant (2016) measure strategic markups using firm-level bidding data, our framework develops system-wide indicators that identify scarcity-driven bid elevation from aggregate market data.

Our findings hold relevance for several stakeholders. For market operators, we provide insights into strategic behavior under market tightness through a comprehensive analysis of empirical bidding data. For policymakers, we propose a number of actionable tools to manage risks in a high-renewables future, supporting the design of robust market rules. For researchers, we demonstrate a systematic methodology to implement empirical bidding strategies in energy system models to improve future scenario analysis.

The remainder of the paper is structured as follows. Section 2 details the institutional setting of the zonal day-ahead market and presents a preliminary analysis of extreme price formation. Section 3 outlines the econometric framework for analyzing behavior under scarcity and deriving the bidding rules implemented in the PowerACE market simulations. Section 4 presents the empirical results and outcomes of the future scenario analysis. Section 5 discusses the study's limitations and explores pathways for future work, while Section 6 concludes with policy recommendations.

2. Data and preliminary analysis

This section provides the necessary background to motivate our methodological framework and analysis. First, we explain the institutional setting, describing bidding behavior in the spot market under the European market design. We subsequently illustrate how the interplay of fundamental market dynamics and bidding behavior can result in extreme price outcomes through a worked example: We discuss the 2024 peak price event in Germany, highlighting its significance by comparison to the peak price observed during the 2021–2022 energy crisis.

2.1. Characteristics of the zonal spot market and data sources

We study the zonal DAM in the European context. European zones participate in the Single Day-Ahead Coupling (SDAC, 2025), in which the clearing process is performed jointly across multiple bidding zones. The market was cleared with hourly time granularity until September 30, 2025, when it switched to 15-minute time intervals. The German market exerts a particularly strong influence on regional price formation, producing notable cross-border effects on neighboring zones (De Blauwe et al., 2025a). Its size, liquidity, and rapidly evolving generation fleet provide a dynamic environment to study bidding dynamics. This is illustrated in Fig. 1(a) and (b), which show the installed capacity per technology type and the annual generation totals in 2024, respectively.

This generation fleet provides the available generation capacity underlying the spot market's merit-order curve. The curves analyzed in this study, however, consist of the aggregated bidding curves published by the exchange rather than this physical supply stack directly (Kulakov and Ziel, 2019). We illustrate the differences by showing an exemplary bidding curve for the German bidding zone for hour 16 on the 24th of April, 2024, presented in Fig. A.1 in Appendix A.

Following the bidding curve from left to right tracks the underlying merit order, but also illustrates how market coupling and complex order structures enter the curve. This German bidding curve shows significant volumes at the floor price, –500 EUR/MWh, reflecting bids for must-run capacities, complex bids, reserve capacities, bids associated with imports from market coupling, in addition to solar generation under Feed-In Tariffs (FIT).¹ The growing share of wind and solar subsequently dominates the negative-to-zero price ranges. Lignite, hard coal, and increasingly competitive Combined-Cycle Gas Turbines (CCGT) form the

¹ For Germany, must-run baseload mainly consists of Combined Heat and Power (CHP) and biofuel plants.

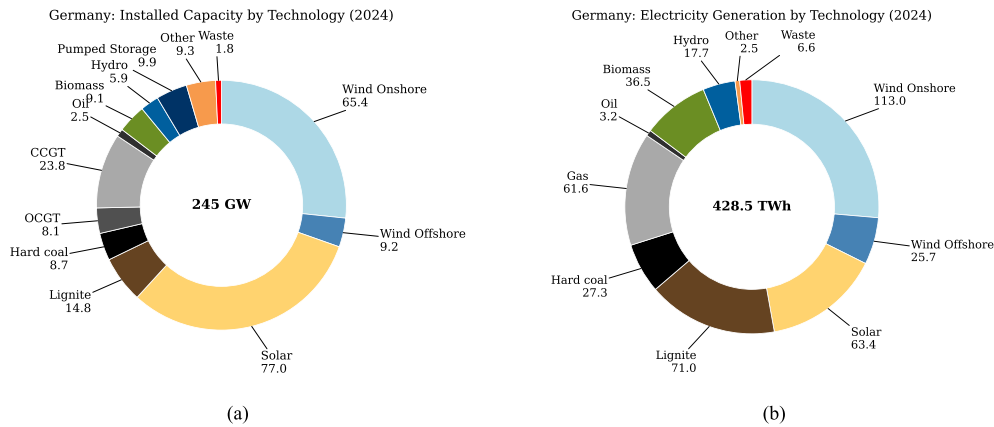


Fig. 1. The installed generation capacity by technology (a) and the actual generation by technology (b) for Germany in 2024.

Table 1

Overview of data sources and variables.

Dataset	Source	Main variables	Granularity	Units
Bidding data	EPEX Spot (2025)	Aggregated supply and demand bids	Hourly	EUR/MWh; MW
Market fundamentals	Entso-E Transparency Platform (2025)	Load, generation by technology, cross-border flows, temperature	Hourly	MW; °C
Fuel and carbon prices	Investing.com (2025)	TTF natural gas, Rotterdam coal, EU ETS carbon permits	Daily	EUR/MWh; USD/t; EUR/tCO ₂
Generation technology parameters	IPCC (2023); VDA (2024); Schröder et al. (2013)	Emission factors, plant efficiencies, variable O&M costs	Time-invariant	tCO ₂ /MWh; –; EUR/MWh
Generation fleet	Bundesnetzagentur (2023)	Installed capacity and annual generation by technology	Annual	MW; MWh

mid-to-upper merit order, leaving Open Cycle Gas Turbines (OCGT) to form the steepest tail end of the curve² (Ghelasi and Ziel, 2026).

Bidding patterns are analyzed using a comprehensive dataset: data and sources are summarized in Table 1, while Table C.1 in Appendix C.1 provides a more detailed description of the hourly variables. Bidding data are acquired from EPEX Spot (2025), while market fundamentals (load, VRE generation, cross-border flows) are compiled from Entso-E Transparency Platform (2025) and Bundesnetzagentur (2023). These sources are combined with input fuel and carbon prices to construct hourly, technology-specific MC estimates, as detailed in Section 3.1.

2.2. Extreme price formation: an illustrative case

Table 2 provides an overview of extreme price formation in the German market in recent years. It presents the annual maximum price, minimum price, number of negative price observations, and the threshold value for the upper 99th percentile of prices.

Table 2 demonstrates that extreme price formation was a defining feature of the year 2024, the focus of the further study.

The year 2024 not only shows much more frequent negative prices, but also a lower minimum than in 2020, which is considered a low-price year. The year 2024 simultaneously shows a higher price peak than in 2022, at the height of the energy crisis, despite a lower threshold for the upper 99th percentile of prices.

The underlying formation mechanisms for extreme price outcomes can differ considerably, depending on whether the system is

² In Germany, rising carbon prices have made CCGT increasingly competitive with coal. Because natural gas has a significantly lower carbon intensity than coal, higher carbon prices disproportionately inflate the marginal operating costs of coal-fired plants, which can cause a fuel switch in the dispatch order (Amer, 2025).

Table 2

Maximum price, minimum price, 99th percentile price threshold, and negative price observations for the German day-ahead market (2020–2024).

Year	Max. price (EUR/MWh)	Min. price (EUR/MWh)	99th percentile threshold (EUR/MWh)	Negative price observations
2020	200.0	–83.9	74.9	298
2021	620.0	–69.0	366.8	139
2022	871.0	–19.0	664.9	70
2023	524.3	–500.0	208.0	300
2024	936.3	–135.5	224.9	457

experiencing a fundamental cost shock or a localized scarcity shock. We examine these distinct pathways by comparing two distinct maxima: the European energy crisis peak in August 2022 (871.0 EUR/MWh) and the scarcity peak in December 2024 (936.3 EUR/MWh). To start illustrating the differences, Table 3 outlines the technology-specific marginal costs for both events.³

Table 3 indicates that the 2022 peak was fundamentally driven by a systemic cost shock. The benchmark TTF gas spot price averaged 201.7 EUR/MWh over the month of the event, driving estimated marginal costs for OCGT peaking units up to 550.22 EUR/MWh. The cost shock was exacerbated by extensive droughts and nuclear outages in France that limited supply, resulting in region-wide price peaks (European Commission, 2022; RTE, 2023).

Conversely, when the price spike reached 936.3 EUR/MWh on December 12th, 2024, the MC estimates suggest that it must have been driven by other causes. The fuel costs remained much lower, with the

³ The methodology used to derive these estimates is laid out in Section 3.1.

Table 3

Comparison of the monthly average marginal costs per technology type during the 2022 and 2024 peak price events.

Index	2022 Event	2024 Event
TTF natural gas (EUR/MWh)	201.7	45.6
Rotterdam Coal (USD/t)	362.4	111.8
Carbon Permits (EUR/tCO ₂)	85.3	69.1
Marginal cost estimates (EUR/MWh)		
Lignite	99.8	82.8
Hard Coal	229.6	103.3
CCGT	393.9	109.3
OCGT	550.2	151.8

Table 4

Sensitivity analysis of the 2022 and 2024 price peaks against hypothetical bid injections at the marginal cost of OCGT (EUR/MWh).

Event	Peak price	OCGT MC	+500 MW	+1 GW	+2 GW	+3 GW
2022-08-29	871.0	550.2	817.5	796.3	723.7	558.5
2024-12-12	936.3	151.8	773.7	768.6	530.0	300.0

TTF gas price averaging 45.6 EUR/MWh over the month of the event, implying an estimated MC for OCGT of 151.84 EUR/MWh.

Instead, market conditions suggest a profound scarcity shock. The system observed a collapse in VRE output, from an hourly average output of 27 GW in the week prior to under 2 GW during the week of the price peak. The low VRE output indicates that more conventional generation must be contracted. While the 80 GW of total installed conventional capacity⁴ should be able to adequately meet the peak demand of 75 GW, especially in addition to imports, we observed that the fraction of it that was participating in the market was remarkably small (Klein, 2024). A convergence of outages further removed several gigawatts, as illustrated in Table B.1 in Appendix B, leading to a thinned-out supply curve and resulting in the market clearing at a very steep price point. The event triggered a regulatory investigation into the considerable volumes of dispatchable generation capacity that remained offline. The investigation reported that between 3 and 10 GW of available capacity was not operating in the market throughout the entire 2024 extreme price period, yet found no proof of market rule violation (Bundeskartellamt, 2024).

These supply shock dynamics suggest a high sensitivity of the prices to additional capacity injections. We quantify this through a sensitivity analysis, exploring counterfactual scenarios in which the original bidding curves are modified to include additional supply bids, placed at the MC of OCGT units. The supply curves, modified with different volumes of these hypothetical bid injections, are then cleared against the historical demand curve to recalculate the MCP. The results of this analysis are shown in Table 4.

During the 2024 event, a hypothetical injection of just 500 MW of capacity bid at OCGT marginal cost would have reduced the clearing price by 17.4%, from 936.3 to 773.7 EUR/MWh. The same injection during the 2022 cost-driven event would have yielded only a 6.1% price reduction.

Rather than an isolated anomaly, the 2024 peak may exemplify a systemic dynamic in energy-only markets with high VRE penetration. In hours of low renewable output and high load, market clearing against the steep tail of dispatchable capacity creates significant price sensitivity to strategic bid placement. This motivates the deeper analysis of underlying bidding dynamics, as laid out in Section 3.

3. Methodology

This section outlines the empirical and simulation framework used to analyze how system scarcity affects bidding behavior and electricity price formation. The methodological approach is summarized in Fig. 2. First, the set of data sources is compiled and used to derive marginal cost estimates for the relevant thermal generation technologies.

Second, an empirical analysis is conducted, focusing on three complementary dimensions. We first (i) examine how bidding curves change in response to scarcity on an aggregate level, evaluating the steepness across the full positive price range. We then (ii) analyze the effects at a more granular level, evaluating the influence of scarcity on the distribution of bidding volumes across price segments of the curve. Subsequently, we (iii) explore how this translates into scarcity-induced markups above estimated marginal cost, identifying the extent to which generators increase bid prices when the system becomes tighter.

Third, the insights from the empirical analysis are incorporated into a simulation of future scenarios using the PowerACE agent-based market model. The strategic bidding markups under scarcity examined in (iii) are integrated into a scenario analysis for the year 2035, and their effects on the energy system are quantified. Finally, a post-analysis evaluates the resulting market outcomes by examining how scarcity-driven bidding behavior affects both observed bidding patterns and longer-term price trajectories, generating insights for stakeholders and deriving policy implications. The following subsections will subsequently describe each component of the methodology in greater detail.

3.1. Marginal cost estimates

To underpin the empirical analysis, we first estimate the short-run marginal cost for the thermal generation fleet active in the German spot market, characterized by lignite and hard coal, and combined cycle and open cycle gas (OCGT and CCGT) generation technologies.⁵

For each technology k , marginal cost in hour t is computed as

$$MC_{k,t} = \frac{P_t^{\text{fuel}}}{\eta_k} + \frac{P_t^{\text{CO}_2} \cdot EF_k}{\eta_k} + VOM_k \quad (1)$$

where P_t^{fuel} denotes the relevant fuel price, η_k the technology efficiency, $P_t^{\text{CO}_2}$ the EU carbon permit price, EF_k the fuel-specific CO₂ emission factor and VOM_k the variable operation and maintenance costs. Fuel-specific CO₂ emission factors are taken from IPCC (2023), and VDA (2024) was used as a source for plant efficiencies, and variable operational cost estimates were based on Schröder et al. (2013). The TTF natural gas, Rotterdam coal futures, and EU ETS carbon permit (ICE CF12) daily settlement prices from Investing.com (2025) serve as the fuel and carbon price inputs. In Appendix C, Table C.2 provides an overview of the technology-specific parameter coefficients to determine the marginal cost functions.

The yearly average marginal cost estimates per technology are shown for 2020–2025 in Table C.3, while Table C.4 shows the monthly averages for 2024 and 2025.

3.2. Analysis of curve slope under scarcity

The relation between market scarcity and bidding behavior is first quantified at an aggregate level through the curve's steepness. To indicate market tightness, the residual load (RL), equaling the expected load minus wind and solar forecasts, has emerged as a key indicator in high renewable systems (Twomey and Neuhoff, 2010). It quantifies how much of the demand must be covered by non-VRE (dispatchable)

⁴ From Entso-E Transparency Platform (2025).

⁵ As discussed in Section 2, CHP and biomass thermal generation are not driven by MC but rather bid at or below zero prices to ensure dispatch. Oil generation accounts for a very small share of the German supply mix (< 1% in 2024), mostly consisting of CHP or reserve units rather than a price-setting technology, and is therefore not included.

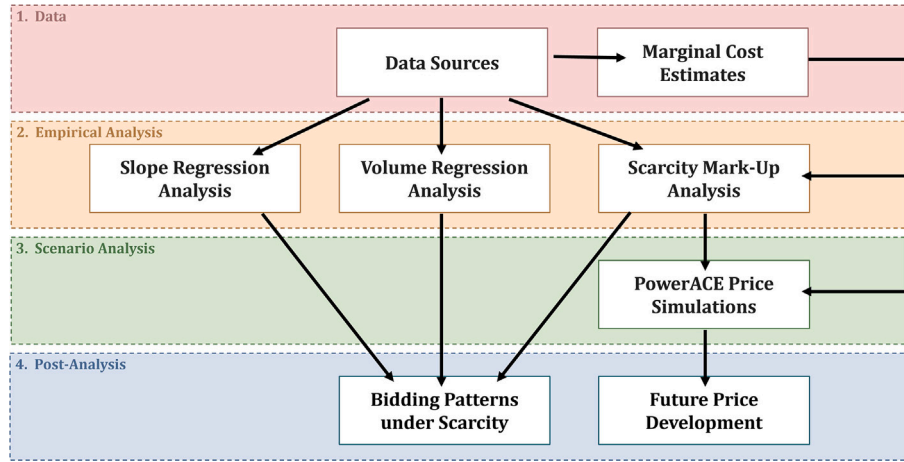


Fig. 2. Methodological approach for the study.

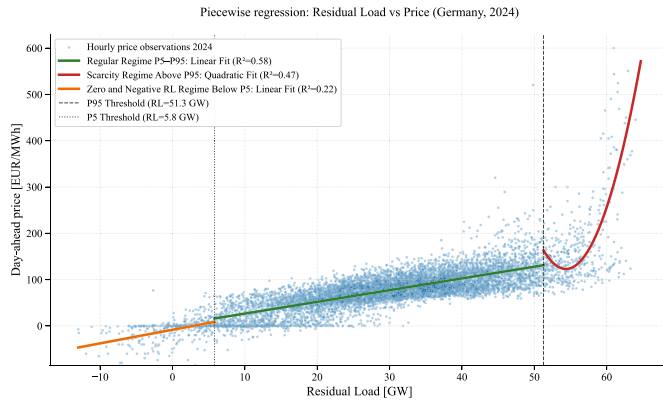


Fig. 3. A piecewise quadratic regression of the MCP as a function of residual load for the German bidding zone in 2024.

sources, where a higher RL predicts that more expensive units will need to be activated, resulting in a higher MCP (Hirth, 2013; Clò et al., 2015). This is illustrated in Fig. 3, showing the relation between the RL and MCP for the German bidding zone in 2024, in a piecewise regression.

The hourly price outcomes are subdivided into regimes according to the distribution of the RL. In the bottom 5th-percentile of RL, termed the oversupply regime, we observe that the renewables entirely cover or even exceed demand, resulting in frequent negative prices. In the intermediate regime (5th–95th percentile of RL), the MCP increases linearly with RL, suggesting that gradually more expensive units are activated as more demand is covered by conventional generation. In the scarcity regime, beyond the upper 95th percentile of RL, the MCP shows a quadratic relationship to the RL. When most of the conventional units are already contracted, the bid offers for peak generation units become increasingly expensive with each RL increment. These three bands characterize the shape of the price–RL relationship and serve here only to motivate the piecewise fit. They are distinct from the regime definitions used in Section 3.4, where the scarcity regimes q are contrasted with a baseline curve averaged over all hours of the period, termed the regular regime.

While a greater RL thus requires the activation of a greater capacity of supply, greater market tightness may similarly induce actors to price their bids more sharply, in anticipation that higher-priced bids may still be accepted (Borenstein et al., 2002). At an aggregate level, these scarcity-induced markups create a steepening of the bidding curve. This

process is illustrated in Fig. 4(a) and (b), showing the clearing process in a theoretical spot market for two scenarios of a lower and higher residual load.

The supply curve in the theoretical market shown in Fig. 4(a) consists of renewables, coal, and gas technologies, following the corresponding merit order ranking. Both a high and a low VRE scenario are depicted, determining the volumes bid at zero price. The bidding of other generation technologies is at marginal costs. These remain identical in both scenarios, as does the demand. Fig. 4(b) displays these market scenarios, but the demand curve has now been shifted by the volume of the renewable generation, signifying the residual demand. Correspondingly, the residual demand curve is lower in the high-renewable case, and the reverse is true for the low-renewable case. Because of the higher RL, the gas generator has a considerably larger volume accepted. Simultaneously, there is room for the bid to be placed at a higher markup while still being accepted. In this scenario, the gas operator could benefit from bidding strategically. In the low RL case, the gas generator has a much lower dispatched volume. Similarly, the potential for a markup is smaller, as a high markup would inhibit the bid from being accepted.

We may correspondingly expect that at an aggregate level, this produces a steepening effect on the bidding by flexible generation as the RL increases (De Blauwe et al., 2025b).⁶ To examine this, we isolate the middle-upper price range of the bidding curve and calculate its average slope. This is calculated by a first-order linear interpolation between points $A : (p_t^a, \text{Vol}(p_t^a))$ and $B : (p_t^b, \text{Vol}(p_t^b))$ of the curve:

$$\text{slope}_t = \frac{(p_t^b - p_t^a)}{(\text{Vol}(p_t^b) - \text{Vol}(p_t^a))} \quad (2)$$

The relation between this slope and the RL is explored using regression analysis, controlling for fluctuations in fuel and carbon prices and the effects of seasonality. The regression framework follows Keles et al. (2020): one-week differences of the variables are utilized to correct for weekly seasonality, and the one-day lag of the weekly-differenced dependent variable is included as a regressor to improve stationarity further. The set of independent variables, $X_{t,h}$, includes the carbon prices

⁶ Importantly, the mechanism sketched here does not suggest the abuse of market power by any individual firm, but rather illustrates that under tight, inelastic conditions, the potential payoff of raising an offer above short-run marginal cost may be positive even for a small unit, reflecting scarcity rent. The results therefore capture a systematic market-level regularity in how scarcity is reflected in aggregated bid curves, but due to the aggregated and anonymous nature of bidding data cannot identify the underlying strategies of individual actors.

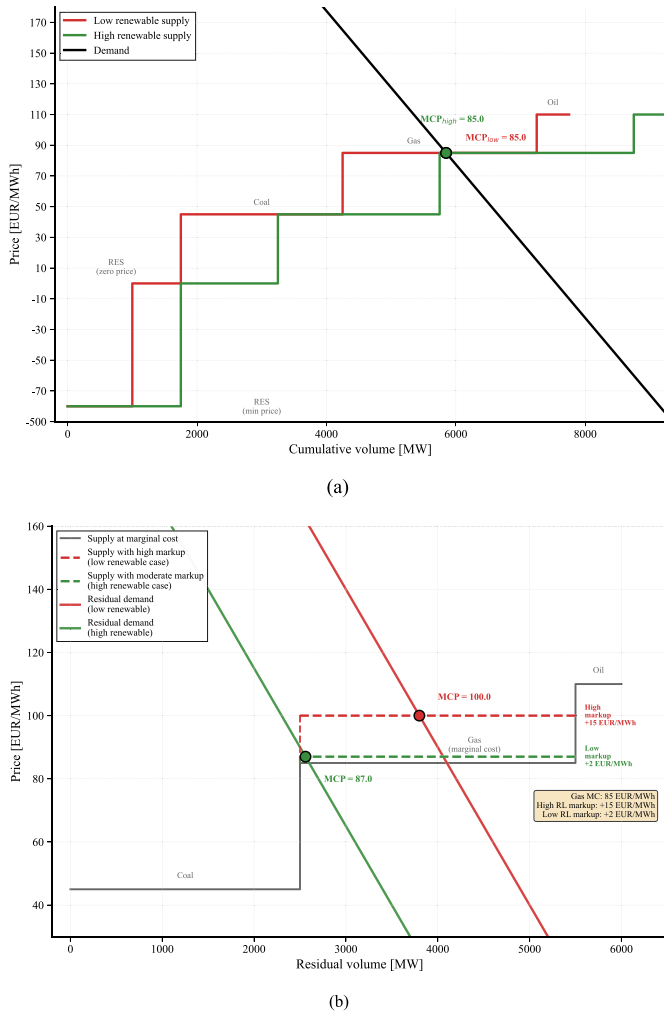


Fig. 4. Supply curves in a hypothetical market situation for a higher and lower renewable generation scenario. Panel (a) shows the clearing process where generators bid at marginal cost, and Panel (b) indicates the potential for markup bidding in both scenarios for a flexible gas generator.

and the TTF gas index. This results in the regression shown in Eq. (3):

$$\Delta_{7d}\text{slope}_{t,h} = \alpha_h + \beta_h \Delta_{7d}RL_{t,h} + \gamma_h \Delta_{7d}X_{t,h} + \rho_h \Delta_{7d}\text{slope}_{t-1,h} + \varepsilon_{t,h} \quad (3)$$

where $\text{slope}_{t-1,h}$ denotes the one-day lag of the dependent variable (slope), included in weekly-differenced form to control for short-run persistence in bidding behavior. Separate regressions are estimated for each hour to capture intraday variation in the relationship between residual load and bidding-curve steepness: a given residual-load level may correspond to different underlying market dynamics across hours. For example, during summer, conventional generators may be reducing output during the morning, whereas they may be ramping up toward the evening peak later in the day. The hour-specific specification therefore allows the estimated response to residual load to differ across these operating conditions.

The independent and dependent variables are standardized, following Eq. (4):

$$\tilde{X}_{j,t} = \frac{X_{j,t} - \mu_X}{\sigma_X} \quad (4)$$

Here $X_{j,t}$ denotes the hourly value of the dependent or independent variable j . The terms μ and σ represent the sample mean and standard

deviation (SD) of the respective variables. After standardization, the regression coefficients can be interpreted as the effect of a one SD change in the independent variable on the dependent variable.⁷

Ordinary least squares is used to calculate regression coefficients, estimated separately for summer (April–September) and winter (October–March) periods. A full year is taken from the 1st of April of that calendar year until the 31st of March of the next calendar year, rather than a calendar year (Jan–Dec), to comprise one entire summer and winter season.

To validate the quality of the regression, Kwiatkowski–Phillips–Schmidt–Shin (KPSS) tests are performed, and the null hypothesis of stationarity cannot be rejected at the 10% significance level. Collinearity among regressors is assessed using the Variance Inflation Factor (VIF), with values remaining below 5.

3.3. Analysis of volume distribution under scarcity

After evaluating the relation between scarcity and curve steepness on an aggregate level, we assess the effects on different sections of the bidding curve separately. The supply curve is therefore first divided into segments, designed to capture separate bidding dynamics. For each segment, the volume is defined by the difference between the bidding volume at the lower price point and the bidding volume offered at the last discrete bid before the upper price point of the bin, thus avoiding overlap between the segments. Curve segmentation is based on the marginal cost estimates per technology made in this study for the main time window (April 2024–March 2025) and those in recent literature (Ghelasi and Ziel, 2026).⁸ Ghelasi and Ziel (2026) present price ranges for bid placement associated with different generation technologies based on expert estimates, including biomass and must-run capacities for which this study did not derive marginal cost estimates. The first segment is set to comprise the minimum price bidding [−500, −499). The −150 EUR/MWh threshold is subsequently set at the lower estimate for the offering price of offshore wind, and the [−10, 10) price segment is designed to capture near-zero price bidding. At 75 EUR/MWh, we observe the lower bound estimate for the MC of lignite baseload generation across the time period, while 100 EUR/MWh forms the corresponding MC lower bound for hard coal. 120 EUR/MWh is subsequently the upper bound for CCGT MC, while the 120 to 160 EUR/MWh price range approximately covers the estimated OCGT MC. Finally, 225 EUR/MWh denotes the threshold for the 99th percentile of price, above which the highest scarcity prices remain.⁹ The curve segments and the bidding dynamics captured in each price bin are summarized in Table 5.

A regression analysis is performed to quantify the effect of RL on the volume offered in each price segment, matching the framework explained in Section 3.2. The independent variables include significant drivers of bidding volumes, consisting of the day-ahead unavailability, positive and negative contracted reserve volumes, and the gas and carbon permit prices. The net export is also incorporated, as it determines the quantity of bids transferred from the zone. The imports, meanwhile, appear in the bidding curve as minimum price bids, and these are correspondingly subtracted from the volumes in the minimum price segment [−500, −499).

To underpin the selection of drivers and curve segmentation, a Feature Importance (FI) analysis is performed through Random Forest Regression (RFR), which can capture nonlinear interactions to estimate the relative importance of each driver for the volumes in that

⁷ The coefficient β_h therefore represents the average effect over the full sample range. The effects in the upper scarcity regimes are treated separately in Section 3.4 (Fig. 5), and the effects of this limitation are discussed in Section 5.

⁸ For our technology-specific marginal cost estimates, we refer to Tables C.3 and C.4 in Appendix C.

⁹ See Table 2.

Table 5
Definition of the supply curve price segments.

Segment	Price Range (EUR/MWh)	Label	Description
1	[−500, −499]	Extreme Negative	Imports, Complex Bids, Solar FIT
2	[−499, −150]	High Negative	Must-Run & Inflexible Baseload
3	[−150, −10]	Moderate Negative	Remunerated VRE & CHP
4	[−10, 10]	Near-Zero	Competitive VRE
5	[10, 75]	Low Positive	Higher-Cost VRE & Low-Cost Thermal
6	[75, 100]	Low-Price Thermal	Lignite & Cheap CCGT
7	[100, 120]	Mid-Range Thermal	Hard Coal & Expensive CCGT
8	[120, 160]	Expensive Thermal	CCGT
9	[160, 225]	Extra-Marginal Thermal	Scarcity Bidding
10	[225, 1000]	Extreme Positive	Scarcity Bidding

segment.¹⁰ Results of this FI analysis are shown in Table 6.¹¹ These are relative and non-causal measures that do not indicate the sign of an effect, and are therefore used here to motivate the choice of regressors and the segmentation of Table 5, while the signed effects are quantified by the regressions in Sections 4.1 and 4.2.

The lowest price segment [−500, −499] is dominated by solar, placed to avoid curtailment and forgone subsidies. For highly negative bidding in [−499, −150], several drivers are of significance, but the generation unavailability shows the highest FI. This could relate to the inflexible baseload, consisting of Biomass and CHP must-run units, which are known to bid in these price ranges. Wind dominates the low negative prices [−150, −10], where feed-in under support schemes becomes competitive. Exports, rather than wind, are the most important drivers in the near-zero segment [−10, 10]. These exports, as explained, cause bids to be transferred from the supply curve. We could, therefore, expect that exports are greatest when there is an abundance of cheap renewable generation, and for the exports to show the greatest effect in the near-zero price range where this generation is offered. For the low positive prices [10, 75], and in the segments for low [75, 100], middle [100, 120], and high-priced thermal generation marginal costs [120, 160], the gas price, serving as a reference for fossil fuel inputs, is a main driver. The price of carbon, the load, and unavailability are also important drivers, with wind still showing some importance. For the extra-marginal thermal segment [160, 225] and in the highest price segment [225, 1000], the gas price remains the only dominant driver. Interestingly, wind gains in significance in this highest price segment, which could reflect scarcity bidding in response to low wind output. Finally, neither the positive nor negative reserve variables have a high feature importance in any of the segments.

3.4. Analysis of bidding markups under scarcity

We finally evaluate the implications of market tightness for the potential for strategic markups, as introduced in Fig. 4. We first distinguish between different high scarcity regimes, defined as follows. For each analysis year, a scarcity regime q comprises all hours whose residual

load lies above the q -th percentile of the annual RL distribution; we report results for $q \in \{90, 95, 97.5, 99\}$. The corresponding thresholds are computed separately for each year to account for differences in fuel-price regimes. From the hourly bidding curves in each such scarcity regime, we construct the average bidding curve by computing the arithmetic mean bid price at each volume interval. We subsequently contrast the resulting mean bidding curve under scarcity with the average bidding curve across all hours of the same period, termed the regular regime. The regular regime is therefore an average across all hours rather than the complement of the scarcity regimes, and it contains the scarcity hours against which it is compared; the reported curve distances are consequently a conservative measure of the scarcity effect. This definition differs from the intermediate band of the piecewise fit in Section 3.2, and we use ‘regular regime’ in the present sense from this section onward, reserving ‘extreme’ for price outcomes. To analyze the potential for markups in both regimes, we subsequently isolate the bidding of flexible generation in the middle and upper segments from bidding in the near-zero and negative-price ranges, associated with must-run capacities, VRE, and imports. The mean bidding curves for the regular and scarcity regimes are therefore cut below the price of 10 EUR/MWh. This price point will intersect each of the curves at a different volume. We therefore shift each of these curves horizontally such that this intersection point becomes the origin for the shifted curves. Practically, this means that the shifted curves contain the upper price range of the original curves aligned to a shared starting point. After this alignment, the mean curves for the scarcity and regular regimes are evaluated at fixed volume steps ΔV from the common reference, to measure each curve’s price gain. These price gains are contrasted with technology-specific marginal cost estimates, and the strategic scarcity markups under each regime can thus be compared. This approach is summarized in Fig. 5, showing how the potential for bidding markups under regular and high scarcity regimes is estimated.

We formalize two market-level indicators from this comparison. The *regime-conditional curve distance* $\Delta P_q(\Delta V) = \bar{P}_q(\Delta V) - \bar{P}_{\text{reg}}(\Delta V)$ measures the scarcity-induced bid-price uplift at a common volume offset from the shared reference anchor. The *excess scarcity markup* $SM_q(\Delta V) = \Delta P_q(\Delta V) - \Delta MC_{k^*(\Delta V),q}$ isolates the component of the price uplift that is not attributable to a shift in the marginal cost of the price-setting technology. To avoid conflating the price uplift with a change in the marginal unit across regimes, the reference technology $k^*(\Delta V)$ is selected offset by offset as the technology whose regular-regime marginal cost is the highest value not exceeding $\bar{P}_{\text{reg}}(\Delta V)$, i.e., the technology that sets the price at that offset under regular conditions. Where $\bar{P}_{\text{reg}}(\Delta V)$ falls below the entire thermal cost stack, the cheapest thermal technology is taken as the reference. Where it exceeds the highest thermal marginal cost, no reference technology brackets the price and $SM_q(\Delta V)$ is reported as an unattributable residual rather than being decomposed into the marginal cost movement and markup.

3.5. Scenario analysis with PowerACE

The final section of this study explores the effects of markup bidding under scarcity, as derived in Section 3.4, within a 2035 energy transition scenario. To this end, we employ the agent-based electricity market model PowerACE (Bublitz et al., 2014; Fraunholz, 2021). A general overview of the model is provided here, while a more detailed description of the model’s input and output data, daily agent bidding iteration, and coupled clearing step is provided in Appendix G.1.

PowerACE simulates spot market operations with daily bidding decisions to produce hourly clearing prices. Hourly supply consists of a portfolio of thermal generation technologies (lignite, hard coal, CCGT, CCGT, biomass, and oil) in addition to renewable generation. Wind and solar bid at zero marginal cost, and their output is determined by exogenous weather profiles. CHP and must-run units likewise submit bids at zero. Dispatchable generation technologies are represented by agents

¹⁰ Note that the residual load is entered in decomposed form, as load, wind, and solar separately, so that the importance ranking indicates which component of the RL drives the volumes in each segment.

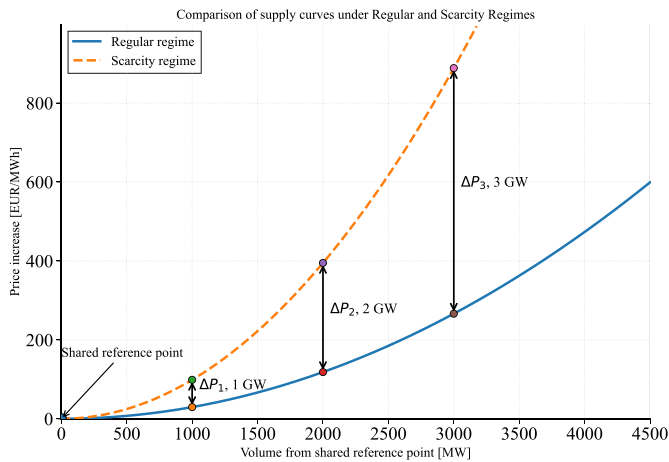
¹¹ The reported values are random-forest feature importances: for each price segment (row), these indicate the share of the model’s total reduction in prediction error for that segment’s bidding volume that is attributable to each driver (column), normalized to 100 across the row. A value of 58 for solar in the minimum-price segment therefore means that solar accounts for approximately 58% of the model’s explanatory power for that segment, relative to the other drivers included. Row totals may deviate from 100 by up to two points due to rounding.

Table 6

RFR feature importances of drivers for the volumes bid in each price segment of the supply curve.

Segm.	Price Range (EUR/MWh)	Unavail.	Pos. Res.	Neg. Res.	Exports	Gas Price	Carbon Permit	Solar	Wind	Load
1	[−500, −499)	3	4	4	5	3	2	58	15	7
2	[−499, −150)	23	4	5	18	12	11	6	14	8
3	[−150, −10)	3	0	0	2	1	1	1	90	1
4	[−10, 10)	3	1	1	56	5	3	5	25	2
5	[10, 75)	13	2	3	16	41	8	2	10	6
6	[75, 100)	22	8	6	8	12	16	6	10	12
7	[100, 120)	21	5	5	6	19	20	3	10	11
8	[120, 160)	8	3	4	5	56	5	3	7	10
9	[160, 225)	7	4	5	8	47	7	7	7	8
10	[225, 1000)	6	2	2	2	55	9	1	20	3

Note: Unavail. = unavailability; Pos. Res. = positive reserve; Neg. Res. = negative reserve.

**Fig. 5.** The mean supply curves under the regular and scarcity regimes, evaluated in the positive price range and shifted to a shared starting point. The price gains of each mean curve can be evaluated at fixed volume shifts from the starting point and compared to marginal cost estimates to assess the potential for markups in each regime.

that submit bids according to predefined strategies. Storage agents—pumped hydro and battery storage—forecast hourly day-ahead prices and derive an optimal charge/discharge schedule from that forecast, whereby hydro availability is determined by weather inputs. Market clearing is organized based on a simplified implementation of the European SDAC mechanism Euphemia, which aggregates the supply offers across the interconnected zones and matches them with deterministic demand profiles, generating the outcomes for each of the coupled markets (Ringler et al., 2017; Fraunholz, 2021).

To explore the effect of strategic bidding under scarcity, agents will incorporate the scarcity-induced markups as derived in Section 3.4. In addition, agents may apply price markdowns during periods of very low scarcity, when the RL is minimal. The agents first estimate their technology-specific marginal cost and evaluate where a bid of this price would be offered in the regular regime, in the absence of scarcity and thus without a markup/markdown.

Agents then forecast the residual load for the following day and infer the associated scarcity regime. When a high scarcity level is anticipated, e.g., the RL value is in the upper 90th percentile, the agent will increase the price of the bid from MC, where it would be placed under the regular (average scarcity level) regime, to the price point under the predicted high scarcity regime, vertically shifted upward from the regular regime curve. Conversely, when very low scarcity is expected (e.g., RL in the lower 10th percentile), the agent may submit a markdown relative to marginal cost. For instance, in the two-regime case shown in Fig. 5, an agent with an initial bid corresponding to 120 EUR/MWh, or MC,

located at the 2000 MW volume point on the regular curve, would adjust this bid to 400 EUR/MWh when forecasting high market tightness.

Accordingly, there exist two distinct bidding strategies for which the implications can be compared: the benchmark, in which agents always bid at exactly their MC, and the strategic bidding scenario, where dispatchable generation bids strategically at a markup/markdown, calibrated to the empirically observed behavior.

To validate the methodology, we simulated the year 2024 during which generators utilized both the markup bidding strategy and the pure marginal cost bidding, using the historical weather patterns and demand data as inputs. The accuracy of the price outcomes for both bidding strategies can then be evaluated against the historical prices. The results, presented in Appendix G.2, indicate that simulations incorporating the markup bidding strategy reproduce historical prices more accurately than the competitive benchmark, reducing the Root Mean Square Error (RMSE) of simulated prices by nearly 20%.

Finally, the 2035 scenario analysis requires assumptions for a number of input parameters. For the installed generation capacities per technology, we utilize projections from the global ambition scenario of the Ten-Year Network Development Plan from Entso-E (TYNDP, 2025), which also serve as the reference for fuel and emission allowance prices. Demand and renewable generation profiles are sourced from the ERAA 2024 modeling data report (ENTSO-E, 2024), which accounts for growth profiles in a representative future weather scenario.

4. Results

The empirical framework is applied to the German bidding zone for 2023 and 2024, and is replicated for the Belgian and Dutch bidding zones over the main 2024 window. This section presents results for the German zone for that main window (April 2024–March 2025), consistent with the 2024 price event motivating this study, while results for the German zone in 2023 and the replications for Belgium and the Netherlands are reported in Appendices D–F.

4.1. Curve steepness under scarcity

Results of the regression analysis of curve slope against residual load for the German zone are presented in Figs. 6 and 7, estimated for the summer (April–September) and winter (October–March) periods of 2024, respectively. Given that these show greater granularity and considering the length of the study, we show the results throughout the period from April 2024 to March 2025, as well as the results for 2023, in Appendix D.1. Figs. 6 and 7 indicate the hourly regression coefficients β_h for the supply curve slope against the residual load, as well as their significance levels. The slope is taken between price levels of 10 and 1000 EUR/MWh, comprising the bidding of conventional generation isolated from VRE and must-run bidding at the zero and negative price levels.

Figs. 6 and 7 show positive coefficients for the RL as a driver of bidding curve steepness at every hour of the day in both seasons. In the summer, the pattern across the day is non-monotonic. Coefficients range around 0.23 to 0.37 in the night and early morning hours (0 to 6),

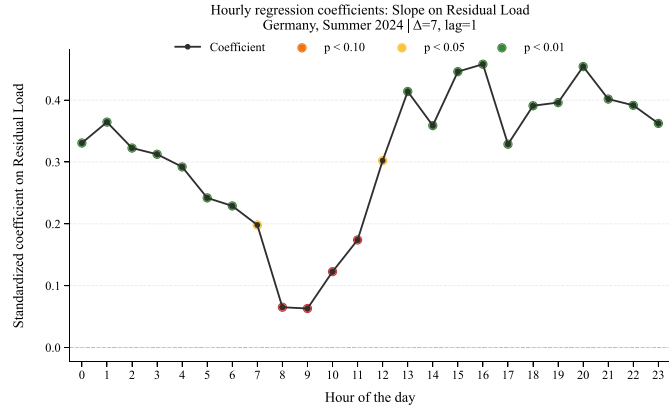


Fig. 6. Regression coefficients from regressing the bidding curve slope against the residual load for the German market in the summer of 2024. Significance levels are color-coded. (For interpretation of the references to colour in this Figure legend, the reader is referred to the web version of this article.)

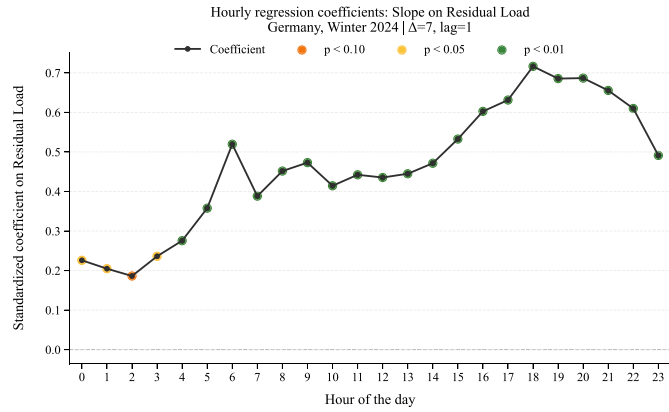


Fig. 7. Regression coefficients from regressing the bidding curve slope against the residual load for the German market in the winter of 2024. Significance levels are color-coded. (For interpretation of the references to colour in this Figure legend, the reader is referred to the web version of this article.)

indicating that a one SD increase in RL induces an increase in the slope of about one fifth to over one third of the slope's SD. Coefficients between hours 7 and 12 show a pronounced trough, falling to about 0.06 at hours 8 and 9, where they do not meet even the 10% level significance level. This trough coincides with the onset of high solar output, when thermal units are frequently priced out of the market and correspondingly have little scope to adjust their bidding in response to scarcity. From hour 13 onward, across the afternoon and evening hours, the coefficients recover to around 0.33 to 0.46, and the RL again shows the strongest relation to the steepening of the bidding curve, which continues in the night hours. In the winter, by contrast, no such midday trough appears: the coefficients range between 0.19 and 0.72 and are significant at the 1% level from hour 4 onward; in the hours 0–3 of the day, they are smallest and reach only the 5% and 10% levels.¹²

¹² These regressions were additionally re-estimated with day-ahead total unavailability and contracted positive and negative reserve volumes as further controls, covering the outage and must-run effects that also drive dispatchable supply. The residual load coefficient remained almost identical ($\bar{\beta}_h = 0.387$ averaged across all hours for the regression with the added controls compared to $\bar{\beta}_h = 0.369$ for the regression without these controls, with coefficients similarly significant at the 1% level for nearly every hour).

4.2. Volume distribution under scarcity

Figs. 8 and 9 present the results for the effect of the RL on the volumes bid in each price segment, estimated for the summer (April 2024 - September 2024) and winter (October 2024 - March 2025) periods for 2024. The analysis across the entire year (April 2024 - March 2025) is shown in Appendix D.2.

Figs. 8 and 9 show similar trends for the effects of RL on the bidding volumes per segment, with seasonal differences in the seventh [100, 120)

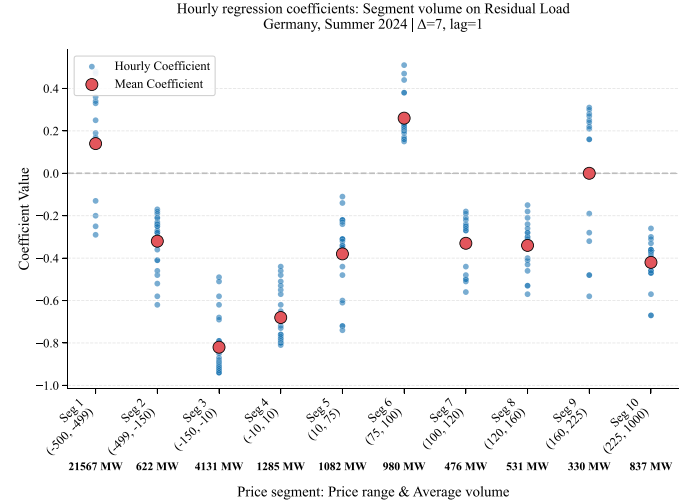


Fig. 8. Standardized regression coefficients from regressing the volumes in different price segments of the bidding curve against the residual load for the German market in the summer of 2024. For each segment, the price ranges and mean bidding volumes are shown on the x-axis labels. The hourly coefficients with p-values below 0.01 are indicated by blue markers, and the mean value calculated across all hours with significant coefficients is indicated in red. (For interpretation of the references to colour in this Figure legend, the reader is referred to the web version of this article.)

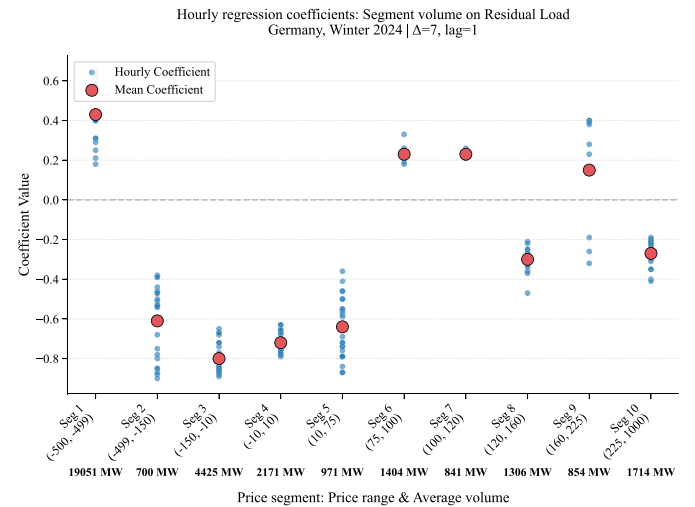


Fig. 9. Standardized regression coefficients from regressing the volumes in different price segments of the bidding curve against the residual load for the German market in the winter of 2024. For each segment, the price ranges and mean bidding volumes are shown on the x-axis labels. The hourly coefficients with p-values below 0.01 are indicated by blue markers, and the mean value calculated across all hours with significant coefficients is indicated in red. (For interpretation of the references to colour in this Figure legend, the reader is referred to the web version of this article.)

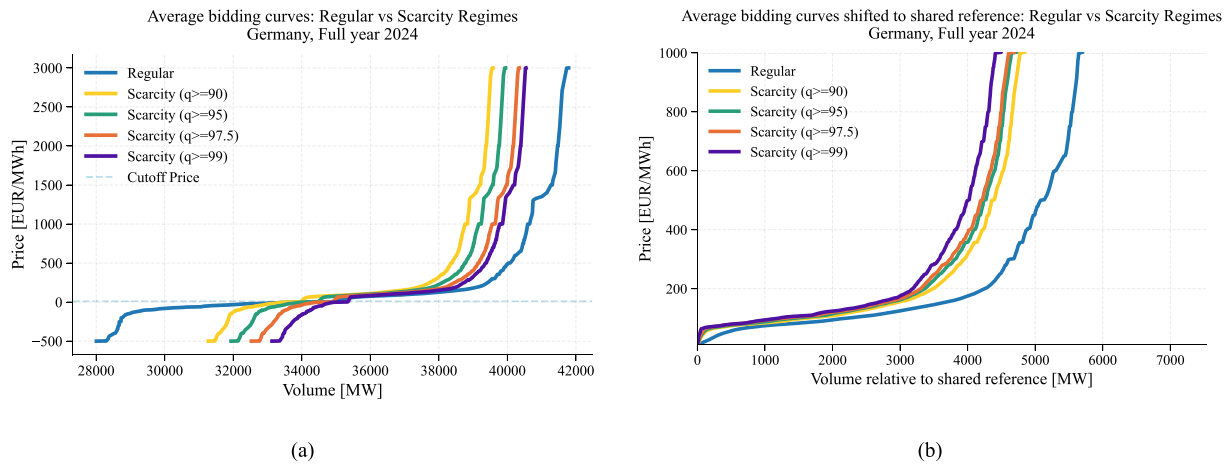


Fig. 10. A comparison of the mean bidding curves for several scarcity regimes and the regular regime across the entire price range (a) and the curves brought to a common reference point by shifting along the volume axis (b) for 2024.

and ninth [160, 225]. The results underpin findings of the slope regression results of Section 4.1. Considering the entire positive price range, from 10 to 1000 EUR/MWh, we observe that for increasing RL values, the volumes in most price bins decrease, which corresponds to the sharpening of the average slope observed in the previous section. The bidding volumes beyond the price floor segment [−500, −499], across the negative price segments, and low positive price segments show significant decreases for RL increases. As these segments are dominated by bidding by solar [−500, −499] and wind ([−150, −10], [−10, 10], and [10, 75]), this decrease in bidding volume as RL rises follows from the inverse relation of RL to renewable output. The [75, 100] segment, comprising the price range of lignite and CCGT thermal generation, shows positive coefficients for the RL. When the RL is low due to high VRE output and low demand, the less flexible lignite baseload units making up the bidding in this range might refrain from bidding. These units can incur high start-up/ramping costs, and the prices must therefore be sufficiently high during these peak morning and evening hours for the operation to be profitable. Instead, during summer, this price range might rather be populated by CCGT power plants, which allow for greater flexibility.¹³

In the summer, we subsequently see negative relations with the RL in both the seventh [100, 120] and eighth segments [120, 160], yet a reversal in the coefficient in segment 9 [160, 225]. Across the three segments, the bidding volumes are generally very low. This may suggest a movement from flexible OCGT units, which could be competitively priced in the [120, 160] range, to the higher price range [160, 225] when the RL becomes higher, which would exemplify scarcity bidding.

In the winter, we observe slight differences in the results. The RL seems to again induce an increase in bidding volumes for the 6th [75, 100] segment, but this is now observed for the 7th segment [100, 120], too. The generation assets bidding in response to higher RL may now be priced slightly higher, correlating with the higher MC during winter, causing the coefficient for the 7th segment to now be positive, as compared to the negative coefficient observed in summer. The negative, then positive coefficients for segments 8 and 9 could again suggest an upward shift in bidding volumes for peak plants when the RL is higher.

¹³ In the midday hours of summer (hours 11 to 15), when the 77 GW of installed solar capacity is most active, and demand is low, the RL is often very low and even becomes negative. At these times, bids at marginal cost for thermal baseload generation are very unlikely to be accepted until the evening. Units with the lowest flexibility might then decide to bid far below their MC to ensure activation throughout the entire day, given that evening peak prices allow for these costs to be recovered (Jha and Leslie, 2025). As an alternative response, inflexible power plants may decide not to participate at all and remain offline for longer periods of time.

The negative relationship between the RL and bidding volumes in the highest bidding segment is notable. While we would expect participants to pursue bidding in this segment for higher RL values to earn scarcity revenues, which would signify a positive coefficient, we must note that prices across both seasons only exceeded 225 EUR/MWh in under 1% of hours. As the relationship between RL and bidding volumes in this segment is determined across all hours of the year, rather than only for the highest RL hours, the negative coefficient may instead be guided by a different influence not apparent from this analysis. The bidding dynamics that appear for the highest scarcity hours are, meanwhile, analyzed in the next section.

4.3. Strategic bidding under scarcity

Fig. 10(a) shows a comparison of the average bidding curves under the regular and high scarcity regimes for the full price range, while Fig. 10(b) shows the shifted curves brought to the shared reference point. Scarcity regimes are defined as the upper 90th, 95th, 97.5th, and 99th percentiles of RL values. Table 7 compares the price increases for the regular and scarcity regimes at each volume shift interval from the shared reference point. Appendix D.3 shows the corresponding analysis for the summer and winter periods of 2024 separately.

Fig. 10(a) shows the gradual thinning of the bidding curves with each increase in scarcity regime. As the RL increases, the supply curves show fewer bids, which is especially notable in the near-zero price range, as increases in RL correlate with decreases in the VRE generation that dominates this range. We observe increases in the minimum price segment for the higher scarcity regimes, related to the increase in import volumes.¹⁴ Fig. 10(b) and Table 7 show a notable increase in the curve steepness for higher scarcity regimes. We observe a consistent relationship between a higher RL regime and greater price differentials per volume shift from the shared reference point, higher marginal costs for thermal generation, and higher MCPs. Interestingly, we do not see a divergence between the regular and scarcity regimes in curve sharpness for the low price ranges. After an initial price jump from 10 to around 50 to 60 EUR/MWh, the curve's steepness appears identical across all regimes until around 100 EUR/MWh.

This is quantified by the regime-conditional curve distances, $\Delta P_q(\Delta V)$, showing the differences in bid prices at each volume increment. The price differentials seem to rise gradually from the 1 GW increment to the 3 GW increment, but remain moderate. At the 4 GW

¹⁴ Note that this motivates the correction of the volume at minimum price by these imports in the regression of bidding volumes against RL presented in the previous section.

Table 7

Price values for mean supply curves for the regular and scarcity regimes in 2024 (Apr 2024 - Mar 2025), evaluated at fixed volume increments from the shared reference point. The reference point at the origin is set at a volume of 0 GW and a price of 10 EUR/MWh, and increments are taken at 1 GW intervals. Technology-specific marginal cost benchmarks, residual load levels, imports, and MCPs per regime are shown for reference. All values are denoted in EUR/MWh except residual load and Import (MW).

Regime	+1 GW	+2 GW	+3 GW	+4 GW	MC Coal	MC Lignite	MC CCGT	MC OCGT	Res. Load	Import	MCP
Regular	74.47	94.40	124.72	174.67	103.65	83.41	98.54	136.76	31,591	7968	89.44
90th	84.04	108.79	156.07	318.51	103.87	83.20	102.66	142.52	53,357	12023	174.99
95th	87.68	114.66	161.78	357.60	104.09	83.27	105.33	146.25	56,525	12653	208.79
97.5th	92.88	120.50	166.74	391.12	104.46	83.47	108.70	150.97	59,307	13366	256.49
99th	93.81	123.68	174.37	495.49	104.94	84.27	111.13	154.38	61,921	13833	355.10

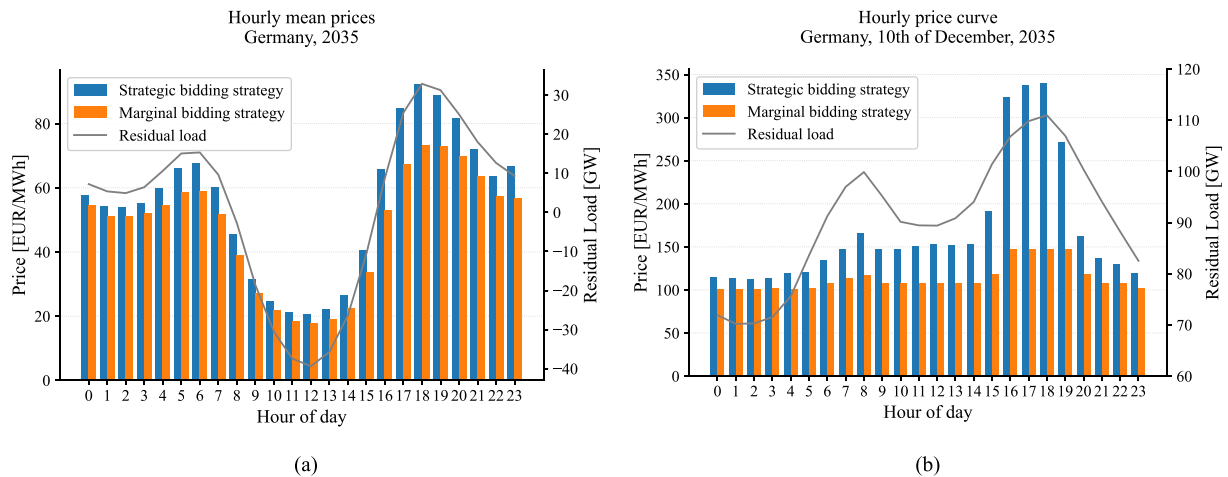


Fig. 11. A comparison of the average hourly prices for Germany under marginal-cost and strategic bidding regimes in the scenario simulation across the entire year 2035 (a) and on an example high RL day on the 10th of December, 2035 (b).

volume increment, the differences widen substantially, coinciding with the bid price exceeding the estimated marginal cost of the most expensive thermal technology, OCGT. At this 4 GW point, the average price increase relative to the starting point is nearly three times higher in the 99th-percentile scarcity regime than in the regular regime.¹⁵

Formalizing the excess scarcity markup as $SM_q(\Delta V) = \Delta P_q(\Delta V) - \Delta MC_{k^*(\Delta V),q}$ with an offset-specific reference technology confirms this pattern quantitatively. For $q \geq 99$, the reference technology at successive offsets shifts up the merit order as the regular-regime price rises: lignite anchors +1 and +2 GW ($\bar{P}_{reg} = 74.5$ and 94.4 EUR/MWh), hard coal anchors +3 GW ($\bar{P}_{reg} = 124.7$ EUR/MWh), while bid prices at +4 GW ($\bar{P}_{reg} = 174.7$ EUR/MWh) exceed the highest thermal marginal cost. The excess markup grows from $SM_{99}(+1 \text{ GW}) = 18.5$ EUR/MWh at the offset where lignite is marginal, to $SM_{99}(+2 \text{ GW}) = 28.4$ EUR/MWh (lignite) and $SM_{99}(+3 \text{ GW}) = 48.4$ EUR/MWh (hard coal). At +4 GW, the excess jumps to 320.8 EUR/MWh, unattributable to a specific thermal marginal-cost band.

The upper marginal cost estimate of OCGT peaking units thereby appears to mark a threshold beyond which the aggregate bidding behavior increasingly shifts to scarcity bidding. When the market clears in this range during the tightest hours, price extremes are expected. This extends the finding of Krzywnicka and Barner (2025), who attribute a substantial share of the 2022 departure from competitive pricing in

the German market to strategic behavior under a fuel cost shock. The scarcity markups documented here arise in 2024, at fuel and carbon costs far below their 2022 levels (Table 3), indicating that the mechanism is tied to a tight supply-to-residual-load ratio rather than being conditional on elevated input costs.

4.4. Analysis of strategic bidding in 2035 scenario

While the empirical results of Sections 4.1–4.3 establish how bid placement responds to scarcity in the current system, this section projects those dynamics into a future high-renewable system. Using PowerACE, we embed the calibrated scarcity-driven markup rules into a 2035 scenario to evaluate the resulting price impacts.

Fig. 11(a) compares the mean hourly electricity prices for Germany under marginal-cost and strategic bidding across the full year.¹⁶ Fig. 11(b) illustrates the corresponding hourly price profile for a selected high-RL winter day. The 10th of December 2035 is selected because its simulated day-ahead price sits exactly at the 95th percentile of the annual simulated price distribution, illustrating the effects of the scarcity-induced markups in the regime where these bind most strongly.

The mean hourly MCPs increase by about 2 to 18 EUR/MWh when the markup strategy is employed, compared with a simulation using pure marginal bidding. Across the entire year, the average price increase amounts to 7.38 EUR/MWh, or 15.49%. The absolute prices and the price gains for strategic bidding closely follow the daily RL patterns. Consequently, the strongest price effects occur during the evening peak hours (16–20 h), when RL is highest.

¹⁵ Notably, the curve sharpening appears to continue across the [160, 225) EUR/MWh price range for the upper scarcity regimes. This provides a deeper understanding of the results shown in Section 4.2. The volume regression analysis showed an increase in bidding volumes with increasing RL in the [160, 225) EUR/MWh price segment, which would instead suggest that the bidding curve becomes flatter. This may indicate a difference in dynamics for the higher scarcity regimes as presented in Fig. 10(b), as compared to the analysis across the entire range of RL values used in Section 4.2.

¹⁶ Results for the Belgian and Dutch zones are shown in Appendices E and F respectively, while results for the backtesting validation checks are shown in Appendix G.2.

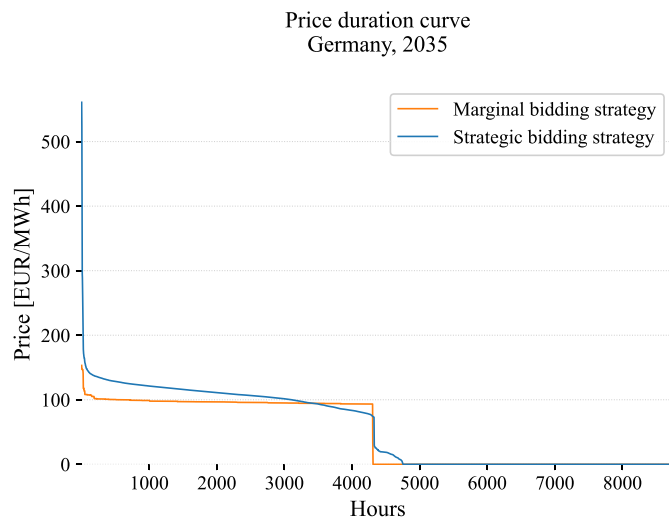


Fig. 12. Comparison of the price duration curve for scenario analysis for the year 2035 using the marginal-cost and strategic bidding strategies.

The effect is particularly evident on the high-RL day depicted in Fig. 11(b), where strategic bidding leads to price increases throughout the day. The evening peak is affected most strongly, with prices in hours 16–18 more than doubling, and markups reaching up to 192 EUR/MWh. This illustrates the mechanism documented in this study: during high RL hours, strategic bidding can drastically amplify price outcomes under scarcity. Relatively minor increases in RL can, for these upper RL hours, thereby produce disproportionate increases in the resulting prices.

Fig. 12 shows the resulting price duration curve across the entire simulated year.

The price duration curve indicates that the markups are not uniformly distributed across all hours. Under the marginal-cost bidding scenario, prices are determined by OCGT generation in roughly half of the hours, while in nearly all remaining hours, prices are effectively set by VRE at 0 EUR/MWh. For about 5% of the time, the price is set by biomass and CHP must-run resources, which bid at zero EUR/MWh under the marginal-cost scenario, yet add markups in the strategic bidding scenario. This outcome reflects the substantial expansion of renewable capacity assumed in the TYNDP scenario. Installed solar capacity increases from 77 GW in 2024 to 384 GW by 2035, while wind capacity grows from 74.6 GW to 192 GW, and average hourly demand is around 82 GW. As a result, VRE output frequently exceeds demand, leaving the market-clearing price at or near zero. In these hours, the strategic bidding scenario produces identical prices to the marginal-cost benchmark.

Differences between the two bidding regimes emerge primarily during periods of tighter system conditions. In approximately 5% of hours (around 400 hours), markdowns lead to prices that are lower than under marginal-cost bidding. In contrast, about 30% of hours exhibit markups exceeding 10% relative to the marginal-cost benchmark, while roughly 0.5% of hours (46 hours) show price increases exceeding 50%.

The largest impact occurs during extreme scarcity periods. The annual peak price rises from 153 EUR/MWh under marginal-cost bidding to 561 EUR/MWh under the strategic bidding scenario—an increase of 268%. This illustrates how strategic bidding during relatively few high-scarcity hours can disproportionately affect the upper tail of the price distribution. This result complements the predictive-quantile literature on extreme prices: whereas Hagfors et al. (2016) identify *when* extreme prices are likely to occur in the German day-ahead market from fundamental drivers, the forward-looking simulation here explores how bidding behavior can affect the magnitude of these price extremes. The results indicate that, under the simulated 2035 market conditions, bidding behavior can materially amplify extreme prices beyond the levels obtained under marginal-cost bidding.

5. Critical discussion and future outlook

This study examined the mechanisms underlying extreme price formation in the day-ahead electricity market by investigating how bidding behavior responded to scarcity indicators. For a fitting interpretation of the results, we critically reflect on some data-related, conceptual, and methodological considerations.

The aggregated nature of the bidding data from EPEX SPOT does not permit the identification of individual market participants, reflecting a broader challenge in electricity market research and bounding what the analysis can identify. Without firm identifiers, firm-level concentration measures such as the Residual Supply Index or Herfindahl–Hirschman Index cannot be constructed. Market-level counterparts of these measures were therefore presented in the paper: the regime-conditional curve distance $\Delta P_q(\Delta V)$ and the excess scarcity markup $SM_q(\Delta V)$ introduced in Section 3.4 measure changes in bidding behavior under scarcity at the aggregated level, where $SM_q(\Delta V)$ quantifies the markups that cannot be attributed to marginal-cost movement across the entire conventional bidding range. However, these market-level indicators cannot inform us of the underlying firm-level strategies, e.g., scarcity pricing under uncertainty, portfolio-level bid optimization, or other strategic behavior. Separating these interpretations requires firm-level bid data.

Spot market bidding may be influenced by a market participant's position across the intraday, balancing, reserve, and forward markets. Reserve market participation may induce bids at the floor price, whereas bids at the upper extreme can reflect reselling of forward contracts. Similarly, plant-level characteristics, e.g., ramping times and costs, shape dispatch decisions but are technology- and unit-specific. However, neither mechanism can be resolved at the aggregate market level from the available data, and they are therefore not included in the empirical framework. An integrated modeling framework, spanning multiple timeframes and markets, could therefore improve the analysis by incorporating opportunity costs in spot market dynamics. However, given the unavailability of granular participant-level data, this is left for future work.

The mechanism quantified for Germany, and replicated for Belgium and the Netherlands, could transfer to other decarbonizing power systems with growing VRE penetration, in which the price-setting margin at scarcity is still a flexible thermal unit, e.g., open-cycle gas. Belgium and the Netherlands reproduced the RL-steepening pattern observed for Germany, with positive coefficients that are significant at the 1% level in nearly all hours (Appendices E and F). However, the observed patterns may vary in magnitude in systems with fundamentally different generation mixes, such as nuclear-dominated markets like France or hydro-dominated systems like Norway, where different mechanisms may shape bidding behavior under scarcity. Testing the transferability of the analysis across zones with different characteristics remains an interesting pathway for future research.

The regression framework to analyze the effects of scarcity on bid pricing and volume placement already included a comprehensive set of drivers, and corrected for several seasonality effects while including rigorous statistical testing. Future work may expand the framework to explore whether other relations exist in certain sub-regimes of the data, e.g., by estimating the regression coefficients under high-scarcity regimes separately. Section 3.4 already takes a first step in this direction by treating the highest-scarcity regimes separately. Further disaggregation would need to be conducted with sufficient caution to ensure that statistically robust results can still be obtained, given the smaller number of observations in each sub-regime.

6. Conclusions and policy recommendations

This study examines the formation of extreme prices in the German day-ahead electricity market, with replications in the Belgian and Dutch bidding zones, by analyzing how scarcity conditions affect bid pricing and volume placement along the aggregated supply curve. Using

bidding data from EPEX Spot combined with fundamental market variables, we identify systematic patterns in how market participants adjust their bidding strategies in response to anticipated market tightness, such as during the significant price peaks in the German zone in 2024.

Our analysis reveals several main findings. First, the steepness of the supply curve in the positive price range increases significantly with residual load, indicating that market participants place sharply priced bids in anticipation of scarcity. This relationship is strongest during winter months, when it is most pronounced during the evening peak hours, when market tightness is greatest, and weakest during the late-morning and midday hours of summer, when solar generation dominates supply and thermal units are frequently priced out of the market.

Second, a more granular analysis of bidding volumes across price segments shows a pronounced reduction in bids in the negative and near-zero price ranges dominated by renewable generators, while in the highest price ranges, bids shift toward the upper tail of the curve under market tightness, suggesting that peaking units seek to capture scarcity rents. In the middle segments, the relationship is more complex, as higher residual load may trigger the activation of additional baseload assets and thereby increase bidding volumes. As VRE output declines and residual load increases, these combined effects contract the effective supply curve, allowing clearing prices to rise rapidly during periods of high scarcity.

Third, comparing the average bidding curves in hours when scarcity is highest to the average bidding curve across all hours of the year reveals that bids under scarcity are substantially elevated compared to the average, far exceeding the movements explained by marginal cost differences. Below the estimated marginal costs of the price-setting open-cycle gas turbines, the excess scarcity markup is already positive but grows moderately with the volume offset, from around 19 to 48 EUR/MWh. Beyond this threshold, it rises by nearly an order of magnitude, producing price increases nearly three times higher than those observed in the regular regime.

Scenario analysis through the PowerACE model reveals that these strategic bidding dynamics can have substantial implications for price formation under an energy transition scenario. Simulating the European power markets in 2035 shows that scarcity-induced markup strategies raise average German wholesale prices by around 7.38 EUR/MWh (15.49%) relative to a competitive marginal-cost benchmark. These increases are highly concentrated at times of high residual load, such as in the winter period during the evening peak hours: while most hours of the year remain largely unaffected due to high renewable generation, 0.5% of hours experience price increases of over 50%, and the annual peak price increases from 153 to 561 EUR/MWh, or by 268%.

These findings have important implications for ongoing energy policy debates concerning electricity market design, generation adequacy, and the exposure to strategic bidding in increasingly renewable-dominated systems.

The analysis highlights the importance of modernized market monitoring. While the relationship between residual load and curve steepness remains consistent with legitimate scarcity pricing, the volume analysis reveals a complex interplay of behaviors. In the market, participants will incorporate operational constraints, extra-market revenue streams, and expectations for future intervals in their bidding decisions. Bidding patterns will therefore vary across residual-load levels, and certain behaviors may only emerge under extreme market tightness. This supports monitoring frameworks built on curve-based indicators—the steepness of the supply curve, the distribution of bid volumes across price segments, and the excess scarcity markup employed here—to better identify the drivers of extreme price formation.

Such monitoring depends on data that are currently not publicly available. The continued lack of disaggregated, firm-level bidding data constrains the ability to distinguish between efficient scarcity pricing and potential exercise of market power. When the 2024 peak price

event triggered concerns regarding the limited offered capacity, the absence of sufficiently detailed data prevented independent researchers from properly evaluating these claims, which could only be resolved by the later report of the regulatory agency, concluding that there was no evidence of market rule violations (Bundeskartellamt, 2024). Enhancing transparency while safeguarding confidentiality is therefore a prerequisite for both effective governance and credible research. Better detection, however, will not by itself remove the behavior: under market scarcity, at times of steep, inelastic residual demand, raising offers beyond marginal costs may become profitable even for small units without significant market power, making scarcity-responsive bidding structural in an energy-only market with limited dispatchable capacity rather than necessarily being evidence of abuse.

The results underscore the importance of policies that both reduce localized scarcity and maintain adequate dispatchable capacity. First, stronger interconnection and increased low-carbon flexibility can reduce the frequency and depth of scarcity by expanding the resources available to meet demand when renewable output is low. This does not limit strategic bidding directly, but reduces the number of hours in which the steep tail of the domestic supply curve sets the price. Second, capacity remuneration schemes, reliability obligations, or strategic reserves may be needed to address the longer-term investment challenge. High VRE penetration can reduce the utilization and profitability of dispatchable generation, while risk aversion and uncertainty about future scarcity revenues may weaken the investment signals provided by energy-only markets (Joskow, 2008; Keppler, 2017; Beck-Bang et al., 2026). By providing greater revenue stability, such mechanisms can help retain sufficient dispatchable capacity to manage extended periods of very low renewable output (*Dunkelflaute*). Both policy approaches should nevertheless preserve scarcity-price signals that support efficient short-term dispatch and long-term investment (Mou et al., 2023). Assessing how interconnection, flexibility resources, and alternative capacity-remuneration designs jointly affect the frequency and magnitude of extreme prices remains an important avenue for future research.

Overall, the evidence suggests that as electricity systems transition toward higher shares of variable renewables, price formation must be analyzed through the combined lens of fundamental supply dynamics, strategic bidding behavior, and market design features related to integration and flexibility provision. Mitigating the resulting risks requires improved oversight of strategic behavior under tightness, stronger cross-border interconnection, and careful monitoring of generation capacity developments. That the same scarcity-responsive bidding is observed in the Belgian and Dutch zones indicates that these challenges are shared across decarbonizing European markets rather than confined to Germany.

CRediT authorship contribution statement

Jilles De Blauwe: Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Thorsten Weiskopf:** Writing – original draft, Visualization, Investigation, Formal analysis, Data curation. **Harshit Gaur:** Formal analysis. **Armin Ardone:** Writing – review & editing, Supervision, Conceptualization. **Dogan Keles:** Writing – review & editing, Supervision, Methodology, Funding acquisition, Conceptualization.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the authors used Grammarly and ChatGPT 4o for language refinement and grammar correction. The authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

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.

Acknowledgements

The authors thank the German Federal Ministry for Economic Affairs and Energy (BMWE), which supported this work within the BETS project under Grant No. 03EI1069 A.

Appendix A. Example bidding curve for the German bidding zone for hour 16 on the 24th of April, 2024

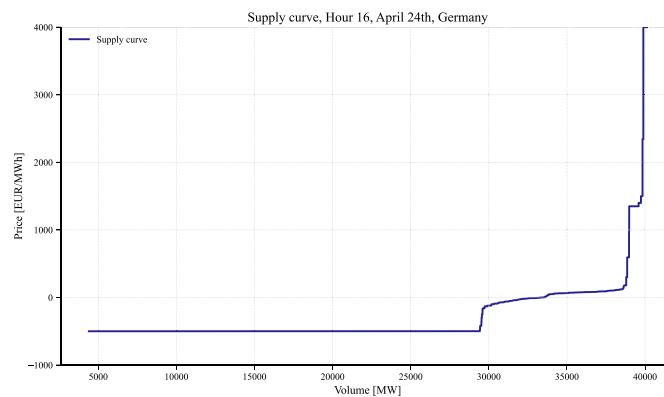


Fig. A.1. Exemplary bidding curve for the German bidding zone for hour 16 on the 24th of April, 2024.

Appendix B. Supplement to the preliminary analysis of extreme price events

Table B.1

Plant unavailability during the December 2024 price peak, indicating the available capacity relative to the total installed capacity.

Outage Type	Unavailability Period	Plant	Technology	Cap. Installed (MW)	Cap. Available (MW)
Planned	09/12 05:02 – 13/12 12:30	Vianden 2	Pumped storage	100	0
Planned	09/12 07:00 – 12/12 16:00	Goldisthal	Pumped storage	265	0
Forced	09/12 09:24 – 14/12 07:00	Heilbronn	Hard coal	778	360
Forced	09/12 16:45 – 12/12 13:30	Waldeck II	Pumped storage	240	0
Forced	11/12 14:30 – 12/12 22:45	DanTysk	Wind farm	288	0
Planned	11/12 15:00 – 12/12 14:00	Huckingen B	Gas-fired plant	300	3
Planned	11/12 16:15 – 13/12 19:15	Huntorf	Gas turbine	321	120
Planned	12/12 05:00 – 12/12 14:00	Markersbach A	Pumped storage	160	0
Planned	12/12 05:30 – 12/12 10:00	Schwarze Pumpe	Lignite	755	326
Planned	12/12 07:30 – 31/12 19:45	Butendiek	Wind farm	288	0
Total				3495	809

Appendix C. Data and cost parameters

This appendix presents the data and cost parameters used in this study. Table 1 in Section 2 lists the underlying datasets.

C.1. Analysis variables

The variables underpinning this analysis are presented in Table C.1.

Table C.1

Analysis variables used in the regressions and curve-distance analysis, with source and granularity.

Variable	Unit	Source	Granularity
Day-ahead price	EUR/MWh	EPEX Spot	Hourly
Aggregated hourly bidding curves	(P, V) pairs	EPEX Spot	Hourly
Load (day-ahead forecast)	MW	ENTSO-E TP	Hourly
Wind generation (day-ahead forecast)	MW	ENTSO-E TP	Hourly
Solar generation (day-ahead forecast)	MW	ENTSO-E TP	Hourly
Residual load = Load – Wind – Solar	MW	Computed	Hourly
Cross-border imports/exports (day-ahead schedule)	MW	ENTSO-E TP	Hourly
Day-ahead total unavailability	MW	ENTSO-E TP	Hourly
Positive/negative contracted reserve volumes (aFRR + mFRR)	MW	ENTSO-E TP	Hourly
Marginal cost by technology (CCGT, OCGT, hard coal, lignite)	EUR/MWh	Computed via the marginal-cost formula in Appendix C.2	Hourly, per technology
TTF natural gas	EUR/MWh	Investing.com	Daily
Rotterdam coal	USD/t	Investing.com	Daily
EU ETS carbon (ICE CFI2)	EUR/tCO ₂	Investing.com	Daily
Temperature	°C	ENTSO-E TP	Hourly
Time fixed effects: hour of day, day of week, month	n/a	–	Hourly

Load, wind, and solar values are the day-ahead forecasts available at gate closure, since the bidding decision is taken on the forecast rather than on the realized value; all series are aligned to Central European Time across our hourly sample.

C.2. Cost parameter assumptions and marginal cost estimation

Table C.2

Assumed cost parameters by generation technology. Note that the lignite cost is assumed to be a fixed 4 EUR per MWh of electricity produced, based on Hermann and Matthes (2017).

Technology	η	Emission factor (tCO ₂ /MWh _{fuel})	Fuel price proxy	VOM (EUR/MWh)
Lignite	0.38	0.40	–	6.0
Hard Coal	0.40	0.34	Rotterdam coal	6.0
CCGT	0.56	0.20	TTF natural gas	3.0
OCGT	0.40	0.20	TTF natural gas	3.0

Table C.3

Average marginal cost estimates by generation technology (2020–2025).

Year	Lignite (EUR/MWh)	Hard Coal (EUR/MWh)	CCGT (EUR/MWh)	OCGT (EUR/MWh)
2020	37.17	45.69	29.21	39.70
2021	68.34	95.83	98.04	136.06
2022	95.23	175.40	271.07	378.29
2023	99.09	120.88	109.42	151.99
2024	79.99	101.24	88.99	123.39
2025	87.99	103.12	94.27	130.78

Table C.4
Monthly average marginal cost benchmarks by technology, Germany (2024–2025).

Panel A: 2024				
Month	Lignite (EUR/MWh)	Hard Coal (EUR/MWh)	CCGT (EUR/MWh)	OCGT (EUR/MWh)
January	77.84	95.54	80.15	111.00
February	69.37	89.37	69.82	96.55
March	73.40	97.52	72.76	100.66
April	82.57	103.63	80.05	110.86
May	87.16	105.50	85.37	118.32
June	83.05	101.88	89.51	124.11
July	81.89	102.89	85.92	119.09
August	84.59	107.43	96.87	134.42
September	77.86	100.85	91.50	126.90
October	77.64	101.82	98.16	136.23
November	81.75	105.15	108.45	150.62
December	82.75	103.31	109.32	151.84

Panel B: 2025				
Month	Lignite (EUR/MWh)	Hard Coal (EUR/MWh)	CCGT (EUR/MWh)	OCGT (EUR/MWh)
January	90.88	108.65	117.30	163.01
February	88.87	104.24	118.88	165.23
March	82.19	98.41	102.36	142.10
April	77.57	95.08	87.01	120.61
May	84.65	99.38	91.15	126.42
June	86.31	103.51	94.10	130.54
July	84.63	102.56	89.38	123.93
August	85.82	101.70	87.16	120.82
September	90.42	103.18	88.20	122.28
October	92.87	104.69	88.70	122.98
November	95.32	108.27	86.61	120.05
December	96.30	107.79	80.44	111.41

Appendix D. Additional results for Germany

This appendix collects the additional results and robustness checks for the German bidding zone that complement the main-text results of [Section 4](#). Cross-zone results for Belgium and the Netherlands are reported in [Appendices E and F](#).

D.1. Additional slope regression results

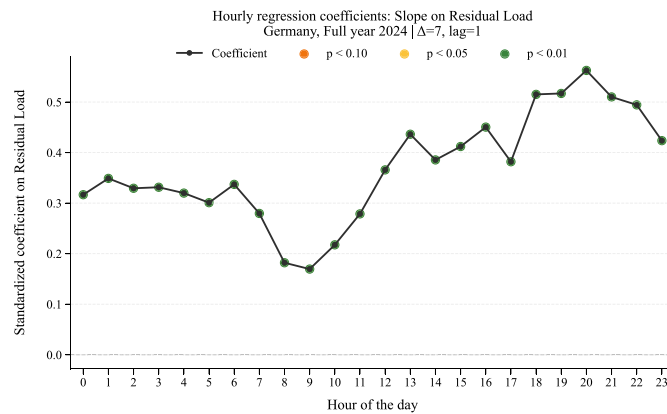


Fig. D.1. Regression coefficients from regressing the bidding curve slope against the residual load for the German market for the full year of 2024 (April 2024–March 2025). Significance levels are color-coded. (For interpretation of the references to colour in this Figure legend, the reader is referred to the web version of this article.)

[Fig. D.1](#) shows the hourly regression coefficients β_h for the supply curve slope against the residual load and their significance levels, estimated for the full year 2024 (April 2024–March 2025). The slope is taken between price levels of 10 and 1000 EUR/MWh. [Figs. D.2–D.4](#) show the corresponding results for the full year, winter (October–March) and summer (April–September) periods of 2023, respectively.

The baseline coefficient on residual load is positive at every hour of the day and significant at the 1% level in the great majority of hours in both years. The 24-hour mean coefficient moves from 0.450 in 2023 (April 2023–March 2024) to 0.369 in 2024 (April 2024–March 2025), despite the substantially different price environments: 2023 was a year of declining but still elevated fuel prices, while 2024 exhibited both a higher peak price and far more frequent negative prices (cf. [Table 2](#)). The pattern is consistent across the day rather than confined to peak hours.

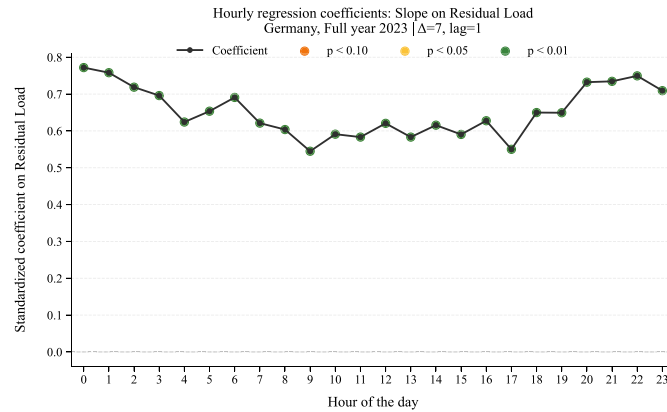


Fig. D.2. Regression coefficients from regressing the bidding curve slope against the residual load for the German market for the full year of 2023 (April 2023–March 2024). Significance levels are color-coded. (For interpretation of the references to colour in this Figure legend, the reader is referred to the web version of this article.)

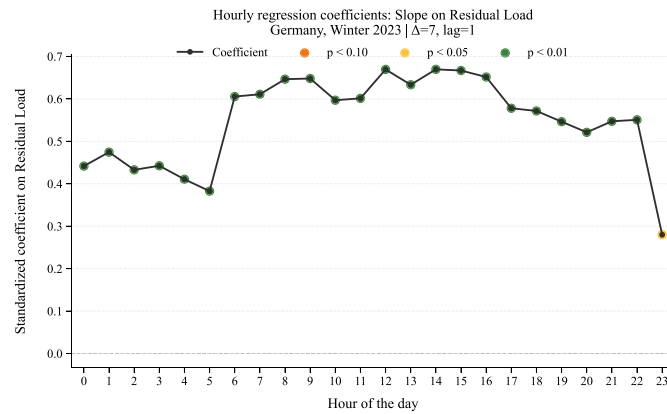


Fig. D.3. Regression coefficients from regressing the bidding curve slope against the residual load for the German market in the winter of 2023. Significance levels are color-coded. (For interpretation of the references to colour in this Figure legend, the reader is referred to the web version of this article.)

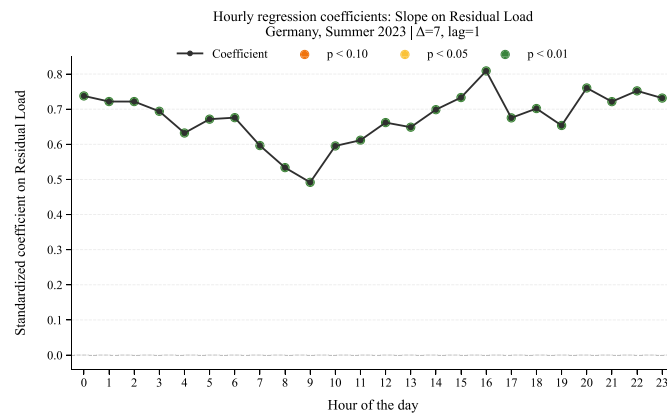


Fig. D.4. Regression coefficients from regressing the bidding curve slope against the residual load for the German market in the summer of 2023. Significance levels are color-coded. (For interpretation of the references to colour in this Figure legend, the reader is referred to the web version of this article.)

D.2. Additional volume regression results

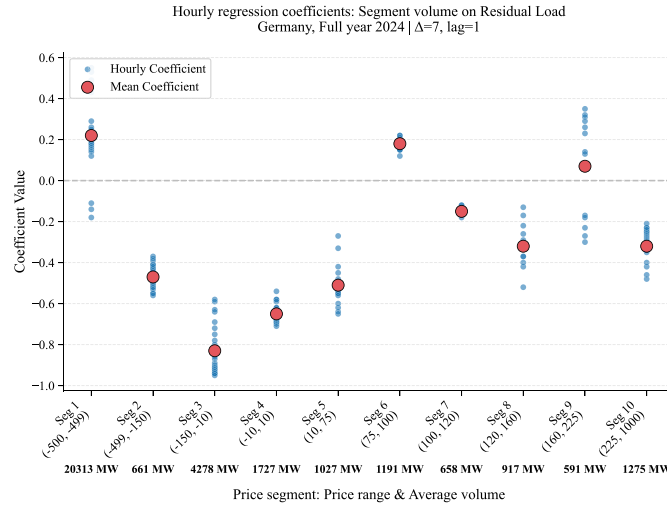


Fig. D.5. Standardized regression coefficients from regressing the volumes in different price segments of the bidding curve against the residual load for the German market across the full year from 2024 (April 2024 to March 2025).

D.3. Additional results for the comparison of bidding curves under regular and high scarcity regimes

Fig. D.6(a) and (b) show the comparison of the average bidding curves under the regular and high scarcity regimes, for the upper 90th, 95th, 97.5th, and 99th percentiles of RL across the entire price range, and the shifted curves brought to the shared reference point for the summer of 2024 in Germany. Table D.1 shows the corresponding analysis of price differentials under both regimes.

Fig. D.7(a) and (b) show the comparison of the average bidding curves under the regular and high scarcity regimes, for the upper 90th, 95th, 97.5th, and 99th percentiles of RL, across the entire price range, and the shifted curves brought to the shared reference point for the winter of 2024 in Germany. Table D.2 shows the corresponding analysis of price differentials under both regimes.

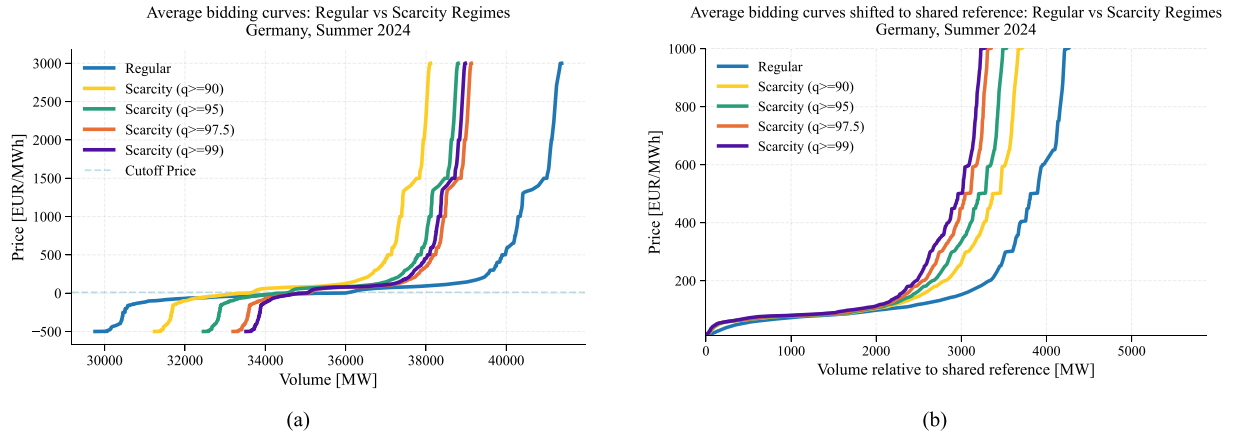


Fig. D.6. A comparison of the mean bidding curves for several scarcity regimes and the regular regime across the entire price range (a) and the curves brought to a common reference point by shifting along the volume axis (b) for the summer of 2024.

Table D.1

Price values for mean supply curves for the regular and scarcity regimes in the summer of 2024 (Apr 2024 - Sep 2024), evaluated at fixed volume increments from the shared reference point. The reference point at the origin is set at a volume of 0 GW, and a price of 10 EUR/MWh, and increments are taken at 1 GW intervals. Technology-specific marginal cost benchmarks, residual load levels, imports, and MCPs per regime are shown for reference. All values are denoted in EUR/MWh except residual load and Import (MW). Values are computed by averaging hourly bidding curves in volume-at-price space and inverting the resulting mean curve to obtain the price at each volume offset; because this inversion is nonlinear, the reported summer, winter (Table D.2), and full-year (Table 7) values at a common offset need not average arithmetically. In summer, the highest scarcity regimes ($q \geq 97.5$) saturate against the 3000 EUR/MWh technical price cap at the +4 GW offset, and only a small subset of high-RL summer hours contribute to the mean regular-regime curve at that offset, which drives the regular +4 GW value considerably above its winter counterpart.

Regime	+1 GW	+2 GW	+3 GW	+4 GW	MC Coal	MC Lignite	MC CCGT	MC OCGT	Res. Load	Import	MCP
Regular	73.00	98.25	152.27	614.46	103.72	82.88	88.22	122.31	28,103.74	8477.54	71.76
90th	78.59	104.59	261.93	1443.14	103.88	83.04	88.06	122.09	47,421.49	11,833.75	134.14
95th	79.07	106.56	335.38	1688.71	103.80	83.03	87.51	121.31	49,610.48	12,095.23	144.98
97.5th	79.61	109.07	449.20	3000.00	103.74	83.00	86.57	119.99	51,202.43	12,205.56	153.58
99th	80.69	113.04	501.55	3000.00	103.27	82.25	85.87	119.02	52,754.65	12,222.46	171.68

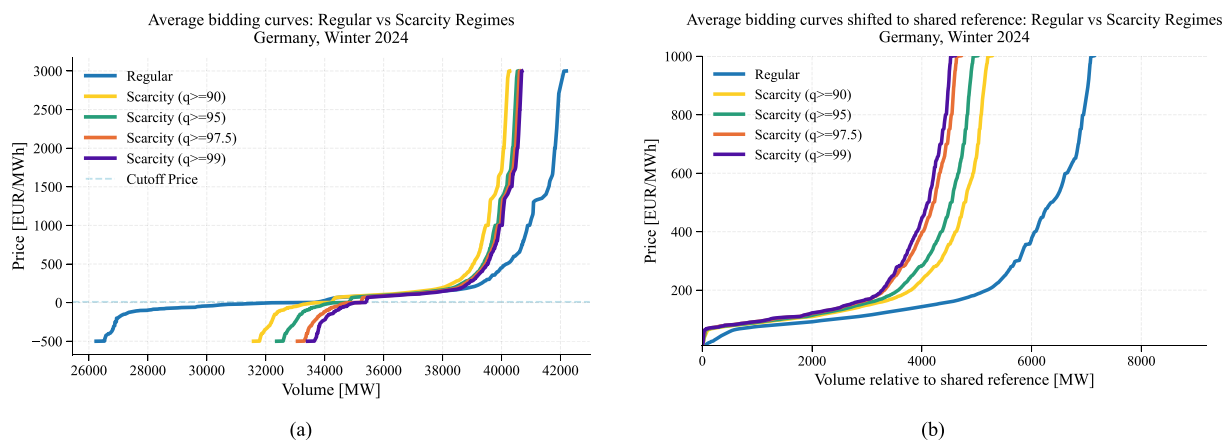


Fig. D.7. A comparison of the mean bidding curves for several scarcity regimes and the regular regime across the entire price range (a) and the curves brought to a common reference point by shifting along the volume axis (b) for the winter of 2024.

Table D.2

Price values for mean supply curves for the regular and scarcity regimes in the winter of 2024 (Oct 2024 - Mar 2025), evaluated at fixed volume increments from the shared reference point. The reference point at the origin is set at a volume of 0 GW, and a price of 10 EUR/MWh, and increments are taken at 1 GW intervals. Technology-specific marginal cost benchmarks, residual load levels, imports, and MCPs per regime are shown for reference. All values are denoted in EUR/MWh except residual load and import (MW).

Regime	+1 GW	+2 GW	+3 GW	+4 GW	MC Coal	MC Lignite	MC CCGT	MC OCGT	Res. Load	Import	MCP
Regular	75.61	91.77	113.57	143.60	103.58	83.95	108.92	151.28	35,097.74	7455.04	107.22
90th	87.85	109.81	148.74	234.73	104.05	84.55	110.41	153.37	57,706.33	12,569.66	211.93
95th	90.32	113.97	156.23	283.32	104.55	85.13	111.52	154.92	60,371.55	13,161.08	261.34
97.5th	92.76	120.49	166.85	396.06	105.00	85.71	112.51	156.31	62,320.60	13,698.29	332.61
99th	92.64	122.06	168.66	445.70	105.52	86.26	113.33	157.46	63,977.79	13,784.02	416.64

Appendix E. Results for the Belgian bidding zone

This appendix replicates the three core analyses of the paper for the Belgian (BE) bidding zone over the main window for 2024 (April 2024–March 2025). All specifications match those used for Germany.

Fig. E.1 shows that the coefficient on residual load is positive across the day and significant at the 1% level in the great majority of hours, mirroring the German pattern of Section 4.1.

Fig. E.2 reproduces the German pattern in the low-price VRE-dominated segments (negative coefficients on residual load), but with the segment-specific coefficient values in the mid-merit and thermal-tail segments differing from those in Germany, reflecting differences in the generation fleet and in bidding dynamics.

Fig. E.3(a) and (b) show that the scarcity-regime bidding curves lie systematically above the regular-regime curve and that the vertical distance grows monotonically with the scarcity threshold q , consistent with the German pattern in Section 4.3. Absolute markup magnitudes are larger than those for Germany because Belgium's smaller thermal fleet places the common volume offset closer to the scarcity tail.

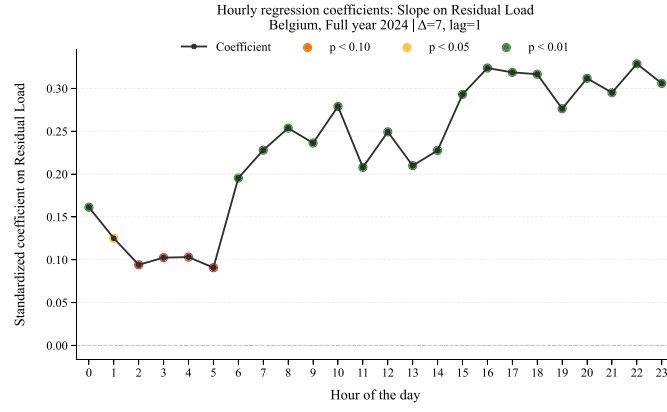


Fig. E.1. Hourly regression coefficients β_h for the supply-curve slope against residual load, Belgium, main window. Slope taken between 10 and 1000 EUR/MWh; significance levels are color-coded. (For interpretation of the references to colour in this Figure legend, the reader is referred to the web version of this article.)

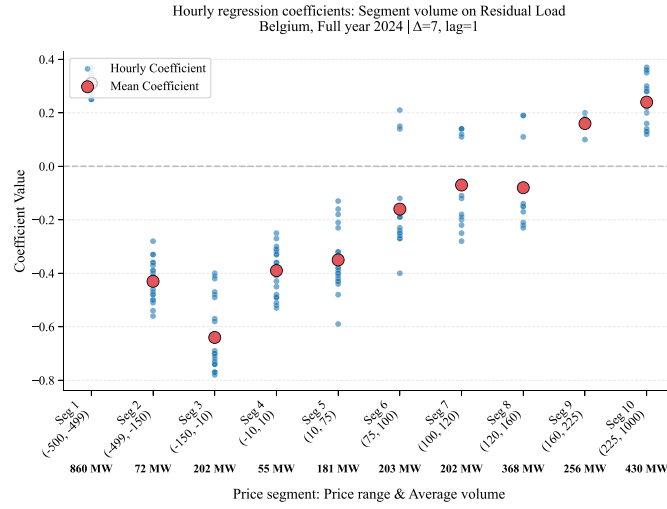


Fig. E.2. Hourly regression coefficients for Bid volume by price segment against residual load, in Belgium, main window.

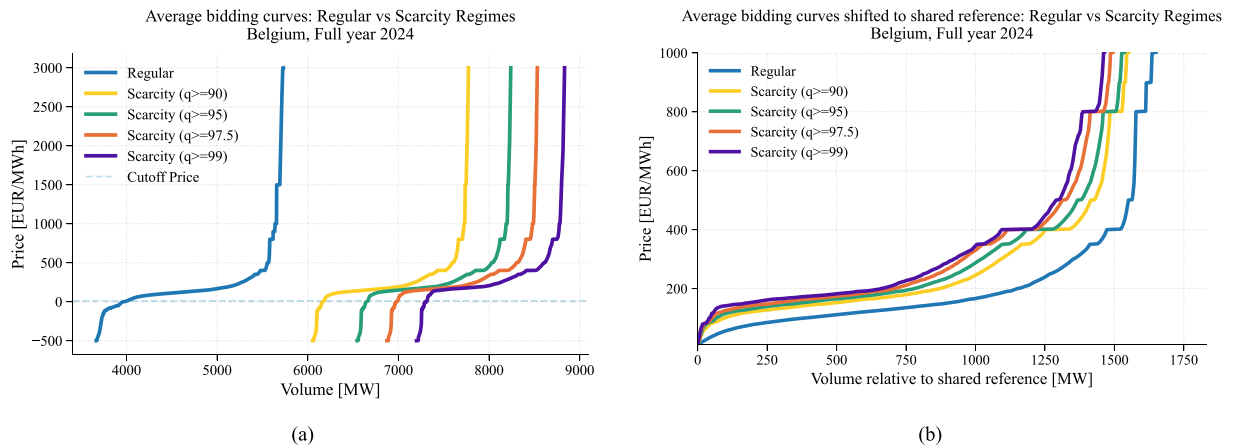


Fig. E.3. A comparison of the mean bidding curves for several scarcity regimes and the regular regime across the entire price range (a) and the curves brought to a common reference point by shifting across the volume axis (b) for Belgium, 2024.

Appendix F. Results for the Dutch bidding zone

This appendix replicates the three core analyses of the paper for the Dutch (NL) bidding zone over the main window for 2024 (April 2024–March 2025). All specifications match those used for Germany.

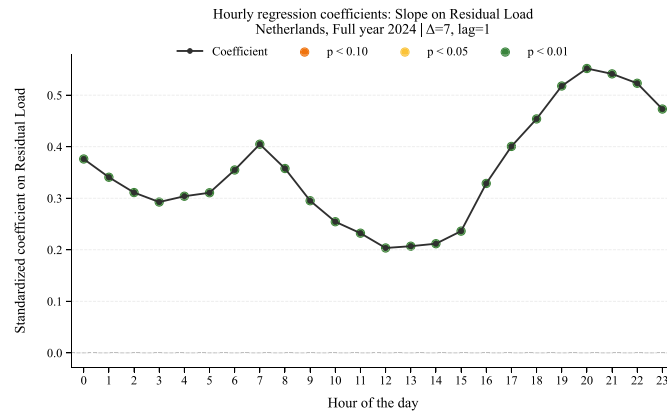


Fig. F.1. Hourly regression coefficients β_h for the supply-curve slope against residual load, Netherlands, main window. Slope taken between 10 and 1000 EUR/MWh; significance levels are color-coded. (For interpretation of the references to colour in this Figure legend, the reader is referred to the web version of this article.)

Fig. F.1 shows that the coefficient on residual load is positive at every hour of the day and significant at the 1% level in the great majority of hours, mirroring the German pattern in Section 4.1 and the Belgian pattern in Appendix E.

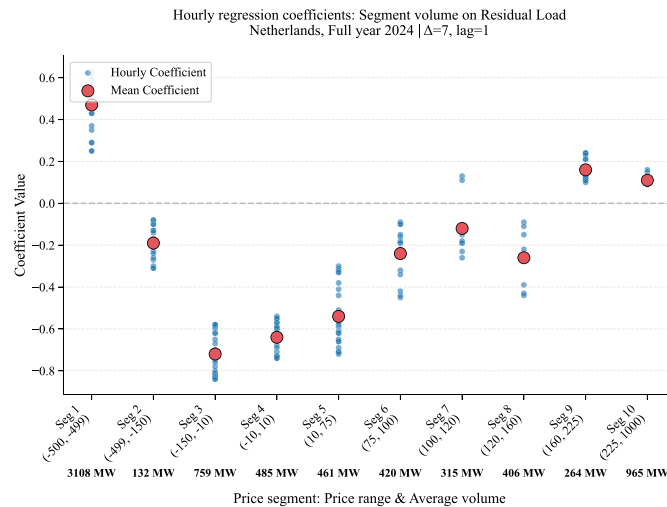


Fig. F.2. Hourly regression coefficients for Bid volume by price segment against residual load, Netherlands, main window.

Fig. F.2 reproduces the German pattern in the low-price VRE-dominated segments (negative coefficients on residual load), but with the segment-specific coefficient values in the mid-merit and thermal-tail segments differing from those in Germany, reflecting differences in the generation fleet and in bidding dynamics.

Fig. F.3(a) and (b) show that the scarcity-regime bidding curves lie systematically above the regular-regime curve and that the vertical distance grows monotonically with the scarcity threshold q , consistent with the German pattern in Section 4.3 and the Belgian pattern in Appendix E.

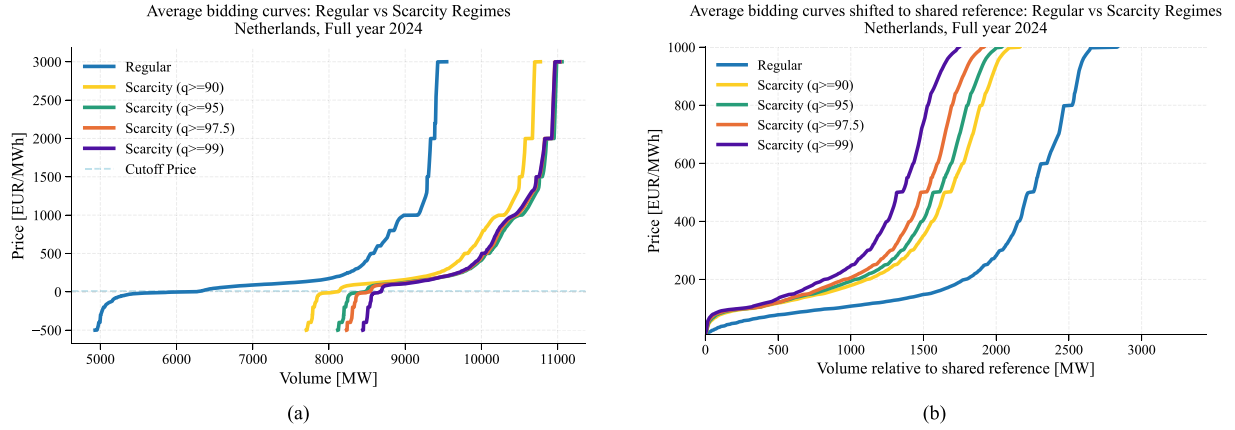


Fig. F.3. A comparison of the mean bidding curves for several scarcity regimes and the regular regime over the entire price range (a) and of the curves brought to a common reference point by shifting along the volume axis (b) for the Netherlands, in 2024.

Appendix G. PowerACE: model description and backtesting validation

This appendix documents the PowerACE agent-based electricity market model as used in this paper. [Appendix G.1](#) gives a compact input-mechanism-output description of the model. [Appendix G.2](#) reports the 2024 back-testing validation exercise that establishes the empirical adequacy of the calibrated markup rule before it is applied to the 2035 forward scenario.

G.1. Model description

PowerACE is a bottom-up agent-based model of the European wholesale electricity market, developed and maintained at the Karlsruhe Institute of Technology ([Bublitz et al., 2014](#); [Fraunholz, 2021](#)). It represents dispatchable generation units and their operators as individual agents that submit bids to a coupled day-ahead market, and clears these bids under a simplified implementation of the SDAC Euphemia mechanism ([Ringler et al., 2017](#); [Fraunholz, 2021](#)). In this paper, PowerACE is used to project the empirically calibrated bidding rules of [Section 3.4](#) forward into a 2035 energy-transition scenario, and to back-test the same rules against 2024 historical prices.

[Table G.1](#) summarizes the model as an input-mechanism-output structure at the level of detail relevant to this paper.

Table G.1

PowerACE input-mechanism-output structure as configured for the 2035 scenario analysis and 2024 back-test of this paper.

Category	Component	Source/determination
Inputs	Installed generation capacity per technology (lignite, hard coal, CCGT, OCGT, biomass, oil, PV, wind, pumped hydro, battery)	TYNDP 2024 Global Ambition scenario (TYNDP, 2025) for the 2035 case; German plant registry (Bundesnetzagentur, 2023), ENTSO-E Transparency Platform (Entso-E Transparency Platform, 2025), and Global Energy Monitor (Global Energy Monitor, 2026) for the 2024 back-test
	Hourly demand profile per zone	ERAA 2024 modeling dataset (ENTSO-E, 2024) for 2035; ENTSO-E Transparency Platform (Entso-E Transparency Platform, 2025) for 2024
	Hourly VRE generation profile (wind, solar) per zone	ERAA 2024 (ENTSO-E, 2024) for 2035; ENTSO-E Transparency Platform (Entso-E Transparency Platform, 2025) for 2024
	Fuel-price trajectories (gas, coal, oil) and CO ₂ certificate price	TYNDP 2024 reference prices for 2035; the same commodity-price sources used for marginal-cost estimation in Section 3.1 for 2024
	Plant-specific must-run capacities and unavailabilities	Empirically calibrated from ENTSO-E Transparency Platform time series (units > 100 MW) as described in the back-test in Appendix G.2
	Regime-conditional markup/markdown parameters	Section 3.4 of this paper (empirically calibrated from the mean supply-curve comparison across scarcity regimes)
Mechanism	Day-by-day agent bidding iteration	For each simulated day, each dispatchable agent (i) estimates its technology-specific marginal cost from the current fuel and CO ₂ prices; (ii) forecasts the next-day residual load from the load and VRE profiles; (iii) infers the scarcity regime q from the forecast RL relative to the annual RL distribution; (iv) applies the empirically calibrated regime-conditional markup or markdown to the MC bid; and (v) submits the resulting price-volume offer to the market
	VRE bidding	Wind and solar bid at zero marginal cost
	Storage bidding	Pumped-hydro and battery agents forecast the following day's hourly prices, derive an optimal charge/discharge schedule from that forecast, and submit price-taker bids at the forecast price levels
	Market clearing	Simplified implementation of the SDAC Euphemia mechanism (Ringler et al., 2017 ; Fraunholz, 2021): offers aggregated across coupled zones, matched against a deterministic demand profile, cleared to yield zone-specific market-clearing prices and dispatch
Outputs	Hourly market-clearing price per bidding zone	8760 values per zone per simulated year
	Hourly dispatch per generation unit per zone	Basis for the price-duration curves, mean-hourly-price profiles, and peak-price statistics reported in Section 4.4 and in Appendix G.2 below

Two features of the model configuration deserve emphasis for this paper. First, the behavioral input on the dispatchable-agent side is empirical rather than optimization-based: agents apply the markup or markdown that was observed in the historical data for the corresponding scarcity regime, rather than solving a profit-maximization program. This underpins the 2035 price simulation. Second, the coupled-zone structure of the market clearing means that price formation across each zone is conditioned on interconnection with neighboring bidding zones, with cross-border flows determined endogenously by the Euphemia clearing rather than being exogenously imposed—a feature that matters directly for the interconnection discussion in Section 6.

The model simplifies several dimensions of real-world electricity market operation that fall outside the scope of the current paper: intraday and balancing markets are not modeled, unit-commitment constraints (ramp rates, minimum-up and minimum-down times, start-up costs) are represented in reduced form, and transmission constraints within each bidding zone are abstracted away. These simplifications are common in agent-based day-ahead simulation studies at the annual-hourly resolution and are documented in the model's reference publication (Bublitz et al., 2014) and in the methodological development at KIT (Fraunholz, 2021).

G.2. Backtesting validation

To validate and calibrate the markups, a back-testing exercise for the year 2024 was conducted using PowerACE. Historical demand and renewable generation profiles from Entso-E Transparency Platform (2025) served as input data. Fuel prices were taken from the sources described in Section 2.

The power plant dataset incorporates several public sources, primarily sourced from the plant registry of the German Federal Network Agency (Bundesnetzagentur, 2023) and the ENTSO-E Transparency Platform. These data were supplemented with additional information from sources such as Global Energy Monitor (2026) and operator communications. For generator units with an installed capacity of over 100 MW, we empirically calibrated estimates for the actual maximum plant capacity based on the historical availability time series published on the ENTSO-E Transparency Platform. The hourly electricity generation output and plant-specific heat extraction data were utilized to determine seasonal must-run levels.

Since 2024 was a leap year and PowerACE is configured for a calendar year of 8760 hours, 31 December 2024 was omitted. This choice was preferred over omitting 29 February in order to preserve a continuous time series. The date of 26 June 2024 was also excluded, as technical problems at the power exchange led to a market decoupling showing hourly electricity prices in excess of 2000 EUR/MWh (EPEX Spot, 2024).

As specified in Section 3.5, the two scenarios were validated through a back-testing exercise. In the first scenario, conventional power plants submitted bids at marginal cost. In the second scenario, bids incorporated the markups shown in Section 4.3.

Fig. G.1 presents the price-duration curves for the 2024 historical market prices and for the simulations with and without markups. The figure shows that the marginal-bidding strategy fails to capture the peak prices, whereas they are more closely matched in the strategic bidding scenario. Neither scenario could accurately capture the historical negative price outcomes, due to the assumption of VRE bidding at zero marginal cost, leading to a minimum of 0 EUR/MWh for the simulated price scenarios.

The simulated price scenario cannot capture the flatter price profile in the lowest price hours of the historical data from hour 7000 to hour 8000. This can be partially attributed to an underestimation of cross-border pricing effects in the PowerACE model. Neighboring countries import renewable-energy generation from Germany to a greater extent in the historical data than in the simulations, thereby lifting the German market prices in these hours.

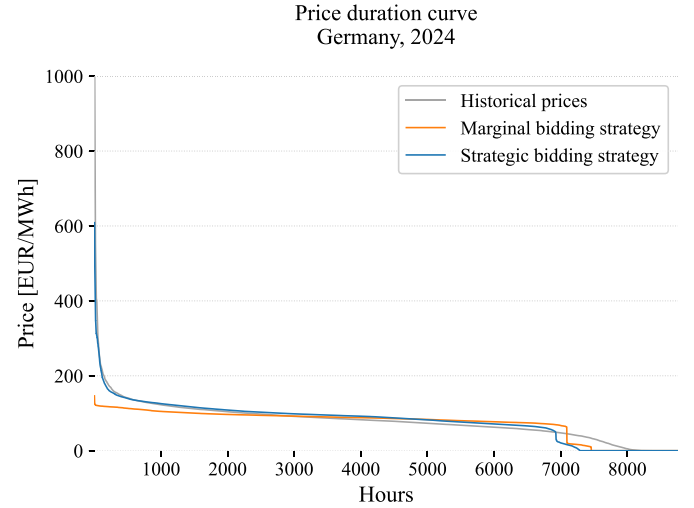


Fig. G.1. Comparison of the price duration curve for simulations in the year 2024 using the competitive and markup bidding strategies against the historical prices.

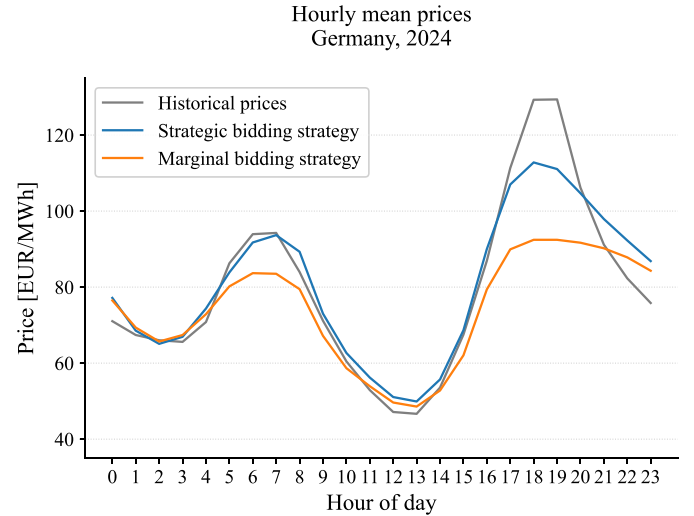


Fig. G.2. Comparison of the hourly mean prices from simulations for the year 2024 using the competitive and markup bidding strategies against the historical prices.

Table G.2

Accuracy metrics and statistical analysis of historical and simulated prices.

	RMSE	Correlation	Mean	Variance
Marginal	41.06	0.64	74.15	1316
Mark-up	33.36	0.80	80.41	2648
Historical	/	/	78.53	2798

Fig. G.2 displays the hourly mean price profile. The nighttime prices are slightly overestimated, whereas the evening peak hours are slightly underestimated. Nonetheless, the inclusion of markups markedly improves the representation of both the absolute price levels and the daily price dynamics.

Table G.2 reports the RMSE and the correlation between simulated and historical time series. These show that incorporating the markups leads to a substantial improvement in both accuracy metrics.

Data availability

The data that support the findings of this study are available from EPEX Spot. Restrictions apply to the availability of these data, which were used under license for this study. Data are available at <https://www.epeexspot.com/en> with the permission of EPEX Spot.

References

- Amer, N., Forschungsstelle für Energiewirtschaft (FfE), 2025. Dynamic illustration of the current merit order of German power plants. <https://www.ffe.de/en/publications/dynamische-darstellung-der-aktuellen-merit-order-deutscher-kraftwerke/> (Accessed: 1 March 2026).
- Beck-Bang, A.C., Overgaard, S.B., Keles, D., 2026. Electricity supply and demand in the European market: the effect on generation adequacy in a dunkelflaute period. *Energy Policy* 208, 114910. <https://doi.org/10.1016/j.enpol.2025.114910>
- Borenstein, S., 2002. The trouble with electricity markets: understanding California's restructuring disaster. *J. Econ. Perspect.* 16, 191–211.
- Borenstein, S., Bushnell, J.B., Wolak, F.A., 2002. Measuring market inefficiencies in California's restructured wholesale electricity market. *Am. Econ. Rev.* 92, 1376–1405. <https://doi.org/10.1257/000282802762024557>
- Brown, D.P., Eckert, A., Silveira, D., 2023. Screening for collusion in wholesale electricity markets: a literature review. *Util. Policy* 85, 101671. <https://doi.org/10.1016/j.jup.2023.101671>
- Bublitz, A., Genoese, M., Fichtner, W., 2014. An agent-based model of the German electricity market with short-time uncertainty factors. In: 11th International Conference on the European Energy Market (EEM14), pp. 1–5. <https://doi.org/10.1109/EEM.2014.6861215>. ISSN 2165-4093.
- Bundeskartellamt, 2024. Ergebnis Der Untersuchung Von Preisspitzen Im Kurzfristigen Stromgroßhandel Im November Und Dezember 2024. investigation report, Bundeskartellamt. https://www.bundeskartellamt.de/SharedDocs/Publikation/DE/Sonstiges/Untersuchungsergebnis_Preisspitzen.html
- Bundesnetzagentur, 2023. Kraftwerksliste der bundesnetzagentur: stand 19.07.2023. <https://www.bundesnetzagentur.de/DE/Fachthemen/ElektrizitaetundGas/Versorgungssicherheit/Erzeugungskapazitaeten/Kraftwerksliste/start.html> (Accessed: 1 March 2026).
- Clò, S., Cataldi, A., Zoppoli, P., 2015. The merit-order effect in the Italian power market: the impact of solar and wind generation on national wholesale electricity prices. *Energy Policy* 77, 79–88. <https://doi.org/10.1016/j.enpol.2014.11.038>
- De Blauwe, J., Deissenroth-Uhrig, M., Mantke, H., Keles, D., 2025a. Cross-border effects on electricity spot prices - a meta-study. *Renew. Sustain. Energy Rev.* 224, 116094. <https://doi.org/10.1016/j.rser.2025.116094>
- De Blauwe, J., Zhang, X., Keles, D., 2025b. Investigating empirical bidding curves in the electricity spot market: expected patterns vs anomalies? *Energy Econ.* 152, 109002. <https://doi.org/10.1016/j.eneco.2025.109002>
- ENTSO-E, 2024. European Resource Adequacy Assessment (ERAA) 2024 Edition – Modelling Data. technical report, ENTSO-E, Brussels, Belgium. <https://www.entsoe.eu/outlooks/eraa/2024/>
- Entso-E Transparency Platform, 2025. EntsoE transparency platform. <https://transparency.entsoe.eu/> (Accessed: 1 March 2026).
- EPEX Spot, 2024. Decoupling session was run according to procedures of single day-ahead coupling. <https://www.epeexspot.com/en/news/decoupling-session-was-run-according-procedures-single-day-ahead-coupling> (Accessed: 1 March 2026).
- EPEX Spot, 2025. EPEX SPOT – European power exchange. <https://www.epeexspot.com/en> (Accessed: 1 March 2026).
- European Commission, 2022. Drought in Europe – July 2022 – GDO Analytical Report. Publications Office of the European Union, <https://doi.org/10.2760/014884>
- Fogelberg, S., Lazarczyk, E., 2019. Strategic withholding through production failures. *Energy J.* 40, <https://doi.org/10.5547/01956574.40.5.sfog> 247–66
- Fraunholz, C., 2021. Market Design for the Transition to Renewable Electricity Systems (Ph.D. thesis). Karlsruher Institut Für Technologie (KIT). <https://doi.org/10.5445/IR/1000133282>
- Ghelasi, P., Ziel, F., 2026. A data-driven merit order: learning a fundamental electricity price model. *Energy Econ.* 154, 109114. <https://doi.org/10.1016/j.eneco.2025.109114>
- Global Energy Monitor, 2026. Global integrated power tracker. <https://globalenergymonitor.org/projects/global-integrated-power-tracker/> (Accessed: 1 March 2026).
- Hagfors, L.I., Kamperud, H.H., Paraschiv, F., Prokopczuk, M., Sator, A., Westgaard, S., 2016. Prediction of extreme price occurrences in the German day-ahead electricity market. *Quant. Finance* 16, 1929–1948. <https://doi.org/10.1080/14697688.2016.1211794>
- Hermann, H., Matthes, F.C., 2017. Die Deutsche Braunkohlenwirtschaft – Historische Entwicklungen, Ressourcen, Technik, Wirtschaftliche Strukturen Und Umweltauswirkungen. Technical Report, Öko-Institut.
- Hirth, L., 2013. The market value of variable renewables: the effect of solar and wind power variability on their relative price. *Energy Econ.* 38, 218–236. <https://doi.org/10.1016/j.eneco.2013.02.004>
- Investing.com, 2025. Investing.com. <https://www.investing.com/> (Accessed: 1 March 2026).
- IPCC, 2023. Carbon Dioxide Emissions Factors. Technical Report, Intergovernmental Panel on Climate Change. <https://archive.ourworldindata.org/20250909-093708/grapher/carbon-dioxide-emissions-factor.html>
- Ito, K., Reguant, M., 2016. Sequential markets, market power, and arbitrage. *Am. Econ. Rev.* 106, 1921–1957.
- Jha, A., Leslie, G., 2025. Start-up costs and market power: lessons from the renewable energy transition. *Am. Econ. Rev.* 115, 690–724. <https://doi.org/10.1257/aer.20211145>
- Joskow, P.L., 2008. Capacity payments in imperfect electricity markets: need and design. *Util. Policy* 16, 159–170. <https://doi.org/10.1016/j.jup.2007.10.003>
- Joskow, P.L., Kahn, E., 2002. A quantitative analysis of pricing behavior in California's wholesale electricity market during summer 2000. *Energy J.* 23, 1–35.
- Keles, D., Dehler-Holland, J., Densing, M., Panos, E., Hack, F., 2020. Cross-border effects in interconnected electricity markets - an analysis of the Swiss electricity prices. *Energy Econ.* 90, 104802. <https://doi.org/10.1016/j.eneco.2020.104802>
- Kepler, J.H., 2017. Rationales for capacity remuneration mechanisms: security of supply externalities and asymmetric investment incentives. *Energy Policy* 105, 562–570. <https://doi.org/10.1016/j.enpol.2016.10.008>
- Klein, O., 2024. Dunkelflaute lässt strompreise explodieren. <https://www.zdfheute.de/wirtschaft/strompreise-rekord-dunkelflaute-100.html> (Accessed: 1 March 2026).
- Krzywnicka, M., Barner, L., 2025. On strategic behavior in electricity markets during the 2022 energy crisis: an ex-post analysis for the German power sector. *Energy Rep.* 13, 5474–5485. <https://doi.org/10.1016/j.egy.2025.04.040>
- Kulakov, S., Ziel, F., 2019. Determining fundamental supply and demand curves in a wholesale electricity market. arXiv preprint, revised November 2019. [arXiv:1903.11383](https://arxiv.org/abs/1903.11383)
- Labandeira, X., Labeaga, J.M., López-Otero, X., 2017. A meta-analysis on the price elasticity of energy demand. *Energy Policy* 102, 549–568. <https://doi.org/10.1016/j.enpol.2017.01.002>
- McRae, S.D., Wolak, F.A., 2009. How do firms exercise unilateral market power? Evidence from a bid-based wholesale electricity market. RSCAS Working Papers Number: 2009/36.
- Mou, Y., Papavasiliou, A., Hartz, K., Dusolt, A., Redl, C., 2023. An analysis of shortage pricing and capacity remuneration mechanisms on the pan-European common energy market. *Energy Policy* 183, 113843. <https://doi.org/10.1016/j.enpol.2023.113843>
- Mount, T.D., Ning, Y., Cai, X., 2006. Predicting price spikes in electricity markets using a regime-switching model with time-varying parameters. *Energy Econ.* 28, 62–80.
- Paraschiv, F., Erni, D., Pietsch, R., 2014. The impact of renewable energies on EEX day-ahead electricity prices. *Energy Policy* 73, 196–210. <https://doi.org/10.1016/j.enpol.2014.05.004>
- Ringler, P., Keles, D., Fichtner, W., 2017. How to benefit from a common European electricity market design. *Energy Policy* 101, 629–643. <https://doi.org/10.1016/j.enpol.2016.11.011>
- Rintamäki, T., Siddiqui, A.S., Salo, A., 2017. Does renewable energy generation decrease the volatility of electricity prices? An analysis of Denmark and Germany. *Energy Econ.* 62, 270–282. <https://doi.org/10.1016/j.eneco.2016.12.019>
- RTE, 2023. Annual electricity review 2022. <https://analysesetdonnees.rte-france.com/en/electricity-review-keyfindings> (Accessed: 1 March 2026). Réseau de Transport D'Électricité (RTE).
- Schröder, A., Kunz, F., Meiss, J., Mendelevitch, R., von Hirschhausen, C., 2013. Current and Prospective Costs of Electricity Generation Until 2050. data documentation no. 68. Prepared within the project “Modeling the Energy Transformation” supported by Stiftung Mercator and others, DIW Berlin, German Institute for Economic Research, Berlin, Germany. https://www.diw.de/documents/publikationen/73/diw_01.c.424566.de/diw_datadoc_2013-068.pdf
- SDAC, 2025. Single day-ahead coupling. https://www.entsoe.eu/network_codes/cacm/implementation/sdac/ (Accessed: 1 March 2026).
- Twomey, P., Neuhoof, K., 2010. Wind power and market power in competitive markets. *Energy Policy* 38, 3198–3210.
- TYNDP, 2025. TYNDP 2024 Scenarios Report. Technical Report Accessed: ENTSO-E and ENTSG. <https://2024.entsoe-tyndp-scenarios.eu/> (1 March 2026).
- VDA, 2024. Emission Factors for Electricity, District Heating, and Fuels. technical report, Verband der Automobilindustrie (VDA). <https://www.vda.de/en/news/publications/publication/emission-factors-for-electricity-district-heating-and-fuels-2024>
- Wolak, F.A., 2003. Measuring unilateral market power in wholesale electricity markets: the California market, 1998–2000. *Am. Econ. Rev.* 93, 425–430. <https://doi.org/10.1257/000282803321947471>
- Wolfram, C.D., 1998. Strategic bidding in a multiunit auction: an empirical analysis of bids to supply electricity in England and Wales. *RAND J. Econ.* 29, 703–725. <https://doi.org/10.2307/2556090>
- Würzburg, K., Labandeira, X., Linares, P., 2013. Renewable generation and electricity prices: taking stock and new evidence for Germany and Austria. *Energy Econ.* 40, S159–S171. <https://doi.org/10.1016/j.eneco.2013.09.011>
- Zhu, L., Zhang, L., Liu, J., Zhang, H., Zhang, W., Bian, Y., Yan, J., 2024. Unpacking the effects of natural gas price transmission on electricity prices in Nordic countries. *iScience* 27, 109924. <https://doi.org/10.1016/j.isci.2024.109924>