Pricing intermittent renewable energy*

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Abstract

Governments use fixed-price contracts to support investment in wind and solar power. These contracts reward production but ignore when it occurs. We show that feed-in tariffs, power purchase agreements, and contracts for difference can implement the efficient renewable portfolio if the price is adjusted with a technology-specific bonus-malus system that depends on the correlation between renewable energy production and the wholesale electricity price. We estimate this adjustment for California, France, Germany, and Spain and show that its size varies across technologies and locations. We then express the bonus-malus with technological parameters instead of market price to assess the optimality of future investment targets in solar and wind power. We find that lower technology costs can be offset by lower output value as renewable penetration rises. Finally, to quantify the investment effect of fixed-price policies, we estimate an empirical model of investment in new capacity for Germany. In a counterfactual policy that preserves total budget, we find that adjusting the FiT using lagged location- and technology-specific bonus-malus terms increases the market value of renewable generation by 3%, or €58 million.

Keywords: Electricity market, levelized cost of energy, climate change, intermittent renewable energy, feed-in tariff, power purchase agreement, contract for difference.
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1 Introduction

Many public policies support investment by guaranteeing a price for the output that the investment produces. Such contracts are attractive because they stabilize revenues and can mobilize capital at scale. They are potentially inefficient, however, when the social value of output varies across states of the world. A payment that depends only on quantity treats all units as equally valuable, even if some are supplied when the system needs them and others when they are redundant. This problem is central to electricity decarbonization.[1] Wind and solar generation is intermittent, electricity is costly to store, and the value of an additional megawatt-hour depends on demand and on the simultaneous output of the rest of the generation fleet. Its environmental value also depends on which conventional generator it displaces. Both dimensions vary across time and location (Borenstein, 2012; Cullen, 2013; Novan, 2015). A policy that rewards renewable production without accounting for these system conditions may therefore induce the wrong mix of technologies and locations even when it succeeds in expanding total capacity.

This concern has become increasingly important as governments rely on long-term fixed-price contracts to organize the energy transition. Feed-in tariffs (FiTs) launched renewable deployment in countries including China, France, Germany, Japan, and the United Kingdom. More recently, renewable auctions have allocated power purchase agreements (PPAs) and contracts for difference (CfDs). Under a PPA, a producer sells electricity to a retailer or a large consumer at a contracted price. Under a two-way CfD, the producer sells into the wholesale market but ultimately receives a prearranged strike price: the counterparty pays the difference when the market price is below the strike price and recovers it when the market price is higher. These arrangements differ institutionally, but they share a central economic feature: remuneration per megawatt-hour (MWh) is insulated, partly or fully, from contemporaneous scarcity. Their use is likely to expand following the European Union's explicit endorsement of PPAs and CfDs for new low-carbon generation in Regulation 2024/1747.[2]

This paper asks how fixed-price contracts should be designed when the value of renewable generation depends on when and where it is produced. We develop a model with stochastic electricity demand, intermittent renewable output, and increasing dispatchable generation

[1] Similar trade-offs arise in advance market commitments for vaccines (Kremer et al., 2020), hospital reimbursement (Dafny, 2005), agricultural insurance (Annan and Schlenker, 2015), and fixed-price infrastructure procurement (Bajari et al., 2014).

[2] According to Article 19d of Regulation 2024/1747 (European Commission 2024), CfDs apply to "investment in new generation of electricity from the following sources: (a) wind energy; (b) solar energy; (c) geothermal energy; (d) hydropower without reservoir; (e) nuclear energy." Since the primary sources of energy in (c) and (e) are not intermittent, our analysis mainly focuses on (a) and (b), and incidentally on (d).

marginal cost. Renewable energy technologies are described by their cost and their capacity factor, which depend on local conditions such as solar irradiance or wind speed. The supply net of renewable generation is backed up with electricity from thermal power generation. We first characterize the socially optimal investment portfolio. The optimality condition equates the expected marginal social cost of dispatchable generation with the cost of an additional unit of renewable output, accounting for the covariance between renewable availability and system marginal cost. This condition converts the conventional levelized cost of energy (LCOE) into what we call the economic cost of energy, ECOE (Joskow, 2011). A renewable technology has an ECOE below its LCOE when it tends to produce in high-value hours and an ECOE above its LCOE when it tends to produce when electricity is abundant.

The covariance term is also the sufficient adjustment to a fixed-price contract. When carbon emissions are priced at their social cost, a competitive wholesale market decentralizes the optimal renewable portfolio under risk neutrality and rational expectations. A fixed price equal to the expected wholesale price does not generally reproduce that allocation because it removes the covariance between output and price. We show that a fixed price implements the efficient portfolio if it equals the discounted expected wholesale price plus a technology-specific bonus or malus proportional to this covariance. Technologies that generate when electricity is scarce receive a bonus; technologies that generate when prices are low receive a malus. The same logic applies to procurement. A single technology-neutral auction can select the efficient portfolio if winning projects receive the marginal winning bid adjusted by their technology-specific bonus or malus. The rule preserves competition across technologies while recognizing that a megawatt-hour delivered in different system states is not the same economic product.

We then quantify this adjustment using hourly data for California, France, Germany, and Spain. The estimated bonus-malus is generally negative, but its magnitude varies across markets and technologies. Over 2015–2020, the estimated malus for wind is highest in Germany, at €5.19/MWh, while the malus for solar reaches €7.33/MWh in California. Spain is the only market in which solar should receive a small bonus over this period. The adjustment also varies within technologies. In Germany, offshore wind should receive a smaller malus than onshore wind, and simulated production profiles reveal meaningful variation across states and solar-panel orientations. These findings show why resource quality alone is an incomplete guide to siting: a location with a high capacity factor need not have a high market value if its output is concentrated in hours of abundant generation.

Because future wholesale prices are difficult to forecast and some electricity systems lack organized wholesale markets, we next express the bonus-malus in terms of technological and

system fundamentals. A second-order approximation decomposes the adjustment into four elements: the curvature of the dispatchable merit-order cost curve; a cannibalization term generated by the variance of output from the same renewable technology and its installed capacity; a complementarity term reflecting covariance with other renewable technologies; and an adequacy term reflecting covariance with electricity demand. This decomposition gives the covariance adjustment a direct economic interpretation. Greater penetration of a technology reduces the marginal value of additional capacity when its plants produce at the same time. Negative covariance across renewable technologies raises value by smoothing aggregate renewable supply. Positive covariance with demand also raises value by directing output toward high-load hours. The slope of the merit order scales each of these effects by the cost of accommodating fluctuations in residual demand. We use this decomposition to evaluate announced solar and wind capacity targets for 2030. The exercise illustrates an important distinction between generation costs and system value. Although projected LCOEs decline, the adjustment associated with intermittency can rise sharply as renewable penetration increases. These margins can materially change integration costs.

Finally, we develop an empirical model for Germany to quantify how remuneration affects investment in new generation capacities. The model implements the theoretical project-cost cutoff at the state-technology level and solves an investment-price fixed point. Using the estimated and calibrated model, we conduct counterfactual exercises to quantify the importance of the bonus-malus adjustment and evaluate a budget-neutral FiT design based only on information available to the policymaker when support is set. Three main results emerge. First, over 2015–2020, the historical FiT-type regime generates 39.1 GW of simulated investment, compared with 11.9 GW under market-only remuneration, confirming that policy support strongly affected renewable deployment. Second, remuneration at the discounted lifetime-average wholesale price increases investment to 14.7 GW because it removes the negative covariance penalty embedded in market-only returns. Adding the model-implied bonus-malus restores approximately the market-only allocation, as predicted by theory. Third, policy design can increase the system value without raising expenditures. Holding simulated FiT spending fixed in each year, a common tariff component differentiated by lagged state-technology bonus-malus terms increases the annual market value of the induced renewable generation by about 3 percent, or €58 million.

Related literature. Our paper first contributes to the literature on public contracting and investment incentives. Long-term contracts can encourage sunk investment by stabilizing revenues, but their effectiveness depends on credible commitment. Ryan (2026) shows that counterparty risk raises prices and reduces investment in Indian solar auctions. More broadly,

advance market commitments can stimulate investment by guaranteeing future demand (Kremer et al., 2020). We study a distinct contractual problem: even credible fixed-price contracts may induce the wrong investment portfolio when payments do not reflect all dimensions of social value. This connects to multidimensional procurement (Lewis and Bajari, 2011). In renewable electricity, fixed-price contracts stabilize revenues, but generally reward production without accounting for when and where it occurs.

Second, the paper contributes to research on differentiated environmental policy when marginal benefits or damages vary across locations. Holland et al. (2016) show that the environmental benefits of electric vehicles depend on the emissions of the local generation mix. Fowlie and Muller (2019) quantify the gains from differentiating emissions regulation across sources while emphasizing the associated informational requirements. We identify a distinct source of heterogeneity in renewable procurement: the value of generation depends on when and where it occurs and, specifically, on its covariance with wholesale electricity prices. Under competitive pricing, this heterogeneity can be incorporated into fixed-price contracts through a technology- and location-specific bonus-malus.

Third, we contribute to the literature on renewable-investment policy. Existing work examines how intermittency, carbon pricing, heterogeneous renewable resources, and electricity-pricing rules affect renewable support and long-run investment (Abrell et al., 2019; Ambec and Crampes, 2019; Reguant, 2019; Holland et al., 2022).[3] This literature shows that conventional renewable subsidies need not induce an efficient investment portfolio and that their performance depends on carbon pricing, resource heterogeneity, and the financing of support. We study whether fixed-price contracts can be corrected while preserving their revenue-stabilization benefits.

Fourth, our paper builds on the literature measuring the system value of intermittent generation. Lamont (2008) shows that the marginal value of renewable output depends on its covariance with the system marginal cost, while Hirth (2013) relates this covariance to captured prices and the decline in market value as the penetration of renewables increases. Other studies quantify the welfare, emissions, and locational value of renewable generation (Gowrisankaran et al., 2016; Callaway et al., 2018) or show how market integration affects renewable entry (Gonzales, Ito, and Reguant, 2023). We take the covariance-based valuation result as our starting point rather than as our main contribution. We show that, under our benchmark assumptions, its normalized value is the sufficient adjustment required to restore efficient investment incentives under fixed-price remuneration. We further allow this adjust-

[3]Related empirical work examines how subsidy design and intertemporal preferences affect renewable adoption. De Groote and Verboven (2019) show that the timing of production subsidies matters for residential solar-PV adoption because investors discount future payments.

ment to vary across technologies and locations and decompose it into market fundamentals.

Finally, we contribute to research on long-term contracts and renewable procurement. Existing work studies how CfD design affects risk allocation and short-run dispatch incentives (Schlecht et al., 2024; Ambec et al., 2025) and how renewable auctions should account for technology heterogeneity, resource quality, and private information (Fabra and Montero, 2023; Kröger et al., 2022; Fabra and Llobet, 2023). Our distinctive contribution is to translate the market-value adjustment into a fixed-price contract and a procurement rule. We show that a common auction can implement the efficient portfolio by comparing projects on the basis of their economic cost of energy rather than their levelized cost alone. Empirically, we estimate the bonus-malus across four electricity markets, document its variation across technologies and locations, and quantify its underlying components. We then estimate an investment model for Germany to evaluate how alternative remuneration rules affect the scale, composition, location, and market value of renewable investment.[4]

The remainder of the paper proceeds as follows. Section 2 characterizes optimal renewable investment and its decentralization through competitive wholesale markets. Section 3 derives efficient fixed prices and procurement rules. Section 4 estimates the market-price-based bonus-malus in four electricity markets and documents heterogeneity across technologies and locations. Section 5 develops and estimates the fundamentals-based decomposition and applies it to future capacity targets. Section 6 estimates the German investment model and evaluates alternative remuneration policies. We conclude in Section 7.

2 The optimal energy mix and its decentralization in competitive markets

In the following, we first present the hypotheses of our model, then determine the optimal investment plan, and finally consider the market outcome if CO2 emissions from fossil-fired power plants are priced at their environmental social cost.

2.1 The model

We consider a model of electricity generation with random demand and supply evolving over time. Time is denoted t. On the supply side, electricity can be produced with existing dis-

[4]Our economic cost of energy is related to the energy-value component of the IEA's Value-Adjusted Levelized Cost of Electricity, which supplements LCOE with energy, capacity, and flexibility values (IEA, 2023). Our contribution is to derive the energy-value adjustment from an intertemporal investment condition and show how it can be implemented in fixed-price contracts and procurement auctions.

patchable generation capacity (coal, natural gas, hydroelectric reservoirs, or nuclear) and new intermittent renewable capacity such as wind and solar power. The social cost of producing Q megawatt-hours (MWh) of electricity with dispatchable capacity at time t is denoted $C_t(Q)$. It includes the cost of greenhouse gases emitted by electricity generation such as a carbon tax priced at the social cost of carbon or the price of emission permits in an emission trading scheme. The cost function is assumed increasing and convex ($C_t'(Q) > 0$ and $C_t''(Q) > 0$ for every $Q > 0$) with $C_t(0) = 0$, and $\lim_{Q\to+\infty} C_t'(Q) = +\infty$ for every t.

New generation from renewable energy sources can be of different types. Each type is denoted by $i = 1, ..., n$. The renewable source i is described by the cost of installing new capacity r_{it} per megawatt (MW), a technical parameter $\bar{k}_{it}$ representing the maximum capacity that can be installed at this cost, and a capacity factor ω_i. The capacity cost r_{it} varies in the range $[\underline{r}_{it}, +\infty)$ according to the density function g_{it} and the cumulative function G_{it} every year t. We denote by $\tilde{r}_{it} \geq \underline{r}_{it}$ the marginal capacity cost of the most expensive generator (e.g., wind turbine or solar panel) of technology i at time t. The total capacity of renewable i installed at time t is therefore $k_{it} = \bar{k}_{it} G_t(\tilde{r}_{it})$ and its cost is $\bar{k}_{it} \int_{\underline{r}_{it}}^{\tilde{r}_{it}} r_{it} dG_{it}(r_{it})$. Capacity deteriorates at a rate $1 - \lambda_i$ per period with $0 < \lambda_i < 1$, so that of 1 MW of capacity installed at time t, only λ_i^j MW remains productive at time $t + j$. Denote the lifespan of a generation facility with technology i by $T_i + 1$. The total capacity of renewables i at time t is thus the sum of the former investments discounted by their deterioration rate until either the current date t or the installation duration T_i if completed:

$$K_{it} = \sum_{j=0}^{\min\{t,T_i\}} \lambda_i^j k_{it-j} \tag{1}$$

Renewable production being intermittent, the capacity factor ω_i varies depending on location and weather conditions, such as sunshine or wind speed. Like for λ_i, we assume that it does not depend on the installation date t. It is determined by the unchanging distribution of natural conditions at the investment location. It is a random variable with support $[\underline{\omega_i}, 1]$, where $\underline{\omega_i} \geq 0$. Installing k_{it} yields $\omega_i k_{it}$ MWh of renewable electricity at time t, $\omega_i \lambda_i k_{it}$ at time $t + 1$, and so forth up to $\omega_i \lambda_i^{T_i} k_{it}$ the last year of life of the equipment. The expected capacity factor of renewable i at time t is denoted $E[\omega_i]$ for $i = 1, ..., n$.[5] Once generation capacity is installed, the cost of producing electricity with renewables is normalized to zero. Greenhouse gas emissions from renewables are also normalized to zero.

On the demand side, we consider a price-inelastic random demand D_t to be served at time

[5]The capacity factor ω_i is assumed to be invariant with time. It is without loss of generality as we could make it time-dependent at a cost of more complex mathematical expressions.

t, with $D_t \in [\underline{D}_t, \overline{D}_t]$. We assume $\overline{D}_t \leq \overline{Q}_t$ for every t, which means that peak demand can be supplied with the dispatchable energy sources, so that we do not need to worry about demand curtailment or blackouts.[6]

We first characterize the optimal investment in renewable energy sources. We then show that the optimal energy mix can be achieved with a carbon price reflecting the social cost of carbon in a competitive wholesale market (assuming that investors correctly anticipate future prices). In Section 3, we determine the investment induced by Contracts for Difference (CfDs), successively when the regulator sets the strike price and when capacity is procured.

2.2 Optimal investment in renewable capacity

Given the dispatchable generation capacity, the optimal energy transition is defined as the investment in renewable energy sources over time $\boldsymbol{k}_t^* = (k_{1t}^*, ..., k_{nt}^*)$ that minimizes the discounted expected cost of electricity generation, anticipating that the capacities will be optimally dispatched. The optimal dispatch is such that, given renewable generation $\boldsymbol{K}_t = \sum_{i=1}^{n} \omega_i K_{it}$, for any realization of demand D_t, renewables enter first in the merit order complemented by thermal and nuclear power up to the quantity demanded. Hence, given D_t and $\boldsymbol{K}_t$, the supply of dispatchable production is

$$Q_t = \max \left\{ D_t - \sum_i \omega_i K_{it}, 0 \right\}, \tag{2}$$

where K_{it} is defined in (1).

At time t, the optimal investment in renewable capacities $\boldsymbol{k}_t^*$ for $t = 0, 1, ...$ can be found by minimizing the discounted expected cost of supplying electricity

$$\sum_{t=0}^{+\infty} \rho^t \left\{ E[C_t(Q_t)] + \sum_i \bar{k}_{it} \int_{\underline{r}_{it}}^{\tilde{r}_{it}} r_{it} dG_{it}(r_{it}) \right\},$$

where ρ denotes the discount factor. Since $k_{it} = \bar{k}_{it} G_{it}(\tilde{r}_{it})$ and $\bar{k}_i$ is fixed, finding k_{it} is equivalent to finding $\tilde{r}_{it}$. As shown in Appendix A, differentiating with respect to $\tilde{r}_{it}$ for

[6] See Bobtcheff et al. (2025) for a model of demand curtailment and blackouts with intermittent renewables.

$i = 1, ..., n$ yields the following first-order conditions for an interior solution:[7]

$$-\sum_{l=0}^{T_i} \rho^l E[C'_{t+l}(Q_{t+l})\lambda_i^l \omega_i \bar{k}_{it} g_{it}(\tilde{r}_{it})] + \bar{k}_{it}\tilde{r}_{it} g_{it}(\tilde{r}_{it}) = 0$$

for $i = 1, ..., n$ and every t, where the expectation operator is conditional on $Q_t > 0$. After simplifying by $\bar{k}_{it}$ and $g_{it}(\tilde{r}_{it})$ that are not random, and denoting $\beta_i \equiv \rho\lambda_i$ the discounted factor of generation capacity (the discounted value of one unit of effective capacity), we obtain the optimal cut-off cost $\tilde{r}^*_{it}$ as a function of the optimal dispatchable production Q^*_t for every renewable unit i with positive investment $k^*_{it} > 0$:

$$\tilde{r}^*_{it} = E\left[\omega_i \sum_{l=0}^{T_i} \beta_i^l C'_{t+l}(Q^*_{t+l})\right]. \tag{3}$$

We denote $\mathcal{B}_i \equiv \sum_{l=0}^{T_i} \beta_i^l$ the generation capacity of the equipment along its lifespan for one MW installed discounted at the investment stage. After using the definition of the covariance[8] and dividing by $\mathcal{B}_i$ both sides of (3) to discount the condition at the investment stage, we obtain

$$\frac{\tilde{r}^*_{it}}{\mathcal{B}_i E[\omega_i]} - \frac{1}{E[\omega_i]} cov\left(\omega_i, \sum_{l=0}^{T_i} \frac{\beta_i^l}{\mathcal{B}_i} C'_{t+l}(Q^*_{t+l})\right) = E\left[\sum_{l=0}^{T_i} \frac{\beta_i^l}{\mathcal{B}_i} C'_{t+l}(Q^*_{t+l})\right], \tag{4}$$

for $i = 1, ..., n$. The above optimality condition trades-off the production from technology i with dispatchable production. The first term on the left-hand side in (4) is the levelized cost of energy (LCOE) of the most expensive renewable energy source of type i. It is the cost per MW installed $\tilde{r}^*_{it}$ divided by the expected production over time discounted at the date of the investment $E[\omega_i]\mathcal{B}_i$. The second term adjusts the LCOE with the covariance between the varying capacity factor ω_i and the discounted marginal cost of dispatchable generation over the lifespan of the windmill or solar photovoltaic panel. The right-hand side displays the discounted expected marginal social cost of dispatchable production (including climate costs) during the same period of time. The optimal cut-off costs $\tilde{r}^*_{it}$ for $i = 1, ..., n$ can be found by combining the first-order conditions (4) for $i = 1, ..., n$ with (2) and (1) for every t.

Note that condition (4) allows one to compare the opportunity to invest in different re-

[7] To simplify our analysis, we assume that new renewable capacity does not modify the upper and lower bounds of dispatchable production Q_t. This is the case, for instance, even though ω_i is sometimes nil during peak demand, implying that the upper bound of Q_t is $\overline{D}_t$, and if the renewable capacity exceeds minimal demand so that the lower bound of Q_t is 0. In this case $Q_t \in [0, \overline{D}_t]$.

[8] For any random variables X and Y, $cov(X, Y) = E[(X - E[X])(Y - E[Y])] = E[XY] - E[X]E[Y]$.

newable technologies given the energy mix at date t. For any two renewable technologies i and j with the same lifespan $T_i = T_j$ and deterioration rate $\lambda_i = \lambda_j$, the discount factor is the same $\beta_i = \beta_j = \beta$, and therefore $\mathcal{B}_i = \mathcal{B}_j = \mathcal{B}$. The right-hand side of (4) is therefore the same for technologies i and j. Hence, the efficiency condition (4) implies that, at time t, we have

$$\frac{\tilde{r}^*_{it}}{\mathcal{B}E[\omega_i]} - \frac{1}{E[\omega_i]} cov\left(\omega_i, \sum_{l=0}^{T_i} \frac{\beta^l}{\mathcal{B}} C'_{t+l}(Q^*_{t+l})\right) = \frac{\tilde{r}^*_{jt}}{\mathcal{B}E[\omega_j]} - \frac{1}{E[\omega_j]} cov\left(\omega_j, \sum_{l=0}^{T_j} \frac{\beta^l}{\mathcal{B}} C'_{t+l}(Q^*_{t+l})\right) \quad (5)$$

The LCOE, net of the covariance between renewable availability and dispatchable power marginal cost (on average over the lifespan of the installed generation capacity and discounted) divided by the average capacity factor, should be the same among renewable energy sources over the lifetime of the equipment.

We call the left-hand term of (5) the *Economic Cost of Energy* (ECOE) of renewable technology i. Condition (5) emphasizes that LCOE is not the only characteristic to be taken into account when choosing between different intermittent generation technologies. The covariance or correlation between production and the marginal cost of production in the energy mix matters. Technologies with a positive correlation should receive a bonus, because their ECOE is lower than their LCOE, while those with a negative correlation should be subject to a penalty, resulting in ECOE>LCOE. We further decompose the bonus-malus adjustment applied to the LCOE in Section 5.

2.3 Market outcome

We analyze the equilibrium outcome when carbon emissions are priced at their social cost and the electricity wholesale market is competitive. We assume that producers are price takers and investors can perfectly forecast future wholesale market prices p.

First, given the available generation capacity of renewables $\boldsymbol{K}_t$, dispatch is optimal. For realizations of D_t and $\boldsymbol{\omega}$ such that $D_t \leq \sum_i \omega_i K_{it}$, demand can be fully served by renewables at zero marginal cost, and thus the wholesale electricity price is $p_t = 0$. In contrast, if $D_t > \sum_i \omega_i K_{it}$, the demand net of renewable generation is $Q_t = D_t - \sum_i \omega_i K_{it} > 0$. It is supplied by dispatchable power plants. The market price is equal to the cost of the last MWh supplied, which includes the cost of carbon emissions, that is:

$$p_t = C'_t(Q_t). \quad (6)$$

The expected discounted profit of the renewable investment $\bar{k}_{it}$ at cost r_{it} at time t is:

$$E[\pi_{it}(r_{it})] = \left(E\left[\omega_i \sum_{l=0}^{T_i} \beta_i^l p_{t+l} \right] - r_{it} \right) \bar{k}_{it}.$$

Second, given the future equilibrium prices, investment in new generation capacity of renewables is optimal at any time t. Under the assumption of perfect competition, the renewable equipment (wind turbine or solar photovoltaic plant) making zero profit determines the equilibrium cut-off cost $\tilde{r}_{it}^e$:

$$\tilde{r}_{it}^e = E\left[\omega_i \sum_{l=0}^{T_i} \beta_i^l p_{t+l} \right], \tag{7}$$

for $i = 1, ..., n$. All new generation plants with cost $r_{it} < \tilde{r}_{it}^e$ are built so that the total production capacity is $k_{it}^e = \bar{k}_{it} G_{it}(\tilde{r}_{it}^e)$.

With carbon priced at its social cost [9], $C(Q)$ reflects the social cost of thermal power generation. Therefore replacing p_t defined in (6) in (7) yields the optimality conditions (3) for $i = 1, ..., n$. Hence $\tilde{r}_{it}^e = \tilde{r}_{it}^*$, and therefore $k_{it}^e = k_{it}^*$ for $i = 1, ..., n$: investment in new generation is socially optimal. Thus, we have established the following result.

Proposition 1 *When investors are risk-neutral and have rational expectations about energy prices, the energy mix achieved in a competitive market with emissions priced at their social cost is efficient.*

Proposition 1 confirms that, in theory, the wholesale market provides investors with the correct price signal when carbon emissions are priced at their social cost. We now investigate the performance of fixed prices in inducing optimal investment in renewables.

[9] If carbon emissions cannot be taxed at their social cost, renewables should be subsidized to improve efficiency. Under inelastic demand, as assumed here, it can be shown that the optimal energy mix can be implemented with a price premium for renewable production if emission intensity does not vary with electricity production. Yet, as shown in Ambec and Crampes (2019), a price premium does not implement the first-best as long as consumers respond to market prices, unless it is corrected by some form of electricity taxation. It could also lead to non-optimal dispatch with ramp-up costs.

3 Public policies for investment in green generation

3.1 Setting prices

Denote p_{it}^s the fixed price assigned to renewable technology i at time t. Let us call this price Feed-in Tariff (FiT). At this price per MWh, the expected profit of a generation plant with type i capacity $\bar{k}_{it}$ and capacity cost r_{it} is:

$$E[\pi_{it}(r_{it})] = \left(\sum_{l=0}^{T_i} \beta_i^l E[\omega_i] p_{it}^s - r_{it} \right) \bar{k}_{it} = \left(\mathcal{B}_i E[\omega_i] p_{it}^s - r_{it} \right) \bar{k}_{it}, \tag{8}$$

where the second equality results from the definition of $\mathcal{B}_i \equiv \sum_{l=0}^{T_i} \beta_i^l$.

The investment implemented by the FiT p_{it}^s at time t is $k_{it}^s = \bar{k}_{it} G_{it}(\tilde{r}_{it}^s)$ where the cut-off capacity cost $\tilde{r}_{it}^s$ is defined by equalizing the expected discounted profits defined in (8) to zero:

$$\tilde{r}_{it}^s = \mathcal{B}_i E[\omega_i] p_{it}^s. \tag{9}$$

Compared to the efficient cut-off implemented with competitive wholesale markets $\tilde{r}_{it}^* = \tilde{r}_{it}^e$ defined in (7), we have:

$$\begin{aligned} \tilde{r}_{it}^* - \tilde{r}_{it}^s &= E\left[\omega_i \sum_{l=0}^{T_i} \beta_i^l p_{t+l} \right] - \mathcal{B}_i E[\omega_i] p_{it}^s \\ &= E\left[\omega_i\right] E\left[\sum_{l=0}^{T_i} \beta_i^l p_{t+l} \right] - \mathcal{B}_i E[\omega_i] p_{it}^s + cov\left(\omega_i, \sum_{l=0}^{T_i} \beta_i^l p_{t+l} \right), \end{aligned} \tag{10}$$

where the last equality is due to the aforementioned definition of covariance.

First, we show that fixing the FiT at the discounted expected wholesale market price during the lifespan of the solar or wind power generation equipment leads to inefficient investment unless the renewable capacity factor is uncorrelated with the price. Substituting

$$p_{it}^s = E\left[\sum_{l=0}^{T_i} \frac{\beta_i^l p_{t+l}}{\mathcal{B}_i} \right] \tag{11}$$

into (10) yields $\tilde{r}_{it}^* - \tilde{r}_{it}^s = cov\left(\omega_i, \sum_{l=0}^{T_i} \beta_i^l p_{t+l}\right)$. For the two cut-offs $\tilde{r}_{it}^*$ and $\tilde{r}_{it}^s$ to coincide the covariance should be nil. With positive covariance, $\tilde{r}_{it}^* > \tilde{r}_{it}^s$ and, therefore, $k_{it}^* > k_{it}^s$. Hence, a fixed price based on average future market prices will trigger underinvestment whenever

the correlation between the capacity factor and future market prices is positive. Conversely, it induces overinvestment if the correlation is negative. The magnitude of the distortion increases with the absolute value of the correlation coefficient.

Second, we derive the optimal FiT. Using (9) and setting (10) equal to zero yield[10]

$$p_{it}^{s} = \sum_{l=0}^{T_i} \frac{\beta_i^l}{\mathcal{B}_i} E\left[p_{t+l}\right] + \frac{1}{E[\omega_i]} \sum_{l=0}^{T_i} \frac{\beta_i^l}{\mathcal{B}_i} cov\left(\omega_i, p_{t+l}\right). \tag{12}$$

The optimal FiT price is equal to the discounted average of wholesale market prices adjusted by a *bonus-malus* featuring the covariance between renewable generation and discounted average market price. If it is positive, then the renewable energy plants are producing mostly when prices are high. Investors should be rewarded for that with a bonus. Conversely, if the covariance is negative, production from this type of renewable tends to occur when prices are low. Therefore, a penalty (malus) should be applied to reduce the payment per MWh below the discounted average of wholesale market prices.

Proposition 2 *Pricing renewable i at $p_{it}^{s} = \sum_{l=0}^{T_i} \frac{\beta_i^l}{\mathcal{B}_i} E\left[p_{t+l}\right] + \frac{1}{E[\omega_i]} \sum_{l=0}^{T_i} \frac{\beta_i^l}{\mathcal{B}_i} cov\left(\omega_i, p_{t+l}\right)$ per MWh attracts the optimal investment in new generation. It rewards energy sources that are positively correlated with market prices and penalizes those that are negatively correlated. A price equal to the discounted average market price over the lifespan of the investment leads to underinvestment (resp. overinvestment) in renewable energy if the market price p_t and the capacity factor ω_i are positively (resp. negatively) correlated.*

Our bonus-malus (the last term in (12)) can be related to the VALCOE for energy computed by the International Energy Agency (IEA 2023). The VALCOE adjusts the LCOE by three elements. One of them called the energy value is the difference between the average value of generation and its realized value per MWh. In our model, it writes $E[p_t] - \frac{E[\omega_i p_t]}{E[\omega_i]} = -\frac{1}{E[\omega_i]} cov(\omega_i, p_t)$, which is the opposite of our per-period bonus-malus that we discount over the lifespan of the solar or wind power generation plant.

3.2 Procuring new generation capacity

Instead of fixing the price, the regulator can auction off new generation capacity with PPAs or CfDs. With PPAs, electricity from renewable technologies is sold to buyers (end consumers or retailers) at the price p_i^s resulting from the auction. With CfDs, the new generation plant

[10] We also use the properties $E[\sum_j X_j] = \sum_j E[X_j]$ and $cov(Y, \sum_j X_j) = \sum_j cov(Y, X_j)$ for any random variables X_j and Y.

of renewable type i is remunerated by a strike price denoted p_i^s regardless of the market price p. If $p < p_i^s$, producers receive $p_i^s - p$ from the regulator in addition to the market price p. They earn $p + (p_i^s - p) = p_i^s$ per MWh. Conversely, if $p > p_i^s$, producers have to pay $p - p_i^s$ to the regulator. By selling at price p on the wholesale market, they earn $p - (p - p_i^s) = p_i^s$ per MWh.

The regulator decides how much capacity to procure and designs the auction mechanism. Investors bid the price at which they are willing to provide electricity. The regulator can set up separate auctions for different types of renewable technologies and locations (e.g., onshore versus offshore wind) or open up a single auction process. In our framework, if the regulator organizes separate tenders for the n renewable energy sources, she decides how much capacity to procure for all renewable technologies. She needs to know the efficient capacity portfolio $\boldsymbol{k}_t^* = (k_{1t}^*, ..., k_{nt}^*)$ at time t with $k_{it}^* = \bar{k}_i G_i(\tilde{r}_{it}^*)$ for $i = 1, ..., n$, where $\tilde{r}_{it}^*$ is defined in (3).

We show that the optimal investment in new generation can be procured in a single auction with a specific rule for setting the price. Investments with the lowest bid are selected, regardless of the technology, to meet the procured capacity. In the following, we will name *winning bid* the highest bid among all the selected investments. The price should be equal to the winning bid adjusted by the bonus-malus associated with the renewable technology. The proof is provided in Appendix B.[11]

Proposition 3 *A single auction on new generation capacity at time t implements the optimal portfolio of renewable technologies with differentiated prices* $p_{it}^s = \widehat{b} + \frac{1}{E[\omega_i]} \sum_{l=0}^{T_i} \frac{\beta_i^l}{\mathcal{B}_i} cov\left(\omega_i, p_{t+l}\right)$ *for* $i = 1, ..., n$*, where* $\widehat{b}$ *is the winning bid.*

In a uniform price auction with a continuum of bidders, bidders have incentives to bid their cost in equilibrium.[12] In our framework, if the price is equal to the winning bid $\widehat{b}$, an investor with technology i and cost r_i would bid its LCOE $b_i(r_i) = \frac{r_i}{\mathcal{B}_i E[\omega_i]}$ in equilibrium. Investments are selected on the basis of LCOE alone, missing an important characteristic of renewables: their adequacy to the energy mix. For allocation to be efficient, new generation technologies should be selected on the basis of their ECOE, that is, not only their expected production cost, but also the correlation between generation and electricity scarcity. This can be done by differentiating the price with the bonus-malus. Investors would then bid their ECOE equal to LCOE adjusted by the bonus-malus. The equilibrium bidding strategy of

[11] Notice that the procurement auction described in Proposition 3 implements the optimal renewable technology portfolio $\boldsymbol{k}_t^* = (k_{1t}^*, ..., k_{nt}^*)$ not only at the first best total capacity $\sum_i k_{it}^*$ but also for any total capacity lower than first-best: $\sum_i k_{it} < \sum_i k_{it}^*$.

[12] With a continuum of bidders, the economy is atomless implying that no bidder can strategically manipulate the winning bid by bidding above its cost.

an investor with cost r_i is $b_i^e(r_i) = \frac{r_i}{\mathcal{B}_i E[\omega_i]} - \frac{1}{E[\omega_i]} \sum_{l=0}^{T_i} \frac{\beta_i^l}{\mathcal{B}_i} cov\left(\omega_i, p_{t+l}\right)$. Investments are selected based on the ECOE. The ECOE is smaller than the LCOE if generation occurs when electricity is expensive (positive covariance). The bonus makes this investment more useful for a same LCOE. Conversely, the LCOE must be inflated when generation occurs when electricity is cheap (negative covariance). The malus is added to the LCOE, making that renewable technology less competitive. Overall, new generation technologies are selected efficiently on the basis of both their cost and their adequacy to the energy mix reflected by the electricity wholesale market price.

4 Estimating the bonus-malus

How should the fixed price p_{it}^s be set to foster optimal investment in renewable capacity? Equation (12) shows that it should reflect the expected value of electricity in the future adjusted with the bonus-malus term. Similarly, in a procurement process for new generation, when investors bid the LCOE, a bonus or malus should be applied to the winning bid.

In this section, we propose a simple way to calculate the strike price and the bonus-malus for wind and solar power in three different European markets and California. We then highlight the impact of location and technology on the bonus-malus correction term, considering onshore and offshore wind as well as solar and wind locations.

4.1 Data and descriptive statistics

For the empirical analysis, we rely mainly on publicly available data from the transparency platform of the European Network of Transmission System Operators (ENTSO-E) and data from the California Independent System Operator (CAISO).[13] For Europe, we focus on three out of the four largest countries in terms of electricity generation capacity: Germany, France, and Spain, which are heterogeneous in terms of renewable energy penetration. California provides an interesting example of a market dominated by one type of renewable technology, namely solar power.

For Europe, we collect hourly market-level data for the period January 2015 to December 2023. The main variables of interest are day-ahead market (DAM) prices, which, assuming competitive markets, correspond to the expected marginal cost of thermal generation, load,

[13]Data can be accessed online. ENTSO-E: `https://transparency.entsoe.eu` and CAISO 'OASIS': `https://oasis.caiso.com/mrioasis/logon.do` and 'Today's Outlook' `https://www.caiso.com/TodaysOutlook/Pages/default.aspx`.

and production from all generation sources, including solar and wind.[14] Finally, we complement these high-frequency data with annual data on installed capacity, which allows us to calculate the observed capacity factors by renewable technology. As for California, we collect similar data from CAISO for the period May 2018 to December 2023, aggregating production and prices at average system-wide hourly values.[15] Figures D.1 and D.2 in the appendix provide an overview of the evolution of renewable penetration (wind and solar) in each market and show the average capacity factors and price levels over time. As the average DAM prices were heavily influenced by the 2021 and 2022 energy crisis, we use data from the period 2015-2020 (2018-2020 in the case of CAISO) for the main calculations.
[16]

Finally, Appendix Figure D.4 reports, at an annual frequency, average renewable capacity factors and their correlation with DAM prices. Average renewable capacity factors, $E[w_i]$, are largely stable over 2015-2023, with the notable exception of wind in California. By contrast, the annual correlation between DAM prices and capacity factors is stable only for wind. For solar, this correlation is generally positive across countries in the early years of the sample, but becomes increasingly negative over time in all countries. This evolution highlights the so-called "cannibalization effect". Solar production from existing plants is typically highly correlated within a given market, and new solar installations tend to mirror the production patterns of existing capacity, making new investment less valuable.

4.2 Estimation

Propositions 2 and 3 give us a direct formula to compute the bonus-malus based on the covariance of the capacity factor with DAM prices and the expected capacity factor. Since all the electricity markets we consider have their own emission trading scheme, we consider that CO2 emissions are priced at their social cost. Hence electricity wholesale market prices internalize the social cost of thermal power CO2 emissions.[17] We rely on the period 2015 to 2020, when market conditions and prices were broadly stable, to obtain estimates of the

[14]For the empirical application, we treat each country in isolation and do not consider imports from or exports to neighboring countries.

[15]We obtain data on production from 'Today's Outlook' and data on DAM prices from 'OASIS'. We aggregate the prices from the three main bidding zones (NP15, ZP26, and SP15) into a single price and convert all prices into €/MWh for comparability, taking into account the average of the annual exchange rate over the sample period.

[16]Figure D.3 in the appendix shows the hourly variation in terms of average load, DAM prices, and capacity factors for wind and solar separately in each market, highlighting differences in terms of renewable penetration and correlation patterns.

[17]In case the allowance price does not fully capture the social cost of carbon, our empirical covariance estimates identify a market-value adjustment, not necessarily the socially optimal bonus–malus.

optimal correction term. Table 1 shows the bonus-malus that should be applied. For the calculation of the net present value, we consider a lifetime of 20 years of the renewable plants and an annual discount rate of 5%.[18] We simulate the 20-year investment horizon based on uniform draws from the annual distribution of capacity factors and covariance term and calculate standard errors via bootstrap. The calculations are based on hourly data.

Table 1: Bonus-malus when considering optimal strike price (in €/MWh)

		Wind		**Solar**	
	DAM	P^s_{wind}	Bonus-malus	P^s_{solar}	Bonus-malus
DE	34.76	29.56	-5.19	32.3	-2.45
	(1.2)	(1.08)	(0.2)	(1.4)	(0.41)
FR	40.41	38.69	-1.71	39.17	-1.23
	(1.39)	(1.43)	(0.12)	(1.57)	(0.37)
ES	46.25	43.21	-3.05	46.77	0.52
	(1.65)	(1.65)	(0.28)	(1.87)	(0.3)
CA	33.82	32.79	-1.03	26.49	-7.33
	(1.43)	(1.77)	(0.35)	(1.78)	(0.43)

Notes: The table displays average day-ahead market (DAM) prices, the optimal strike price P^s and the bonus-malus for wind and solar technologies defined by Equation (12) for Germany (DE), France (FR), Spain (ES), and California (CA). We assume a lifetime of installations of 20 years and a 5% annual discount rate. Calculations based on data 2015-2020, but in case of California (2018-2020). Prices in US-$ have been converted to € using the average annual exchange rates. Standard errors obtained via bootstrap (100 draws).

We find important heterogeneity in the bonus-malus that should be applied to solar and wind technologies in the four different markets. Also, even within the same technology (solar or wind), there exist important differences across markets. In the case of wind energy, we find the largest penalty in Germany, where the average wholesale price should be reduced by 5.19 €/MWh.[19] This corresponds to about 15% of the average wholesale price of 34.8 €/MWh in this period. The correction factors are smaller in the other countries, reflecting both different covariances between wind capacity factors and prices and differences in the average capacity factors.

Focusing instead on solar technology in the right panel of Table 1, we generally find penalties increasing with the share of solar production in the energy mix as becomes very clear in the case of California with a malus of 7.33 €/MWh (approximately 22% of the

[18]The annual discount rate of 5 % for generation capacity corresponds to a yearly discount rate of 4% for the investment and a deterioration rate of 1% for the equipment, i.e., $\rho = 0.96$ and $\lambda = 0.99$ so that $\beta = \rho\lambda \approx 0.95$.

[19]For ease of exposition, we refer only to 'price setting' (Section 3.1) when interpreting the bonus-malus. However, the same logic applies in case of quantities (see Proposition 3).

average DAM price). An outlier is Spain, where we find a positive value (bonus). Yet, as indicated by Appendix Figure D.4 the correlation has become more negative over time and more recent periods are related to a malus as well.

4.3 Differentiating the bonus-malus by location and technology

While there is important heterogeneity across countries, the bonus-malus could be further refined by focusing on specific regions within a given country and by exploiting different technologies. We therefore proceed distinguishing between onshore and offshore wind and consider heterogeneity across onshore wind locations within the same country. We also examine how the spatial placement of solar installations affects the optimal correction factor using simulated renewable output and how different panel orientation can impact the bonus-malus.

For this analysis, we focus on one country, Germany, as it features both types of wind technologies during the sample period 2015–2020 and exhibits substantial spatial variation in average production profiles for both solar and wind (see Panels (a) and (b) of Appendix Figure D.5).

First, using observed data for offshore and onshore wind production, we compute the bonus-malus for the period 2015–2020, following the same methodology as in Table 1. We find a substantially smaller average malus for offshore wind of -2.58 (0.18), compared to -5.71 (0.22) for onshore wind (standard errors in parentheses). This difference is mainly explained by disparities in average capacity factors, which are approximately twice as high for offshore wind as for onshore wind (0.43 versus 0.21). The covariance term between prices and wind production is comparable across the two technologies.

Second, we use simulated production profiles based on observed weather patterns to highlight spatial heterogeneity in the bonus-malus for onshore wind and solar technologies in Germany.[20] Appendix Table D.1 presents how the bonus-malus in the simulated data differs across states and highlights substantial heterogeneity in the relative malus, ranging from -1.55 to -2.15 €/MWh for solar and from -4.2 to -5.3 €/MWh for wind.[21] This variation is driven entirely by differences in local production profiles and their correlation with national wholesale market prices, as we simulate a common technology with fixed parameters across

[20] We obtain hourly capacity factors for wind and solar plants for a representative location in each state using *Renewables Ninja*, which relies on observed weather data(see Pfenninger et al. 2016 and Staffell et al. 2016). Additional details of the data are provided in Appendix D.2.

[21] The average bonus-malus in the simulated data is comparable to that in the observed data, although slightly smaller in magnitude. This difference may reflect the higher capacity factors in the simulation, which result from optimized technological parameters such as renewable plant siting, panel orientation and tilt, and turbine height.

locations.

Comparing the average bonus-malus for wind and solar to the resource availability in Appendix Figure D.5 shows that, in the case of wind, basing the bonus-malus solely on production potential fails to capture the economic value of the energy source. The key determinant is its correlation with wholesale market prices, as formalized in Equation (12). For wind, the largest malus occurs in central Germany, a region with only moderate wind potential. For solar, by contrast, we observe a negative correlation between resource availability and the malus, as locations with higher solar irradiation receive a smaller malus.

Additional heterogeneity may arise, however, from technological characteristics such as wind turbine height or solar panel orientation. To highlight this potential for differentiation, we simulate output for four locations in Germany with solar panels facing either east, south, west, or that are flat. Panel (a) of Appendix Figure D.6 plots the average production profile, together with DAM prices, for Bavaria as an example. Panel (b) calculates the optimal bonus-malus at the four locations with the distinct panel orientation. While a south-facing panel maximizes total production, its output is valued less as it produces during low demand hours and hence leads to a larger malus compared to an east facing panel, whose production profile is more closely aligned with the load curve. We find that, even within the same location, panel orientation can lead to important differences in bonus-malus payments. In case of Bavaria the optimal malus can more than double from -1.12 to -2.46 €/MWh (east vs. west-facing panels). Technology might thus be an important factor in determining the optimal bonus-malus.

Taken together, the findings from this section raise the question of whether uniform incentives, such as a Germany-wide bonus-malus, may lead to suboptimal siting decisions (Lamp and Samano, 2023). We return to this question in Section 6, where we simulate the impact of different types of bonus-malus payments on renewable investment and siting decisions.

5 Adjusting the LCOE by decomposing the bonus-malus with technological parameters

One of the shortcomings of the previous analysis is that the definition of the bonus-malus depends on market prices and that these prices are typically hard to predict, as the existence of recent shocks to demand (COVID pandemic) as well as supply (energy price spikes due to wars and other geopolitical events) illustrate. Moreover, many jurisdictions do not have wholesale markets. We therefore propose now an alternative approach that allows to decompose the bonus-malus in terms of technological parameters that are easier to forecast. We use this decomposition to adjust the LCOE and obtain the ECOE of solar and wind power, allowing us

to compare the efficiency of renewable energy policy objectives in California, France, Germany, and Spain.

5.1 Theory

To better quantify the ECOE, which measures the cost of an additional MWh of renewable energy production, we decompose the term that corrects the LCOE. In Appendix C, we use a Taylor quadratic approximation of $C_t(Q_t)$ around the average electricity production denoted $Q^*_{0t} := E[Q^*_t]$ in (4) to obtain

$$\frac{\tilde{r}^*_{it}}{\mathcal{B}_i E[\omega_i]} + \sum_{l=0}^{T_i} \frac{\beta_i^l}{\mathcal{B}_i} \underbrace{C''_{t+l}(Q^*_{0t+l})}_{(a)} \left\{ \underbrace{\frac{V[\omega_i]K_{it+l}}{E[\omega_i]}}_{(b)} + \underbrace{\frac{\sum_{j\neq i} cov(\omega_i,\omega_j)K_{jt+l}}{E[\omega_i]}}_{(c)} - \underbrace{\frac{cov(\omega_i, D_{t+l})}{E[\omega_i]}}_{(d)} \right\} \quad (13)$$
$$\approx \sum_{l=0}^{T_i} \frac{\beta_i^l}{\mathcal{B}_i} E\left[C'_{t+l}(Q^*_{t+l})\right],$$

where $V[\omega_i]$ is the variance of ω_i. Condition (13) is an optimality condition for the investment in renewable technology i. Both sides of the approximation quantify the expected cost of one additional MWh depending on whether it comes from the current energy mix on the right-hand side, or from investment in renewable technology i on the left-hand side. Hence, the left-hand side of (13) tells us how intermittency should correct the LCOE to assess the cost of a MWh with renewable technology i to be compared with its (expected) marginal cost in the current energy mix. It is decomposed into four terms labeled from (a) to (d):

(a) The term that multiplies the curly bracket is the slope of the marginal-cost curve. It measures how rapidly the marginal cost of dispatchable generation rises as residual demand increases. [22]

(b) The numerator of the first term inside the curly brackets $V[\omega_i]K_{it}$ captures the additional cost of renewable i's generation variability by itself, ignoring the variability of electricity demand and of other renewable energy sources (everything else being constant). It is increasing with the variance of power generation (capacity factor) through $V[\omega_i]$, as well as with the total production capacity with the same technology K_{it}.

[22] In a different setting, Liski and Vehviläinen (2026) use the shape of supply and demand functions to determine the efficiency gains resulting from the introduction of new technologies, such as storage, on equilibrium prices.

(c) The numerator of the second term is the sum of the covariances between the capacity of renewable i and other renewables $j \neq i$ multiplied by their capacity K_{jt}. It measures the extent to which the renewable i complements the other renewables. It does so in the case of negative covariance, which increases the marginal value of renewable i. It thus reduces the LCOE of i by an amount that is inflated by the installed capacity of technology j. Conversely, if the covariance is positive, renewables i and j produce at the same time, which reduces i's marginal value and thus gives an ECOE larger than the LCOE.[23]

(d) The numerator of the last term is the covariance between renewable generation and electricity demand (or load) $cov(\omega_i, D_t)$.[24] Intermittency is particularly bad if production is low when demand is high, i.e., when the covariance is negative. Such a renewable technology is less valuable and therefore this term is added to the LCOE. Conversely, intermittency is less of a problem if electricity is produced when demand is high. The covariance is therefore positive, so that the third correction term is negative. The renewable technology is then more valuable, and thus this term reduces the LCOE to assess the social cost of renewable i.

All correction terms are divided by the average capacity factor $E[\omega_i]$ to obtain the additional costs per MWh of electricity produced on average instead of MW of generation capacity.

5.2 Estimation

In the following, we first estimate each individual element inside the curly brackets of the decomposition (numerators of Terms (b) to (d) in Equation (13)) focusing separately on wind (w) and solar (s) technologies in the four different markets. We consider the same 20-year lifespan and 5% discount rate of the technology as in Section 4.2, when calculating the individual terms. For ease of exposition, we focus on point estimates and do not report standard errors. The results are presented in Table 2, where we express the covariance between load and the renewable capacity factor in terms of the maximum load share, θ_D.

Focusing on maximum load, $\overline{D}$, we find that France stands out from the other countries because of its particularly high peak demand. This is mainly due to the widespread use of electric heating in winter. This seasonal pattern also affects the covariance terms, which are

[23] Note that this term disappears if technology i is the only intermittent renewable energy technology.

[24] If we denote θ as the fraction of maximum demand $\overline{D}_t$, we have $D_t = \theta \overline{D}_t$ so that $cov(\omega_i, D_t) = \overline{D}_t cov(\omega_i, \theta)$ with $\theta \in [0, 1]$. In this case, we have covariances between random variables in the interval 0 and 1 multiplied by MWh/MW in the correction term. We follow this approach in the empirical implementation of the decomposition.

Table 2: Individual elements of decomposition

		Wind			**Solar**			
	$\overline{D}$	$cov(\omega_w, \theta_D)$	$V[\omega_w]$	K_w	$cov(\omega_s, \theta_D)$	$V[\omega_s]$	K_s	$cov(\omega_w, \omega_s)$
DE	79939	0.0026	0.0282	51914	0.0061	0.026	42222	-0.0054
FR	94492	0.0046	0.0257	13048	-0.0004	0.0391	7562	-0.0056
ES	41015	0.0007	0.0207	23130	0.0116	0.0717	6985	-0.0068
CA	46933	0.0014	0.0433	5980	0.0067	0.0964	13245	-0.0118

Notes: Decomposition following Equation (13). We express $cov(\omega_i, D) = \overline{D} cov(\omega_i, \theta_D)$ with $i \in \{s; w\}$ and $\theta_D \in [0, 1]$. The first column shows the maximum load (in MW) over the sample period. The average installed capacity for wind and solar (K_w and K_s, respectively) are both in MW. Main sample: 2015-2020 (CA: 2018-2020), based on hourly data.

significantly larger for wind and smaller, or even slightly negative, for solar in France. More generally, the correlation between renewable generation and electricity demand varies across countries, with both wind and solar showing heterogeneous patterns depending on national load profiles. Differences are also observed in the variance of renewable generation, with California showing the highest volatility of the four markets analyzed. In all regions, solar and wind generation are negatively correlated, indicating a complementarity between the two sources. This is consistent with their typical daily generation profiles: wind tends to be more available during nighttime hours, while solar is limited to daytime hours (see also Figure D.3 in the Appendix). It is also in line with the seasonal availability: wind in winter and solar in summer. Based on the individual elements of the decomposition, Table 3 calculates the Terms (b) through (d) of Equation (13).

Table 3: Main elements of decomposition

Term in (13)	**Wind**			**Solar**		
	$\frac{V[\omega_w]K_w}{E[\omega_w]}$ (b)	$\frac{cov(\omega_s,\omega_w)K_s}{E[\omega_w]}$ (c)	$-\frac{cov(\omega_w,\theta_D)\overline{D}}{E[\omega_w]}$ (d)	$\frac{V[\omega_s]K_s}{E[\omega_s]}$ (b)	$\frac{cov(\omega_s,\omega_w)K_w}{E[\omega_s]}$ (c)	$-\frac{cov(\omega_s,\theta_D)\overline{D}}{E[\omega_s]}$ (d)
DE	6480.35	-1013.37	-919.55	10401.5	-2684.57	-4586.68
FR	1497.22	-189.3	-1881.07	2087.37	-521.11	296.08
ES	1959.96	-196.26	-123.59	2232.19	-693.88	-2098.57
CA	803.5	-479.27	-199.35	4894.13	-273.86	-1222.12

Notes: The table presents estimates for the elements (b) to (d) in (13). Each term is calculated over the 20-year project horizon and weighted accordingly ($\sum_{l=0}^{T_i} \frac{\beta_i^l}{\mathcal{B}_i^l}$). Positive values increase the ECOE (additional cost), while negative values decrease it (lower cost). Main sample: 2015-2020 (CA: 2018-2020), based on hourly data.

Term (b) quantifies the "cannibalization effect" of a high penetration of the same renewable technology and thus increases the ECOE of renewable investment. It is particularly strong in countries with a large production capacity like Germany and Spain for both solar and wind, or California for solar. Note that small capacity factors, such as solar in Germany, further increase this penalty. Two factors are reducing the ECOE of wind and solar power: the negative covariance between the two intermittent energy sources (Term (c), middle column for wind or solar in Table 3) that helps to smooth aggregate supply, and the positive covariance with demand (Term (d), right-hand column for wind or solar in Table 3). Note that in line with Equation (13) we express this last term as benefit by pre-multiplying it by -1, as if it were a decrease in cost.

Focusing on Term (c) the covariance between renewable technology availability, we find large values for Germany that are again driven by low relative capacity factors and a large installed capacity base. Finally, focusing on Term (d), we find that France is an outlier because the covariance between generation and electricity consumption turns out to be negative for solar, which increases the ECOE of solar (a cost). It is a benefit for all other countries for both solar and wind investment as it lowers their ECOE. We find strong heterogeneity in this last parameter depending on daily load as well as seasonal differences in electricity demand.

When all components are combined, the adjustment from LCOE to ECOE is positive in every case except for wind in France and solar in Spain. The negative adjustment for Spanish solar, indicating a benefit to the energy system, is consistent with the aggregate results in Table 1. The result for French wind is less expected. It is driven primarily by the strong positive covariance between wind generation and electricity load, captured by term (d), whose adequacy benefits more than offsets the cannibalization penalty in Term (b). The difference compared to results based on market prices reflects the imperfect relationship between load and day-ahead market prices. Although French prices follow a temporal pattern broadly similar to German prices (Figure D.3 in the Appendix), French load is more variable, with pronounced winter peaks and relatively high demand during late-evening hours. Wind availability appears to align more strongly with these high-load periods than with high-price hours, causing the fundamentals-based decomposition to assign French wind a larger adequacy benefit than the price-based measure.

5.3 Comparison of the market-based and cost-based estimates of the bonus-malus

To compare the price-based bonus-malus with its cost-based decomposition, we need an estimate of the slope of the merit-order curve evaluated at the expected load, represented by

Term (a) in Equation (13). We estimate this term using hourly merit-order cost curves constructed from detailed wholesale-market bid data for Spain and California, where individual supply and demand bids are publicly available. Under the assumption that producers bid their marginal costs, these data allow us to reconstruct the aggregate hourly supply curve and estimate its local slope around expected residual demand.

Appendix Section D.4 describes the detailed data as well as the data cleaning procedure that we use to obtain hourly supply and demand bids. As for Spain, we have a total of 93 million individual bids available for the years 2015-2020, and 23 million bids for California. To estimate the slope of the supply curve, we perturb the average hourly load by 1% to obtain counterfactual market clearing prices and use this estimate to calculate the hourly derivatives. Since there is heterogeneity in the hourly load pattern, we report the load-weighted average.

As detailed bid data are not available in all jurisdictions, we adopt an alternative strategy based on the estimates from Section 4.2 to obtain the cost-based estimates in all countries of our analysis. Specifically, we equate the implied bonus-malus from Table 1 to the decomposition in Table 3 to recover the slope of the supply curve that reconciles both sets of estimates. For this approach to be valid, the original estimates and the decomposition must yield comparable results and implied slope parameters. We can assess this assumption in the case of Spain and California, where both sets of estimates are available.

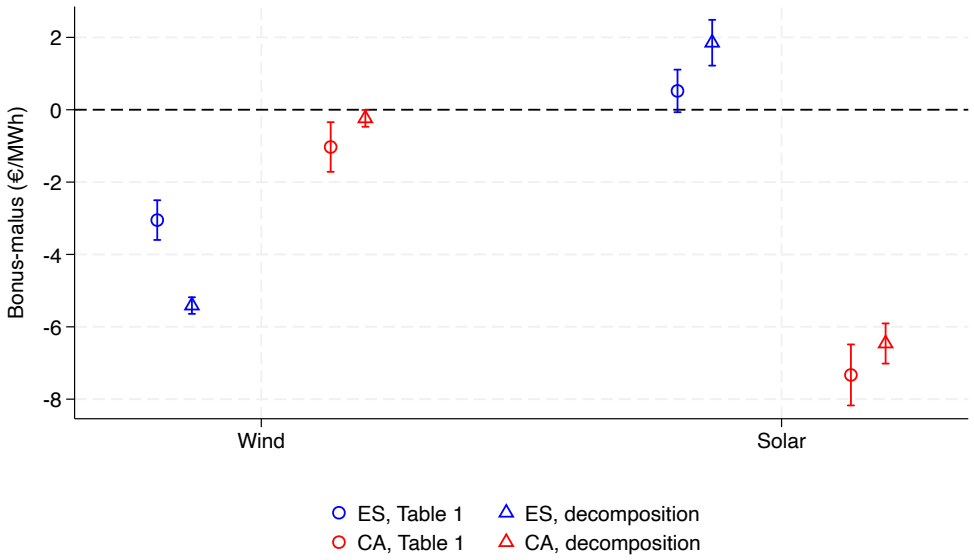
Figure 1 compares the bonus-malus estimates obtained using the price-based and fundamentals-based approaches. The 95% confidence intervals overlap for solar in both markets and for wind in California. For wind in Spain, the point estimates differ quantitatively, although they have the same sign and remain qualitatively consistent.[25]

Appendix Table D.2 reports the point estimates of the bonus-malus under both approaches, together with the corresponding implied supply-curve slopes. In the next subsection, we combine the fundamentals-based decomposition with these slope estimates for all four jurisdictions to conduct counterfactual simulations. These simulations examine how the optimal bonus-malus changes under alternative assumptions about electricity demand and renewable deployment following future policy scenarios.[26]

[25] Observed differences may be due to our assumption of perfect competition in Table 1. If there is market power in supply, DAM prices may not perfectly correspond to the social cost of providing electricity. Similarly, even small changes in the covariance between load and DAM prices, as highlighted for the case of France, can lead to differences in estimates.

[26] We allow the implied slope to differ between wind and solar within each jurisdiction. Although both technologies face the same hourly merit order, they may produce at different hours and therefore place different weights on the local slope of the supply curve. Using a common country-level average slope does not change the qualitative conclusions. Note further that, for wind in France, the difference between the covariance of capacity factors with prices and the covariance of capacity factors with demand leads to inconsistent estimates of the implied slope parameter (see Appendix Table D.2). Since this would make the dispatchable

Figure 1: Bonus-malus comparison



Notes: Bonus-malus estimates with 95% confidence interval from the optimal strike price based on the results in Table 1 and the decomposition analysis (Equation (13) in Section 5) for California and Spain: wind (left panel) and solar (right panel).

5.4 Efficiency of the future energy mixes

We next assess the economic implications of prospective policy scenarios for investment in solar and wind capacity. For each scenario, we calculate the adjustment term that converts the LCOE to an economic cost measure, the ECOE, that can be compared across technologies and jurisdictions.

We start by collecting capacity targets by 2025 and 2030 in solar and wind power capacities set by public authorities in California, France, Germany and Spain (see Appendix Table D.3). In line with our estimation sample, we rely on targets defined around 2020. We then substitute these prospective capacities into the decomposition while holding the variances and covariances reported in Table 2 fixed at their estimated values. This assumes that the temporal profiles of solar and wind capacity factors and electricity load remain unchanged as capacity expands. To allow for increasing electricity use associated with electrification, we assume that demand grows by 1% annually. This implies an increase of approximately 16% between 2020 and 2035.[27] Finally, we multiply the variance and covariance components by

cost function non-convex, we use the slope parameter for solar in this case.

[27]These growth rates in demand refer to approximate average historic growth rates in 2020. For the period 2026-2030, the IEA projects a slightly higher, but similar annual growth rate of about 2% in electricity demand in Europe and the USA. Source: `https://www.iea.org/reports/electricity-2026/demand`, last

the estimated slope of the merit-order cost curve, corresponding to Term (a) in Equation (13). To apply a consistent methodology across all four jurisdictions, we use the technology-specific implied slopes reported in Appendix Table D.2, rather than the slopes constructed directly from bid data for Spain and California.

Figure 2 presents the simulated adjustment terms for wind and solar in each jurisdiction. The vertical lines mark the installed-capacity levels implied by the approximate 2025 and 2030 renewable-policy targets. We consider four simulations. The first three vary one component at a time, holding all other components fixed: electricity demand in Simulation 1, wind capacity in Simulation 2, and solar capacity in Simulation 3. Simulation 4 jointly incorporates growth in electricity demand and investment in both wind and solar capacity. Positive values represent a system-value penalty that raises the ECOE above the LCOE, whereas negative values represent a system-value benefit that lowers the ECOE below the LCOE.

Several patterns emerge. For both wind and solar, a moderate increase in demand (of 1 % per year) has only a marginal effect on the adjustment term, all else equal. By contrast, capacity investment in the other renewable technology (solar in the case of wind, and wind in the case of solar) generates an additional benefit, reflecting the negative covariance between solar and wind capacity factors across all jurisdictions. The main factor increasing the LCOE in both technologies is the variance term (investment in the same renewable technology) that reflects the cannibalization effect of renewable energy sources.

In the case of solar, the overall adjustment term in the joint scenario (Simulation 4) tracks closely the variance term in all jurisdictions. The 2030 targets can lead to a significant increase in the adjustment term ranging from 9.0 €/MWh in the case of France to 48.3 €/MWh in the case of California. This relationship is less clear in the case of wind, where the simulated adjustment term can lead to both benefits and costs, as can be seen in the case of California (-7.0 €/MWh) and Germany (13.7 €/MWh).

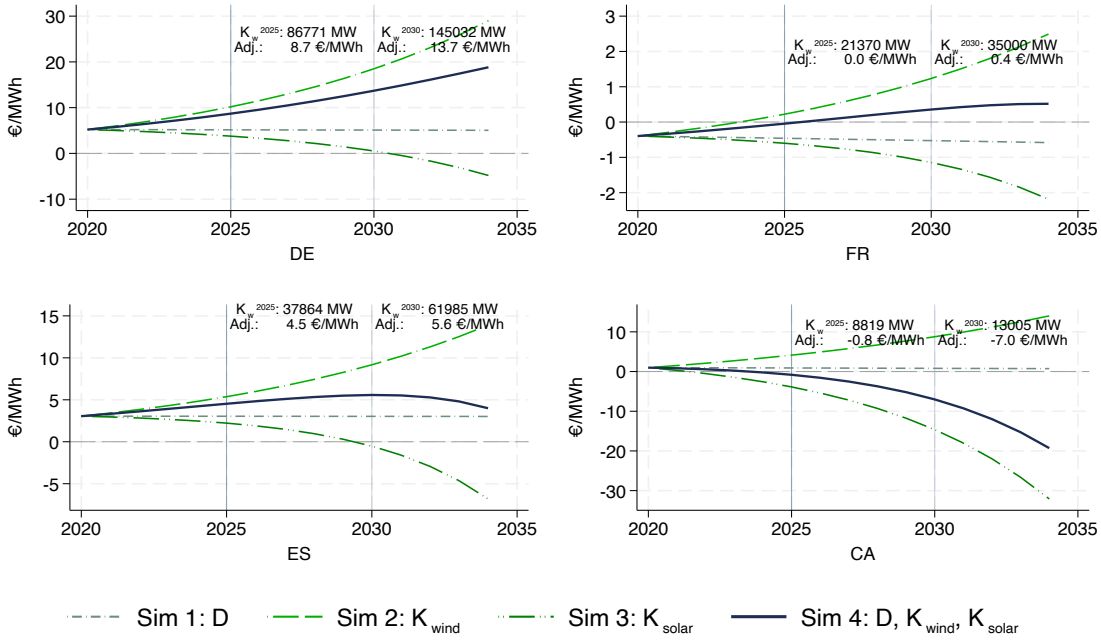
Overall, these results raise the question in how far the ECOE (LCOE + adjustment term) are comparable across technologies when focusing on future policy goals. According to Equation (5), optimal investment implies that the ECOE should be equalized across technologies. When this is not the case, there might be too much investment in any specific technology. To test for this possibility, we collect additional data on the 2020 LCOE and expected LCOE for 2030 that we combine with the adjustment terms in Table 4.

The table suggests that in 2020, the ECOE closely tracks LCOE, as the adjustment component is relatively small across countries and technologies. Spain exhibits the lowest ECOE for both solar and wind, while Germany, France, and California remain substantially higher.[28]

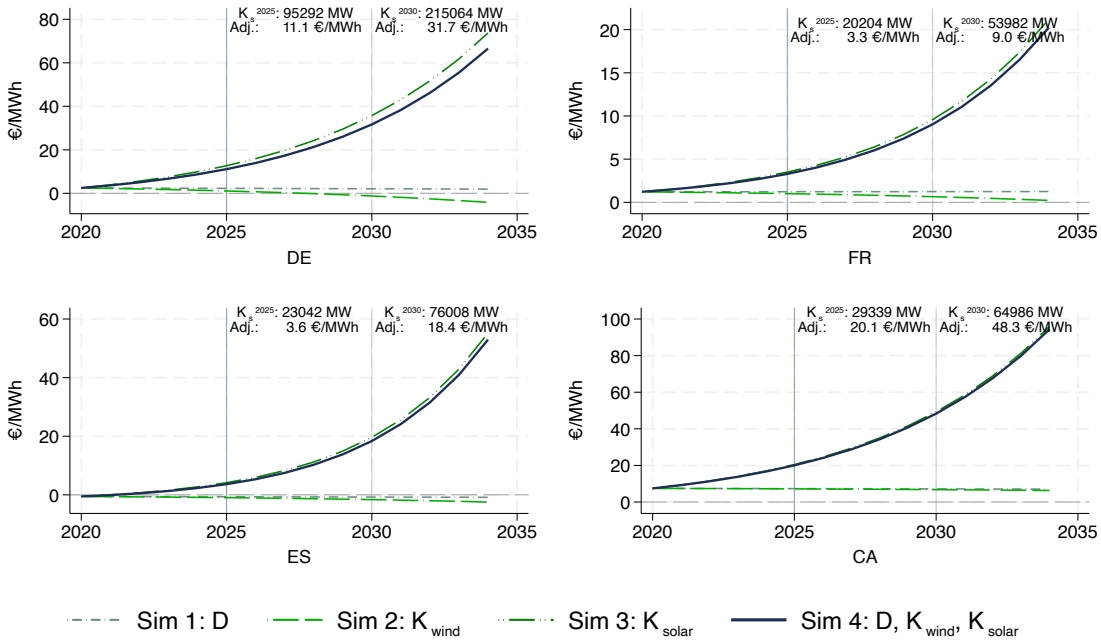
accessed 21/05/2026.

[28]Note that the Spanish data are based on renewable energy auctions rather than a calculation of the

Figure 2: Simulated adjustment term



(a) wind



(b) solar

Notes: Simulated adjustment for wind (Panel a) and solar (Panel b) based on Table 2 and assumptions regarding demand growth and renewable energy investment. The vertical line indicates approximate 2025 and 2030 policy targets for wind and solar, respectively. Adjustment (Adj.) reported for the joint simulation, Simulation 4, considering demand growth as well as both wind and solar investment.

By 2030, however, the adjustment term becomes more important, particularly for solar PV. Although solar LCOE declines in all regions, ECOE increases markedly in Germany and California because larger system-level adjustments offset the generation-cost reductions. Wind technologies are less affected by this pattern: ECOE remains broadly stable or declines in most regions, with especially large reductions for California wind. Overall, the ECOE metric alters the apparent cost ranking relative to LCOE, highlighting that declining technology costs do not necessarily translate into lower system-relevant costs, especially for solar PV in high-penetration settings. Nevertheless, although the ranking of individual technologies can change, we do not find strong evidence that the 2030 policy targets imply excessive investment in any particular technology. Once the adjustment term is incorporated, the relative closeness of the resulting ECOE estimates across technologies is broadly consistent with the equalization condition implied by the theory.

These findings rely on LCOE estimates that are inherently uncertain, reflecting assumptions about plant lifetimes, discount rates, capacity factors, and future cost trajectories. Nonetheless, LCOE remains a standard benchmark used by policymakers and investors to compare technology costs, making the adjustment term potentially important for relative cost rankings. Our calculations also hold other system parameters and covariance structures fixed over time and should therefore be seen as conditional projections. While these are likely to evolve with storage deployment (e.g., Butters et al., 2025), demand-side flexibility (e.g., Imelda et al., 2024), and other technological changes, this assumption allows us to isolate the role of renewable energy policy targets without making additional assumptions.

6 Investment under fixed-price rules

To quantify how fixed-price support and bonus-malus adjustments affect renewable investment, we build an empirical model that closely tracks the theoretical framework developed in Sections 2 and 3. We estimate and calibrate the model for Germany[29] under the historical FiT-type regime over 2015–2020 and use the estimated parameters to conduct counterfactual simulations.[30] We compare the simulated historical-policy baseline with counterfactual remu-

LCOE based on technological cost factors.

[29]Because FiT policies and institutional settings differ substantially across jurisdictions, we restrict the analysis to a single country and explore regional heterogeneity on renewable capacity investment.

[30]We represent the historical baseline as a FiT-type remuneration scheme. Although large solar and wind projects began competing in auctions in 2017, the auctions determined the guaranteed support level (in the form of CfDs) rather than exposing projects fully to wholesale-price risk. The resulting remuneration was economically similar to the earlier administratively determined FiT system, but with projects and support levels selected competitively. Smaller residential and commercial installations remained eligible for

Table 4: ECOE comparison, solar and (onshore) wind

		Baseline 2020			Forecast 2030		
	Technology	LCOE	Adjustment	ECOE	LCOE	Adjustment	ECOE
DE	Solar	44.1	2.45	46.55	36.1	31.7	67.8
	Wind	61.2	5.71	66.91	56.7	13.7	70.4
FR	Solar	63	1.23	64.23	51.5	9	60.5
	Wind	60.5	1.71	62.21	56.3	0.4	56.7
ES	Solar	24.5	-0.52	23.98	20	18.4	38.4
	Wind	25.3	3.05	28.35	23.5	5.6	29.1
CA	Solar	37.4	7.33	44.73	19.2	48.3	67.5
	Wind	65.7	1.03	66.73	45.5	-7	38.5

Notes: LCOE baseline values (2020) from engineering estimates Fraunhofer ISE (2021) in case of Germany (DE), ADEME (2020) in case of France (FR), and NREL (2020) in the case of California. Spanish data (ES) is based on quantity-weighted bids from renewable energy auctions IEA (2022). For 2030, we assume a similar cost trajectory as in Fraunhofer ISE (2021) in all countries Adjustment term = - bonus–malus.

neration schemes: market-price remuneration and an average-market-price policy, considered both with and without a bonus–malus adjustment. Finally, we use the model to simulate an implementable, budget-neutral FiT design in which the regulator announces a common annual FiT component adjusted by lagged state-technology bonus-malus terms. This exercise allows us to quantify by how much an alternative FiT design, that takes into account the observed bonus-malus adjustment from the previous year, could improve on the value per FiT compared to historic policy.

6.1 Empirical model

The empirical model jointly simulates wholesale electricity prices in Germany and state-level investment in wind and solar capacity under alternative policy regimes. This section explains how we adapt our theoretical model for estimation. The formal implementation details are provided in Appendix E.

Wholesale prices are generated in two steps. First, a national German merit-order curve maps hourly residual demand (net of renewable generation) into a raw marginal-cost price. Second, we apply a year-specific post-merit-order price calibration based on the raw merit-order price, residual demand (as defined in (2)), aggregate renewable output, and indicators for residual demand and total renewable output above their respective 90th percentiles (see Appendix E.2). This procedure preserves the structural residual-demand channel, so

administratively determined FiT rates even after 2017.

renewable investment feeds back into wholesale prices, while improving the model's fit to price dispersion, negative-price frequency, and the covariance between renewable output and prices.[31]

Investment is modeled at the state-technology-year level. Let $u = (s, i)$ denote a state–technology pair. We convert the installation cost per MW of project j into a levelized project cost, $c_{j,u,t} = \frac{r_{j,u,t}}{Y_{u,t}}$, where $Y_{u,t}$ is expected discounted lifetime generation per installed MW. Project costs follow a logistic distribution,

$$c_{j,u,t} = \mu_i + \xi_{i,t} + s_i \varepsilon_{j,u,t}, \qquad \varepsilon_{j,u,t} \sim \text{Logistic}(0, 1),$$

where μ_i is the technology-specific baseline midpoint, s_i controls project-cost dispersion, and $\xi_{i,t}$ combines an externally measured LCOE cost trend with a quadratic residual time shifter. Given policy-specific discounted lifetime revenue per MWh $R_{u,t}$, investment is

$$k_{u,t} = \bar{k}_u G_{i,t}(R_{u,t}), \qquad G_{i,t}(x) = \Lambda\left(\frac{x - \mu_i - \xi_{i,t}}{s_i}\right).$$

Thus, investment follows the theoretical zero-profit cutoff: projects with levelized costs below policy-specific lifetime revenue are built.[32]

The feasible annual build potential $\bar{k}_u$ is time-invariant within each state–technology and is calibrated from observed state-level capacity scale. Productive capacity is updated using the finite-vintage accumulation equation in (1), with pre-2015 capacity treated as a depreciating legacy stock. State heterogeneity enters through renewable production profiles, captured prices, existing capacity, and feasible build potential; project-cost distribution parameters are otherwise common across states within a technology.

Because investment changes renewable capacity, residual demand, and prices, the complete 2015–2020 investment path is solved as an investment–price fixed point. Given a candidate investment path, the model constructs renewable capacity, dispatches residual demand against the national merit order hour by hour, generates calibrated wholesale prices, computes each state–technology cell's discounted lifetime revenue index, and updates investment according to the cutoff rule.

We estimate the investment parameters by minimum distance, matching simulated and observed investment, wholesale-price, captured-price, and auction moments. The resulting

[31] The uncalibrated merit-order model performs reasonably well in matching average wholesale prices but understates price dispersion. This matters because price dispersion and its covariance with renewable output determine captured prices and the model-implied bonus–malus.

[32] Note that time variation in $G_{i,t}$ comes from the deterministic shift $\xi_{i,t}$, while μ_i and s_i remain technology-specific and constant over time.

framework combines estimated investment parameters with externally calibrated technological inputs and an auxiliary post-merit-order price mapping. Figure 3 plots the year-to-year investment fit and shows that the model reproduces the broad expansion of solar and the decline of wind investment after 2017, although it smooths some annual variation. Given the ex-post price calibration, prices match closely the in-sample price-distribution moments (see Appendix Table E.5). Appendix Section E provides further details on the model specification, data, estimation procedure, parameter estimates, and robustness checks. We next use the estimated model to conduct the counterfactual exercises.

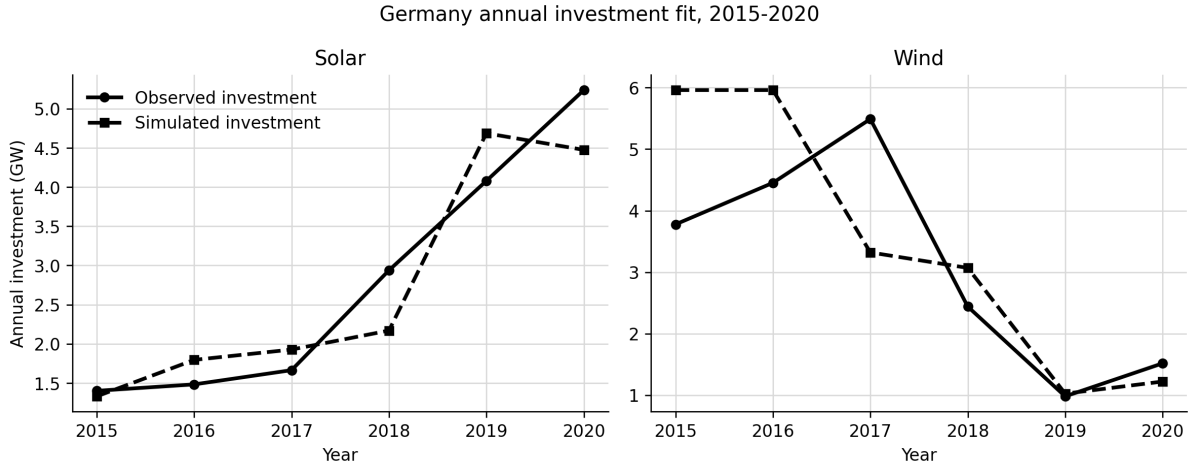


Figure 3: Observed and simulated annual renewable investment in Germany, 2015–2020. Simulated output is based on the estimated model.

6.2 Counterfactual price policies

We first examine how alternative remuneration rules affect total investment. Competitive market remuneration implements efficient investment when investors face the full covariance-adjusted value of generation, captured empirically by the lifetime price $R^M_{u,t}$. Average-price remuneration removes this covariance component, while bonus-malus remuneration attempts to restore it. We quantify the aggregate investment effect by re-solving the investment–price fixed point under four remuneration rules:

1. **Historical FiT (baseline)**. Producers receive the historical German FiT for the 20-year project horizon.

2. **Market only**. Producers receive the lifetime captured market price. This is the empirical analogue of the competitive-market benchmark in the theory.

3. **Average price**. Producers receive the discounted lifetime average wholesale price, p_t^L.[33]

4. **Average price plus bonus-malus**. Producers receive $\bar{p}_t^L + BM_{u,t}$, where $BM_{u,t}$ is the technology-specific model-implied *average adjustment*, computed from the market-only simulation.[34]

Table 5 reports cumulative investment over 2015–2020. In the model, the historical FiT regime generates approximately 39 GW of investment, whereas removing policy support under market-only reduces investment to 11.9 GW. This result indicates that historical support played a quantitatively important role in explaining observed investment patterns. Remunerating renewables at the discounted lifetime average wholesale price increases investment to 14.7 GW because it removes the negative covariance penalty faced by wind and solar under market-only remuneration.[35] Thus, in the German setting fixed-price remuneration generates over-investment relative to the market-only benchmark, particularly for solar.

Adding the model-implied average bonus–malus in Column (4) brings total investment close to the market-only level. The bonus-malus adjustments implied by the model are also similar to those reported in Table 1, which are calculated using observed market data only. The average model-implied lifetime adjustment is -3.72 €/MWh for solar and -5.77 €/MWh for wind. This consistency provides reassurance that the calibrated model captures economically meaningful variation in the market value of renewable generation.

6.3 Budget-neutral adjusted FiT design

The second counterfactual addresses a different question. We consider an implementable fixed-tariff policy in which the regulator announces an annual FiT component that is adjusted by lagged state–technology-specific bonus–malus terms. We implement two budget-neutral adjusted-FiT designs:

1. **Common adjusted FiT.** Producers receive a common annual base tariff plus a lagged bonus–malus adjustment in each state and for each technology (wind or solar). The

[33]Rather than using the sample average price, our preferred empirical specification uses the discounted lifetime average $\bar{p}_t^L = \frac{\sum_{\ell=0}^{T_i-1} \beta^\ell \mathbb{E}_h[p_{t+\ell,h}]}{\sum_{\ell=0}^{T_i-1} \beta^\ell}$., which is forward-looking and consistent with the lifetime valuation used in the market-only benchmark. We perform robustness using the simple average wholesale price over 2015–2020.

[34]By construction, this will lead to an outcome closer to the market-only solution. Alternatively, applying the model-implied bonus–malus adjustment at the state-technology-year level fully restores the market-only allocation in the model.

[35]Using the average wholesale price over 2015–2020 rather than the lifetime average wholesale price yields a similar level of total investment of 14.1 GW.

Table 5: Counterfactual investment by technology in MW, 2015–2020

	Historical FiT (1)	Market only (2)	Avg. price (3)	Avg. price + BM (4)
Solar	16,219	1,685	3,130	1,822
	[14,966, 18,203]	[1,421, 1,841]	[2,787, 3,377]	[1,565, 1,982]
Wind	22,855	10,172	11,549	10,164
	[21,751, 24,013]	[9,070, 11,076]	[10,670, 12,135]	[9,053, 11,075]
Total	39,075	11,857	14,679	11,986
	[37,344, 41,194]	[10,611, 12,720]	[13,582, 15,336]	[10,742, 12,847]

Notes: Total simulated renewable investment in Germany during 2015–2020 under alternative remuneration rules, together with 95% confidence intervals obtained from 100 state-cluster bootstrap resamples, capturing finite-sample uncertainty from regional variation. All figures are expressed in megawatts (MW). Column (4) applies the model-implied national average bonus–malus (BM) by technology.

common base component applies to both solar and wind. It is calibrated separately in each year so that the annual support for the investment cohort installed in that year equals the corresponding obligation under the historical FiT policy.[36] This design permits support to shift both across states and between technologies.

2. **Technology-specific adjusted FiT.** Producers receive a technology-specific annual base tariff plus the lagged state–technology-specific bonus–malus adjustment. The base tariff is calibrated separately for solar and wind. This design preserves the historical division of the support envelope between solar and wind.

Lagging the bonus–malus term makes both designs implementable using information available before the investment decision. These counterfactuals ask whether differentiating fixed tariffs by a covariance-based correction could have induced more valuable renewable investment while holding total spending fixed.

Table 6 shows the counterfactual results and highlights that the common adjusted-FiT increases investment and annual market value relative to the historical FiT baseline, while the technology-specific adjusted-FiT is nearly identical to the historical baseline. In all cases, we keep total spending for the 2015-2020 cohorts at €5.06 billion.

For the common adjusted FiT, we find total investment of 43.48 GW, compared with 39.07 GW in the baseline. Total annual market value over the 2015-2020 period increases from €1.96 billion to €2.02 billion, corresponding to an increase of approximately €58 million, or

[36]Payments to earlier vintages and the lifetime present value of support are excluded.

3%.[37] Under the technology-specific adjusted FiT, by contrast, market value increases by only €0.60 million. The difference between the two scenarios can be explained by the fact that the common adjustment shifts investment incentives from wind to solar (see Appendix Figure E.1). Finally, the common adjusted FiT also changes the spatial distribution of renewable investment across states. The alternative FiT rule induces additional investment primarily in Southern Germany, while reducing overall investment in some Northern states. This pattern is also reflected in the changes in total market value across states (see Appendix Figure E.2).

Table 6: Historical FiT versus budget-neutral adjusted FiT, 2015–2020

	Investment GW	Output TWh	Market value €bn	FiT cost €bn	Market value/FiT cost
Historical FiT	39.07	71.78	1.959	5.06	0.388
Common adjusted FiT	43.48	73.59	2.017	5.06	0.399
Technology-specific adjusted FiT	39.02	71.77	1.960	5.06	0.388

Notes: Investment is cumulative across the 2015–2020 cohorts. Output refers to expected production of the capacity installed in that year during one representative operating year. The values displayed are the sum of these one-year production measures across the six installation cohorts. Market value evaluates each cohort's annual-equivalent output using the corresponding simulated hourly prices.

6.4 Discussion and policy implications

The empirical model implements the theory's investment cutoff with state-level renewable heterogeneity and endogenous national prices. It abstracts from firm conduct and strategic bidding and should therefore not be interpreted as structural estimates of firm entry. Nevertheless, as shown above, the model is able to replicate aggregate investment in solar and wind energy in Germany, and the implied bonus-malus adjustments are economically meaningful. We therefore consider the counterfactuals informative for policy evaluation.

The results yield three policy lessons. First, revenue support strongly affected deployment: the historical FiT regime generates substantially more investment than market-only remuneration. Second, fixed average-price support is not equivalent to market remuneration. It removes price risk but also suppresses the covariance between renewable output and scarcity prices. Average-price remuneration therefore raises investment relative to the market benchmark, whereas adding the estimated malus restores an allocation close to the efficient

[37] The estimate ranges from approximately €48 million to €58 million across the reported modeling assumptions and from €56 million to €58 million across near-optimal multistart solutions. These ranges measure specification and numerical sensitivity rather than sampling uncertainty.

outcome. Third, policy design can increase system value without increasing expenditure. The budget-neutral adjusted FiT reallocates incentives across states and technologies, increasing investment, output, and market value, primarily through greater solar investment in higher-value southern states.

Our findings rely on several simplifying assumptions that should be considered when interpreting the model's policy predictions. First, all states face a single national wholesale electricity price. This is consistent with Germany's national day-ahead wholesale market, but abstracts from congestion, redispatch, local grid constraints, and balancing markets. Second, state-level renewable output profiles are based on representative projects within each state and use simulated capacity factors under standard assumptions about panel orientation, turbine height, and other related technical characteristics. These profiles generate the heterogeneity in $\omega_{u,t,h}$ that is central to the theory, but cannot fully capture the project-specific heterogeneity observed in empirical data. Finally, as highlighted in the model section, we parameterize the unobserved project-cost distribution as logistic and perform an ex-post calibration of wholesale prices to match the overall price distribution. These assumptions are not implied by the theory, but they make the model tractable for estimation and improve its fit to the data.

7 Conclusion

Decarbonizing electricity requires substantial investment in wind and solar generation, whose output depends on weather conditions. Supporting renewable production without accounting for when and where it occurs can therefore induce the wrong portfolio of technologies and locations. Fixed-price contracts stabilize revenues and can mobilize investment at scale, but they also suppress information about the state-contingent value of generation. The relevant policy question is not only how much renewable capacity to support, but which capacity to support.

This paper shows that fixed-price remuneration can preserve efficient investment incentives if it includes a technology-specific bonus or malus. The required adjustment is the covariance between renewable output and wholesale prices, normalized by expected generation. It rewards technologies and locations that produce during high-value hours and penalizes those that produce when electricity is abundant. The adjustment can be incorporated into FiTs, PPAs, CfDs, or a common procurement auction. It transforms the LCOE into an ECOE that reflects both production cost and system value.

Estimates for California, France, Germany, and Spain show that the adjustment is generally negative over the main sample: wind and solar tend to produce in relatively low-price

hours and should therefore receive a malus if the common fixed price is set equal to the expected wholesale price. Its magnitude nevertheless varies substantially across markets, technologies, locations, and technical designs. The fundamentals-based decomposition explains this variation through same-technology cannibalization, complementarities across renewables, alignment with demand, and the slope of the dispatchable supply curve. It also shows why declining generation costs need not translate one-for-one into declining economic costs as renewable penetration rises.

The German investment model confirms that these mechanisms matter for policy. Historical FiT-type support produces substantially more investment than market-only remuneration. Paying the discounted lifetime-average wholesale price also raises investment relative to the market benchmark because it removes the negative covariance penalty, while adding the model-implied bonus-malus restores an allocation close to the market-only outcome. In an implementable policy exercise, adjusting a common annual FiT component by lagged state-technology bonus-malus terms increases the market value of renewable generation by approximately 3 percent, or €58 million, without raising the policy budget. The smaller gain when solar and wind budgets remain separate indicates that flexibility across technologies can be as important as improved siting within a technology.

These results do not imply that renewable support should be reduced whenever the estimated adjustment is negative. The overall level of support may reflect unpriced emissions, innovation spillovers, financing constraints, or other policy objectives. The bonus-malus does not determine the overall level of support; instead, it directs incentives within a given support envelope toward technologies and locations with greater system value. In practice, regulators could define a limited number of transparent technology and location classes and update their adjustments periodically using pre-announced, lagged information. This would preserve revenue stability while directing support toward projects with greater system value.

The results remain subject to important limitations. The analysis abstracts from risk aversion, energy storage, flexible demand, network congestion, market power, and strategic bidding. The future scenarios also hold key technological relationships and covariance structures fixed. These margins will change wholesale prices and the bonus-malus as technology and the climate evolve. The broader lesson nevertheless extends beyond electricity: when policy supports output whose social value depends on aggregate conditions, separating a common payment from a state-contingent adjustment can mobilize investment without ignoring differences in the value of what that investment produces.

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Online Appendix

A Solving the minimization program

Denoting μ_{it} the multiplier associated with the constraint $\tilde{r}_{it} \geq \underline{r}_{it}$ for every i and t, the Lagrangian of the minimization program writes:

$$\mathcal{L} = -\sum_{t=0}^{+\infty} \rho^t \left\{ E[C_t(Q_t)] + \sum_i \left[\bar{k}_{it} \int_{\underline{r}_{it}}^{\tilde{r}_{it}} r_{it} dG_{it}(r_{it}) - \mu_{it}(\tilde{r}_{it} - \underline{r}_{it}) \right] \right\}$$

To simplify notation we assume that the expectation operator is conditional on $Q_t > 0$ (or equivalently to $C_t(Q_t) > 0$), and thus we remove the condition $Q_t > 0$ from the equations. Given that $Q_t = D_t - \sum_i \omega_i K_{it}$ for every $Q_t > 0$, $K_{it} = \sum_{j=0}^{\min\{t,T_i\}} \lambda_i^j k_{it-j}$ and $k_{it} = \bar{k}_i G(\tilde{r}_{it})$, we have $Q_t = D_t - \sum_i \omega_i \sum_{j=0}^{\min\{t,T_i\}} \lambda_i^j \bar{k}_i G(\tilde{r}_{it-j})$ for every t. Hence differentiating the Lagrangian with respect to $\tilde{r}_{it}$ yields:

$$\frac{\partial \mathcal{L}}{\partial \tilde{r}_{it}} = -\rho^t \left\{ -\sum_{l=0}^{T_i} \rho^l E[C'_{t+l}(Q_{t+l}) \lambda_i^l \omega_i \bar{k}_{it} g_{it}(\tilde{r}_{it})] + \bar{k}_{it} \tilde{r}_{it} g_{it}(\tilde{r}_{it}) - \mu_{it} \right\}. \tag{14}$$

The solution to the minimization program is characterized by the conditions $\frac{\partial \mathcal{L}}{\partial \tilde{r}_{it}} = 0$ and $\mu_{it}(\tilde{r}_{it} - \underline{r}_{it}) = 0$ for every i and t. Given (14), the condition $\frac{\partial \mathcal{L}}{\partial \tilde{r}_{it}} = 0$ yields

$$\tilde{r}^*_{it} = E\left[\omega_i \sum_{l=0}^{T_i} \beta_i^l C'_{t+l}(Q^*_{t+l}) \right] + \frac{\mu_{it}}{\bar{k}_{it} g_{it}(\tilde{r}^*_{it})}, \tag{15}$$

with $\beta_i \equiv \rho \lambda_i$. First by $\mu_{it}(\tilde{r}_{it} - \underline{r}_{it}) = 0$, $\mu_{it} > 0$ implies $\tilde{r}^*_{it} = \underline{r}_{it}$ and, consequently, a corner solution $k^*_{it} = 0$ (no investment in renewables). Combined with (15), it implies

$$\underline{r}_{it} > E\left[\omega_i \sum_{l=0}^{T_i} \beta_i^l C'_{t+l}(Q^*_{t+l}) \right],$$

that is the cost of the cheapest generation capacity with technology i at time t (left-hand side) is higher than the expected discounted product of technology i's capacity factor and the marginal social cost of production with the dispatchable energy mix (right-hand side).

Second, for an interior solution $k^*_{it} = \bar{k}_{it} G_{it}(\tilde{r}^*_{it}) > 0$, since $\tilde{r}^*_{it} > \underline{r}_{it}$, we must have $\mu_{it} = 0$ and, therefore, (15) becomes (3).

B Proof of Proposition 3

Let us denote $b(r_i)$ the bidding strategy of investors in technology i with cost r_i for an auction at a given time t (we omit the time index t to save notation). We rule out multi-period bidding strategies to avoid the complexity of dealing with repeated games. Similarly to the investment decision with fixed or market prices, the bidding strategy is set for the current period. Consider the following bidding strategy :

$$b_i^e(r_i) = \frac{r_i}{\mathcal{B}_i E[\omega_i]} - cov\left(\omega_i, \sum_{l=0}^{T_i} \frac{\beta_i^l p_{t+l}}{\mathcal{B}_i}\right) \frac{1}{E[\omega_i]} \tag{16}$$

for $i = 1, ..., n$.

We first derive the equilibrium outcome when investors bid $b_i^e(r_i)$, and show that investment in renewable capacities satisfy the optimality conditions. With a winning bid $\widehat{b}$, all bidders with costs r_i such that $b_i^e(r_i) \leq \widehat{b}$ are selected for $i = 1, ..., n$. The cost of the last bidder selected with technology i at time t is denoted $\tilde{r}_i$. It satisfies the following condition: $b_i^e(\tilde{r}_i) = \widehat{b}$ for $i = 1, ..., n$. Combined with (16), it yields:

$$\frac{\tilde{r}_i}{\mathcal{B}_i E[\omega_i]} - cov\left(\omega_i, \sum_{l=0}^{T_i} \frac{\beta_i^l p_{t+l}}{\mathcal{B}_i}\right) \frac{1}{E[\omega_i]} = \frac{\tilde{r}_j}{\mathcal{B}_i E[\omega_j]} - cov\left(\omega_j, \sum_{l=0}^{T_j} \frac{\beta_j^l p_{t+l}}{\mathcal{B}_j}\right) \frac{1}{E[\omega_j]} = \hat{b},$$

which, combined with (6), leads to the optimality conditions (5). With a total capacity $\sum_i k_{it}^*$ auctioned off, the winning bid is

$$\widehat{b} = \frac{\tilde{r}_i^*}{\mathcal{B}_i E[\omega_i]} - cov\left(\omega_i, \sum_{l=0}^{T_i} \frac{\beta_i^l p_{t+l}}{\mathcal{B}_i}\right) \frac{1}{E[\omega_i]} \tag{17}$$

for technology $i = 1, ..., n$. Hence, the investment portfolio is the first-best vector $\boldsymbol{k}^*$.

Next we show that $b_i^e(r_i)$ defined in (16) are equilibrium strategies because investors have no incentive to deviate from it in equilibrium. The expected profit with a given strategy $b_i(r_i)$ for the investor with technology i, cost r_i and investment k_i is

$$E[\pi_{it}(r_i)] = \begin{cases} \left(\mathcal{B}_i E[\omega_i] p_{it}^s - r_i\right) k_i & \text{if} \quad b_i(r_i) \leq \widehat{b}, \\ 0 & \text{if} \quad b_i(r_i) > \widehat{b}. \end{cases} \tag{18}$$

Substituting the strike price p_{it}^s defined in Proposition 3, the above expected profit with a given strategy $b_i(r_i)$ becomes

$$E[\pi_{it}(r_i)] = \begin{cases} \left[\mathcal{B}_i \left(E[\omega_i]\widehat{b} + cov\left(\omega_i, \sum_{l=0}^{T_i} \frac{\beta_i^l p_{t+l}}{\mathcal{B}_i}\right) \frac{1}{E[\omega_i]}\right) - r_i\right] k_i & \text{if} \quad b_i(r_i) \leq \widehat{b}, \\ 0 & \text{if} \quad b_i(r_i) > \widehat{b}. \end{cases} \tag{19}$$

Plugging the winning bid defined by (17) in (19) yields

$$E[\pi_i(r_i)] = \begin{cases} (\tilde{r}^*_{it} - r_i)\, k_i & \text{if} \quad b_i(r_i) \leq \widehat{b}, \\ 0 & \text{if} \quad b_i(r_i) > \widehat{b}. \end{cases} \tag{20}$$

Consider an investor in technology i with cost r_i. First, suppose that $b^e_i(r_i) \leq \widehat{b}$ so that the investment is implemented with the investor bidding $b^e_i(r_i)$. Suppose that the investor deviates by bidding lower $b_i(r_i) < b^e_i(r_i)$. The project is still implemented. The investor's payoff does not change unless it manages to lower the winning bid, in which case his or her profit is lower. The investor is thus worse-off. Suppose now that the investor deviates by bidding higher $b_i(r_i) > b^e_i(r_i)$. If $b^e_i(r_i) < \widehat{b}$, the investor's payoff changes if $b_i(r_i) > \widehat{b}$, in which case the investment is not implemented and the investor's profit is nil. If $b^e_i(r_i) = \widehat{b}$, bidding higher does not change the winning bid $\widehat{b}$ because, with a continuum of bidders with different technologies, there exists at least another investor who bids $\widehat{b}$: either an investor with the same cost r_i, or with a different but very close cost $r_i + \epsilon$ with $\epsilon \approx 0$, or with a different technology j but with r_j such that $b^e_j(r_j) = b^e_i(r_i)$. Hence the investor is not selected, her or his payoff is nil. Hence the investor is never better-off by bidding above $b^e_i(r_i)$.

Second, suppose that $b^e_i(r_i) > \widehat{b}$ so that the investment is not implemented with the investor bidding $b^e_i(r_i)$. If the investor deviates by bidding lower $b_i(r_i) < b^e_i(r_i)$, his payoff changes only if $b_i(r_i) \leq \widehat{b}$, in which case, the investor is selected. However, using the definition of $b^e_i(r_i)$ in (16) and $\hat{b}$ in (17), one can show that $b^e_i(r_i) > \widehat{b}$ implies $r_i > r^*_i$ and, therefore, the investor's expected profit defined in (20) is negative. Hence the investor is worse-off bidding lower than $b^e_i(r_i)$. If the investor deviates by bidding higher $b_i(r_i) > b^e_i(r_i)$, she or he is not selected and thus the investor's payoff is unchanged, equal to 0.

C Decomposition of the bonus-malus in the energy mix

To save notation we omit the "t" superscript. A Taylor approximation of the social cost of electricity generation yields $C(Q) \approx C(Q^*_0) + C'(Q^*_0)(Q - Q^*_0) + \frac{1}{2}C''(Q^*_0)(Q - Q^*_0)^2$. Differentiating this approximation with respect to Q yields $C'(Q) \approx C'(Q^*_0) + C''(Q^*_0)(Q - Q^*_0)$. Therefore $cov(\omega_i, C'(Q))$ is approximated by

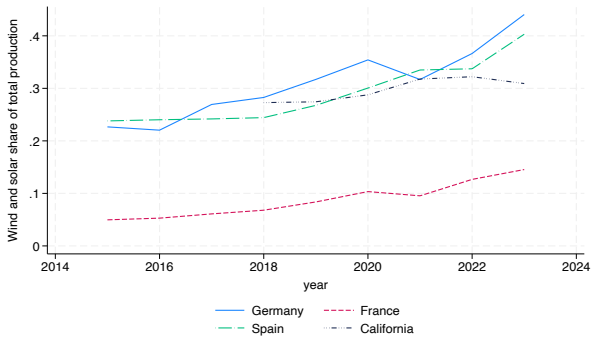
$$\begin{aligned} cov(\omega_i, C'(Q)) &\approx cov(\omega_i, C''(Q^*_0)Q) \\ &= C''(Q^*_0) cov(\omega_i, Q) \\ &= C''(Q^*_0) cov(\omega_i, D - \textstyle\sum_j \omega_j K_j) \\ &= C''(Q^*_0) \left\{ cov(\omega_i, D) - \textstyle\sum_{j \neq i} cov(\omega_i, \omega_j) K_j - V[\omega_i] K_i \right\} \end{aligned}$$

where the equality in the second line is due to the fact that $C''(Q^*_0)$ is not random, the third line is derived by substituting Q as defined in (2), and the last line uses the definition of the variance and of the covariance implying $V[\omega_i] = cov(\omega_i, \omega_i)$. Substituting $cov(\omega_i, C'(Q))$ in (4) by the above approximation yields (13).

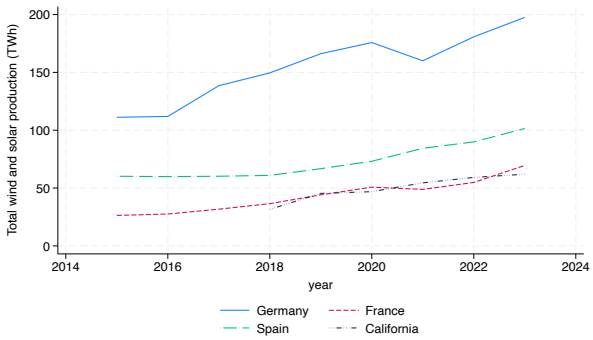
D Data Appendix

D.1 Background on energy markets under consideration

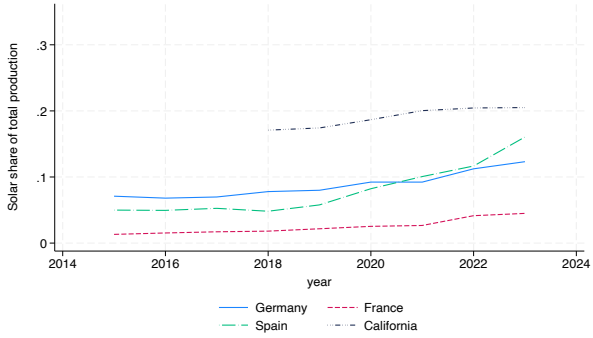
Figure D.1: Evolution of renewables (RES) in total energy production



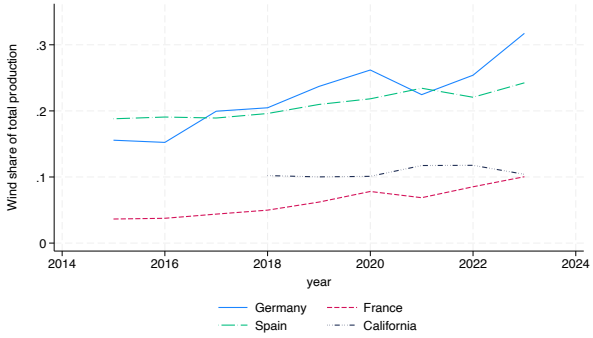
(a) Share of RES (wind and solar) in total production



(b) Total RES production in terrawatt-hours (TWh)



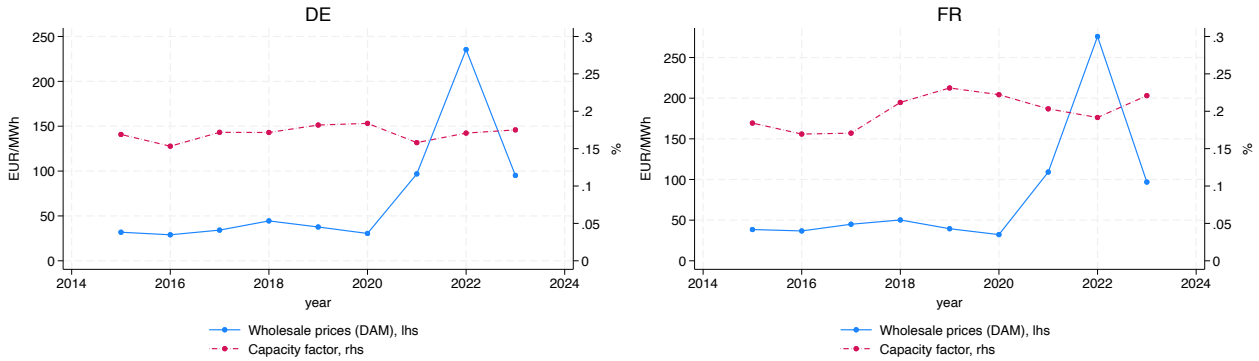
(c) Share of solar in total production



(d) Share of wind in total production

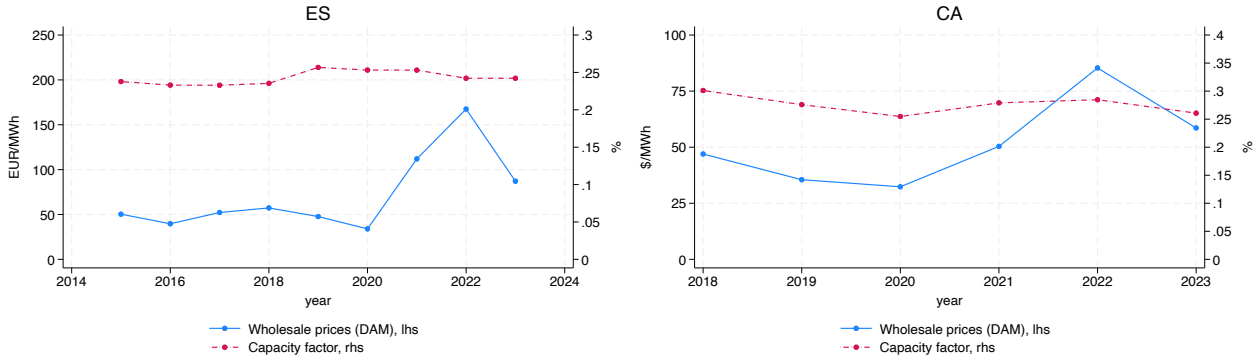
Note: Share of renewable production in total energy production for each country. Imports and exports are not considered for the construction of the variables.

Figure D.2: Day-ahead market (DAM) prices and average capacity factor for solar energy and wind energy



(a) Germany

(b) France

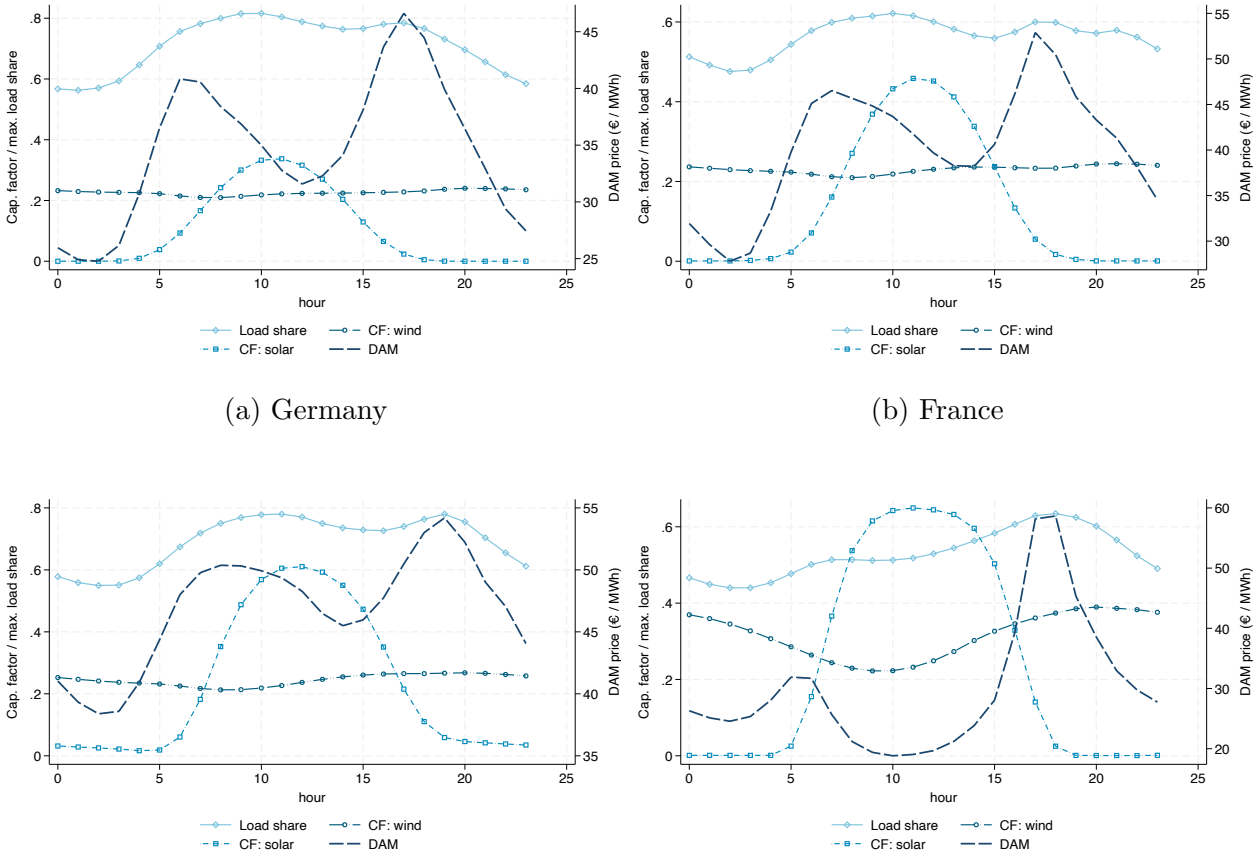


(c) Spain

(d) California

Note: Annual average DAM prices and capacity factors for renewables (wind and solar combined). Note that for the main analysis we convert US-$ to € using the average annual exchange rate over the sample period.

Figure D.3: Average hourly load, capacity factors, and DAM prices



(a) Germany

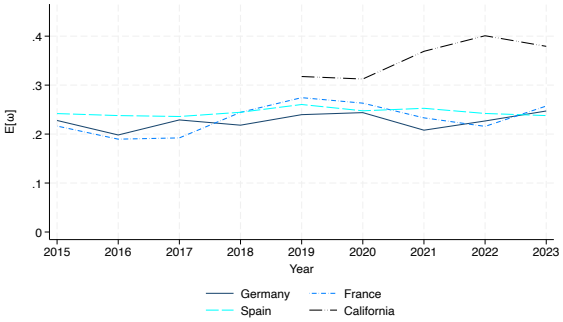
(b) France

(c) Spain

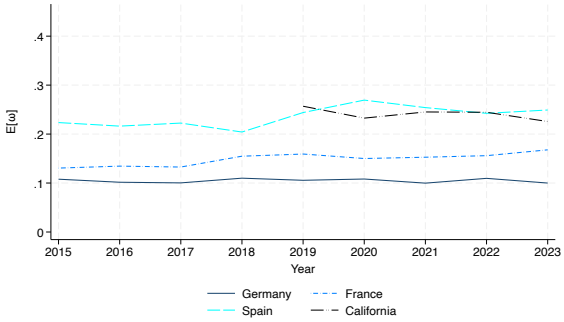
(d) California

Note: Hourly average load share (of maximum observe load) and capacity factors for wind and solar on left axis, and DAM prices (in €/MWh, on right axis) based on main estimation samples. Time expressed in Coordinated Universal Time (UTC) for European countries (one hour difference to Central European time) and Pacific Standard Time.

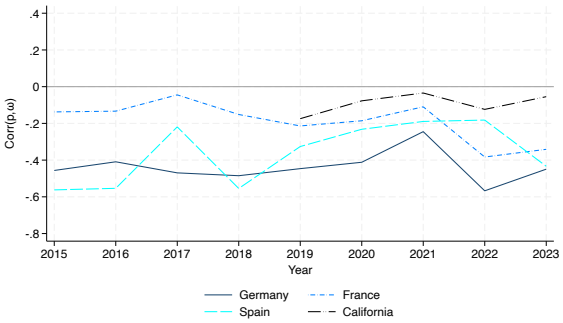
Figure D.4: Average capacity factors and correlation of market price and capacity factor over time



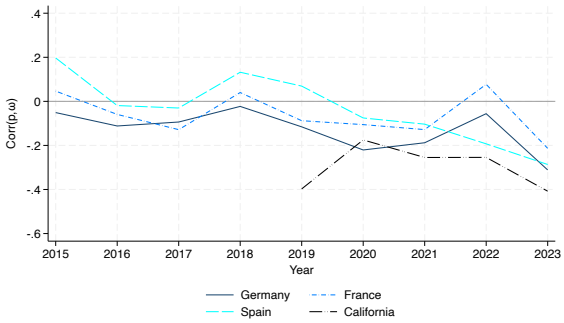
(a) $E[\omega_w]$, wind



(b) $E[\omega_s]$, solar



(c) $Corr(p, \omega_w)$, wind



(d) $Corr(p, \omega_s)$, solar

Notes: The figure shows the evolution of the annual capacity factors and the correlation $corr(p, \omega_i)$ $i \in \{s, w\}$ for the four markets separately. Calculation based on observed hourly data.

D.2 Differentiating the bonus-malus by location and technology

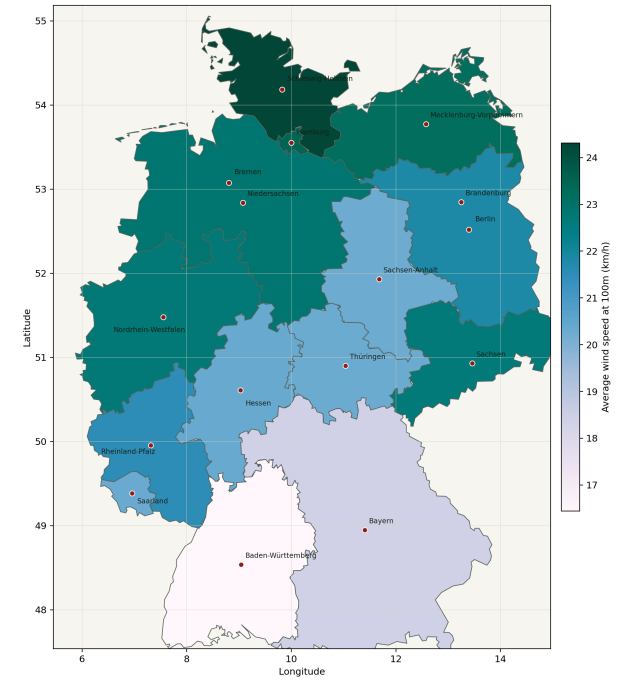
Capacity Factor Simulations. Renewable production based on simulated output from *Renewables Ninja*. *Renewables Ninja* simulates hourly production data for specific locations based on observed weather data (Pfenninger et al., 2016; Staffell et al., 2016). Source: `https://www.renewables.ninja`.

Table D.1: Covariance, capacity factor, and implied bonus-malus in €/MWh by German state.

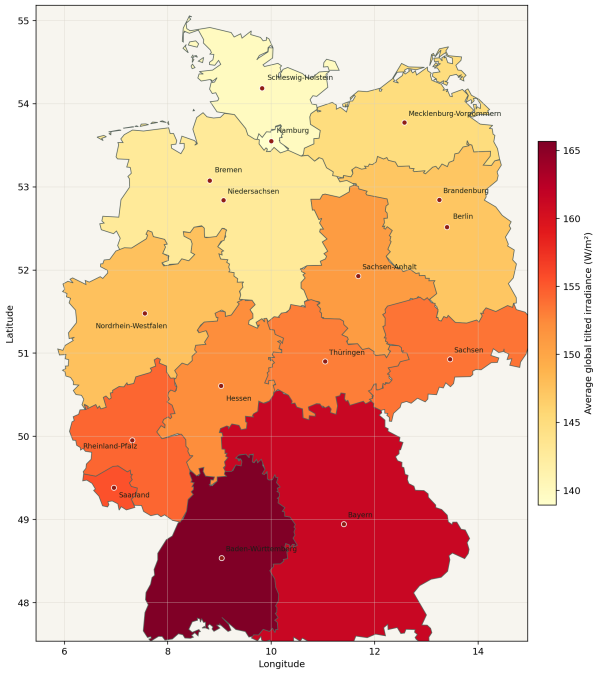
	Solar			Wind (onshore)		
State	Cov	Cf	Bonus-malus	Cov	Cf	Bonus-malus
Baden-Württemberg	-0.226	0.145	-1.555	-0.819	0.184	-4.440
Bavaria	-0.240	0.142	-1.688	-0.878	0.193	-4.546
Berlin	-0.272	0.130	-2.100	-1.163	0.253	-4.604
Brandenburg	-0.260	0.128	-2.029	-1.207	0.261	-4.633
Bremen	-0.266	0.125	-2.128	-1.486	0.285	-5.217
Hamburg	-0.253	0.125	-2.025	-1.434	0.290	-4.940
Hesse	-0.264	0.135	-1.955	-1.072	0.216	-4.956
Mecklenburg-Vorpommern	-0.252	0.127	-1.991	-1.339	0.319	-4.201
Lower Saxony	-0.271	0.126	-2.153	-1.463	0.276	-5.294
North Rhine-Westphalia	-0.254	0.131	-1.941	-1.258	0.267	-4.703
Rhineland-Palatinate	-0.265	0.137	-1.934	-1.060	0.224	-4.731
Saarland	-0.253	0.135	-1.867	-0.965	0.226	-4.274
Saxony	-0.238	0.137	-1.738	-1.103	0.247	-4.465
Saxony-Anhalt	-0.257	0.135	-1.908	-1.255	0.244	-5.145
Schleswig-Holstein	-0.261	0.124	-2.109	-1.464	0.335	-4.375
Thuringia	-0.257	0.137	-1.877	-1.154	0.219	-5.267

Notes: Covariance, $Cov(\omega_i, p_{t+l})$, expected capacity factors (Cf), $E[\omega_i]$, and implied bonus-malus from simulated renewable production data for solar and onshore wind in Germany. One observation per state (see also Panels (a) and (b) of Figure D.5)

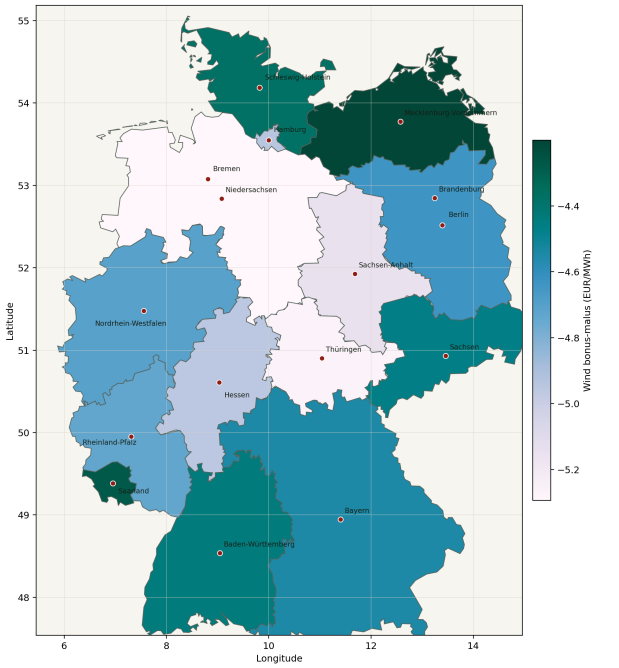
Figure D.5: Average resource availability based on simulated data and implied bonus-malus



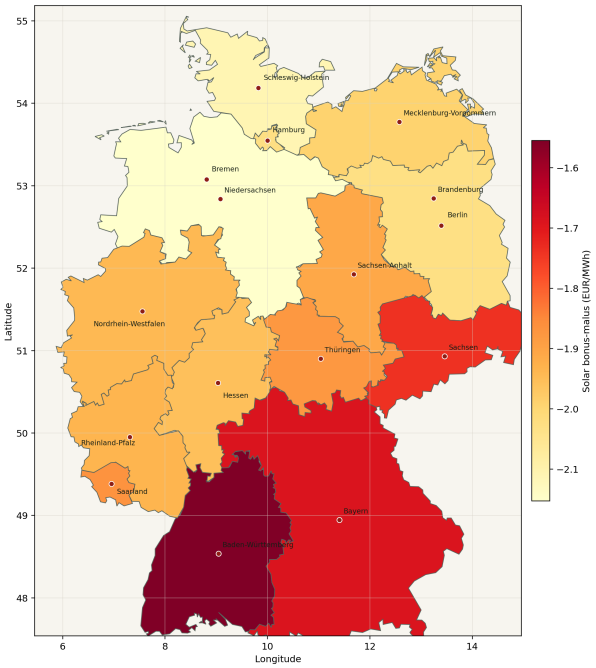
(a) Wind availability, per state



(b) Solar radiation, per state



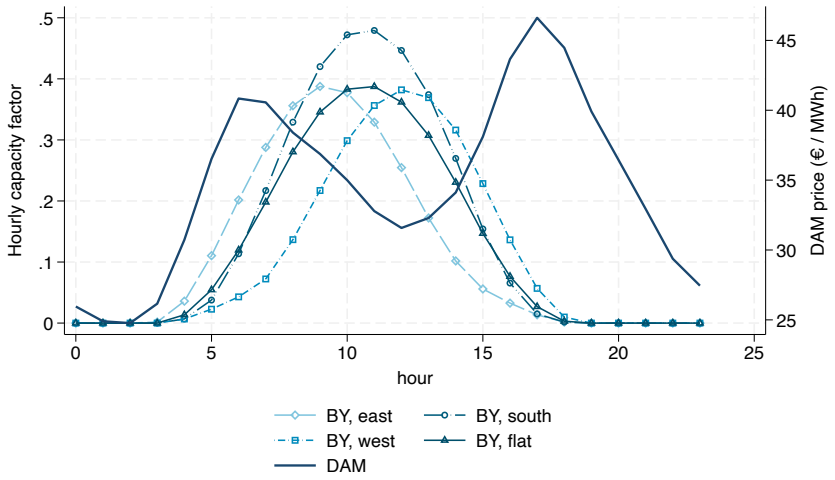
(c) Wind, Bonus-malus



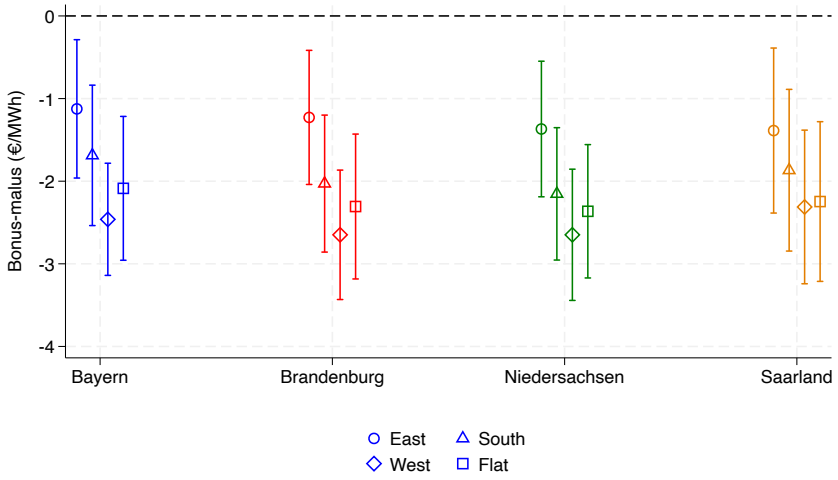
(d) Solar, Bonus-malus

Notes: Average resource availability for wind and solar in Panels (a) and (b), respectively, over the period 2015-2020 together with implied bonus-malus payments in Panels (c) and (d). Darker areas represent higher resource availability and lower malus. Renewable output based on representative state locations (state centroids, as indicated by the red dots). Source: *Renewables Ninja*.

Figure D.6: Heterogeneity in solar production, by technology (panel orientation)



(a) Simulated average capacity factors for Bavaria



(b) Bonus-malus for four locations and different panel orientation

Notes: Panel (a) shows the average simulated hourly capacity factors for a 1 MW solar plant in Bavaria, Germany, with different panel orientation (west-facing, east-facing, south-facing, and flat) together with average DAM prices over the sample period 2015-2020. Panel (b) shows for four representative locations the implied bonus-malus with different panel orientation, mean and 95% confidence intervals. Time expressed in Coordinated Universal Time (one hour difference to Central European time).

D.3 Additional data for scenario analysis

Table D.2: Bonus-malus estimates and merit-order slopes

	Wind		Solar		Slopes		
Country	Table 1 (1)	Decomp. (2)	Table 1 (3)	Decomp. (4)	Bid data (5)	Wind (6)	Solar (7)
DE	-5.19	–	-2.45	–	–	0.001	0.001
FR	-1.71	–	-1.23	–	–	-0.003	0.001
ES	-3.05	-5.41	0.52	1.85	0.0033	0.002	0.001
CA	-1.03	-0.25	-7.33	-6.80	0.002	0.008	0.002

Notes: The table reports bonus-malus estimates for wind and solar from Table 1 and the decomposition analysis in Section 5, expressed in €/MWh. Slopes refer to the merit-order cost curve estimated from bid data (Column 5) and to the implied slopes that equalize bonus-malus payments across the two approaches (Columns 6 and 7), computed separately for wind and solar. Because the bonus-malus estimates for wind in France have opposite signs across the two approaches, the simulation exercise in Figure 2 uses the solar slope parameter throughout.

Table D.3: Renewable energy targets for wind and solar

Country	**Technology**	**2025**	**2030 targets**	**Implied annual growth rate (%)**	**Source**
Germany	Solar	∼100 GW	∼215 GW	17.68	EEG, WindSeeG, NECP
	Wind	∼75 GW	∼145 GW	10.82	
France	Solar	∼30 GW	∼54–60 GW	21.72	PPE (Programmation pluriannuelle de l'énergie)
	Wind	∼25 GW	∼35 GW	10.37	
Spain	Solar	∼30 GW	∼76 GW	26.96	PNIEC (NECP)
	Wind	∼30–35 GW	∼62 GW	10.36	
California	Solar	∼45–50 GW	60% RE share	17.24	SB100, CPUC / CEC
	Wind	∼6–7 GW		8.08	

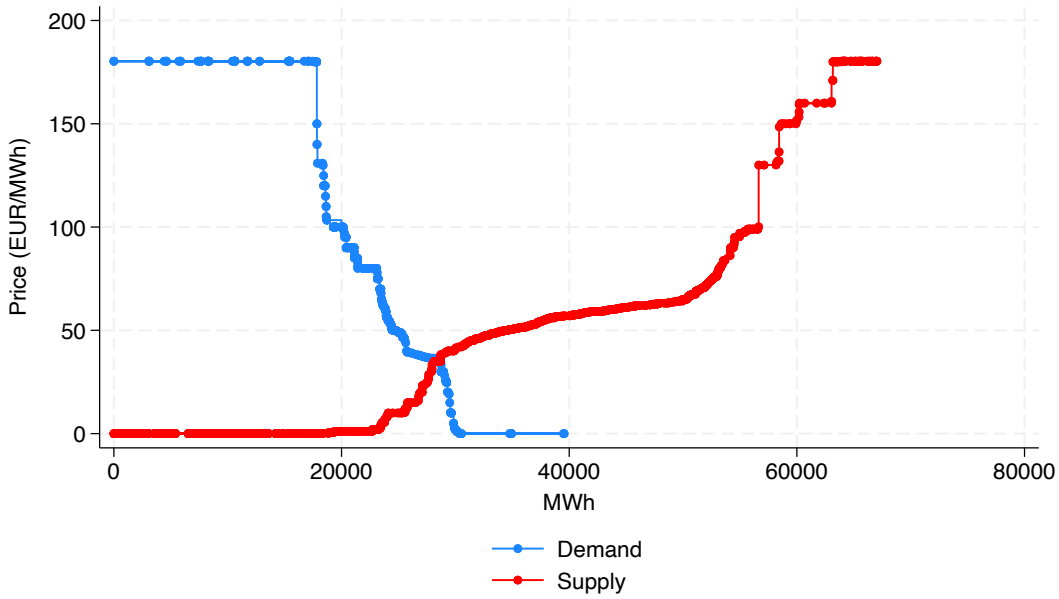
Notes: Targets are based on official government policy documents from, or close to, 2020. Implied annual growth rates calculated over the period 2020-2030. European countries report capacity targets (GW), while California defines targets in terms of renewable electricity shares rather than installed capacity. Sources: DE (Clean Energy Wire, last accessed: 27.04.2026), FR (Enerdata, last accessed: 27.04.2026) ES (Enerdata, last accessed: 27.04.2026), and CA CPUC, last accessed: 27.04.2026).

D.4 Bidding data from Spain and California

In order to decompose the bonus-malus in Section 5, we need an estimate of $C''(Q_0^*)$, which represents the slope of the merit-order cost curve (marginal cost) at the expected electricity production Q_0^*. We rely on public bid data from the day-ahead market (DAM) in Spain and California to obtain an estimate of this parameter.

Data. In the case of Spain, we obtain individual bid data for the years 2015 to 2020 from the Iberian market operator OMIE.[38] The data include all individual demand and supply bids for each hour of the sample. OMIE reports separately the *raw* supply and demand bids and the *matched* supply and demand bids. The matching is done after the bids have been submitted, taking into account network constraints, ramping constraints, etc. Since we do not know how the matching process would have affected unallocated bids (OMIE does not disclose the exact matching procedure), we calculate the market clearing prices based on the raw bids by equating cumulative supply and demand for each hour in the sample. Figure D.7 shows an example for a given hour in the sample.

Figure D.7: OMIE bidding data (Spain)



Notes: Example supply and demand bids in the Iberian Market for Thursday, 18 April 2019, 10am.

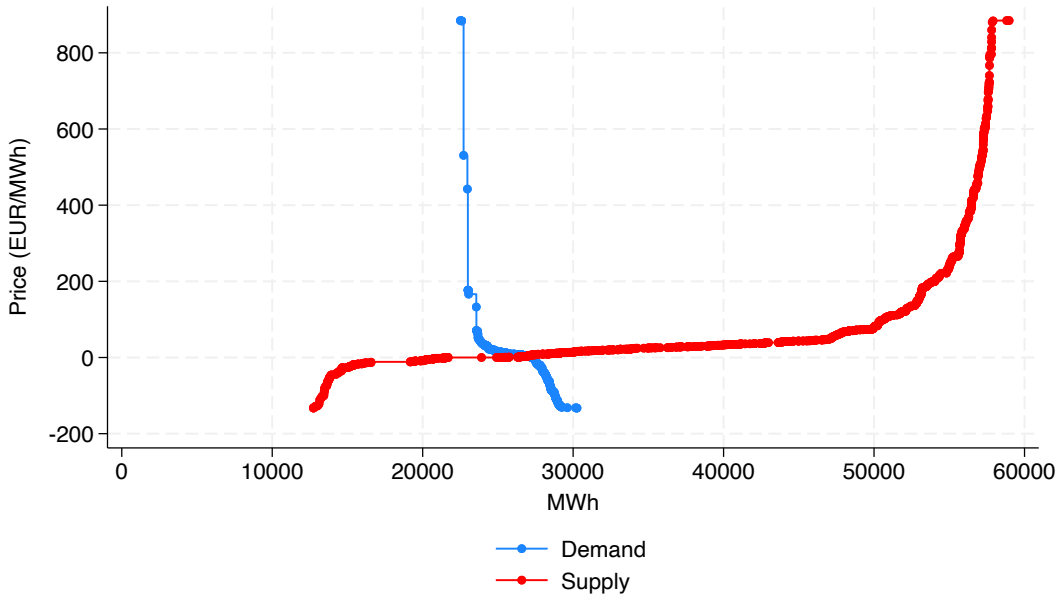
Since there are a few hours in which the Portuguese and Spanish markets are separated, for our calculation we focus only on hours in which the market was integrated. Note that

[38] Data for the last 5 years approximately can be downloaded from OMIE (`https://www.omie.es/en/file-access-list?parents=/`. Data for previous years can be requested from the website administrator. Main data files: curva_pbc (see also: Day Ahead Market / Curves / Aggregate Demand and Supply Curves).

the market separation only affects 5% of the total number of bids. For the period 2015-2020, there are a total of 93 million (m) bids in the Iberian market, of which about 70m are supply bids, that we use in the estimation.

For California (CAISO), we focus on 2019-2020 so that we can use full annual bid data that match the main estimation sample period. Data for the last 5 years can be obtained from OASIS.[39] We focus our analysis on the *public bid data*. The main challenge, however, is that in CAISO each bidder can offer the same resource to the day-ahead energy market and potentially to one or more of the ancillary services markets. In addition, there is locational pricing (each bid submitted in CAISO is associated with a node of the power network) and different bid types (economic bids, multi-stage bids, and convergence bids) need to be considered. Since we are interested in a dataset comparable to the Spanish market, where we have individual price-quantity bids in the DAM, we rely on the work of Liski and Vehviläinen (2026) to pre-process the data.[40] Figure D.8 shows an example of the cumulative demand and supply bid curves based on individual bids for the same day: Wednesday, 18 April 2019, 10am. The 2019-2020 data consists of a total of 23m individual bids, of which 17.4m are supply bids. We convert the hourly bids to €/MWh in line with the main estimates of the bonus-malus and to be able to directly compare the European and US estimates.

Figure D.8: CAISO bidding data (California)



Notes: Example supply and demand bids for Thursday, 18 April 2019, 10am.

Estimation. In a first step, for each hour of the sample we construct the market clearing price based on the demand and supply bids so that all demand is covered. Note that we do

[39] `https://oasis.caiso.com/mrioasis/logon.do`

[40] The authors would like to thank Iivo Vehviläinen for making the dataset available and refer to the data appendix in Liski and Vehviläinen (2026) for a detailed description of the data cleaning procedure.

not consider electricity flows to neighboring markets (imports/exports). Second, we calculate the average load for each hour of the day in the sample period.[41] We take this average load as the expected electricity production in that hour (Q_0^*). Finally, to determine the value of the derivative, we first compute the market clearing price that corresponds to the average load in a given hour, and then increase the load by 1% of the average load to determine the counterfactual market clearing price that corresponds to this higher load level, $p_{Q_1^*}$. The derivative is then given by $(p_{Q_1^*} - p_{Q_0^*})/\Delta load$. Since there is heterogeneity in the hourly load pattern, we report the load-weighted average in Appendix Table D.2 and use this single value to determine the value of the bonus-malus with the decomposition.

E Empirical model for renewable energy investment

Section 6 summarizes the empirical model. This appendix gives additional implementation details and discusses the main data sources and model estimates.

E.1 Data and sample

We estimate the empirical model using state–technology-level investment in solar PV and onshore wind in Germany over the period 2015–2020. Our preferred specification excludes the city-states of Berlin, Bremen, and Hamburg, where investment dynamics may be governed by different constraints because of their high population density and limited land availability. The remaining states are characterized by state-specific simulated hourly wind and solar capacity factors (see also Appendix Section D.2) as well as state–year observations on installed capacity and investment. All states face a common national hourly wholesale electricity price.

The model inputs combine hourly observed day-ahead electricity prices and load, simulated state-level renewable-generation profiles, exogenous investment cost shifters, and an annual German merit-order curve for conventional technologies, such as nuclear, lignite, coal, gas, oil, and biomass. Hydro generation, pumped storage, and net imports are incorporated through the construction of effective demand rather than modeled as dispatchable technologies in the merit-order stack. We summarize the main data sources in the following list:

- **Investment and installed capacity.** State-by-year installed capacity and implied annual investment for solar and wind, in MW. Investment is approximated as the annual change in installed capacity.

  Source: Derived from official statistics, Marktstammdatenregister (see also Hülk et al., 2023) .

- **Hourly state-technology capacity factors.** Simulated hourly wind and solar capacity factors by German state, 2015–2020.

  Source: Renewables Ninja (Pfenninger et al. 2016 and Staffell et al. 2016).

[41] Given the large amount of data in the case of Spain, we perform the estimation on an annual sample.

- **Hourly demand and observed prices.** German hourly load and day-ahead market prices.

  Source: ENTSO-E.

- **Investment-cost shifters.** Technology-year LCOE midpoint series for German solar PV and onshore wind. The estimation uses the change relative to 2015 as an exogenous cost shifter.

  Source: Fraunhofer ISE (2021).

- **Merit order.** Annual merit-order stack built from Open Power System Data (OPSD) conventional plant capacity and fuel/CO_2/VOM assumptions.

  Source: OPSD, `https://open-power-system-data.org`. Marginal costs combine fuel prices (Agora Energiewende, industry estimates), EUA prices, IPCC emission factors, plant- or technology-level efficiency, and variable operating and maintenance (VOM) costs.

- **Historical policy.** German historical policy rates by technology and year.

  Source: Federal Ministry for Economic Affairs and Energy, Renewable Energy Sources Act - RES Act 2014. FiT tariffs and average quantity-weighted auction winning prices for solar and wind from 2017 onward Bundesnetzagentur (BNetzA).

- **Model-implied bonus-malus.** Lifetime captured-price minus lifetime average-price adjustments generated from the calibrated market-only simulation.

  Source: Model output.

- **Renewable auction outcomes.** Solar PV and onshore wind auction overview data used to discipline average awarded prices.

  Source: Bundesnetzagentur (BNetzA).

- **Wind bid distribution.** Auction round-level onshore wind bid support, including minimum and maximum bid values, awarded maximum bids, and losing- or excluded-bid information where available.

  Source: Bundesnetzagentur (BNetzA).

- **Solar bid distribution.** Solar bid quantiles $p10, p25, p50, p75, p90$ for the first 15 auction rounds. Missing rounds are extrapolated.

  Source: Proprietary data.

E.2 Details on the empirical model

The empirical model applies the theoretical investment cutoff at the state–technology level. For each state–technology pair $u = (s, i)$, where s indexes the state and $i \in \{\text{solar}, \text{wind}\}$ indexes the technology, let $k_{u,t}$ denote investment in year t. Productive capacity follows the same finite-vintage structure as in the theoretical model.[42]

Wholesale prices. Wholesale prices are generated in two steps. First, a national German merit-order curve maps residual demand into a raw scarcity price. In year t and hour h, residual demand is

$$Q_{t,h} = \max\left\{ D_{t,h} - \sum_{u} \omega_{u,t,h} K_{u,t}, 0 \right\},$$

and the raw merit-order price is

$$p_{t,h}^{MO} = MC_t(Q_{t,h}).$$

Because the engineering merit order does not capture bidding behavior, outages, ramping constraints, storage, cross-border scarcity, and negative prices, we augment it with a post-merit-order calibration:

$$p_{t,h} = \Phi_t\big(p_{t,h}^{MO}, Q_{t,h}, W_{t,h}, S_{t,h}\big),$$

where $W_{t,h} = \sum_{u \in \mathcal{W}} \omega_{u,t,h} K_{u,t}$ and $S_{t,h} = \sum_{u \in \mathcal{S}} \omega_{u,t,h} K_{u,t}$ are aggregate wind and solar output implied by state-level capacity factors and installed capacity. The mapping $\Phi_t(\cdot)$ is calibrated separately by year using observed German day-ahead prices. It includes the raw merit-order price, residual demand, aggregate renewable output, and indicators for residual demand and total renewable output above their respective 90th percentiles. This procedure preserves the structural residual-demand channel, so renewable investment feeds back into wholesale prices, while improving the model's fit to price dispersion, negative-price frequency, and the covariance between renewable output and prices.[43]

Define

$$x_{t,h} = \big(p_{t,h}^{MO}, Q_{t,h}, Q_{t,h}^2, W_{t,h}, S_{t,h}, W_{t,h} + S_{t,h}, \mathbf{1}\{Q_{t,h} \geq q_t^{90}\}, \mathbf{1}\{W_{t,h} + S_{t,h} \geq r_t^{90}\}\big)',$$

where q_t^{90} and r_t^{90} are the within-year 90th percentiles of residual demand and total renewable

[42] In line with Section 4.2, we set the lifetime of a renewable plant to $T_i = 20$ years, equal to the policy horizon, and assume $\lambda_i = 0.99$ and $\rho = 0.96$ for both technologies. Hence, $\beta_i = \rho\lambda_i \approx 0.95$. We examine alternative lifetime and discounting assumptions in the robustness analysis. Pre-sample capacity is treated as a depreciating legacy stock.

[43] The uncalibrated merit-order model performs reasonably well in matching average wholesale prices but understates price dispersion. This matters because price dispersion and its covariance with renewable output determine captured prices and the model-implied bonus–malus.

output. The calibrated price is

$$p_{t,h} = \Phi_t(x_{t,h}) = \mathcal{Q}_t\left[\gamma_{0t} + \sum_{j=1}^{8} \gamma_{jt} \frac{x_{j,t,h} - \bar{x}_{jt}}{\sigma_{jt}}\right].$$

We estimate the first-stage price mapping using ridge regression, which minimizes the sum of squared prediction errors plus a small penalty, $\kappa \sum_j \gamma_{jt}^2$, on the standardized slope coefficients. We set $\kappa = 10^{-6}$ and leave the intercept unpenalized. The penalty ensures a numerically stable solution in the presence of highly correlated price, residual-demand, and renewable-output regressors.

The year-specific coefficients are reported in Table E.6. We keep the coefficients fixed in all policy counterfactuals. Counterfactual investment nevertheless changes prices through residual demand and renewable output. The two 90th-percentile thresholds are recomputed within each counterfactual year. If the first-stage index lies outside its historical support, the quantile map assigns the observed within-year minimum or maximum price. The counterfactuals should therefore be interpreted as policy simulations under a stable calibrated price mapping.

Investment. The empirical model has two layers. The inner layer solves the renewable investment equilibrium implied by a candidate parameter vector θ, a policy regime P, and feasible build potentials $\bar{k}_u$. The outer layer estimates θ by matching simulated and observed moments.

For a project installed in year t, define expected discounted lifetime output per MW, $Y_{u,t}$, and expected discounted market revenue per MW, $M_{u,t}$, as

$$Y_{u,t} = 8760 \sum_{\ell=0}^{T_i-1} \beta_i^\ell \mathbb{E}_h[\omega_{u,t+\ell,h}], \qquad M_{u,t} = 8760 \sum_{\ell=0}^{T_i-1} \beta_i^\ell \mathbb{E}_h[\omega_{u,t+\ell,h} p_{t+\ell,h}].$$

Thus, $Y_{u,t}$ is measured in discounted MWh per installed MW and $M_{u,t}$ in discounted Euro per installed MW. Under market-only remuneration, the corresponding lifetime revenue per MWh is $R_{u,t}^M = \frac{M_{u,t}}{Y_{u,t}}$, which is the discounted lifetime captured price of the project. Under a FiT, producers receive a fixed price $F_{i,t}$ per MWh over the contract horizon. Because the contract horizon equals the assumed project lifetime in the preferred specification, the relevant levelized revenue is $R_{u,t}^{FiT} = F_{i,t}$.[44]

Let $c_{j,u,t} \equiv \frac{r_{j,u,t}}{Y_{u,t}}$ be the project j's levelized cost in €/MWh, where $r_{j,u,t}$ is the cost per MW installed as defined by the theoretical model. Because project-level costs are unobserved, we parameterize heterogeneity in levelized project costs as

$$c_{j,u,t} = \mu_i + \xi_{i,t} + s_i \varepsilon_{j,u,t}, \qquad \varepsilon_{j,u,t} \sim \text{Logistic}(0,1),$$

[44] More generally, if the project lifetime exceeds the support horizon, $R_{u,t}^{FiT}$ combines fixed-tariff revenue during the contract period with market revenue over the remaining lifetime.

where μ_i determines the baseline midpoint of the technology-specific cost distribution, $\xi_{i,t}$ shifts that distribution over time, and $s_i > 0$ controls dispersion across projects. Let

$$G_{i,t}(x) \equiv \Pr(c_{j,u,t} \leq x) = \Lambda\left(\frac{x - \mu_i - \xi_{i,t}}{s_i}\right).$$

The share of feasible projects satisfying the profitability condition is $G_{i,t}(R_{u,t})$, so aggregate investment is

$$k_{u,t} = \bar{k}_u G_{i,t}(R_{u,t}).$$

The empirical logistic CDF is therefore a parametric representation of the theoretical project-cost distribution after installation costs and revenues have both been normalized by expected discounted lifetime generation. In the preferred specification, we further assume that the technology-year cost shift can be decomposed into two terms:

$$\xi_{i,t} = \Delta c_{i,t}^{\text{LCOE}} + \eta_{i,t}, \qquad \Delta c_{i,t}^{\text{LCOE}} = c_{i,t}^{\text{LCOE}} - c_{i,2015}^{\text{LCOE}}.$$

We normalize the external LCOE component to zero in 2015. It thus disciplines the common evolution of technology costs rather than their absolute level. The parameter μ_i determines the baseline level, while $\eta_{i,t}$ captures residual technology-year investment conditions not explicitly modeled, including financing and permitting conditions, supply-chain constraints, auction design, and public acceptance.[45]

Finally, the feasible state-technology build potential $\bar{k}_u$ is constrained using observed state-level capacity scale:

$$\bar{k}_u = \alpha_i \max_t K_{u,t}^{obs}.$$

The technology-specific build-rate α_i is calibrated from the maximum observed investment-to-capacity ratio across states in the sample. This prevents the model from allocating unlimited investment to states with the highest estimated revenue.

Because project-level cost data are unavailable, the preferred specification imposes common cost-distribution parameters within each technology and year. State heterogeneity consequently enters primarily through renewable output profiles, captured prices, existing capacity, and feasible build potential rather than through directly observed state-specific project costs. Investment in each state-technology-year is thus the solution to a cutoff problem. A continuum of projects has heterogeneous costs distributed according to a logistic CDF $G_{i,t}(\cdot)$. Projects invest when their policy-adjusted lifetime revenue exceeds their cost. Aggregating

[45] The external LCOE series depends on assumptions about financing, plant lifetimes, operating costs, and representative capacity factors. We therefore interpret $\Delta c_{i,t}^{\text{LCOE}}$ as an external proxy for the technology-level cost trend rather than as a direct observation of each project's structural cost. The model is also estimated without this shifter as a robustness check.

over projects gives:

$$k_{u,t}(\theta, P) = \bar{k}_u G_{i,t}\left(R_{u,t}(K(\theta, P), P) - \xi_{i,t}; \mu_i, s_i\right).$$

Because renewable capacity changes residual demand and therefore prices, investment is solved as a fixed point, which is an investment-price equilibrium. Given an investment path, the model constructs renewable capacity, clears the national wholesale market hour by hour, computes each state-technology cell's discounted revenue index, and updates investment using the cutoff rule. The numerical algorithm iterates on the cutoff-implied investment path. If $\widetilde{k}_{u,t}(k^m)$ denotes the investment level implied by applying the cutoff rule to the capacity and price path generated by the current iterate k^m, the damped log update is

$$\log k_{u,t}^{m+1} = (1-\zeta)\log k_{u,t}^{m} + \zeta \log \widetilde{k}_{u,t}(k^m), \qquad \zeta = 0.6.$$

Iterations stop when the maximum absolute change in log investment is below 10^{-6}. The numerical damping weight ζ determines how much weight to put on the newly implied investment path. Damping improves numerical stability because a discrete investment update can substantially affect residual demand, wholesale prices, and subsequent investment incentives.

Model solution and estimation. For a given parameter vector θ, policy regime P, and feasible build potential $\bar{k}_u$, investment in each state-technology-year is the solution to the above stated cutoff problem. Under remuneration schemes in which project revenue depends on wholesale prices, renewable investment changes residual demand and prices, which in turn affect investment incentives. We therefore solve the following investment–price fixed point:

$$\begin{cases} k_{u,t} = \bar{k}_u G_{i,t}(R_{u,t}(\mathbf{K}, P)), \\ K_{u,t} = \lambda_i^{t-t_0} K_{u,t_0}^{legacy} + \sum_{a=0}^{\min\{t-t_0, T_i-1\}} \lambda_i^a k_{u,t-a}, \\ p_{t,h}^{MO} = MC_t\left(\max\left[D_{t,h} - \sum_u \omega_{u,t,h} K_{u,t}, 0\right]\right), \qquad p_{t,h} = \Phi_t(p_{t,h}^{MO}, Q_{t,h}, W_{t,h}, S_{t,h}). \end{cases}$$

Here, $R_{u,t}(\mathbf{K}, P)$ denotes policy-specific discounted lifetime revenue per MWh, calculated using the wholesale-price path generated by the aggregate capacity path $\mathbf{K}$. The term $K_{u,t_0}^{\text{legacy}}$ denotes productive capacity installed before the first modeled investment year.

Forward-looking revenue driver and terminal value. Revenue drivers are computed over the lifetime of the asset, with $T_i = 20$, $\lambda_i = 0.99$, $\rho = 0.96$. For market-only remuneration, $R_{u,t}$ is the discounted lifetime captured price. For FiT remuneration, the model pays the historical tariff $F_{i,t}$ during the 20-year contract window. Because hourly price and capacity-factor data are observed only through 2020, the preferred terminal-value convention repeats the 2020 price and capacity-factor environment whenever $t+\ell > 2020$. This preserves lifetime incentives for late-sample investments, but it rules out post-2020 structural changes in prices, technology costs, and renewable profiles.

Time shifters. Our preferred specification uses a smooth quadratic time shifter for both technologies:

$$\eta_{i,t} = a_i \tau_t + b_i \tau_t^2, \qquad \tau_t = \frac{t - 2015}{2020 - 2015}.$$

The first year is normalized to zero, $\eta_{i,2015} = 0$. The shifter captures common technology-year changes not otherwise captured by market value, policy rates, state-level capacity factors, and the exogenous LCOE trend. Economically, it is best interpreted as a residual time-varying investment wedge: permitting constraints, auction design, financing conditions, local acceptance, grid access, supply-chain factors not captured by the LCOE midpoint, or other non-modeled factors. A negative combined wedge $\xi_{i,t}$ raises effective investment incentives because the cutoff is applied to $R_{u,t} - \xi_{i,t}$. A positive value lowers effective incentives.

E.3 Identification and Estimation

E.3.1 Moments

The model is estimated by minimizing a weighted sum of moment losses. We use five sets of moments that are equally weighted, where all revenue and price quantities are expressed in €/MWh (number of moments in parentheses).

1. **Investment (156)**: log deviations between observed and simulated state-year-technology investment.
2. **Wholesale prices (42)**: Germany annual mean, standard deviation, negative-price frequency, $p05$, $p50$, $p90$, and $p95$ of day-ahead prices.
3. **Captured prices (156)**: state-technology captured prices computed from observed hourly prices and simulated state capacity factors.
4. **Auction outcomes (18)**: annual awarded auction prices for solar and wind.
5. **Bid-distribution (90)**: annual solar bid quantiles $p10, p25, p50, p75, p90$ as well as minimum bid, maximum bid, awarded-maximum bid, and losing- or excluded-bid information for wind bids.

E.3.2 Objective Function

Let $m_g(\theta)$ denote the normalized loss for moment group g. The estimator solves:

$$\widehat{\theta} = \arg\min_{\theta} \sum_{g} w_g m_g(\theta),$$

with $w_g = 1$ for all five moment groups in the preferred specification. The calibrated objective is evaluated by solving the investment-price fixed point, fitting the post-merit-order

price calibration, and re-solving the fixed point with calibrated prices. We minimize the loss function using the derivative-free Powell algorithm. The optimization is initialized at the parameter estimates from the preceding specification and subject to the parameter bounds reported below.

$$\mu_i \in [0, 200], \qquad s_i \in [1, 100], \qquad a_i, b_i \in [-250, 250].$$

More explicitly, the investment component is:

$$m_{\text{inv}}(\theta) = \frac{1}{N} \sum_{u,t} \left[\log\left(k_{u,t}^{obs} + \epsilon\right) - \log\left(k_{u,t}^{sim}(\theta) + \epsilon\right) \right]^2,$$

where $\epsilon = 10^{-6}$. Price, captured-price, auction-price, and bid-distribution losses are mean squared percentage deviations from the corresponding observed moments. For each candidate θ, the inner model first solves an uncalibrated investment-price fixed point. The resulting market-only capacity path is used to fit $\Phi_t(\cdot)$ to observed day-ahead prices. The model then re-solves the investment-price fixed point using calibrated prices, and the moment losses are evaluated on this calibrated equilibrium. Thus the estimation problem is nested:

$$\min_{\theta} \mathcal{L}\left(k^{sim}(\theta), p^{sim}(\theta), CP^{sim}(\theta), Q^{bid,sim}(\theta)\right) \quad \text{subject to investment fixed point above.}$$

We report state-cluster bootstrap confidence intervals. The bootstrap resamples the 13 German states with replacement, keeps the full 2015–2020 panel for each sampled state, re-weights the state-level investment and captured-price moments by the bootstrap state counts, and re-estimates the calibrated full-hour model from the baseline parameter vector. The confidence intervals therefore capture approximate finite-sample uncertainty arising from regional variation, conditional on the national data and other model inputs, rather than the model's full sampling uncertainty.

We address two potential sources of numerical multiplicity. Ten parameter multi-starts are used for the non-convex outer estimation problem. At the selected parameters, the inner investment-price fixed point is re-solved from 14 dispersed initial investment paths, all of which converge to the same allocation within numerical tolerance. We therefore find no evidence of equilibrium multiplicity at the preferred estimates, although this exercise is not a formal proof of global uniqueness or global optimality.

E.4 Estimation Results

E.4.1 Parameter Estimates

Table E.1 reports the estimated model parameters together with their 95% confidence interval. The objective value is 0.317, and was derived from a 10 multi-start solution. Bootstrap standard errors and confidence intervals are based on 100 state-cluster bootstrap draws.

The parameter estimates should be interpreted through the effective cutoff $c_{i,t}^{eff} = \mu_i + \xi_{i,t}$. The raw wind midpoint is $\mu_{\text{wind}} = 2.83$ €/MWh and should not be interpreted as an

Table E.1: Estimated parameters, empirical investment model

Parameter	Estimate	Boot. SE	95% CI	Interpretation
μ_{solar}	90.20	0.89	[88.19, 91.91]	Solar normalized 2015 project-cost midpoint.
s_{solar}	4.20	0.43	[3.25, 4.80]	Solar project-cost dispersion / investment responsiveness.
a_{solar}	-44.70	1.34	[-47.33, -41.89]	Linear component of residual solar investment shifter.
b_{solar}	32.02	1.32	[29.14, 34.79]	Quadratic component of residual solar investment shifter.
μ_{wind}	2.83	1.95	[0.00, 6.63]	Wind normalized 2015 project-cost midpoint.
s_{wind}	3.96	0.38	[3.34, 4.63]	Wind project-cost dispersion / investment responsiveness.
a_{wind}	181.63	0.99	[179.60, 183.83]	Linear component of residual wind investment shifter.
b_{wind}	-109.13	1.84	[-112.22, -104.80]	Quadratic component of residual wind investment shifter.

engineering cost. Rather, it is the normalized 2015 intercept left after the LCOE shifter and the residual wind time shifter are included. The effective wind cutoff rises strongly over the sample, mainly because the positive residual wind shifter more than offsets the modest LCOE decline. Economically, this points to a worsening residual investment environment for wind after the policy transition, consistent with permitting, auction, grid, and local-acceptance constraints that are not captured by market value or LCOE alone. The solar midpoint starts near 90 €/MWh and the effective cutoff falls substantially by 2020, reflecting the large solar LCOE decline and a negative residual solar shifter over most of the sample. The dispersion parameters remain small, implying steep but not deterministic investment responses around the cutoff. As in the case of wind, this should be interpreted as a reduced-form project-opportunity schedule rather than a directly observed cost distribution.

Table E.2: Bootstrap uncertainty for effective cutoffs, €/MWh

Technology	Statistic	Bootstrap mean	Bootstrap SE	95% CI
Solar	2015 effective cutoff	90.12	0.91	[88.21, 92.01]
Solar	2020 effective cutoff	44.79	0.61	[43.56, 45.89]
Solar	$\Delta_{2020-2015}$	-45.33	0.84	[-46.72, -43.55]
Wind	2015 effective cutoff	2.57	1.96	[0.00, 6.61]
Wind	2020 effective cutoff	66.44	1.02	[64.82, 68.35]
Wind	$\Delta_{2020-2015}$	63.87	2.19	[60.05, 67.97]

Table E.3: Implied time shifters $\eta_{i,t}$, €/MWh

Technology	2015	2016	2017	2018	2019	2020
Solar	0.00	-7.66	-12.76	-15.29	-15.27	-12.68
Wind	0.00	31.96	55.19	69.69	75.46	72.49

E.4.2 Investment Fit and Price Calibration

Table E.4 summarizes aggregate investment fit over 2015–2020. The fit is reasonably good for both wind and solar, although it is tighter for solar. Figure 3 in the main text further shows that the model matches the broad time profile of solar investment, as well as the decline in wind investment after 2017. The model's excess wind investment is concentrated mainly in the first two years of the sample.

Table E.4: Investment fit by technology, 2015–2020

Technology	Observed MW	Fitted MW	Fit/Observed	RMSE MW
Solar	16,801	16,219	96.5%	74.8
Wind	18,653	22,855	122.5%	165.8
Total	35,455	39,075	110.2%	–

Price fit is summarized in Table E.5. The post-merit-order calibration substantially improves the fit of the price distribution, as shown by comparing Columns (1) and (2). The raw merit-order specification in Column (2) evaluates the same estimated parameters without the ex-post calibration of the price distribution. It shows that the merit-order curve alone performs reasonably well in matching average and median prices, but performs less well in capturing the extremes of the price distribution.

We report the year-specific coefficients from the ex-post calibration in Table E.6.

Table E.5: Germany price calibration, 2015–2020

Statistic	Calibrated simulated (1)	Raw merit order (2)	Observed (3)
Mean price, €/MWh	34.63	32.67	34.60
Standard deviation, €/MWh	16.87	8.03	16.58
Negative-price frequency	2.0%	0.0%	1.9%
$p05$, €/MWh	9.97	18.94	9.98
$p50$, €/MWh	34.04	31.81	34.03
$p90$, €/MWh	53.27	43.72	53.32
$p95$, €/MWh	60.62	45.03	60.42

Table E.7 reports the model-implied bonus-malus values.

E.5 Counterfactuals

E.5.1 Investment Under Alternative Remuneration Rules

Table E.8 reports bootstrap confidence intervals for the main counterfactual differences in total investment. It shows that the qualitative ranking is stable to resampling the regional

Table E.6: Post-merit-order price-calibration coefficients

Variable	2015	2016	2017	2018	2019	2020
Intercept	31.8351	28.9822	34.1855	44.4697	37.6681	30.4717
Raw merit-order price, p^{MO}	-0.8557	0.3422	-1.8493	0.0175	0.2515	-0.0600
Residual demand, Q	8.9166	4.4735	16.9157	-5.9963	9.0990	9.0837
Residual demand squared, Q^2	-3.7601	-0.0972	-11.2781	11.2118	-3.6376	-1.8556
Wind output, W	-3.3045	-3.0422	-5.2203	-5.6889	-5.3263	-5.3631
Solar output, S	1.3794	1.0512	1.3769	1.9716	1.7641	0.5596
Total renewable output, $W + S$	-1.3693	-1.4051	-3.1099	-2.8883	-2.6600	-3.5091
High-residual-demand indicator	0.6497	-0.1479	0.6833	-1.6410	1.1105	0.0593
High-renewable-output indicator	0.4482	-0.2268	1.0956	-0.7580	-0.4200	-0.3614

Notes: Coefficients apply to within-year standardized regressors.

Table E.7: Model-implied lifetime bonus-malus values, €/MWh

Technology	All years, 2015–2020			Last year, 2020		
	Mean	Min.	Max.	Mean	Min.	Max.
Solar	-3.72	-4.81	-2.56	-4.34	-4.81	-3.54
Wind	-5.77	-6.80	-4.53	-5.72	-6.80	-4.58

investment environments.

Table E.8: State-cluster bootstrap intervals for counterfactual investment, GW

Scenario	Investment	Diff. vs mkt	95% CI diff. vs mkt	Diff. vs FiT	95% CI diff. vs FiT
Historical FiT	39.07	27.40	[25.70, 29.64]	0.00	[0.00, 0.00]
Market only	11.86	0.00	[0.00, 0.00]	-27.40	[-29.64, -25.70]
Lifetime average price	14.68	2.80	[2.50, 3.06]	-24.60	[-26.69, -23.04]
Avg. price + model avg. BM	11.99	0.13	[0.12, 0.15]	-27.27	[-29.51, -25.58]
Avg. price + model state BM	11.86	0.00	[0.00, 0.00]	-27.40	[-29.64, -25.70]

E.5.2 Budget-neutral adjusted FiT design

Finally, we report additional results for the budget-neutral adjusted-FiT counterfactual. The annual base component is determined endogenously. In the technology-neutral version, the target is the annual-equivalent support obligation associated with the simulated historical-policy investment cohort installed in year t:

$$B_t^{\text{cohort,hist}} = \sum_u k_{u,t}^{\text{hist}} \bar{\omega}_{u,t} 8760 F_{i(u),t}^{\text{hist}},$$

where $i(u)$ denotes the technology associated with state-technology cell u. This measure is the expected tariff payment for one representative operating year to the cohort installed in t. For a trial value of the common base component F_t, the model applies

$$F_{u,t}^{\mathrm{adj}}(F_t) = \max\left\{F_t + BM_{u,t-1}^{\mathrm{model}}, 0\right\},$$

re-solves the investment-price fixed point, and computes the resulting annual-equivalent cohort obligation:

$$\widehat{B}_t^{\mathrm{cohort,adj}}(F_t) = \sum_u k_{u,t}^{\mathrm{adj}}(F_t)\bar{\omega}_{u,t}8760F_{u,t}^{\mathrm{adj}}(F_t).$$

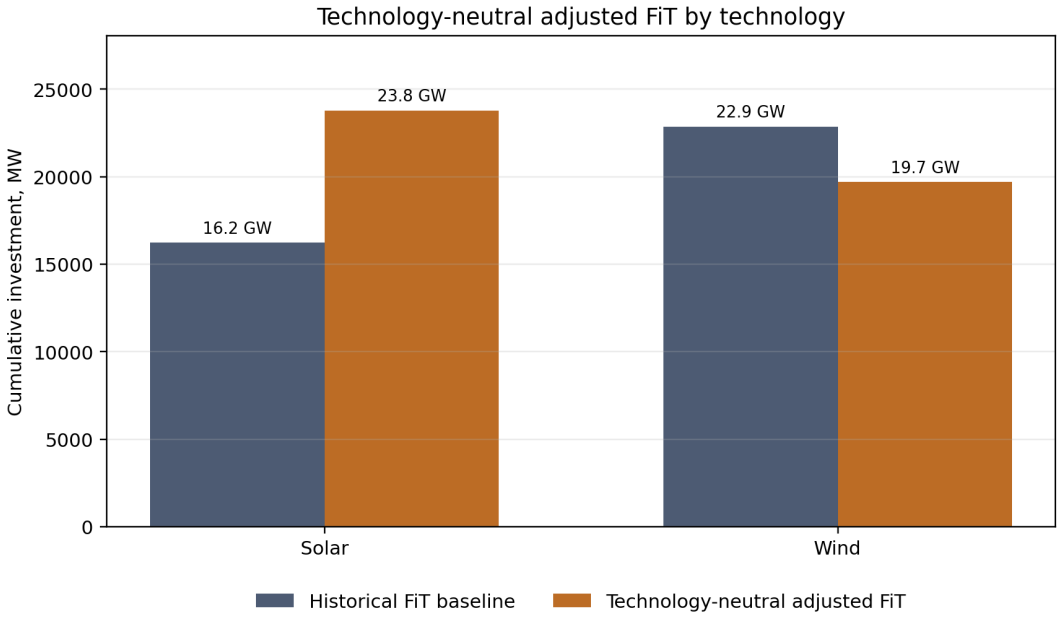
The common component F_t is chosen so that

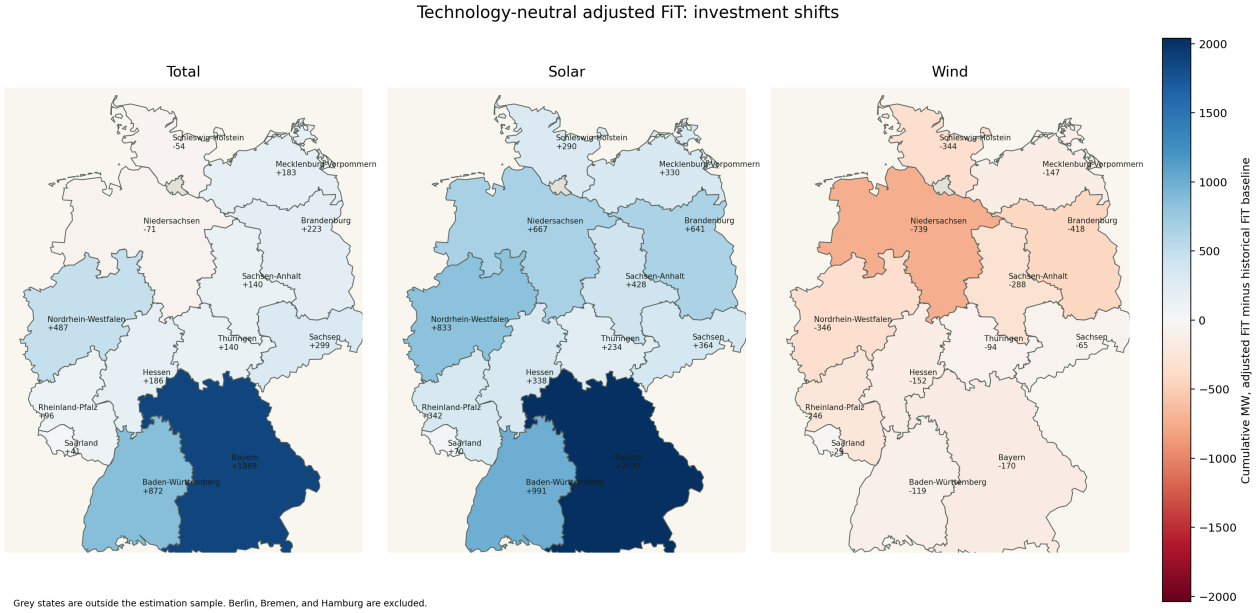
$$\widehat{B}_t^{\mathrm{cohort,adj}}(F_t) = B_t^{\mathrm{cohort,hist}}$$

up to numerical tolerance. Investment is re-solved at every trial value, so the calculation incorporates the endogenous investment response to the tariff.

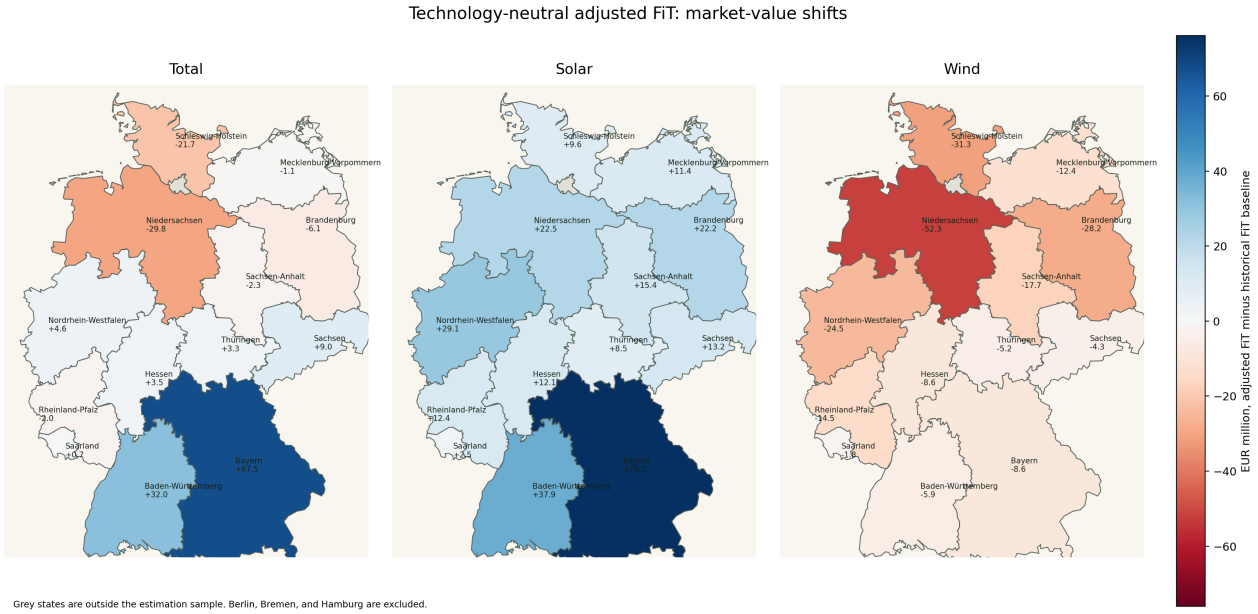
Figures E.1 and E.2 show the impact of the technology-neutral adjusted FiT on the technology mix and geographic distribution of investment, together with its implied market value.

Figure E.1: Investment shifts by technology under the technology-neutral pooled adjusted FiT.





(a) Total investment (MW)



(b) Shifts in market value

Figure E.2: State-technology shift in investment and market value under the pooled adjusted FiT.

E.5.3 Robustness

To assess the robustness of our numerical estimates, we re-estimate the model under alternative assumptions about discounting and asset lifetimes, and also omit the exogenous cost shifters. Changing the discount factor has only modest effects on the scale of market-based investment, and the qualitative ranking remains unchanged. Extending the accounting horizon to 25 years while keeping the FiT contract length fixed at 20 years has a larger effect on market-based investment. However, because this specification places additional weight on 2020 values, we prefer to keep the valuation horizon aligned with the observed German 20-year FiT contract in the main specification and treat longer-horizon specifications as robustness checks.

Excluding the cost shifters has only a limited effect on simulated investment, but slightly worsens the overall model fit and makes the time shifters more difficult to interpret. We therefore retain the cost shifters in our preferred specification.

Table E.9: Robustness to lifetime and discounting conventions

Specification	Objective	Historical FiT GW	Market only GW	Lifetime average price GW	Lifetime average + state BM GW
Main: $T_i = 20, \rho = 0.96$	0.317	39.07	11.86	14.68	11.86
Robustness: $T_i = 20, \rho = 0.93$	0.317	39.07	11.90	14.75	11.90
Robustness: $T_i = 20, \rho = 0.975$	0.317	39.07	11.83	14.64	11.83
Robustness: $T_i = 25, \rho = 0.96, H^{FiT} = 20$	0.321	37.60	13.76	16.96	13.76
Robustness, no cost shifter	0.335	39.08	11.86	14.68	11.99